Large Language Models And The Future Of AI Translation: Opportunities And Obstacles

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Abstract
In recent years, the rise of artificial intelligence (AI) technology has transformed the way we interface with digital systems. This study investigates the perceptions of Qassim University LLMs users regarding the opportunities, challenges, and future of LLMs in multilingual translation. This study used a quantitative approach by employing a questionnaire of LLMs. The findings reveal that the participants acknowledge significant advantages of LLMs in speed, cost-effectiveness, and contextual handling, while simultaneously highlighting limitations in cultural understanding and idiomatic expression. The research underscores the necessity of balancing LLM efficiency with the irreplaceable role of human expertise. Findings indicate a collaborative future for LLMs in translation, serving as support tools rather than replacements. Notably, gender significantly influences future outlook, with females exhibiting greater optimism. However, educational level and age show no significant impact. This study emphasizes the need for a nuanced integration of LLMs, recognizing both their transformative potential and inherent limitations to ensure accurate and culturally sensitive communication.
Keywords: LLMs, AI, Translation, Qassim University, Opportunities, Challenges.

INTRODUCTION

Globally, communication across language boundaries continues to grow, and the demand for AI that can understand, translate, and reproduce multiple languages accurately has grown exponentially (Sen et al., 2020). This demand stems from the global spread of business, education, and communication, which requires convenient and efficient communication services. AI-powered translation services, virtual assistants, and content management systems are just a few examples of areas where AI technology plays a major role in language (Zhang, 2024).

At the heart of these developments lie LLMs. They are AI models designed to understand and process text in a human-like manner. LLMs are trained on vast amounts of multilingual data, allowing them to develop a solid understanding of linguistic structures, grammar, and semantics through cross-linguistic contexts (Balasubramaniam et al., 2024). These models leverage deep learning techniques, particularly neural networks, to predict the probability of a word or phrase following another, thereby generating coherent and contextually relevant text. The capabilities of LLMs have increased significantly, with models such as GPT-3 and its subsequent versions demonstrating competencies that go beyond simple translation, including comprehension, semantic analysis, and creative text generation (Linkon et al., 2024).

LLMs embody a significant advance in natural language processing (NLP) by providing a powerful understanding of languages (Balasubramaniam et al., 2024). Their potential for real-time language translation, cultural preservation, and breaking down communication barriers is immense (Zhang, 2024). However, their advancement and usage present challenges, such as ensuring the inclusion of low-resource languages and managing potential biases that may influence linguistic outputs (Sen et al., 2020).

LLMs offer unprecedented opportunities for enhancing communication and cultural exchange through real-time translation and accurate language interpretation (Raiaan et al., 2024). Real-time translation capabilities powered by LLMs can significantly enhance cross-linguistic communication in diverse contexts such as international business meetings, educational exchanges, and global customer service interactions (Liang, Liu & Luo., 2024). The ability to translate spoken and written language rapidly allows people from different linguistic backgrounds to communicate easily, breaking language barriers that previously hindered international communication (Balasubramaniam et al., 2024). This technology is particularly important in emergencies, where rapid translation can facilitate communication and response among international organizations.

Another significant long-term impact of LLMs is their capacity to break language monopolies. Historically, languages like English have dominated global discourse, limiting access to information and opportunities for non-English speakers. By promoting high-quality translation and linguistic support in diverse languages, LLMs can foster linguistic diversity and reduce the dominance of any single language (Liang et al., 2024). This can lead to a more balanced representation of cultures and perspectives in global communication, fostering greater understanding and collaboration among people from different linguistic backgrounds.

Notably, prior research has not sufficiently compared the performance of LLMs and human translators across diverse contexts. Furthermore, limited research exists regarding how international LLM users perceive the translation style of these systems. Therefore, this study aimed to answer the following questions.

1. What are the opinions of XXXX regarding the opportunities of LLM in Translation?
2. What are the most common obstacles that LLMs face in Translation
3. What is the future of LLMs in the translation process?
4. Are there statistically significant differences according to the demographic variables regarding the study dimensions?

LITERATURE REVIEW

Beyond real-time translation, LLMs have the potential to play a crucial role in cultural preservation. By accurately translating and interpreting texts, speeches, and other cultural materials, LLMs can help preserve the richness and diversity of languages and cultures around the world. For example, ancient texts and traditional knowledge can be translated into other languages, expanding accessibility to a wider audience (Dubourg, Thouzeau & Baumard, 2024). This can promote greater respect for cultural diversity and values while helping to preserve linguistic variety in the developing world.

