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Uses of AI Translation in UK Public Service Contexts

A Preliminary Report

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Author
Lucas Nunes Vieira
University of Bristol
United Kingdom
E-mail: l.nunesvieira@bristol.ac.uk

Reviewers
Lynne Bowker, Université Laval, Canada
Mary Nurminen, Tampere University, Finland

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Foreword

The Chartered Institute of Linguists (CIOL) is pleased to have partnered with the University of Bristol on the Uses of AI Translation in UK Public Service Contexts. This groundbreaking research, authored by Dr Lucas Nunes Vieira of the University of Bristol, examines a previously unstudied aspect of our public services: the use of machine translation tools by frontline workers.

The findings presented here are both informative and concerning. They reveal significant use of AI-powered translation tools, including Google Translate and ChatGPT, in healthcare, legal, emergency, and police services - a practice that has largely gone unnoticed and unregulated. The data, from over 2,500 UK professionals, shows that a third of respondents have used machine translation in their work, often in public-facing situations where miscommunication could have serious consequences.

Of particular concern is the lack of institutional awareness and acknowledgement of this practice and the absence of appropriate policy frameworks to protect the public and public service workers themselves. The majority of respondents reported that machine translation had never been mentioned in their workplace training, despite its frequent use. This institutional silence means frontline workers are navigating complex linguistic situations with public service users and the public in ad hoc ways without guidance or support.

We must also address the potential for AI to create a false sense of linguistic competence. The language industry's complexities are already poorly understood by the general public and by frontline workers, and the advent of seemingly capable AI translation tools risks further obscuring the vital importance of human linguistic expertise. This misconception could lead to a further devaluing of language skills, ultimately impoverishing the UK's linguistic capabilities.

We wholly endorse the recommendations put forth in this report. The call for organisations to acknowledge the existence and potential use of AI/machine translation, to address that use in policies, and to place much more emphasis on staff education and training on AI and machine translation are all crucial steps. However, we believe these recommendations should be seen as a starting point rather than the end state. They should be implemented alongside robust safeguards and a commitment to maintaining human oversight by professional translators and experienced linguists in critical translation tasks.

The risks of getting translation wrong in public service contexts, through mistranslation, cultural insensitivity, or loss of nuance are simply too high to not use appropriately qualified language professionals. Another concern is the potential for AI to perpetuate or even amplify biases present in its 'training data', leading to systemic discrimination in translated content.

In light of these concerns, we strongly advocate for maintaining and, where possible, increasing public service budgets for professional translation services. While we recognise that it may not be realistic for human translation to be used in every circumstance, it is crucial that funding for skilled linguists is protected, especially in high-stakes situations where accuracy and cultural sensitivity are paramount. If facts are misrepresented or key messages are mangled, public services quite simply fail the publics they serve. It is clear that the current situation of unacknowledged and unmanaged use of AI for translation in public services cannot continue.

Dom Hebblethwaite

Head of Membership & Ventures
Chartered Institute of Linguists (CIOL)
www.ciol.org.uk

Executive Summary

Machine or artificial intelligence (AI) translation tools are used in a range of contexts as a communication aid. These tools can provide helpful assistance in the face of a language barrier. Their benefits may include greater linguistic diversity and increased access to information, but machine translation is also risky. Translation errors are common and may be difficult to identify for users who do not speak both the starting language and the language translated into. Existing research has shown that machine translation is used in contexts where miscommunication can be highly consequential, such as in healthcare and policing. This type of machine translation use has so far tended to go under the radar, with little public discussion and, importantly, little evidence of the extent and nature of the reliance on machine translation tools in these contexts.

This report therefore presents preliminary results of a survey of machine translation use in health and social care, legal and emergency services, and the police. The focus of the survey is on uses of unedited machine translations. A sample of 2,520 UK professionals submitted valid responses to this survey. A total of 33% of them had used machine translation at work, most often in contexts involving direct communication with others in a shared physical space. The professionals were highly satisfied with the tools they used. They were also confident in their ability to use the tools successfully, even though it was uncommon for machine translation to be mentioned in workplace training. Google Translate was by far the tool used most often. The use of generative AI tools such as ChatGPT also ranked highly. The tools were often accessed on personal devices using an openly available browser interface, practices which pose significant risks to privacy and information security.

While the report does not present the full data collected in the study and is not intended to provide detailed guidance or a best practice model, it offers three basic recommendations aimed at greater transparency and awareness-raising:

1. **At a minimum, organisations need to recognise (in training, staff communication, the organisation's literature) that AI/machine translation exists, and that staff and members of the public may be instinctively inclined to use it.** The potential presence of AI/machine translation in the contexts covered by this report cannot be institutionally ignored.

2. **The use of AI to overcome language barriers needs to be addressed in policy.** Institutional policies need to be sufficiently flexible to keep up with technological developments while also protecting the community from the risks posed by machine translation. Policies ideally need to involve dedicated language access teams, a mechanism for assessing needs and reviewing the policy, as well as protected budgets for professional language services and information on where these services should be prioritised.

