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EVALUATION OF TYPING SPEED, USER EXPERIENCE, AND COGNITIVE LOAD ACROSS KAZAKH, RUSSIAN, AND ENGLISH LANGUAGES AMONG KAZAKHSTANI USERS

This paper presents an experimental study on typing speed, typing accuracy, user experience and cognitive load of people when typing in Kazakh, Russian and English languages. Kazakhstan's multilingual environment creates unique challenges for digital communication requiring people to have advanced keyboarding skills in three languages. However, there is lack of research on how such multilingual trends affect the user experience, cognitive load and usability of Kazakh, Russian and English languages in the era of Artificial Intelligence (AI). In this work, we designed an experimental study involving 41 human participants taking typing speed tests in three languages, Kazakh, Russian and English. After completing the typing speed test, participants reflected on the experienced cognitive load for each of the three languages, as well as the tying habits and preferences. The evaluation of the typing speed was performed in words per minute (WPM) metric and typing accuracy was reflected on character error rate (CER) metric. We found that the difference in typing speed and accuracy for three languages was statistically significant, with typing speed for English being 32.53±8.31 WPM that is 1.41 times higher than typing speed for Kazakh 23.04±6.59 WPM and 1.12 times higher than typing speed for Russian 29.15±7.58 WPM. Typing accuracy CER metric showed that participants made more errors when typing in Kazakh than in Russian and English languages. CER for Kazakh equals 5.73±5.00 that is 1.09 times more than 5.24±5.27 CER for Russian and 1.78 times more than 3.22±3.59 CER for English. We also found statistically significant differences in experienced cognitive load by our participants in terms of physical demand, effort and frustration. In addition, the results showed the low usability of keyboard typing in Kazakh language using the Cyrillic alphabet among study participants in comparison to typing in English using the Latin alphabet keyboard layout and typing in Russian using the Cyrillic alphabet layout.

Key words: Keyboard Typing Speed, Keyboard Typing Accuracy, Cognitive Load, NASA Task Load Index, Large Language Models (LLMs), Artificial Intelligence (AI), Human-Computer Interaction (HCI).

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Қазақстандық пайдаланушылардың қазақ, орыс және ағылшын тілдерінде мәтін теру жылдамдығын, пайдаланушылық тәжірибесін және когнитивтік жүктемесін бағалау

Осы мақалада адамдардың қазақ, орыс және ағылшын тілдерінде мәтін теру жылдамдығы, теру дәлдігі, пайдаланушылық тәжірибесі мен когнитивтік жүктемесіне қатысты эксперименттік зерттеу ұсынылған. Қазақстанның көптілді ортасы цифрлық коммуникация үшін бірегей қиындықтар тудырып, адамдардан үш тілде мәтін терудің жоғары деңгейдегі дағдыларын меңгеруді талап етеді. Алайда, мұндай көптілді үрдістердің пайдаланушылық тәжірибеге, когнитивтік жүктемеге және қазақ, орыс пен ағылшын тілдерін пайдалану ыңғайлылығына жасанды интеллект (ЖИ) дәуірінде қалай әсер ететіні әлі белгісіз. Осы жұмыста біз 41 адамның қатысуымен эксперименттік зерттеу жүргіздік, онда қатысушылар қазақ, орыс және ағылшын тілдерінде мәтін теру жылдамдығына арналған тесттерден өтті. Тест аяқталғаннан кейін қатысушылар әр тілге қатысты сезінген когнитивтік жүктемесін бағалап, сондай-ақ мәтін теру бойынша өз әдеттері мен қалауларымен бөлісті. Мәтін теру жылдамдығы сөз/минут (WPM) көрсеткіші бойынша бағаланды, ал теру дәлдігі таңба қателерінің коэффициенті (CER) арқылы өлшенді. Біз үш тілдегі теру жылдамдығы мен дәлдігінің айырмашылығы статистикалық тұрғыдан маңызды екенін анықтадық: ағылшын тілінде теру жылдамдығы 32,53±8,31 WPM болып, қазақ

(23,04±6,59 WPM) 1,41 есе және орыс тіліндегіден (29,15±7,58 WPM) 1,12 есе жоғары болды. Мәтін теру дәлдігінің CER көрсеткіші қазақ тілінде қатысушылардың қателерді орыс және ағылшын тілдеріне қарағанда көбірек жібергенін көрсетті. Қазақ тілі үшін CER мәні 5,73±5,00 құрап, орыс тіліне қарағанда (5,24±5,27) 1,09 есе және ағылшын тіліне қарағанда (3,22±3,59) 1,78 есе жоғары болды. Біз сондай-ақ физикалық сұраныс, күш салу және фрустрация тұрғысынан біздің қатысушылардың сезінген когнитивтік жүктемесінде статистикалық маңызды айырмашылықтарды таптық. Бұдан бөлек, нәтижелер қазақ тілінде кириллица арқылы мәтін терудің зерттеу қатысушылары үшін ыңғайсыз болғанын көрсетті. Бұл ағылшын тілінде латын әліпбиінің пернетақта жаймасын қолдану және орыс тілінде кирилл әліпбиінің пернетақта жаймасын қолданумен салыстырғанда анық байқалды.

Түйін сөздер: мәтін теру жылдамдығы, мәтін теру дәлдігі, когнитивтік жүктеме, NASA жүктеме индексі, Үлкен Тілдік Модельдер (LLMs), Жасанды Интеллект (ЖИ), Адам-компьютер өзара әрекеттестігі (HCI).

