National and Kapodistrian University of Athens

Department of English Language and Literature

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Artificial Intelligence (AI) in Translation and Interpreting: Exploring AI's Potential in Translation and Interpreting Profession and Pedagogy in the Medical Context and its Ethical Implications

Chrysoula Gatsiou

ID number: 7563112200002

Supervisor:

Dr. Effrosyni Fragkou

Examination Committee:

Asst. Prof. Anna Hatzidaki

Dr. Diamantoula Korda

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Declaration

This submission is my own work. Any quotation from, or description of, work of others is acknowledged herein by reference to the sources, whether published or unpublished.

Author

Chrysoula Gatsiou

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To Dimitra

Abstract in English

Artificial Intelligence has a central place in modern life due to its vast applicability to several domains of human activity. Within this context, artificial intelligence interacts in a dynamic way with the fields of translation and interpreting. This new state of affairs raises serious questions about the evaluation of the impact that artificial intelligence-inspired technology has on the professional practice of translation and interpreting. This study aims at addressing this concern by exploring the synergy between artificial intelligence and translation and interpreting. To this end, our work focuses on exploring the potentiality of artificial intelligence in professional and educational settings as well as the ethical implications of this synergy. The research design draws upon the mixed methods approach to scientific inquiry and uses an embedded design for data collection, coding, analysis and interpretation. The data are collected, processed, and interpreted both quantitively and qualitatively. The research instrument of the study is a tripartite web-based survey addressing three different categories of respondents, namely professional translators and/or interpreters, educators and students within the translation and interpreting field. Its goal is twofold: (1) to examine the targeted respondents 'attitudes towards embedding artificial intelligence technologies in the translation and interpreting profession and especially in medical/healthcare settings and (2) to gain insight into the perspectives of educators and students in the field of translation and interpreting studies. The findings show that there is a consensus as to the advantages and disadvantages of the interplay between artificial intelligence and the practice of translation and interpreting and the ethical prerequisites that should be in effect to ensure trustworthy artificial intelligence use.

Keywords: artificial intelligence, educators, ethical implications, medical/healthcare setting, professionals, students

Abstract in Greek

Η Τεχνητή Νοημοσύνη διαδραματίζει κεντρικό ρόλο στη σύγχρονη ζωή λόγω της ευρείας εφαρμογής της σε διάφορους τομείς της ανθρώπινης δραστηριότητας. Στο πλαίσιο αυτό, η τεχνητή νοημοσύνη αλληλεπιδρά δυναμικά με τους τομείς της μετάφρασης και της διερμηνείας. Αυτή η καινούργια πραγματικότητα εγείρει σοβαρά ερωτήματα σχετικά με την αξιολόγηση του αντίκτυπου που έχει η τεχνολογία τεχνητής νοημοσύνης στην επαγγελματική πρακτική της μετάφρασης και της διερμηνείας. Η παρούσα μελέτη αποσκοπεί στην εξέταση του προβληματισμού σχετικά με τη σύμπραξη μεταξύ της τεχνητής νοημοσύνης και της μετάφρασης και διερμηνείας. Για τον σκοπό αυτό, η έρευνά μας επικεντρώνεται στη μελέτη των δυνατοτήτων της τεχνητής νοημοσύνης σε επαγγελματικά και εκπαιδευτικά περιβάλλοντα, καθώς και των ηθικών επιπτώσεων αυτής της συνέργειας. Ο ερευνητικός σχεδιασμός βασίζεται στην προσέγγιση των μεικτών μεθόδων επιστημονικής έρευνας και χρησιμοποιεί έναν ερευνητικό σχεδιασμό που στηρίζεται στην ενσωμάτωση μεθόδων για τη συλλογή, κωδικοποίηση, ανάλυση και ερμηνεία δεδομένων. Τα δεδομένα συλλέγονται, επεξεργάζονται και ερμηνεύονται τόσο ποσοτικά όσο και ποιοτικά. Το ερευνητικό εργαλείο της μελέτης αποτελεί μια τριμερής διαδικτυακή έρευνα που απευθύνεται σε τρεις ομάδες, δηλαδή σε επαγγελματίες μεταφραστές και/ή διερμηνείς, εκπαιδευτικούς και φοιτητές στον τομέα της μετάφρασης και της διερμηνείας. Ο στόχος της είναι διττός: (1) να εξετάσει τη στάση των επιλεχθεισών ομάδων απέναντι στην ενσωμάτωση τεχνολογιών τεχνητής νοημοσύνης στο επάγγελμα της μετάφρασης και της διερμηνείας και ιδίως σε περιβάλλοντα ιατρικής/υγειονομικής περίθαλψης και (2) να αντλήσει πληροφορίες σχετικά με τις προοπτικές των εκπαιδευτικών και των φοιτητών στον τομέα των σπουδών μετάφρασης και διερμηνείας. Τα ευρήματα δείχνουν ότι υπάρχει σύμπνοια όσον αφορά τα πλεονεκτήματα και τα μειονεκτήματα της αλληλεπίδρασης μεταξύ της τεχνητής νοημοσύνης και της πρακτικής της μετάφρασης και της διερμηνείας και τις ηθικές και δεοντολογικές προϋποθέσεις που θα πρέπει να ισχύουν για να διασφαλιστεί η αξιόπιστη χρήση της τεχνητής νοημοσύνης.

Λέξεις-κλειδιά: εκπαιδευτικοί, επαγγελματίες, ηθικές επιπτώσεις, περιβάλλοντα ιατρικής/υγειονομικής περίθαλψης, τεχνητή νοημοσύνη, φοιτητές

Table of contents

Chapter 1

Introduction

Today, Artificial Intelligence (henceforth AI) has entered many spheres of human activity, including the Language Services Industry (Presas, Cid-Leal and Torres-Hostench 2016). Translators and Interpreters are integral parts of the Language Services Industry and, as such, are directly faced with the new state of affairs that AI has brought about in their professional life. The increasing attention that AI draws in the field of Translation and Interpreting is evidenced by the worldwide mobilisation on the part of several stakeholders directly influenced by the dynamic emergence of AI-powered translation and interpreting technology, including, among others, authorities (e.g., the European Union's Directorate-General for Translation), national and international translator and interpreter associations (e.g., the International Association of Conference Interpreters). Examples of action towards increasing awareness and educating translators and interpreters regarding the interplay between AI and translation (regardless of medium) are, among other things, the Translating Europe Workshops[1] organised under the auspices of the European Commission.

Building on the 'new' AI-inspired reality in Translation and Interpreting, this study aims at exploring the potentiality of AI applications in the Greek Translation and Interpreting professional and pedagogical context, and the ethical implications of integrating AI technology in performing translation and interpreting tasks. Although the study situates the research inquiry in the medical domain, in essence, it attempts a holistic exploration of the synergy between AI, on the one hand, and Translation and Interpreting, on the other hand. The study starts with a comprehensive review of the up-to--date literature regarding the technological, professional, pedagogigal, and ethical facets of AI as they

[1] https://commission.europa.eu/about-european-commission/departments-and-executive-agencies/translation/translating-europe/translating-europe-workshops-tew_en

manifest in the Translation and Interpreting domain (*Chapter 2*). In *Chapter 3*, we focus on presenting the methodological foundations of the research. The research design abides by the principles of *Mixed Methods Approach* to research and utilises an *Embedded Design* for the collection and analysis of the data which are of both quantitative and qualitative nature. The following chapter delves into the primary axes of the research. To this end, we offer an extensive overview of the birth and evolution of AI technology while exploring the synergy between AI and Translation and Interpreting pedagogy. With regards to pedagogy, this part of *Chapter 4* examines the degree of AI-inspired technology integration in the context of tertiary education worldwide (i.e., Europe, United States of America, United Kingdom, Asia, and Australia) and in Greece. *In Chapter 5*, we analyse the findings we collected from the web-based survey which targeted three groups of respondents, namely professional translators and interpreters, educators, and trainers in the field of Translation and Interpreting Studies, and student translators and interpreters. The analysis of the findings is carried out on two levels, i.e., the first level involves the quantitative analysis of the data (sections 5.1-5.3), whereas, at the second level, we implement a qualitative approach to data analysis focusing on identifying and classifying commonalities and/or deviations discourse-wise (section 5.4). In *Chapter 6,* we underline central limitations inherent to our research design. Finally, *Chapter 7* summarises the main findings of the study, highlights the significance of the study, and suggests inquiry pathways for future research.

Chapter 2

Literature Review

Ever since the very first inception of a machine that would assist translators during performing a translation task, AI is believed to be capable of overcoming the language barriers involved in interlingual communication. A prime example is the integration of AI-inspired MT technology into the Directorate-General for Translation of the European Commission that dates back to the 1970s and still continues today (Rummel 2019).

In the translation and interpreting reality specifically, AI's impact, being a synergy among various disciplines (i.e., computing science, computational engineering, linguistics, to name a few) has been significant. Historically, the groundbreaking "news" regarding a computer-like machine with a capacity to facilitate translation tasks gained momentum via Weaver and Booth's groundbreaking work in the 40s[2]. From that point on, but especially, nowadays, the growing interest in an in-depth study of the use of AI in the field of Translation and Interpreting (henceforth T&I) lies at the center of research inquiry. The increased attention to the synergy between AI and T&I is reinforced by the recent advances in AI and its applicability to the translation (Herbig, Pal, van Genabith, Krüger 2019) and interpreting industry (Fantinuoli 2018) which are reflected in the language mediation practice, i.e., Machine Translation (henceforth MT), Computer Assisted Interpreting (henceforth CAI), Natural Language Processing (henceforth NLP),and Post-editing (henceforth PE).

The contribution of the recent advances in AI and its growing applicability to the translation (Herbig et. al 2019) and interpreting industry (be it to a lesser extent) (see Fantinuoli, 2018), Machine Translation (henceforth MT), Computer Assisted

[2] See section 4.

Interpreting (henceforth CAI), Natural Language Processing (henceforth NLP), and Post-editing (henceforth PE) have almost monopolised the interest of researchers.

To provide the reader with an overview of the core issues which have stem from the corresponding literature, this review will explore the depth and breadth of AI implementation in T&I. Our focus is three-fold. Firstly, the review will cover works that aim at studying the points of intersection between AI and T&I. Secondly, we will discuss the integration of AI into T&I pedagogy, whilst the final section will offer an account of AI's ethical component in relation to the professional practice in translation and interpreting in the era of transhumanism.

2.1 Reviewing AI in T&I

The potency of AI's impact in the T&I industry is shown in the proliferation of works discussing the multileveled (re-)shaping of the T&I environment brought about by the integration of AI. Since the emergence of AI, that is in the early 1950s, the corresponding literature evidences the decisive role that AI—as a controversial, yet more and more utilised component of T&I—has had in the T&I fields.

AI's emergence into the T&I disciplines is closely linked to the evolution of the systems that were devised to assist and perform translation and interpreting tasks. To comprehend the specifics of this common course of cooperation between AI and T&I, one should follow the timeline of MT development from the perspective of system architecture. To this end, MT history can be divided into three generations of system architecture, namely rule-based MT, statistical MT, and neural MT[3]. The study of MT system generations offers insights into the research dialogue that was incited by dint of each and every milestone reached in the course of MT evolution.

[3] For an extensive overview of AI's history, consult chapter 4.2.

2.1.1 AI technology in translation

In Translation Studies, the co-existence between AI and the discipline of translation has occupied the central point of interest of the pertinent publications. Among the very first researchers, Bar-Hillel (1951), who in Vauquois' words was "[…] the first full time researcher" (1976: 333) of automatic translation (i.e., MT), strongly rejected the possibility of an efficient and high-quality automated translation system. In the years that followed, several other publications observed closely and reviewed the stages of AI's development with regard to translation; (e.g., Vauquois 1976, Melby 1981, Hutchins 1986, Somers 1992, Wilss 1993, Sager 1994).

Vauquois (1976) drafted a review of the three pillar-approach to automated translation (each pillar corresponding to the three generations of MT system design) by focusing on delineating the main features of each approach. A few years later, Melby (1981) explored the possibility of human-machine cooperation in the context of translation. To do so, he touched upon fundamental questions regarding the nature of MT and provided the historical background of machinated translation. Furthermore, Melby described an experiment in cooperative translation, known by the initials ITS (Interactive Translation System), which he evaluated with a view to to predict future developments. Lastly, he addressed translators by offering suggestions for effective use of machine aids in translation. In 1986, Hutchins published his seminal work on the history and evaluation of the evolution of mechanical translation; this work constitutes a in-depth record of automatic approaches to the translation of natural languages. Somers (1992) published a critique-like paper on current research projects in MT, in which he aimed at foregrounding the transition from the state of the art in MT before AI integration towards AI- infused MT system design. In 1994, Wilss elaborated on the intricacies of current MT systems to bring up the importance of the human factor for efficient translation performance. Lastly, Sager (1994), in his book, sought to bridge the gap between translation practice and translation technology by sharing his views on core problems of the language and translation industry and showing how these two parameters can co-exist effectively both for prospective translators as well as future MT system designers and language engineers in the context of the interplay between computational linguistics and modern languages.

More recent literature builds on the work of previous scholars and researchers to examine AI's presence in translation. In his study about the blueprint of translation technologies on translational process and product, Doherty (2016) postulates that MT an integral tool at the disposal of translators because it provides them with the opportunity to amend the quality of the target output, thus facilitating effective interlingual communication . A year later, Neubig (2017) researched Neural Machine Translation (henceforth NMT), where he discussed the benefits of NMT systems; among the most important advantages of NMT, he included amended translation quality, ease of processing complex input patterns, and capacity to be trained and adapted into a vast number of languages and domains (see also Koehn, P., & Knowles, R., 2017). By contrast, Das (2018), who tested Google Translation from English to Hindi, argues that, despite advances in the field of AI in translation, NMT still features certain deficiencies, which are greater in languages of lower frequency of use. Specifically, he refers to NMT's inability to process and ensure equivalence for culturally ingrained meaning, issues with over, under, and mistranslation of the selected input, innate limited neural technology capacity with regard to large input processing, lack of input self-evaluation capability on the part of the NMT system. The findings of this study were corroborated by research conducted by Baltabay (2023), who examined MT software's advantages and drawbacks for qualified Kazakh translators. Baltabay also drew attention to the advantages that MT can offer to translators since it can function as "an auxiliary tool [that] can increase translation quality and efficiency while maintaining the role of human translators in the overall process" (*ibid*.: 62); these advantages included effort, time, and cost saving, ease of availability and plurality of language selection. Additionally, Popel et al.'s study (2020) was another instance in the MT literature in favour of the latter's integration into the practice of translation. In their work, they tested English to Czeck news article translations using CUBBITT, a neural-based translation system, and found that the translation results outperformed human-moderated translation and excelled in terms of adequacy. Yet, they argued that MT can only take precedence over the human translators, if they are less qualified and have "[…] infinite amount of time and resources" at their disposal (Popel et al. 2020: 11; see also Al-Onaizan & Papineni, 2002). A recent study by Wang (2023), which experimented with Chinese-to-English AI translation on three different text types (i.e., news, business, literary), also suggested that, besides certain challenges that are primarily related to Chinese language specificities and exert strong influence on the translation output (especially in the case of literary texts that involve complex language style), AI-assisted translation is possible to achieve accurate results and even outperform human practitioners.

2.1.2 AI technology in interpreting and speech translation

AI implementation into the field of interpreting has also been discussed in the corresponding literature. However, when attempting to observe and examine the world of interpreting, one should always take into consideration the disproportional amount of emphasis that is given to the study of interpreting and its specificities compared to (the overstressed) translation. As far as this work is concerned, the author will try to underscore significant literature-derived perspectives by touching upon three categories of foci, namely, research on the use of AI in interpreting, research on the impact of AI on interpreters, and research on industry adoption and assessment of the interplay with AI.

In the context of AI's utilisation in interpreting, Xiao studied AI-powered interpreting as a trending facet of the current information technology reality (Xiao 2021). Xiao (*ibid.*) was interested in exploring the (in)ability of AI-driven interpreting to tackle the challenges that language barriers pose in interlingual communication. Specifically, she intended to validate the assumption that AI MT cannot take the place of human interpreting. To do so, she embarked upon identifying the primary deterrents. Moreover, the study was concerned with eliciting information about people's estimate as to when AI's reign over human interpreting will take place and the predominant scenarios as to the domains where AI-powered interpreting could be applied first. This study yielded very interesting findings through a mixture of methods, ranging mainly from literature review to case analysis, experience summary, and comparative analysis; first, it showed that the time needed for AI MT to dominate over human interpretation was estimated to exceed ten years (57% of the questionnaire responses) (Xiao 2021: 17). Second, it was found that AI-generated interpreting was favoured in the fields of tourism (65), social interaction (56), trade (42), and education (21), compared to literature (9), and other domains (7)[4](*ibid*.). Most importantly, the study highlighted three central variables that hold human interpreting's replacement from AI-interpreting back, i.e., (1) lack of emotion (38%), (2) subjectivity of language (28%), and (3) accurate speech recognition capacity (25%) (*ibid*.: 18).

The speech recognition parameter invites the expansion of our discussion towards speech translation. Speech translation, and specifically automated speech translation (henceforth AST), as another area of oral language processing where AI has made its presence known, has been equally examined in the literature. More than a decade ago, Nakamura (2009) identified inherent technological challenges in AST systems design of that time: (1) individual differences in speaking style, accent, and form of expression, (2) immediacy of the AST process, (3) evaluation of output's correctness, (4) multilingual system support capacity, (5) speech translation technology standardisation, (6) copyright-pertinent considerations for AST system training via the web, and (7) proper nouns usage according to AST user's location (45-46). Recently, Horváth (2021), in his work on the comparison between speech translation and human interpreting, provided several arguments to support his view that AST is not capable of replacing human interpreters, thus aligning with the results drawn by Xiao (2021). Horváth distinguishes among three categories of limitations of AST, i.e., cognitive and communicational limitations, i.e., cultural awareness, appropriateness and sensitivity, pragmatic and linguistics dimensions of oral interaction, system design-pertinent limitations, and domain applicability magnitude (*ibid*.: 181-183).

Concerning the relationship between technology and interpreting and against the general disinterest of the academic community with respect to AI and Interpreting, Fantinuoli (2018) has argued that, indeed, this type of synergy had occupied a peripheral place in academia; it was not until the advent of the first interpreter-oriented programmes that people started expressing interest on the impact CAI had on interpreters. Furthermore, Corpas Pastor (2018) made some noteworthy assumptions regarding the reasons why interpreters appear to be reluctant towards CAI. These

[4] The numbers in the parentheses correspond to the number of votes gathered from the study.

reasons include the irrelevance of CAI technology in the workflow of an interpreter, concerns regarding declined interpretation quality, the negative effects AI might have on the interpreters' cognitive effort, and—not surprisingly—the fear of technological domination over human practitioners (*ibid*.: 166). However, Corpas Pastor's view echoed previous research and paved the way for others. Horvath (2014), for instance, stated that there is a significant difference between the impact that MI had on the interpreting industry and the professionals that operate within the field, a conclusion that is in line with Fantinuoli's (2018) postulations on the topic.

A third perspective through which the literature has viewed AI in interpreting relates to the industry adoption and impact assessment. Jekat (2015: 242), who examined machine interpreting (henceforth MI), supported that regardless of the progress made lately, MI "is still limited to specific domains and linguistic contexts and a narrow range of highly standardised natural speech inputs". On the contrary, Herbig et al. (2019) favoured the synergy between human practitioners and AI and proposed a list of approaches to achieve a harmonious pattern of collaboration. Following Herbig et al.'s rationale, Corpas Pastor (2021) suggested that a positive impact could be yielded from integrating AI into T&I.

2.1.3 Quality evaluation

The issue of quality assessment has been one of the primary concerns in Translation Studies literature (House 2014). The need to perform quality evaluation of the output derived by the processes of T&I has been even more intensified following the introduction of AI.

In 2009, a study by Fiederer and O'Brien showed that MT does not affect quality output. Instead, when a variety of parameters are considered , it is possible to avoid poor-quality translational output (see also O' Brien & Coghlan 2019). Statistical evidence provided by Wilks (2009) suggests that the quality of MT systems was positively evaluated by product consumers (65-70%) as to the correctness of translated sentences (p.6). Aiken (2010), who tested quality on automatic interpretation of speech in the English language, argued that, despite challenges, it is possible to achieve accurate interpreting outputs.

On the opposite side of the spectrum, several findings have underlined the negative impact of AI on the quality of the translation output. For instance, in a study about NMT systems' capacity to translate under-resourced rare words, Currey, Heafield and Koehn (2019) found that quality reduction of the translated output can be a decisive factor. Their findings were corroborated by newer studies, such as those carried out by Wang et al. (2020) and Baltabay (2023).

2.1.4 Medical domain

Considerations regarding MT's role and practicality in the healthcare domain have also been documented in MT literature. Of course, this comes as no surprise since the need to overcome language barriers and find immediate solutions to problems that arise in interlingual communicative environments are integral to the provision of healthcare services. Haddow, Birch and Heafield (2021: 114) distinguish three areas of MT application in healthcare: (1) MT utilisation for assisting the translation of healthcare-pertinent information addressing the general public, (2) MT usage for translating specialist healthcare-pertinent publications (e.g., scientific papers), and (3) MT mediated doctor-patient interaction.

From a research-oriented angle, the potentiality of MT incorporation into medical settings gained traction only after the emergence of the neural paradigm in MT, that is, the transition from statistical modeling towards neural network architecture of systems[5] (*ibid*.). In this work, I will refer initially to two projects devised for interpersonal use in the healthcare domain and involve both text-to-text and speech-to-speech designs. Then, I will discuss the results of some studies that tested the efficacy of an openly accessible MT tool, namely Google Translate, in healthcare settings.

The first project is among the earliest projects in MT for healthcare and was conceived by Somers and Lovel in 2003. Somers and Lovel's (2003) computer-based proposal was a text-based MT system that could facilitate doctor-patient interaction in

[5] See chapter 4.2 and 4.3 for more details.

cases of LEP (Limited English Proficiency) or patients who were unable to speak English at all. Their patient-centered framework was inspired by the UK's immigrant populations and the pressing need to ensure effective doctor-patient communication, focusing on the translation to and from Somali and English , as well as Urdu and English. In essence, they envisaged a "hybrid multi-engine embedded MT system" that comprised rule-based MT, example-based MT accompanied by a translation memory, and word-by-word lexical look-up facility (Somers and Lovel 2003: 43). The system was trained by a data-corpus of translated doctor-patient interviews and operated in two separate interfaces, i.e., the doctor's interface and the patient's interface. The doctor's interface had a hybrid design as it accommodated both the possibility for free text typing and for a menu-based approach, building on dynamic domain knowledge. The system placed significance on input controlling. Consequently, the use of the free typing option was to be utilised when the menu-driven interface did not meet the doctor's communicative purposes during the doctor-patient encounter. The patient's interface was not fully examined in Somers and Lovel's work; yet the authors highlighted issues related to patients' limited technological literacy, especially for Urdu speakers, as well as their inability to use the Latin alphabet.

The second project, focusing on speech-to-speech translation, was developed by Bouillon, Rayner and colleagues at the University of Geneva (Bouillon et al. 2005, Rayner et al. 2008). The system is called MedSLT and is an open-source, multilingual spoken language translation system adapted for serving the needs of encounters taking place within medical settings[6]. The architecture of the system is interlingual-driven (i.e., it uses an artificial language as a mediator between the source and the target languages involved in the communicative event at hand), rule-based, and builds on an one -way translation modelling, i.e., the doctor can ask only "yes-no" questions. It also involves speech recognition technology, back-translation and context-dependent translation capacity, and an intelligent help component. The main advantage of this design resides in its potential for high-accuracy performance. On the contrary, its shortcomings

[6] https://www.issco.unige.ch/en/research/projects/medslt/

are found in the limited nature of the interactions the system can process (i.e., limited-domain system) and of its restricted vocabulary (from about 350 to 1000 words per domain and language).

As far as the studies on NMT usage in the medical domain are concerned, there are some that may offer insights into the efficiency of merging MT with healthcare. The first study I will be focusing on was carried out by Börner et al. (2013). The researchers set out to test the performance of an internet-based translation programme, i.e., Google Translate, as an alternative for professional interpreters since the physical presence of the latter is not a given in real-life medical encounters. To this end, the materials of the study comprised a corpus of twenty standardised sentences from a neonatal doctor-/nurse- relative-interview. The translation direction was from German to English, Portuguese, and Arabic. The procedural design involved three steps: first the selected sentences were assessed in terms of accuracy at both the level of grammar and content; subsequently, the sentence structure of the incorrect sentences was simplified, and lastly, the simplified sentences were translated via Google Translate and were then re-assessed. The findings showed that 58% of the utterances used were not correctly translated in terms of both grammar and content. Incorrectly translated utterances would range from 45 to 70%, whereas 25% of them were correctly translated following simplification. The results demonstrated a dissatisfactory performance of Google Translate when it comes to grammar and content processing of input; these results correlate with previous studies' findings, e.g., Khanna et al. 2011. The researchers hypothesised that the probabilistic (statistical) architecture of Google Translate was responsible for the poor performance and insufficiency of the program. One year later, another study was presented by Patil and Davies (2014), who were interested in evaluating the accuracy and usefulness of Google Translate in transferring interlingually the meaning of ten common English medical statements. The translations were carried out from English to a total of twenty-six languages, i.e., 8 Western European, 5 Eastern European, 11 Asian, and 2 African. This produced a total of 2660 translated phrases/utterances. Upon completion of the translation with Google Translate, the output utterances were sent to native speakers of these languages for them to perform a back-translation to English. The back-translated English utterances were compared against the corresponding original input and assessed for accuracy of meaning. The results showed that 57.7% of the translations were correct (i.e., made sense or were factually correct). From the total of correct translations, African languages had the lowest score (45%) whilst Western European languages were assessed as being mostly accurate (74%). Furthermore, Swahili had the lowest correctness score (10%), whilst Portuguese had the highest (90%); significant errors were observed in translation towards Swahili, Marathi, Bengali, and Polish. The researchers concluded that Google Translate offers limited usefulness for the translation of medical utterances frequently occurring in doctor-patient encounters and as agreed with Börner et al (2013) regarding the error-proneness of the statistical modelling upon which the online programme is designed. Along the same lines, a 2019 study assessed the use of Google Translate for Spanish and Chinese translations regarding emergency department (henceforth ED) discharge instructions (Khoong et al. 2019). The primary objective of the study was to test the accuracy of Google Translate-generated translations of one hundred free-texted ED discharge instructions in Spanish and Chinese. The study took place in two phases; first, the sentences were translated from English into Chinese and Spanish using Google Translate and then, the output was back- translated into English by bilingual translators. The translations were evaluated in terms of content category, Flesch-Kincaid readability[7] score, medical jargon, and presence of nonstandard English. Research findings indicated that, overall, both the Spanish and Chinese translations were accurate and only a minor proportion of inaccurate translations could be detrimental for patients, i.e., Spanish (28%), and Chinese (40%). Additionally, grammatical or typographical errors that were responsible for content-related inaccuracies were attributed to erroneous input in English and not to efficiency of the Google Translate software per se. The final remarks of the study suggested that, besides the satisfactory accuracy performance, Google Translate should

[7] Placed within a USA-specific "school grades" scale, the Flesch-Kincaid Readability score is interpreted as follows: 0-30= college graduate, 30-50= college, 50-60= 10th and 12th grade (high school), 60-70= 8th and 9th grade, 70-80= 7th grade, 80-90= 6th grade, 90-100= 5th grade (Rudolf, Flesch. 1979. Chapter 2: Let's Start With the Formula. In *How to Write Plain English: A Book for Lawyers and Consumers.* New York Harper & Row. https://web.archive.org/web/20160712094308/http://www.mang.canterbury.ac.nz/writing_guide/writing/flesch.shtml)

be used cautiously to avoid potential detrimental effects on patients who receive MT-generated materials.

Other studies have addressed the utilisation of Google Translate from the angle of speech synthesis. One such study was designed by Birkenbeuel et al. (2021) to assess Google Translate's ability to accurately interpret a corpus consisting of 83 single sentences and a series of sentences that are commonly used in the context of medical encounters from English into Spanish. The focus of the experiment was three-fold: to test Google Translate's accuracy in (1) transcribing English input, (2) real-time translation of the English transcriptions into Spanish, and (3) to evaluate Google Translate's speech synthesis ability to preserve the meaning of the English input following the translation to Spanish. To facilitate the objectives of the study, Birkenbeuel et al. (2021) asked 18 English-speaking participants to read the selected sentences. According to the findings, sentence number played an important role in the accuracy performance and original input's meaning preservation after speech synthesis, i.e., single sentences scored 89.4% (≤8 words), single sentences with more than 8 words scored 90.6%, 52.2% accuracy for two sentences, and 26.6% accuracy for three sentences. Analogous results were observed with respect to transcription and translation errors per sentence(s), i.e., the larger the sentences' number, the more the errors in transcription and translation of the transcribed input.

The sample of studies illustrates clearly that, going beyond the vested interest in examining Google Translate's (and MT's altogether) full capacity, the appropriateness of Google Translate, as a promising, free access MT programme, has not been established yet in the purely clinical field (see also Rodriguez et al. 2020). The Commonwealth of Massachusetts Board of Registration in Medicine (henceforth CMBRM) strongly discourages any incautious use of Google Translate and similar MT services programmes as means to overcome language barriers with LEP patients. Such programmes "may provide erroneous or nonsensical translations that can lead to patient misunderstandings and potentially compromise patient safety" (CMBRM 2016: 1).

2.2 The pedagogical integration of AI

Issues concerning the integration of AI in the translation and interpreting curricula constitute a controversial matter in several scholarly discussions. Existing literature showcases reluctance on behalf of instructors and educators to fully embrace the state of affairs that AI has brought upon the T&I field. This reluctance, however, clashes apparently with the increasing popularity of the use of AI-driven T&I technology in both professional and non-professional contexts.

Concerning the professionals' position vis-a-vis the technological turn initiated by AI, it is important to distinguish between the "world of translation" and the "world of interpreting", as the approach differs in the two disciplines; in the case of interpreting, several scholars have been particularly concerned with the unequal technological progress that is observed in the toolkit available for professional interpreters (e.g., Costa et al., 2014; Corpas Pastor and Fern, 2016; Fantinuoli, 2018; Sandrelli, 2015). Prandi (2020) argues, this is due to the interpreter trainers' lack of knowledge that interpreting training has not been satisfactorily technology-infused. By contrast, research evidence from translation shows that the integration of AI-driven tools in the training curriculum has been more horizontal compared to interpreting (Corpas Pastor 2018). The reasons for this discrepancy have been extensively outlined by Fantinuoli (2018), who identified a number of impediments ranging from the reluctance on the part of the interpreters towards CAI, to difficulties designing interpreting-appropriate software to facilitate the interpreting processes, the marginal aspect of interpreting operations, and the stance of universities vis-a-via CAI integration (p.8). At the same time, Fantinuoli favors the integration of CAI tools in the training curricula for interpreter trainees as there is a need to reform professional interpreting through technology.

At the opposite end of the spectrum, several studies have attempted to emphasize the significance of translation technology in developing translation trainees' professional competence. One such study was conducted by Wang (2023), who used a multileveled examination of AI in the context of translation education. In his research, Wang claims that AI is a useful tool for students' competence development:

> The survey results demonstrated that the use of AI technologies in education practices could have a constructive impact on the development of key competencies of a future translator. (*ibid.*: 1525)

Along the same lines, the view of integrating AI-driven technologies into training programmes in T&I has been interestingly embraced by the scholarly community (e.g., O'Brien and Kenny 2001; Kenny 2018; He 2021; Organ 2021); it is argued that AI may provide students with the opportunity to become acquainted with the potentiality of AI in the field and yield the benefits it can offer by letting go of any prejudice regarding the substitution of practitioners by machines:

> It is therefore clear that translator education institutes should continue to keep abreast of technological developments, giving students as much direct experience as possible with the tools, processes, and practices with which they are likely to be confronted in their professional lives. This can only be achieved by regular and sustained use of CAT tools and TM in practical translation courses and not just in translation technology courses. (Massey and Ehrensberger-Dow 2017:307)

In work published by Moorkens (2018) and Sánchez Ramos (2022), we are given a sample of concrete evidence regarding attempts to envisage T&I training from the viewpoint of AI-devised technology. More specifically, Moorkens (2018) organised a practical in-class task for the evaluation of NMT assisted translation. The evaluation exercise was implemented in two cohorts of tertiary education students, i.e., a cohort of 46 second-year translation undergraduates and another one comprised of 9 postgraduate students and university staff, who were asked to assess SMT and NMT on three levels, namely, PE effort (time expended to complete PE), adequacy (concerning the input) and error typology (word order, errors, mistranslations, omissions, additions) (*ibid*.: 380).The findings of the study showed that most participants (62%), regardless of the cohort they belonged to, favoured NMT instead of SMT (*ibid*. :381). In the first cohort, 62% of the participants required less time to complete NMT's output PE (*ibid*.). Accuracy-related average ratings scored 2.95 for SMT and 3.46 for NMT respectively ; lastly, students found fewer errors in NMT (*ibid*.). Similar results were yielded from the second cohort's evaluation. Overall, the contribution of this study relies on the first-hand experience that students gained in working with current MT tools, particularly with the SMT and NMT paradigms, and on underpinning the need for professionals to embrace the technological imperatives of our times to be able to keep up with the industry's state-of-the-art products (Moorkens 2018: 383-384). Another insightful perspective into students' attitudes towards AI-based translation tools is explored by Sánchez Ramos (2022). Her study took place in the context of a 10-weeks compulsory course in a Master's programme in Intercultural Communication, Public Service Interpreting and Translation (henceforth PSIT) at the University of Alcalá. The study was conducted during the 9th and 10th week of the course, which focused on the proper integration of MT and PE in translation as PSIT tools, and set out to offer insight into: (1) students' perception of MT and PE integration in the course's technological apparatus, and (2) assessing of the usefulness yielded from such synergy (Sánchez Ramos 2022:297-299). The participants were comprised of 42 English-Spanish MA students of the aforementioned programme. They were asked to answer a quantitative questionnaire addressing the first objective stated above and, to write a qualitative reflective essay addressing objective (2) at the end of the MA programme. Regarding the questionnaire results, only 22% of the respondents had been exposed to MT and PE training, with this training being either of a theoretical nature or dispensed over talks and seminars (Sánchez Ramos 2022: 300-301). Furthermore, on the one hand, students indicated that they have used MT systematically throughout their master's programme and held that MT and PE exerted a positive influence on their interest in translation technology (69% of the responses). On the other hand, they maintained that the content of the course did not align with competence enhancement (71%) in using translation technology of this type, nor did it facilitate their training in PSIT tools (60%). Lastly, as to the usefulness of MT and PE integration in their training curriculum, 64% of the participants maintained that the content of the course was appropriate , 57% held that these tools should be mandatory components of the master's programme, and 71% perceived MT and PE-oriented training content as facilitating their professional development (Sánchez Ramos 2022: 301).

