

Internationalization and Globalization in Higher Education: An Insight on Effect of Machine Translators on Team Performance among Multicultural Students Working and Studying in Hungary

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Abstract

Language barrier impedes team performance among employees working in a multilingual environment. Guided by the Technology Acceptance Model this study seeks to determine the effect of machine translators on team efficiency, collaboration, trust building, and training among students on work-study jobs in Hungary. International students (N=105) from the University of Debrecen participated in the study. Findings indicate that machine translators significantly and positively contributed to team performance by boosting efficiency, collaboration, trust, and training. Every unit increase in use of Machine Translators translated to a corresponding increase in team efficiency, collaboration, trust, and training: a significant finding that indicates their instrumental role in breaking the language barrier in a linguistically diverse workplace. This study recommends the full adoption of machine translators to bridge the communication gap arising from language barriers in any multicultural environment consisting of multi-lingual team members.

Keywords: Internationalization, Language Barrier, Team Performance, Machine Translators, Management.

Introduction

Was the invention of machine translators intentionally motivated by the need for enhanced teamwork in a multicultural environment or a gold rush with hidden motives aimed at spying on ‘enemy’ countries? The invention of Machine translators (MT) can be traced back to political and ideological cold war between the Soviet Union and the United States in the 1950s. United States invested a lot of financial resources and manpower to develop MT to help in outwitting the Soviets but the program was abandoned later in the 1970s. However, the idea continued its development journey in other countries. (Stapleton & Kin 2019). The field of automated translation is comparable to the modern gold rush (De Vries, Schoonvelde, & Schumacher, 2018). The task of translating one language to another is credited to human beings for communication and socialization (Carl, Dragsted, B., Elming, Hardt, & Jakobsen, 2011). The use of machines to aid in bilingual or multilingual translation dates back to the 17th century when it was first recommended that mechanical dictionaries could be used to overcome language barriers. The 20th century opened doors to the first formal proposals pioneered by a Russian, Petr Smirnov Troyanskii, and George Artsrouni a French-Armenian in 1933, who patented their works independently (Hutchins,1995). Troyanskii’s work was more comprehensive and significantly instrumental in the development of MT because it clearly outlined a method for developing an automatic bilingual dictionary, a scheme for coding inter-lingual grammatical roles, and a proposal of harnessing analysis and synthesis for automated translations(Hutchins,2014).

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Machine Translators have become communication aid tools both for individual freelance translators and professionals working in organizations (Yang, Wang, & Yuan, 2021) because research indicates possible increased productivity and quality when used alongside post-editing MT raw output (Plitt & Masselot, 2010). At the beginning of the 1990s, statistics indicate that 1.3% of the total translation market was done via MT where only 6 million pages were translated through MT against 450 million done by human translators. This meager figure led researchers to predict slow growth for MT by 2007 (Oren, 2004). Hutchins, (2007) traces the use of MT to the many years of successful pioneering by large institutions European Commission and the Pan American Health Organization and multinational corporations including Ford, General motors, Xerox among others, which made achievements in cutting translation costs and attaining translation efficiency.

Craciunescu, Gerding-Salas, & Stringer-O’Keeffe, (2004) acknowledge that technological advancements in internet use have transformed access to instant information and communication which has effectively and efficiently eased the work of translators like never before. For a comprehensive understanding of machine translators, it is advisable to analyze and appreciate the differences by looking at their classifications, their different uses, intended applications, and linguistic techniques that the MT uses to facilitate translations (Slocum 1985). There is fear of the unknown as human translators continue to wage a war of resistance against MT because they see it as a threat (Gaspar et al., 2015), despite technological advancement and improvement of MT. This is largely attributed to job security concerns if MT will be fully adopted to replace human translators (Cadwell et al., 2017). Many corporations are harnessing MT where they use customized software in the language of the target market, which has seen an upward shift in the growth of total sales (Puchala-Ladzińska, 2016).

A robust MT should address translation challenges which include linguistic obstacles (e.g. language understanding, language generation, and language mapping pairs) and different operational considerations (Dorr, Jordan, & Benoit, 1999). Computerized automated translations are either rule-based (RBMT) where bilingual dictionaries and rules that are written manually are used, or, corpus oriented translators (e.g. example-based machine translation (EBMT), statistical machine translation (SMT), and neural machine translation (NMT) (Wang, Wu, He, Huang, & Church, 2021).

Language Barrier Among Multilingual Teams

When working in an organization, management often delegates duties to employees as a way of empowering them to work in collaboration with each other (Kirkman & Rosen, 1999), and to participate in decision-making and problem-solving to enable an organization to achieve its goals. The adoption of collaborations as a strategy of organizational operations management is motivated by studies that show a positive correlation between teamwork and improved organizational performance (Cohen & Bailey, 1997; Kirkman & Rosen, 1999). Teams have become the solution for organizations dealing with complex and tough tasks (Salas, Cooke, & Rosen, 2008), and when an organization is aiming at minimizing errors, enhancing efficiency as well as maximizing a united workforce for competitiveness.

Studies indicate that the language barrier remains the greatest headache for organizations operating in multilingual markets but scanty research linking MTs in address the language barrier challenge is available (Maclean, 2006). A study on a merger involving three Dutch and German companies indicates that the issue of the language barrier was overlooked and considered a minor challenge not worth serious attention to the management (Olie, 2005). An effort by international business and management studies researchers to emphasize the critically important role of language as a medium for thought (Brannen & Doz, 2012), has led to the conclusion that language is instrumental in an organization’s social and economic success. (Brannen & Doz, 2012). The role of language and its impact on teamwork and organizational performance has however, been given little attention than it deserves by international researchers (Harzing, Köster, & Magner, 2011).

Research indicates that collaboration technologies unites workers to work toward achieving a goal (Brown, Dennis, & Venkatesh, 2010). Success in teamwork lies heavily on equal responsibility where each member’s contribution will be pooled together into a common outcome (Ellis, Bell, Ployhart, Hollenbeck, & Ilgen,

(2005) because Collaboration Information communication technologies facilitate socialization in the workplace (Maruping & Agarwal, 2004). During the translation process, it is imperative to prioritize choice in decision-making to drop the unnecessary, pick the best, revise together, and make the final decision. (Tirkkonen-Condit, 1993; Gonzalez, 2014). There is a need for translators to use a dual model of translation where decision-making and problem-solving are integrated to streamline the translation process (Wilss, 1996).