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Оценка умений скорости набора текста, пользовательского опыта и когнитивной нагрузки на казахском, русском и английском языках среди казахстанских пользователей

В статье представлено экспериментальное исследование по оценке умений скорости набора текста, точности набора текста, пользовательского опыта и когнитивной нагрузки людей при наборе текста на казахском, русском и английском языках. Многоязычная среда Казахстана создает уникальные вызовы для цифровой коммуникации, требуя от людей владения продвинутыми навыками набора текста на трех языках. Пока неясно, как такие многоязычные тенденции влияют на пользовательский опыт, когнитивную нагрузку и удобство использования казахского, русского и английского языков в эпоху искусственного интеллекта (ИИ). Было проведено экспериментальное исследование с участием 41 человека, которые проходили тесты на скорость набора текста на трех языках: казахском, русском и английском. После завершения теста участники оценивали испытываемую когнитивную нагрузку для каждого из трех языков, а также делились своими привычками и предпочтениями при наборе текста. Оценка скорости набора текста проводилась в показателе слов в минуту (WPM), а точность набора текста отражалась через показатель коэффициента ошибок символов (CER). Мы обнаружили, что разница в скорости и точности набора текста на трех языках была статистически значимой: скорость набора на английском языке составила 32,53±8,31 WPM, что в 1,41 раза выше, чем на казахском (23,04±6,59 WPM), и в 1,12 раза выше, чем на русском (29,15±7,58 WPM). Показатель точности набора текста CER показал, что участники допустили больше ошибок при наборе текста на казахском языке по сравнению с русским и английским. Значение CER для казахского составило 5,73±5,00, что в 1,09 раза больше, чем для русского (5,24±5,27), и в 1,78 раза больше, чем для английского (3,22±3,59). Мы также выявили статистически значимые различия в испытываемой участниками когнитивной нагрузке с точки зрения физической нагрузки, усилий и уровня фрустрации. Кроме того, результаты показали неудобство набора текста на казахском языке с использованием кириллицы среди участников исследования по сравнению с набором текста на английском языке с использованием раскладки клавиатуры латинского алфавита и набором текста на русском языке с использованием кириллической раскладки.

Ключевые слова: Скорость Набора Текста, Точность набора текста, Когнитивная Нагрузка, Индекс Нагрузки NASA, Большие Языковые Модели (LLMs), Искусственный Интеллект (ИИ), Человеко-компьютерное взаимодействие (HCI).

Introduction

Kazakh belongs to the Kipchak branch of the Turkic language family. There are more than 20 million ethnic Kazakhs living worldwide with most living in Kazakhstan, China, Mongolia and South Russia (Kadirova, 2018). Kazakh is the state language of Kazakhstan, while most Kazakhs are bilingual (i.e., speak both Kazakh and Russian) due to the political, economic and social background of the country. Kazakhstan experienced an alphabet change a few times (Kadirova, 2018). From the 15th and to the 19th century, Kazakh Khanate used a modified Arabic script. Then it became part of the Soviet Union as the Kazakh Autonomous Socialist Soviet Republic (Kazakh ASSR). From 1929 to 1940, Ka-

zakh ASSR used the Latin script and switched to the Cyrillic script in 1940. Kazakhstan declared independence on 16 December 1991 and Kazakhstani authorities started the policy of moving back to the Latin script in 2006 (Mukhamedova, 2015).

Kazakhstan is a bilingual country with 80.1% of the population speaking in Kazakh and 83.7% speaking in Russian (National Census, 2021**)**. According to the National Census (2021), the percentage of the population of the country speaking in English is 35% and 2.7% speak other languages. Reforms in the 2000s introduced the concept of trilingualism to the country, where Kazakh is the state language, Russian is a language of interethnic communications and English is the language integrating Kazakhstan to the global economy. Since Kazakhstan's independence, Kazakh, Russian and English have been taught at schools as independent subjects. Trilingual educational policy involved teaching of non-language courses at schools in three languages (Karabassova, 2020). The implications of the trilingual education policy on strengthening the national identity and enhancing the global competitiveness of the nation are discussed by Sarmurzin et al. (2024). To explore the importance of trilingual education in higher education of Kazakhstan, Tussupbekova et al. (2018) designed an interview with 63 university students. The authors found that students prefer to know three languages equally. The students claim this can help them to continue education abroad, be competitive in the global multilingual environment and successfully pass the international exams (Tussupbekova, 2018).

Currently, advances in technology are transforming the daily life of people all over the world including those living in Kazakhstan. For example, increased computing power, availability of large amounts of linguistic data, capable machine learning algorithms, and deeper understanding of human language structure led to technological breakthroughs in computational linguistics (Hirschberg, 2015). Natural language processing (NLP) explores how computational technologies can be used for learning, understanding and generating human language content (Chowdhary, 2020). Over recent years, large language models (LLMs) such as generative pre-trained transformers (GPTs) made significant progress and impact in NLP and artificial intelligence (AI) (Zhao, 2023). Many nations worldwide motivated by economic growth and technological advancements introduced by country-specific LLMs are developing their own LLMs, including China, United States, Korea, European Union, India and United Arab Emirates. Kazakhstan also developed its own LLM at the Institute of Smart Systems and Artificial Intelligence. Recent research and applications of LLMs in education are overviewed by Kasneci et al. (2023).