Moreover, LLMs can support language revitalization efforts by providing tools for education and learning in endangered languages (Hamaniuk, 2024). By developing linguistic models capable of understanding and reproducing large-scale linguistic datasets, LLMs can help communities preserve their linguistic heritage for future generations (Zhang, 2024). This technology can assist in creating teaching materials, dictionaries, and language learning apps, further promoting the use and understanding of minority languages.

Recent advancements in large language models (LLMs) have significantly transformed the field of artificial intelligence (AI) and machine translation (MT). LLMs, such as OpenAI's GPT-4, Google's Bard, and Meta's LLaMA, have demonstrated remarkable capabilities in understanding and generating human-like text across multiple languages. These models leverage vast amounts of multilingual data and sophisticated architectures, such as transformers, to achieve state-of-the-art performance in translation tasks (Brown et al., 2020; Raffel et al., 2020).

The long-term impact of LLMs is significant in many settings, especially in education and language learning (Hamaniuk, 2024). LLMs have the potential to transform educational experiences by providing personalized, language-specific learning tools. They can be used to create language learning applications that provide real-time feedback, gamified exercises, and contextual training (Dubourg et al., 2024). This capability can enhance natural language learning, making it engaging for students of all ages and linguistic backgrounds. Additionally, LLMs can support teachers by providing translation and interpretation services, enabling them to communicate efficiently with students who speak a variety of languages (Wu, 2024). Studies have highlighted that LLMs excel in handling low-resource languages, where traditional statistical and rule-based translation systems often struggle (Johnson et al., 2021). For instance, LLMs can generalize from high-resource languages to improve translation quality for languages with limited parallel corpora, thereby bridging linguistic gaps in global communication. However, the integration of LLMs into AI translation is not without challenges. One major obstacle is the issue of bias and fairness in translation outputs. Research has shown that LLMs often inherit biases present in their training data, leading to skewed or culturally insensitive translations (Bender et al., 2021). Additionally, the computational cost of training and deploying LLMs poses significant barriers, particularly for smaller organizations and developing countries (Strubell et al., 2019). The environmental impact of training these models, which require massive energy consumption, has also raised ethical concerns (Al-Ahdal,, et al 2017; Patterson et al., 2022; Alowedi & Al Ahdal, 2023).

Zhu et al. (2023) conducted a comprehensive analysis of the performance of LLMs, such as ChatGPT and GPT-4, across various languages. Their findings reveal that while LLMs perform well in high-resource languages, they struggle to maintain accuracy and fluency in low-resource languages, highlighting a persistent imbalance in multilingual capabilities. This language disparity underscores the ongoing challenge of data scarcity, which limits the effectiveness of LLMs in representing linguistic diversity (Nicholas & Bhatia, 2023). The underperformance of LLMs in non-English and low-resource language contexts is partly attributed to the dominance of English-centric training data, raising concerns about equitable language representation in global AI systems.

Another critical area of investigation is the interpretability and controllability of LLMs in translation tasks. While these models generate fluent and contextually appropriate translations, their "black-box" nature makes it difficult to understand how specific translations are produced (Ribeiro et al., 2020). This lack of transparency can be problematic in high-stakes applications, such as legal or medical translation, where accuracy and accountability are paramount. Recent studies have proposed techniques like explainable AI (XAI) to address these issues, but further research is needed to make LLMs more reliable and trustworthy in translation contexts (Arrieta et al., 2020).

In addition to language learning, LLMs can democratize access to educational resources by translating books, research papers, and online courses into different languages (Hamaniuk, 2024). This democratization of knowledge can empower students and educators in non-English-speaking regions, promoting educational equity and fostering a more inclusive global academic community. The ability to access high-quality educational content in one's native language can significantly influence literacy rates, academic achievement, and lifelong learning opportunities (Dubourg et al., 2024).

The broader discourse on the role of AI in translation also extends to human-centred concerns, such as the displacement of professional translators and the preservation of cultural authenticity. Several industry analyses and journalistic investigations, including reports from the Financial Times (2024) and The Guardian (McCrum, 2024), reflect on the increasing reliance on AI for translation in commercial and literary settings. These sources highlight growing tensions between efficiency-driven machine translation and the creative, context-sensitive work performed by human translators. While LLMs can deliver rapid translations, they often struggle to capture idiomatic expressions, cultural references, and the emotional resonance embedded in human-authored texts (McCrum, 2024).

