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Investigating Artificial Intelligence as a Threat to Translators' Positions

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Abstract
The career of human translators is currently under threat due to automation, which many anticipate will eventually be supplanted by artificial intelligence. According to translators, Artificial intelligence is projected to replace human translators shortly soon. This article examines the various viewpoints of translators and experts on the controversial topic of machine translation as an artificial intelligence component, which is expected to eliminate thousands of jobs in the near future and automate the translation industry instead of being performed by human translators. The analysis focuses attention on MT and the threat of replacement. Two key findings are mentioned. First, translators and specialists disagree on the claims and threats despite advances in machine translation. Second, although there has been continuous progress in machine translation, the Arabic Language has a complex system that cannot be readily outperformed by Artificial intelligence. This article argues for the proper use of AI to ensure a high-quality translation.
Keywords: positions, Machine Translation, Neural MT, post-editing

1. Introduction

The translation market is fast expanding, and many agencies tend to expect that translations are of excellent quality and low cost and that thousands of pages can be translated quickly into numerous languages. The translation market, like any other, is driven by the supply and demand of available workers. Translators' attitudes regarding the medium have shifted due to the rise of artificial intelligence in translation. Translation services have seen a decline in demand as the use of machines as a medium has grown. This raises concerns for professional translators. Some translation experts like Marr (2018) express concern about AI's threat (machine translation) to human translators. There may soon be no need for half a million human translators and 21,000 translation businesses, since machine translation quality has grown by leaps and bounds in the last few years. Other experts disagree with the anti-AI arguments, claiming that AI has beneficial effects and can be used to help human translators by enhancing machine translation accuracy and efficiency. It is claimed that AI provides faster transmissions than manual translations. This article, therefore, attempts to examine the divergent views of the opponents and proponents of the AI threat idea.

Furthermore, the article will discuss the rapid development of artificial intelligence, and the advancement of automation in all areas of life is seen by many experts as the downside of human achievement, by others as progress. It was this issue that sparked this study's focus. Moreover, artificial intelligence, or machine translation, is making significant development and is expected to be capable of performing some translations without human assistance. As a result, it is expected that tens of thousands of human translators will be laid off. The article is arranged in this way; the first section reviews the general literature on automation developments and their potential impact on translation. It then analyzes and discusses the research findings through a survey conducted by experts and translators. There is a conclusion on a few essential things to consider when discussing translation's future.

2. Literature Review

In 1955, John McCarthy coined the term "artificial intelligence" which refers to the science and technology involved in the development of intelligent devices and software capable of using and analyzing data, algorithms, and programming to perform actions, anticipate problems, and adapt to a variety of circumstances with or without supervision. . According to Coppin (2004:4), computing is the study of systems that behave in ways that appear intelligent to any observer, and It comprises solving complicated issues via the use of strategies that promote logical conduct in humans and other animals. According to Jackovich and Richards (2018:2), it is any machine intelligence, any device that recognizes its environment and takes steps to increase its chances of success.

Artificial Intelligence is typically classified into neural networks, machine learning, and deep learning. Artificial neural are networks that simulate and process nonlinear interactions between inputs and outputs in parallel Settings, much like biological neural networks. Machine learning improves machine functions by using statistics and data, and it computes neural networks in several more advanced knowledge layers. Artificial Intelligence is frequently classified as advanced or general, robust or weak based on its implementation. When we consider the difference between strong and weak AI, this distinction becomes more evident. A machine translation is an example of robust Artificial Intelligence. Proponents of strong AI argue that by providing a computer program with enough processing power and Intelligence, a computer can think and process information in the same way that humans do. On the other hand, weak AI believes that intelligent behavior can be modeled and used by computers to solve complex problems. This viewpoint demonstrates that just because a computer behaves intelligently does not imply that it is as intelligent as humans.

The concept of "intelligent devices" can be traced back to ancient Greek times when myths were about engines and robots' built-in engineers, Chinese and Egyptian myths. Modern artificial intelligence was traced back to traditional philosophers describing human thinking as a symbolic system. A group of scientists in various areas discussed the possibility of developing artificial intelligence (artificial brain) during the 1940s and 1950s.