Machine Translators

Real-time face to face communication in a team consisting of multilingual members is arguably an inevitable scenario where MT is the only solution. such as real-time online face-to-face communication where MT is the only solution (Way, 2013). This view agrees with that of Aragonés Lumeras & Way (2017) who posited that MTs are already serving translations needs among users in situations where human intervention is impossible

MT has been used as a socio-political empowerment tool for minorities (Bowker, 2008), for healthcare service delivery in multilingual environments (Somers & Lovel, 2006) and in the intelligence sector as a scrutinizing aid (Koehn, 2010). Students employ MT to interpret questions when tackling assignments in foreign languages (Niño, 2008) because many researchers are advocating MT used to promote electronic literacy together with language learning (Alley, 2005; Burton, 2003; Williams, 2006). In Europe, MT is used to help the European Union and public servants eliminate language barriers and exchange information efficiently and effectively across member countries (European Commission 2016).

Although rapid technology changes have continually improved MT, their language coverage has little focus on minority groups and the immigrant group which face language barrier challenges. There is however a growing research interest in MT (Hutchins,2009). MT currently available in the market are either distributed as commercial products or fully online and accessible through the internet, hence their descriptions as closed and static products. Most successful machine translation (MT) systems built until now use proprietary software and data and are either distributed as commercial products or are accessible on the net with some restrictions but no research targets the performance of the MTs in team performance in linguistically diverse environments.

While there is substantial research on the history of MT, and the literature on the available options in the market, there is little research mostly in blogs available which aim at evaluating MT role in team performance in job the market (Hampshire & Salvia, 2010). Language Translators can best be categorized broadly into two: the free open-source MTs and the commercial-oriented versions. Machine translators initially targeted paying customers with no free versions in the market. The beginning of 1998, brought along the free versions of MT which became fully accessible to the general public (Watters & Patel 1999). Machine translators are powerful tools against the language barrier for all groups because it facilitate intercultural collaboration and can be used by teams from diverse backgrounds but working on a common goal (Morita & Ishida 2009).

Although MT use in the workplace has enhanced teamwork, the task of language translation is too complex to be solved by automated translators alone (Kozłowski 2002; Puchala-Ladzińska 2016), because the output language after machine translation is often characterized by errors which have caused mutual misconceptions and lack of comprehension (Nomura, Ishida, Yamashita, Yasuoka, & Funakoshi, 2002). The probability of errors occurring, however, is greatly reduced through collaborative translation, where non-bilingual partners use MT interchangeably to arrive at the intended message (Morita& Ishida 2009). MT is also vulnerable to typological errors (Climent, Moré, Oliver, Salvatierra, Sánchez, Taulé, & Vallmanya, 2003). The advantage of machine translators is that it enable people to communicate despite their lack of accuracy, which most users consider to be a minor challenge (Aiken, 2002). Machine Translators have also been discovered to be gender biased with preferential rooms given to male defaults (Cho et al., 2019; Prates et al., 2020; Rescigno et al., 2020

The available free online machine translators confuse the consumers on which one has to choose because the available research is scanty and generally non-academic mostly found on online blogs and web articles, where only a handful of studies are available about Google translate, Babelfish among others (Hampshire & Salvia, 2010). Most available articles on Google Translate focus on its shortcomings and rarely attempt to find its impact on language translation and jobs in foreign environments. (Bowker & Ciro, 2019; Tsai, 2020). This trend is attributed to too much academic research focus on Commercial versions of machine translators (Zervaki, 2002). This study seeks to do a comprehensive study on the effect of machine translators on team performance

Technology Acceptance Model

In an attempt to understand the motivating factors surrounding the adoption and use of technology by users, Davis discovered that the perceived usefulness of the technology and how easily the technology can be customized for use, actually informs the reasons why humans choose technology. The emphasis is from the point of view of the user and not the creator of the Technology unless the motivation to create the technology is inspired and driven by the potential users. In our study, the adoption and utility of Machine Translators will be studied from TAM's view of perceived usefulness to understand the reasons international students working in foreign countries use them and their reasons for choosing MT while interacting in host country.

The conceptual framework in Figure 1.0 illustrates the relationship between the independent Variable (Machine Translators) and the dependent variables; team efficiency, collaboration, trust building and team training based on MT technology acceptance and use by the study population. The assumption is based on null hypotheses outlined below.

The Research Hypotheses

H01: There is no significant effect of machine translators on team efficiency during work in a multilingual environment.

H02: There is no significant effect of Machine Translators on team collaboration among multicultural teams.

H03: Machine Translators have no significant contribution to trust building among team members in a multilingual environment.

H04: Machine Translators play no significant role in team training for multilingual teams.

Methodology

This study uses a primary research approach. Primary research is instrumental in collecting highly customized, specific information from the qualified target population. Descriptive research design defined, described, analyzed, compared, contrasted, and quantifies data before tabulating the results for a comprehensive outcome. The researchers were guided by a relevant literature review to develop a data collection procedure, triangulation, and analysis for comparison (Yin, 2003). The study used tailored questionnaires in online surveying (Christian et al., 2009) to investigate the role of machine translators in team training, evaluate the effect of machine translators on team collaboration, determine the effect of machine translators on team efficiency, and evaluate the role of machine translators on trust building among students on work-study jobs in Hungary. Primary research provided an adequately trusted representative research outcome representing the entire population as recommended by Maxwell (2013). Stratified random sampling was used. The descriptive research design was chosen because it allows the researchers to generalize the findings to a larger population.

Sampling Procedure

Participation in this study was purely voluntary where the respondents were randomly stratified according to their job sector. A census of the target population of 350 respondents was recruited from social media network groups of international students namely Facebook and WhatsApp. 30% of the targeted population was considered adequate as recommended by Mugenda & Mugenda (2003). In this study, the sample size was 105 respondents. Questions were adapted from the works of Gaspari, (2001); Burchardt, Mautner, & Holloway, (2020) and O'Brien, & Don, (2021). Questionnaires were designed, distributed and collected using Google Forms shared in social media groups (WhatsApp, Facebook and Telegram). Data analysis was done with the aid of SPSS. The sampling table is presented in the following table:

Descriptive Analysis

Demographic Summary

As shown in Table 1.0 on job sector, Customer care had the highest number of workers from the sample size, (21.9%) Followed by Telecommunications (13.3%) and manufacturing/factory jobs (10.5%). Education, retail stores, and online/remote jobs had the same number of workers each (9.5%) while supermarkets and healthcare had 6.7% and 4.8% respondents each. While the Transport and logistics, research, and farming sectors had a relatively lower number of respondents each (2.9%), the Boutique, marketing, and food industries had the lowest percentage of workers each (1.9%).