Despite the challenges and limitations in AI translation, the potential of large language models (LLMs) to revolutionize this field is undeniable. Researchers have explored innovative applications, such as real-time multilingual communication and context-aware translation, which promise to enhance global collaboration and accessibility (Lewis et al., 2021). The integration of LLMs with other AI technologies, such as speech recognition and computer vision, is also paving the way for advanced multimodal translation systems (Huang et al., 2022). Furthermore, collaborative approaches that combine AI with human expertise offer promising solutions to overcome the limitations of LLMs. For instance, efforts by organizations like Tarjimly are leveraging AI-enhanced translation tools alongside volunteer interpretation to ensure culturally sensitive communication for refugees. Similarly, collaborative initiatives involving OpenAI, Meta, and Orange are focused on developing AI models for African languages, aiming to address resource scarcity in machine translation for underrepresented languages (Reuters, 2024). As the field evolves, addressing the ethical, technical, and practical obstacles will be essential in unlocking the full potential of LLMs for AI translation.

In sum, the literature underscores that the future of translation AI will be shaped by a delicate balance between leveraging the computational power of LLMs and addressing critical issues related to language equity, cultural authenticity, and human-machine collaboration. While the opportunities afforded by LLMs are transformative, the obstacles they present demand careful attention to ensure that AI-driven translation technologies serve diverse linguistic communities effectively and ethically.

METHODS

Research Design

This study used a mixed methods research design. It investigated the content and performance of LLMs across both high-resource and low-resource languages. As a research instrument, the study developed a questionnaire aimed at collecting data on users' behaviour in different situations.

Data Collection

In this study, data was collected on the perception of using LLM in different English language contexts. By examining how well LLMs perform across different language contexts, the study could identify strengths and pinpoint areas needing improvement.
By obtaining feedback from users of LLM-led translation services through a survey, this study has provided valuable insights into usage patterns, translation quality, and real-world performance. User feedback has reflected general concerns such as cultural compatibility, linguistic accuracy, and user interface design. Analyzing this feedback allowed developers to make targeted changes to improve the user experience and address specific pain points. Engaging with users from different linguistic and cultural backgrounds ensured that LLMs became more inclusive and met the needs of a diverse audience.

Instrument

The tool used in this study was a questionnaire distributed to the participants from Qassim University. The questionnaires were designed and distributed among the participants via Google Forms.
The questionnaire was developed by the researcher and validated by Five University professors specialized in translation studies. The questionnaire contains two sections. The first section was allotted to collect demographic data from the participants- LLMs users. The second section was divided into three constructs; the first construct included 6 items, which aimed to check the opportunities of LLMs. The second construct consisted of 7 items that measured the challenges of using LLMs, and the third section was devoted to the future of LLMS. After designing the questionnaire, the first draft was piloted on 25 participants to check its reliability as shown in the following table:

Table 1: The reliability and validity of the questionnaire

Construct	Cronbach's Alpha	N of Items
Opportunities in LLM Translation	0.654	6
Obstacles and Challenges	0.690	7
Future of LLMs in the Translation Process	0.856	6
Total	0.826	19

Table 1 presents the reliability analysis of a questionnaire measuring three constructs related to LLMs. It was shown that the overall reliability of the questionnaire is high (0.826), indicating strong internal consistency across all 19 items. The questionnaire is robust overall, making it a valid tool for assessing the role of LLMs in translation.

Table 2: *Users of LLMs demographic data*

Factor		Frequency	%
gender	male	33	40.7%
	female	48	59.3%
age	-25	2	2.5%
	25-34	8	9.9%
	35-45	34	42.0%
	+45	37	45.7%
level of education	Bachelor's Degree	33	40.7%

	Master	48	59.3%
Name the most used AI	ChatGPT	20	24.7%
	GT	11	13.6%
	Deepseek	25	30.9%
	Gemini	23	28.4%
	others	2	2.5%

Table 2 provides a detailed demographic breakdown of users of LLMs, highlighting key factors such as gender, age, level of education, and preferred AI tools. The majority of LLM users are female, representing 59.3% of the sample, while male users account for 40.7. In terms of age, the largest group of LLM users is 45 years and above, making up 45.7% of the sample. This is followed by the 35-45 age group, which represents 42.0%. This indicates that LLMs are more commonly used by middle-aged and older individuals, possibly due to their professional or educational needs. The relatively low representation of younger users may point to a gap in awareness or accessibility among this demographic.