Generally, the dialogue within the tertiary education environment has held tow directly opposite sides as to the attitudes towards AI integration in the training curriculum of future professionals. As showcased above, there have been fundamental technological discontinuities between the two pillars of interlingual communication, i.e., T&I, which, have played their role in the (non)acceptance of AI. On the other side, positively-valenced perspectives as to AI's infusion are also a fact, but, interestingly enough, they are not a popular trend in T&I-oriented curriculum design discussions; scholars' insistence on the effectiveness of combining more sophisticated technology (e.g., AI-inspired technological aids) with T&I teaching echoes the ideas of the 90s (e.g., Clark, 1994; Kingscott, 1996, DeCesaris 1996), whilst, according to Kenny (2020), the first steps towards technological integration into T&I teaching date back to the 80s. Within this context, in this dissertation, I am interested in further investigating the practical aspects of AI integration in translators and interpreters' training around the world and, especially, in Greece.

2.3 Ethics and Transhumanism

2.3.1 AI-Ethics in T&I

This subsection should start by the premise that the ethics of using AI in T&I coincide largely with the ethical imperatives associated with AI as a wide-ranging technological phenomenon whose applications cover almost every aspect of human activity. In my view, the reasons behind this agreement are two-fold: first, the discussion about delineating the ethical and legal imperatives solely in relation to AI-powered T&I is in its infancy nowadays, and second, the founding principles and values that are outlined in the existing ethical codes for T&I are overlapping the ethics of the AI-T&I synergy. As regards the latter, Jobin, Lenca and Vayena's (2019) study verifies our argument through showing that their sample of AI-oriented ethical guidelines' publications build upon five ethical principles, namely transparency, justice and fairness, non-maleficence, responsibility, and privacy, which correspond to the founding general ethical imperatives. In more detail, they listed a corpus of 84 documents issued both by authorities and/or stakeholders, including national and international organisations, corporations, professional associations, and non-for-profit organisation that share their ethical agenda concerning AI adoption. These findings corroborate the second statement regarding the convergence between general ethical principles and values and AI-specialised principles. Thus, perceiving the universal ethical principles of fidelity (or else fairness) and confidentiality (or else privacy) as being leading ethical prerequisites for harmonized and successful AI integration would be acceptable.

Keeping this interconnection in mind, we need to acknowledge that the world has realised the need to (re)define the ethical foundations of AI and to take action towards that direction; a study by Bird, Fox-Skelly, Jenner, Larbey, Weitkamp, and Winfield (2020) reports on several ethical initiatives taken both within the European borders and beyond (38-41)[8], as well as on national and international strategies on AI up until May 2019 (71-79; Table 1).

Table 1 National and International Strategies on AI until May 2019 as reported in Bird et al. (2020)

Europe	
Finland, May 2017	Artificial Intelligence Programme
France, March 2018	AI for Humanity
European Union, April 2018	Strategy on AI for Europe
United Kingdom, April 2018	AI Sector Deal
Sweden, May 2018	National Approach for Artificial Intelligence
Nordic-Baltic Region, May 2018	Declaration on AI in the Nordic-Baltic Region
Denmark, March 2019	National Strategy for Artificial Intelligence
Estonia, May 2019	Estonia's National AI Strategy
Malta, October 2019	Malta's ethical AI framework
North America	
Canada, March 2017	Pan-Canadian Artificial Intelligence Strategy
South America	
Mexico, June 2018	AI-MEX 2018
USA	
Executive Order issued by President Trump that established the *American Artificial Intelligence Initiative*, February 2019	
Asia	
Singapore, May 2017	AI Singapore
Japan, March 2017	Artificial Intelligence Technology Strategy
China, July 2017	Next Generation Artificial Intelligence Development Plan
Taiwan, January 2018	Taiwan AI Action Plan
South Korea, May 2018	Artificial Intelligence Information Industry Development Strategy

[8] The number of ethical initiatives is not mentioned in the text for space economy purposes. For a detailed analysis, use the references as provided in this text.

India, June 2018	AI for All

From 2019 until today, more work has been done towards laying the AI ethical foundations at a national and international level (Table 2).

Table 2 AI ethics literature from 2019 until today

European Union , April 2019	Ethics guidelines for trustworthy AI
UNESCO, November 2021	Recommendation on the Ethics of Artificial Intelligence
Canada, June 2022	The Artificial Intelligence and Data Act
Australia, Department of Industry, Science,Energy and Resources (Governmental body of the Department of Industry, Science, Energy and Resources), 2021	Australia's AI Action Plan
European Union, April 2021	Proposal for a Regulation of the European Parliament and of the Council laying down harmonized rules on Artificial Intelligence (Artificial Intelligence Act) and amending certain union legislative acts
Greece, April 2022	Law No 4961/2022
China, April 2023	Draft Administrative Measures for Generative Artificial Intelligence Services released by the Cyberspace Administration of China[9]
USA, October 2023	Executive order on Safe, Secure, and Trustworthy Artificial Intelligence
UK, August 2023	A pro-Innovation approach to AI regulation

[9] This addition to the AI-focused regulatory literature is of major significance as it targets generative AI, which is the form AI-powered technology that bears the closest relation to translation and interpreting as it refers to content generation " in the form of text(s), picture(s), audio, video(s) and code(s) based on algorithms, models, and rules" (Article 2). https://perma.cc/T6NX-9S5F

Besides the obvious interest in framing AI ethics and creating ethically-informed policies, AI adoption is still not thoroughly or sufficiently (if not at all in some cases) integrated into a legal framework; this generates critical and risk-prone gaps in settings where AI is actually practices and/or used. On this point, Lewicki, Lee, Cobe, and Singh (2023) argue that AI-pertinent regulations are based on "non-legal sets of principles or ethical standards proposed by academics, civil society groups, and others" targeting responsibility and fairness of AI usage (3). Their argument is validated by Jobin, Lenca and Vayena's (2019) prior work.

Focusing on T&I, lately we have witnessed ethical and legal concerns embedding AI in the multifaceted field of T&I. It seems that such concerns gain popularity (e.g., Bowker 2020, Pöllabauer and Topolovec 2020, Horváth 2021, Lewicki et al. 2023, Ramirez-Polo and Vargas-Sierra 2023). In the area of interpreting, Horváth (2022) delineated the primary ethical challenges for AI utilisation in the interpreting practice. She touched particularly on data-pertinent concerns, namely bias, quality, privacy, and ownership, as well as transparency issues (*ibid*.:7). As for translation, it can safely be assumed that such ethical issues are also relevant to AI-assisted translation tasks. Finally, another ethical concern generated in the context of AI-mediated translation technology prioritises the assessment of AI's cultural implications. For instance, UNESCO's Recommendations on the Ethics of Artificial Intelligence states that:

> [the] Member States are encouraged to examine and address the cultural impact of AI systems, especially natural language processing (NLP) applications such as automated translation and voice assistants, on the nuances of human language and expression. Such assessments should provide input for the design and implementation of strategies that maximize the benefits from these systems by bridging cultural gaps and increasing human understanding, as well as addressing the negative implications such as the reduction of use, which could lead to the disappearance of endangered. *(UNESCO 2022:32)*

2.3.2 AI-related ethical discussion in T&I pedagogy

Apart from the ethical challenges found at the professional sphere, we should also direct our interest towards the literature about ethical considerations at the level of T&I

education and training in the era of AI domination. The case of exposing translation students to the ethical imperatives of a technology-immersed profession is substantially complex. It is part of a vicious circle that originates in what Bowker (2020: 269) describes as the "lack of technology-related guidance in professional associations' codes of ethics". Research evidence has been previously provided by McDonough (2011: 45), whose study showed that ethical concerns of technological nature constitute one of the major gaps in seventeen codes of professional associations for translators, all of which belong to the International Federation of Translators. The space in professional ethical documentation vis-à-vis technology integration in T&I in an ethical way has strongly impacted T&I pedagogy. Li (2023) stresses that "no systematic discussion or technology-related ethical coursework exists across the university curriculum or among professional practitioners (541). Bowker (2020) has also commented on the educators' insufficient course of action to cultivate students' "deep understanding" of the ethical imperatives in the era of the AI-mediated technological uptake in T&I (273).

On the bright side, the need to perceive translation technology ethics as integral components in translator pedagogy and training curricula has been strongly advocated in the T&I literature (Kenny and Doherty 2014, Massey and Ehrensberger-Dow 2017, Kenny 2020, Horváth 2022, Li 2023).

2.3.3 AI ethics in medical T&I professional practice

Professional T&I service provision in healthcare is also affected by the absence of ethical and legal regulatory framework prescribing the ethical guidelines for effective AI embedding in the domain. To compensate for the absence of ethical documentation focusing on AI-mediated T&I service provision in medical and healthcare environments, we will explore the existing ethical framework in medical and health sciences, also known as *bioethics*, concerning AI. Our goal will be to draw inferences as to how this framework can serve as a basis for considering the (re)form of the medical T&I code of ethics.

Universal bioethics build on four basic principles, namely respect for autonomy, nonmaleficence, beneficence, and justice (Beauchamp and Childress 2001, Beauchamp 2010). The technological innovation of our times, especially AI application, in medicine and healthcare raise reasonable concerns as to the ethical (and legal) foundations which *should* guide AI-powered medical practice. From that standpoint, research-originated assessments of existing AI-focused ethical guidelines and principles across the globe have identified substantial points of convergence between AI ethics and the four pillars of bioethics (Floridi et al. 2018, Mittelstadt 2019, Jobin et al. 2019, Hagendorff 2020). This overlapping of ethical imperatives is not coincidental; Floridi (2013) has argued that bioethics bear the closest resemblance to digital ethics (or else, computer ethics or information ethics) compared to other areas of applied ethics[10]. On that note, Schneider, Vayena, and Blasimme (2023: 783) put forth a term for describing the fusion of bioethics and digital ethics in the context of the-all evolving digitalisation trends in medicine, i.e., *digital bioethics*.

Unfortunately, detecting the convergence between medical ethics and digital ethics does not suffice; this insufficiency has not gone unnoticed in the literature; for instance, Floridi et al. (2018) and Mitellbrandt (2019) postulate that more work needs to be done in bioethics to maximise the *ethicality* of AI as a component of increasing popularity and amplitude of use in medicine and healthcare. According to Floridi et al. (*ibid.:* 696), the quadripartite framework of bioethics does not provide for an "exhaustive" account of the ethical challenges associated with AI, and therefore, the framework should be enriched with the principle of "explicability". The explicability principle captures the "need to *understand* and *hold to account* the decision-making processes of AI" (also referred to as "transparency", "accountability", "intelligibility", "understandable and interpretable" in documents aiming at delineating the guidelines for AI ethics), revealing the invisibility and unintelligibility of AI's nature (*ibid*.: 700). In turn, Mittelbrandt (2019:2) underpinned four core deficits in the ethics of medical AI development, namely lack of common aims and fiduciary duties, professional history and norms, proven methods to principles into practice, and legal and professional accountability. Adding to the above, Whittlestone, Nyrup, Alexandrova, and Cave (2019:197) point to the excessively broad and ambiguous nature of AI ethical principles as well as the clash existing between theory (i.e., the principles) and practice of

[10] See also: Mishra, Abhishek, Julian, Savulescu and Alberto, Giubilini. 2023. The Ethics of Medical AI. In Carissa Véliz (ed.), *The Oxford Handbook of Digital Ethics* (online edn), C25.S1–C25.N7. https://doi.org/10.1093/oxfordhb/9780198857815.013.25

embedding AI in medical and healthcare settings. To amplify even more the scope of bioethical challenges, Gerke, Minssen and Cohen (2020) detected some integral challenges to AI-powered healthcare of both ethical and legal nature. At the level of ethics, Gerke et al. (*ibid*.) give salience to issues regarding informed consent to use, safety and transparency, algorithmic fairness and biases, and data privacy. At the legal level, they touch upon challenges related to safety and effectiveness, liability, data protection and privacy, cybersecurity, and intellectual property law (*ibid*.).

All the weaknesses mentioned above intensify the need to review the specifics of medical AI ethics on the part of policymakers, institutions, organisations and other competent bodies or authorities. Recently, one approach to medical AI ethics that seems to be gaining more ground is the embedded ethics approach (McLennan et al. 2020, Bezuidenhout and Ratti 2020). Embdedded ethics, as a collaborative, interdisciplinary approach, aims at facilitating AI technology development to devise "ethically and socially responsible" technologies that "benefit and do not harm individuals and society" (McLennan et al. 2022). As expected, embedded ethics has been contested in the literature (e.g., Bonnemains, Saurel and Tessier 2018, Kostick-Quenet et al. 2023) for featuring certain technical and ethical challenging aspects. However, we should not overlook its potential to address and possibly remedy AI-related issues in the context of bioethics. McLennan et al. (2022) believe in the potentiality of an embedded ethics approach for regulating medical AI application and thematize three overarching strengths of the approach, i.e., its potential to: (1) address the unique nature of medical AI; (2) alleviate the problem with the commonly invoked quadripartite framework of bioethics; and, (3) address gaps in regulation concerning AI use in medicine.

2.3.4 Transhumanistic impulses in AI-infused T&I

Situating T&I within a converging relationship to transhumanism is more relevant now than ever before. The term "transhumanism" denotes the movement that "seeks to use technology to fundamentally change the human condition, improving our bodies and minds to the point where we become something other and better than the animals we are" (Cronin 2020: 279). The agenda of transhumanism is informed by the overarching goal to create a "posthuman" by investing in the potential of technological evolution (Porter 2017). In this context, translators and interpreters' professional identity is subject to a substantial change that places the brain-machine interface at the centre of the current state-of-the-art technology in language mediation and perceives this connection as being vital for assisting humans in changing themselves according to the imperatives of transhumanism (O'Thomas 2017). The identity that transhumanism construes for translators and interpreters has been described by Cronin (2003: 112) as "translational cyborgs". He did so in his attempt to emphasise the interdependence between the agents partaking in a translational task (i.e., translators) and translation technologies. Cronin (*ibid.*) argues that the markedness of technological imperialism and automation has impacted the translation task's orientation to the extent that the enhanced processing capacity of the translation machine has brought about the "externalisation of the brain" (Bourg 1996: 185), or in Humbert's terms the infamous "cerebrofacture" (Humbert 1993:54).

The dialogue as to the impact assessment of transhumanism in the realm of T&I revolves around the utopia-dystopia dichotomy to which AI serves as a catalyst (Eszenyi, Bednarova-Gibova and Robin 2023). The utopian end perceives AI-powered translation technology as a useful tool in the hands of the human translator, whilst the dystopian end depicts an AI-dominated industry where the translator's presence is superfluous (*ibid.*, Crawford 2021). The undisputable changing character of the translation profession encourages the reconceptualization of the roles that transhumanism breathes into the practice of T&I. These cover a spectrum that includes data engineering, engine management, subject matter expertise, training data management, training data management and post-editing (Bessenyei 2022).

Regardless of where someone positions themselves on the utopia-dytopia spectrum, the incentives and theory of transhumanism should not be left uncriticised. Cronin (2020) raises some very interesting questions pertaining to the challenges that transhumanism invokes to translation, with the latter being viewed as one of the catalysts in the process of transhumanising the world (e.g., the military communication paradigm). Interestingly, all of them feature ethical undertones of great relevance to the preponderance of issues discussed previously in this work. More specifically, Cronin (2020) problematises over six areas; he discusses (1) the synergy between transhumanism and translation in the era of globalization; (2) labour exploitation concerns as part of the translators' new professional identity; (3) translation data exploitation ; (4) translation manipulation for serving the patronising purposes of those in power; (5) what it means to be a human translator in the age of transhumanism ; (6) the interplay between human and posthuman. Lastly, one could perhaps safely assume that Porter's (2017) parallel viewing of bioethics and transhumanism constitutes a basis for guiding the inquiry as to the exploration of T&I practice in healthcare in the times of AI's omnipresence. Porter encourages thorough exploration of the ethical sphere which circumscribes biotechnology under the influence of transhumanism.

Chapter 3

Methodology

To address the objectives of the study, namely the exploration of AI integration in the T&I industry and the education of future professionals, we opted to design a tripartite questionnaire-driven survey[11]. As a methodological path, surveys enjoy a special place in the research-oriented publications (Kitchenham and Pfleeger 2008). Fink (2003) attributes the popularity of this method to the comprehensiveness that governs the process of data gathering and analysis of knowledge, attitudinal, and behavioural patterns. In a survey-oriented research design, questionnaires are seen as the most commonly implemented data collection method (Ponto 2015). Gathering data via questionnaire distribution features a set of advantages, including economic data collection, flexibility of distribution, enhanced participants' recruitment ability, and systematisation of data (Bork and Francis 1985: 907).

In light of the advantages, we proceeded with the design and piloting of our questionnaires by applying the six prerequisites underpinned by Charlton (2000), i.e., appropriateness, intelligibility and succinctness, unbiasedness and clarity, ease of coding, ability to deal with any given response, and ethicality (356). The questionnaires were created and distributed via a cloud-based survey administration software, i.e., *Google Forms,* to facilitate our goal regarding maximal possible participation (Frippiat, Marquis, Wiles-Portier 2010). Research literature has highlighted the contribution of web-based surveys (e.g., Gosling, Vazire, Srivastava and John 2004, Frippiat and Marquis 2010, Fox, Murray and Warm 2010). The main advantages of this method include: (1) immediacy of implementation (Fox et al. 2010), (2) motivation (Gosling et al.2004), (3) speed of data gathering (Frippiat et al. 2010), (4) maximisation of respondents' reachability (Gosling et al. 2004, Frippiat et al.2010, Jones, Baxter and

[11] See Appendix I,II,III and the *Analysis* chapter.

Khanduja 2013), (5) economical and systematised administration (Jones et al. 2013), and data gathering (Gosling et al. 2004).

In essence, our work identifies with the mixed method approach (henceforth MMA) and specifically, with the embedded (or else nested) design (henceforth ED). MMA is a type of research based on the conflation between qualitative and quantitative approaches to facilitate data gathering and analysis as well as integration and interpretation of findings (Tashakkori and Creswell 2007). Cresswell and Plano Clark (2007:5) define MMA as "a research design (or methodology) [which] focuses on collecting, analyzing, and mixing both quantitative and qualitative data in a single study or series of studies [to offer] a better understanding of research problems than either approach alone". Its distinctiveness is found in the holistic understanding that is targeted through the mixing of approaches (*ibid*.) and in its compensating force towards weaknesses as well as in the prioritisation of strengths that are inherent to the methods which are being "mixed" (Greene 2007: xiii)[12]. Within the context of MMA, we estimated that an ED experimental model would facilitate our research purpose. ED was first described by Caracelli and Greene (1997) and involves the simultaneous presence of one prevailing component[13] and another one, of a complementary nature (Doyle, Brandy and Byrne 2009). Creswell and Plano Cark (2007) distinguish two types of ED research models, namely the embedded *experimental model*[14] and the *correlational model.* Our work is mostly oriented towards the first type of ED research, i.e., the embedded experimental model, which prescribes that "qualitative and quantitative data are collected concurrently and analyzed together during the analysis phase" (Harwell 2011: 156). Terrel (2012) argues that the primary strength of ED is the wider perspective allows the researcher, who can yield the benefits by combining two methods for data collection and by treating each method individually. Additionally, Almeida (2018) argues that ED is more fitting in cases where the percentage of one data

[12] To be discussed below.
[13] Component, i.e., data type or data collection method (e.g., qualitative or quantitative data).
[14] Previously known as "concurrent nested mixed methods design".

type exceeds the percentage of the other. In our MMA- and ED-informed design, the qualitative component is embedded in the prevailing quantitative approach to research.

Quantitative research is deductive (Harwell 2011, Rovai, Baker and Ponton 2014) and is founded on the assumption that there is “an objective reality independent of any observations” (*ibid*.: 4, see also Lincoln and Guba 1985). A key feature of this approach is that, upon information gathering, data processing is facilitated through statistical “treatment of data” (Almeida 2018: 138) to ensure maximal “objectivity, replicability and generali[s]ability of findings” (Harwell 2011: 149). On the contrary, *qualitative research* is inductive (Rovai et al. 2014) and emphasises “the meaning individuals or groups ascribe to a social or human problem” (Creswell 2014: 4) through attempting to locate and comprehend “the experiences, perspectives, and thoughts of participants” (Harwell 2011: 149). Denzin and Lincoln’s (2018: 45) definition perceives qualitative research as “a situated activity that […] involves a naturalistic approach to the world”. The “naturalistic” element refers to the study of a phenomenon or thing within its “natural setting” to facilitate comprehension and/or interpretation of the meaning(s) that people ascribe to it (*ibid*.). This research approach prioritises “individuality, culture and social justice” (Rovai et al. 2014: 4) and invests in the subjectivity that is brought about by the adoption of an *emic approach* to data collection (Tracy 2013). Unlike quantitative research, qualitative inquiry does not aim at replicability and generalizability (Harwell 2011).

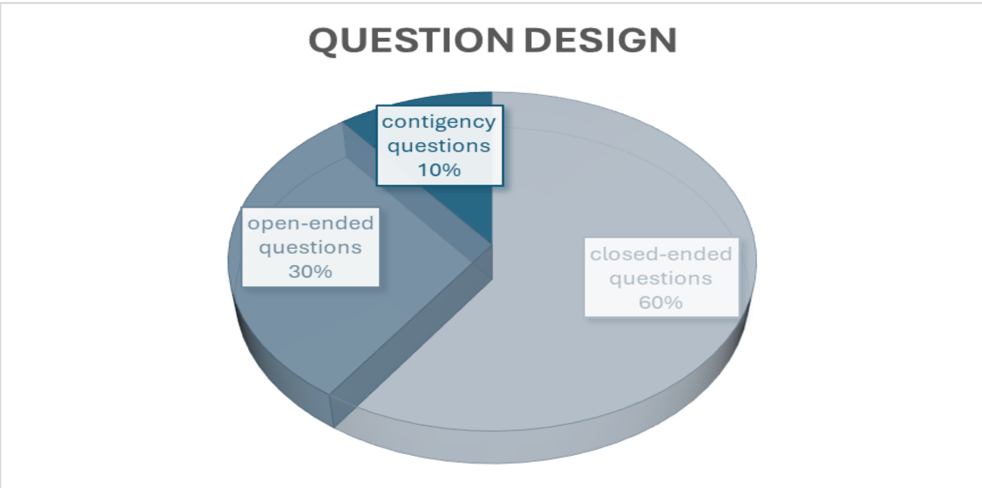
Taking together the two extremes, we considered that giving more weight to the quantitative aspect in our ED would offer maximal possible assistance on two levels: (1) the process of coding, analysing, and interpreting the collected data, and (2) the process of making connections to the objectives of the study and attempting generalisation of findings.

In practice, our MMA survey is divided into three web-based questionnaires, each of which addresses one distinct cohort, namely T&I students, professional interpreters and translators, and T&I educators[15]. All three questionnaires share the same organisational

[15] See chapter 5 for more details about the cohorts employed in the survey.

pattern since they consist of three types of questions, i.e., closed-ended questions, open-ended questions, and contingency questions. *Closed-ended questions* constitute the core of our survey and realise the quantitative research type which is being prioritised in our design. Closed-ended questions limits respondents' answers to a fixed and, thus, restricted number of predefined responses. In our work, these responses are of three types, i.e., "yes/no/I am not sure", multiple choice, and scaled questions. The latter category is informed by the *Likert Scale*, a psychometric rating scale deployed to measure opinions, attitudes, and/or behaviours[16]. The percentage of closed-ended questions equals 60% of the question types found in all three questionnaires (Figure 1). The main strengths of closed-ended questions include a speedy response (Boynton and Greenhalgh 2004), ease in providing a response, a less demanding process of responding, and quickness in data coding, listing, and analysis (Hyman and Sierra 2016: 3). However, we are also aware of certain disadvantages that characterise such question types; specifically, the confining nature of closed-ended questions limits the "richness" of the responses, which may, in turn, frustrate the respondents (Boynton and Greenhalgh 2004: 1314). Additionally, they involve a high risk of acquiescence bias (Krosnick 1999), lack of reliability, vagueness, and inability to sufficiently cover "characteristics [that] are broader in scope" (Spector 1992: 4).

Figure 1 Question Design



[16] In our work Likert Scale-informed questions are mainly opinion-oriented and attitudinal.

The second type of questions in our design is *open-ended questions.* In this type, the respondents are free to express themselves without the constraints posed by the presence of fixed possible answers. Open-ended questions make up for 30% of the questions included in the questionnaires and do not necessitate any specific structure (Figure 1). A key strength of an open-ended question is the leeway it offers to the respondents whilst they engage in the process of giving answers. Concerning the shortcomings, open-ended questions bear the risk of misinterpretation of the initial question which could lead to irrelevant or confusing answers and consequently, cause difficulties during the coding and analysis phases (Kitchenham and Pfleeger 2008:71). Moreover, questions of this sort may be unintentionally biased by the respondent's "articulateness[17]" (Hyman and Sierra 2016: 4) or intimidate respondents with lower literacy levels or certain disabilities who do not feel comfortable with expressing themselves in the written form (Connor Desai and Reimers 2019). The third question type in the survey is *contingency questions;* the term describes questions that are answered only if the respondent provides a specific answer to a previously posed question. In this way, we can avoid asking individuals to answer questions that do not apply to them or that are irrelevant to their interest and/or line of work Also, contingency questions are useful in cases where the respondents wish to elaborate on the answer they provided in a previous closed-ended question, thus contributing to the enrichment of our quantitative data (Boyton and Greenhalgh 2004). In our work, contingency questions amount to 10% of the overall question design (Figure 1). Their presence is invited by certain closed-ended questions that require further explanation or argumentation, generating a cascading effect.

Open-ended questions and contingency questions comprise the qualitative component of the survey that is embedded in the predominant quantitative design. As previously stated, their role is integral to our study since we can benefit from each type's strengths to reinforce the quantitative data and facilitate our analysis. In the analysis phase, both open-ended and contingency questions are explored at the level of discourse to help us code, interpret the data, and create taxonomies (if possible) regarding the attitudes and

[17]The ability to express oneself with ease and in a clear way.

opinions towards AI in T&I professional settings and pedagogy. This means that our emphasis is placed on *discourse analysis*; in the context of qualitative research, we perceive discourse analysis as an approach to data analysis that builds on the principles of *discourse tracing.* Discourse tracing is a method that allows for insightful investigation of "descriptions of contextual and personal experience" (LeGreco and Tracy 2009: 1522). This approach favours naturalistic generalisation (Stake and Trumbull 1982), which is a key feature of qualitative research (Denzin and Lincoln 2018) as it invites individuals to engage themselves in a given situation (LeGreco and Tracy 2009).

Chapter 4

Presenting the axes of the research

4.1 Preliminary definitions on AI

Defining AI is an intricate task. The challenge arises immediately when someone attempts to account for the AI's numerous nuances, which are informed by the scope of its application, into an all-inclusive . In the absence of a universally accepted definition of AI, the plethora of denotations ascribed to the term creates a never-ending exploration of the literature.

However, for the purposes of this analysis, it should suffice to start with Green's (2018: 10)[18] definition, according to which "artificial intelligence seeks to re-create particular aspects of human intelligence in computerized form"[19]. Furthermore, AI is primarily divided into two types, namely Artificial General Intelligence (henceforth AGI) and Functional AI[20]. AGI or "strong AI" corresponds to what Etzioni and Etzioni (2017: 411) call "AI minds". They define AGI as "[the] software that seeks to reason and form cognitive decisions the way people do (if not better), and thus aspires to be able to replace humans" (*ibid*.). On the other hand, Functional AI, or else "weak AI" or "narrow AI", is in Etzioni and Etzioni's (*ibid*.) terms the "kind of AI [that] only requires that the machines be better at rendering decisions in some matters than humans, and that they do so effectively within parameters set by humans or under their close

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[18] For more definitions of AI, see also pages 97-98 from: Wayne, Holmes, Jen, Persson, Irene-Angelica, Chounta, Barbara, Wasson, Vania, Dimitrova. 2022. *Artificial intelligence and education: a critical view through the lens of human rights, democracy and the rule of law*. Council of Europe and High-Level Expert Group on Artificial Intelligence. 2018. *A definition of AI: Main capabilities and scientific disciplines*. Brussels: European Commission: Directorate -General for Communication.

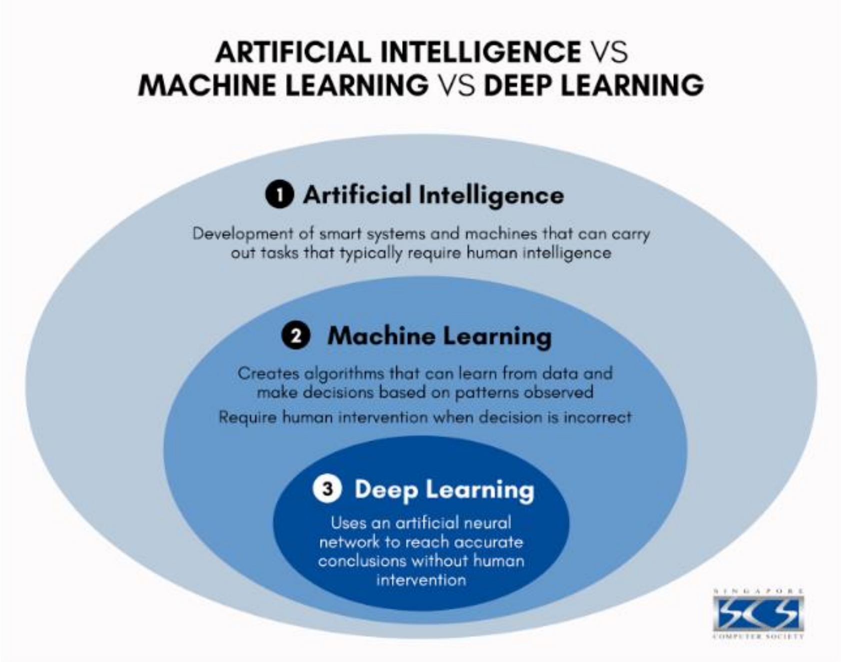
[19] See also: John, McCarthy, Marvin, Minsky, Nathaniel, Rochester, Claude Shannon. 2006. A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence, August 31, 1955. *AI Magazine*, *27*(4), 12. https://doi.org/10.1609/aimag.v27i4.1904

[20] For more subdivisions, see: https://www.ibm.com/blog/understanding-the-different-types-of-artificial-intelligence/

supervision" or "AI partners". As of today, what we have available is Functional AI, whilst AGI continues to be of a strictly theoretical nature.

Having delineated the meaning of AI, it is now essential to discuss the concepts of Machine Learning (henceforth, ML) and Deep Learning (henceforth, DL) ; both belonging to the wider spectrum of AI (Figure 2).

Figure 2 The interplay between AI, ML and DL. (Illustration by the Singapore Computer Society. Singapore Computer Society. Nd. SIMPLIFYING THE DIFFERENCE: MACHINE LEARNING VS DEEP LEARNING, https://www.scs.org.sg/articles/machine-learning-vs-deep-learning)



First, we will introduce the term ML. ML refers to "a computational method that is a subfield of artificial intelligence and that enables a computer to learn to perform tasks by analyzing a large dataset without being explicitly programmed"[21]. According to the

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[21] *Merriam-Webster.com Dictionary*, s.v. "machine learning," accessed January 3, 2024, https://www.merriam-webster.com/dictionary/machine%20learning.

definition provided by IBM[22], ML is targeting at simulating the human learning process. ML utilises primarily statistical analysis, data analogies, logic and symbols (Mueller and Massaron 2019:17). It is also human-dependent since its algorithms are developed and regulated by field experts such as analysts and scientists (*ibid*.). Janiesch, Zschench and Heinrich (2020: 687) identify three types of ML, namely *supervised learning, unsupervised learning, and reinforcement learning.* Supervised learning builds on training datasets that provide examples for the input and labels or target values for the output (*ibid*.). Unsupervised learning operates without the aid of training datasets and is expected to be able to detect patterns from unlabeled data (*ibid*.). Lastly, reinforcement learning is devised by a *self-reliant* system modeling which involves specifying a goal, a set of allowable actions and outcome constraints based on the allowable actions (*ibid*.).

DL is a subset of ML "in which the computer network rapidly teaches itself to understand a concept without human intervention by performing a large number of iterative calculations on an extremely large dataset"[23]. DL processes data via utilising *neurons* (i.e., computer units) that are organised into *layers* (i.e., ordered sections through which data passes in the course of learning and predicting), comprising altogether the *neural network* (Mueller and Massaron 2019: 17). Compared to ML, DL features greater autonomy in terms of feature configuration as it does not require human interference owning to its multiple layers which, at the same time, makes DL exceeding ML in activities such as image and voice recognition and text understanding (*ibid*.).

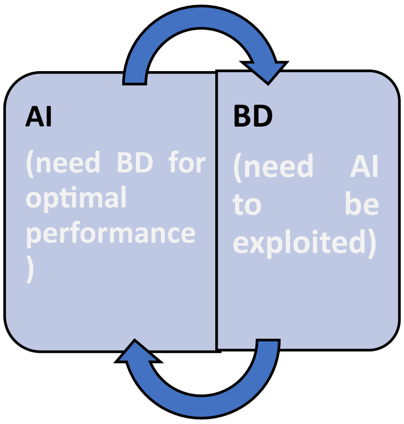
Another vital component for reaching an understanding of AI's workings and its full potentiality is *Big Data* (henceforth, BD). The term designates the "gigantic, complex datasets that have been made available through digitali[s]ation and cannot be processed or analysed through the use of conventional data processing techniques" (Stankovic, Garba and Neftenov 2021:22). As shown in Figure 3, BD and AI relate reciprocally in

[22] IBM. n.d. What Is Machine Learning? *IBM*. https://www.ibm.com/topics/machine-learning.

[23]*Merriam-Webster.com Dictionary,* s.v. "deep learning", accessed January 3, 2024, https://www.merriam-webster.com/dictionary/deep%20learning

that the one invites the interference of the other for both to be optimally exploited (*ibid*., Iafrate 2018).