In 1956, the area of AI discipline was established in New Hampshire. However, it was first created by John McCarthy, the father of Artificial intelligence. McCarthy categorized it into seven original aspects with other academic concepts in 1955: language AI programming, automatic computers, measuring problem complexity, hypothetical neuron networks used to develop concepts, creativity, allegiance, abstraction, and self-improvement.

Researchers found it extremely difficult to produce machines for several decades despite a well-funded global effort intelligently, in the 1970s and 1990s, scientists faced an acute lack of Artificial intelligence Research funding. These years have come to be called the 'AI Winters.' However, by the end of the 1990s, American corporations were again inquisitive about AI. Besides, the Japanese government proposed developing a computer to improve artificial intelligence in the fifth generation. Garry Kasparov, the world chess champion, was defeated by the first computer, IBM Deep Blue victory, in 1997.

Besides, as computer hardware improvements for government programs and enterprises began to develop artificial intelligence and its technology successfully, its processes began to be employed across several other areas. Thanks to their AI technology, companies like Amazon, Google, Baidu, and many others have achieved enormous commercial advantages over the past 15 years. Therefore, many online services are involved in artificial intelligence in today's world, and AI has impacted every part of life and is a crucial stock market element. . The machine-based translation system is one of these fields.

Poibeau (2017:6) defines translation as a complex process involving advanced linguistic and cognitive abilities. Therefore, when working with the two languages involved, a translator must be diligent and have a specific ability to reformulate SL with the exact phrases or structures in TL. Computers do not have direct access to such kinds of competencies, and artificial systems are still in their early years and, as far as reasoning, inferring, and reformulating are concerned, are far away from a human being's ability. To reformulate a sentence, a translator must have a strong command of the Language itself, but one must also master the quest for an analogy between terms, which is far more complicated than the equivalence between words and phrases.

Machine Translation, a sub-field of Artificial intelligence, is a computer program designed to translate an item from one Language (SL) to another language (TL) without human intervention. Such programs are to manage and solve problems creatively rather than respond to commands and identify problems. In other words, it performs functions similar to those of a human brain. Sober (2013:54) often describes it as a computer application or program designed to convert text from SL to TL without human assistance. Ronald Schmelzer (2020) defines machine translation as using Artificial intelligence to translate from one human language to another. Therefore, machine translation in AI aims to ensure that translations from SL and TL are carried out smoothly, automatically, and precisely from verbal to other languages. Machine translation is an automatic translation/computer translation of written text and speech form from one language to another and Natural Language Processing (NLP). This field combines the elements of IT and linguistics, Kozłowski (2002:64).

Sheila Castilho (2018:9) has classified machine translation based on its type and quality. Translation, she claims, is a complex cognitive, linguistic, social, cultural, and technological process. This complexity was reflected in the translation process and the evaluation of the quality of its outputs, making operationalization and measurement of quality difficult. As a result, translation quality definitions attempt to capture these dimensions and their relationships to develop a method for determining translation quality for a given purpose. The growing amount of data available online necessitates machine translation, Ayah ElMaghraby (2018). As a result, machine translation and artificial intelligence are still behind.

Machine translation is a relatively old task that has been used to achieve automation since the 1970s. Over the previous decades, several prominent MT approaches emerged, including Rule-based Machine Translation (RBMT) from the 1970s-1990s, Statistical Machine Translation (SMT): 1990s-2010s, and Neural Machine Translation (NMT) in 2014.

The first approach to machine translation was rule-based, which is distinguished by the use of linguistic rules in translation and its systems, which typically consist of a series of processes analyzed in a text: morphological, syntactic, and semantic analysis; the process of generating a text as a result of a series of structural conventions based on an internal structure or some intralingual, Bhattacharyya (2015:139).

A dictionary and grammar control these processes, often checked by a linguist or a bunch of linguists and infrequently entails a slow, time-consuming development process, mainly hindered by what has come to be called a "knowledge" acquisition bottleneck because the team of developers first has to fully understand the difficulty before it is going to be described in terms of rules exceptions. However, several complex problems do not seem to be sufficiently well understood or depend upon.