As shown in Table 1.1 on age, Language background, Team size and degree of workplace language barriers, the majority of the respondents were male (55.2%) followed by women (40.0%) while the other gender was the minority (4.8%) respectively. The findings indicate that men participate more as compared to females and other genders in part-time student jobs. The table indicates a relatively evenly distributed age brackets of respondents as follows: 18 - 25 years (21%), 26 - 35 years (38.1%), 36 - 45 years (29.5%), 45-55 years (10.5%) and 56-65 years (1%). This can be analyzed further to indicate the majority of student employees (88.6%) range from 18 years to 45 years of age. This may be considered the most productive and active age who are also capable of using machine translators at their workplace. The language background of the respondents was as follows; English 13.3%, German 9.5%, Russian 11.4%, Swahili 19%, Chinese 13.3%, Hindu 8.6%, Arabic 8.6%, Other African languages 2.9%, other Asian languages 5.7%, other European languages 5.7%, other indigenous languages 1.9%. The findings indicate a multi-lingual workforce coming from different cultural and ethnic backgrounds. From the table, a team of 1-5 members represented 27.6%, 6-10 (28.6%), 11-15 members (14.3%), 16-20 (12.4%), 21-30 (7.6%), and more than 30 members (9.5%). The results show more than half of the student workers are working in teams of 1-15 members as contrasted to a team of 21- 30 workers (17.1%). On the degree of workplace language barriers, 5 workers (4.8%) find the language barrier not a problem while 5 (4.8%) find it a slight barrier. 23 Workers (21.9%) experience language as a moderate barrier whereas 72 workers (68.6%) find the language barrier as an extreme challenge justifying the use of machine translators to overcome the problem.

Regression Analysis

According to the Model Summary results in Table 1.2, 26.6% of the variance in efficiency, 28.8% in collaboration, 17.2% in trust, and 26.2% in team training is explained by a unit use of MT. Based on the results in the Coefficients Table 1.3, MT contributed significantly to team efficiency ($t=6.109$, $p=0.000<0.001$), collaboration ($t=6.454$, $p=0.000<0.001$), trust ($t=4.747$, $p=0.000<0.001$) and team training ($t=6.454$, $p=0.000<0.001$). With a unit increase in the use of Machine translators, there is a 51.6% increase in teamwork efficiency. Further findings indicate a 53.7% increase in team collaboration for every unit increase in the use of MT. The results indicate that with a unit increase in the use of machine translators, there is a corresponding 42.4% increase in team trust among team members working in a multicultural environment. Based on the results a unit increase in the use of MT leads to a 51.9% corresponding boost in team training.

As shown in ANOVA results on table 1.4, a linear regression run to predict Team efficiency, collaboration, trust and training from MT displayed the following outcome; MT use significantly and positively predicted team efficiency, $F(1, 103) = 37.0317$, $p = 0.000 < 0.001$, team collaboration ($1,103$) 41.656 , $P = 0.000 < 0.001$, team trust, $F(1,103) = 22.539$, $p = 0.000 < 0.001$ and team training ($1,103$) 37.902 , $p = 0.000 < 0.001$. The Durbin-Watson significantly supports the results for the contribution of MT on team efficiency, collaboration, trust, and training at 1.662, 1.886, 1.828 and 1.617 respectively.

The hypothesis summary results in Table 1.5, show that all the null hypotheses were rejected. Research outcome confirmed that MT significantly and positively enhanced team efficiency, contributed to team collaboration, helped in trust building, and was instrumental in team training among international students working abroad hence boosting team performance.

Results, Discussion, and Conclusion

This study investigated the role of machine translators in team efficiency, collaboration, trust-building, and team training, which were selected as indicators of the study among international students working on part-time jobs in Hungary.

On the null hypothesis H01, stating that there is no significant effect of machine translators on team efficiency during work in a multilingual environment, findings show that MT significantly played a role in enhancing team efficiency among international student workers. H01 was therefore rejected as shown on Table 1.5. This finding supports the earlier conclusion by O'Brien, (2018) that MT saves time and enhances efficiency in team communication. Instead of relying on manual translation or waiting for a bilingual colleague to assist, team members can quickly translate documents, emails, or messages using machine translators. This efficiency allows teams to maintain productivity and meet deadlines, reinforcing trust among team members who rely on each other's timely contributions (O'Brien, (2018). According to Désilets, (2007), Machine translators enable employees who speak different languages to communicate and collaborate effectively. By providing an instant translation of text or speech, machine translators eliminate language barriers, facilitating smoother and more efficient teamwork. Employees can exchange ideas, share information, and work on projects without struggling with language obstacles. Machine translators aid in real-time interpretation during international meetings and conferences, making them more inclusive and efficient. Participants can speak in their native languages, and the translations are provided instantaneously, eliminating the need for traditional interpretation services. O'Brien, (2011) demonstrated that using machine translation for simultaneous interpretation significantly reduced meeting durations and improved overall efficiency. (Tripepi Winteringham, 2010)

Machine translators can speed up the workflow within a team by providing quick and accurate translations. Instead of waiting for human translators or struggling with language comprehension, team members can instantly understand documents, emails, and other written materials in their preferred language. This expedites decision-making processes, reduces delays, and enhances overall productivity (Ehrensberger-Dow, & Massey, 2014).

Machine translators provide real-time translation capabilities, enabling team members to communicate efficiently across language barriers. MT facilitates seamless and immediate communication, enhancing team collaboration. Whether it is during meetings, video conferences, or instant messaging, machine translation ensures that messages are understood in multiple languages, enabling effective collaboration (Kenny, (Ed.). 2022).

Machine translators promote trust among team members by eliminating language barriers through the provision of accurate translations of written or spoken content. This accuracy helps prevent misinterpretations and misunderstandings, ensuring that everyone receives clear and consistent messages. By enabling accurate communication, machine translators build trust among team members by minimizing the potential for errors or confusion (Maybury, 2018). Building trust among team members at the workplace requires Accurate Communication which is a great challenge among multi-lingual employees. Machine translation facilitates better communication and reduces the risks of miscommunication between these

employees through engagement in reliable translations. The findings from this study support earlier findings of research by Gao, Zhang, & Zhang (2016) who observed that accurate machine translations are key ingredients in building trust among multi-lingual employees by minimizing language-related misunderstandings and promoting effective communication.