3. **Organisations need to place more emphasis on education and staff training.** AI and machine translation literacy need to be embedded in the workplace culture to equip workers with the skills necessary to make decisions in what are increasingly challenging and technologized working environments.

Introduction

The University of Bristol has partnered with the Chartered Institute of Linguists to publish a survey of UK professionals on their uses of machine or AI translation in health and social care, legal and emergency services and the police. The focus of the report is on uses of unedited machine translation as a communication tool. The survey was conducted by Dr Lucas Nunes Vieira as part of *Critical Language Barriers*, a project funded by the UK's Arts and Humanities Research Council. The present report summarises key results of this survey. Full details, including analysis of open-text responses, will be available in future publications.

While not all sectors covered by the report are necessarily or directly publicly funded, the term 'public service contexts' is used here to emphasise the sectors' potential to serve and affect all members of society. The sectors' reach and community-facing nature therefore justified their inclusion.

Other important public sectors such as education and government administration are not covered because they were considered either too broad or too different from the selected sectors to be examined in the same investigation.

Although machine translation tools like Google Translate have been available for some time, little is known about the prevalence of these tools in the public service contexts selected for the study. The survey sought to ascertain whether the professionals use machine translation in their work, how they use it, what kind of guidance or training they might have received and, more generally, how they assess the use of these tools. The terms machine and AI translation are used here interchangeably to cover both the output of dedicated translation tools, such as Google Translate, and translations provided by generative AI applications, such as ChatGPT.

Data collection and methodology

Following a series of pilot studies, the survey took place between 23rd February and 7th April 2024. The data was collected through Prolific.com, a database of pre-registered individuals who can be invited to participate in online research. The use of this service involves methodological and ethical considerations. First, just the fact that the survey was conducted online may pre-determine the participants by naturally selecting those who are more frequent internet users. This limitation notwithstanding, this was not a significant concern for this study since the use of machine translation will in most cases require some familiarity with the internet and with digital technologies, so the populations favoured by this method are likely to overlap with the populations targeted by the investigation. Second, only studies that offer remuneration to participants can be distributed through Prolific. Remuneration has advantages and disadvantages. Paying participants may involve a higher risk of obtaining satisficing responses submitted by those who are only interested in the payment.[1] On the other hand, fair remuneration can be considered a desirable way of recognising the importance of participants' contribution. Using a paid service like Prolific also allows samples to be more systematically selected, so it was the strategy adopted here. A series of quality control measures were used to filter out irrelevant or low-quality responses.

Pre-existing demographic descriptors of the Prolific pool were used to select potential participants. The survey was only distributed to those marked as belonging to one of the following industry categories: "police", "medical/healthcare", "health care and social assistance", "emergency service", "legal services".

While these industry labels allow for interchangeable choices (for example, "medical/healthcare" partly overlaps with "health care and social assistance"), selecting all of them ensured maximum coverage of key sectors of interest. Users of Prolific belonging to these sectors were first asked to complete a screening questionnaire to identify those who had used machine translation at work. Those who had were invited to complete a longer questionnaire to describe their experience.

The questionnaires defined machine translation quite broadly. Participants were presented with the following explanation:

> This study is about computer programs that convert texts or speech from one language to another automatically. Google Translate is a well-known example of this type of tool. This study calls any programs that produce this type of translation "automatic translators". The technology is also known as "machine translation" or "AI translation". Automatic translators can be embedded into websites, social media platforms, online meeting apps and other communication tools. Some automatic translators are open to the public. Others may be available only within an organisation. The output of this technology is not produced by humans.

1 Participants received £1 to complete a short screening questionnaire. Those who progressed to the full study received a further £2. The payments were therefore symbolic gestures of appreciation. The paid amounts were nevertheless in Prolific's highest tier of fairness since the questionnaires were relatively quick to complete: 1-3 minutes for the screening questionnaire and approximately 10 minutes for the main study.

To cover a range of machine translation use methods, the definition mentions not only Google Translate, but also AI and the possibility that machine translation can be an embedded service. The questionnaire then adopted the phrase 'automatic translators', a descriptive, non-technical term used effectively in previous work.[2]

After reading the paragraph above, participants saw a series of options and were told to select the one that confirmed the study's machine translation definition. To avoid making participants feel like they were taking a test, they were told what option to select. This question was therefore an attention (rather than a comprehension) test that served to confirm that participants were reading instructions. The question nevertheless also reinforced the study's definition of machine translation. The options sought to clarify potential confusions with similar technologies or services. The options are presented in Figure 1. Those who failed this attention check were automatically invited to leave the survey without submitting a response.

Figure 1. Attention check

This is a test question. Please select option B below to confirm that you are paying attention.*

Automatic translators are...