There are a set of competencies and literacies needed for students and teachers to understand and use LLMs (Lehmann, 2024). For example, when using GitHub Copilot, users first type the comments describing what needs to be done, then LLM generates the code (Dakhel, 2023). In general, users interact with LLMs by writing the prompts composed of typed instructions or comments. Better keyboarding skills such as keyboarding speed, accuracy and technique can benefit the user interaction with LLMs that are becoming an important part of people's activity at school and at work.

According to Donica et al. (2019), keyboarding speed and accuracy are common measures used to evaluate the students' keyboarding skills at school. In their study with the elementary schools in the United States, authors overviewed how keyboarding instructions help to improve students' keyboarding speed and accuracy. Many professionals emphasize the importance of developing keyboarding skills as early as possible. According to Connelly et al. (2007), when a child is not fluent in keyboarding, then they spend more time on key searching than on composing the text. According to Feng et al. (2019), advanced keyboarding skills help students get better grades and achieve higher academic outcomes. Further research by Dell'Acqua et al. (2023) indicated better productivity at work thanks to higher keyboarding speed. Brynjolfsson et al. (2023) in their work overviewed many studies exploring the positive impact of information technologies (IT) on the workers productivity among firms in the customer service sector. Authors also present many examples of positive implications of generative AI on the workers productivity in the economy highly integrated with AI technologies within industry, writing, marketing, etc. LLMs bringing an unprecedented boost in workers productivity in various sectors of the economy is presented by Alto et al. (2023). Keyboarding is emerging as an important skill not only for economic growth, education outcomes and interaction with LLMs, but also directly relates to the global competitiveness of the country in the global AI landscape.

There are many works exploring the keyboarding skills of individuals knowing different languages in other bilingual countries (Bi, 2012; Barkaoui, 2014). In the literature, there is a lack of research ex-

ploring the keyboarding skills including keyboarding speed, accuracy and technique in the trilingual environment of Kazakhstan. In addition, research concerning local people's experience of keyboarding in three languages (i.e., Kazakh, Russian and English) in terms of usability and cognitive load has not yet been explored. In this paper, we designed a user study investigating measures such as keyboarding speed and accuracy in the scenario of typing predefined text in three languages. We also overview the qualitative and subjective metrics such as people's experience and cognitive load evaluation. The keyboarding study was performed in the academic environment of Nazarbayev University (Astana, Kazakhstan). In the study, we also recorded the language preferences of participants when keyboarding and to what extent it is convenient for them to type using the Kazakh Cyrillic alphabet, Russian Cyrillic alphabet and English Latin alphabet. We found that typing in Kazakh with the current Cyrillic alphabet layout on the computer keyboard requires more effort during typing in comparison to Russian and English.

Literature review

Digital literacy has become an essential skill over the world's extensive digitization (Yesilyurt, 2023). According to Martin et al. (2008), digital literacy includes many components such as computer literacy, information literacy, technological literacy, and digital competence. The authors emphasize the diversity of concepts forming the term of digital literacy and corresponding applications. According to Siok et al. (2018), modern education is becoming highly dependent on computer-mediated communication, mobile and interactive technologies. Nikou et al. (2021) present an extensive study revealing the interdependence between people's literacy skills and digital technologies among 249 Finnish universities. Feng et al. (2019) refer to digital literacy including digital writing or keyboarding as an important component of computer-mediated communication. Morphy et al. (2012) discuss the concept of computer-assisted writing in which writing is supported by word processing programs in computers including spelling and grammar checkers, text formatting software, tools for basic text-to-speech and speech-to-text conversion, and planning and outlining software.

Feng et al. (2019) in their work overview the effects of computer-assisted writing on learning attitudes, interactions, instructional strategies and written outcomes of students. Morphy et al. (2012) discuss the positive implications of word processing tools on students' general writing that included both handwriting and keyboarding from elementary schools to college education (Morphy, 2012). According to Freeman et al. (2005), keyboarding becomes an alternative to handwriting, when the keyboarding speed is as fast as handwriting speed. Many studies reveal that better keyboarding skills of students can result in better writing, as they spend less cognitive activity on the process of writing and have more capacity for composing. Stevenson et al. (2014) present three stages in learning keyboarding skills including the keyboarding speed and accuracy. Specifically, in the first stage, the user relies on vision and cognitive skills to identify and locate the letters on the keyboard. In the second stage, the user learns the keys and develops the muscle memory for selecting the keys. During the third stage, users type based on the learned muscle memory and use less vision and cognition for locating the keys. In this stage, keyboarding speed increases and keyboarding becomes more automated. This helps people focus more on text composing rather than on the keyboarding process. Moreover, in times when AI is being extensively integrated into people's everyday life, advanced keyboarding skills can help people during interaction with LLMs. There are two ways people can communicate with LLMs: 1) typing the prompts and 2) having speech-based conversations with voice assistants (Lehmann, 2024).