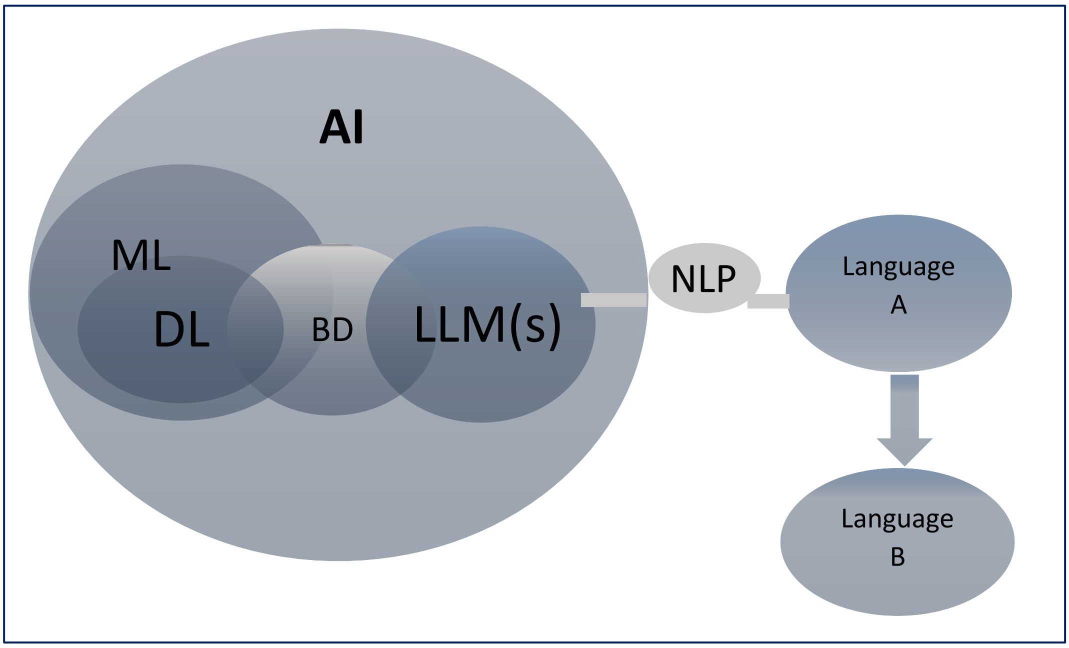
Figure 3 The converging relation between AI and BD



The elements introduced above constitute the foundation of AI-driven T&I. But, before analysing the relationships between AI, DL, ML regarding T&I, it is essential to introduce two more terms, namely *Natural Language Processing* (henceforth, *NLP*) and *Large Language Model(s)* [henceforth, *LLM(s)]*. *NLP* is an AI facet, which enables machines to read, process, understand, and interpret natural language (or human language). The term LLM(s) is used to describe the language model(s) that "utilize[s] deep learning methods on an extremely large data set as a basis for predicting and constructing natural sounding text"[24]. By bringing all those terms together, we end up with a synergy of variables that regulate AI-inspired T&I (Figure 4).

[24] *Merriam-Webster.com.Dictionary*, s.v. "large language model", accessed January 4, 2024, https://www.merriam-webster.com/dictionary/large%20language%20model

Figure 4 AI-driven T&I in a nutshell



As seen in Figure 4, AI-powered T&I applies ML and DL processes and exploits LLM(s) to facilitate, and, eventually, fulfill the desired purpose, i.e., transferring meaning from a specified language A to a specified language B. This is accomplished thanks to the contribution of BD and NLP.

The schematic representation depicts plainly the translation mechanism that informs the procedural design of AI-generated T&I output. Translation mechanisms of that type are the basis of AI-assisted translation tools including software, (online) services, etc.[25] Simultaneously, the components illustrated above constitute integral features of other technologies, which partake in the translation process, i.e., term bases and translation databases.

[25] See section 4.3 for information on current AI-driven translation tools.

4.2 Birth and evolution of AI

4.2.1 Historical Overview: AI in translation

Historical evidence shows that the origins of MT, as a process of automatically decoding a source language (henceforth SL) input and encoding it into a target language (henceforth TL) output, were first traced in the ninth century. They are closely related to the techniques of cryptanalysis, statistics, frequency analysis, and probability that flourished owing to the work of Arab scholars of the time (DuPont 2018). Specifically, DuPont (*ibid.*) states that among the precursors of cryptanalysis was the Arab scholar and cryptographer al-Kindi, who, in his work titled *"Risala fi 'istikhrag al-mu'amma",* at present the oldest work focusing on cryptology and cryptanalysis, "revealed a deep and sophisticated understanding of language and statistics"(5).

The second milestone in MT history relates to the interests of the seventeenth century incited by the need to facilitate international and scientific communication (Hutchins 1986). Up until that time, the construction of a machine was not involved in the attempts to establish a universal code of interlingual interaction. However, the ideas of Leibniz, Descartes, Beck, Becher, Kircher and Wilkins on the potentiality of numerical codes working as interlingual mediators functioned as catalysts for laying the foundations of MT[26]. The distinctiveness of their work lies in that they are considered the forerunners of *interlingua* i.e., "a formal language independent of the structure of any particular language and adequate for the intermediate stage of coding between source and target language" (Wilks 1987: 569).

Although the preliminary steps towards AI-powered MT (as we know it now) had already been made, the actual onset of facilitating the human-driven translational action commenced during the nineteenth and twentieth centuries thanks to the invention of mechanical calculators (Hutchins 1986). At this period, the world seemed to have started envisaging the development of a machine that would be integral to the process of translation. As Hutchins (1986) reported, such thoughts hadn't been generated before

[26] In his seminal work, Hutchins (1986) offers a brief overview of the proceedings in the field of MT during the seventeenth century.

1933, when the first suggestions regarding the creation of mechanical dictionaries first immerged in France and Russia (*ibid*.: 9).[27] The pioneering work of George Artsrouni and Petr Petrovic Troyanskii in France and Russia respectively constituted the first steps towards reorganizing the translation workflow at that time. The new reality enabled the departure from the expectation that a human translator would perform translation tasks in a machine-like manner, towards the presence of an actual translation machine that is an invaluable tool in the hands of the human translator. Artsrouni issued a patent on the 22 July 1933 in which he demonstrated his proposal regarding the 'Mechanical Brain' (Hutchins 1986: 9). His proposal evolved around the idea of a translation machine that would assist the process of translation owing to its huge storage capacity; this machine was intended to be used in professional contexts such as the railway, banking, telephony, telegraphy, and even anthropometry. Artsrouni's mechanical dictionary patent comprised of four motor-driven main parts, namely a word memory in four languages with an infinite storage capacity, an input device, a search mechanism, and an output mechanism[28]. The 'Mechanical Brain' was showcased at the Paris Universal Exhibition in 1937 and managed to attract the attention of significant state organisations, such as the French Postal Office, the French Railways, the Ministry of Defense, etc. However, its implementation ceased during the start of the Second World War.

Two months later, i.e., on 5 September 1933, Troyanskii applied for a patent regarding his invention in Moscow. He envisaged a machine that, according to Panov (1960), would be used "for the selection and printing of words while translating from one language into another or into several others simultaneously" (3). Practically, Troyanskii thought of a machine-assisted translation process that comprised three stages, i.e.,

[27] For more information on the first proposals about mechanical translation, Hutchins (1986) suggested two works of his: (1) John Hutchins. (unpublished). Two precursors of machine translation: Artsrouni and Troyanskii. https://aclanthology.org/www.mt-archive.info/IJT-2004-Hutchins.pdf and (2) John Hutchins and Evgenii Lovtskii. 2000. Petr Petrovich Troyanskii (1894–1950): A Forgotten Pioneer of Mechanical Translation. *Machine Translation* 15 (3): 187–221. https://doi.org/10.1023/A:1011653602669

[28] See the first work of Hutchin cited in footnote no. 2 about Artsrouni's proposal and especially pages 3-5.

analysis, transfer, and, lastly, synthesis. According to his idea, the translation machine was a dictionary with entries in six languages and was invented to assist the human operator during the second stage of the three-stage translation process mentioned above[29]. This stage involved the analysis of the SL input (first matched with a target language equivalent by a human operator) that would be logically parsed using 'signs for logical parsing' (i.e., a coding method devised by Troyanskii), which corresponded to the linguistic properties of the word in focus. After the logical parsing phase, the pre-selected target language equivalent would be seen on a tape along with the pertinent 'sign for logical parsing'. In 1939, Troyanskii proceeded to make significant amendments to his patent by adding features such as photo-electric coding, item reading ability from the glossary, and parallel translation performance in different languages and by different operators.[30] Troyanskii was the first to advocate the synergy between the human translator and machine translation and, most importantly, to lead the way towards automated translation. His work was not recognised until the late 1950s when MT started gaining importance in the discussions within Translation Studies.

Regardless of the impressive start of MT history throughout the 1930s, the subsequent decade would mark of the beginning of substantial work towards automatisation of translation with the help of a machine. The advent of the electronic digital computer in the 1940s constituted a major milestone, as it incited scientific inquiry into the

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[29] For more details on Troyanskii's three-stage translation process see:
Andrew D. Booth. 1958. *Translating Machines.*
Claudio Fantinuoli. 2018. 'Interpreting and Technology: The Upcoming Technological Turn'. In *Zenodo*. https://doi.org/10.5281/ZENODO.1493289
Ildikó Horváth,. 2022. AI in Interpreting: Ethical Considerations. *Across Languages and Cultures* 23 (1): 1–13. https://doi.org/10.1556/084.2022.00108
John W. Hutchins. 1986. *Machine Translation: Past, Present, Future*. Ellis Horwood Series in Computers and Their Applications. Chichester [West Sussex] : New York: Ellis Horwood ; Halsted Press.
Juan C. Sager. 1994. *Language Engineering and Translation: Consequences of Automation*. Vol. 1. Benjamins Translation Library. Amsterdam: John Benjamins Publishing Company. https://doi.org/10.1075/btl.1.
Wu Yonghui et al. 2016. Google's Neural Machine Translation System : Bridging the Gap between Human and Machine Translation. arXiv. http://arxiv.org/abs/1609.08144.

[30] See page 12 from : John W. Hutchins, John. (unpublished). Two precursors of machine translation: Artsrouni and Troyanskii. https://aclanthology.org/www.mt-archive.info/IJT-2004-Hutchins.pdf

potentiality of translation mechanisation. In this context, the diachrony of MT can be divided into five eras of evolution, each of which is reflected in the three generations of MT[31] (Table 3).

Table 3 MT History Development Scheme

MT History Development Scheme					
Eras of MT evolution	1st era: from 1949 until the early 1950s	2nd era: from 1954 until 1966	3rd era: from 1966 until 1975	4th era: from 1975 until the late 1980s	5th era: from 1990 onwards
MT generations	1st generation: rule-based systems (1950s-early 80s)			2nd generation: statistical/corpus-/example-based systems (late 1980s-early 1990s)	3rd generation: NMT systems (early 2000s-today)

As shown in Table 3, the first era of MT revolution started in 1949 and spanned until the early 1950s. Nevertheless, the beginning of MT history is marked by Warren Weaver's first thoughts that date back to 1945; they concern the possibility of a computer-like machine used either for partial or full completion of automatic translation tasks. Such thoughts emerged owing to of the invention of the computer at the

[31] According to Lehrberger and Bourbeau's taxonomy (1988), MT history can be divided into four sophistication levels that correspond to the generations of MT in diachrony. Their classification is the following: the first generation builds on the interlinear model of translation developed in the Middle Ages and refers to a 'word-for-word substitution'; the second generation covers 'machine aided human translation'; the third generation involves 'human-aided machine translation', and the fourth generation relates to 'fully automatic machine translation'. (See: John Lehrberger and LaurentBourbeau. 1988. *Machine Translation: Linguistic Characteristics of MT Systems and General Methodology of Evaluation* (Vol. 15). Linguistic Investigationes Supplementa. Amsterdam: John Benjamins Publishing Company. https://doi.org/10.1075/lis.15

beginning of this decade and of the beginning of the study regarding the potential fields of electronic computer integration.[32] Four years later, Weaver, who, at the time, was the Director of the Natural Sciences Division of the Rockefeller Foundation, issued the historical memorandum of 15 July 1949[33], in which he shared explicitly his views on translation[34]:

> I have wondered if it were unthinkable to design a computer, which would translate. Even if it would translate only scientific material (where the semantic difficulties are very notably less), and even if it did produce an inelegant (but intelligible) result, it would seem to me worthwhile.

Also knowing nothing official about, but having guessed and inferred considerable about, powerful new mechanized methods in cryptography—methods which I believe succeed even when one does not know what language has been coded—one naturally wonders if the problem of translation could conceivably be treated as a problem in cryptography. When I look at an article in Russian, I say: "This is really written in English, but it has been coded in some strange symbols. I will now proceed to decode."(Weaver 1955:2). His views, being strongly influenced by the ideas of the nineteenth and twentieth centuries, showcased the preliminary steps towards mechanical translation. Weaver maintained a strong belief in the *universality of human languages*, and it is in the principle of universality (or commonality) that he based his vision. With this realisation in mind, Weaver attempted to account for practical MT issues and provide possible solutions to them; such issues related to contextualised and ambiguous meaning, stylistic and grammatical specificities of natural languages, which he approached with optimism and resolution

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[32] For more information consult: John W. Hutchins. 1997. From First Conception to First Demonstration: The Nascent Years of Machine Translation, 1947–1954. A Chronology. *Machine Translation* 12 (3): 195–252. https://doi.org/10.1023/A:1007969630568

[33]Warren Weaver. 1949. *Translation*. Rockefeller Foundation Archives. https://aclanthology.org/1952.earlymt-1.1.pdf

[34] He had already communicated his ideas in 1947 in a letter that he sent to Professor Norbert Wiener of the Massachusetts Institute of Technology. Consult the following sources for more details: Warren Weaver. 1947. Letter to Norbert Wiener, 4 March 1947. https://aclanthology.org/www.mt-archive.info/50/Weaver-1947-typescript.pdf and John W. Hutchins. 1986. *Machine Translation: Past, Present, Future*. Ellis Horwood Series in Computers and Their Applications. Chichester [West Sussex] : New York: Ellis Horwood ; Halsted Press.

aiming at the development of a mechanised dictionary capable, under certain conditions, of addressing translation problems. At that time, however, Weaver's idea did not seem to echo the way the rest of the scientific and academic community viewed the future of translation.

Another emblematic figure in the history of MT was Andrew Booth, who, along with Weaver, was and is still considered the forefather of MT. Like Weaver, Booth pondered also the idea of using computers to assist the translation process. What he envisaged was in alignment with the technological advances achieved at the time that coincided, to a significant extent, with the work of his fellow pioneer in MT, Weaver (Hutchins 1986). Booth's work in 1947 evolved around the creation of a machine that would operate as a dictionary-like translation tool combined with elements from cryptography, sound, and text recognition (Booth 1958)[35].

During that time, Alan Turing exerted strong influence the idea of an interrelation between the electronic computer and intelligence. As Hutchins (1986) argued, Turning's contribution to the establishment of AI was invaluable; especially in the field of T&I, he was a strong advocate of the potentiality of AI's incorporation in translation (12). Turing's approach clearly illustrates the meeting of minds that would unite him with Weaver's vision as far as the mechanisation of translation was concerned.

The visions and discussions that marked the point of departure for reforming the translation process triggered a scientific debate around parameters pertinent to MT and its potentiality. Hutchins (1986) offered insights into the onset of MT literature proliferation by providing an account of the first literature samples (i.e., surveys) on MT. One of the most influential surveys fueled by the pressing need to shift from the state of enthusiasm towards a realistic investigation of the feasibility of the proposals regarding the incorporation of MT in translation was offered by Bar-Hillel. Bar-Hillel (1951) endeavoured to offer salience to the efficacy of a fully automated machine translation model by highlighting the centrality of ensuring high-quality translation

[35] See also: Andrew D. Booth. 1953. Mechanical Translation. *Computers and Automation* 2 (4): 6-8. https://aclanthology.org/www.mt-archive.info/CompAutomation-1953-Booth.pdf

output and explore the possibilities of a successful partnership between MT and the human translator. To this end, he surveyed the up-to (that)-date state of affairs in MT to minimise the extent of quality imperilment in automatically generated MT. The stance he adopted was disheartening as to the potentiality of a fully automatic MT tool since such development would require real-world knowledge on the part of the machine and would negatively affect the accuracy of MT output, thus resulting in quality deterioration. Being a pivotal contributor to quality, the element of accuracy played a central role in Bar-Hillel's work as he viewed high accuracy as a "conditio sine que non" which a fully automatic MT was not able to fulfill at that time (Bar-Hillel 1951: 230). Overall, his paper illuminated many of the issues which dominated the subsequent MT-pertinent dialogue by touching upon several aspects, including fully automatic MT, post-editing, syntactic analysis, universal grammar, logical language analysis, and the case of restricted languages in terms of vocabulary and sentence configuration.

Revolutionary contributions to the invention and development of MT reached a climax at the first MT Conference that took place at the Massachusetts Institute of Technology (henceforth MIT) in 1952 under the aegis of the Rockefeller Foundation. The conference hosted the presentations of eighteen field specialists who had an interest in MT. The conference's agenda was informed primarily by pre- and post-editing considerations, and the idea of a mechanized dictionary as they were all devised by the up-to (that)- date pertinent literature in MT[36].

The first MT Conference served as a point of reference for signaling the end of the first era in the history of MT and the beginning of the second which spanned until 1966. The commencement of the second era in MT history coincided with the first MT Conference and even more with another subsequent event of historical importance for MT, i.e., the Georgetown-IBM demonstration. The Georgetown-IBM demonstration became a

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[36] For more details see: John W. Hutchins. 1986. *Machine Translation: Past, Present, Future*. Ellis Horwood Series in Computers and Their Applications. Chichester [West Sussex]: New York: Ellis Horwood; Halsted Press and John W Hutchins. 1997. Looking back to 1952: the first MT conference. In *Proceedings of the 7th Conference on Theoretical and Methodological Issues in Machine Translation of Natural Languages*, July 23-25, 1997, New Mexico (USA): St John's College, Santa Fe, 19-30. https://aclanthology.org/1997.tmi-1.3.pdf

reality owing to the success of the first MT Conference of June 17-20, 1952. The significant contributions to the solid understanding of MT's workings and potentialities obtained at the conference incited the interest of Leon Dosert, a linguist, translator and major proponent of MT, and its team to start a pilot study to explore the feasibility of MT from the perspective of practicality[37]. The pilot study started in 1952 and lasted two years until January 7, 1954, when the public demonstration of the MT program that Dosert and its team created took place at IBM's Technical Computing Bureau in New York. This event constituted another milestone in the history of MT since it was the first time that MT was demonstrated using an electronic computer.

The Georgetown-IBM demonstration gave rise to a period of excessive activity in the field of MT study and experimentation. An indicative example was Booth and Locke's (1955) major publication exclusively focused on MT, for which they collected works of historical significance, including Weaver's memorandum among other equally significant contributions. This period of avid interest in MT served also as the breeding ground for the organisation of the first International Conference on MT by MIT in October 1956. According to Hutchins (1986), the conference's presentations were in alignment with the three divisions into which the MT-oriented research community had been divided; the first division was preoccupied with lexicography-, dictionary- and semantics-related problems; the second one involved the dichotomy between empirical and theoretical approaches towards MT research; and, lastly, the third division was divided into groups favoring the development of operational MT systems and those insisting on the centrality of ensuring high-quality MT output (21).

The same year, John McCarthy was the first to coin the term "Artificial Intelligence" in a publication and by dint of his work, he is regarded as the father of AI from the perspective of computer science. Together with Turing's earlier references as to the potentiality of incorporating AI in translation, McCarthy's seminal contribution to the

[37] For more details on the demonstration's specifics see: John W. Hutchins. 2004. The Georgetown-IBM Experiment Demonstrated in January 1954. In Robert E. Frederking and Kathryn B. Taylor (eds.), *Machine Translation: From Real Users to Research*. Berlin, Heidelberg: Springer, 102-114. https://doi.org/10.1007/978-3-540-30194-3_12

establishment of AI as a scientific discipline was an additional steppingstone to the conception of MT as one of the components within the broad scope of the discipline of AI. From that point onwards, the relationship between AI and MT was subject to intensive investigation on the part of the research community, giving rise to the emergence of both optimism and criticism[38]. Within this context, however, the highly promising optimistic attitude that had prevailed in the MT environment ended abruptly due to the issuing of the famous Automatic Language Processing Advisory Committee's (henceforth ALPAC) Report of 1966[39]. Among the major issues that were covered, the ALPAC Report was particularly concerned with a holistic assessment of MT. As a result, it touched upon issues such as the existing state of the art in the translation industry, the place of translators in the MT reality of the time, the cost of both the translation and the post-editing phase, and MT output quality. The ALPAC Report had a tremendous impact on the course of MT history since it did not openly support MT. Instead, it maintained the view that "there is no immediate or predictable prospect of useful machine translation" (ALPAC 1966: 32). To the detriment of progress in MT development, the ALPAC Report assessed MT as being, in Hutchin's (2003: 1060) words, "slower, less accurate, and twice as expensive as human translation". A direct negative consequence of the report's condemnation of MT was the suspension of the funding for MT-oriented research by the USA.

The dismissive views of MT by the ALPAC Report were subject to intense criticism. An exemplary piece of critical literature against the Report of 1966 was offered by Hutchins in the same year. In his "ALPAC: the in(famous) report", Hutchins (1966) emphasized the biased nature of the Report and its narrowness of perspective. He also raised the issue of the damage caused to the US computer science and linguistics community due to ALPAC's disbelief towards MT's efficiency:

[38] See section 4.2.3

[39] Automatic Language Processing Advisory Committee. 1966. Language and Machines: Computers in Translation and Linguistics. Washington, D.C.: National Academy of Sciences; National Research Council. https://nap.nationalacademies.org/resource/alpac_lm/ARC000005.pdf

> ALPAC reinforced an Anglo-centric insularity in US research which damaged that country's activities in multilingual NLP at a time when progress continued to take place in Europe and Japan. It took two decades for the position to begin to be rectified in government circles, with the report for the Japan Technology Evaluation Center (JTEC 1992) and with ARPA support of US research in this field during the 1990s. Hutchins 1986: 135)

The aftermath of the ALPAC Report was a period of disillusionment as to MT's potentiality that lasted almost ten years, i.e., from 1966 until 1975. Parallel to the disillusionment period during the 1960s, the decisive breakthrough of AI into a variety of disciplines, played a pivotal role in the study and establishment of its relationship with MT. On that note, MT was perceived as a "touchstone in AI work" as well as "a source of dispute about the relation of language understanding to knowledge of the world" (Wilks 1987: 564). The two extremes that defined this controversy were informed by the prevailing views around which AI's integration into MT had been perceived and critiqued (*ibid.*: 564). Specifically, the one extreme comprised the perspective of those who consider natural language understanding a fundamental prerequisite for ensuring AI's effectiveness in natural language computation (achieved through MT). This extreme reflected Bar-Hillel's point of view (and of those of like-mind), who argued that real-world knowledge understanding was not possible for an automatic translation mechanism (Bar-Hillel 1951). The other extreme of this equilibrium posited that full natural language understanding is not imperative to produce machine-generated translation output. The fine line between those opposing extremes, as Wilks (1987: 564) stated, shows difficulty in delineating the notion of "understanding" in a precise and sufficient manner and the "level" of understanding that is necessary for successful AI-powered MT. Then again, the literature of that era highlighted AI researchers' negligence of imperative natural language analysis aspects, e.g., syntactic parsing, by solely focusing on semantic-oriented models of language parsing (Hutchins 1986: 203).

Under these circumstances, AI's coexistence with MT flourished significantly during the 1970s, with the period of MT "resurrection" extending until the 1980s. Among the most important developments of the early 1970s was the transition from the previous state of the art in MT towards an AI-informed approach. Before the adoption of the AI approach, the MT reality involved the utilisation of rule-based, dictionary-like systems like Systran that belonged to the so-called “first generation MT”[40]. The Systran system, originally developed in 1968 under the auspices of the Georgetown University, served as a point of reference for the development of the succeeding AI-powered systems. As Wilks (1987: 568) postulated, it was due to Systran’s compatibility with AI features, ranging from feedback provision, sense of naturalness, and modular programming in the process of producing machine-generated output which enabled Systran to overcome impediments and ensure the success of translation completion, and efficient pattern matching capacity, that made its proximity to the AI approach explicit. In the course of MT’s re-generation and after the emergence of second-generation MT systems, MT re-invented itself and re-adjusted its scope to encompass the new perspectives that AI-based research had started to introduce into the workings of machine-assisted translation. Since an analytical account of all the research projects carried out at the time is not the purpose of this chapter, I will choose to refer to what I believe to be the most illustrative works,; such as Wilks contributions that date back to the early 1970s. Wilks’ pioneering work was based on an AI semantics-oriented approach to MT known by the term “Preference Semantics”. The rationale behind his approach was to create a system whose primary aim would be the selection of “a maximally coherent structure” (Wilks 2009: 94) or preference from the available candidates operating with an English-to-French translation direction with the aid of an interlingua. The selection of the most coherent French interpretation of a given English input was based on an algorithmic method that combined semantic parsing with inference rules and discoursal dependency analysis (Hutchins 1986)[41]. Another work of significance in the developing field of AI-

[40] See section 4.2.3 for a detailed account of MT generations.

[41] See the following sources:

a) Yorick Wilks. 1973. The Stanford machine translation project. In Rustin 1973, 243-290.

b) Yorick Wilks. 1975. An intelligent analyzer and understander of English. *Communications of the ACM* 18(5), 264-274.

c) Yorick Wilks. 1975. Preference semantics. In Edward L. Keenan (ed.), *Formal semantics of natural language*. Cambridge: Cambridge University Press, 329-348. file:///C:/Users/30694/Downloads/1-4020-5285-5.pdf

d) Yorick Wilks. 2009. An Artificial Intelligence Approach to Machine Translation. In Machine Translation: Its Scope and Limits. New York: Springer, 27-64.

assisted MT was produced by Schank. Schank's MARGIE system operated along the lines of English-to-German translation direction and was similar in Wilks' rationale. He developed his system by introducing the conceptual dependency theory, that is, a model of natural language processing applied in AI. Schank's system was programmed to process small English sentence input by translating it into a "semantic-network-based interlingua" type, and with the additional aid of inference rules, it produced output in German (Wilks 1987: 570)[42]. Both Schank and Wilks' works focused on the development of a special component in AI research in relation to interlingual transfer of meaning known as "semantics-based parsing". Along with other areas, i.e., a conceptual representation of textual meaning and knowledge databases "trained" to semantically decipher textual meaning to serve the process of input interpretation via "conventional event schemata", inference rules, and "commonsense expectations" (Hutchins 1986), MT entered a new, AI-oriented, era that established the baseline for the reform of the translation field.

Being influenced by the new perspectives in MT research during the 1970s, the period that followed the embrace of the AI approach to MT marked the fourth era in MT history. This period extended until the end of 1980s and featured the advances in natural language processing (of which MT is an integral subdomain) in the context of the overall development in the area of computational linguistics (Sager 1994): 306). Throughout the decade, the foci in the MT research community concerned the improvement of MT quality by delving into the potentiality of the AI-informed domain of natural language processing (Hutchins 2001: 13). During the 1980s, MT research in the USA, Japan, and Europe expanded the scope of its application by working on the development of more advanced systems, capable of addressing the needs of a wide range of users and areas of expertise (Hutchins 2003: 1061). More importantly, the end of the decade introduced a new state of affairs in MT as a result of numerous advances; first, a statistical turn to MT programming based on IBM research projects' results in

[42] See also: Roger C. Schank. (ed.). 1975. Conceptual Information Processing. Amsterdam: New Holland; New York: American Elsevier

the USA, whilst, simultaneously, research in Japan focused on experimentation by implementing a corpus-based approach[43][44].

In the 1990s, the state of the art in MT was largely influenced by the political scenery and its implications for the research hotspots on a global scale. As Hutchins (2003) stated, MT research in Russia and Eastern Europe fell victim to the political changes that impacted not only the course of Europe's history but also MT research, whilst Western Europe continued to explore new avenues for amending translation both as a professional practice and as a discipline (1061). In the USA and Asia, the 1990s signaled a euphoric period for MT research and a phase of sharp increase in MT software sales addressing mainly non-professional translators, who could now install software of that type in their computers and ease of online access to MT services (ibid.). Additionally, the optimistic attitude towards MT facilitated its integration into new fields of human activity such as that of telecommunication networks, and allowed for the optimization of professional practice via an array of translation aids; these aids included multilingual word processing, generation of glossaries and term banks in in-house professional contexts, utilising interactive or batch MT systems, and translation memory development (ibid.: 1065).

The end of the decade found MT's state of affairs in a constantly evolving era. In the early 2000s, neural language models in conjunction with neural network technologies entered the MT world and constituted the core of AI-powered MT. The earliest signs of a neural machine translation (henceforth, NMT) orientation to the interlingual transfer of meaning can be traced around 2007, when the first literature samples on this new approach to MT began to minimise the dominance of the previously prevailing statistical-based trends (e.g., Schwenk et al. 2007). Just for reference, only one proposal in NMT systems by Jean, Firat, Cho, Memisevic, and Bengio (2015b)45was submitted to the 10th Workshop on Machine Translation that took place in 2015. NMT's presence

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[43] See section 4.2.3 for delineating the meaning of the terms "statistical- "and "corpus-based-approach" respectively.

[44] Another innovation reported in the late 1980s referred to the advances in the area of speech translation that are explained in detail in section 4.2.2.

[45] See the list of proposals here: https://machinetranslate.org/wmt15

in the translation domain became resonant in 2015 by virtue of the pioneering work of Sutskever, Vinyals and Le (2014), Bahdanau, Cho and Bengio. (2014), Jean et al. (2015a; 2015b), proposed a new modelling type (the so-called "sequence-to sequence" model46) and new features that took MT research to a new neural technology-oriented level47. As Koehn (2017) stated, it was not until 2017 that NMT gained significant momentum and displaced the prior state of the art in MT, i.e., statistical machine translation (6). In 2016, Google made a breakthrough by launching its own NMT system (i.e., Google Neural Machine Translation system), targeting higher levels of accuracy and fluency of its translation services (provided via Google Translate) (Yonghui et al. 2016, Johnson et al. 2017). On this basis, NMT appeared to be a promising new avenue research-wise with remarkable influence on the quality of the output (Bentivogli et al. 2016, Moorkens 2018: 377-378)48. As expected, however, the quality variable was not exclusively evaluated positively, since AI was and still is not devoid of deficiencies; the corresponding research literature has offered counterarguments regarding quality-related considerations yielded from NMT-generated output (e.g., Castilho et al. 2017).

4.2.2 AI in interpreting

Being a sister discipline to translation and beyond the individual differences of each, interpreting's history of evolution regarding AI integration has several points of convergence. This practically means that the major turning points described in section 4.2.1 in the context of machine translation were equally instrumental for AI-mediated interpreting.

[46] See also: Graham Neubig. 2017. Neural Machine Translation and Sequence-to-Sequence Models: A Tutorial. arXiv. http://arxiv.org/abs/1703.01619.

[47] These research contributions serve as examples of the growing interest and confidence in the potentiality of NMT. To achieve maximal comprehension of their content, the reader is advised to have basic knowledge of math and programming.

[48] Research evidence has shown quality improvement in specific language pairs. Moorkens (2018) has provided an account of research-based results in the following language combinations and directions of translation, i.e., English-German, English-Spanish/French/Simplified Chinese, and vice versa (379-378).

As regards the exploration of interpreting's synergy with AI, history shows that the period between the end of 1980s and the onset of 1990s laid the foundations for AI-informed automated speech translation (henceforth AST)[49]. This period foregrounded the growing relevance of spoken language translation's potentiality, providing incentives for the application and amendment of speech recognition, linguistic analysis and interpretation of spoken language input, and speech synthesis technologies that constitute the apparatus for speech translation. Nakamura (2009) has stressed the shortcomings surrounding speech translation technologies, including difficulties related to grammar, colloquialisms, absence of punctuation, and speech recognition-related problems (37).

The pioneers in AST research were the contributors to the speech translation research project based on spoken travel conversation initiated by the Advanced Telecommunications Research Institute International (henceforth, ATR) in Japan in 1986 (Hutchins 2001; 2003, Morimoto and Kurematsu 2003, Nakamura *et al*. 2006, Nakamura 2009). Several research projects in different spoken discourse environments followed the paradigm of ATR across the globe, including Verbmobil in Germany, Nespole! and TC-Star in the EU, and TransTac and GALE in the USA (*ibid.*, Jekat 2015). Chronologically speaking, from the very first motivation to examine automated speech translation possibilities in the 1980s, it was obvious that the field had been in a continuous state of evolution. Not only did it encompass the milestones achieved in the context of AI-driven technological advances of the time, but also aligned with the systems in effect regardless of the mode of translation, i.e., either written or spoken interlingual transfer meaning (Figure 5).

Figure 5 Speech translation technology evolution. (Table by Satoshi Nakamura. 2009. Overcoming the language barrier with speech translation technology. *Science and Technology Trends-Quarterly Review* 31: 35-48*)*

[49] The literature about AST has used several other equivalent expressions to describe this type of interpreting, including machine interpreting, automated interpreting, speech translation or translation of speech.

Table 1 : Trends in the Research and Development of Speech Translation

Research Phase	1980s Confirmation of Feasibility	1990s Extension of Technology	2000s Attempts at Practical Systems
Fields	Simple reservations (ATR-phase 1)	Reservations and scheduling (ATR-phase 2, Verbmobil)	*Everyday travel conversation (ATR-phase 3) *Translation of keynote speeches (TC-Star) *Conversation for military use (TranTac) *Intelligence collection (Gale)
Linguistic features	Grammatically correct expressions	Everyday expressions that may be context-dependent or ungrammatical	Expressions including a wide range of topics and proper nouns
Phonological features	Clear pronunciation	Unclear pronunciation	Audio including background noise
Translation method	Rule-based translation Translation using artificial intermediate language	Example-based translation Translation using English as intermediate language	Statistically-based translation Direct translation of multiple languages

Note: ATR-phase 1: 1986 to 1992; ATR-phase 2: 1993 to 1999; ATR-phase 3: 2000 to 2005. For other projects, refer to the text.

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Nowadays, AI and machine learning technology represent the current state of the art in AST. At present, the available AI-informed toolkit in the field of AST can facilitate both consecutive and simultaneous modes of interpreting (Horváth 2022: 2). Nevertheless, AST's current language technology is still not devoid of shortcomings and is evaluated as being relatively limited in capacity and magnitude of application (*ibid*., Horváth 2021)(Figure 6).

Figure 6 Domains of AST application. (Table by Ildikó Horváth. Horváth, Ildikó. 2021. Speech Translation vs. Interpreting. *Language Studies and Modern Humanities* 3(2):174-187)

Table 2. Examples of AST use cases

Use case	Devices	Mode
healthcare	Prolingua	consecutive
military	IBM Mastor, Phraselator	consecutive
travel and tourism	Jibbigo, ILA, Skype Translator	consecutive
business	Vebmobil, ILA	consecutive, simultaneous
government (e.g. immigration, border patrol)	ILA	simultaneous
university lectures	EU-Bridge	simultaneous
education (e.g. parent-teacher meetings)	Skype Translator	simultaneous
accessibility (deaf/hard of hearing; blind/low vision)	ILA, EP, Skype Translator	simultaneous
conversations	various	consecutive, simultaneous

From a purely technological perspective, the taxonomy of the current AST tools comprises two types of AI-assisted models: (1) the cascade models, and (2) the end-to-end models (henceforth E2E). The former model applies a four-stage process to facilitate the interlingual transfer of spoken language input: speech-to-text (STT) conversion using automatic speech recognition (ASR), machine translation (MT), and text-to-speech (TTS) synthesis (Hovárth 2022:3, see also Fantinuoli 2018b, Hovárth 2021). The latter type deviates from the cascade models in that E2E models omit the STT stage and start immediately with ASR. However, the cascade model has managed to reign over the E2E models in the speech translation devices industry (Niehues 2020).