- A Tools primarily designed to provide word definitions such as the online Oxford English Dictionary
- B Computer programs that automatically translate texts or speech. These programs may work as standalone applications, such as the Google Translate app, or they can be embedded into other tools or websites.
- C Human translators or interpreters who convert texts or speech into other languages
- D Databases of images and set phrases that have been checked by professionals

Participants were also asked to confirm their industry when completing the screening questionnaire to ensure that their answer was consistent with the Prolific demographics. Those who selected the option "Other Industry/None of the Above" were excluded.[3]

In addition, the Prolific demographics were inspected to check participants' employment status. Where inconsistencies were spotted (for example, participants who had selected one of the industry categories above but who were also marked as unemployed or looking for work), the corresponding submissions were disregarded. Where employment status data was unavailable, the responses were retained as long as the participant's industry selection was consistent with the Prolific demographics.

Participants who were timed out were also excluded. Timed-out participants were those who did not confirm their submission on Prolific within a specified time limit. This limit is automatically set based on completion time estimates provided by the researcher. Prolific excludes these participants by default. Most of them took long breaks during the study that were likely to affect data quality (for example, due to poor recall of previous questions).

Lastly, two responses to the main questionnaire indicated that machine translation had not in fact been used in a professional capacity or at all. These responses were excluded. Some other responses raised doubt about whether the participant had understood the study's definition of machine translation. For example, when asked about their opinion on how different the use of automatic translators would be in 20 years' time – a question not analysed in this report – one participant replied, "Hopefully there will be an app so that we can type in what we need translated so we [don't] always have to do it over a phone call". Machine translation apps are already widely available, so this participant was most likely referring to human-mediated services rather than machine translation. Responses where misunderstandings of this nature were apparent were excluded, as were responses that were sufficiently ambiguous to raise doubt

2 Vieira, Lucas N, Carol O'Sullivan, Xiaochun Zhang, and Minako O'Hagan. "Machine Translation in Society: Insights from UK Users." Language Resources and Evaluation 57 (2023): 893-914. https://doi.org/10.1007/s10579-022-09589-1.

3 One participant who selected "medical/healthcare" was a veterinary surgeon. This participant was less relevant to the study because they did not work in human healthcare. The response was nevertheless retained since it was a single case and there were no inconsistencies with the Prolific demographics despite the unusually broad understanding of the industry category.

about the participant's understanding.[4] The increasingly technology-mediated nature of professional language services can lead to conflations in terminology and in understanding. Human interpreting services can now be accessed via apps, for instance,[5] so even terms such as 'translation apps' can be ambiguous. Therefore, the data had to be checked to avoid considering responses that were referring to human services rather than machine translation. Table 1 presents a breakdown of total submissions and exclusions.

The study was approved by the Faculty of Arts Ethics Committee at the University of Bristol.

Table 1. (Exclusions)/Submissions

Screening questionnaire	
Total submissions	3,007
Declined consent	(2)
Duplicates	(99)
Ineligible industry selection	(295)
Failed attention question	(5)
Timed out	(4)
Ineligible employment status	(82)
Final sample	2,520

Main questionnaire	
Total submissions	937
Duplicates	(7)
Ineligible industry selection	(2)
Failed attention question	(1)
Timed out	(1)
Ineligible employment status	(19)
No relevant use of machine translation	(2)
Unclear understanding of machine translation/the study	(76)
Final sample	829

Screening questionnaire

The screening sample had 2,520 valid responses. The sample was not evenly balanced across sectors. The combination of the health and social care categories accounted for over 80% (42.7% + 38.5%) of the responses, as shown in Table 2. This distribution was mirrored by the broader Prolific pool. The National Health Service (NHS) is the biggest UK employer,[6] so the larger number of healthcare workers relative to the other categories probably reflects the national picture. The representativeness of the sample's internal sector distribution is nevertheless difficult to ascertain because these categories do not map directly onto industry categories used in national statistics.

Table 2. Distribution of industry categories in the screening sample. Total valid responses = 2,520. Those who selected a sixth option, "Other Industry/None of the Above", were automatically invited to leave the study without submitting a response.

Which of the following categories best describes the industry you primarily work in (regardless of your actual position)?	count	%
Health Care and Social Assistance	1076	42.7
Medical/healthcare	969	38.4
Legal services	247	9.8
Emergency service	125	5.0
Police	103	4.1

Participants were asked whether they had used any type of machine translation before. All those who had used machine translation were subsequently asked to select the contexts in which they had used it. The options were "While travelling on holiday", "For any work-related purpose in the industry you primarily work in", "To study or when learning a new language", "When being interviewed for a job", and "Other". Only those who selected "For any work-related purpose in the industry you primarily work in" were invited to proceed to the full questionnaire. A total of 998 participants selected this option. At this point participants had not yet been told that the focus of the study was on professional settings.

4 Ambiguous responses were excluded where open-text answers did not clearly distinguish human and non-human language services and at least one of the following was also true: the participant provided information about human language services when asked about the machine translation systems used; the participant did not select any option that included the name of a specific machine translation tool; the participant declared using a non-publicly-available tool without providing more information elsewhere; the participant declared that machine translation use was recommended by their employer without providing more information elsewhere. Without clear distinctions between human and machine, these options were more likely to suggest that technology-mediated human services were being conflated with machine translation.