Speech-based conversations with computer systems have become a possibility thanks to advances in AI including LLMs and NLP technologies. There are a wide range of consumer products available in the market, such as Apple's Siri, Microsoft's Cortana, Google Now and Skype Translator (Hirschberg, 2015). According to Magueresse et al. (2020), there are 7,000 languages in the world, while most of the NLP and AI research is focused on a narrow set of around 20 languages that are considered as high resource ones such as English, Chinese, and Spanish. At the same time, most languages are left understudied, including Kazakh. They are often referred to as low-resource languages, meaning they are low density, less resourced, less computerized, and less commonly taught (Cieri, 2016). For example, there are works in the literature exploring the effectiveness of pronunciation-based input systems for English and Chinese languages (Ruan, 2016). However, there is a lack of literature exploring speech-based technologies and applications for low-resourced languages including Kazakh. Local LLMs, speech-based technologies and AI tools are essential for low-resource

language-based digital writing, communications and human-computer interaction (HCI) saving the language from the potential future extinction (Besacier, 2014). Until effective trilingual speech recognition systems become available and are seamlessly integrated into LLM interfaces, keyboarding remains the only alternative in Kazakhstan.

Many works in the literature explore the virtual keyboard layout in virtual/augmented reality (McGill, 2022), dynamic personalized keyboard layouts on touchscreens (Findlater, 2012) and applications of word-gesture keyboards in HCI (Adhikary, 2021; Zhai, 2012). There are also works exploring the potential implications of switching from handwriting to digital writing from perspectives of embodied cognition (Mangen, 2016). In addition, many studies overview the role of digital writing, keyboarding (Donica, 2018) and speech-based input technologies (Clark, 2019) addressing issues of accessibility and inclusion in education and HCI.

The study by Dhakal et al. (2018) reported the average word per minute (WPM) metric for keyboarding speed for English as 51.56 with SD = 20.2 among 168,000 participants from the United States (US) aged between 11-30 years with an average age of 24.5. Barkaoui (2014) designed a study with participation of 97 university students of Canada taking the TOEFL-IBT test. The first language of participants was mostly Chinese, Spanish, Farsi, and Korean. According to the results, typing speed of students with low English language proficiency was 23.94 WPM (SD = 4.05) among students with low keyboarding skills and 44.78 WPM (SD=4.78) among students with high keyboarding skills. Typing speed recordings of students with high English language proficiency was 28.56 WPM (SD=3.93) for those having low keyboarding skills and 53.30 WPM (SD=8.23) for students with high keyboarding skills. There are also works exploring the typing speed on mobile devices. For example, Palin et al. (2019) reported an average mobile typing speed in English as 36.17 WPM with SD = 13.22 among 37,370 US participants.

Goals and Methods

Participants

Our study involved 41 participants from the community of Nazarbayev University (NU), a research university in Astana, Kazakhstan. Participants were individuals between 20-40 years old who were undergraduate and graduate students, researchers, faculty, and staff members. The average age was 26.49 years old (SD=5.36) among 19 female and 22 male participants. Enrolled participants were randomly divided into three groups to take the typing test in Kazakh, Russian and English languages in three different orders. All participants reported that they type on keyboards on a daily basis for more than 2 hours on average. Desktop typing involved a QWERTY layout keyboard with Kazakh, Russian and English alphabets (see Figure 1 c).

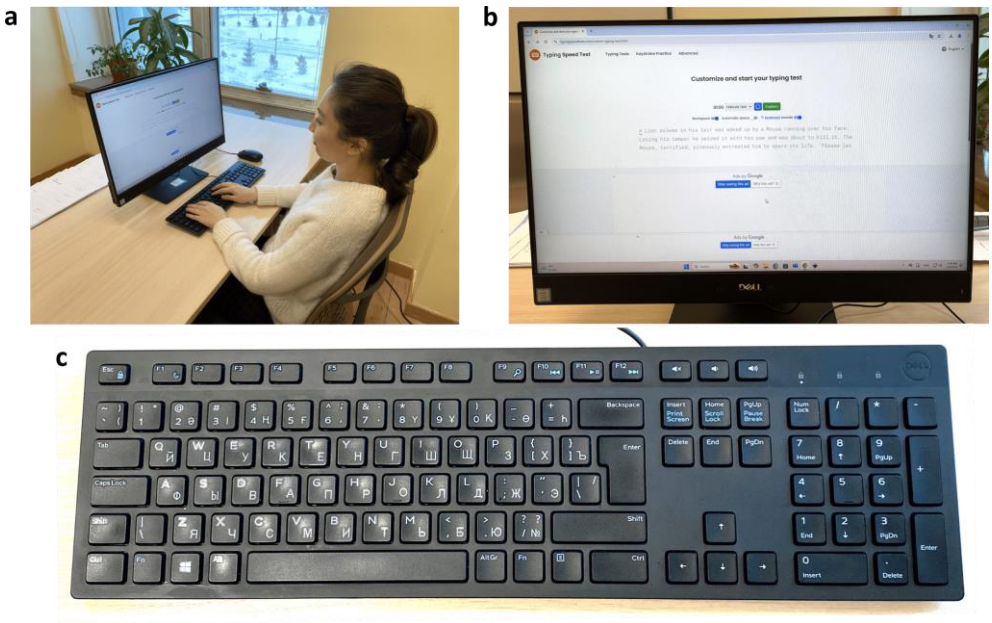

Figure 1 – A picture of the setup (a) with a close shot of the screen (b) and the keyboard (c)

Procedure

Our methodology follows a similar procedure as in other desktop typing studies (Dhakal, 2018; Barkaoui, 2014). Participants were asked to complete a set of 1-minute typing tests on an online typing platform (Typing speed tests, 2024), see Figure 1 (a-b). On the platform, one can upload custom texts, set a time limit, and start typing the shown text. During the typing test, participants retype the shown text as fast as possible considering capital letters and various punctuation marks (see Figure 2 a-c). Once time finishes, participants receive a report with calculated typing speed in words per minute (WPM), total number of typed symbols, number of correctly typed symbols, missed symbols and number of backspaces.