Apart from a strictly procedural application, AI is regarded equally integral for facilitating computer-assisted interpreting (henceforth CAI) terminology management. Indeed, if we accept that enhanced quality interpreting service is a fixed requirement in the industry, professionals need to ensure maximum possible practicality in accessing, processing, and mastering assignment-relevant information and terminology (Hovárth 2022: 4). Such views informed Rütten's work in the early 2000s; she devised a five-model software to ease the process of CAI terminology management: (1) Online and Offline Research, (2) Document Management, (3) Terminology Extraction and Analysis, (4) Terminology Management, and (5) Trainer[50] (Rütten 2004). Following Rütten's model, the market welcomed the first CAI terminology management tools that served as database generator and did not interfere during interpreting (Hovárth 2022). Concerning the recent state of the art, Fantinuoli (2018a) classified the current CAI tools under the scope of the "second generation" technology[51] which "offer[s] advanced functionalities that go beyond terminology management, such as features to organise textual material, retrieve information from corpora or other resources (both online and offline), learn conceptualised domains, etc." (165).

4.2.3 AI in MT: Generation overview and critique

As implied in the previous subsection, there are two levels of mapping the coexistence of AI with the fields of T&I, i.e., the chronology level and that of generations of MT

[50] This module assists the interpreter to consolidate assignment-pertinent terms (See Rütten 2004: 173-174).
[51] See 4.2.3 for details.

systems (Table 3, Figure 7)[52]. In this subsection we will focus on the observation of MT systems' generations and the ensuing criticism.

Figure 7 Machine Translation Evolution. (Illustration by Ildikó Horváth. Horváth, Ildikó. 2021. Speech Translation vs. Interpreting. Language Studies and Modern Humanities 3(2):174-187)

<table>
<tr><td colspan="3">Machine translation (MT)</td></tr>
<tr><td>rule-based</td><td colspan="2">corpus-based</td></tr>
<tr><td></td><td>statistical machine translation (SMT) / error-based machine translation (EBMT)</td><td>neural network-based machine translation (NMT)</td></tr>
</table>

We will start our analysis by stating that defining the generations of MT systems is a rather complex task. This is because the succession pattern among them is both moderated and influenced by the continuous contributions to the initial model types that intersect with the innate system-specific features (Wilks 1987). Having made this clarification, the framing of MT systems coincides with the emergence of the first generation, rule-based MT (henceforth RBMT) systems. *First-generation MT systems* entered the field of translation in the 1950s and were operational until the early 1980s. Their mechanics, however, were based on early research in the field of automatic language translation back in the 1930s. These earliest versions of MT systems built on the ideas put forth by Artsrouni (i.e., 'Mechanical Brain') and Troyanskii (i.e., analysis-transfer-synthesis pattern) about the potentiality of devising mechanical dictionaries (or else, translation machines) to serve interlingual transfer of lexical items by using an automated syncing procedure. In practice, the basis of the programs developed in the 1950s was a dictionary that contained all the lexicosyntactic data and the target

[52] There are several ways of establishing MT system typology; for instance, Sager (1994) argues that MT systems can be also classified according to text types or degree of automation. In this work, I rendered the levels of chronology and generations as being more practical.

language equivalent term(s) for each entry in the given SL, and a word-for-word system configuration. The strategic design of first-generation RBMT systems deployed three knowledge-driven[53] approaches to MT, with the "direct translation" approach being the first to be applied (Figure 8).

Figure 8 Illustration of the direct translation system (Illustration by John W. Hutchins. Hutchins, W. John. 1986. Machine Translation: Past, Present, Future. Ellis Horwood Series in Computers and Their Applications (Chichester [West Sussex] : New York: Ellis Horwood ; Halsted Press), 32, Fig.6.)

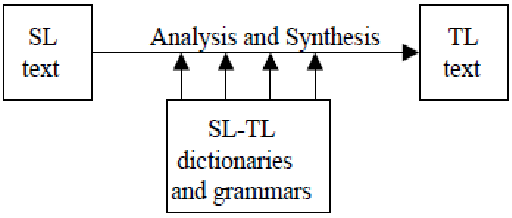


Fig.6. 'Direct translation' system

Vauquois (1976) described the general procedural design of first-generation MT systems as follows: first, the system conducted a dictionary look-up based on the provided textual input. When the dictionary look-up was completed, each source text occurrence was matched with a dictionary entry. The second step involved the replacement of source text input by the matching dictionary entry. Following the replacement phase, the next step entailed disambiguating lexical meaning via applying a "subroutine" process, which is informed by a set of syntax-oriented characteristics that are fed into the system a priori and facilitate the process of selecting the most fitting match. The subsequent steps continued with the application of translation routines within a restricted context to address the interlingual transfer of words or groups of words by manipulating word order. Lastly, the system applies a morphological routine to regulate grammatical agreement and condition morphological alternations (128-129).

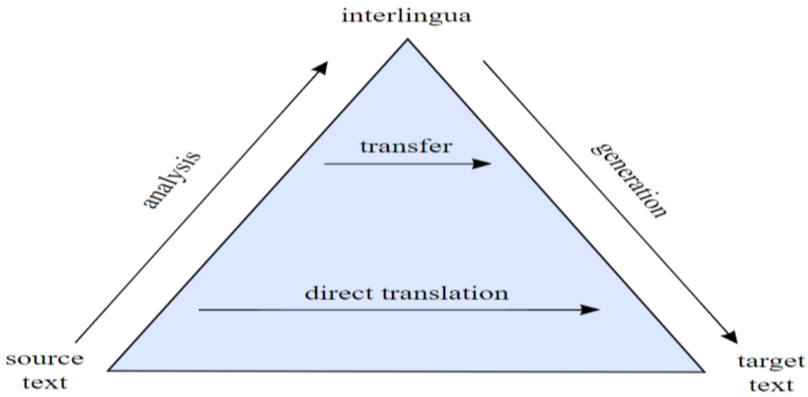
[53] Relying on the knowledge of the designer of the MT system.

By default, such system programming was subject to several weaknesses, including technical problems related primarily to limited storage capacity and slowness of access, issues with polysemy and semantics (Hutchins 1986: 22-24), decontextualised grammars, and underestimation of semantics (Hutchins 1978). Moreover, Bar-Hillel (1960) identified the incapacity of processing extralinguistic knowledge on the part of the machine as being another shortcoming of this system design. At the same time, he also brought about concerns regarding human-machine cooperation and the deficiencies that stem from the current state in RBMT (*ibid*.). Such shortcomings pertained to more "on the job"/practical issues, i.e., high demands in time, expenditure, and effort requested by the post-editors/translators, the costly nature of scalability and improvement of RBMT programs (Bar-Hillel 1962, ALPAC 1966).

In turn, these weaknesses were at the heart of the negative critique that was voiced in the literature. For instance, Sager (1994) emphasized the fact that first-generation systems were devised by people who were not specialists in linguistics or translation, with whatever this entails. He also stressed the absence of pragmatic textual analysis as another core limitation (*ibid*.). Earlier, Bar-Hillel (1959) maintained that RBMT systems were far from realising the notions of translation (per se) and high-quality translation (4). Additionally, Bar-Hillel (1951,1960) expressed his pessimism toward the reasonableness and efficacy of the RBMT systems of that time (see also Somers 1990). Melby (1981) also adhered to Bar-Hillel's arguments and highlighted the incapacity of current MT systems to process pragmatic and semantic specificities of texts. Later, Romanov *et al.* (2003) attributed the limited efficacy of the first-generation systems and the state of AI stagnancy in MT to lack of semiotic, psycholinguistic, and cognitive features that were later valuated by the second-generation systems, focusing exclusively on the AI-MT synergy (216).

Throughout the course of MT generations evolution, the field witnessed the emergence of two other approaches in RBMT system design: (1) the 'Interlingual system' approach, and (2) the ‘Transfer system’ approach (Figure 9)[54]. Both alternatives aimed to address the challenges that direct translation systems had brought about.

Figure 9 Bernard Vauquois’ visualisation of the three system types in the history of RBMT systems (Illustration by Bernard Vauquois. Vauquois, Bernard.1968. A survey of formal grammars and algorithms for recognition and transformation in mechanical translation. IFIP Congress (2): 1114-1122)



Both new approaches to MT system design had their basis in Weaver’s thesis:

> the way to translate… is not to attempt the direct route, shouting from tower to tower… [but]… to descend, from each language, down to the common base of human communication… and then re-emerge by whatever particular route is convenient. (Weaver n.d., as quoted in Hutchins 1978:12)

Simply put, this “common base of human communication” refers to a universal language (interlingua) and the translation process he proposed through this metaphor corresponds to the operational design of indirect MT systems (Figure 10).

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[54] For more details about each system type (including the ‘direct translation’ system mentioned earlier) see: John W. Hutchins, W. John. 1986. *Machine Translation: Past, Present, Future. Ellis Horwood Series in Computers and Their Applications* (Chichester [West Sussex] : New York: Ellis Horwood ; Halsted Press), 32-34.

Figure 10 Interlingual system. (Illustration by John W. Hutchins. Hutchins, W. John. 1986. Machine Translation: Past, Present, Future. Ellis Horwood Series in Computers and Their Applications (Chichester [West Sussex] : New York: Ellis Horwood ; Halsted Press)

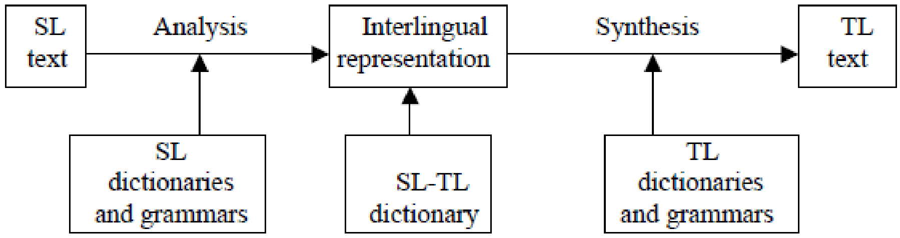

Fig.7. 'Interlingual' system

In practice, Weaver's vision led second-generation system developers to conceptualise two interrelated approaches to indirect MT: (1) Interlingual systems and (2) Transfer systems (Figure 11). The first system type involves a two-stage process: first, the translation input is analysed into interlingual representations and then, these interlingual representations are used to synthesise translation output (Hutchins 1978; 1986). The latter approach comprises a three-level strategy where the 'transfer' component plays the intermediary role between SL and TL text (*ibid.*). Thus, the first stage involves SL analysis that yields SL representations, the intermediary stage is the 'transfer' of these SL representations into TL representations, and the third involves TL synthesis (*ibid.*).

Figure 11 Transfer system (Illustration by John W. Hutchins. Hutchins, W. John. 1986. Machine Translation: Past, Present, Future. Ellis Horwood Series in Computers and Their Applications (Chichester [West Sussex] : New York: Ellis Horwood ; Halsted Press)

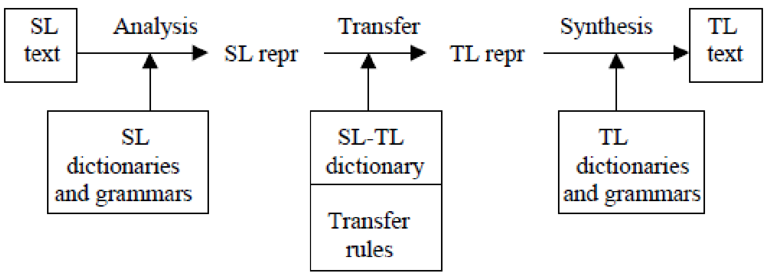

Fig.8. 'Transfer' system

A common feature of both approaches is the use of more than one dictionary; a monolingual SL dictionary facilitates the analysis phase through the provision of morphosyntactic and semantic information; a bilingual SL-TL dictionary carries mainly semantic information, and a monolingual TL one is used in the synthesis phase (Hutchins 1978: 12). This feature significantly increased the efficiency and practicality of second-generation indirect systems since it required only one program for the analysis and synthesis phase respectively for each language fed into the systems, thus making them more economical both at a linguistic and computational level (*ibid.*: 12-13, Vauquois 1978). However, these approaches were not error-free. Somers (1992) made explicit negative comments on the stratificational orientation of such MT architectural modeling by emphasizing that insistence on literal output is essentially inefficient and obsolete (234).

Building upon the limitations of first-generation RBMT systems, second-generation MT systems (re-)emerged as a new paradigm in MT around late 1980s[55]. Second-generation systems introduced a statistical approach to MT (henceforth SMT) by deploying corpus-based models. In SMT, the system architecture operates automatically with the assistance of parallel (SL-TL pairs) and monolingual (TL example sentences) corpora (Osborne 2011). SMT systems are powered by a probalistic modeling that aims to find the most probable translation for a submitted SL input out of a multitude of TL candidates. Systems of this type operate thanks to three essential components; (1) a translation model that employs parallel corpora to specify a set of likely TL candidates for an SL input to which it distributes probabilities based on their “relative correctness”, (2) a language model that retrieves data from monolingual TL corpora to compute the fluency of the TL candidate sentence via assigning higher probabilities to sentences that display closer resemblance to natural language use, and (3) a decoding phase (the argmax operation) that refers to a process applied for limiting the space of possible TL candidates by retaining the highest possible target output (Osborne 2011: 913). The process of SMT involves three

[55] Weaver’s ideas back in the 1950s laid the foundations for the emergence of second-generation MT systems as well. Since we accepted that a neat chronological classification of MT generations cannot be realised, it is equally safe to acknowledge the intersectionality in the course of MT evolution.

stages[56]; in the first stage, the system divides SL text into phrases. Subsequently, the translation model is activated to find possible TL matches to the given SL input, and lastly, the language model indicates the highest probable translation in the desired TL. There are different approaches to SMT, which include word-based models (earliest model), phrase-based models, syntax-based models, and hierarchical phrase-based models (models that combine syntax-based and phrase-based model architecture) (Koehn 2003, Chiang 2005, Osborne 2011).

The essential features of the statistics-based approach were the emphasis on the semantic and syntactic aspects of language (Vauquois 1978, Hutchins 1986) and the turn towards AI-oriented system design (Hutchins 1986). An important strength of SMT is found in the phrase-based modeling of the systems which appears to be less error-prone compared to the previous word-based system design (Osborne 2011). Another positive evaluation of SMT is offered by Jekat and Volk (2010) who acknowledged the amendments that the statistical approach has brought about in terms of data access and processing capacity.

Nevertheless, SMT literature states several concerns about the weaknesses of the statistical turn to MT. The most obvious challenge in SMT relates to the dependency between data abundance and system performance. Since SMT corpora need to be trained with large amounts of data so that they can ensure satisfactory performance, the problem that arises concerns both the process of feeding data into the system and the data quality variable that determines the overall assessment of the TL output. The qualitative variable is difficult to assess, especially when it comes to more rare languages, where the processing hindrances multiply (Poibeau 2017). The case of rare languages constitutes the second weak point in SMT; the problem with rare languages lies in that since the driving force of statistical MT systems is the data-riddled corpora, limited disposal of data in such languages poses serious threats in the process of

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[56] This procedural description refers to phrase-based modelling; the earliest SMT models were word-based, i.e., for each individual SL word the system could select the highest probable TL equivalent lexical item.

producing accurate, sufficient, and high quality output (Poibeau 2017:170-172). Logically, the rare languages argument invites the emergence of a superordinate category of SMT insufficiencies, namely the linguistic and structural distance between world languages compared to English, which is unanimously recognised as the lingua franca of interlingual communication. As Poibeau (2017) argued, the proximity between the source and target languages that are involved in SMT needs to be close enough to allow effective system operation. Lastly, SMT limitations include the issue of restricted context awareness due to the exclusive focus on the phrase level, which, subsequently, gives rise to ambiguous, inconsistent, and error-prone output (Carpuat and Simard 2012, Hardmeier 2012).

Another corpus-based method in MT that had emerged before SMT during the second-generation phase was the example-based MT (henceforth EBMT). EBMT entered MT history owing to the work of Makoto Nagao in 1984. He envisaged an approach to MT that was informed by "the mechanism of human translation of elementary sentences at the beginning of foreign language learning" (Nagao 2003: 351). The human translation mechanism relies on an inference-driven process that requires exposure to an array of examples to allow the person to translate an SL input into the TL. The translation is achieved through comparing and evaluating the similarity between the available structures and the SL input. EBMT's architecture did not necessitate deep linguistic analysis; instead, it required input sentence reduction into phrases, translation of these phrases into target language phrases, and lastly unification of the translated phrases into a sentence (i.e., TL output).

Nagao attempted to devise an MT system that could apply to languages with linguistic and structural distance, such as in the case of English and Japanese. To this end, he implemented the principle of MT by analogy (or MT "by example-guided inference") and relied on the utilisation of ordinary word dictionaries and thesauri (*ibid.*:353). The principle of translation by analogy is essentially founded on the use of a corpus (i.e., data repository) of already translated examples (TL examples) and involves a process of identifying proper TL matches to the SL input that is, in turn, "recombined" analogically to compose the correct output in the desired TL (Figure 12). The dictionaries are enriched with TL example sentences that are compared to a specified

SL input for testing the degree of similarity (Nagao 2003: 352). A parallel examination of the example sentences and SL input takes place in two stages: first, the system checks the overall syntactic similarity[57] between the SL input and the example sentences (found in the dictionary), and then, it deploys the thesaurus to check the "replaceability" of the words that are found in the example sentences by locating "synonym and upper/lower concept relations" to obtain an output (*ibid.*: 353)[58].

Figure 12 Operational scheme for EBMT (Illustration by Harold Somers. Sommers, L. Harold. 1999. Review Article: Example-based Machine Translation. *Machine Translation* 14(2): 113-157)

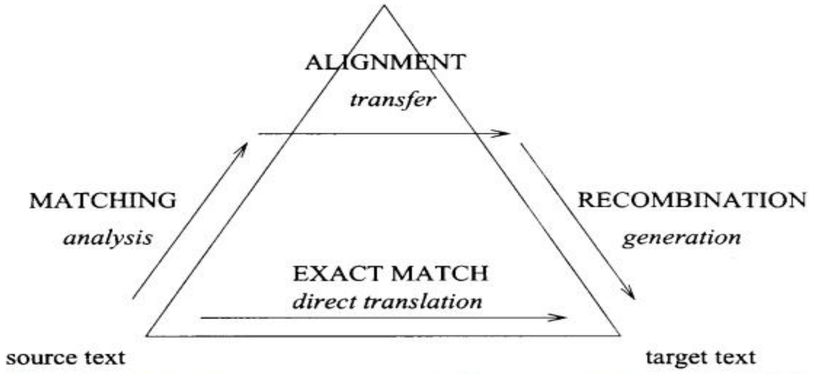

Figure 1. The "Vauquois pyramid" adapted for EBMT. The traditional labels are shown in *italics*; those for EBMT are in CAPITALS.

A distinctive feature of EBMT is that of the "augmentation stage of the system" (Nagao 2003). System augmentation refers to the constant update of the parallel corpora to maximise the efficiency of the system by adding new data, i.e., words and usage examples, and their TL corresponding output. In Nagao's system conceptualisation, augmentation is a prerequisite for achieving "learning", that is, the translation of the SL input.

The EBMT-pertinent literature has shed light on the vulnerabilities stemming from the specifics of system configuration. Among the most thorough and representative

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57 In EBMT, syntactic analysis addresses the "wider sentential context"; it does not intend to provide a deep syntactic analysis of the SL sentence (Nagao 2003: 352).

58 The thesauri-driven process is also guided by the similarity parameter.

arguments regarding the weaknesses of EBMT are the those made by Harold Somers. Somers (1999) described the general problems of EBMT as falling under eight interrelated categories, namely parallel corpora, granularity of examples, size of databases, suitability of examples, way(s) for example storage, matching, adaptability and recombination, and computational problems.

The utilisation of parallel corpora is inextricably related to ensuring proper data alignment, i.e., establishing correspondences among the data, especially when it comes to the highly complex case of languages with typological distance (Somers 1999: 118). Closely related to the challenge mentioned above, concerns on the appropriateness and efficiency of example granularity are thematised; Somers (*ibid*.:118) quotes Nirenburg, Domanshnev and Grannes to communicate the flawed aspects of EBMT architecture concerning example processing:

> The longer the matched passages, the lower the probability of a complete match (...). The shorter the passages, the greater the probability of ambiguity (…) and the greater the danger that the resulting translation will be of low quality, due to passage boundary friction and incorrect chunking. (Nirenburg, Domanshnev and Grannes 1993:48)

The third problem concerns database sizing considerations which, as in SMT, plays a decisive role in conditioning the quality of the TL output. Research has shown that the abundance of data can yield high-quality output (Mima, Iida, and Furuse 1998). By contrast, Somers (1999) draws attention to two variables, namely the appropriateness of examples and ways of storing the data in corpora, to emphasize the complexity of the process and the interference of factors that condition translation quality. In turn, data storage conditions the probability-driven matching process that makes way for the adaptability and recombination process. The problem with matching is influenced and regulated by the method of data storage since it interferes with the probabilistic mechanism of EBMT systems. Adaptability and recombination challenges cannot be easily addressed as it is particularly difficult to devise an optimal mechanism for carrying out these complex processes (Somers 1999). Lastly, computational problems involve the speed of EBMT systems and the overall complex architecture of system operation (*ibid.*). Interestingly, Nagao (2003) underlined the speed parameter by overtly commenting on the overall time-consuming experience that EBMT offers.

Having presented the previous MT generations, it is now time to elaborate on the third generation of system design, i.e., Neural Machine Translation (henceforth NMT). The neural turn to MT had preoccupied neural network research in the 1980s and 1990s (e.g., Allen 1987, Weibel *et al*. 1991, Forcada and Ñeco 1997, Castaño, Casacuberta and Vidal 1997). However, NMT's systematisation became a reality in the 21st century[59]. Specifically, NMT-pertinent studies proliferated after 2014, when researchers showed interest in examining the reliance on the potentiality of neural networks for optimising the probabilistic force of machine-driven translation systems (Bahdanau *et al*. 2014: 1).

The system architecture for NMT builds on the corpus-based, statistical modeling that had dominated the second-generation MT state of affairs (Moorkens 2018). NMT is built on the potentiality to stimulate the workings of the human brain activity via utilising deep learning technology and machine learning system architecture (Koehn 2017;2020) and big data. Its innovative feature compared to SMT lies in NMT's autonomous system configuration; unlike SMT, NMT departs from the phrase-based, multilayered procedural architecture and "attempts to build and train a single, large neural network that reads a sentence and outputs a correct translation" (Bahdanau *et al.* 2014:1). Moreover, NMT systems follow an E2E modelling as only one model is needed to facilitate the translation process. As Yonghui et al. 2016 put it, "[t]he strength of NMT lies in its ability to learn directly, in an end-to-end fashion, the mapping from input text to associated output text" (1).

The preponderance of the currently proposed NMT systems operates according to the encoder-decoder model that uses a recurrent neural network (henceforth RNN) to organise the encoder-decoder design of the translation system (Figure 13).

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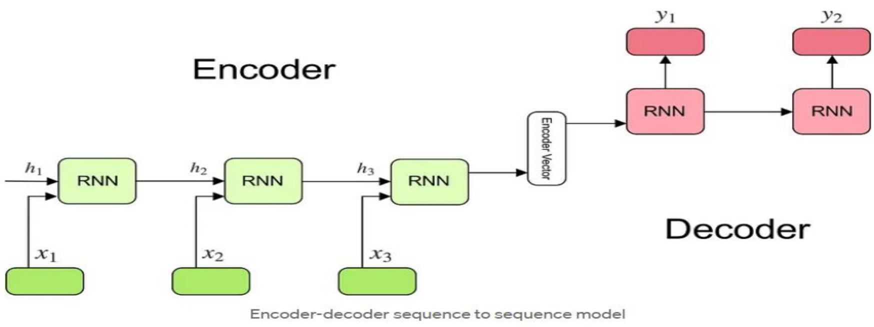
[59] See section 4.2.1

Figure 13 Visualising the encoder-decoder design (Illustration by Simeon Konstantinov. Kostadinov, Simeon.2019. Understanding Encoder-Decoder Sequence to Sequence Model. Towards Data Science. https://towardsdatascience.com/understanding-encoder-decoder-sequence-to-sequence-model-679e04af4346)



The translation process within the encoder-decoder model comprises three components: (1) the encoder, (2) the encoder vector (or context vector), and (3) the decoder (Muñoz 2020, Moses 2021). The encoder processes an input sentence by dividing it into tokens and encodes the information obtained during the processing phase into a fixed-length vector, i.e., the encoder vector. In turn, the encoder vector is responsible for transferring the full-meaning properties of the input sentence to the decoder to maximise its performance. Then, the decoder produces the output sentence based on the information it receives from the encoder vector (Figure 14).

Figure 14 Example of a translation produced with the encoder-decoder model (Illustration by Kris Moses. Moses, Kris. 2021. Encoder-Decoder Seq2Seq Models, Clearly Explained!! A step-by-step guide to understanding Encoder-Decoder Sequence-to-Sequence models in detail! Analytics Vidhya, March 12, 2021. https://medium.com/analytics-vidhya/encoder-decoder-seq2seq-models-clearly-explained-c34186fbf49b)

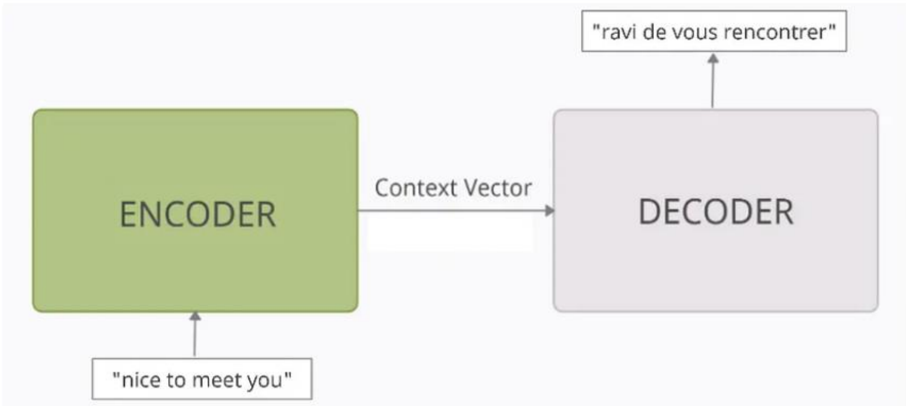


Image by author

Concerning the evaluation of NMT systems, the advantages are taxonomized into three axes; (1) simple system architecture, (2) emphasis on context understanding, and (3) multilingual adaptability. The directness of the neural approach to MT (1) due to the RNN-based and E2E design is undoubtedly one of the major assets of the third-generation systems. Furthermore, NMT features an enhanced contextual processing capacity (2) of the input inserted into the system and can yield more contextually appropriate output. Lastly, the NMT design can be adapted to a wide range of language pairs (3) which makes it more versatile compared to earlier MT generation models.

The advantages, however, need to be balanced by reference to the shortcomings of NMT. Research findings have highlighted issues pertinent to the ability of the encoder-decoder approach to operate satisfactorily in the case of long sentences (Cho *et al*. 2014, Koehn 2017). Problems of such nature might arise due to the fixed length of the encoder vector (Bahdanau *et al.* 2014). Lastly, Koehn (2017) has identified five other challenges in NMT systems, namely domain mismatch, which emerges in cases of polysemy, the decrease in system performance when the amount of training data is small, the impact of meaningless data on sentence pair alignment, word alignment intricacies, quality decrease with increased beam size, and challenges posed by infrequent words.

4.3 Current tools and the realm of their application

Nowadays, the rapid development and spread of AI have made a tremendous impact on the design of the technological aids that are used for carrying out T&I tasks. The AI-T&I technology synergy proliferates as more work is expended on conflating AI features into the apparatus of current tools. This subsection sets out to offer an account of some of the currently trending, to our knowledge, T&I tools which will be taxonomised based on the nature of the service they are devised to offer. The tools mentioned below were selected on the basis of the following criterion, i.e., they function as technological aids that are available in the Greek language so that they can assist the work of translators and interpreters working from and to Greek.

4.3.1 Terminology-related technology

The first type of T&I technological equipment is terminology-pertinent tools. These include terminology databases[60] (henceforth, TD) and terminology management systems (henceforth, TMS). The term TD describes a list-like database that contains single word entries or clusters of words (i.e., expressions) related to a specific subject area. TD and TMS are closely interrelated since they both target at ensuring accuracy, consistency, thus contributing to the overall quality of the T&I output. In practice, TMS can be perceived as the hypernym under which TD operates. Table 4 enlists some terminology-oriented tools that facilitate T&I activities.

Table 4 Terminology Tools

Tool	Type
IATE	TMS
EuroTermBank	TD
ClARIN:EL	*TD
ELETO	TD

The first entry in the list is *IATE*[61], which is a TMS operating under the auspices of the EU. The current version of IATE has been used within EU environment since November 7, 2018 and constitutes the fruit of cooperation of a number of significant EU institutions and agencies. *EuroTermBank*[62] is an online TD which involves both EU

[60] or else, term banks/term bases.
[61] https://iate.europa.eu/home
[62] https://www.eurotermbank.com/

and Icelandic languages and is linked to other TD and resources. *Clarinel* [63] is the National Infrastructure for Language Resources and Technologies in Greece and is the Greek counterpart of the CLARIN ERIC European Infrastructure. It is an open access online service that addresses all sectors of human activity ranging from academia to the general public. Lastly, *ELETO*[64]'s TD *is* developed by the Hellenic Society for Terminology as part of its overarching aim to study, preserve, develop, emphasise and promote the Greek language and its importance terminology-wise on an international level.

4.3.2 Translation aids

Another highly powerful AI-influenced T&I technology in the hands of professionals operating in the T&I industry is online translation service tools. Tools of this sort utilise core AI features, including ML, DL, NLP, and BD technology. In this category, we mention three greatly popular free online translation tools, namely Google Translate (henceforth, GT), DeepL and Linguee (Table 5a).

Table 5a Technological aids for translation

Tool	***Type***
Google Translate	NMT
DeepL	NMT
Linguee	Bilingual concordance

GT [65] [66] is a free web-based MT translation service whose current version builds on the workings of NMT. It has the capacity to process natural language in a vast number of languages and translate multiple textual forms and media, i.e., text, speech, websites, visual content (e.g., images). *DeepL*[67] is also an online NMT service that supports 29 languages, the preponderance of which are European ones. Depending on the text

[63] https://www.clarin.gr/en
[64] https://eleto.gr/en/terminology-resources/terminological-databases/search/
[65] See section 4.2.1 for more information on GT NMT.
[66] https://translate.google.com/
[67] https://www.deepl.com/translator

length it can be utilised either free of charge (up to 1,500 characters) or with subscription (*DeepL Pro*). *Linguee*[68] is a free online bilingual concordance that supports 25 languages and a number of language pairs resulting from the combination of the available corpus of working languages. This tool incorporates a human-trained ML system that is devised to facilitate the user in the process of interlingual transfer of meaning.

Special mention should be made to EU's language technology and especially to its variety of language tools, including AI-powered ones that are devised for assisting translation tasks. EU's language technology was developed in the context of its *Digital Europe* programme, whose leading force, with respect to multilingualism, is to transgress language barriers across and beyond the European borders. To this end, EU's institutions contributed to the design of a multifaceted toolkit comprised of language tools, term extractors, terminology management tools and corpora analysers[69]. Although all categories of tools have a role to play in producing translation output, for the purposes of this work we focused only on those bearing immediate relation to the translation process per se (Table 5b).

Table 5b EU tools for T&I

Tool	Type
eTranslation	MT
WEB-T	Free Multi-Language Website Translation Tool.

eTranslation[70] is a machine translation service that enables the interlingual transfer of meaning across all 24 EU languages, Icelandic, Norwegian and Russian with the contribution of neural network technologies and deep machine learning. It has the capacity to translate both formatted documents and plain text by maintaining the format of the original input as much as possible and conduct batch translation of multiple texts.

68 https://www.linguee.com/
69 https://knowledge-centre-interpretation.education.ec.europa.eu/en/terminology-tools , https://language-tools.ec.europa.eu/
70 https://cef-at-service-catalogue.eu/catalogue/browse/e4fc4c58-39fa-43b5-877b-16098ef0d45c/

The service is intended to facilitate the work of translators EU institutions, Public administrations and EU Small and Medium-sized Enterprises and is available upon request[71]. In turn, *WEB-T*[72] is another tool conceived within the broad scope of EU's vision as regards the promotion of multilingualism. It is a website translation alternative that facilitates the production of multilingual content on the part of web-based entities ranging from personal blogs and e-commerce stores, to nongovernmental organisations. *WEB*-T's core strengths include safe plugin, high quality translational output, free of charge availability, tailored plugin options based on the website's setup, multilingual SEO[73], and trustworthy data processing consonant to EU's GDPR policy.

4.3.3 Translation Software and Systems

Translation software plays a pivotal role in today's state of the art in translation industry. This subsection is devoted to AI-powered translation software solutions that satisfy two criteria: (1) they support translation from and towards the Greek language and (2) their use is popular within the Greek T&I education as our analysis will show [74] (Table 6).

Table 6 Software and systems for translation

Tool	**Type**
Phrase	Localisation and Translation Software (LTS)
MemoQ	Computer-Assisted Translation Software (CATS)
Trados Studio	CATS
Wordfast	Translation Memory Software (TMeS)

Phrase is a user-friendly, platform-based LTS that offers a variety of services, namely MT, website, game, application and software localisation, continuous, collaborative or string localisation, translation management, document translation, technical translation,

[71] https://webgate.ec.europa.eu/etranslation
[72] https://website-translation.language-tools.ec.europa.eu/web-t-multilingual-automated-translation-solution_en?prefLang=el , https://website-translation.language-tools.ec.europa.eu/index_en?prefLang=el
[73] Search Engine Optimisation .
[74] See chapter 5 for more information.

multilingual UX[75]. Apart from its multi-purposefulness, another distinctive characteristic of *Phrase* is that it brings together MT technology and AI via its *Phrase Language AI* and *Phrase Custom AI* solutions. *MemoQ* is a CATS[76] offering advanced translation services and enhanced compatibility with other translation tools, whilst it supports more than 100 languages and a plethora of file formats. It addresses core industries, such as life sciences, game localisation and audiovisual translation and a wide spectrum of customers, i.e., enterprises, language service providers and professional translators. *Trados Studio* is also a CATS that incorporates three essential translation technologies, i.e., translation memory, terminology management and MT. Its latest version[77] embeds AI -inspired features, such as generative AI, LLMs, and NMT. Lastly, *Wordfast* is a TMeS which is designed to offer desktop, web-based and even server translation experiences. Its flexible solutions allow for great adaptability to the needs of professional translators, LSPs , corporations and educational institutions.

4.3.4 Cloud Translation

Cloud Translation is, put simply, a translation solution that enables websites and applications to translate textual content through an API[78]. This subsection focuses on two cloud-based systems, namely *XTM Cloud*[79] and *Google Cloud Translation*[80]. *XTM Cloud* is a translation management system designed to facilitate localisation tasks by deploying state of the art technology, including AI. In its turn, *Google Cloud Translation* provides users with the opportunity to translate textual, website, application and multimedia content with the contribution of NMT-based technology and several AI-driven features, e.g., ML.