The basic idea in EBMP is straightforward: in translating a sentence using previous translation examples or similar sentences, the assumption is that many translation symbols modify previous translations. Consistent with this view of translation, it is reasonable to mention that an honest translator could be a lazy translator, which means that the assembly often should employ the utmost amount of fabric the previous translation as possible. Translation saves time and it promotes consistency in terminology and magnificence, Trujillo (1999:203).

The first MT system was developed globally in the 1950s; it depends on grammatical structure, lexicon, and software to process these structures. Translation occurs by pattern matching rules. The critical attribute of this method is that it permits the avoidance of matching unfruitful rules. The strong trait of rule-based translation is its capability to research language at semantic and syntactic levels. One of its disadvantages is the sizable number of rules that govern each language, which can contradict each other and, therefore, the "mechanic" sound of it sometimes.

As one of the machine learning problems, statistical machine translation (SMT) deals with translating natural language. SMT algorithms are able to translate by inspecting many samples of human translation. SMT has made tremendous progress in just a few decades, andmany new procedures have been developed in the last few years. Adam Lop's (2007) system applies a learning algorithm to a large body of previously translated text, and then uses this algorithm to translate texts that have never been translated before. Experts in the field believe that (SMT) is appropriate for documents that focus on a single topic, and one of its benefits is the abundance of existing new algorithms and platforms. This type of translation training is performed on CPU servers and is simple to implement. The decoding process is quick and similar to "a massive translation memory" in which sentences, phrases, expressions, and collocations are grouped. Most systems of this type were statistical until 2016 when Google published a paper on the subject (NMT). One disadvantage is that it is designed to work in a specific context and is inappropriate for colloquial Language or idioms; it works better with close languages, but it does not perform well in syntactic re-ordering.

Hybrid MT refers to the mix of MT methods. This method employs several AI programs within one system. There are numerous sorts of hybrid AI. Combining a statistical approach and a rules-based approach is one of the most effective hybrid samples of MT. The Hybrid computational linguistics approach differs from the purely rules-based and statistical-based approaches in flexibility, precision, and control. Both, however, necessitate a pre-and post-processing stage.

Deep learning is a modern term beyond the neuroscientific perspective on the existing breed of machine learning models (Goodfellow et al. (, 2016: 13). It demands a further general principle of learning multiple levels of composition, which can be utilized in machine learning models that are not necessarily neutrally inspired."

In the case of MT, deep learning makes it possible to envisage systems where very elements are specified manually, and it lets the system infer by itself the best representation of the data. A translation system is merely based on deep learning (neural MT or DLMT). Thus, DL is made up of an "encoder" and a "decoder," with the encoder referring to the system's data analysis component. The "decoder" is the part of the Machine that uses the encoder's data analysis to convert a given sentence into another language automatically.

Neural Machine Translation is the most up-to-date approach in industry and the one most closely related to AI. Thanks to its target fluency, it reduces post-editing effort. In many ways, it is called an "ultra-statistical" approach, with several layers processing knowledge and nodes passing information and ensuring accuracy. It had been given the name neural because the way layers and nodes work is comparable to how neurons add humans.

Neural Machine Translation is defined by Forcada (2017:5) as a "new breed of corpus-based machine translation" as it requires enormous corpora of SL and TL sentences to be trained. The innovation lies in the computational approach which has been introduced, namely, neural networks.

Neural MT has three exciting characteristics. A variety of its features assist it in understanding word similarities, analyzing entire sentences, and assessing the fluency of a sentence within the target language by analyzing some words at a time. NMT is simply one of many exciting methods for eliciting more natural, fluent-sounding translations within the target language. However, academia remains trying to determine what happens inside the "black box" once the neural network begins to coach.

Translation is a human activity that undergoes the constant pressure of automation, and this automation could lead to the dominance of machine translation conducting the work of humans. Advances in artificial intelligence predominated human translators' stance and raised fears of laying off many translators' positions and affecting the translation industry and labor market. AI is the science making machine does the thing that would require Intelligence if done by humans Ricardo: | (2013). Artificial Intelligence is expected to witness more advancement in healthcare, manufacturing, geopolitical implications and efficiency of neural networks, automated AI development, machine translation, and more.