5 See "Language Line App." Language Line Solutions, 2024. https://www.languageline.com/en-gb/interpreting/languageline-app

6 "The NHS Workforce in Numbers." The Nuffield Trust, 2024. https://www.nuffieldtrust.org.uk/resource/the-nhs-workforce-in-numbers

Machine translation users

As shown in Table 1, the main questionnaire had a final sample of 829 valid responses. Based on these responses, the prevalence of machine translation use at work in the overall sample of 2,520 submissions is 33%. All details presented from this point onwards pertain to the 829 responses provided by those who had used machine translation in a professional context.

The industry distribution of the main sample largely followed the distribution of the screening sample – the health and social care categories were the largest ones (medical/healthcare: 41.9%; health care and social assistance: 37.7%). Legal services, the police and emergency services had fewer participants (9.0%, 6.9% and 4.5%, respectively).

Basic participant descriptors were obtained from the Prolific demographics. Their mean age was 37.3 (range: 19–72). Details of their employment and student status are presented in Table 3. Table 4 shows a breakdown of the five most common first languages in the sample.

Table 3. Machine translation users' employment and student status. These are separate overlapping categories (for example, because part-time workers can also study at the same time).

	count	%
Employment status		
Full-Time	517	62.4
(Missing)	158	19.0
Part-Time	154	18.6
Student		
No	581	70.1
(Missing)	141	17.0
Yes	107	12.9

Table 4. Machine translation users' five most common first languages

First language	count	%
English	770	92.9
Portuguese	8	1.0
Polish	6	0.7
Italian	5	0.6
Other	5	0.6

Other participant descriptors were collected through the questionnaire itself. Participants were asked if there were any non-native languages they had enough proficiency in to read a restaurant menu. A total of 486 (58.6%) of them said yes and then typed up to three non-native languages. Table 5 presents the five most common of these languages.

Table 5. Machine translation users' five most common non-native languages

Five most common non-native languages	count	%
French	258	31.1
Spanish	174	21.0
German	95	11.5
Italian	39	4.7
English	33	4.0

As can be seen in Tables 4 and 5, most participants were native speakers of English, and the most common non-native language in the sample was French.

Table 6 shows participants' highest level of education. Tables 7 and 8 show their most common occupations and length of professional experience, respectively.

Table 6. Highest level of education

What is the highest level of education you have completed?	count	%
University/college undergraduate programme	387	46.7
University/college postgraduate programme	252	30.4
A-Levels or equivalent	118	14.3
GCSEs or equivalent	30	3.6
Doctoral degree	25	3.0
(Missing)	16	1.9
Primary school	1	0.1

Table 7. Occupation responses provided more than five times

What is your occupation in your industry?[7] Frequent (>5) responses	count	%
nurse	51	6.2
social worker	33	4.0
doctor	29	3.5
police officer	17	2.1
solicitor	16	1.9
support worker	13	1.6
midwife	12	1.4
pharmacist	11	1.3
physiotherapist	11	1.3
(Missing)	10	1.2
speech and language therapist	9	1.1
administrator	8	1.0
occupational therapist	8	1.0
healthcare assistant	7	0.8
paralegal	7	0.8
advanced nurse practitioner	6	0.7
detective	6	0.7
medical secretary	6	0.7
operations manager	6	0.7
paramedic	6	0.7

Table 8. Length of professional experience

For how long have you had this occupation?	count	%
1–5 years	357	43.1
6–15 years	290	35.0
16–25 years	94	11.3
Less than a year	50	6.0
26 years or more	36	4.4
(Missing)	2	0.2

Most participants had a university degree (Table 6), as it would be expected of a sample of public service workers. Nurses, social workers, doctors, police officers and solicitors were the most common occupations in the sample (Table 7). Participants had been working in their sectors for varying lengths of time, most of them between 1 and 15 years (Table 8).

Machine translation use

Tables 9–19 present several aspects of how participants used machine translation and for what purposes.

Machine translation was not used very frequently, although over a third of the sample used it at least once a month (Table 9). Participants needed machine translation most often for translations between English and Polish (Table 10).

Table 9. Machine translation use frequency

In the past 12 months, how often did you use automatic translators in your work in your industry?	count	%
More than once a week	49	5.9
Once a week	99	11.9
Once a month	184	22.2
A few times	396	47.8
The last time was more than 12 months ago	97	11.7
(Missing)	4	0.5

Table 10. Ten most common language pairs

Ten most common language pairs for which machine translation was used	count	%
English to Polish	220	26.5
Polish to English	135	16.3
English to Romanian	84	10.1
English to Arabic	59	7.1
French to English	57	6.9
Spanish to English	57	6.9
English to Urdu	56	6.8
English to Spanish	52	6.3
English to Punjabi	49	5.9
Romanian to English	49	5.9
German to English	42	5.1
English to French	36	4.3

7 This question automatically recalled participants' previous industry selection (for example, "What is your occupation in the medical/healthcare industry?"). Since the industry changed depending on the participant, the ending "in your industry" is used here for all questions that used the automatic recall feature.