[75] UX, i.e., User Experience.
[76] It also offers a TMS solution.
[77] Trados Studio 2022 Service Release 2.
[78]Application Programming Interface. For more information, see: https://www.ibm.com/topics/api
[79] https://xtm.cloud/

[80] https://cloud.google.com/?hl=el

4.3.5 Interpreter-oriented technology

The interpreters' case is of special interest with respect to the use of AI-inspired technology. Today, professional interpreters can leverage the same AI-assisted tools as the ones deployed by professionals who offer translation services. We should therefore revisit the previously stated argument concerning the convergent relation between the two disciplines involved in the process of interlingual transfer of meaning, i.e., T&I, and, most importantly, underpin the presence of a shared technology toolkit.

Focusing, however, our attention solely on interpreting tools, the one that has been unanimously recognised as highly effective is *InterpretBank*. It is a CAI tool intended to assist the practice of professional interpreters in manifold ways; it enables users to carry out specialised tasks, manage terminology and create and edit glossaries through advanced AI-driven technology. What is more, Functional AI enjoys a central place in the workings of *InterpretBank* as it introduces four cutting-edge services, namely AI Speech Recognition, AI-powered glossary creation from webpage data, AI-powered glossary development through topic-based search, and AI-powered glossary development from inserted document data.

This technological overview allows further insights into the current technological resources within the T&I market and particularly in the tools that support Greek. Simultaneously, it can mark an important starting point for more innovation in the field of T&I technology, especially with regard to the Greek language and the consolidation of its place within the language services industry in this constantly evolving and AI-inspired era.

4.4 Introducing AI in T&I curricula

4.4.1 Current state of affairs around the world

The undisputed interference of technology in several strands of professional activity has also come to the attention of Language Service Providers (including translators and interpreters) (Presas, Cid-Leal and Torres-Hostench 2016, Sakamoto, Rodríguez de Céspedes, Berthaud and Evans 2017, Su and Li 2023). T&I educators and trainers have equally witnessed the changes that this new reality has brought about. Evidence of this is the increasingly held belief that one of the main imperatives in translator and interpreter education should be, and seems indeed to be, to keep abreast of the technological developments that shape the professional identity of translators and interpreters of our times (Rodríguez de Céspedes 2017; 2019, Bowker 2023).

Technological competency is a key feature of translators' and interpreters' professional identity. The Directorate-General for Translation (2022:9)[81] defines technological competency as the "competence [which] includes all the knowledge and skills used to implement and advise on the use of present and future translation technologies within the translation process. It also includes basic knowledge of machine translation technologies and the ability to implement machine translation according to potential needs". This definition serves as the connecting line between the employability standards that need to be met for effective professional integration into the industry and the responsibility on the part of the training and educational sector to prepare future translators and interpreters based on the technological breakthroughs in their profession. The aforementioned responsibility echoes the advances in the field of AI and T&I automation and the way(s) they have contributed to the (re)formation of the training and education curriculum of future professionals in the T&I domain (Wang 2023).

Exploring T&I pedagogy about AI integration is of primary importance for serving one of the fundamental objectives of this dissertation; to this end, this section is dedicated to a global-scale study of the curriculum organisation of universities offering postgraduate studies in the fields of T&I with a particular focus on T&I technology-pertinent aspects. The overarching aim of this review is to document the reality of T&I training in the context of the Greek tertiary education technology-wise, after having previously explored AI technology infusion into postgraduate programmes around the world. To facilitate the process of investigation, I created a classification of the universities offering AI-pertinent courses into six categories divided according to the

[81] https://commission.europa.eu/system/files/2023-05/EMT_Annual_Report_2022.pdf

geographical areas they belong to (Table 7, 8, 9, 10, 11, 12). The analysis will proceed as follows: firstly, I present and comment on the six lists of universities. Then, I attempt to provide an evaluation of the curriculum's content by pointing towards the fine line that exists between AI translation and Computer-Assisted T&I (henceforth, CATI) and discuss how and to what extent they intersect.

The first list focuses on the T&I tertiary-level pedagogy within the European borders. Before presenting and analysing the data, some preliminary remarks are necessary; firstly, the European universities listed in Table 1 are all included in *the list of EMT members 2019-2024*[82] which appears on the official website of the European Union (henceforth EU). Second, the entries were selected because the official webpages of the universities offered an English version of their content, except for some content available in German, in which I am a competent user. In total, the EMT members' list included seventy-one master's degree programmes (henceforth MA programme) offered in twenty-four EU countries. The research showed that only sixteen out of the seventy-one (22.5% approximately) EU universities offer a T&I technology-oriented training curriculum to introduce future translators and interpreters to the potentiality of technology in professional practice.

Table 7 Europe

Europe			
Provider	**Context of provision**	**Course/Module & Course/Module Type**	**Useful Links**
University College of Cork, School of Languages, Literatures and Cultures & Department of Modern Irish	MA in Translation Studies	Introduction to Translation Technologies (compulsory module)	https://www.ucc.ie/en/cke77/ https://ucc-ie-public.courseleaf.com/modules/?details&code=LL6026

[82]https://commission.europa.eu/resources-partners/european-masters-translation-emt/list-emt-members-2019-2024_en#Malta

***Dublin City University, Faculty of Humanities and Social Sciences, School of Applied Language and Intercultural Studies**	MSc in Translation Technology	Translation Technology (compulsory module) Artificial Intelligence, Info & Info Seeking (elective module)	https://modspec.dcu.ie/registry/module_contents.php?function=2&subcode=LC501 https://modspec.dcu.ie/registry/module_contents_archive_years_plus.php?subcode=CA652A&function=2&module_archive_year=2023
***Dublin City University, Faculty of Humanities and Social Sciences, School of Applied Language and Intercultural Studies**	MA in Translation Studies	Translation Technology (compulsory module)	https://modspec.dcu.ie/registry/module_contents.php?function=2&subcode=LC501
Universitat Autònoma de Barcelona, Faculty of Translation and Interpreting	MA in Tradumatics: Translation Technologies	Automation of Translation (compulsory module) Localisation and AT (compulsory module) Translation Automation (compulsory course)	https://www.uab.cat/web/estudiar/official-master-s-degrees/general-information/-1096480962610.html?param1=1345695508762 https://guies.uab.cat/guies_docents/public/portal/html/2023/assignatura/43775/en https://www.uab.cat/doc/HorariSMUTT_en
Universitat Rovira i Virgili	Masters in Professional Spanish-English Translation	Translation Technologies (compulsory module): Translation tools for specialised	https://www.intercultural.urv.cat/en/masters/masters-courses/#technologies

		translation (compulsory course)	
Università di Bologna, Dipartimento di interpretazione e traduzione	MA in Specialised Translation, Specialisaton: Translation and Technology	Translation Technologies (I.C.): Computer-assisted Translation (compulsory course) Machine Translation (compulsory course)	https://corsi.unibo.it/2cycle/SpecializedTranslation/course-structure-diagram/piano/2023/9174/C09/000/2023
University IULM, Faculty of Interpreting and Translation	Master in Specialised Translation	IT Tools for Translation: Computer-Assisted Translation and Localization (compulsory course) Machine Translation and Post-Editing (compulsory course)	https://www.iulm.it/wps/wcm/connect/iulm/c5938d13-0253-42ed-865e-b1cdaab4b2f8/guida_IULM_31-01-2023_WEB_en.pdf?MOD=AJPERES
Università Degli Studi di Trieste, Department of Legal, Language, Interpreting and Translation Studies	MA in Specialised Translation and Conference Interpreting	Advanced Technologies for Translation and Interpreting (compulsory course)	https://units.coursecatalogue.cineca.it/insegnamenti/2023/114641/2010/9999/10306?coorte=2023&schemaid=12132
University of Malta, Faculty of Arts, Department of Translation, Terminology, and Interpreting Studies	MA in Translation and Terminology Studies MA in Translation and Interpreting Studies	 Computer-Aided Translation (compulsory course)	 https://www.um.edu.mt/courses/overview/pmttftt-2023-4-o/

Leiden University, Faculty of Humanities, Leiden University Centre for Linguistics	MA in Linguistics, Specialisation in Translation Theory and Practice	The Translator's Tools (compulsory course)	https://studiegids.universiteitleiden.nl/en/courses/120990/the-translators-tools
University of Vienna, Centre of Translation Science	MA in Translation and Interpreting, Specialisation in Specialised Translation and Language Industry	Methods, Processes and Technology (compulsory module)	https://transvienna.univie.ac.at/fileadmin/user_upload/z_translationswiss/Studium/Curricula/Curriculum_MA_Translation_Juni2018.pdf
Jagiellonian University, Faculty of Philology, Chair for Translation Studies	MA in Translation Studies	MA seminar 1 (Computer-Assisted Translation (CAT), Machine Translation (MT) and AI, as well as contemporary translator education, including translator competence and methods in Translation Pedagogy)	https://przeklad.filg.uj.edu.pl/en_GB/seminaria
Pedagogical University of Kraków, Institute of English Studies, Chair for Translator Education	MA in Translation Studies and New Technologies	Digital Translation Tools Computer Assisted Translation (CAT) Translation Technologies and Postediting (courses type not specified)	https://kdp.up.krakow.pl/en/ma/ https://kdp.up.krakow.pl/en/studies/

University of Warsaw, Institute of Applied Linguistics	MA in Applied Linguistics, Specialisation in Translation and Translation Technologies	Computer-aided translation (CAT) – advanced level (specialisation course) Machine translation and post -editing (specialisation course)	https://ils.uw.edu.pl/wp-content/uploads/sites/110/2023/12/Full-time-MA-programme-Applied-Linguistics.pdf
University of Porto, Faculty of Arts and Humanities	MA in Translation and Language Services, Specialisation in Computer Technology for Translation	Course list not available, yet there is detailed description of the objectives	https://sigarra.up.pt/flup/en/CUR_GERAL.CUR_VIEW?pv_ano_lectivo=2018&pv_origem=CUR&pv_tipo_cur_sigla=M&pv_curso_id=437
Constantine the Philosopher University, Faculty of Arts, Department of Translation Studies	MA in Translation and Interpreting	Machine Translation (not thoroughly specified course type)	http://www.ktr.ff.ukf.sk/index.php/en/for-students/master-s-study-programme (EN-DE combination indicatively selected)

The second MA programmes' list covers the technological turn to T&I education in the UK. Data were extracted primarily from the results yielded by a filtered search on *FindAMasters*, an online repository of MAs and postgraduate programmes across the globe[83]. The number of universities offering MA programmes with a curriculum organisation consonant to the study's objective amounted to eleven and the number of programmes covering both disciplines, i.e., T&I, to seventeen (Table 8).

[83] https://www.findamasters.com/

Table 8 United Kingdom

United Kingdom			
Provider	**Context of provision**	**Course& Course Type**	**Useful Links**
University of Birmingham, School of Languages, Cultures, Art History and Music, Department of Modern Languages	MA in Translation Studies (campus-based and distance learning) MA in Translation Studies Arabic-English MA in English-Chinese Interpreting with Translation	Translation Technology module (optional module)	https://www.birmingham.ac.uk/postgraduate/courses/taught/arts-law-inter/translation-studies.aspx#CourseDetailsTab
University of Leeds, School of Languages, Cultures and Societies	MA in Conference Interpreting and Translation Studies MA in Business and Public Service Interpreting and Translation Studies	Principles and Applications of Machine Translation (elective module)	https://courses.leeds.ac.uk/i411/conference-interpreting-and-translation-studies-ma#content https://courses.leeds.ac.uk/i409/business-and-public-service-interpreting-and-translation-studies-ma#content

University of Swansey, Faculty of Humanity and Social Sciences, School of Culture and Communications	MA in Translation and Interpreting (2+3 Year Part-time versions) Professional Translation (Extended, with Université Grenoble Alpes), MA	Translation Tools (compulsory module)	https://intranet.swan.ac.uk/catalogue/default.asp?type=moddetail&dept=any&mod=MLTM03&ayr=24%2F25&psl=TB1&detailOnly=false&_gl=1*wb8l3t*_gcl_au*Nzk0MTc3NTU1LjE3MDI2NzI3MjI. https://www.swansea.ac.uk/postgraduate/taught/culture-communication/modern-lang-translation-interpretation/ma-translation-interpreting/?utm_source=findamasters&utm_campaign=postgraduate21&utm_medium=courselisting&utm_content=FooterBarButton#modules=is-expanded https://www.swansea.ac.uk/postgraduate/taught/culture-communication/modern-lang-translation-interpretation/ma-professional-translation-extended-universite-grenoble-alpes/
University of Surrey, Faculty of Arts and Social Sciences	*MA in Translation and Interpreting	Smart Technologies for Translation (optional module) Hybrid Practices For Live Speech-to-Text Communication (optional module)	https://catalogue.surrey.ac.uk/2024-5/module/TRAM502 https://catalogue.surrey.ac.uk/2024-5/module/TRAM506
University of Sheffield, Faculty of Arts and Humanities, School of Languages and Cultures,	Ma in Translation Studies	Translation Technologies (compulsory module)	https://www.sheffield.ac.uk/postgraduate/taught/courses/2024/translation-studies-ma-pg-certificate-pg-diploma?utm_source=findamasters&utm_campaign=

			courseid(MDLT35)&utm_medium=courselisting&utm_content=FooterBarButton#modules
University of Strathclyde, Faculty of Humanities and Social Sciences, School of Humanities	MSc/ PGDip in Applied Translation and Interpreting	Translation and Language Technology	https://www.strath.ac.uk/courses/postgraduatetaught/appliedtranslationinterpreting/#coursecontent
University College London, Faculty of Arts and Humanities, Centre for Translation Studies	MSc in Translation and Technology (with Interpreting)	Translation Technologies 1 (compulsory module) Translation Technologies 2 (optional module)	https://www.ucl.ac.uk/module-catalogue/modules/translation-technologies-1-CMII0101 https://www.ucl.ac.uk/module-catalogue/modules/translation-technologies-2-CMII0102
The University of Edinburgh, School of Literatures, Languages and Cultures	MSc in Translation Studies	****Technology and Translation in the Workplace (elective course)	http://www.drps.ed.ac.uk/23-24/dpt/cxcllc11065.htm https://www.ed.ac.uk/studying/postgraduate/degrees/index.php?r=site/view&id=251?utm_source=findamasters&utm_medium=programme&utm_campaign=pg_institution_profiles&utm_term=&utm_content=listing
***University of York, Department of Language and Linguistic Science**	MA Interpreting, Translation and Applied Technologies	Technologies in the Language Services Industry (compulsory module) Linguistic Computations: Real and Artificial Intelligence (elective course)	https://www.york.ac.uk/study/postgraduate-taught/courses/ma-interpreting-translation-applied-technologies/#course-content
Herriot-Watt University	MSc in Translation and Interpreting	Emphasis on the use of computer aided translation tools (programme's objective)	https://www.hw.ac.uk/uk/study/postgraduate/interpreting-translating.htm

	MSc in Translating	Translation Technology (compulsory course)	https://www.hw.ac.uk/uk/study/postgraduate/translating.htm
University of Leicester, College of Social Sciences, Arts and Humanities, School of Arts	MA in Translation	Computer Assisted Translation Tools (elective module)	https://le.ac.uk/modules/2024/ts7033

The third list comprises MA programme providers from the United States of America. As in the research in the state-of-the-art in T&I pedagogy in the UK, this body of data was also elicited from *FindAMasters***.** In this case, the customised search led to a total of four tertiary education institutions and six MA programmes (Table 9).

Table 9 United States of America

United States of America			
Provider	**Context of Provision**	**Course/Course type**	**Useful Links**
Middlebury Institute of International Studies at Monterey	MA in Translation and Localisation Management MA in Translation and Interpretation MA in Conference Interpretation MA in Translation	Translation Technology (compulsory course) Advanced Translation Technology (compulsory course)	https://www.middlebury.edu/institute/academics/degree-programs/translation-localization-management/curriculum https://www.middlebury.edu/institute/academics/degree-programs/translation-interpretation/curriculum
New York University, School of Professional Studies	MS in Translation and Interpreting	Translation Technologies (compulsory course) Machine Translation and Postediting (elective course)	https://www.sps.nyu.edu/homepage/academics/masters-degrees/ms-in-translation/curriculum.html

La Salle University, School of Arts and Sciences	MA in Translation and Interpretation	Technology: Applications in Translation and Interpretation (compulsory course)	https://catalog.lasalle.edu/graduate/masters/translation-interpretation-ma/#coursestext
Kent State University, College of Arts and Sciences, Department of Modern and Classical Language Studies	MA in Translation	Terminology and Computer Applications in Translation (compulsory course) Software Localisation (compulsory course)	https://catalog.kent.edu/colleges/as/mcls/translation-ma/#courseworktext

The fourth table (Table 10) is intended to display the state of affairs in Canada; as shown below, the online research[84] resulted to only one university in Ottawa, namely the University of Ottawa. This university offers three MA programmes in T&I independently. Their curriculum illustrates the need for ensuring technological competency for future professional translators and interpreters. This fact becomes especially apparent in the shared seminar-type curriculum content with respect to translation technology.

Table 10 Canada

Canada			
Provider	Context of provision	Course/Course type	Useful links
University of Ottawa, Faculty of Arts	MA in Translation Studies	Computers and Translation (seminar) Machine Translation (seminar)	https://catalogue.uottawa.ca/en/graduate/master-arts-

[84] Via FindAMasters.com as in the previous cases.

	MA in Conference Interpreting MA in Translation Studies and Concentration Literary Translation	Developments in Translation Studies II (seminar)	translation-studies/#Coursestext

In Asia, the data appearing in Table 11 were collected via parallel research on *FindAMasters* and *HotcoursesAbroad*[85], the latter being **a** website similar to FindAMasters. As shown in the table below, there are three tertiary education institutions offering MA programmes in T&I that exhibit interest in the technological facet of professional practice.

Table 11 Asia

Asia			
Provider	**Context of provision**	**Course/course type**	**Useful links**
The Chinese University of Hong Kong, Department of Translation	**MA in Translation**	**Computer Translation (elective course)** **Post-editing for Machine Translation (elective course)**	**http://traserver.tra.cuhk.edu.hk/en/pro_student.php?cid=2&id=31**

[85] https://www.hotcoursesabroad.com/

Nanyang Technological University, College of Humanities, Arts, and Social Sciences	**MA in Translation and Interpretation**	**The programme's description mentions the embedding of "cutting-edge technologies" including the area of machine translation**	**https://www.hotcoursesabroad.com/study/course/singapore/m-translation-and-interpretation/57284988/program.html**
University of Sharja, College of Arts Humanities and Social Sciences, Department of Foreign Languages	**MA in Translation**	**Machine-aided Translation (elective course)**	**https://www.sharjah.ac.ae/en/academics/Colleges/ahss/dept/eld/Pages/Master-of-Arts-in-Translation.aspx#desc**

The last point of focus in this review is T&I training in Australia. After a filtered search on *Hotcourses Abroad*, the number of Australian universities providing students the opportunity to receive training in T&I and, most importantly, gain insights into the technological component of the current professional profile of translators and interpreters amounts to five (Table 12).

Table 12 Australia

Australia			
The University of Newcastle, School of Humanities, Creative Industries and Social Sciences	MA in Translation Studies	Introduction to Machine Translation Evaluation (compulsory course)	https://www.newcastle.edu.au/course/LING6801
The University of Queensland, Faculty of Humanities and Social Sciences, Languages and Cultures School	MA in Translation and Interpreting	Translating with Digital Tools (compulsory course)	https://my.uq.edu.au/programs-courses/course.html?course_code=TRIN7240
Macquarie University, Faculty of Arts, Department of Media, Communications, Creative Arts,	MA in Translation and Interpreting Studies	Technology for Translating and Interpreting (core course)	https://coursehandbook.mq.edu.au/2024/units/TRAN8071

Language, and Literature	MA in Translation and Interpreting Studies (Advanced) MA in Conference Interpreting		
The University of Melbourne, Graduate School of Humanities and Social Sciences	MA of Translation and Interpreting	Translation Technologies (elective course)	https://study.unimelb.edu.au/find/courses/graduate/master-of-translation-and-interpreting/what-will-i-study/
Western Sydney University, School of Humanities and Communication Arts	Master of Interpreting and Translation	Translation Technologies (not specified)	https://hbook.westernsydney.edu.au/subject-details/lang7036/#text

4.4.2 The Case of Greece

In the Greek university-level educational environment, translator and interpreter training relies mainly on three universities, namely the Ionian University (henceforth, IU), the Aristotle University of Thessaloniki (henceforth, AUTH), and the National and Kapodistrian University of Athens (henceforth, NKUA).

In this subsection, the focus is on studying the content of T&I tertiary education from the point of view of technology, to examine AI's integration. As shown in Table 13, the first university in the list is IU; the case of IU, being the only Greek university with a pure T&I philosophy and orientation of studies, is examined both at the level of undergraduate and postgraduate studies. IU's undergraduate studies, especially its translation and interpreting programme, offer a compulsory course titled "Translation Technology" that introduces students to core T&I technology. The course focuses on CATI tools such as Trados, and Memsource, and MT with NMT being at the heart of T&I technology. Following the same rationale, IU's MA programme in "Science of Translation" offers the compulsory course titled "Translation Tools". The second university entry in the Greek list is AUTH; its "Joint Postgraduate Studies Programme in Conference Interpreting and Translation, Specialisation in Translation-Translation

Studies" is an EMT member and, as seen in the table below (Table 13), it offers a bipartite course, i.e., Information Technology I & II. Lastly, T&I education has been one of the primary concerns of NKUA and its two postgraduate programmes, i.e., MA in English Language, Linguistics and Translation, Specialisation: Translation Studies and Interpreting and Interdepartmental Postgraduate Studies Programme in Translation: Greek, English, Russian. Both programmes afford students the opportunity to gain first-hand experience in state-of-the-art technology of today's translation industry as part of the compulsory course titled "Practicum-Translation Technologies.

Table 13 Greece

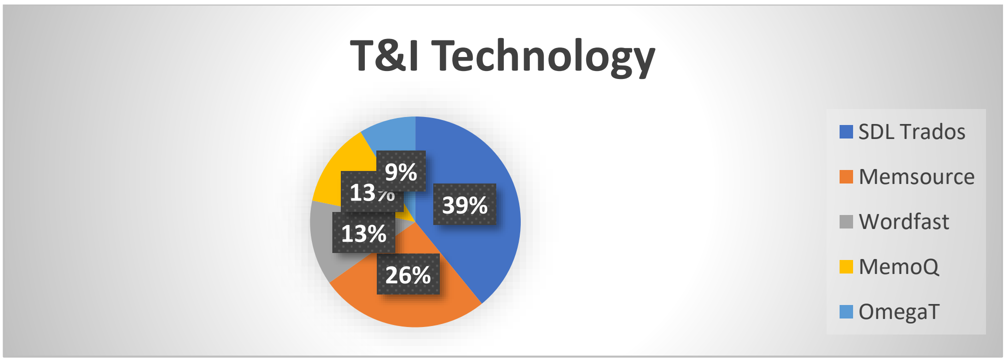
Greece			
Provider	**Context of provision**	**Course & Course Type**	**Useful Links**
Ionian University, Department of Foreign Languages	Undergraduate Studies, Translation and Interpreting Programme	Translation Technology (compulsory course)	https://dflti.ionio.gr/en/undergraduate-studies/courses/yk-5001/
Ionian University, Department of Foreign Languages	Postgraduate Studies Programme" Science of Translation"	Translation Tools (compulsory course)	https://dflti.ionio.gr/sot/en/description/programme/
Aristotle University of Thessaloniki	Joint Postgraduate Studies Programme in "Conference Interpreting and Translation", Specialisation in Translation-Translation Studies	Information Technology I (Electronic Translation Tools) & Information Technology II (Electronic Tools-Post-Editing of Machine Translation) (compulsory series of one course)	https://gp.enl.auth.gr/en/masters/ma-in-conference-interpreting-and-translation/#
National and Kapodistrian University of Athens-Department of English Language and Literature	MA in English Language, Linguistics and Translation, Specialisation: Translation Studies and Interpreting	Practicum-Translation technologies (compulsory course)	http://en-old.enl.uoa.gr/postgraduatestudies/ma-programmes/english-language-linguistics-and-translation.html

	Interdepartmental Postgraduate Studies Programme in Translation: Greek, English, Russian		https://translate.enl.uoa.gr/

4.4.3 Examining the content of T&I curricula

The results of the review serve as a basis for furthering the discussion towards an in-depth analysis of the curriculum's content. In such a context, the very first assumption one should be able make, is that T&I training systems' regulatory authorities have perceived the vitality of technological incorporation. Departing from that assumption, it is interesting to look closer at the specific tools that constitute the core technology in the courses, modules and seminars outlined above. To this end, I embarked on investigating the specifications offered at the courses' description, which revealed significant information about translation technology preferences in the context of tertiary education addressing future translators and interpreters. Figure 15 situates the said data into a statistical representation to facilitate the analysis of the T&I educational curriculum's content in 42 universities across the globe, including Greece.

Figure 15 T&I Technology preferences at university level translator and interpreter training



As shown in the graph above, the most frequently incorporated translation tool is found to be SDL Trados[86] (39%) followed by Memsource[87] (26%), Wordfast[88] (13%), MemoQ[89] (13%), and OmegaT[90] (9%). Other tools identified in the sample include Phrase[91], KantanMT[92], Google Translate[93], DeepL[94], ChatGPT[95], Lionbridge translation workspace[96], Sketchengine [97], Alchemy Catalyst[98], WinCaps[99], Zoodubs[100], Déjà Vu[101]. All these tools are part of a diverse body of tools devised to assist translation and interpreting procedures regardless of the medium of practice. Simultaneously, the plurality of tools and technology implementation displayed in this data corpus offer insights into and illustrate the multitude of technologies applied in the field(s) of T&I (Table 14).

Table 14 T&I Technology identified in the review

Facets of T&I Technology
Machine-Translation (Statistical Machine Translation, Rule-based Machine Translation, Hybrid Machine Translation, Neural Machine Translation)
Large Language Models
GPT systems
Cloud-based Translation Memory systems
Natural Language Processing
Computer-assisted Translation
Voice recognition systems
Generative AI

86 https://www.trados.com/
87 https://phrase.com/ (Memsource acquired Phrase in 2021)
88 https://www.wordfast.com/
89 https://www.memoq.com/
90 https://omegat.org/
91 https://phrase.com/
92 https://www.kantanai.io/
93 https://translate.google.com/
94 https://www.deepl.com/translator
95 https://openai.com/chatgpt
96 https://translate.translationworkspace.com/auth/saml?o=P
97 https://www.sketchengine.eu/
98 https://www.alchemysoftware.com/products/alchemy_catalyst.html
99 https://broadstream.com/products/wincaps/wincaps-q4-standard/
100 https://www.zoodigital.com/technology/zoodubs/
101 https://atril.com/

Crowdsourcing
Translation Memory systems
Terminology Extraction
Interpreter-based and automated technology
Terminology Banks
Translator Workstations Localisation Software
Language Corpora
Online Dictionaries

Another, equally important, observation relates to the increased popularisation of MT in T&I training curricula; a thorough study of the curricula specifications with respect to their ability to embed T&I technology showcases that MT occupies the core of prospective translator and interpreter's training. These observations raise reasonable questions and stimulate a wide-ranging discussion as to where T&I technology stands in the times of AI's proliferation in the T&I industry. The most crucial question one should be asking is whether there are fine lines between AI-based T&I tools and conventional CATI technologies, since AI has become a buzzword in Language Service Provision, among several other domains of human activity. Or else, is everything AI or not?

It has been already argued[102] that we cannot propose a single, sufficient definition of AI, and consequently, elicit a yes-or-no answer to this question stated above. What we can do, instead, is to maintain that translation tools in their current form feature AI-inspired functionalities to a greater or lesser extent. The need to adopt this attitude emerges from the urgency to implement reforms in the way future professionals are to be qualified in terms of T&I technological competence. To that effect, one should mention that SDL Trados latest update involves an array of AI-inspired potentialities, including Trados Copilot, Linguistic AI, Smart Help, Generative Translation and LLM, Smart Review, Language Weaver, LLM integration[103].

[102] See chapter 4.1.
[103] For more details on the features, visit https://www.trados.com/blog/elevate-efficiency-with-ai-enabled-features-in-trados-studio-2022-service-release-2/

Speaking strictly about AI-centered education for translators and interpreters, the universities' sample shows that 11.9 % (i.e., 5 out of 42) of the universities have a direct AI orientation in their MA programme's curriculum (Table 15).

Table 15 Universities offering AI -oriented T&I training

Dublin City University, Ireland	Artificial Intelligence, Info & Info Seeking (elective module)
University of Edinburgh, Scotland, UK	Technology and Translation in the Workplace (elective course)
Jagiellonian University, Krakow, Polland	MA seminar 1 (Computer-Assisted Translation (CAT), Machine Translation (MT) and AI, as well as contemporary translator education, including translator competence and methods in Translation Pedagogy)
University of York, North Yorkshire, UK	Linguistic Computations: Real and Artificial Intelligence (elective course)
Ionian University, Department of Foreign Languages	Translation Technology (compulsory course), Translation Tools (compulsory course)

As illustrated in the table above, Dublin City University offers an elective module in AI and information seeking in the context of its MSc programme in Translation Technology. Although the programme's official website does not offer a detailed description of the module[104], the understanding that AI is a relevant topic in the translation technology spectrum is evidence of the growing interest, within T&I Studies, to adapt to the new dynamics that AI has brought about in the Language Service Industry. Another example of the synergy between AI and T&I is the University of Edinburgh; its MSc in Translation Studies provides students with the opportunity to select the "Technology and Translation in the Workplace" course, which is an attempt to offer a holistic overview of the available translation technologies. The added value of this course is its emphasis on AI-driven translation technology, e.g., ChatGPT,

[104] See Table 7 for useful links.

generative AI , as well as on the legal and ethical considerations as to implementing AI in T&I[105].The third instance, Jagiellonian University[106], is a particularly interesting one as it combines core aspects of current T&I pedagogy; as part of its MA programme in Translation Studies, it delivers a seminar dealing with AI-centered translation technology, translator competence, and training methods. The MA in Interpreting at University of York offers a module titled "Translation and Applied Technologies", which aims at facilitating students' understanding of the workings of computational linguistics and cognition while touching upon the ethical and socioeconomic challenges of AI [107]. Finally, the Ionian University's translation technology-focused courses [108] allow students to become familiar with a state-of-the art technology around AI features.

From a statistical point of view, the percentage of the universities that have integrated AI as a specific area of study within their T&I curriculum is low. However, the very fact of AI's presence into the curriculum (either in the form of a distinct module or via AI-inspired features in T&I technology) could be possibly perceived as a positive sign towards reforming translator and interpreter training.

It is also purposeful to consider the ethico-legal undertones of this reality. In essence, we could look at academic integrity as forming an intersection with the ethical, legal, and deontological agenda of considerations in the field of AI. Such an approach has been already introduced in the literature (e.g., Kumar, Eaton, Mindzak, and Morisson 2023), showing that higher education has been concerned about the impact of the convergence between AI and academic integrity. Academic integrity lies upon a value-centered framework; the International Centre for Academic Integrity's (henceforth ICAI) delineates academic integrity as "a commitment to six fundamental values: honesty, trust, fairness, respect, responsibility, and courage" (ICAI 2021: 4). The values mentioned in ICAI's definition of academic integrity bear close resemblance with the core ethical principles that need to be in effect to ensure trustworthy AI utilisation[109].

[105] See Table 7 for useful links.
[106] See Table 7 for useful links.
[107] See Table 8 for useful links.
[108] See Table 13 for useful links.
[109] See: High-Level Expert Group on Artificial Intelligence. 2019. Ethics Guidelines for Trustworthy AI. Brussels: European Commission and section 2.3.

This type of principle agreement is another proof of the convergence existing between general and specialised[110]AI frameworks in an array of sectors of human activity[111]. That being said, it becomes obvious that the process of breathing AI ethics into the principles' agenda of academic integrity will only be successful when a unified ethical, legal and deontological set of guidelines will come to life.

[110] Frameworks targeting at specific domains, e.g., AI in medicine, AI in education.
[111] See section 2.3 for a detailed analysis.

Chapter 5

Analysis

The design of our research follows the MMA. As mentioned in the chapter on *Methodology*[112], the MMA type is used for the purposes of our work is the *ED*. By default, ED necessitates a hybrid type of data (or data collection methodology), i.e., a combination of both quantitative and qualitative, one of which is the guiding approach whilst the other serves as a supportive source of data. In our case, the leading component is the quantitative type to which the qualitative component is embedded to facilitate the stages of data collection, analysis, and interpretation of findings. Quantitative data are collected via closed-ended questions, whereas qualitative data are gathered by using open-ended and contingency questions.

Regarding the procedural aspect of the research, we utilised a tripartite set of web-based surveys. Specifically, we designed three questionnaires to address the three different cohorts of our study, namely T&I professionals, educators, and students. Our research aims to study *whether* and *to what extent* AI has been integrated into the T&I market, professional life, and education of future translators and interpreters by gathering information about the knowledge and attitudes of the population to which the study applies. To this end, each questionnaire was tailored to the knowledge of the group of participants to whom they were intended. Tailoring as well as careful sample selection are central to ensuring that the respondents can answer the questions (Kitchenham and Pfleeger 2008). Another feature of our questionnaire design is anonymity, which is key to minimise the possibility of gathering data of poor or lower validity and/or accuracy (Adams and Cox 2008). In doing so, we are also aware of a serious shortcoming that anonymity may bring about in relation to the quality of our findings, i.e., limited richness and adequacy of data (Murdoch *et al*. 2014).

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[112] See chapter 3.

Since our ED is characterised by the prevalence of quantitative data, the data analysis stage is informed by the process of *quantitising.* Quantitising is a data transformation strategy in which qualitative data are converted to and thus, interpreted as quantitative, i.e., they are numerically and statistically represented (Teddlie and Tashakkori 2009, see also Caracelli and Greene 1993). We deployed this strategy for two reasons: (1) to compensate for inherent limitations of open-ended and closed-ended questions[113] and (2) to simplify the process of interpretation and pattern recognition in our qualitative data (Miles & Huberman 1994, Ryan & Bernard 2000, Sandelowski 2001).

The following subsections are concerned with the analysis of the data from our questionnaire. The analysis is organized in two levels; the first involves the analysis of each questionnaire separately to help us explore, de-code and interpret each cohorts' views on the synergy between AI and T&I. The second level focuses on examining at the macro-level the findings from all three questionnaires to identify commonalities and/or deviations among the data. Demographic questions, although integral to all three questionnaires, are not included in the question total for each survey to facilitate the statistical representation of both question type distribution and (in)valid answers.