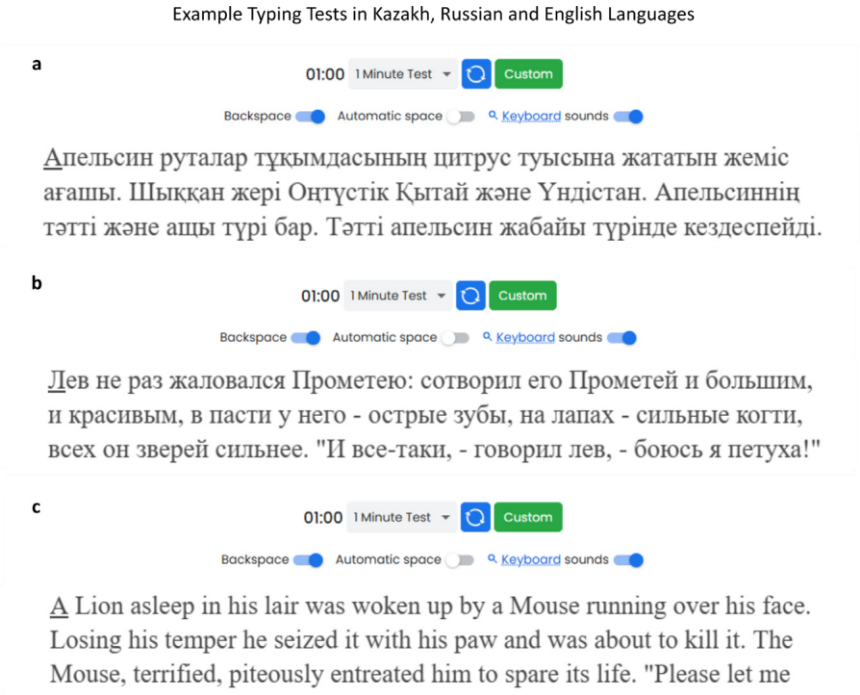

Figure 2 – Example typing tests in Kazakh (a), Russian (b), and English (c) languages

Three Kazakh texts with average 90 words, three Russian texts with average 125 words, and three English texts with average 158 words were selected from the pool of texts offered on the online typing platform (Typing test, 2024). This ensured that the participants with all levels of typing skills will have enough text to type during the typing test. The test duration was set to 1 minute. The popular study on keyboarding speed and accuracy used 200-word English passages for the 2-minute typing test (Barkaoui, 2014).

At the beginning, we asked participants to read the instructions for the user study and give their consent for the data collection. Prior to the study, we received approval for human subject research by the Nazarbayev University Institutional Research Ethics Committee (IREC). After participants agreed to take part in the study and signed the informed consent, we randomly assigned them to three groups with 13 people in each group. The first group of participants completed a 1-minute typing test in English three times (see Figure 3). Then they filled out the NASA Task Load Index (NASA-TLX) questionnaire reflecting the experienced cognitive load. NASA-TLX is a popular post-task method for subjective evaluation of the cognitive load. After a short break, participants proceeded to the similar 1-minute typing test in Kazakh language three times, followed by the NASA-TLX questionnaire and break. Then, after a 3-minute break, participants moved to the typing test in Russian lasting for 1-minute three times and filled the corresponding NASA-TLX questionnaire. At the end of the study, participants took one more questionnaire asking for their age, gender, educational level, language proficiency, work occupation, typing habits and preferences (Tables with this in-

formation are given in Appendix A). Participants in the second and third groups followed the same data collection procedure but in different language orders (see Figure 3). Specifically, the second group of participants first typed in Kazakh, then in Russian and English. The third group completed the typing tests first in Russian, then in English and Kazakh (Figure 3).