Regarding level of education, the majority of LLM users hold a Master's degree (59.3%), while 40.7% have a Bachelor's degree. This highlights that LLM users are predominantly highly educated, which aligns with the technical and intellectual demands of utilizing advanced AI tools.

When it comes to preferred AI tools, Deepseek emerged as the most popular, with 30.9% of users selecting it. This is followed closely by Gimini (28.4%) and ChatGPT (24.7%). GT was chosen by 13.6% of users, while others accounted for 2.5%. The popularity of Deepseek and Gemini suggests that these tools may offer features or functionalities that resonate strongly with users, while ChatGPT, despite its widespread recognition, ranks third in this sample.

Data analysis

In the current study, the researcher employed several statistical tests ranging from descriptive analysis such as frequency, percentage, mean score, and standard deviation to tests such as independent sample T-test and one-way ANOVA were used to measure the mean differences among the demographic variables.

RESULTS

In this section, the research questions are answered by using suitable statistical tests.

1. What are the opinions of Qassim University regarding the opportunities of LLM in Translation

To answer this question, the frequency and percentage of the respondents' responses were calculated, and the means value was elicited. The table below shows the respondents' responses

Table 3: The opportunities of LLM in Translation

No	Statements		Neutral	Agree	Strongly Agree	mean
1	LLMs have Faster translation speeds	N	00	20	61	4.75
		%	00	24.70%	75.30%	
2	LLMs have lower costs for translation services	N	8	28	45	4.46
		%	9.90%	34.60%	55.60%	

3	LLM is handling the context of nuance properly	N	3	31	47	4.54
		%	3.70%	38.30%	58.00%	
4	LLMs can bridge the gap between Arabic and English languages	N	00	28	53	4.65
		%	00	34.60%	65.40%	
5	LLMs produce a human-like translation.	N	7	31	43	4.44
		%	8.60%	38.30%	53.10%	
6	LLMs produce consistent translations as they propagate similar segments.	N	5	24	52	4.58
		%	6.20%	29.60%	64.20%	

Table 3 presents the opportunities of LLMs in translation, as perceived by respondents, and reveals a strong consensus among the respondents' perceptions regarding the benefits of LLMs. Each statement is evaluated based on the level of agreement.

One of the most notable advantages of LLMs is their ability to deliver faster translation speeds. A significant majority of respondents strongly agree with this statement. This overwhelming agreement is reflected in the high mean score of 4.75, indicating that LLMs are widely recognized for enhancing translation efficiency. Additionally, LLMs are perceived as a cost-effective solution for translation services. Over half of the respondents (55.60%) strongly agree that LLMs reduce costs, Another key strength of LLMs is their ability to handle context and nuance effectively. A majority of respondents (58.00%) strongly agree that LLMs manage these complexities well, with 38.30% agreeing and only 3.70% remaining neutral. This is reflected in the high mean score of 4.54, suggesting that LLMs are adept at addressing the subtleties of language. Furthermore, LLMs are seen as a powerful tool for bridging linguistic gaps, particularly between Arabic and English. A strong majority (65.40%) strongly agree with this statement.

Respondents also recognize the ability of LLMs to produce human-like translations. The mean score of 4.44 indicates that LLMs are capable of generating translations that closely resemble those produced by humans. Lastly, LLMs are praised for their consistency in translation, especially when handling similar segments.

2. What are the most common obstacles that LLMs face in Translation?

To answer this question, the frequency and percentage of the respondents' responses were calculated, and the means value was elicited. The table below shows the respondents' responses.