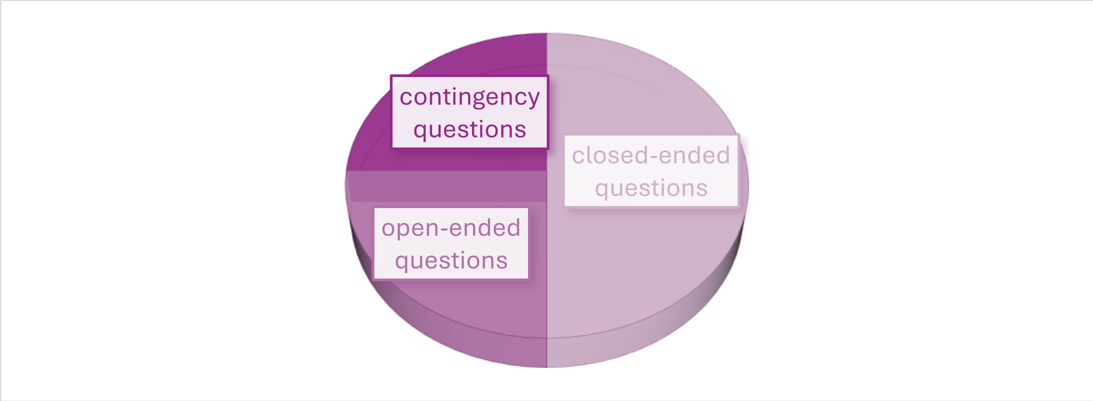
5.1 Surveying T&I Professionals

5.1.1 Profiling the Professionals

The questionnaire addresses professional translators and interpreters (Appendix I) offering their services within the T&I industry. It consists of 17 questions of closed-ended (9), open-ended (1), and contingency (7) type (Figure 16).

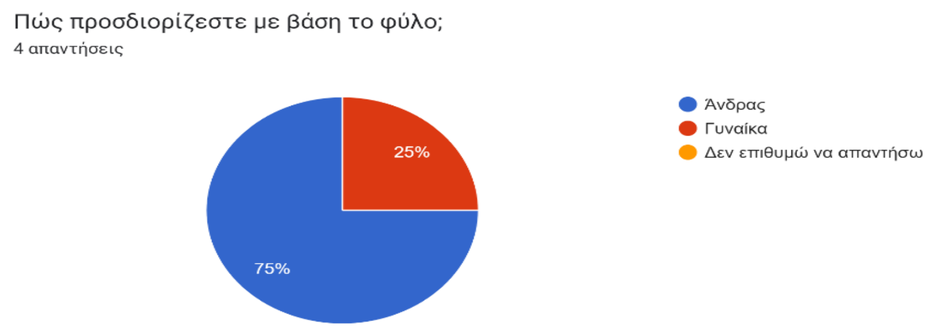
Figure 16 Question type allocation in professionals' survey

[113] See chapter 3.



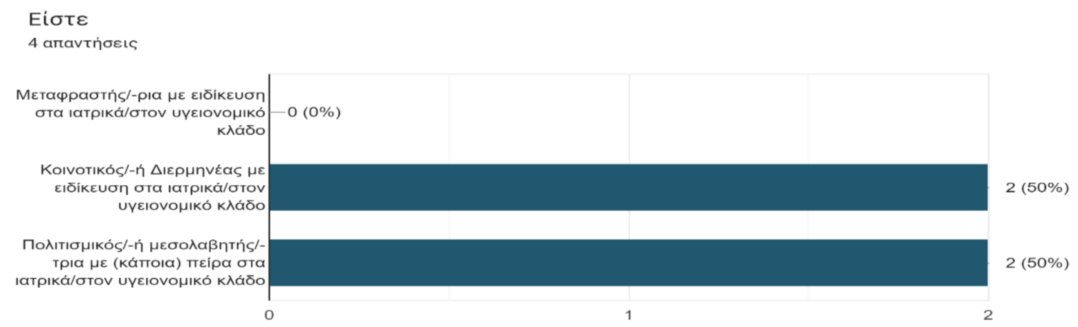
The participation rate is significantly low since the total number of answers amounts to 4. The demographic data for this group of respondents are collected through a set of 9 questions to assist us in the process of profiling our sample. The findings show that the participants are primarily males (75%) (Figure 17).

Figure 17 Gender identification of participants



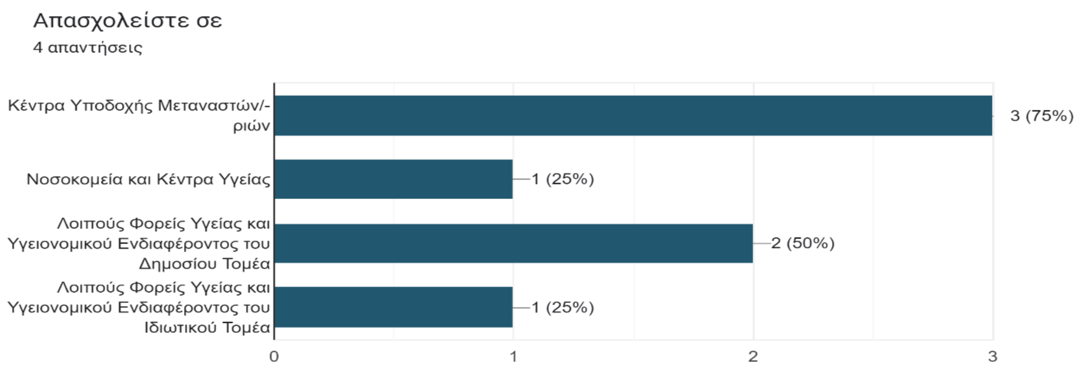
With regard to their professional identity, 50% of them are “community/public service interpreters specialising in medical/healthcare interpreting”, with the remaining responddents (50%) self-identifying as “cultural mediator with (some) professional experience in medical/healthcare interpreting” (Figure 18).

Figure 18 Professional identity



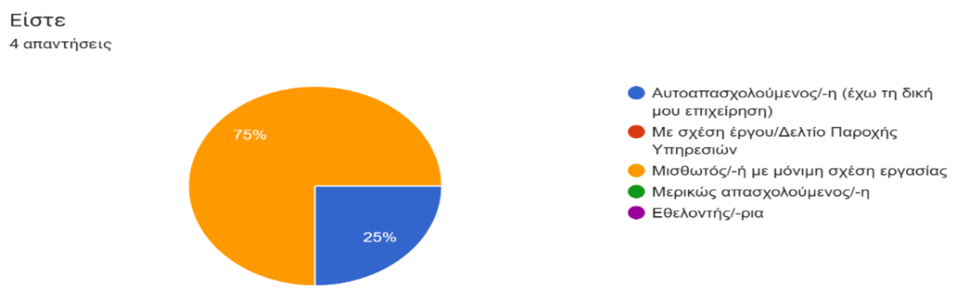
Questions 3 and *4* concern the respondents' workplace and their employment relationship, respectively. Based on the responses, at least 75% of the professionals work at reception camps, in addition to working in other places (Figure 19).

Figure 19 Workplace



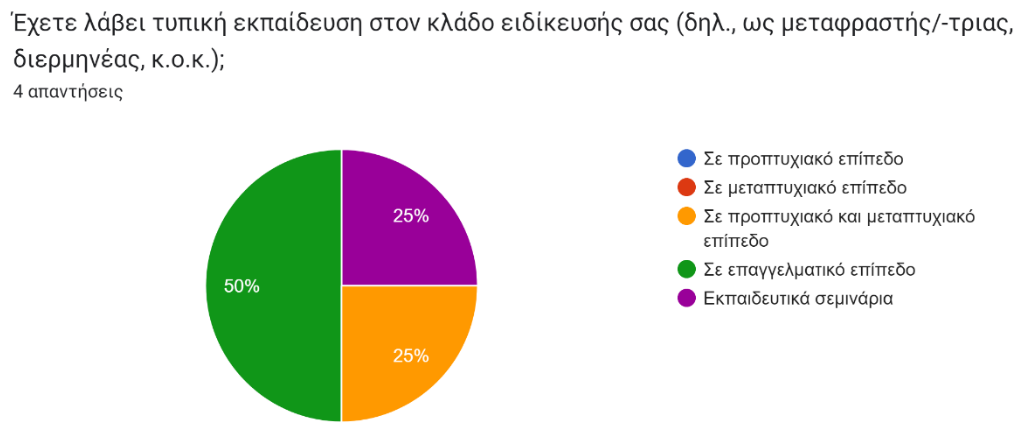
Concerning their employment relationship, the preponderance of participants (75%) provides their services within the context of a permanent employment contract, whilst 25% are self-employed (Figure 20).

Figure 20 Employment relationship



The following three questions (*5, 6, 7*) emphasise the cohort's educational background, i.e., whether they have received formal education in their field of specialisation and place of studies. The data reveal that 25% of the participants have received formal education in the field of their specialisation, whereas 25% attended seminars and 50% gained specialisation whilst working as professionals in the T&I industry (Figure 21).

Figure 21 Participants' formal education



When asked about the place of their undergraduate studies, our data suggests that the majority (75%) has studied abroad (Figure 22a). Additionally, when asked whether they have studied (regardless of the level of studies) or received training abroad, the data show that all of the participants provided a positive answer (Figure 22b).

Figure 22a Undergraduate studies in Greece

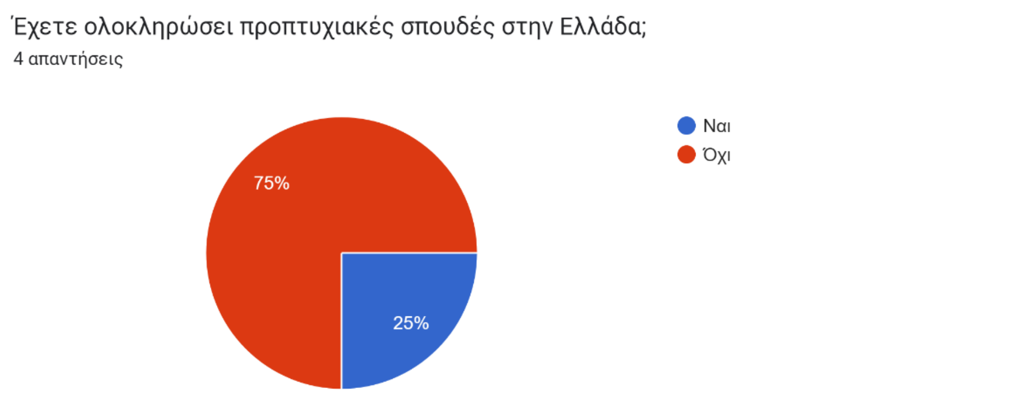


Figure 22b Studies abroad

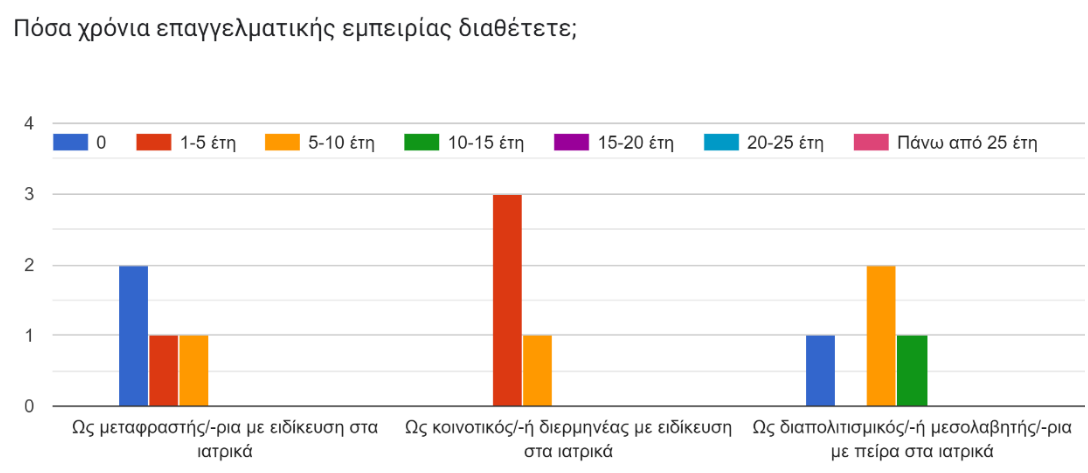
When asked to specify the place of studies or training along with the level and field of studies (*Question 8*), we received the following answers (Table 16):

Table 16 Information about the respondents' studies

Level of studies	Field of studies	Place of studies
Undergraduate studies	Mathematics	Turkey
Undergraduate studies	Not specified	Egypt
Not specified	Theology and Philology	Iraqi Kurdistan
Secondary education	Child Psychology	Iran

Lastly, the sample profiling phase concluded with *Question 9* regarding the years of professional experience with specialisation in medical/ healthcare T&I. As shown in Figure 23 below, the participants have zero professional experience in medical/healthcare translation and cultural mediation respectively, 1-5 years in medical/healthcare translation and community interpreting, 5-10 years in all three lines of profession (i.e., community interpreting, translation, cultural mediation), and 10-15 years in cultural mediation.

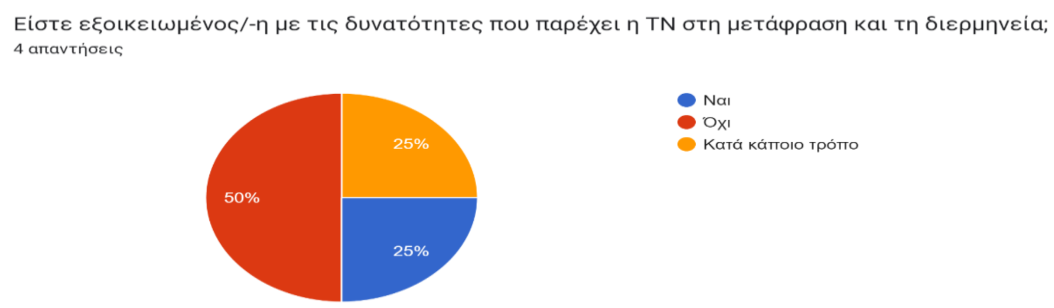
Figure 23 Years of professional experience



5.1.2 Familiarisation with AI

In *Question 10*, the participants were asked to evaluate their familiarity with AI's potentialities (Figure 24). Half of the respondents (50%) responded negatively, while the remaining percentage answered 'Yes'(25%) and 'Somehow' (5%).

Figure 24 Familiarity with AI

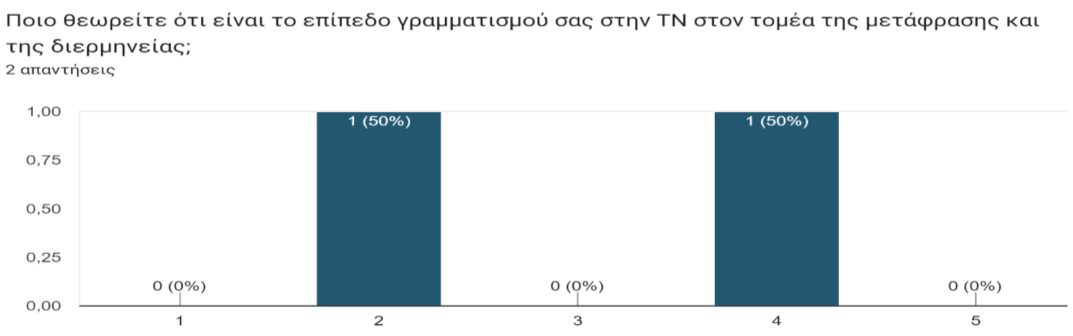


Question 11 addresses the respondents who provided a negative answer to Question 10 (25%). Respondents were asked to explain their choice. In numerical representation, the answers provided in this question are two and mention: (1) lack of knowledge on how to use AI and explore its potential (2) lack of knowledge of the very nature of AI.

5.1.3 AI literacy

Question 12 sets out to measure the cohort's degree of literacy in AI-inspired technology based on a scale from 1 to 5 (Likert Scale) (Figure 25). The data suggest that 50% consider themselves as being relatively AI-iliterate whereas 50% are close to highly AI-literate. This percentage is statistically insignificant given that only 2 out of the 4 respondents answered the question since it was not a mandatory one.

Figure 25 AI literacy



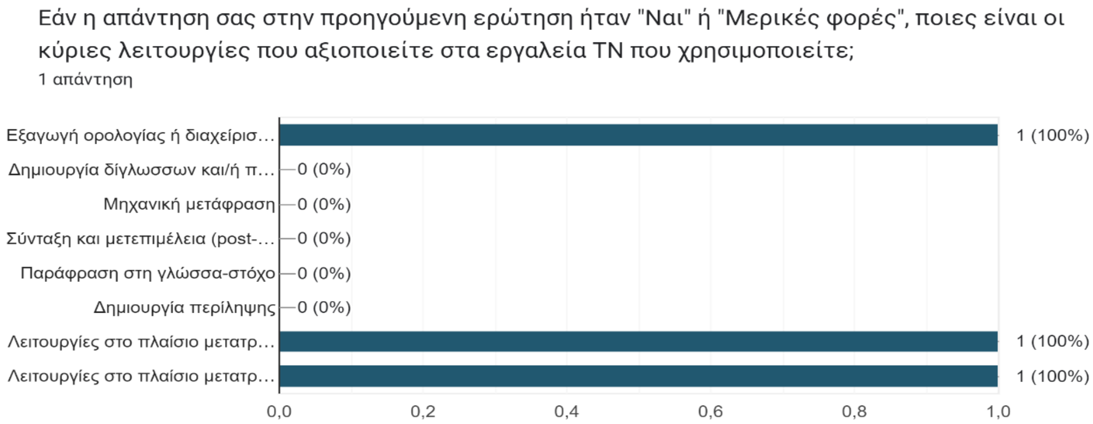
In *Question 13,* the participants assess the ability to consult and/or use AI tools before, during, and/or after the translation and/or interpreting task they have been assigned. The information we gathered from this question reveals that 50% of the professionals, who answered this question (i.e., only 2), avoid AI tools in all three stages of task performance, whereas the rest has occasionally recourse to the AI-inspired tools. (Figure 26).

Figure 26 Use of AI tools

ls

Question 14 addresses the respondents who answered 'Yes' or 'Sometimes' in the previous question. They are asked to choose among several functions that are available in AI tools. We observe that we received only one answer, according to which (1) term extraction and management, (2) speech-to-text conversion and (3) text-to-speech conversion are the most commonly preferred functions (Figure 27). It is worth noting that low participation is one of the shortcomings of non-mandatory questions, as in this case, which renders results statistically insignificant, hence difficult to assess as such or in relation to other topic-related questions.

Figure 27 Preferred functions in AI tools

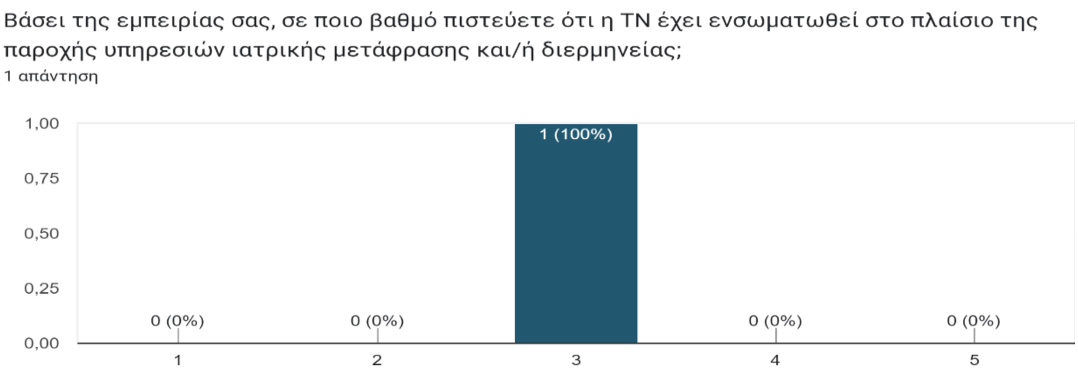


Question 15 addresses only those who provided a negative answer to Question 13 and asks for an explanation was to whether recourse to AI tools is not a option (voluntary or involuntary). In this case, the only explanation provided by the respondent was that ‘there was no need for using AI tools up until now’.

5.1.4 AI in T&I

Question 16 examines how professionals assess AI integration in the context of medical T&I service provision on a scale from 1 to 5. This question yielded one answer (3/5), namely that there is a limited integration of AI in the said filed (Figure 28).

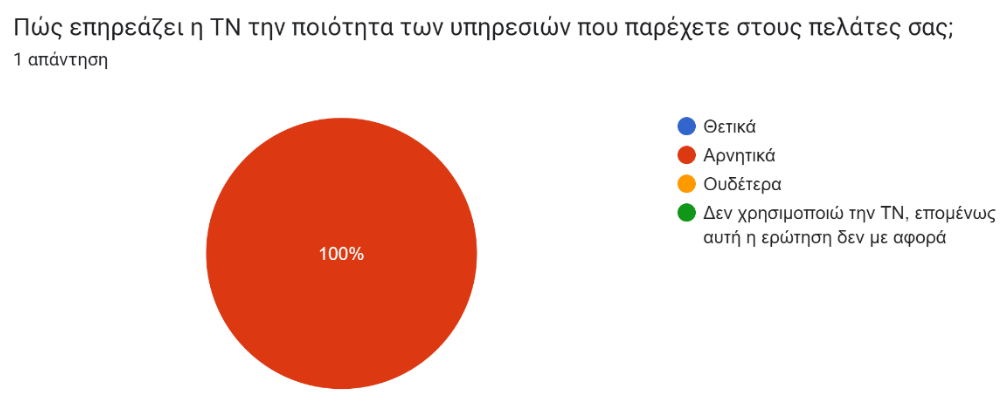
Figure 28 AI integration in medical T&I service provision



5.1.5 AI and quality of services

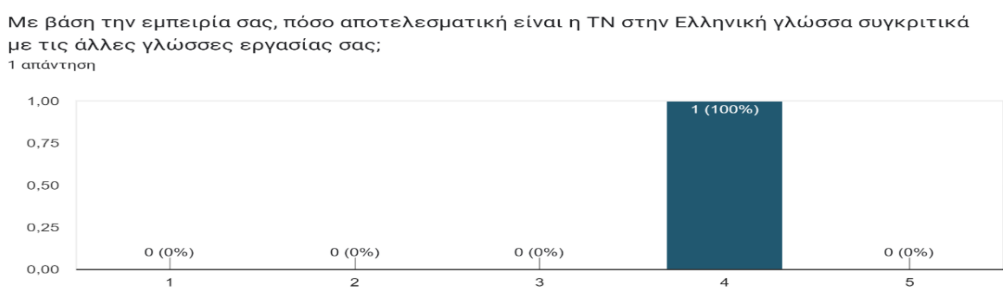
Question 17 aims at gathering information about how the respondents assess AI's influence on the quality of their services. Only one respondent answered this question. The participant was of the opinion that AI integration negatively impacts the quality of interpreting services. This is further justified in (Figure 29) where the respondent claimed that because AI tools are currently of poor quality, they can contribute in decreased provision of interpreting services on the job.

Figure 29 Quality of services and AI



Question 19 is interested in gaining insight into the respondents' views about AI's effectiveness when working into Greek compared to the rest of their working languages. One respondent assessed AI's effectiveness as standing at 4 on a scale from 1 to 5 (Figure 30)

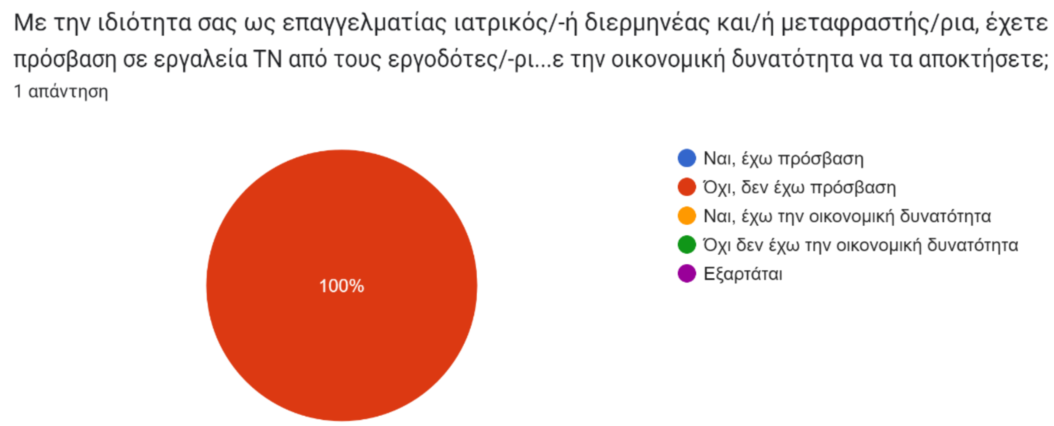
Figure 30 AI's effectiveness



5.1.6 Access to AI

Question 20 asks the respondents if they have access to or can afford AI tools. Again, only one response was submitted (Figure31) stating that the said participant does not have access to AI-inspired tools.

Figure 32 Access to AI tools.



Question 22 aimed at collecting data as to whether the respondents were willing to invest in AI technology (if it was affordable) to increase their productivity, effectiveness, and quality of services. Once again, only one response was given, i..e, and would state a participants willingness to explore such a venue ('yes' answer) (Figure 33).

Figure 33 Attitudes towards buying AI tools

5.1.7 AI and Humans

Question 24 targeted the repondents views on whether AI will replace the human medical translator/interpreter and other types of language service providers in the medical/healthcare domain (Figure 34). As shown below, 66.7% of the responses are 'I don't know/can't predict' while 33.3% (1) is 'Yes'.

Figure 34 AI vs. Humans from the point of view of professionals

5.1.8 Ethical considerations about AI-medical T&I synergy

Question 26 (an open-ended question) invited participants to share their views as to whether legal and ethical prerequisites should be enforced to achieve harmonised integration of AI in the field of medical T&I. There have been three answers: 1) 'I don't know', 2) 'I don't have an opinion' and 3) 'Yes, because it is important to ensure confidentiality in medical/healthcare-pertinent issues. Therefore, access to sensitive content (i.e., translation data) should be legally and ethically outlined.

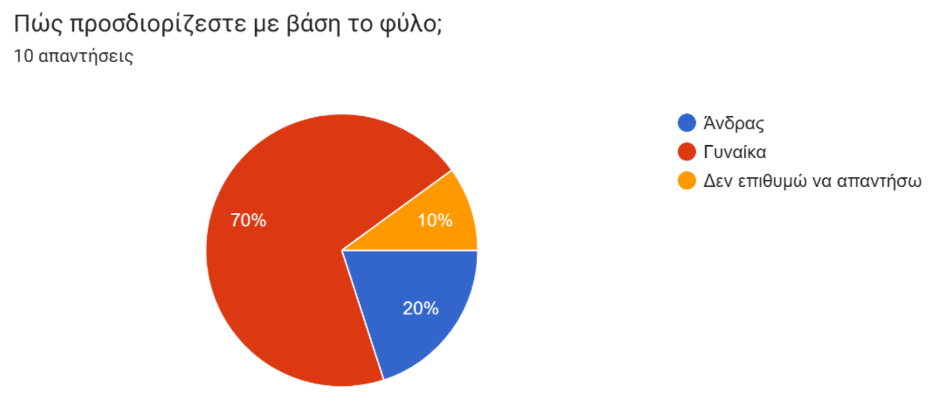
5.2 Surveying T&I Educators

5.2.1 Profiling the Educators and Trainers

This questionnaire consists of 13 questions, i.e., 8 closed-ended, 3 open-ended, and 2 contingency questions (Appendix II), and addresses T&I educators and trainers in Greece. The total number of responses received was 10. At the sample profiling section, we were interested in identifying the gender of the respondents. As illustrated in Figure

35, the majority of respondents (70%) are females, 20% identify as males and 10% do not wish to answer the question.

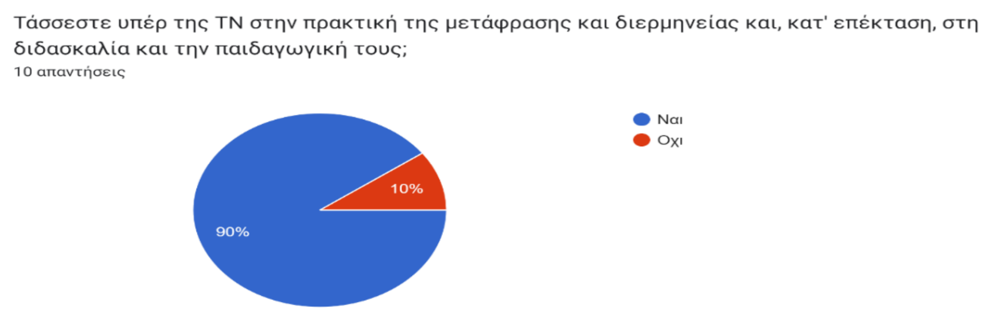
Figure 35 Gender of the survey sample



5.2.2 AI in T&I

In *Question 2,* asked participants to express their position as to whether they are in favour of or against AI integration in the practice of T&I, and thus in T&I education and pedagogy (Figure 36). The data show that 90% of the participants hold a positive view on AI integration in the T&I fields mentioned.

Figure 36 AI in T&I pedagogy



5.2.3 Familiarisation with AI (Educators)

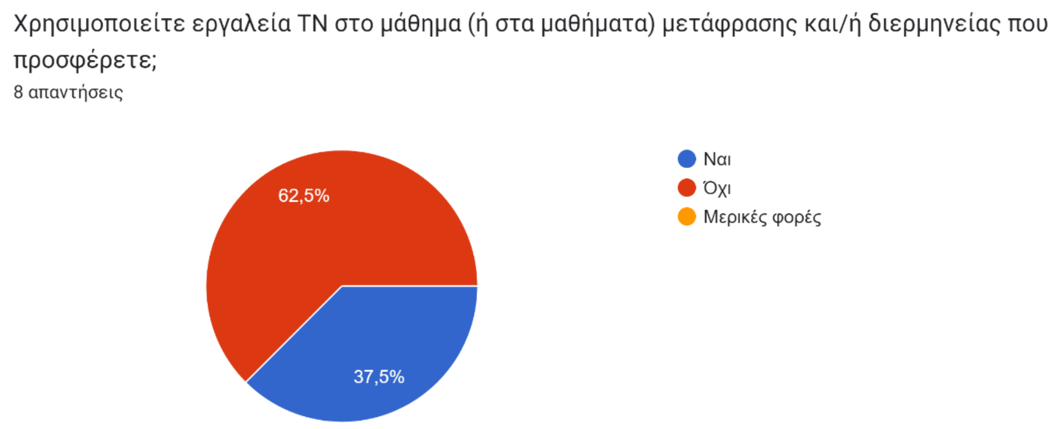
Question 3 is intended to measure participants' familiarity with AI's potentialities in T&I education. The answers to this question are coded as follows: 1) 60% responded 'To some extent', 2) 20% responded 'Yes', and 3) 20% responded 'No' (Figure 37).

Figure 37 AI potentiality in T&I pedagogy

5.2.4 Use of AI technology

Question 4 explores the use of AI-powered technology by educators in the context of the T&I courses they deliver. The response rate to this question is estimated at 80% and indicates that 62.5% of the educators do not utilise AI technology (Figure 38).

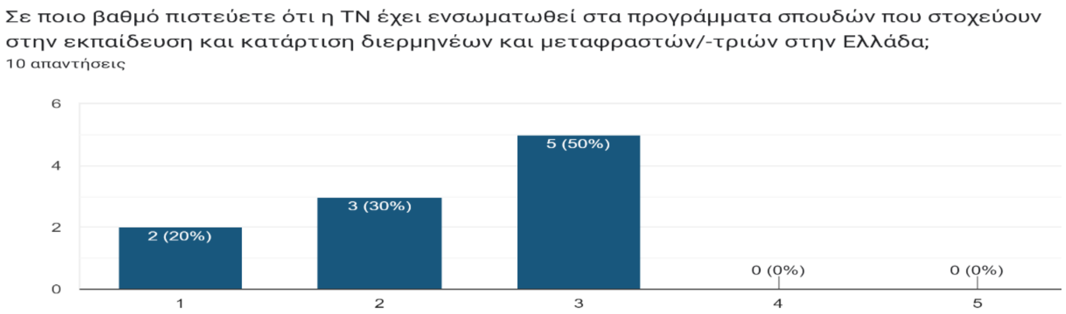
Figure 38 AI technology and educators



5.2.5 Views on AI integration in the curriculum of T&I education in Greece

Question 5 was created to gauge the respondents' understanding of the presence of AI in the T&I education and training using a Likert scale from 1 to 5. The question was answered all the respondents and the data suggest the following: 50% believe that AI integration has only been achieved partly (3), 30% believe that AI is barely integrated in the T&I curriculum (option 2 on the 1-5 scale) (i.e., hardly), whereas 20% of them believe that AI is 'not at all' integrated (Figure 39).

Figure 39 AI in T&I education



Question 6 aimed at gathering information as to the educators' thoughts on the advantages and disadvantages found in a AI-inspired T&I training context. From the 9 responses received, we found the following (Table 17a, 17b):

Table 17a Advantages of AI integration

keeping up with the current state of affairs in the profession (37.5%)	**speed of task completion (37.5%)**	**assistance in ensuring quality of services (12.5%)**

Table 17b Disadvantages of AI integration

(over)relying uncritically to AI (75%)	**lack of agility on the part of AI users (50%)**	**privacy and confidentiality issues (12.5%)**	**institutional contraints (12.5%)**

Question 7 set out to thematise the main constraints in the process of embedding AI technology in the T&I curriculum. To this end, we provided respondents with a set of what we considered as possible impediments based on the corresponding literature and field experience. The data yielded are illustrated in Figure 40. The most popular answer would associate the absence of AI in T&I curricula with the lack of sufficient infrastructure to support AI-inspired technology integration (80%). Other reasons included technological literacy of both students and educators (60% respectively), curriculum design and overall orientation (40%), constant tool updating (40%), institutional constraints (40%), cost of AI tools (60%), and legal issues (40%).

Figure 40 Hindrances in AI integration into T&I education

5.2.6 AI in T&I education

Question 9 offered participants the opportunity to suggest ways to smooth AI integration in T&I education and training. Out of a total of 7 responses, it became obvious that further training is considered on of the key factors in paving he way for AI integration in T&I education and training following by seminars and allowing free access to such tools. See Table 18 below:

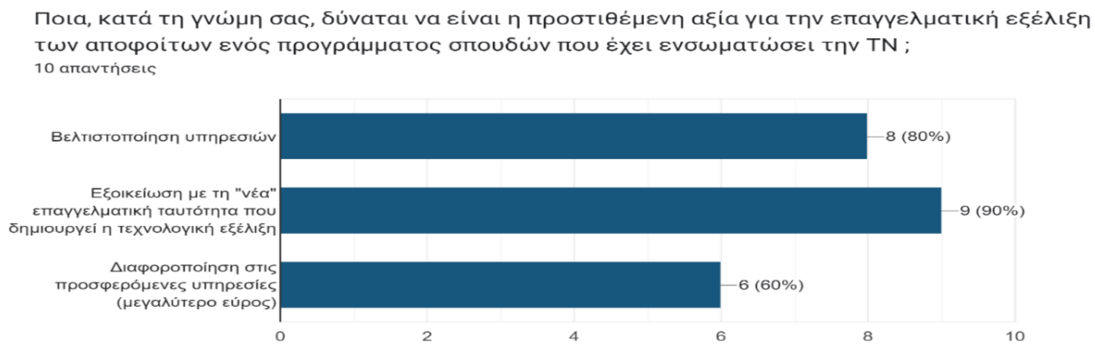
Table 18 Ways to facilitate AI embedding in T&I education

seminars (28.5%)	**more training (42.8%)**	**free access (14.28%)**

5.2.7 AI's added value

Question 10 collected information concerning the cohort's opinion about the added value that AI can bring to future professionals (i.e., current students of T&I). As shown in Figure 41, 90% of the respondents perceived AI as an integral component that shapes the 'new' technology-infused professional identity of translators and interpreters; 80% acknowledged AI's contribution to enhanced quality of service, whereas 60% believed in the broad scope of AI's in the field of training and education.