AI is split into deep learning, machine learning, and neural networks. A neural network may be a biological network that models and processes the link between inputs and outputs. Machine learning employs data and statistics from machine functions, whereas deep learning employs multi-layer neural networks for more advanced learning.

Machine translation is not intended to replace human translators but rather to boost the precision and speed of human translation. It also created a marketplace for fast translation, which a human translator cannot do due to the massive amount of data. EDiscovery is another feature for MT that reduces the number of time editors spend on correction, proofreading, and post-editing, due to sophisticated algorithms and methods of thoroughly analyzing words, phrases, and sentences. Many experts believe that when the neural output quality is accurate, the role of the post-editor will evolve into that of a "reviewer."

Translation of neural machines will probably boost over time as neural spec improves, quality data is vetted, and computing power increases. The transition in neural AI technology would necessitate human translators adapting to the advantages of the technology while specializing in the great of humans. Because neural AI can produce accurate first drafts in seconds, humans may spend longer posting or reviewing translated computer texts. This year, both Google and Facebook announced that they were abandoning the statistical artificial intelligence paradigm in favor of a brand new model supported by neural networks. Statistical models mine bilingual text corpora for corresponding elements. Still, this data often comprises formal documents composed in a standardized language that does not have much in common with everyday speech.

Google and Facebook have recently announced a shift away from the computational AI paradigm and toward a modern neural network-based model. Statistical models mine bilingual text corpora for corresponding components, but the content is often structured documents written in a very standardized language that has nothing in common with everyday discourse.

In short, the goal is to use AI and more informal data like social media posts to accurately interact between the Language's figures of speech, idiomatic phrases, regionalisms, slang, and other spoken components. While the impact of this enormous breakthrough in MT development is yet to be determined, one thing is definite – machines are logical and process language logically, whereas people are irrational, emotional, and imperfect and process Language accordingly. All of these uniquely human characteristics and limitations are essential components of both verbal and nonverbal communication. An MT paradigm that will replace human translators must be capable of operating at both logical and illogical levels simultaneously. We cannot predict what will happen in The Millennia to come, but it does not seem likely right now.

Machine translation is a type of translation used to describe the process of translating performed by a computer software program as an alternative to translation performed by a human's translation. MT belongs to AI, and the latter is a branch of computer science that deals with using computers to simulate human thinking. Its purpose is to make programs that will solve problems creatively instead of merely responding to commands. In other words, they operate a bit like the human brain. However, Davenport and Kirby (2015: 60) argue that many of the tasks carried out by professionals today will be automated soon, resulting in laying off many translators.

In the late 1950s, programmers in organizations such as the United States Air Force predicted that computers would soon accept human language input and translate it into English or the opposite Language. Many organizations and other entities spent millions of dollars over the next fifty years in the hope of enabling computers to exchange human translation. So far, the results have been pretty limited, for two main reasons: while computers appear to have an infinite capacity for processing data, they are far from having the ability to think creatively like citizens, and human Language is not simply a collection of signs and symbols that can be easily programmed, manipulated, and translated.

Developers of artificial systems are responsive to these limitations. However, few academics have attempted to construct computational linguistics systems for literary writings; practically everyone argues that artificial intelligence is a challenging issue that remains unsolved, and that only commonplace texts (e.g., news articles, technical documents) should be handled. The aim isn't to switch translators who can only translate novels or poetry.

Even technical texts pose specific difficulties since they employ a very technical vocabulary that must be introduced into the system to obtain relevant translations. The purpose of machine translation is today primarily regarded to be that of giving the user some assistance and, in certain professional circumstances, allowing the user to select whether or not a human translator should be consulted. Thierry Poibeau (2017:6)

Translating a text using a machine depends on analyzing the text, whether semantically or syntactically. Unless the Machine can conduct this analysis, the translation is inaccurate and only a word-for-word replacement, which is little or no value. Moreover, high-quality automated translation requires a complete analysis of the ST as an in-depth analysis of human translation, John Lehrberger (1988: 8).