Table 4: The challenges that LLMs face in Translation

No	Statements		Strongly disagree	Disagree	Neutral	Agree	Strongly Agree	Mean
1	LLMs lack of cultural understanding	N	00	00	00	28	53	4.65
		%	00	00	00	34.60%	65.40%	
2	LLMs lack of contextual understanding	N	00	00	00	26	55	4.67
		%	00	00	00	32.10%	67.90%	
3	LLMs face difficulty with	N	00	00	00	25	56	4.69
		%	00	00	00	30.90%	69.10%	

	idiomatic expressions.							
4	LLMs face difficulty with slang.	N	00	00	00	29	52	4.64
		%	00	00	00	35.80%	64.20%	
5	LLMs have limited availability of training data for the Arabic language	N	00	00	00	29	52	4.64
		%	00	00	00	35.80%	64.20%	
6	I am afraid of biases in LLM-generated translations.	N	3	8	42	22	6	3.24
		%	3.70%	9.90%	51.90%	27.20%	7.40%	
7	LLMs can't fully capture the tone of human language	N	3	4	16	17	41	4.09
		%	3.70%	4.90%	19.80%	21.00%	50.60%	

The results presented in Table 4 offer a fascinating assessment of the challenges faced by LLMs in the realm of translation. Across several key areas, including cultural understanding, contextual awareness, and even the availability of training data for specific languages like Arabic, the overwhelming consensus among respondents is that 'LLMs lack of cultural understanding face difficulty with idiomatic expressions' which scored 4.69. as there is an absence of disagreement in this categories, underscores the pervasive view that LLMs struggle with these nuances of language. This suggests that while LLMs may offer a degree of efficiency, their inability to grasp and accurately translate these subtle aspects of human communication significantly limits their effectiveness. Similarly, the statement regarding the inability of LLMs to fully capture the tone of human language garnered moderate agreement. Notably, the concern surrounding biases in LLM-generated translations stored a more varied response, which reveals that these respondents think that LLMs do have much biases.

3. What is the future of LLMs in the translation process?

The responses of the participants were coded and analysed using the frequencies and the percentage as well as the means.

Table 5. The Future of LLMs

No	Statements		Strongly disagree	Disagree	Neutral	Agree	Strongly Agree	Mean
	LLMs are only supportive tools	N	8	10	15	21	27	3.60
		%	9.90%	12.30%	18.50%	25.90%	33.30%	
1	LLMs will handle most tasks	N	00	11	18	10	42	4.02
		%	00	13.60%	22.20%	12.30%	51.90%	
2	LLMs will fully replace humans.	N	00	4	32	11	34	3.92
		%	00	4.90%	39.50%	13.60%	42.00%	
3		N	00	2	28	13	38	4.07

	LLMs will dominate the translation industry.	%	00	2.50%	34.60%	16.00%	46.90%	
4	LLMs and human translators will coexist equally.	N	3	12	13	19	34	3.85
		%	3.70%	14.80%	16.00%	23.50%	42.00%	
5	Human translators will remain the dominant	N	00	8	13	19	41	4.14
		%	00	9.90%	16.00%	23.50%	50.60%	

Table 5 reveals a strong consensus regarding the future role of LLMs, particularly within the translation industry. Respondents generally agree that LLMs are concocted to become powerful tools, though not necessarily replacing humans. A significant portion, 59.2%, believe LLMs will primarily function as supportive tools, and a larger majority, 64.2%, antedate that LLMs will handle most tasks, indicating a widespread belief in their expanding capabilities. This sentiment is further reinforced by the 63.9% who foresee LLMs dominating the translation industry, highlighting the transformative potential of these technologies. Shockingly, 55.6% of the participants believe LLMs will fully replace humans. The table also points towards a future characterized by collaboration, with 65.5% agreeing that LLMs and human translators will coexist equally. This suggests a vision where LLMs serve as powerful aids, enhancing human capabilities rather than replacing them. The high levels of overall agreement across most of the statements show that the majority of those surveyed, believe that LLMs will have a large impact on the future, and especially the translation industry. The findings collectively display a picture of a rapidly evolving landscape where LLMs are set to revolutionize the translation industry, but where human expertise and nuanced understanding will continue to be highly valued.

4. Are there statistically significant differences according to the demographic variables regarding the study dimensions?