Figure 41 AI's added value



5.2.8 AI and the Man-translator/interpreter

Question 11's goal was to examine how educators and trainers perceive the possibility of an AI-inspired T&I curriculum in relation to its impact on professional translators and interpreters' deskilling and role as service providers. The respondents seemed to believe that AI 'maybe' be to blame for deskilling and devaluation of the translator's/interpreter's role downgrade (80%), whilst 20% of the respondents associated AI had a more positive outlook on the relationship between technology and professional status. (Figure 42)

Figure 42 AI and deskilling of professionals

5.2.9 AI, Ethics and Deontology

Question 13 referred to the participants' opinions as to the ethical and legal prerequisites for proper AI integration in T&I education and pedagogy. The data indicate that all 10 respondents prioritised safety and cyber security (100%), data protection (90%) and transparency (80%) (Figure 43).

Figure 43 Ethical and legal requirements for AI-infused T&I education

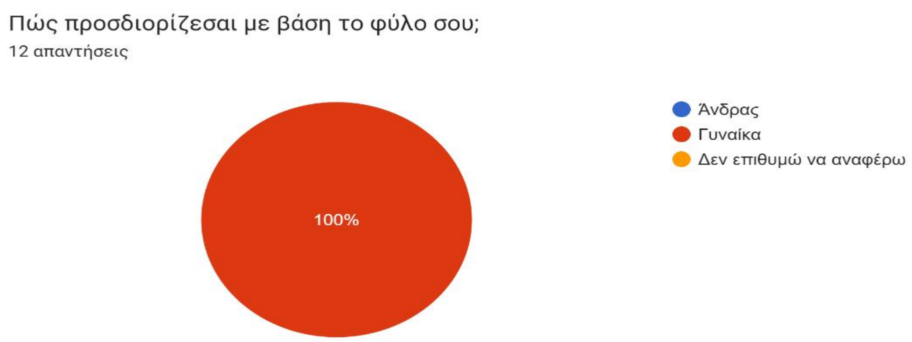
5.3 Surveying T&I Students

5.3.1 Profiling the Students

The questionnaire focused on exploring the attitudes of students of translation and/or interpreting in Greece concerning AI and its use in the field of T&I (Appendix III). To that effect, we designed a total of 16 questions, 7 closed-ended, 8 contingency questions, and 1 open-ended question. Concerning the number of responses, 12 students answered our questionnaire.

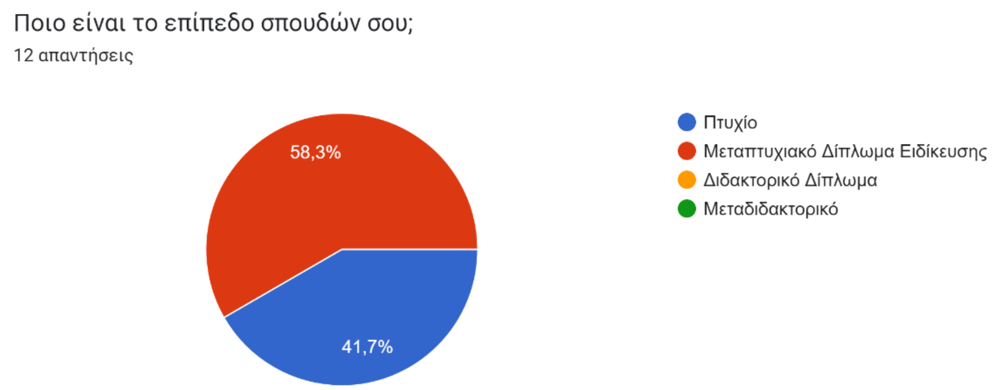
First, we are interested in profiling our respondents. To this end, Question 1 provided information about their gender (Figure 44); specifically, we observed that all participants identified themselves as females.

Figure 44 Gender identification



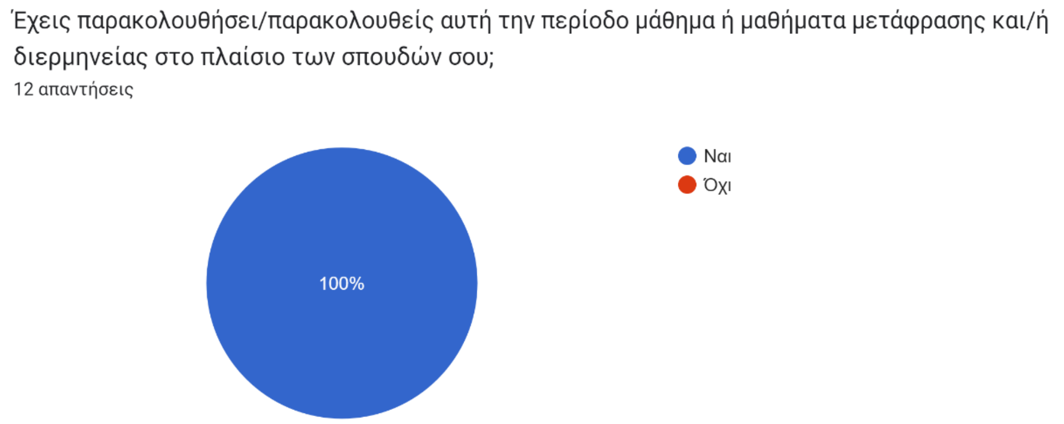
Questions 2, 3 and *4* were focusing on the respondents educational background and helped us gain insight into the level and specialisation of participants' T&I studies as well as the educational institutions where they study. In *Question 2* students stated their level of studies (Figure 45); The data showed that 58.3% were postgraduate students and 41.7% were undergraduate students.

Figure 45 Level of studies



Question 3 aimed at gathering related to the translation or interpreting course(s) respondents might have taken throughout the course of their studies. The answers to this question featured homogeneity, as all respondents claimed having taken translation and/interpreting courses (Figure 46).

Figure 46 T&I course(s) attendance



Lastly, *Question 4* provided participants, who responded positively to Question 2, with the opportunity to share specific information about their T&I courses. The findings are summarized in the tables below (Figure 47a, 47b and Table 19).

Figure 47a Institutions

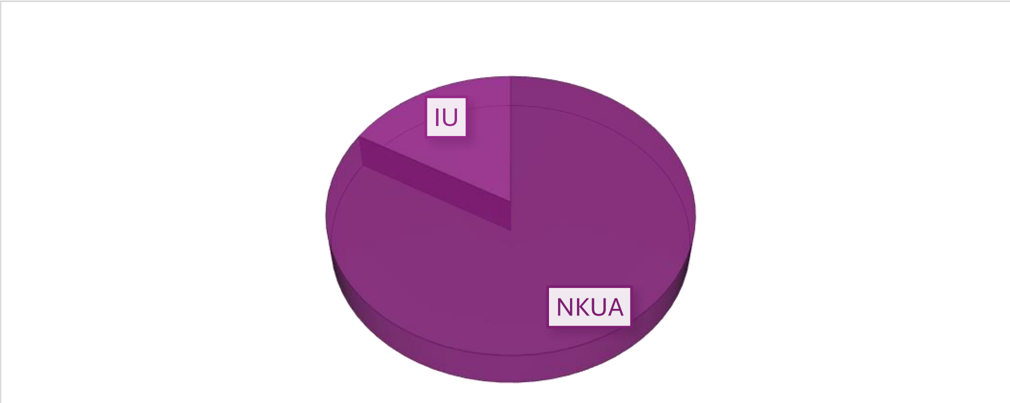


Figure 47b Level of studies

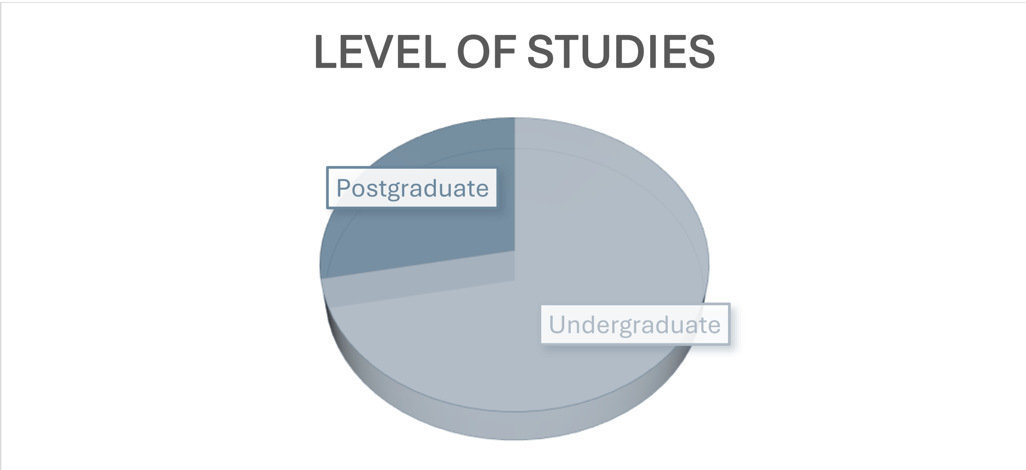


Table 19 Programme of Studies (per title)

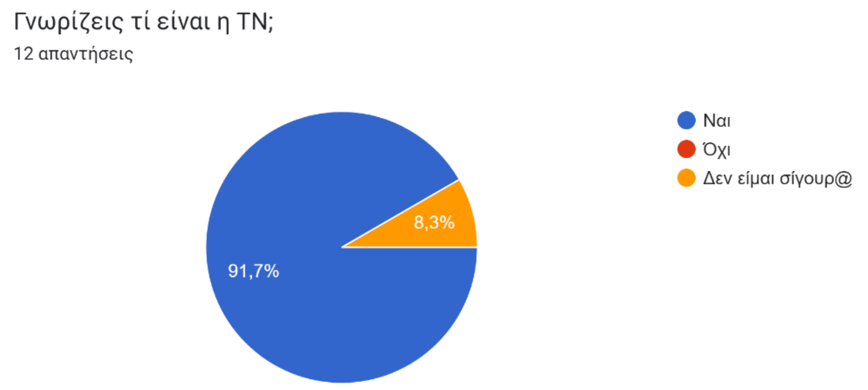
Title & Place	**Percentage**
MA Programme 'Translation and Interpreting Studies', NKUA	33.3%
MA Programme 'Translation and Interpreting Studies: English, Greek, Russian', NKUA	50%
(level not specified)Foreign Languages, Translation and Interpreting, specialisation in	8.3%

interpreting in two directions, i.e., English-Greek and German-English	
(level not specified) Consecutive and simultanous interpreting in the English-French direction	8.3%

5.3.2 AI and You

Question 5 asks respondents about whether they are aware of what is AI. As shown in Figure 48, 91.7% of the respondents are aware of what AI is.

Figure 48 Concept awareness



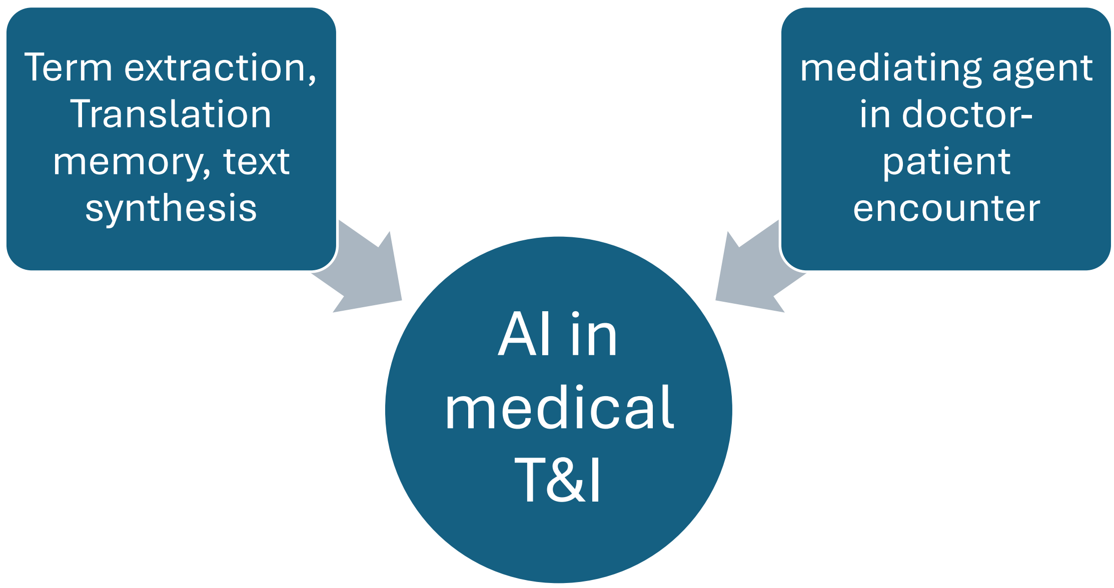
Question 6 encouraged students, who answered positively to the previous question, to provide their own definitions of AI, the purpose of this question being to gauge their understanding of what AI is. From a total of 12 responses collected, the results are the following: 75% of respondents see AI as a stimulation of the human brain and its capacity to process information, 2) 8.3% define AI as a technology-informed programme that performs tasks quickly, 3) 16.6% provide irrelevant answers (i.e., advantages of utilising AI-powered technology in T&I).

Question 7 reformulates Question 6, this time focusing on the synergy between AI and medical T&I. The responses collected showed that 50% of the students are not aware of any such synergy, compared to 8.3% who are and 41.7% who are in doubt (not sure) (Figure 49).

Figure 49 AI in medical T&I

Question 8 addressed those who provided either a 'Yes' or 'I'm not sure' answer and asked them to interpret how they perceive the relationship between medical-oriented AI and T&I. According to the data, the responses are divided into two categories as to how AI interacts with the medical T&I domain (Figure 50).

Figure 50 Students' views about AI in medical T&I

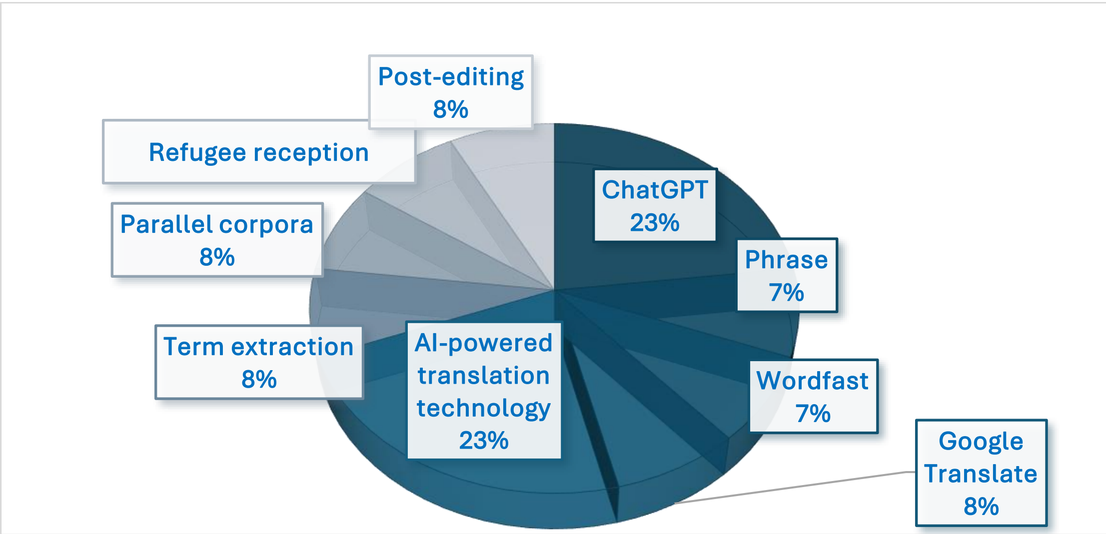


Question 9 examined the degree of students' familiarisation with using AI technology in T&I. The analysis indicates 41.7% of positive responses, against 33.3% of 'I am not sure' and 25% negative responses (Figure 51).

Figure 51 Students's familiarity with the AI-T&I synergy

This section ends with *Question 10* which addresses those who provided positive or 'I am not sure' responses. The respondents were asked to give examples in support of their previous answers (Figure 52). As showcased in the figure below, most answers mention ChatGPT (28%) and AI-powered translation technology (27%). However, it is important to mention that the responses involve mainly examples focusing on the practice of translation; interpreting-related examples were rarely found in the data. Specifically, only one respondent refers to the use of ChatpGPT for obtaining information pertaining to interpreting tasks (namely Refugee Reception Centers).

Figure 52 Students'examples



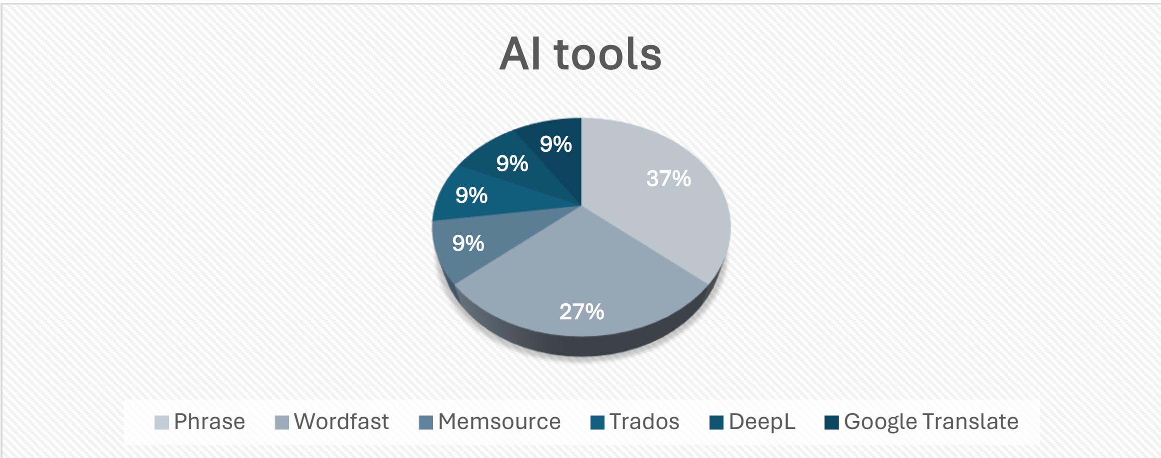
5.3.3 Working with AI

Question 11 set out to gather data concerning whether students use or have been introduced to AI tools in the context of their T&I studies. It constitutes the core of a series of subsequent questions producing a cascading effect in data collection. The data illustrated in Figure 53 show that 41.7% of the respondents provided a 'Yes' answer, 33.3% opted for a 'No' answer and 25% were not sure that the tool they were introduced to fell under the AI-powered category.

Figure 53 AI in the classroom

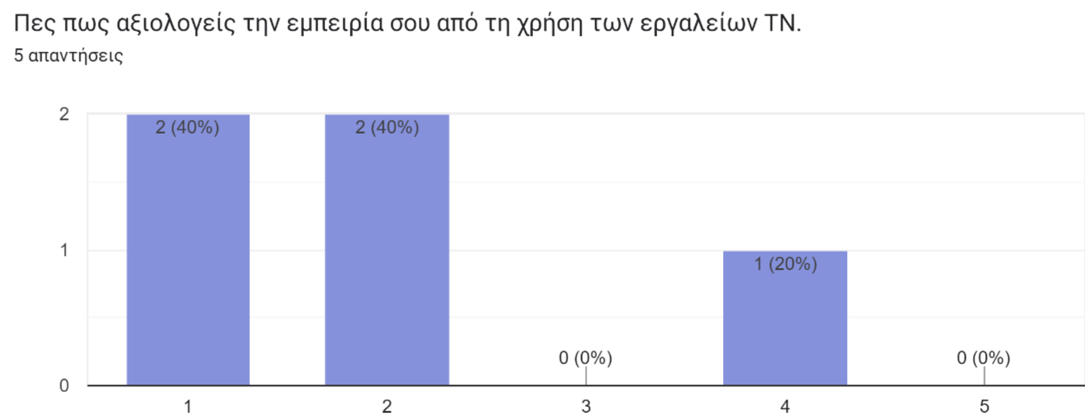
Question 12 encouraged the participants who submitted a 'Yes' answer to give examples of such tool(s). Only 5 out of the 12 students answer this question and their answers: mostly identify the following tools: Phrase (37%) and Wordfast (27%) (Figure 54).

Figure 54 Naming AI tools



Question 13 asked the same cohort to assess their experience whilst making use of the AI tools they indicated in Question 12. The data showed that 40% of the sample assessed their experience as 'Very satisfying', another 40% believed that their experience was simply 'Satisfying', whereas the remaining 20% thought of their experience as being practically a 'Waste of time and money' (Figure 55).

Figure 55 Experience with AI



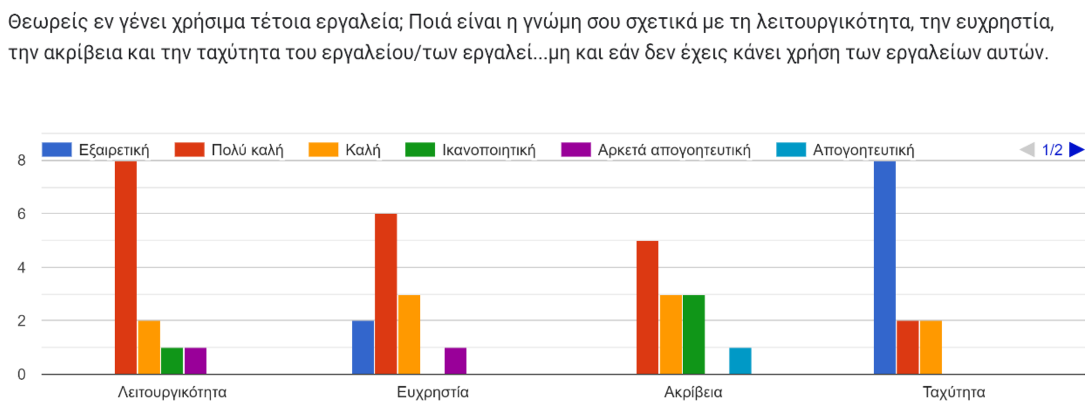
Question 14 allowed for further elaboration on the previous one. The collected data showed that three respondents (60%) considered that AI tools do not always ensure high-quality output. One of them mentioned that the tools they have used lack pragmatic, stylistic and contexual knowledge. On the contrary, the remaining 40% recognised AI's contribution during a translation task, i.e., the creation of translation memories, glossaries, and time-saving.

Question 15 addressed the participants who claimed they were 'not sure that the tool they used was AI-powered. This question received three answers, from which two were invalid, while the remaining one echoes the data shown in Question 12. Concerning the invalid responses, one respondent answered "I am not aware of any tools of this sort" and the other respondent answered "cat tools" which is a very general response.

5.3.4 Assessing AI

Question 16 helped us discover students' attitudes toward AI in terms of four variables, namely functionality, usability, accuracy, and speed [Figure 56). From the total of 12 respondents, 66.6% of the respondents viewed AI tools as being highly functional, 16.6% graded AI tools' functionality as 'Good', whereas and 8.3% said that AIis 'Satisfactory' or 'Quite disappointing' respectively. In terms of usability, 50% of the respondents opted for 'Very Good', 25% chose 'Good', 16.6% assessed AI's usability as being 'Exceptional' and the remaining 8.3% found AI's usability 'Quite disappointing'. Regarding accuracy, 41% chose the option 'Very Good', 25% opted for 'Good' and another 25% chose the 'Satisfactory' option; only 8.3% said that AI was 'Disappointing'. Lastly, the speed of AI technology was found to be 'Exceptional' by 66% of the respondents contrary to 16,6% who said it was 'Good' and 'Very Good' respectively.

Figure 56 Assessing the AI experience



5.3.5 AI or Humans

Question 17 was designed so that students would report and reflect on their attitudes towards utilising AI technology to assist translation or interpreting tasks. The majority of students (75%) were in favour of incorporating AI technology in their T&I tasks to ensure higher quality of completion, whilst 25% argue that they it may be too early to say whether AI could help in this particular context (i.e., "I do not know yet" answer) (Figure 57).

Figure 57 Attitudes towards AI technology during T&I tasks

Question 18 addressed participants who provided an 'In favour' answer to Question 17. Specifically, they are asked to explain the reasons that informed their response as to their opinion regarding incorporating AI tools during task performance. Students' answers (9 in total) allow us to classify the most frequently appearing reasons in the data (Table 20):

Table 20 Reasons 'in favour of' AI

Reason	Times of appearance
Assistive/supportive role	4
Efficiency of services	4
Speed of task completion	5

Question 20 was aimed at those who answered by 'I do not know yet'(in Question 17). As in Question 18, students were asked to give reasons to support their choice. The reasons provided by the sample of respondents in (3 in total) are listed in the table below (Table 21).

Table 21 Reasons 'I do not know yet'

Reason	Times of appearance
1. Concerns regarding the replacement of the human translator/interpreter by AI	2

2. Not experienced enough to answer this question	1

Reason 1 is particularly interesting in terms of the way respondents express the ideas that fall under this category. Respondents base their arguments on the need to reassess the power of the human brain when comparing it to AI.

5.4 Emphasising the 'bigger picture'

In this section, the analysis emphasizes creating a taxonomy of 'meanings'. This is achieved through a holistic examination of the data we collected during the implementation of the web-based survey across the three different groups of participants. In this section we will examine the data from a discursive viewpoint, contrary to the quantitising, statistics-based approach that was used in the previous sections. Our analysis builds on the framework of *discourse tracing* and shifts towards a qualitative, emic approach to data analysis. The aim is to pay close attention to the outlook of the selected groups of people[114] that comprise the survey's participants as to AI-assisted T&I. To this end, we are interested in tracing and documenting the commonalities and/or the deviations in the attitudes and views of the respondents with respect to the synergy between T&I professional practice and education/training and AI-inspired technology. The data used in the discourse analysis phase originate from the contingency and open-ended questions of the survey.

The quantitative data of the survey reveal commonalities rather than deviations in the respondents' answers. The commonalities can be classified under two categories, i.e., *ethical and deontological prerequisites* and *advantages and disadvantages of AI*. Ethical and deontological prerequisites constitute a prevalent thematic pattern in both the questionnaire design and the research. During the data coding phase that preceded the statistical analysis of our study, we found that two groups of respondents, namely

[114] T&I professionals, educators and students in the field of T&I.

professionals and educators, maintain a common line of reasoning regarding the ethical prerequisites that should be enforced to ensure proper AI integration in the T&I professional practice and education. This observation allows us to create taxonomies of the shared themes governing their argumentation. Specifically, both groups emphasised four common prerequisites for successful and trustworthy AI embedding in T&I[115]: 1) Data privacy, 2) Confidentiality, 3) Data Protection, and 4) User responsibility.

The second point of convergence concerns attitudes towards AI's strengths and weaknesses [116]. In this case, a different combination of respondents was involved, namely educators and students. Both cohorts were asked to evaluate the use of AI-powered technology in T&I. Their answers reveal a consensus as to the main advantages and disadvantages of AI-assisted T&I. Regarding the *advantages*, educators, and students identify the following facets of AI: 1) speed of task completion, 2) enhanced efficiency of services, 3) AI's decisive role in the construction of the new professional identity of translators and interpreters. Finally, the two cohorts share and express the same concerns about the impact of AI on T&I. Their arguments build on the 'human vs. AI' controversy; they stress the need to guard against the substitution of the human brain by AI as well as the underestimation of human capacity. Discourse-wise, the analysis showed that there are common thought patterns among the three categories of T&I (professionals, educators, and students) that corroborate existing work. The ethics-related data yielded from professionals and educators are consonant with prior literature focusing on delineating the AI-pertinent ethical imperatives that should be enforced to facilitate the synergy between T&I and AI technology. Specifically, the ethical requirements highlighted by these two groups of respondents echo Floridi et. al (2018) and Gerke et al.'s (2020) statements as to the importance of the concepts of 'explicability' that relates to 'User responsibility', data protection, privacy and confidentiality. Furthermore, the data we collected from the educators' cohort validate the work of Kenny and Doherty (2014), Massey and Ehrensberger-Dow (2017), Kenny (2020), Horváth (2022) and Li (2023), who claimed that T&I literature has highlighted

[115] See Appendix I (question 26) and Appendix II (question 14).
[116] See Appendix II (question 6) and Appendix III (question 18).

the integral role that translation technology ethics should enjoy in T&I pedagogy. Finally, the discoursal elements regarding students and educators' attitudes towards the advantages and disadvantages of the integration of AI in T&I supported previous studies on the evaluation of the AI efficacy. As shown in the literature review, previous research findings (e.g., Khanna et al. 2011, Börner et al. 2013, Khoong et al. 2019) have also highlighted the same strengths and weaknesses.

Chapter 6

Limitations

Besides its novelty, especially for the Greek tertiary educational world, this study is subject to a considerable number of limitations. Firstly, the participation and response rates of the survey are statistically low which makes the generalisation of the findings impossible. However, the limited sample size is not surprising or unheard of in such type of research; we were aware of the possibility of having a restricted pool of respondents since the T&I industry in Greece represents a very small portion of the Greek service market. Therefore, recruiting large numbers of participants would be rather impossible. Among the three groups of participants, professionals displayed the lowest participation rate, as only 4 respondents took part in the survey.

Another aspect to consider is non-responsiveness. Non-responses are critical limiting factors and, indeed, posed difficulties throughout the analysis phase of our study. One reason behind the non-responsiveness is perhaps the non-obligatory modeling of some questions, mainly belonging to the contingency type of questions, in the questionnaires. In turn, this allowed respondents to avoid providing answers to non-obligatory. Similar to non-responsiveness, invalid questions, being a shortcoming of the open-ended question type, distort the interpretability and overall quality of our findings. Although the questions were tailored to tap the expected background knowledge of the targeted respondents, we identified invalid and/or irrelevant responses in all three questionnaires[117].

Thirdly, the absence of triangulation restricts the credibility and validity of our findings. As in the case of limited sample size, we were also aware of how our choice of survey would affect the quality of our analysis. Unfortunately, conducting interviews Such a

[117] See Appendix IV.

triangulation method is time-consuming and the process of organising research interviews is highly demanding.

Lastly, limitations are observed in our findings concerning the integration of AI in the training curriculum of tertiary education institutions[118]. These refer primarily to the confined scope of inquiry in relation to the limited sources we consulted. As a result, the collected data rely solely on research in three web-based resources[119]. Thus, they cannot be considered fully representative or credible.

[118] See Section 4.4.

[119]List of EMT members 2019-2024, https://www.hotcoursesabroad.com/ , https://www.findamasters.com/

Chapter 7

Conclusion

The present study aimed at exploring AI's potential in T&I in the medical context and the ethical implications that underly its integration in the field. To this end, the research examined AI's integration on two levels, i.e., professional settings and education and training in the field of T&I. Both contexts are of primary importance for the facilitation of the study since they comprise the core of the T&I industry. To explore these settings, we focused on three groups of agents who interfere directly with T&I, namely professional translators and interpreters, T&I educators and trainers and students of T&I. Professional translators and interpreters are witnessing the major technological breakthrough that AI-inspired technology brings about in their professional reality. The new AI-influenced state of affairs has reshaped the professional identity of T&I service providers. As far as they are concerned, educators and trainers play a pivotal role in realising the reform of the T&I profession, keeping up with the developments in translation and interpreting technology, and most importantly, preparing student translators and interpreters for entering the industry. Lastly, student translators and interpreters are the third group of agents examined in this study. The exploration of their point of view contributes equally significantly to laying the foundations of proper AI integration in T&I.

To facilitate the examination of the objectives, the study was based on a combination of qualitative and quantitative approaches to research organised within an embedded design for data collection. The research instrument of the study consisted of surveys, especially web-based questionnaires. The survey addressed three groups of population, namely professional translators and interpreters, T&I educators and students, with the aim of observing their attitudes and opinion towards AI-mediated T&I. Besides the limiting factors of the research, the analysis of the data shows that there are points of convergence among all groups of respondents. Such points relate mainly to the participants' evaluation of AI's advantages and disadvantages during the performance of translation and/or interpreting tasks and the emphasis on the ethical, legal, and deontological prerequisites that should be enforced to ensure ethical use of AI.

Apart from the survey-based data, the study offered insights into the global agenda of ethics and deontology with regard to both general and field-specialised AI applications. This data type was collected via a systematic review of the existent literature. The main goal of this literature review was to create a basis for the composition and/or amendment of the Greek AI-oriented ethical guidelines and the Greek Code of Ethics for professional translators and interpreters by placing emphasis on ethically and legally framing trustworthy AI use.

In this study, the synergy between AI and T&I pedagogy was investigated both through the web-based surveys and as a distinct field of inquiry. Regarding the latter, we conducted a world-wide research focusing on representing statistically the degree of AI integration in tertiary education institutions offering T&I MA programmes. Although limited in scope, the findings show that only 9.52% of the universities included in our sample have a direct AI orientation in their MA programme's curriculum.

Due to the absence of triangulation, our findings cannot be confirmed in terms of validity and credibility nor can they be generalised. However, the significance of the present study lies in the multilevel exploration of AI applications in the domain of T&I. Moreover, it displays a high degree of novelty based on the up-to- date research in the country. Future research can utilise the insights of this work regarding the ethical agenda of AI as a basis to inform an in-depth exploration of the ethical, deontological and legal environment within which AI develops and interacts with T&I.

Appendix I

Questionnaire (Professionals)

Τεχνητή Νοημοσύνη (ΤΝ) στην Ιατρική Μετάφραση και Διερμηνεία

(Επαγγελματίες)

Πατώντας τον σύνδεσμο, συμμετέχετε σε έρευνα σχετικά με τη θέση που κατέχει η ΤΝ στην ιατρική μετάφραση και διερμηνεία, τόσο σε επίπεδο πρακτικής όσο και σε επίπεδο εκπαίδευσης.

Το ερωτηματολόγιο αποτελεί μέρος μεταπτυχιακής ερευνητικής διατριβής που πραγματοποιείται στο Μεταπτυχιακό Προγράμμα Σπουδών στη Μετάφραση και Διερμηνεία του Τμήματος Αγγλικής Γλώσσας και Φιλολογίας του ΕΚΠΑ.

Προτού προβείτε στη συμπλήρωση του ερωτηματολογίου, θα θέλαμε να σας διαβεβαιώσουμε ότι δεν συλλέγουμε προσωπικά δεδομένα και δεν προβαίνουμε σε καταγραφή του προφίλ των συμμετεχόντων/συμμετεχουσών. Η διεύθυνση ηλεκτρονικού ταχυδρομείου σας δεν αποθηκεύεται από το σύστημα για μελλοντική χρήση, καθώς σεβόμαστε το απόρρητο. Αν επιθυμείτε να επικοινωνήσετε απευθείας μαζί μας, μεταβείτε στο τέλος του ερωτηματολογίου για πληροφορίες επικοινωνίας.