The constant improvements in the computer field have tripled and qua-drupled the professional translator's output and made translating much easier. Computers will play an even more significant role in the translation field in years to come, translating more afford-able and widely used. (A word of caution: those who maintain that computers will soon replace human translators altogether are not familiar with all the facts. The consensus among the experts today is that computer technology will continue to enhance translation, but only as an aid to, rather than a replacement for, human translation, Morry Sofer (2013:4).

Translation systems for machines are developed, but the most detailed results are currently insufficient for many applications. Together with an individual’s translator, they'll be used a technique. The Machine system can provide a rough translation, so the human can check up the results, ensuring the correctness of the ambiguities and the natural and grammatical correctness of the text. Ben Coppin (2004:592) artificial Intelligence doesn't replace human translation. At best, the previous can do around 60 percent accuracy when the goal is as near 100% as possible. Consequently, the expectations regarding MT are modified, and it's now recognized that to attain complete accuracy, such translations must be post-edited by an individual's translator, Morry Sofer (2013: 54).

Machine translation has made numerous advances in recent years as a result of advancements in technology. As an example, translation deficiency is significantly improved. However, MT ads are not still translated as those by a knowledgeable human translator. As a result, the person tendency in AI could be a collaboration between artificial Intelligence and human translation. Human translation is now guilty of post-editing work, Jia-Wei Chang, Jason C. Hung, Neil Y. Yen (2019:717).

However, Marcos Dinnerstein (2019) says Google warns that Machine Translation is not ready to replace human translators in reviewing refugee status applications. Machine translation, abbreviated as MT, means to use the software in translating text or a speech from one natural language source language to another target language on this subfield of computational linguistics. Machine translation is also named automatic translation, but it cannot be confused with this computer-aided translation, machine-aided human translation, interactive translation, Jason C. Hung, Neil Y. Yen, Jia-Wei Chang (2019:712). Without a doubt, 2018 is already proving to be an exciting time in the age of artificial intelligence. Human translators are still in vogue. However, another scholar like Ross (2016:160), who discussed translators' professionalism, believes that professional translators will work on translation software in the next ten years. A remark made by Timothy Hunt is worth noting: 'Computers will never replace translators, but computer-assisted translators will.'(Sofer 2009: 88, cited in Chan Sin-Wai 2015:15).

Post-editing (PE) "is the correction by a human translator of the raw computer-translated output according to clear guidelines and consistency requirements "O'Brien (, 2011: 197–198). Allen (2003: 297) describes Post-Editing as "the process of editing, adjusting and correcting pre-translated text from an SL into SL processed by an MT method," and the post-edited text should the expected quality levels of the end-user. Post-Editing is the new Human Input. Pym and Simon (2016:8) express fear of technology, which is expected to overcome human translators. That fear runs the gamut from seeing humans marginalized as "glorified copy editors" to having computers completely replace human translators.

Over the last decade, several studies from different post-editing viewpoints have been explored the variations between post-editing and from-scratch translation. Processing speed is one of the foremost frequently investigated factors in these comparisons, and this is often also a problem of primary concern for the industry. Domain-specific texts will be published more frequently than scratch-related texts Masselot 2010). Nevertheless, post-editing is not always faster in general linguistic texts. Daem et al. (2017) found that post-edited texts of stories were considerably faster, while the speed of post-editing text texts (e.g., Carl et al.' 2011) and available information text other studies have reported no significant increase (e.g., Screen 2017).

Temporal aspects are essential, but they do not offer information on how a process is edited, what distinguishes it from traditional translation, what it demands of post-editors and how acceptable it is" (Krings 2001: 61). Therefore, Krings (2001) argues that post-editing feasibility compared to human translating should not be determined by time interval alone. O'Brien (2011:198) further argues that post-editing productivity means "not just the quantity and quality ratio with time, but also the cognitive effort spent.

PE has been a feature of the translation industry for decades now. The developments of usable MT systems and PE have always gone together. A professional translator's task is to comprehend and evaluate a text by a given author in making modifications to this text following the assignment or mandate given by the client. Such modifications may target aspects of information, organization, or form to improve the text's quality and enhance just communicational effectiveness (Bisaillon 2007: 296 cited in De Sutter, Lefer and Delaere 2014:116).