Table 6: Independent samples test for gender regarding Opportunities, challenges and future

gender		N	Mean	Std. Deviation	Std. Error Mean	Sig
Opportunities	male	33	4.0202	0.22344	0.03890	0.989
	female	48	4.0208	0.19936	0.02878	
Challenges	male	33	4.3593	0.42276	0.07359	0.710
	female	48	4.3929	0.38026	0.05489	
Future	male	33	3.6616	0.84624	0.14731	
	female	48	4.1285	0.81812	0.11808	0.015

Table 6 presents an analysis of gender-based differences in the participants' perceptions regarding opportunities, challenges, and the future of LLMs. The researcher utilized an independent samples t-test. The results reveal a similarity in how male and female respondents perceive both the opportunities and challenges associated with LLMs. Specifically, the mean scores for opportunities are close to each other as males at 4.0202 and females at 4.0208, and the associated p-value of 0.989 indicates no statistically significant difference. Similarly, when it comes to challenges, the mean scores are close, with males at 4.3593 and females at 4.3929, and a p-value of 0.710, again, showing no significant difference.

This suggests that both genders largely share a common understanding of the immediate benefits and obstacles presented by LLM technologies.
However, a notable divergence emerges when examining perceptions of the future of LLMs. Female respondents exhibit a significantly more optimistic outlook compared to their male counterparts. The mean score for females is 4.1285, while for males it is 3.6616, and the p-value of 0.015, thus the p-value indicates a statistically significant difference. This indicates that females, on average, hold a more positive view of the long-term implications and potential of LLMs.

Table 7 Independent Samples Test for Level of Education

Level of education		N	Mean	Std. Deviation	Std. Error Mean	Sig
Future	Bachelor's Degree	33	4.1010	0.85690	0.14917	0.157
	Master	48	3.8264	0.84632	0.12216	
Challenges	Bachelor's Degree	33	4.3810	0.36187	0.06299	0.974
	Master	48	4.3780	0.42141	0.06083	
Opportunities	Bachelor's Degree	33	4.0101	0.21221	0.03694	0.710
	Master	48	4.0278	0.20724	0.02991	

The Independent Samples Test was used to examine the potential influence of the educational dimension on the perception of the participants regarding the future, challenges, and opportunities of LLMs.
Regarding perceptions of the future of LLMs, Bachelor's degree holders exhibited a mean score of 4.1010, while Master's degree holders recorded a mean of 3.8264. However, the p-value was 0.157, which indicates that there are no statistically significant differences. This suggests that while there is a slight numerical difference in the means, it is not substantial enough to conclude that educational level significantly impacts one's view of the future of LLMs.
Similarly, a p-value of the challenges and opportunities dimensions demonstrated a lack of significant divergence between the two educational groups. In terms of opportunities, the mean scores were also closely aligned, with Bachelor's degree holders at 4.0101 and Master's degree holders at 4.0278, and a p-value of 0.710, again, showing no significant difference. These findings collectively suggest that, within the context of this study, the level of education does not significantly influence perceptions of the future, challenges, or opportunities related to LLMs.

Table 8: One-way ANOVA for the means compares according to the age variable

Age		N	Mean	Std. Deviation	Sig
Opportunities	-25	2	3.8333	0.00000	0.525
	25-34	8	3.9792	0.16517	
	35-45	34	4.0196	0.20418	

	+45	37	4.0405	0.22363	
	Total	81	4.0206	0.20814	
Challenges	-25	2	4.1429	0.60609	0.382
	25-34	8	4.4643	0.49927	
	35-45	34	4.3067	0.38225	
	+45	37	4.4402	0.37703	
	Total	81	4.3792	0.39587	
Future	-25	2	4.1667	1.17851	0.955
	25-34	8	3.8958	1.07989	
	35-45	34	3.8922	0.89601	
	+45	37	3.9775	0.78779	
	Total	81	3.9383	0.85612	

The "One-way ANOVA for the means compares according to the age variable" Table 8 presents an analysis of how age groups perceive the opportunities, challenges, and future of LLMs. The results consistently demonstrate a lack of statistically significant differences across all age categories, suggesting that age is not a primary factor influencing these perceptions. Similarly, the analysis of perceived challenges reveals similar findings. The mean scores for challenges are relatively consistent across age groups, and the associated p-value of 0.382 which further confirms the absence of statistically significant differences. Moreover, the perception of the future of LLMs also shows no significant variation among age groups.