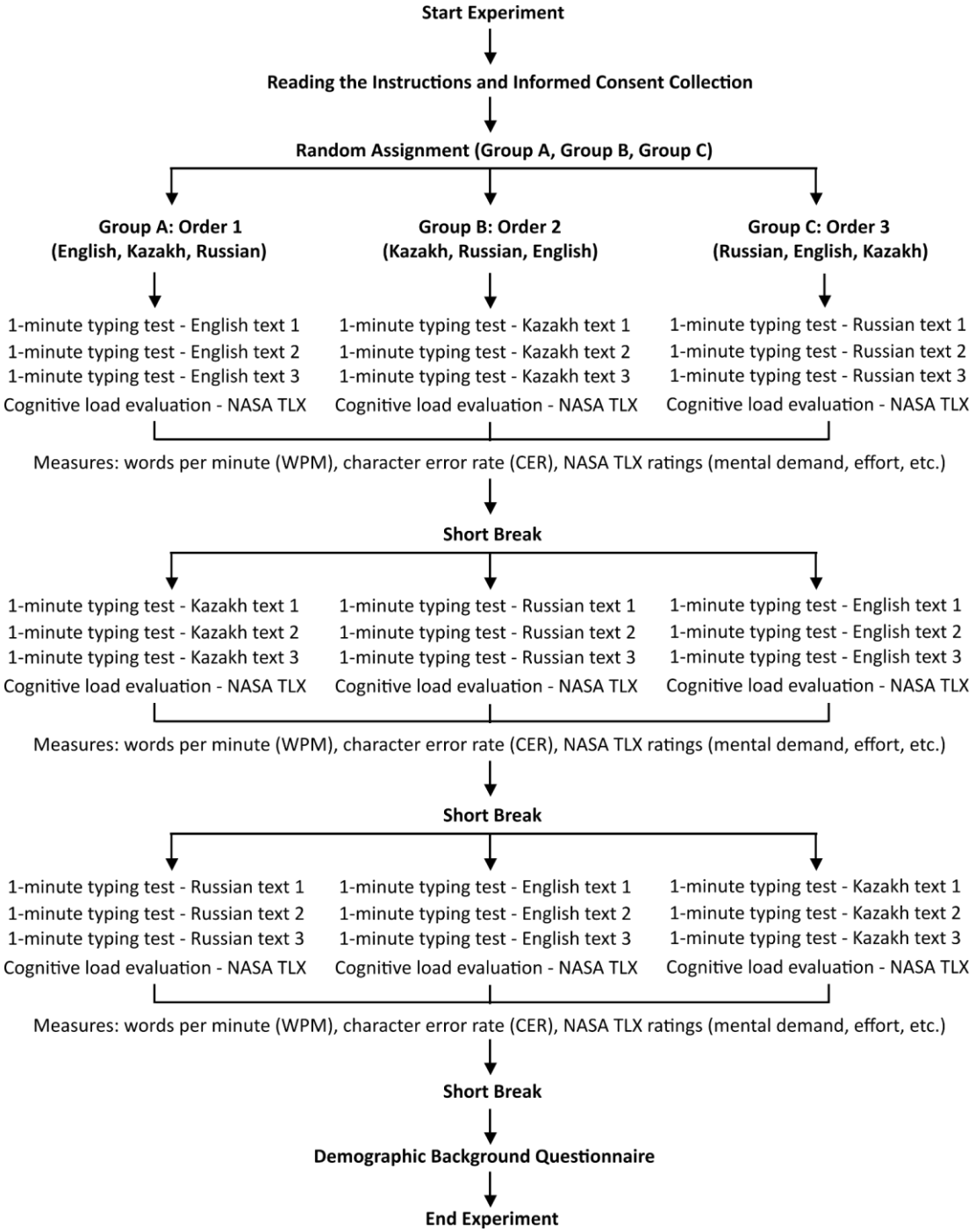

Figure 3 – Flowchart showing the experimental procedure for the three groups

Measures

Keyboarding speed was measured in WPM and reported in online typing software. Accuracy measures have several calculating techniques. In our study we used character error rate (CER) metric to measure participants' keyboarding accuracy. CER is the ratio of incorrectly typed symbols by total number of entered symbols. It is presented in percentage. For the evaluation of the participants' cognitive load, we have used the Raw NASA task load index (NASA-RTLX) (NASA-TLX, 2024) questionnaire. In NASA-RTLX, cognitive load is evaluated across six dimensions including mental demand, physical demand, temporal demand, performance, effort, and frustration. On the questionnaire, participants can rate the experienced demand or effort on the scale from 0 to 20, while the calculated value of the cognitive load ranges between 0 and 100. The usability of desktop typing on three alphabetic layouts (i.e., Kazakh, Russian and English) was studied on the custom questionnaire. In addition to the demographics data such as user age, gender and native language, the questionnaire also explored convenience of typing in three languages, daily typing habits of participants and preferences.

Data analysis

For the data analysis we used measures of descriptive statistics such as mean (M) and standard deviation (SD). The normality of the data was analyzed using the Shapiro-Wilk test (Hanusz, 2016). For the analysis of gender and age distribution across three groups we used one-way ANOVA (ANalysis Of VAriance) with post-hoc Tukey HSD (Honestly Significant Difference) test (Ross, 2017; Abdi, 2010). One-way ANOVA with Tukey HSD test was also applied for the analysis of the typing speed calculated in WPM, typing accuracy measured in CER metric and cognitive load ratings evaluated through NASA-RTLX in each of the three typing procedures using Kazakh, Russian and English languages.

Results and discussion

Statistical analysis of the age and gender of participants randomly distributed across three groups revealed no significant difference between any group pairs (i.e., Group A, Group B and Group C). Age analysis with one-way ANOVA test using F distribution, right tailored, showed F (2, 38) = 0.77, p = 0.47. The same test applied for the typing speed analysis in WPM across three languages (i.e., Kazakh, Russian and English) indicated that the difference is statistically significant [one-way ANOVA data F (2, 120) = 16.73, $p < 0.001$]. Similarly, statistical analysis of the typing accuracy measured in CER for three languages reported that differences between these cases are significant [one-way ANOVA data F (2, 120) = 3.31, p = 0.04]. The results of participants' keyboard typing speed and accuracy on three alphabetic layouts, Kazakh, Russian and English are shown in Figure 4. The typing speed and accuracy results are shown for each of the three groups of participants completing the typing test in different orders and the overall results for all participants in total. According to Figure 4a, the typing speed was the highest when participants were typing using the English keyboard layout with 32.53 ± 9.31 WPM, then in Russian with 29.15 ± 7.58 WPM and Kazakh with 23.04 ± 6.59 WPM. As shown in Figure 4b, typing accuracy metric, i.e., the character error rate (CER), was lowest for the English language layout with 3.22 ± 3.59 CER, then in Russian with 5.24 ± 5.27 CER, and highest in Kazakh with 5.73 ± 5 CER.