On the null hypothesis that states that there is no effect of MT on team collaboration among multicultural teams, results from the study indicate that MT significantly contributed to team collaboration among international students working in Hungary and as shown in Table 1.5, H02 was rejected. This finding is supported by Karamanis, Luz, & Doherty, (2011) who postulate that machine translators actively support collaborative work if translators are given training on how to work best with machine translators in fostering organizational change. Findings from other scholars indicate that there is a need for dynamic and enhanced collaboration between translators and remote contributors. This can only be achieved through a comprehensive organizational alignment as per the organizational mission and vision at all stages of organizational growth (Buxton 2007). An effective collaborative approach is through the implementation of user-friendly and centered methods which are based on fidelity prototyping and storyboarding (Karamanis, Luz, & Doherty, 2011).

In diverse teams where members speak different languages, machine translators promote inclusivity by enabling all team members to actively participate in discussions and collaborations. By removing language barriers, team members can contribute their ideas and perspectives, leading to a more inclusive and equitable work environment. This inclusivity fosters trust as it demonstrates that every team member's input is valued and respected (Kurokawa, 2019).

The findings support earlier Liang et al. (2018) who concluded in their research outcome that machine translators are the best tools for creating and improving collaboration among multilingual teams working in organizations. This is further supported by Sajjad et al. (2020) who observed that machine translators are effective tools for breaking language barriers when working in cross-lingual teams.

O'Brien et al. (2014) while examining the critical role of machine translators in collaborative writing discovered that writers speaking different languages can collaborate using the machine translators, however, their study shows that the machine translators can be a source of errors and misunderstandings. In diverse teams where members speak different languages, machine translators allow individuals to communicate and collaborate more effectively. By providing real-time translation of written and spoken language, machine translators help team members overcome language barriers and engage in productive discussions. This fosters a sense of inclusion and equal participation, which contributes to building trust within the team (Wei, Weng, Hu, Xing, Yu, & Luo, 2020).

The findings of this study further support earlier research outcomes done by the European Commission (2019) which posited that seamless collaboration among members of multi-lingual groups is facilitated by the machine translators through the elimination of language barriers. It ensures effective communication and active participation among team members. This results in the effective sharing of knowledge and skills by members of international teams.

Machine translators are particularly valuable in supporting remote collaboration, where team members may be geographically dispersed. They enable smooth communication and collaboration, regardless of language differences, promoting efficient remote teamwork. According to a study by Bélanger et al. (2020), machine translation assists in overcoming language barriers in remote collaboration settings, facilitating effective team communication and collaboration. Machine translators contribute to inclusive collaboration by ensuring that all team members, regardless of their native languages, can actively participate and contribute to discussions and meetings. This fosters a sense of inclusivity, trust, and equal participation within the team. In their research on the impact of machine translation, O'Brien & Don (2021) discovered that machine translation promotes inclusive collaboration, enabling team members to work together efficiently.

Machine translators aid in document collaboration among team members who speak different languages. They can quickly translate documents, presentations, and other textual content, enabling team members to

collaborate on shared materials. This promotes efficient teamwork and ensures that all members can contribute effectively (Morita, & Ishida, 2009).

By promoting transparent collaboration machine translators contribute largely to building mutual trust among team members through active, seamless interactions, and exchange of insights as well as opinions among the team members (Cross, Ehrlich, Dawson, & Helderich, 2008). Modern machine translators are designed and built to respond to cultural sensitivity. These systems take into account cultural nuances and appropriately translate content, avoiding offensive or misleading translations. By respecting cultural diversity, machine translators contribute to an inclusive work environment, promoting trust and collaboration (Park, Jun, & Suh 2020).

As shown in Table 1.5, the null hypothesis stating that MT have no significant contribution to trust building among team members in a multilingual environment was rejected after research findings showed that MT play a significant and positive role in trust building among international students while studying and working abroad. This conclusion agrees with Huffaker, & Gouravajhala, (2022) who in their research advocate for use of MT to foster trust among team members. Their study advocates for the use of machine translators that prioritize data security and adhere to strict privacy for sensitive information. This way, the users of machine translators will fully utilize MT without fearing that their confidential information is not compromised during the translation process. A study conducted by Voigt et al. (2020) emphasizes the need for secure machine translation systems to build trust in the context of data privacy concerns. By enabling accurate communication, promoting transparency, considering cultural sensitivities, and ensuring data security, machine translators contribute to building trust among multi-lingual employees in the workplace.

Results on the contribution of MT in team training at the workplace show that machine translators significantly and positively play a role in team training when used in a diverse cultural environment. This outcome led to the rejection of the null hypothesis as indicated in Table 1.5. This observation supports the earlier conclusion that machine translators can facilitate effective communication between employees who speak different languages and who can effortlessly translate written or spoken content, enabling employees to understand training materials, instructions, and other essential information. (Burchardt et al., 2020).

Research indicates that machine translators are instrumental in facilitating cross-cultural training programs in organizations having multicultural diversity by helping employees understand cultural nuances, etiquette, and business practices of different regions, fostering effective intercultural communication. According to Yamanaka & Sasaki (2020), machine translation tools were beneficial for improving cross-cultural training in a Japanese workplace by aiding in understanding and bridging the gap between different cultures. Machine translators are useful in employee training during real-time engagements where trainers speak a different language from that of the audience. The tools immediate comprehension and interaction, enhancing the experience of the audience (Li et al., 2018).

Conclusion

While the use of Technology in Translation is inevitable, this study discovered that the users of MT did not care about the quality of MT output, but rather the ability to bridge the communication gap associated with language barrier in a work environment consisting of multilingual groups. This basic role of MT is however beneficial to users if the MT output contains minimal translation errors that may necessitate post-editing processes because the post-editing process of the MT output is as demanding as traditional translation as concluded by Sycz-Opoń, & Galuskina, (2017).

To maximize team performance in a multilingual work place, choice of MT to be used should be guided by community specific linguistic translation expectations. This should be anchored on customized multilingual translators that can function online and offline. According to Lagoudaki, (2008), MT should have language-specific add-ins that can make language translations more user-friendly. It is important to note that while machine translators can be valuable tools, they may not be perfect and can have limitations. They might struggle with idiomatic expressions, cultural nuances, or complex technical terminology.