Communicating out loud in the same physical space was the most common machine translation use context (Table 11). This is unlike results of previous surveys showing that just consuming or understanding information is the most common machine translation use purpose.[8] The more interactive type of use reported here is typical of public services. Indeed, machine translation was most often used for public-facing communication (Table 12).

Table 11. Use purposes

For what purpose(s) have you used automatic translators in your industry? (Multiple selection)	count	%
I needed to communicate with someone out loud in the same physical space	467	56.3
I needed to read or understand something (without replying or talking back)	373	45.0
I needed to exchange written messages with someone via chat, email, WhatsApp or similar	198	23.9
I needed to communicate with someone out loud on the phone or in an online meeting	164	19.8
I needed to publish or distribute information	121	14.6
Other	20	2.4
(Missing)	1	0.1

Table 12. Whether machine translation was used in frontline tasks

Has your use of automatic translators in your industry ever involved frontline tasks or public-facing information? For example: • Interacting with patients, customers, civilians • Publishing information on websites or pamphlets • Sending letters or e-mails to members of the public	count	%
Yes	649	78.3
No	179	21.6
(Missing)	1	0.1

Participants' most typical experience was for them to decide to use machine translation, but machine translation use was also recommended by employers or initiated by members of the public (Table 13). Existing NHS guidance available for primary care advises against machine translation use.[9] Some NHS Trusts have also published Freedom of Information responses (not requested by this project) stating that machine translation is not used.[10] At least one Trust has also stated that it is used ad hoc even if this is not recommended.[11]

The number of participants indicating that machine translation was recommended by their employer is therefore contextually large and thereby surprising (n=124, 15.0%). Three points are worth noting in this respect. First, institutions' official positioning may differ from actual practice. Since this project consulted workers directly, the results reported here may well be closer to the reality on the ground. Second, machine translation is not the only communication method used. Machine translation may be endorsed with caveats or as part of a range of different resources (see Table 19). The use of multiple communication methods is clear in this participant's description of their employer's recommended procedure: "Getting interpreters, using the AI, trying pictures, charts, gestures, signs" (Mental Health Worker, medical/healthcare). Third, participants' understanding of what was recommended was more closely aligned with what they saw as common practice than with official policies. For example, this participant's description of their employer's recommendation points to a disconnect between what is seen as ideal and what is feasible: "Usually calling a professional translator, but these have to be booked and rarely match the times [when] we have [language] barriers!" (Nurse, medical/healthcare). When participants say that their employer recommends machine translation, they may therefore be referring not to institutional directives but rather to what is understood among their colleagues to be common or necessary.

8 Vieira, Lucas N, Carol O'Sullivan, Xiaochun Zhang, and Minako O'Hagan. "Machine Translation in Society: Insights from UK Users." Language Resources and Evaluation 57 (2023): 893-914. https://doi.org/10.1007/s10579-022-09589-1; Nurminen, Mary, and Niko Papula. "Gist MT Users: A Snapshot of the Use and Users of One Online MT Tool." In Proceedings of the 21st Annual Conference of the European Association for Machine Translation, Alicant, Spain, May 2018, edited by Juan Antonio Pérez-Ortiz, Felipe Sánchez-Martínez, Miquel Esplà-Gomis, Maja Popović, Celia Rico, André Martins, Joachim Van den Bogaert and Mikel L. Forcada, 199-208: European Association for Machine Translation, 2018.

9 NHS England/Primary Care Commissioning. "Guidance for Commissioners: Interpreting and Translation Services in Primary Care." NHS England, 2018. https://www.england.nhs.uk/wp-content/uploads/2018/09/guidance-for-commissioners-interpreting-and-translation-services-in-primary-care.pdf.

10 See, for instance, Solent NHS Trust. "FOI_1414_2023-24 – FOI Request Interpreting and Translation." NHS England, n.d. https://www.solent.nhs.uk/media/5278/foi_1414_disclosure.pdf; Essex Partnership University, NHS Foundation Trust. "Freedom of Information Request EPUT. FOI.23.3228." NHS England, 2023. https://eput.nhs.uk/media/yxcbpnbd/eput-foi-23-3228.pdf.

11 Royal Devon University Healthcare, NHS Foundation Trust. "Translation Services and Technologies." NHS England, 2023. https://www.royaldevon.nhs.uk/media/1oedvjsz/foi-rdf2042-23-translation-services-and-technologies.pdf.