DISCUSSION

The data analysis above reveals a multifaceted understanding of LLMs within the translation domain. Respondents overwhelmingly recognize the significant opportunities presented by LLMs, particularly in enhancing translation speed and cost-effectiveness. A strong consensus emerges regarding their ability to handle contextual nuances and bridge linguistic gaps, especially between Arabic and English, alongside their capacity to produce human-like translations. However, the data also highlights substantial challenges, most notably the perceived lack of cultural understanding and difficulty with idiomatic expressions, which respondents consistently identify as significant limitations. This finding goes in the same direction as Khasawneh (2023) and Khoshafah (2023) who identified the limitations of the use of AI translation tools in tackling some tasks in cross-cultural communication. This suggests that while LLMs provide to some extent efficient translation, their ability to accurately capture the subtle aspects of human communication remains a point of concern. Looking toward the future, participants generally anticipate a collaborative landscape where LLMs serve as powerful supportive tools. A substantial proportion foresees LLMs handling most translation tasks and potentially dominating the industry, there's a strong belief in the continued relevance of human expertise, this notion was emphasized by Moorkens, and Guerberof-Arenas, (2024) who reported AI has been forecast for many years, but now that these technologies are being organized, the effects are varied and, at times, unanticipated. Neural MT, in particular, can produce an output of greater quality compared to previous MT paradigms. Interestingly, gender plays a role in future outlook, with female respondents exhibiting a significantly more optimistic view compared to males. Conversely, educational

level (Bachelor's vs. Master's degrees) and age demonstrate no significant influence on perceptions of opportunities, challenges, or the future of LLMs. This suggests that while gender may shape expectations, other demographic factors do not significantly differentiate perceptions within the context of this study.
The findings showed that LLMs as transformative tools with considerable potential in translation, but also acknowledge their inherent limitations. Respondents perceive them as efficient and capable of handling many tasks, yet they recognize the crucial role of human translators in navigating cultural complexities and ensuring nuanced communication. The study underscores the importance of a balanced perspective, acknowledging both the advancements and the remaining challenges in the integration of LLMs within the translation industry.

CONCLUSION

LLMs are perceived as powerful, yet imperfect, tools within the translation industry. While respondents overwhelmingly acknowledge the significant advantages of LLMs in terms of speed, cost-effectiveness, and handling contextual nuances, they also consistently highlight the critical limitations related to cultural understanding and idiomatic expression. This duality underscores the essential balance between appreciating the efficiency and potential of LLMs and recognizing the irreplaceable role of human expertise in navigating the complexities of language and culture. The anticipated future of LLMs in translation is one of collaboration, where they serve as valuable support tools rather than complete replacements for human translators. Interestingly, gender significantly influences perceptions of the future of LLms, with females exhibiting a more optimistic outlook, while educational level and age do not appear to be significant differentiating factors. This study emphasizes the necessity of a nuanced approach to integrating LLMs, acknowledging their transformative potential while remaining cognizant of their inherent limitations and the continued importance of human translators in ensuring accurate and culturally sensitive communication.

Recommendations

Despite the promising future and perception towards LLMs, developers should focus on improving cultural understanding by LLMs, creating hybrid solutions that combine AI with human expertise, and mitigating biases. Translators should upskill in LLM technology, specialize in cultural nuances, and embrace LLMs as productivity tools. Overall, the focus should be on practical applications, transparency, ethical use, and collaboration to maximize LLMs' potential.

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Appendix
Section 1: Demographic Information

Gender
Male
Female

Age
-25
25-34
35-45
+45

Level of education
Bachelor's Degree

Master's Degree
PhD or higher

Name the most used AI.
ChatGPT, Google Translate, DeepL

No	Section 2: Opportunities in LLM Translation	Strongly Disagree	Disagree	Neutral	Agree	Strongly Disagree
1	LLM has Faster translation speeds					
2	LLM has lower costs for translation services					
3	LLM is handling context and nuance properly					
4	LLMs can bridge the gap between Arabic and English languages					
5	LLMs produce a human-like translation.					
6	LLMs produce consistent translations as they propagate similar segments.					
	Section 3: Obstacles and Challenges					
1	LLMs lack of cultural understanding					
2	LLMs lack of contextual understanding					
3	LLMs face difficulty with idiomatic expressions.					
4	LLMs face difficulty with slang.					
5	LLMs have limited availability of training data for the Arabic language					
6	I am afraid of biases in LLM-generated translations.					
7	LLMs can't fully capture the tone of human language					
	Section 4: Future of LLMs in Translation process					
1	LLMs are only supportive tools					
2	LLMs will handle most tasks					
3	LLMs will fully replace humans.					

4	LLMs will dominate the translation industry.					
5	LLMs and human translators will coexist equally.					
6	Human translators will remain the dominant					