Therefore, human trainers and interpreters should also be available to provide additional support and ensure accurate comprehension.

References

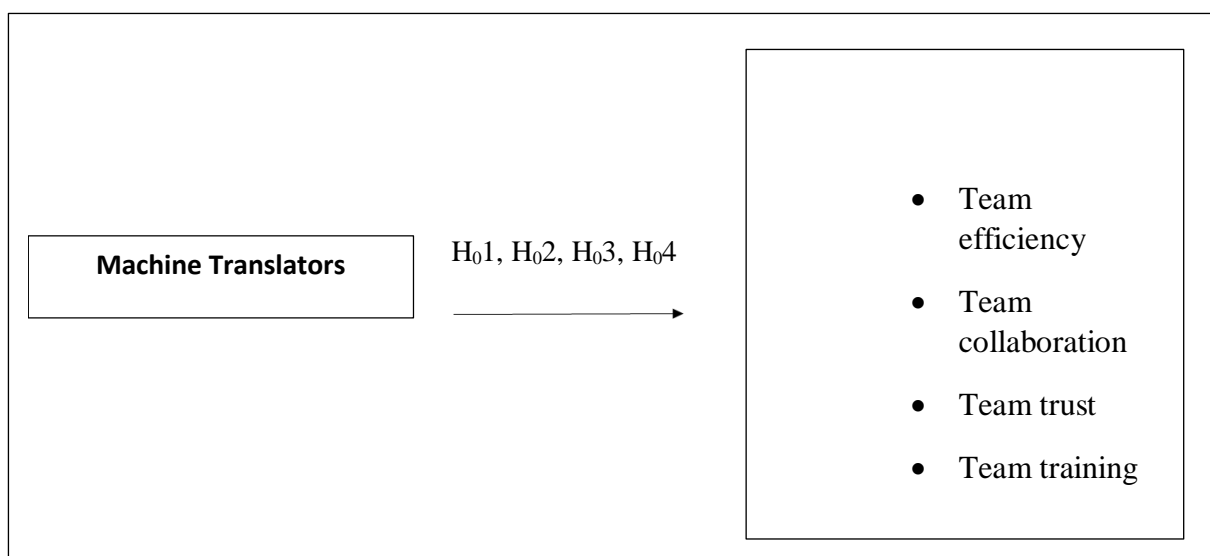
- Aiken, M. (2002). Multilingual communication in electronic meetings. *ACM SIGGROUP Bulletin*, 23(1), 18-19. doi:<https://doi.org/10.1145/945541.945543>
- Aiken, M. (2002b). Multilingual communication in electronic meetings. *ACM SIGGROUP Bulletin*, 23(1), 18-19. doi:<https://doi.org/10.1145/945541.945543>
- Alley, D. C. (2005). Using computer translation websites to further the objectives of the foreign language standards. *Languages and Language Learners*, Dimension, , 63-74. Retrieved from <https://files.eric.ed.gov/fulltext/ED503091.pdf#page=73>
- Alsalem, R. (2019). The effects of the use of google translate on translation students' learning outcomes. *AWEJ for Translation & Literary Studies*, Volume3, Number4, doi:<https://dx.doi.org/10.2139/ssrn.3483771>
- Aragón Lumeras, M., & Way, A. (2017). On the complementarity between human translators and machine translation. *Hermes*, (56), 21-42. doi:<http://dx.doi.org/10.7146/hjlc.v0i56.97200>
- Bisiada, M. (2021). Empirical studies in translation and discourse (volume 14) *Language Science Press*. doi:<https://doi.org/10.5281/zenodo.4450014>
- Blatt, A. (1998). Translation technology at the european commission: Description of a workflow. *Terminologie & Traduction*, , 38-43. Retrieved from <https://mt-archive.net/90/T&T-1998-Blatt-2.pdf>
- Brannen, M. Y., & Doz, Y. L. (2012). Corporate languages and strategic agility: Trapped in your jargon or lost in translation? *California Management Review*, 54(3), 77-97. doi:<https://doi.org/10.1525/cmr.2012.54.3.77>
- Brown, S. A., Dennis, A. R., & Venkatesh, V. (2010a). Predicting collaboration technology use: Integrating technology adoption and collaboration research. *Journal of Management Information Systems*, 27(2), 9-54.
- Brown, S. A., Dennis, A. R., & Venkatesh, V. (2010b). Predicting collaboration technology use: Integrating technology adoption and collaboration research. *Journal of Management Information Systems*, 27(2), 9-54. doi:<https://doi.org/10.2753/MIS0742-1222270201>
- Burton-Jones, A. (2014). What have we learned from the smart machine? *Information and Organization*, 24(2), 71-105. doi:<https://doi.org/10.1016/j.infoandorg.2014.03.001>
- Carl, M., Dragsted, B., Elming, J., Hardt, D., & Jakobsen, A. L. (2011). The process of post-editing: A pilot study. *Copenhagen Studies in Language*, 41(1), 131-142. Retrieved from <https://pure.au.dk/ws/files/96479802/s#page=131>
- Cho, W. I., Kim, J. W., Kim, S. M., & Kim, N. S. (2019). On measuring gender bias in translation of gender-neutral pronouns. *arXiv Preprint arXiv:1905.11684*, doi:<https://doi.org/10.48550/arXiv.1905.11684>
- Climent, S., Moré, J., Oliver, A., Salvatierra, M., Sánchez, I., Taulé, M., & Vallmanya, L. (2003). Bilingual newsgroups in catalonia: A challenge for machine translation. *Journal of Computer-Mediated Communication*, 9(1), JCMC919. doi:<https://doi.org/10.1111/j.1083-6101.2003.tb00360.x>
- Cohen, S. G., & Bailey, D. E. (1997). What makes teams work: Group effectiveness research from the shop floor to the executive suite. *Journal of Management*, 23(3), 239-290. doi:<https://doi.org/10.1177/014920639702300303>
- Craciunescu, O., Gerding-Salas, C., & Stringer-O'Keefe, S. (2004). Machine translation and computer-assisted translation. *Machine Translation and Computer-Assisted Translation*, Retrieved from <https://aclanthology.org/www.mt-archive.info/TranslationJ-2004-Craciunescu.pdf>
- Christian, L. M., Parsons, N. L., & Dillman, D. A. (2009). Designing scalar questions for web surveys. *Sociological Methods & Research*, 37(3), 393-425.
- Cross, R., Ehrlich, K., Dawson, R., & Helferich, J. (2008). Managing collaboration: Improving team effectiveness through a network perspective. *California Management Review*, 50(4), 74-98. doi:<https://doi.org/10.2307/41166457>
- De Bonis, G., & Agorni, M. (2022a). Collaboration in translation: From training to platforms and publishing. *Collaboration in Translation*, , 1-219. Retrieved from <http://digital.casalini.it/9791281068049>
- De Bonis, G., & Agorni, M. (2022b). Collaboration in translation: From training to platforms and publishing. *Collaboration in Translation*, , 1-219. Retrieved from <http://digital.casalini.it/9791281068049>
- De Vries, E., Schoonvelde, M., & Schumacher, G. (2018a). No longer lost in translation: Evidence that google translate works for comparative bag-of-words text applications. *Political Analysis*, 26(4), 417-430. doi:10.1017/pan.2018.26
- De Vries, E., Schoonvelde, M., & Schumacher, G. (2018b). No longer lost in translation: Evidence that google translate works for comparative bag-of-words text applications. *Political Analysis*, 26(4), 417-430.
- Dorr, B. J., Jordan, P. W., & Benoit, J. W. (1999). A survey of current paradigms in machine translation. *Advances in computers* (pp. 1-68) Elsevier. doi:[https://doi.org/10.1016/S0065-2458\(08\)60282-X](https://doi.org/10.1016/S0065-2458(08)60282-X)
- Ehrensberger-Dow, M., & Massey, G. (2014a). Translators and machines: Working together. *Man Vs.Machine*, 1, 199-207. Retrieved from https://d1wqtxts1xzle7.cloudfront.net/76166453/Translators_and_machines_working_together20211212-14866-1xv3tyr.pdf?1639305541=&response-content-disposition=inline%3B+filename%3DTranslators_and_machines_working_together.pdf&Expires=1711460212&Signature=GpjbvF8duBiAAbyuQ3sPq8YsRO6FWpqEFIFOoZqvqzAPU55TVme7u4VPYZDp2CF4ruQTxmLydHiTGUNW8uFdWN07050-VPOoxeWjgOyK2lwiyvUE1~SkcsYBRxgt95eWGvhagbsHCDV7XyUwcu4fs8AA7hf8v6p9ZInuEF8qI71tM7H9UNmck-4Ie62B32tv79j39U1iCuZfEecp3Qybd5Dl3zVeDd1-411AcevXTXua6j0rC~Du9A9jXdSWYQ0j2Kji-6aDFwc9LRWTYUIPUCdlYhrzc-