Participants' cognitive load when typing in three languages was explored using the Raw NASA-TLX subjective cognitive load evaluation method. Corresponding results are given in Figure 5. Mental demand, Effort, Frustration and Physical demand ratings as shown in Figure 5 a-b indicate that participants experienced much less load when typing in English, in comparison to typing in Kazakh and Russian. Specifically, mental demand ratings for the Kazakh, Russian and English languages are 39.63 ± 30.57, 35.73 ± 28.19 and 26.34 ± 22.94. Similarly, the rating of the effort is 55.37 ± 21.52, 45.37 ± 22.9 and 37.56 ± 24 for Kazakh, Russian and English languages. Ratings of the frustration and physical demand differ among three languages, showing 34.39 ± 27.71 and 40.49 ± 31.7 for Kazakh; 32.2 ± 25.76 and 33.41 ± 27.12 for Russian; and 20.98 ± 15.78 and 24.63 ± 19.38 for English. On the other hand, temporal demand ratings are almost the same among three languages, 54.39 ± 27.6 for Kazakh, 53.54 ± 26.18 for Russian, and 52.07 ± 25.86 for English. Performance ratings also indicate similar results among three languages, showing the highest performance for the English language with the value 56.95 ± 24.36, then the Kazakh and Russian languages with the values of 53.41 ± 25.33 and 52.56 ± 21.13. Statistical analysis applied on the cognitive load ratings reported by NASA-RTLX for three languages (i.e., Kazakh, Russian and English) revealed that the dif-

ference is not statistically significant for the ratings of the mental demand [one-way ANOVA data $F(2, 120) = 2.55$, $p = 0.083$], temporal demand [one-way ANOVA data $F(2, 120) = 0.08$, $p = 0.92$], and performance [one-way ANOVA data $F(2, 120) = 0.397$, $p = 0.67$]. On the other hand, the difference is statistically significant for the reported values of the effort [one-way ANOVA data $F(2, 120) = 6.2$, $p = 0.003$], physical demand [one-way ANOVA data $F(2, 120) = 3.67$, $p = 0.028$], and frustration [one-way ANOVA data $F(2, 120) = 3.8$, $p = 0.025$].

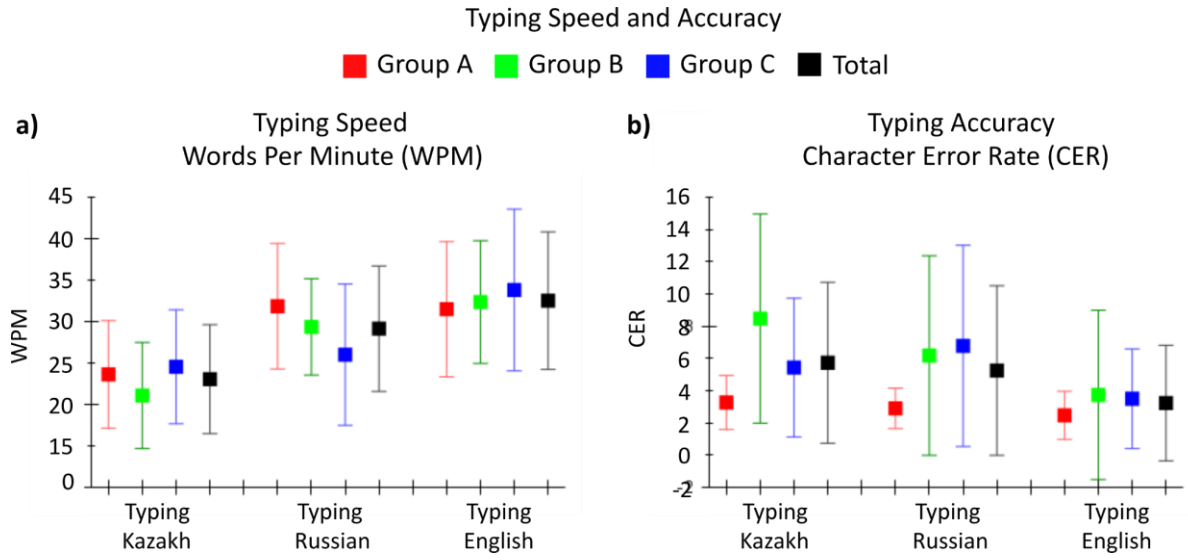

Figure 4 – Typing speed in WPM metric (a) and typing accuracy in character error rate (CER) (b) when typing in Kazakh, Russian and English languages

The results of the demographic survey questionnaire taken by participants at the end of the experimental study are given in Figure 6. According to results (see Fig. 6 b and d), 4.88% of our participants were undergraduate students and 6.59% pursued graduate studies. Among those who were involved in the offline work, 21.95% had a bachelor's degree, 34.15% and 2.44% had the highest master's and PhD degrees, correspondingly. 41.46% of participants indicated Kazakh as a native language, 48.78% of participants chose Russian as native language and 2.44% of participants selected English as their native language. 39.02% of participants reported that they are fluent in English, 48.78% indicated their English language skills as advanced, 9.76% as upper intermediate and none of the participants had the elementary level in English. Similarly, 41.46 % of participants indicated that they are fluent in Russian, 9.76 % rated their Russian language knowledge as advanced, and none of the participants chose intermediate and elementary levels for the Russian language. On the other hand, 14.63 % of participants rated their Kazakh language skills as fluent, 14.63 indicated their Kazakh knowledge as advanced, 17.07% and 12.20% of participants selected intermediate and elementary levels in Kazakh language.