According to Brian Mossop (2019), content editing is checking the text for its ideas. At the macro level, includes changes in the topic's coverage at the micro-level, including the correction of factual call logical and mathematical errors. Copyediting is the process of ensuring that a document adheres to a set of predetermined criteria, such as the publisher's house style, usage guidelines, and the language's grammar, punctuation, and spelling conventions. Checking a text's physical structure in order to assist readers to unsersatnd its conceptual structure is called structural editing. Style editing is the process of enhancing a piece of writing in order to make it easier to read and more relevant to the intended audience.

3. Methodology

3.1. Research Objectives

The present research aims to achieve the following objectives:

1) To investigate the possibility of replacing the human translator with a

machine.
2) To give a theoretical overview of the nature of artificial intelligence and machine translation.
3) To show the views of experts on this controversy about the human translator's role in the proliferation of artificial intelligence.

Questions of the study

1) To what extent are the claims of replacement true?
2) Is it possible to use artificial intelligence for all translation domains?

3) Why is artificial intelligence seen as a replacement rather than a development?
The study's objectives were achieved quantitatively. The researcher designed a 15-item survey to gather data on the MT threat to HT positions. This survey has 15 items. This scale rated each claim. An example of a typical scale is strong agree/agree/not sure/strongly disagree. Participants in this study worked in translation studies, particularly MT translations, computational linguistics, and AI. They were both male and female with MA or Ph.D. degrees in translation studies and worked at several Saudi universities. A random sample of 50 respondents was chosen to represent the study's target group, including translation students, teachers, and novice and expert translators. Piloting was done online due to the Covid-19 pandemic. However, the received responses were 31. The responses were analyzed online and utilizing the Google program.
The study's participants were chosen based on the quality of their translations and the potential for future growth they represent. When the researchers contacted the survey participants to ask if they would be interested in participating, only 31 responded that they would be willing to do so, even though 80.65% of participants were males and just 11% were girls when the survey was sent out (19.35 %)..

4. Results and discussions

Only 31 responses were received from the translators who took part in the survey piloted with 55 machine translation professionals. Although most respondents were male (80%) and female (19.35%), the survey found no gender differences in the responses. This means that no gender differences in the data were found. Degrees of participation in the survey were recorded. They were divided into MA and Ph.D. holders. There were participants with a master's degree in MT translation (41.94 %) and participants with a doctoral degree in translation (41.94 %), respectively (58.06 %). Differences in degree are not statistically significant, however. All of the participants' experiences were taken into consideration. They were categorized into two groups: one year and another for more than a year. Participants with less than a year of MT translating experience made up only 3.33 percent of the group (96.67 %). The differences in experience between individuals do not affect the results.
The significance of the automation of translation has been served and shown in the following table1.

Table 1. The automation of translation is significant in the digital world of today.

Scale	Percentage (%)	Responses

SD			3.23%	1
D			16.13%	5
N			16.13%	5
A			41.94%	13
SA			22.58%	7
Analysis	Mean	3.65		
	SD	1.09		

It has been observed from the table1 that when the respondents have surveyed, the automation of translation is significant in the digital world, and (41.94%) of respondents agreed with the statement, and 22.58% strongly agreed with the statement. In comparison, only 16.13% of participants were neutral with the statement. The mean score and SD are 3.65 and 1.09, respectively. Thus, an average of 66.25 % of respondents agreed with that, and this indicates that automation is indispensable in the translation industry.

Table 2. Artificial intelligence facilitates human translation.

Scale			**Percentage (%)**	**Responses**
SD			3.23%	1
D			6.45%	2
N			35.48%	11
A			25.81%	8
S A			29.03%	9
Analysis	Mean	3.71		
	SD	1.11		

In accordance with Table 2, when respondents were asked whether artificial intelligence makes human translation easier, 25.81 percent of those who answered the poll said they agreed. and 29.03% strongly agreed with this statement. In contrast, 35.48% of participants were neutral with the statement. The mean score and SD are 3.71 and 1.05, respectively. Thus, the average 67.75 % of respondents ultimately agreed with the statement.