PKoOwbvfgqBcNHNAPkcKX1ZwShXXFsY21KjQiMb6h00rj141aFtg~SQ__&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA

- Ehrensberger-Dow, M., & Massey, G. (2014b). Translators and machines: Working together. *Man Vs.Machine*, 1, 199-207.
- Ellis, A. P., Bell, B. S., Ployhart, R. E., Hollenbeck, J. R., & Ilgen, D. R. (2005). An evaluation of generic teamwork skills training with action teams: Effects on cognitive and skill-based outcomes. *Personnel Psychology*, 58(3), 641-672. doi:<https://doi.org/10.1111/j.1744-6570.2005.00617.x>
- Gaspari, F. (2001). Teaching machine translation to trainee translators: A survey of their knowledge and opinions. Paper presented at the Workshop on Teaching Machine Translation,
- Harzing, A., Köster, K., & Magner, U. (2011). Babel in business: The language barrier and its solutions in the HQ-subsidiary relationship. *Journal of World Business*, 46(3), 279-287. doi:<https://doi.org/10.1016/j.jwb.2010.07.005>
- HUFFAKER, J. S., & GOURAVAJHALA, S. (2022). Shaping trust in machine translation suggestions through AI-assisted context building. Retrieved from https://public.websites.umich.edu/~jhuffak/CHI2022_Context_Building.pdf
- Hutchins, J. (2007). Machine translation: A concise history. *Computer Aided Translation: Theory and Practice*, 13(29-70), 11. Retrieved from <https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=af3c86b695176de562a93e9b69d8689e8ae80816>
- Hutchins, J. (2009a). Multiple uses of machine translation and computerised translation tools. *Machine Translation*, 13-20. Retrieved from <https://aclanthology.org/www.mt-archive.info/05/ISMTCL-2009-Hutchins.pdf>
- Hutchins, J. (2009b). Multiple uses of machine translation and computerised translation tools. *Machine Translation*, 13-20.
- Hutchins, W. J. (1995). Machine translation: A brief history. *Concise history of the language sciences* (pp. 431-445) Elsevier. doi:<https://doi.org/10.1016/B978-0-08-042580-1.50066-0>
- Hutchins, W. J. (.), & Somers, H. L. (1992). An introduction to machine translation Academic Press. Retrieved from <https://cir.nii.ac.jp/crid/1130282273013561088>
- Kirkman, B. L., & Rosen, B. (1999). Beyond self-management: Antecedents and consequences of team empowerment. *Academy of Management Journal*, 42(1), 58-74. doi:<https://doi.org/10.5465/256874>
- Koehn, P., & Senellart, J. (2010). Convergence of translation memory and statistical machine translation. Paper presented at the Proceedings of the Second Joint EM /CNGL Workshop: Bringing MT to the User: Research on Integrating MT in the Translation Industry, 21-32.
- Kozłowski, R., McCoy, K. F., & Vijay-Shanker, K. (2002a). Selectional restrictions in natural language sentence generation. Paper presented at the Proceedings of the 6th World Multiconference on Systemics, Cybernetics, and Informatics SCI, 2
- Kozłowski, R., McCoy, K. F., & Vijay-Shanker, K. (2002b). Selectional restrictions in natural language sentence generation. Paper presented at the Proceedings of the 6th World Multiconference on Systemics, Cybernetics, and Informatics SCI, 2
- Lagoudaki, E. (2008). The value of machine translation for the professional translator. Paper presented at the Proceedings of the 8th Conference of the Association for Machine Translation in the Americas: Student Research Workshop, 262-269.
- Maclea, D. (2006). Beyond english: Transnational corporations and the strategic management of language in a complex multilingual business environment. *Management Decision*, 44(10), 1377-1390. doi: <https://doi.org/10.1108/00251740610715704>
- Maruping, L. M., & Agarwal, R. (2004). Managing team interpersonal processes through technology: A task-technology fit perspective. *Journal of Applied Psychology*, 89(6), 975. doi:<https://psycnet.apa.org/doi/10.1037/0021-9010.89.6.975>
- Morita, D., & Ishida, T. (2009). Collaborative translation by monolinguals with machine translators. Paper presented at the Proceedings of the 14th International Conference on Intelligent User Interfaces, 361-366. doi:<https://doi.org/10.1145/1502650.1502701>
- Niño, A. (2008). Evaluating the use of machine translation post-editing in the foreign language class. *Computer Assisted Language Learning*, 21(1), 29-49. doi:<https://doi.org/10.1080/09588220701865482>
- Oren, T. G., & Petro, P. (2004). *Global currents: Media and technology now* Rutgers University Press.
- Osmanović, J. (2022). Kenny, dorothy, ed. 2022. machine translation for everyone: Empowering users in the age of artificial intelligence. translation and multilingual natural language processing 18. berlin: Language science press. Hieronymus: *Journal of Translation Studies and Terminology*, (9), 106-113. Retrieved from <https://hrcaj.srce.hr/file/432707>
- Pérez-González, L. (2014). Multimodality in translation and interpreting studies. *A Companion to Translation Studies*, 119-131. Retrieved from https://web.archive.org/web/20170922153352id_/https://www.escholar.manchester.ac.uk/api/datastream?publicationPid=uk-ac-man-scw:256648&datastreamId=FULL-TEXT.PDF
- Plitt, M., & Masselot, F. (2010). A productivity test of statistical machine translation post-editing in a typical localisation context. *Prague Bull.Math.Linguistics*, 93, 7-16. doi:10.2478/v10108-010-0010-x
- Prates, M. O., Avelar, P. H., & Lamb, L. C. (2020). Assessing gender bias in machine translation: A case study with google translate. *Neural Computing and Applications*, 32, 6363-6381. doi:<https://doi.org/10.1007/s00521-019-04144-6>
- Puchała-Ladzińska, K. (2016a). Machine translation: A threat or an opportunity for human translators?
- Puchała-Ladzińska, K. (2016b). Machine translation: A threat or an opportunity for human translators?
- Puchała-Ladzińska, K. (2016c). Machine translation: A threat or an opportunity for human translators? Retrieved from <http://repozytorium.ur.edu.pl/handle/item/2740>
- Rasmussen, C. E., & Williams, C. K. (2006). *Gaussian processes for machine learning*, ser. adaptive computation and machine learning. Cambridge, MA, UsA: MIT Press, 38, 715-719.