Table 13. Machine translation use decision

How has the decision to use an automatic translator come about in your industry? Please select a single answer corresponding to your typical experience.	count	%
I decided to use it	564	68.0
It is the procedure recommended by my employer	124	15.0
Someone I was speaking to started using it and I continued interacting with them in that way	124	15.0
Other	15	1.8
(Missing)	2	0.2

Regarding aspects of technical infrastructure, machine translation was most often used on mobile phones (Table 14). The devices on which it was used were most often provided by employers, although in many cases these were personal devices (Table 15). The most common method of accessing the technology was to use a browser-based interface (Table 16). Google Translate was by far the most used system, although generative AI tools such as ChatGPT also ranked highly and were selected more often than some established tools such as Microsoft Translator (Table 17). ChatGPT had been available for a little over a year at the point the data was collected, so the comparatively high take-up of this type of tool is notable.

Table 14. Device types on which machine translation was used

On what type(s) of device have you used automatic translators in your industry? (Multiple selection)	count	%
Mobile phone	607	73.2
Laptop	353	42.6
Desktop	281	33.9
Tablet	125	15.1
Automatic translator device	30	3.6
Smart speaker	10	1.2
Smartwatch	4	0.5
Other	3	0.4
(Missing)	1	0.1

Table 15. Device ownership

How would you describe the device(s) where you used automatic translators in your industry? (Multiple selection)	count	%
Device(s) provided by my employer	544	65.6
My own personal device(s)	479	57.8
Device(s) that belonged to individual(s) with whom I was communicating	154	18.6
(Missing)	2	0.2
Other	1	0.1

Table 16. Machine translation use methods

How did you access the automatic translation(s) you used in your industry? (Multiple selection)	count	%
I used an openly available tool via a browser (for example, https://translate.google.co.uk/)	636	76.7
I used an app or tool that is publicly available for download (for example, in the Apple App Store or Google Play Store)	244	29.4
The automatic translator was available by default on the device I used	93	11.2
I asked a chat bot like ChatGPT to provide translations[12]	74	8.9
It was a specialised automatic translator provided by my employer and which is not publicly available	74	8.9
Other	7	0.8
(Missing)	2	0.2

12 This option overlaps with using an openly available tool via a browser, which likely explains the small difference in the number of those who selected ChatGPT in this question (74) and those who selected it in the question displayed in Table 17 (84).

Table 17. Machine translation systems or system interfaces

What specific automatic translator(s) have you used in your industry? (Multiple selection)	count	%
Google Translate	797	96.1
The default[13] automatic translator in my web browser	85	10.3
I asked a chat bot like ChatGPT to provide translations	84	10.1
The default automatic translator available on my smartphone	42	5.1
The default automatic translator in a text editor such as Microsoft Word	37	4.5
The default automatic translator available in a meeting tool, for example Zoom, Skype or Microsoft Teams	34	4.1
Apple's Translate app	33	3.9
Bing or Microsoft Translator	27	3.3
Other	26	3.1
The default automatic translator available on a social media platform, for example Facebook or Twitter	20	2.4
iTranslate	15	1.8
DeepL	12	1.4
Speak and Translate	12	1.4
SayHi Translate	9	1.1
Translate Now	7	0.8
Reverso	6	0.7
Systran	3	0.4
(Missing)	2	0.2
Yandex	1	0.1
PROMT	0	0.0

As mentioned, many participants used machine translation at the same time as other communication methods (Table 18). Common types of additional language support included other individuals who spoke the relevant language, web searching, and printouts with images and set phrases (Table 19).

Table 18. Whether machine translation was used together with other communication methods

In your typical experience in your industry, did you use automatic translators at the same time as other methods of communicating or accessing information?	count	%
Yes	440	53.1
No	372	44.9
(Missing)	17	2.0

Table 19. Other communication methods used together with machine translation. Base = 440 (those who had used other methods).

What other methods did you use together with automatic translators? (Multiple selection)	count	%
Other individuals who spoke the relevant language	262	59.5
Googling/web searching	189	43.0
Printouts with images or set phrases	128	29.1
I used my own basic knowledge of the language alongside the automatic translator	109	24.8
Other	39	8.9
Dictionaries	29	6.6
Another type of language technology (for example, tools that provide set phrases)	12	2.7
(Missing)	9	2.0

Workplace training and machine translation use evaluation

Tables 20–21 show, respectively, whether machine translation was mentioned in workplace training and participants' confidence in their ability to use machine translation successfully. Figure 2 shows their evaluation of the technology.

For most participants, machine translation had not been mentioned in workplace training (Table 20). Some participants (n = 63, 7.6%) indicated that they had never received workplace training in the first place. It may be that these participants did not consider on-the-job training (for example, shadowing or close supervision) when answering this question. They may have thought instead of more formal training activities (for example, on-site courses), which they might not have been asked to attend. In any case, just the fact that in these participants' opinion they

13 While some of these options may overlap in terms of the underlying system (for example, Microsoft Translator is the default system in the Microsoft Edge browser), these options helped to capture the type of tool used even if users were not aware of what the underlying system was.

had never received workplace training may suggest a perception that best practices or expectations are not clearly communicated.