Table 3. Artificial intelligence is expected to translate without human translators' intervention

Scale			**Percentage (%)**	**Responses**
SD			35.48%	1
D			41.94%	2
N			9.68%	11
A			6.45%	8
S A			6.45%	9
Analysis	Mean	2.06		
	SD	1.29		

It can be seen in Table 3 that when respondents were asked whether they believed that Artificial intelligence will be able to interpret without the need for human translators, 6.45 percent of respondents agreed. , and 6.45% strongly agreed as well with this statement. In contrast, 41.94% of participants disagree with the statement and 35.48% strongly disagree with the statement. The mean score and SD are 2.06 and 1.29, respectively. Thus, the average 67.75 % of respondents ultimately agreed with the statement.

Table 4. AI is expected to develop the aspects of human emotion and culture in translation.

Scale			Percentage (%)	Responses
SD			16.13%	5
D			22.58%	7
N			25.81%	8
A			29.03%	9
S A			6.45%	2
Analysis	Mean	2.87		
	SD	1.4		

According to table 4, AI is supposed to establish human emotion and culture in translation, and 29.03 percent of respondents strongly agreed with the statement, with 6.45 percent. At the same time, 25.81% of participants were neutral with the statement. The mean score and SD are 2.87and 1.18, respectively. Thus, the average 46.75 % of respondents ultimately agreed with that. This indicates that nearly half of the respondents agree with the statement.

Table 5. Artificial intelligence applications are expected to produce an accurate translation in the near future.

Scale			Percentage (%)	Responses
SD			6.67%	2
D			36.67%	11
N			26.67%	8
A			23.33%	7
S A			6.67%	2
Analysis	Mean	2.87		
	SD	1.12		

According to the results of Table 5, when respondents were asked whether they agreed or disagreed with the assertion that artificial intelligence applications are projected to generate reliable translations in the near future, 23.33 percent agreed and 6.67 percent strongly agreed with the statement. In contrast, 26.67% of participants were neutral with the statement. The mean score and SD are 2.87and 1.12, respectively. Thus, the average 46.75 % of respondents ultimately agreed with that. This indicates that nearly half of the respondents agree with the statement.

Table 6. Statistical-based and rule-based strategies are the paradigms of AI that enhance the competence of translation

Scale			Percentage (%)	Responses
SD			0.00%	0
D			9.68%	3
N			32.26%	10
A			45.16%	14
S A			12.90%	4
Analysis	Mean	3.61		
	SD	0.69		

According to the results of the poll, 45.16 percent of respondents believed that statistical-based and rule-based tactics are the paradigms of artificial intelligence that improve the competence of translation. and 12.90% strongly agreed with this statement. At the same time, 32.26% of participants were neutral with the statement. The mean score and SD are 3.61 and 0.83, respectively. Thus, the average 65.25 % of respondents ultimately agreed with that. This indicates that more than 50% of the respondents agree with the statement.

Table 7. Language processing through Artificial intelligence is faster than human natural language processing.

Scale			Percentage (%)	Responses
SD			6.45%	0
D			25.81%	3
N			12.90%	10
A			38.71%	14
S A			16.13%	4
Analysis	Mean	3.32		
	SD	1.44		

Table 7 shows that when the respondents were surveyed that Language processing through Artificial intelligence is faster than human natural language processing, 38.71% of respondents agreed, and 16.13% strongly agreed with this statement. In comparison, 12.90% of participants were neutral with the statement. The mean score and SD are 3.32 and 1.44, respectively. Thus, an average of 58 % of respondents agreed with that. This indicates that more than 50% of the respondents agree with the statement.

Table 8. MT systems use a language modeling system to overcome translation barriers.