- Rescigno, A. A., Eva, V., Monti, J., & Andy, W. (2020). A case study of natural gender phenomena in translation-A comparison of google translate, bing microsoft translator and DeepL for english to italian, french and spanish. Paper presented at the CEUR Workshop Proceedings, 359-364.
- Salas, E., Cooke, N. J., & Rosen, M. A. (2008). On teams, teamwork, and team performance: Discoveries and developments. *Human Factors*, 50(3), 540-547. doi:<https://doi.org/10.1518/001872008X288457>
- Shigenobu, T. (2007). Evaluation and usability of back translation for intercultural communication. Paper presented at the Usability and Internationalization. Global and Local User Interfaces: Second International Conference on Usability and Internationalization, UI-HCII 2007, Held as Part of HCI International 2007, Beijing, China, July 22-27, 2007, Proceedings, Part II 2, 259-265. doi:<https://doi.org/10.1007/978-3->
- Skadiņa, I., Vasiļjevs, A., Pinnis, M., Bērziņš, A., Aranberri, N., Bogaert, J. V. d., . . . Hajič, J. (2023). Deep dive machine translation. *European language equality: A strategic agenda for digital language equality* (pp. 263-287) Springer. doi:https://doi.org/10.1007/978-3-031-28819-7_40
- Slocum, J. (1985). A survey of machine translation: Its history, current status and future prospects. *Computational Linguistics*, 11(1), 1-17. Retrieved from <https://aclanthology.org/J85-1001.pdf>
- Somers, H. L., & Lovel, H. J. Can AAC technology facilitate communication for patients with limited english? Retrieved from <https://personalpages.manchester.ac.uk/staff/harold.somers/ESRCfinal.pdf>
- Stapleton, P., & Kin, B. L. K. (2019). Assessing the accuracy and teachers' impressions of google translate: A study of primary L2 writers in hong kong. *English for Specific Purposes*, 56, 18-34. doi:<https://doi.org/10.1016/j.esp.2019.07.001>
- Sycz-Opoń, J., & Gałuska, K. (2017). Machine translation in the hands of trainee translators—an empirical study. *Studies in Logic, Grammar and Rhetoric*, 49(1), 195-212. doi:10.1515/slgr-2017-0012
- TSAI, Y. (2020). Collaborative translation in the digital age. *Research in Language*, 18(2) doi:10.18778/1731-7533.18.2.01
- Wang, H., Wu, H., He, Z., Huang, L., & Church, K. W. (2022). Progress in machine translation. *Engineering*, 18, 143-153. doi:<https://doi.org/10.1016/j.eng.2021.03.023>
- Watson, B. (2003). *Han feizi: Basic writings* Columbia University Press.
- Watters, P. A., & Patel, M. (1999). Semantic processing performance of internet machine translation systems. *Internet Research*, 9(2), 153-160.
- Way, A. (2013a). Emerging use-cases for machine translation. Paper presented at the Proceedings of Translating and the Computer 35,
- Way, A. (2013b). Emerging use-cases for machine translation. Paper presented at the Proceedings of Translating and the Computer 35,
- Wilss, W. (1996a). Knowledge and skills in translator behavior. *Knowledge and Skills in Translator Behavior*, , 1-273. doi:<https://doi.org/10.1075/btl.15>
- Wilss, W. (1996b). Knowledge and skills in translator behavior.
- Yamashita, N., & Ishida, T. (2006). Automatic prediction of misconceptions in multilingual computer-mediated communication. Paper presented at the Proceedings of the 11th International Conference on Intelligent User Interfaces, 62-69.
- Yang, Y., Wang, X., & Yuan, Q. (2021). Measuring the usability of machine translation in the classroom context. *Translation and Interpreting Studies*, 16(1), 101-123.
- Zervaki, T. (2002). Online translation services. Paper presented at the Proceedings of Translating and the Computer 24,