Εάν επιθυμείτε να συνδράμετε στην έρευνα μας, παρακαλείστε να λάβετε υπόψη τα εξής:

- για να προχωρήσετε σε κάθε επόμενη ερώτηση, πρέπει να απαντήσετε αυτήν που προηγείται. Μόνο μερικές ερωτήσεις ανοικτού τύπου δεν είναι υποχρεωτικές. Οι περισσότερες ερωτήσεις είναι κλειστού τύπου (πολλαπλών επιλογών) και συμπληρώνονται γρήγορα.
- θα χρειαστείτε περίπου 10 λεπτά για να συμπληρώσετε το ερωτηματολόγιο, εάν οι περισσότερες από τις απαντήσεις σας είναι «Όχι» .
- θα χρειαστείτε περίπου 15 λεπτά για να συμπληρώσετε το ερωτηματολόγιο, εάν οι απαντήσεις σας είναι «Ναι» , «Εξαρτάται», ή παρόμοιες.

Θα θέλαμε να σας ευχαριστήσουμε εκ των προτέρων για τη συμμετοχή σας. Οποιαδήποτε παρατήρηση σχετικά με το ερωτηματολόγιο είναι ευπρόσδεκτη, καθώς μπορεί να συμβάλει στη βελτίωσή του στο πλαίσιο μεταγενέστερης έρευνας.

Το προφίλ σας

1. Πώς προσδιορίζεστε με βάση το φύλο;

- o Άνδρας
- o Γυναίκα
- o Δεν επιθυμώ να απαντήσω
- o Άλλο:

Η επαγγελματική σας ιδιότητα

2. Είστε :

Επιλέξτε όλα όσα ισχύουν.

- o Μεταφραστής/-ρια με ειδίκευση στα ιατρικά/στον υγειονομικό κλάδο
- o Κοινοτικός/-ή Διερμηνέας με ειδίκευση στα ιατρικά/στον υγειονομικό κλάδο
- o Πολιτισμικός/-ή μεσολαβητής/-τρια με (κάποια) πείρα στα ιατρικά/στον υγειονομικό κλάδο

Πού απασχολείστε

3. Απασχολείστε σε:

Επιλέξτε όλα όσα ισχύουν.

- o Κέντρα Υποδοχής Μεταναστών/-ριών Νοσοκομεία και Κέντρα Υγείας
- o Λοιπούς Φορείς Υγείας και Υγειονομικού Ενδιαφέροντος του Δημοσίου Τομέα
- o Λοιπούς Φορείς Υγείας και Υγειονομικού Ενδιαφέροντος του Ιδιωτικού Τομέα
- o Άλλο:

Σχέση εργασίας

4. Είστε:

- o Αυτοαπασχολούμενος/-η (έχω τη δική μου επιχείρηση)
- o Με σχέση έργου/Δελτίο Παροχής Υπηρεσιών Μισθωτός/-ή με μόνιμη σχέση εργασίας
- o Μερικώς απασχολούμενος/-η Εθελοντής/-ρια

Σπουδές

5. Έχετε λάβει τυπική εκπαίδευση στον κλάδο ειδίκευσής σας (δηλ., ως μεταφραστής/-τριας, διερμηνέας, κ.ο.κ.);

- o Σε προπτυχιακό επίπεδο
- o Σε μεταπτυχιακό επίπεδο
- o Σε προπτυχιακό και μεταπτυχιακό επίπεδο
- o Σε επαγγελματικό επίπεδο
- o Άλλο:

Τόπος σπουδών

6. Έχετε ολοκληρώσει προπτυχιακές σπουδές στην Ελλάδα;

Ναι

Όχι

7. Έχετε σπουδάσει ή εκπαιδευτεί στο εξωτερικό;

- o Ναι
- o Όχι

8. Εάν η απάντηση σας στην προηγούμενη ερώτηση ήταν "Ναι", παρακαλούμε αναφέρετε τη χώρα στην οποία φοιτήσατε, διευκρινίζοντας το επίπεδο σπουδών (προπτυχιακό, μεταπτυχιακό ή άλλο) και τη φύση των σπουδών σας

(π.χ. Ιατρική Μετάφραση, Διερμηνεία, κ.ο.κ.).

Επαγγελματική εμπειρία

9. Πόσα χρόνια επαγγελματικής εμπειρίας διαθέτετε;

Επιλέξτε όλα όσα ισχύουν.

	0 έτη	1-5 έτη	5-10 έτη	15-20 έτη	20-25 έτη	Πάνω από 25 έτη
Ως μεταφραστής/--ρια με ειδίκευση στα ιατρικά						
Ως κοινοτικός/--ή διερμηνέας με ειδίκευση στα ιατρικά						
Ως διαπολιτισμικός/--ή μεσολαβητής/--ρια με πείρα στα ιατρικά						

Εξοικείωση με τις νέες τεχνολογίες και χρήση τεχνολογιών που έχουν ενσωματώσει την ΤΝ

10. Είστε εξοικειωμένος/-η με τις δυνατότητες που παρέχει η ΤΝ στη μετάφραση και τη διερμηνεία;

- Ναι
- Όχι
- Κατά κάποιο τρόπο

11. Εάν απαντήσατε "Όχι", παρακαλούμε εξηγήστε γιατί.

Γραμματισμός στην ΤΝ

12. Ποιο θεωρείτε ότι είναι το επίπεδο γραμματισμού σας στην ΤΝ στον τομέα της μετάφρασης και της διερμηνείας;*

	1	2	3	4	5	
Εξαιρετικά χαμηλό	○	○	○	○	○	Πολύ υψηλό

13. Χρησιμοποιείτε και/ ή συμβουλεύεστε εργαλεία ΤΝ πριν, κατά τη διάρκεια και/ή μετά τη μεταφραστική εργασία και/ή την αποστολή διερμηνείας που έχετε αναλάβει ή που σας έχει ανατεθεί;

- Ναι
- Όχι
- Μερικές φορές

14. Εάν η απάντηση σας στην προηγούμενη ερώτηση ήταν "Ναι" ή "Μερικές φορές", ποιες είναι οι κύριες λειτουργίες που αξιοποιείτε στα εργαλεία ΤΝ που χρησιμοποιείτε;

Επιλέξτε όλα όσα ισχύουν.

- Εξαγωγή ορολογίας ή διαχείριση και επεξεργασία όρου
- Δημιουργία δίγλωσσων και/ή πολύγλωσσων γλωσσαριών
- Μηχανική μετάφραση
- Σύνταξη και μετεπιμέλεια (post-editing)
- Παράφραση στη γλώσσα-στόχο Δημιουργία περίληψης
- Λειτουργίες στο πλαίσιο μετατροπής ομιλίας σε κείμενο
- Λειτουργίες στο πλαίσιο μετατροπής κειμένου σε ομιλία
- Άλλο:

15. Εάν απαντήσατε "Όχι", παρακαλούμε εξηγήστε γιατί.

Η ΤΝ στη Μετάφραση και Διερμηνεία

16. Βάσει της εμπειρίας σας, σε ποιο βαθμό πιστεύετε ότι η ΤΝ έχει ενσωματωθεί στο πλαίσιο της παροχής υπηρεσιών ιατρικής μετάφρασης και/ή διερμηνείας;

	1	2	3	4	5	
Καθόλου						Πλήρως

ΤΝ και Ποιότητα Υπηρεσιών

17. Πώς επηρεάζει η ΤΝ την ποιότητα των υπηρεσιών που παρέχετε στους πελάτες σας;

- Θετικά
- Αρνητικά
- Ουδέτερα
- Δεν χρησιμοποιώ την ΤΝ, επομένως αυτή η ερώτηση δεν με αφορά

18. Παρακαλούμε δώστε μερικά παραδείγματα για να αιτιολογήσετε την απάντησή σας.

19. Με βάση την εμπειρία σας, πόσο αποτελεσματική είναι η ΤΝ στην Ελληνική γλώσσα συγκριτικά με τις άλλες γλώσσες εργασίας σας;*

	1	2	3	4	5	
Αναποτελεσματική						Ιδιαίτερα αναποτελεσματική

Πρόσβαση στα εργαλεία ΤΝ

20. Με την ιδιότητα σας ως επαγγελματίας ιατρικός/-ή διερμηνέας και/ή μεταφραστής/ρια, έχετε πρόσβαση σε εργαλεία ΤΝ από τους εργοδότες/- ριες σας ή έχετε την οικονομική δυνατότητα να τα αποκτήσετε;*

- o Ναι, έχω πρόσβαση
- o Όχι, δεν έχω πρόσβαση
- o Ναι, έχω την οικονομική δυνατότητα
- o Όχι δεν έχω την οικονομική δυνατότητα
- o Εξαρτάται

21. Εάν η απάντηση στην προηγούμενη ερώτηση ήταν "Όχι..." ή "Εξαρτάται",

παρακαλούμε εξηγείστε τους λόγους.

22. Εάν τα εργαλεία με ενσωματωμένη ΤΝ ήταν προσιτά, θα επενδύατε σε αυτά προκειμένου να αυξήσετε την παραγωγικότητά σας, την αποτελεσματικότητά σας και, κατ' επέκταση, την ποιότητα των παρεχόμενων υπηρεσιών;

- o Ναι
- o Όχι
- o Δεν γνωρίζω

23. Παρακαλούμε αιτιολογήστε την απάντησή σας.

ΤΝ και Άνθρωπος

24. Πιστεύετε πως η ΤΝ θα αντικαταστήσει τον άνθρωπο στην ιατρική μετάφραση/διερμηνεία και τα συναφή επαγγέλματα;

- o Ναι
- o Όχι
- o Δεν γνωρίζω/Δεν μπορώ να προβλέψω

25. Παρακαλούμε αιτιολογήστε την απάντησή σας

Δεοντολογικοί προβληματισμοί ως προς τη συμπόρευση ΤΝ και ιατρικής μετάφρασης και διερμηνείας.

26. Πιστεύετε ότι θα πρέπει να υπάρχουν νομικά και δεοντολογικά προαπαιτούμενα για την ενσωμάτωση της ΤΝ στην άσκηση της ιατρικής μετάφρασης και διερμηνείας; Εάν ναι, ποια είναι τα εν λόγω προαπαιτούμενα; Πώς θα επηρέαζαν το έργο σας;

Ευχαριστίες

Ευχαριστούμε για τον χρόνο που αφιερώσατε στη συμπλήρωση του ερωτηματολογίου. Γνωρίζουμε ότι ο χρόνος σας είναι πολύτιμος και η συμμετοχή σας μας τιμά ιδιαιτέρως.

Οι απαντήσεις σας αποτελούν σημαντικό κομμάτι της έρευνάς μας.

Εάν ενδιαφέρεστε να μάθετε περισσότερα σχετικά με τα αποτελέσματα της έρευνας, μπορείτε να επικοινωνήσετε με την ερευνήτρια Χρυσούλα Γάτσιου, στο chrysoulag@enl.uoa.gr, και την επιβλέπουσα της, Δρ. Ευφροσύνη Φράγκου, στο effiefragkou@enl.uoa.gr.

Appendix II

Questionnaire (Educators)

Τεχνητή Νοημοσύνη (ΤΝ) στην Ιατρική Μετάφραση και Διερμηνεία (Διδακτικό προσωπικό)

Πατώντας τον σύνδεσμο, συμμετέχετε σε έρευνα σχετικά με τη θέση που κατέχει η ΤΝ στην ιατρική μετάφραση και διερμηνεία, τόσο σε επίπεδο πρακτικής όσο και σε επίπεδο εκπαίδευσης.

Το ερωτηματολόγιο αποτελεί μέρος μεταπτυχιακής ερευνητικής διατριβής που πραγματοποιείται στο Μεταπτυχιακό Προγράμμα Σπουδών στη Μετάφραση και Διερμηνεία του Τμήματος Αγγλικής Γλώσσας και Φιλολογίας του ΕΚΠΑ.

Προτού προβείτε στη συμπλήρωση του ερωτηματολογίου, θα θέλαμε να σας διαβεβαιώσουμε ότι δεν συλλέγουμε προσωπικά δεδομένα και δεν προβαίνουμε σε καταγραφή του προφίλ των συμμετεχόντων/συμμετεχουσών. Η διεύθυνση ηλεκτρονικού ταχυδρομείου σας δεν αποθηκεύεται από το σύστημα για μελλοντική χρήση, καθώς σεβόμαστε το απόρρητο. Αν επιθυμείτε να επικοινωνήσετε απευθείας μαζί μας, μεταβείτε στο τέλος του ερωτηματολογίου για πληροφορίες επικοινωνίας.

Εάν επιθυμείτε να συνδράμετε στην έρευνα μας, παρακαλείστε να λάβετε υπόψη τα εξής:

- για να προχωρήσετε σε κάθε επόμενη ερώτηση, πρέπει να απαντήσετε αυτήν που προηγείται. Μόνο λίγες ερωτήσεις ανοικτού τύπου δεν είναι υποχρεωτικές. Οι περισσότερες ερωτήσεις είναι κλειστού τύπου (πολλαπλών επιλογών) και συμπληρώνονται γρήγορα.
- θα χρειαστείτε περίπου 10 λεπτά για να συμπληρώσετε το ερωτηματολόγιο, εάν οι περισσότερες από τις απαντήσεις σας είναι «Όχι» .
- θα χρειαστείτε περίπου 15 λεπτά για να συμπληρώσετε το ερωτηματολόγιο, εάν οι απαντήσεις σας είναι «Ναι» ή παρόμοιες.

Θα θέλαμε να σας ευχαριστήσουμε εκ των προτέρων για τη συμμετοχή σας. Οποιαδήποτε παρατήρηση σχετικά με το ερωτηματολόγιο είναι ευπρόσδεκτη, καθώς μπορεί να συμβάλει στη βελτίωσή του στο πλαίσιο μεταγενέστερης έρευνας.

Το προφίλ σας

1.Πώς προσδιορίζεστε με βάση το φύλο;

- Άνδρας
- Γυναίκα
- Δεν επιθυμώ να απαντήσω
- Άλλο:

ΤΝ στη Μετάφραση και τη Διερμηνεία

2. Τάσσεστε υπέρ της ΤΝ στην πρακτική της μετάφρασης και διερμηνείας και, κατ' επέκταση, στη διδασκαλία και την παιδαγωγική τους;

    - Ναι
    - Όχι

Εξοικείωση με την ΤΝ

3. Είστε εξοικειωμένοι/-ες με τις δυνατότητες που παρέχει η ΤΝ στη διδασκαλία και την παιδαγωγική στον χώρο της μετάφρασης και της διερμηνείας ;

- Ναι
- Όχι
- Κατά κάποιο τρόπο

ΤΝ και Χρήση

4. Χρησιμοποιείτε εργαλεία ΤΝ στο μάθημα (ή στα μαθήματα) μετάφρασης και/ή διερμηνείας που προσφέρετε;

- Ναι
- Όχι
- Μερικές φορές

Η άποψή σας σχετικά με την ενσωμάτωση της ΤΝ στη διδακτική της μετάφρασης και διερμηνείας

5. Σε ποιο βαθμό πιστεύετε ότι η ΤΝ έχει ενσωματωθεί στα προγράμματα σπουδών που στοχεύουν στην εκπαίδευση και κατάρτιση διερμηνέων και μεταφραστών/-τριών στην Ελλάδα;

	1	2	3	4	5	
Καθόλου						Απολύτως

6. Κατά τη γνώμη σας, ποια είναι τα πλεονεκτήματα και ποια τα μειονεκτήματα που χαρακτηρίζουν ένα πρόγραμμα σπουδών στο οποίο η ΤΝ αποτελεί σημαντικό στοιχείο της διδασκαλίας;

7. Κατά τη γνώμη σας, ποια είναι τα βασικά εμπόδια που δυσχεραίνουν την ορθή ενσωμάτωση της ΤΝ στα προγράμματα σπουδών μετάφρασης και/ή διερμηνείας;

Επιλέξτε όλα όσα ισχύουν.

- Ο τεχνολογικός γραμματισμόςτων εκπαιδευτών/-τριών
- Ο τεχνολογικός γραμματισμός των φοιτητών/-τριών
- Κατάλληλες υποδομές (εργαστήρια και πρόσβαση σε λογισμικά)
- Το πρόγραμμα σπουδών, η φιλοσοφία και ο προσανατολισμός του προγράμματος σπουδών
- Η διαρκής εξέλιξη των εργαλείων και η ικανότητά μου να συμβαδίζω με τις τρέχουσες και τις μελλοντικές τάσεις
- Εμπόδια σε επίπεδο θεσμικό
- Το κόστος των εργαλείων
- Τα νομικά ζητήματα που εγείρει η χρήση τους

8. Εάν οι επιλογές στην παραπάνω ερώτηση δεν σας κάλυψαν, αναφέρατε άλλους λόγους.

Ενσωμάτωση της ΤΝ στην εκπαίδευση των μεταφραστών/-τριών και των διερμηνέων

9. Ποιους τρόπους προτείνετε ώστε να επιτευχθεί η ενσωμάτωση της ΤΝ στην εκπαίδευση των μεταφραστών/-τριών και των διερμηνέων;

Προστιθέμενη αξία της ΤΝ

10. Ποια, κατά τη γνώμη σας, δύναται να είναι η προστιθέμενη αξία για την επαγγελματική εξέλιξη των αποφοίτων ενός προγράμματος σπουδών που έχει ενσωματώσει την ΤΝ ;

Επιλέξτε όλα όσα ισχύουν.

- Βελτιστοποίηση υπηρεσιών
- Εξοικείωση με τη "νέα" επαγγελματική ταυτότητα που δημιουργεί η τεχνολογική εξέλιξη
- Διαφοροποίηση στις προσφερόμενες υπηρεσίες (μεγαλύτερο εύρος)
- Άλλο:

ΤΝ και Άνθρωπος (μεταφραστής/-ρια, διερμηνέας)

11. Πιστεύετε ότι ένα πρόγραμμα σπουδών με βασικό πυλώνα την ΤΝ θα μπορούσε να οδηγήσει σε υποβάθμιση του ρόλου και των προσόντων των μελλοντικών επαγγελματιών μετάφρασης και διερμηνείας;

- Ναι
- Όχι
- Ίσως
- Άλλο:

12. Εάν η απάντησή σας στην προηγούμενη ερώτηση ήταν "Άλλο", παρακαλούμε διευκρινίστε.

ΤΝ, Ηθική και Δεοντολογία

13. Ποια είναι τα ηθικά και νομικά προαπαιτούμενα για την εισαγωγή της ΤΝ στη διδακτική και την παιδαγωγική της διερμηνείας και της μετάφρασης;

Επιλέξτε όλα όσα ισχύουν.

- Διαφάνεια
- Εξηγησιμότητα (η ΤΝ πρέπει να είναι εξηγήσιμη, να επιτρέπει στο χρήστη-άνθρωπο να έχει πλήρη εικόνα της λειτουργίας των συστημάτων ΤΝ)
- Ασφάλεια και Κυβερνοασφάλεια
- Αποτελεσματικότητα
- Συναίνεση μετά από ενημέρωση
- Ευθύνη και υποχρεώσεις χρήστη
- Δίκαιος/ηθικός αλγόριθμος
- Ποιότητα δεδομένων
- Προστασία δεδομένων
- Ιδιοκτησία δεδομένων
- Άλλο:

14. Ποιες είναι οι ηθικές και νομικές προεκτάσεις της εισαγωγής της ΤΝ στη διδακτική και την παιδαγωγική της διερμηνείας και της μετάφρασης;

Ευχαριστίες

Ευχαριστούμε για τον χρόνο που αφιερώσατε στη συμπλήρωση του ερωτηματολογίου. Γνωρίζουμε ότι ο χρόνος σας είναι πολύτιμος και η συμμετοχή σας μας τιμά ιδιαιτέρως.

Οι απαντήσεις σας αποτελούν σημαντικό κομμάτι της έρευνάς μας.

Εάν ενδιαφέρεστε να μάθετε περισσότερα σχετικά με τα αποτελέσματα της έρευνας, μπορείτε να επικοινωνήσετε με την ερευνήτρια Χρυσούλα Γάτσιου, στο chrysoulag@enl.uoa.gr, και την επιβλέπουσα της, Δρ. Ευφροσύνη Φράγκου, στο effiefragkou@enl.uoa.gr.

Appendix III

Questionnaire (Students)

Τεχνητή Νοημοσύνη (ΤΝ) στην Ιατρική Μετάφραση και Διερμηνεία (Φοιτητές)

Πατώντας τον σύνδεσμο, μπορείς να συμμετάσχεις στην έρευνα σχετικά με την θέση που κατέχει η ΤΝ σε εκπαιδευτικά προγράμματα μετάφρασης και διερμηνείας προσφερόμενα τόσο σε προπτυχιακό όσο και σε μεταπτυχιακό επίπεδο σπουδών στην Ελλάδα.

Προτού προχωρήσεις στη συμπλήρωση του ερωτηματολογίου, σε βεβαιώνουμε ότι δεν συλλέγονται τα προσωπικά σου δεδομένα και δεν καταγράφεται το προφίλ σου. Η διεύθυνση ηλεκτρονικού ταχυδρομείου σου δεν αποθηκεύεται από το σύστημα για μελλοντική χρήση, εκτός αν επιθυμείς να επικοινωνήσεις απευθείας μαζί μας (για πληροφορίες επικοινωνίας, δες στο τέλος του ερωτηματολογίου).

Το ερωτηματολόγιο αποτελεί μέρος μεταπτυχιακής ερευνητικής διατριβής στα πλαίσια του Μεταπτυχιακού Προγράμματος Σπουδών Μετάφρασης και Διερμηνείας του

Τμήματος Αγγλικής Γλώσσας και Φιλολογίας του ΕΚΠΑ. Εάν επιθυμείς να συνδράμεις την έρευνα μας, λάβε υπόψη σου τα εξής:

- για να προχωρήσεις σε κάθε επόμενη ερώτηση, πρέπει να απαντήσεις αυτήν που προηγείται.
- θα χρειαστείς περίπου 10 λεπτά για να συμπληρώσετε το ερωτηματολόγιο, εάν οι περισσότερες από τις απαντήσεις σου είναι «Όχι» .
- θα χρειαστείς περίπου 15 λεπτά για να συμπληρώσεις το ερωτηματολόγιο, εάν οι απαντήσεις σου είναι «Ναι» , «Δεν είμαι σίγουρ@» ή παρόμοιες.

Θα θέλαμε να σε ευχαριστήσουμε εκ των προτέρων για τη συμμετοχή σου και θα θέλαμε τη γνώμη σου και κυρίως τις προτάσεις ως προς τα ερωτήματα που θέσαμε.

Θα θέλαμε να σε ευχαριστήσουμε εκ των προτέρων για τη συμμετοχή σου. Οποιαδήποτε παρατήρηση σχετικά με το ερωτηματολόγιο είναι ευπρόσδεκτη, καθώς μπορεί να συμβάλει στη βελτίωσή του στο πλαίσιο μεταγενέστερης έρευνας.

Το προφίλ σου

1. Πώς προσδιορίζεσαι με βάση το φύλο σου;

- Άνδρας
- Γυναίκα
- Δεν επιθυμώ να αναφέρω
- Άλλο:

Επίπεδο σπουδών

2. Ποιο είναι το επίπεδο σπουδών σου;

- Πτυχίο
- Μεταπτυχιακό Δίπλωμα Ειδίκευσης
- Διδακτορικό Δίπλωμα
- Μεταδιδακτορικό
- Σπουδές εστιασμένες στην Μετάφραση και/ή τη Διερμηνεία

3.Έχεις παρακολουθήσει/παρακολουθείς αυτή την περίοδο μάθημα ή μαθήματα μετάφρασης και/ή διερμηνείας στο πλαίσιο των σπουδών σου;

- Ναι
- Όχι
- Άλλο:

4. Εάν απάντησες "Ναι", δώσε μας μερικές επιπλέον λεπτομέρειες (π.χ., τίτλος και κατεύθυνση σπουδών ή εξειδίκευση, ίδρυμα, κ.ο.κ.)

Η Τεχνητή Νοημοσύνη (ΤΝ) και Εσύ

5. Γνωρίζεις τί είναι η ΤΝ;

- Ναι
- Όχι
- Δεν είμαι σίγουρ@

6. Εάν η απάντησή σου στην προηγούμενη ερώτηση ήταν "Ναι" ή "Δεν είμαι σίγουρ@", δώσε τη δική σου ερμηνεία.

7. Γνωρίζεις τί είναι η ΤΝ στην ιατρική μετάφραση και/ή διερμηνεία; *

- Ναι
- Όχι
- Δεν είμαι σίγουρ@

8. Εάν η απάντησή σου στην προηγούμενη ερώτηση ήταν "Ναι" ή "Δεν είμαι σίγουρ@", δώσε τη δική σου ερμηνεία.

9. Είσαι εξοικειωμέν@ με ή γνωρίζεις ότι έχεις τη δυνατότητα να χρησιμοποιείς την ΤΝ στη μετάφραση και τη διερμηνεία;

- Ναι
- Όχι
- Δεν είμαι σίγουρ@

10. Εάν απάντησες "Ναι" ή "Δεν είμαι σίγουρ@" στην προηγούμενη ερώτηση, δώσε μερικά παραδείγματα εφαρμογής της ΤΝ στη μετάφραση και τη διερμηνεία;

Δουλεύοντας με την ΤΝ

11. Έχεις χρησιμοποιήσει ποτέ εργαλεία ΤΝ ή σου έχουν δείξει τέτοια εργαλεία ΤΝ σε κάποιο από τα μαθήματα μετάφρασης ή διερμηνείας που έχεις παρακολουθήσει ως τώρα;

- Ναι
- Όχι
- Δεν είμαι βέβαι@ ότι επρόκειτο για εργαλείο ΤΝ

12. Εάν η απάντησή σου στην προηγούμενη ερώτηση ήταν "Ναι", ανάφερε το ή τα εργαλείο(-α).

13. Πες πως αξιολογείς την εμπειρία σου από τη χρήση των εργαλείων ΤΝ.

	1	2	3	4	5	
Εξαιρετικά ικανοποιητική (άξιζε η επένδυση για την απόκτηση του εργαλείου)						Σπατάλη χρόνου και χρημάτων

14. Περίγραψε με λίγα λόγια με την εμπειρία σου με την ΤΝ.

15. Εάν η απάντησή σου στην προηγούμενη ερώτηση ήταν "Δεν είμαι βέβαι@" ότι * επρόκειτο για εργαλείο ΤΝ", ανάφερε το εργαλείο για το οποίο δεν είσαι σίγουρ@ ότι ανήκει στην κατηγορία της ΤΝ.

Αξιολόγηση της ΤΝ

16. Θεωρείς εν γένει χρήσιμα τέτοια εργαλεία; Ποιά είναι η γνώμη σου σχετικά με τη λειτουργικότητα, την ευχρηστία, την ακρίβεια και την ταχύτητα του εργαλείου/των εργαλείων. Απάντησε βάσει όσων νομίζεις ακόμη και εάν δεν έχεις κάνει χρήση των εργαλείων αυτών.

	Εξαιρετική	Πολύ καλή	Καλή	Ικανοποιητι-κή	Αρκετά απογοη-τευτική	Απογοητευ-τική	Πολύ απογοητευτκή
Λειτουργικότητα							
Ευχρηστία							
Ακρίβεια							
Ταχύτητα							

ΤΝ ή Άνθρωπος;

17. Είσαι υπέρ ή κατά της χρήσης εργαλείων ΤΝ ως μέσου υποστήριξης ενός μεταφραστικού έργου ή μιας αποστολής διερμηνείας;

- o Υπέρ
- o Κατά
- o Δεν γνωρίζω ακόμα

18. Εάν η απάντησή σου στην προηγούμενη ερώτηση ήταν "Υπέρ", εξήγησε τους λόγους.

19. Εάν η απάντησή σας στην προηγούμενη ερώτηση ήταν "Κατά", εξήγησε τους λόγους.

20. Εάν η απάντησή σου στην προηγούμενη ερώτηση ήταν "Δεν γνωρίζω ακόμα", εξήγησε τους λόγους.

Ευχαριστίες

Σε ευχαριστούμε πολύ για τη συμμετοχή σου!

Ευχαριστούμε για τον χρόνο που αφιέρωσες στη συμπλήρωση του ερωτηματολογίου μας. Γνωρίζουμε ότι ο χρόνος σου είναι πολύτιμος και η συμμετοχή σου μας τιμά ιδιαιτέρως.

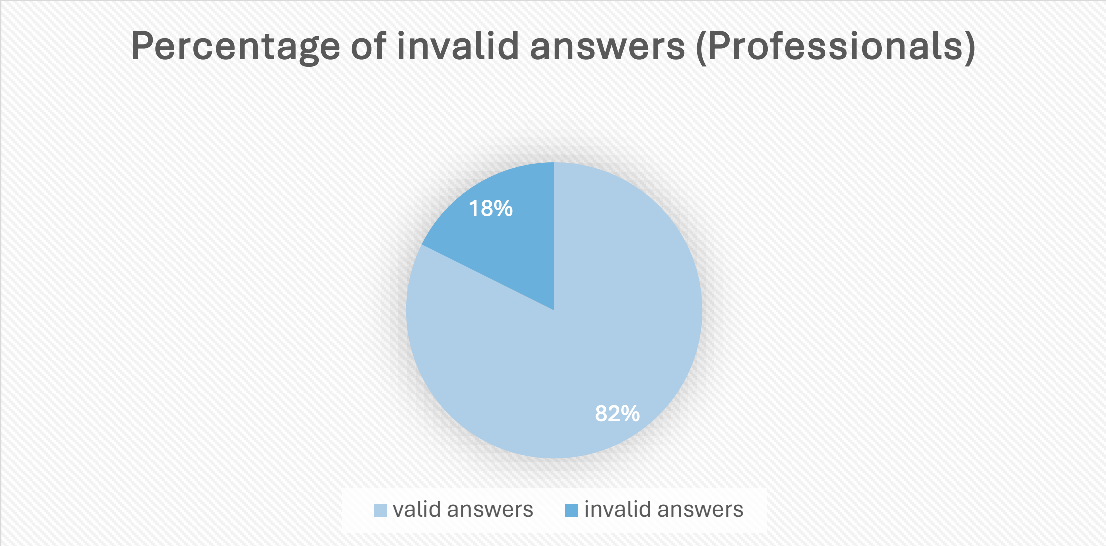
Οι απαντήσεις σου αποτελούν σημαντικό κομμάτι της έρευνάς μας.

Εάν ενδιαφέρεσαι να μάθεις περισσότερα σχετικά με τα αποτελέσματα της έρευνας, μπορείς να επικοινωνήσεις με την ερευνήτρια Χρυσούλα Γάτσιου, στο chrysoulag@enl.uoa.gr, και την επιβλέπουσα της, Δρ. Ευφροσύνη Φράγκου, στο effiefragkou@enl.uoa.gr.

Appendix IV

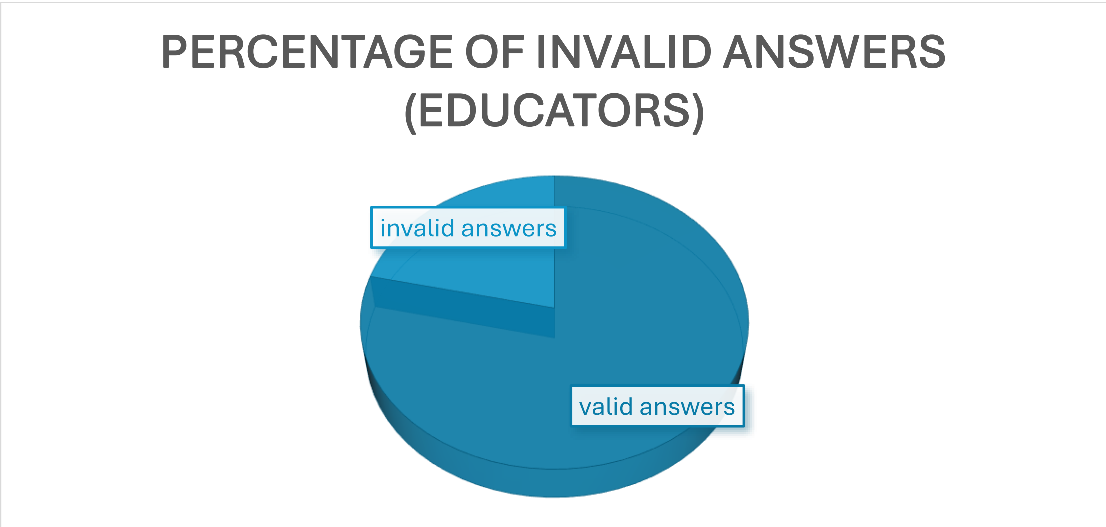
Invalid answers

Figure 58 Professionals



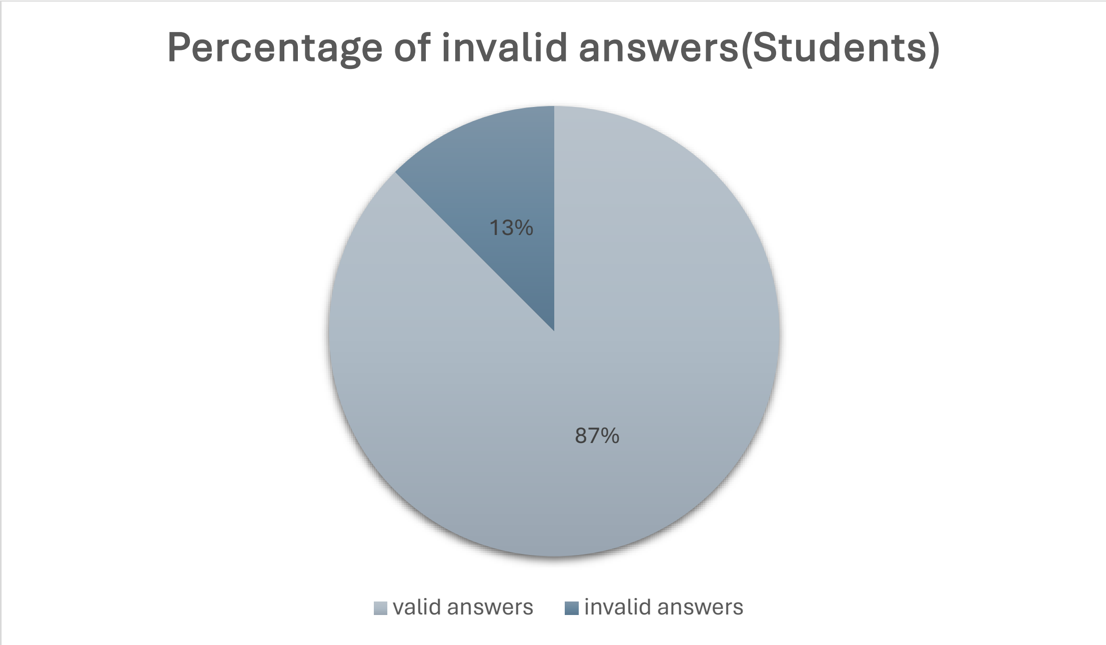
All invalid questions (3 in total) belong to the 'contingency questions' type.

Figure 59 Educators



The types of the invalid answers detected in the survey are two, i.e., contingency questions (2 out of 3) and open-ended (1 out of 3).

Figure 60 Students



The analysis identified two invalid answers to the survey's questions; Both are found in contingency questions,

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