Table 20. Whether machine translation featured in workplace training

Were automatic translators ever mentioned in any workplace training you received in your industry?	count	%
No	599	72.2
Yes	93	11.2
Not sure or I don’t remember	71	8.6
I never received any workplace training	63	7.6
(Missing)	3	0.4

Participants’ levels of satisfaction with machine translation were extremely high. They were asked to rate the extent to which they agreed or disagreed with six statements about the potential usefulness of machine translation in their work. The statements are presented in Figure 2 together with participants’ ratings.[14] The ratings ranged between 1 (strongly disagree) and 5 (strongly agree).

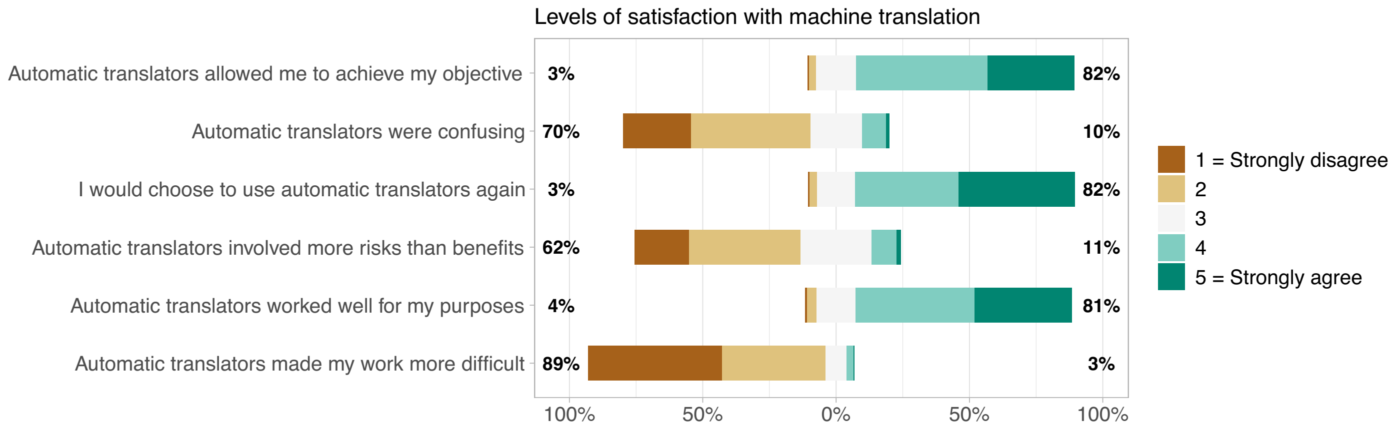
Some of the statements expressed positive assessments of machine translation (for example, “Automatic translators allowed me to achieve my objective”). Others expressed negative assessments albeit without using grammatical negation to avoid confusion (for example, “Automatic translators involved more risks than benefits”). As can be seen, most participants agreed with the statements that favoured machine translation and disagreed with the ones that disfavoured it. The level of consensus among participants was also high, for example with 89% disagreement with the statement “Automatic translators made my work more difficult”.

Table 21. Confidence in own ability to use machine translation successfully

How confident do you feel in your ability to overcome language barriers using automatic translators in your industry?	count	%
1 = Not at all confident	15	1.8
2	71	8.6
3 = Somewhat confident	303	36.5
4	331	39.9
5 = Very confident	101	12.2
(Missing)	8	1.0

When asked about their levels of confidence in their ability to overcome language barriers using machine translation, most participants were at least somewhat confident (Table 21). Only 1.8% of them selected the option “Not at all confident”.

Figure 2. Levels of satisfaction with machine translation. The percentages for each statement show total disagreement (levels 1 and 2, left) and total agreement (levels 4 and 5, right). Neutral ratings (level 3) have been excluded from the percentage totals.



14 The internal consistency of participants’ ratings was high, with a Cronbach’s Alpha of 0.85 across all six statements.

Discussion

Whether the translations are produced by dedicated systems like Google Translate or large language model tools like ChatGPT, machine translation can be extremely helpful and convenient. The translations are fast and cheap to obtain, but they are also unreliable since inaccuracies are always possible or indeed likely. Inaccuracies can also be difficult to spot for individuals who are not proficient in the languages involved. Like many other types of AI, therefore, machine translation often presents a conundrum to end users. The services offered by professional translators and interpreters are the uncontroversial gold standard. As the data above indicates, however, public service workers are not guaranteed to always use these services.

This report shows that uses of machine translation in UK public service contexts are possibly more common than what existing policies and official statements may suggest. At least 33% of the 2,520 professionals who submitted a valid response to the study's screening questionnaire had used machine translation at work. Machine translation assistance was usually sought in public-facing contexts or for translating public-facing information, most often when communicating with others in the same physical space. Google Translate was by far the most used system. For most respondents, machine translation had not been mentioned in any workplace training. Most of them were nevertheless at least somewhat confident in their ability to use the technology successfully. They were also highly satisfied with it.