Scale	Percentage (%)	Responses

SD			0.00%	0
D			12.90%	4
N			32.26%	10
A			45.16%	14
S A			9.68%	3
Analysis	Mean	3.52		
	SD	0.84		

It has been observed from the Table 8 that when the respondents were surveyed that MT systems use the language-modeling system to overcome translation barriers, 45.16% of respondents agreed, and 9.68% strongly agreed with this statement. In contrast, 32.26% of participants were neutral with the statement. The mean score and SD are 3.52 and 0.84, respectively. Thus, an average of 63 % of respondents ultimately agreed with the statement. This indicates that more than 50% of the respondents agree with the statement.

Table 9. Artificial Intelligence enables humans to produce accurate translation through translation memory applications.

Scale			Percentage (%)	Responses
SD			16.13%	5
D			22.58%	7
N			19.35%	6
A			35.48%	11
S A			9.68%	3
Analysis	Mean	3.1		
	SD	1.62		

Table 9 shows that this is the case when the respondents were surveyed that Artificial intelligence enables humans to produce accurate translation through translation memory applications (35.48%), respondents agreed, and 9.68% strongly agreed with this statement. At the same time, (19.35%) participants were neutral with the statement. The mean score and SD are 3.1 and 1.62, respectively. Thus, an average of 52 % of respondents ultimately agreed with that. This shows that more than 50% of the respondents are in agreement with the statement.

Table 10. MT is expected to replace human translation in ten years' time.

Scale			Percentage (%)	Responses
SD			22.58%	7
D			32.26%	10
N			32.26%	10
A			9.68%	3
S A			3.23%	1
Analysis	Mean	2.39		
	SD	1.08		

According to the data in Table 10, the respondents were surveyed that MT is expected to replace human translation in ten years. (9.68%) respondents were agreed, and 3.23% were strongly agreed with this statement. In comparison, (32.26%) participants were neutral with the statement. The mean score and SD are 2.39 and 1.08, respectively. Thus, an average of 35 % of respondents ultimately agreed with that. This indicates that more than less than half of the respondents agree with the statement. This assures that there is a growing concern that MT may replace human translation in ten years.

Table 11. Artificial intelligence is a threat to thousands of human translators' jobs.

Scale			Percentage (%)	Responses
SD			22.58%	7
D			12.90%	4
N			12.90%	4
A			35.48%	11
S A			16.13%	5
Analysis	Mean	3.1		
	SD	2.02		

It has been observed from table 11 that when the respondents were surveyed that Artificial intelligence is a threat to thousands of human translators' jobs (35.48%), respondents agreed, and 16.13% strongly agreed with this statement. In comparison, (12.90%)of the participant were neutral to the statement. The mean score and SD are (3.1) and (1.02), respectively. Thus, an average of 52.42 respondents ultimately agreed with that. This shows that more than 50% of the respondents agree with the statement. This assures half of the respondents support that artificial intelligence is a threat to thousands of human translators' jobs.

5. Conclusion

This article aimed to look into the potential threat that machine translation (MT) poses to human translators. It is mentioned that there are two significant findings. As a starting point, it appears that human translators and specialists cannot agree on the claims, and threats despite technological advances. Even though machine translation has improved steadily, the Arabic system is too complex to be quickly and thoroughly impacted by artificial intelligence. Although these findings are based on a wide range of viewpoints, I argue that the threats are unjustified because human Language is not fully comprehended, processed, and represented by Machines. The article discussed the perspectives of experts who frequently work in translation environments. Most experts confirmed that the translation market's supply and demand are not as they were in previous years, so they expressed their reservations about the replacement claims.

Additionally, the role of translators in dealing with artificial translation and machine translation as a beneficial and effective tool for facilitating the translation process was revealed. Machine translation and artificial translation can positively impact the translation process if used correctly by translators. Although machine translation (MT) can produce translations as accurately as human translators, it can still not grasp cultural and linguistic nuances. Generally, the study's findings lead to some recommendations. Because translation technology is so crucial in today's digital world, translators must be experts at integrating it into their work to maximize its efficiency and effectiveness. As AI assists human translation, translators must educate themselves on which Machine and process will yield the best results in terms of time and cost. Because MT systems use language modeling to overcome translation barriers, translators should carefully evaluate their LRs and language requirements before deciding on the best MT systems. As a result, a study into machine translation by translators has been proposed.

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