Figures



*Descriptive Analysis***Table 1.0: Population and Job Sector Sample Size**

Job Sector	Population	Sample Size(30%)	Percent	Cumulative Percent
Manufacturing/Factory	37	11	10.5	10.5
Telecommunications	46	14	13.3	23.8
Customer Care	77	23	21.9	45.7
Education	33	10	9.5	55.2
Retail Stores	33	10	9.5	64.8
Supermarkets	23	7	6.7	71.4
Boutique	7	2	1.9	73.3
Healthcare	17	5	4.8	78.1
Marketing	7	2	1.9	80.0
Transports and Logistics	10	3	2.9	82.9
Online/Remote Jobs	33	10	9.5	92.4
Research	10	3	2.9	95.2
Food Industry	7	2	1.9	97.1
Farming Sector	10	3	2.9	100.0
Total	350	105	100.0	

Source: Researchers (2024)

Table 1.1: Demographic Information

Gender of the respondents					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	58	55.2	55.2	55.2
	Female	42	40.0	40.0	95.2
	Other	5	4.8	4.8	100.0
	Total	105	100.0	100.0	
Age of respondents	18-25	22	21.0	21.0	21.0
	26-35	40	38.1	38.1	59.0
	36-45	31	29.5	29.5	88.6
	45-55	11	10.5	10.5	99.0
	56-65	1	1.0	1.0	100.0
	Total	105	100.0	100.0	
Language Background of the respondents	English	14	13.3	13.3	13.3
	German	10	9.5	9.5	22.9
	Russian	12	11.4	11.4	34.3
	Swahili	20	19.0	19.0	53.3
	Chinese	14	13.3	13.3	66.7
	Hindu	9	8.6	8.6	75.2
	Arabic	9	8.6	8.6	83.8
	Other African Language	3	2.9	2.9	86.7
	Other Asian Language	6	5.7	5.7	92.4
Other European Language	6	5.7	5.7	98.1	

	Other languages not on the list	2	1.9	1.9	100.0
	Total	105	100.0	100.0	
Team Size at the Workplace	1-5	29	27.6	27.6	27.6
	6-10	30	28.6	28.6	56.2
	11-15	15	14.3	14.3	70.5
	16-20	13	12.4	12.4	82.9
	21-30	8	7.6	7.6	90.5
	More than 30	10	9.5	9.5	100.0
	Total	105	100.0	100.0	
Degree of workplace Language barriers	Not a Barrier	5	4.8	4.8	4.8
	Somewhat of a barrier	5	4.8	4.8	9.5
	Moderate barrier	23	21.9	21.9	31.4
	Extreme barrier	72	68.6	68.6	100.0
	Total	105	100.0	100.0	

Source: Researchers (2024)

Regression Analysis

Table 1.2: Model Summary: Machine Translators and Team Performance

Model summary											
Dependent Variables	Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin - Watson
						R Square Change	F Change	df1	df2	Sig. F Change	
Team efficiency	1	.516	.266	.259	4.73063	.266	37.317	1	103	.000	1.662
Team collaboration	1	.537	.288	.281	2.16580	.288	41.656	1	103	.000	1.886
Team trust	1	.424	.180	.172	2.71625	.180	22.539	1	103	.000	1.828
Team training	1	.519	.269	.262	2.76800	.269	37.902	1	103	.000	1.617

Predictors: (Constant) Machine Translators

Source: Researchers (2024)

Table 1.3: Coefficients: Use of Machine Translators and Team Performance

Coefficients										
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations		
	B	Std. Error				Beta	Lower Bound	Upper Bound	Zero-order	Partial
(Constant)	14.484	2.507		5.778	.000	9.513	19.455			

Team efficiency	3.488	.571	.516	6.109	.000	2.356	4.621	.516	.516	.516
(Constant)	14.454	1.148		12.595	.000	12.178	16.730			
Team collaboration	1.687	.261	.537	6.454	.000	1.169	2.206	.537	.537	.537
(Constant)	15.199	1.439		10.560	.000	12.344	18.053			
Team trust	1.557	.328	.424	4.747	.000	.906	2.207	.424	.424	.424
(Constant)	17.544	1.467		11.963	.000	14.636	20.453			
Team training	2.057	.334	.519	6.156	.000	1.394	2.720	.519	.519	.519
(Constant)										

Predictors: (Constant) Machine Translators

Source: Researchers (2024)

Table 1.4: Analysis of Variance of Team Efficiency, Collaboration, Trust and Training.

ANOVA						
Model		Sum of Squares	df	Mean Square	F	Sig.
Team Efficiency	Regression	835.109	1	835.109	37.317	.000
	Residual	2305.024	103	22.379		
	Total	3140.133	104			
Team collaboration	Regression	195.394	1	195.394	41.656	.000
	Residual	483.139	103	4.691		
	Total	678.533	104			
Team trust	Regression	166.291	1	166.291	22.539	.000
	Residual	759.937	103	7.378		
	Total	926.229	104			
Team training	Regression	290.395	1	290.395	37.902	.000
	Residual	789.167	103	7.662		
	Total	1079.562	104			

a. Dependent Variables: Team Efficiency , Team collaboration , Team trust ,Team Training

b. Predictors: (Constant) Machine Translators

Source: Researchers (2024)

Table 1.5: Hypotheses Test Results

Null Hypothesis	Statistical Test	P-Value	Statistical Conclusion	Practical Conclusion
H₀1: There is no significant effect of machine translators on team efficiency during work	ANOVA	.000	.000 < 0.05	MT significantly played a role in enhancing team efficiency among

in a multilingual environment.				international student workers. H ₀ 1 is rejected.
H₀2: There is no effect of Machine Translators on team collaboration among multicultural teams.	ANOVA	.000	.000<0.05	MT significantly contributed to team collaboration among international students working in Hungary. H ₀ 2 is rejected.
H₀3: Machine Translators have no significant contribution to trust building among team members in a multilingual environment.	ANOVA	.000	.000<0.05	MT plays a significant role in trust building among international students while studying and working abroad. H ₀ 3 is rejected.
H₀4: Machine Translators play no significant role in team training for multilingual teams.	ANOVA	.000	.000<0.05	MT have a significant contribution during team training for international students working abroad. H ₀ 4 is rejected.

Source: Researchers (2024)