Despite participants' confidence and satisfaction, they were not necessarily well placed to identify machine translation's drawbacks. Machine translation was most often needed for communication between English and Polish. Most participants were native speakers of English. Although just under a third of them had some knowledge of French, not many spoke Polish. Language needs and personal linguistic profiles did not therefore match, which means that in most cases participants would not be able to rely on their own linguistic knowledge to identify errors or risk-assess the technology.

Risk-assessing machine translation is in any case not straightforward because the technology's risk-benefit ratio is dynamic. It varies based on a long list of context-dependent factors including the availability of professional language services and the urgency of the communication. While in some contexts machine translation may be acceptable, language services provided in a timely manner by qualified professionals will always be safer. There is a need, therefore, for institutions and their staff to be alert to the risks of using machine translation when safer communication strategies may be available.

It is in any case clear from the findings that machine translation is usually combined with other communication methods. These methods included printouts with set phrases and other individuals who spoke the language. Combining methods is likely to mitigate miscommunication risks, but the reliability of additional methods, like that of machine translation itself, will vary significantly. Individuals who offer help may not themselves be proficient in the language. The success of web searching and of other types of cross-checking is likely to depend on individuals' language proficiency and ability to critically search and assess information sources. It will also depend on time pressure, which is common in the contexts examined in this report[15] and may influence the professionals' decision-making. Risk perception is therefore an important factor to consider in analyses of this topic. Potential power and knowledge asymmetries in service provision are also factors to consider. Community members may be unfamiliar with subject-specific vocabulary, for instance, which may exacerbate any potential communication difficulties caused by machine translation. Real or perceived power imbalances may also exacerbate communication difficulties, especially if community members feel unable to ask questions or raise concerns. While the survey's open-text data includes information that is relevant to analyses of risk and of some of these broader factors, this data is not examined in this preliminary report.

15 See, for example, Iacobucci, Gareth. "British GPs are more stressed and time pressured than international colleagues, survey shows." British Medical Journal 368 (2020). https://doi.org/10.1136/bmj.m926

In any case, further to the risk of miscommunication, which in critical public services can be highly consequential, two other risks can be identified based on the data presented. First, some of the uses of machine translation reported have concerning implications for privacy and confidentiality. Most respondents reported using machine translation by accessing an openly available tool via a browser. Over half of them also declared using machine translation on personal devices. These methods of accessing the technology involve potentially significant privacy and information security risks since personal devices may be unencrypted and the information may be accessible to third parties as part of users' browsing history.[16] Second, and more broadly, there is a risk that machine translation use may become a de facto standard practice that remains unspoken in policy and official statements.

This type of institutional silence risks leaving frontline workers on their own while they try to overcome language barriers in environments marked by high stress and tight budgets. The potentially risky presence of AI translation in public service settings is therefore ultimately an organisational matter that should not fall exclusively on the shoulders of individual frontline workers.

AI presents tremendous potential to make communication faster and easier and to increase access to services and information. However, for this potential to be harnessed responsibly, the risks of these tools need to be considered and their use openly discussed. While the present report is preliminary and does not present the full data collected in the survey, its findings are hoped to offer something of use to this type of discussion.

16 For an example where a police officer in Germany inadvertently leaked sensitive information while using Google Translate, see Eckert, Svea, and Andreas Dewes. "Dark Data." DEF CON 25, Las Vegas, 2017. https://www.youtube.com/watch?v=1nvYGi7-Lxo

Recommendations

Although this report is not intended to provide detailed best practice guidance,[17] three recommendations can be offered to organisations concerning basic aspects of their approach to uses of AI/machine translation:

1. At a minimum, organisations need to recognise (in training, staff communication, the organisation's literature) that AI/machine translation exists, and that staff and members of the public may be instinctively inclined to use it. The potential presence of AI/machine translation in the contexts covered by this report cannot be institutionally ignored.

2. The use of AI to overcome language barriers needs to be addressed in policy. Institutional policies need to be sufficiently flexible to keep up with technological developments while also protecting the community from the risks posed by machine translation. Policies ideally need to involve dedicated language access teams, a mechanism for assessing needs and reviewing the policy, as well as protected budgets for professional language services and information on where these services should be prioritised.

3. Organisations need to place more emphasis on education and staff training. AI and machine translation literacy need to be embedded in the workplace culture to equip workers with the skills necessary to make decisions in what are increasingly challenging and technologized working environments.

17 Guidance of this nature is available through initiatives such as the "Interpreting Safe AI Task Force Guidance: AI and Interpreting Services." SAFE-AI Task Force, 2024. https://safeaitf.org/wp-content/uploads/2024/07/SAFE-AI-Guidance-07-01-24.pdf) and the "Generative AI Framework for HM Government." HM Government, 2024. https://www.gov.uk/government/publications/generative-ai-framework-for-hmg. For European Union legislation, see the Artificial Intelligence Act, Regulation (EU) 2024/1689 of the European Parliament. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32024R1689&qid=1722960546953.

CIOL Chartered Institute of Linguists

UKRI Arts and Humanities Research Council

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