As shown in Figure 6a, 85.37% of the participants rated keyboard typing using the English alphabet layout as being "somehow comfortable". That is 1.94 and 3.5 times higher than the same rating for the Russian and Kazakh languages. Specifically, 43.9% and 24.39% of participants rated typing in Russian and Kazakh alphabet layouts as being "somehow comfortable". On the other hand, the ratings of the "somehow not comfortable" and "not comfortable at all" are the highest for the Kazakh language. This way, 43.9% of the participants rated typing in Kazakh as being "somehow not comfortable". The same rating for the Russian and English languages are 12.2% and 17.7% respectively. "Not comfortable at all" rating for Kazakh language is 12.2%, 4.88% is for Russian and none of the participants selected "not comfortable at all" rating for English. 19.51% of participants chose "neural" when assessing typing in Kazakh, 39.02% selected "neutral" for Russian and 9.76% selected "neutral" rating when typing in English.

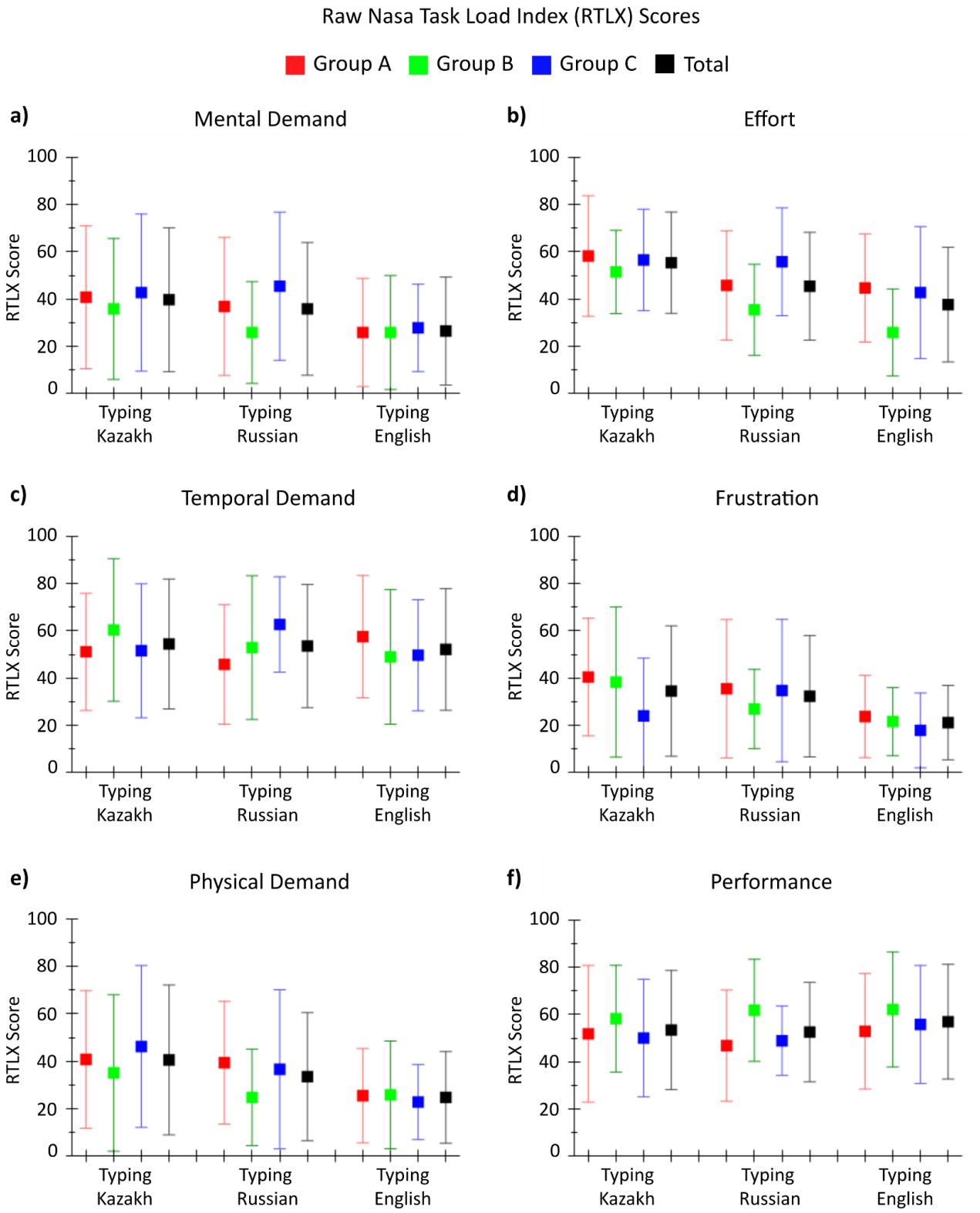

Figure 5 – Raw Nasa Task Load Index (RTLX) ratings when typing in Kazakh, Russian and English languages: a) mental demand, b) effort, c) temporal demand, d) frustration, e) physical demand, and f) performance

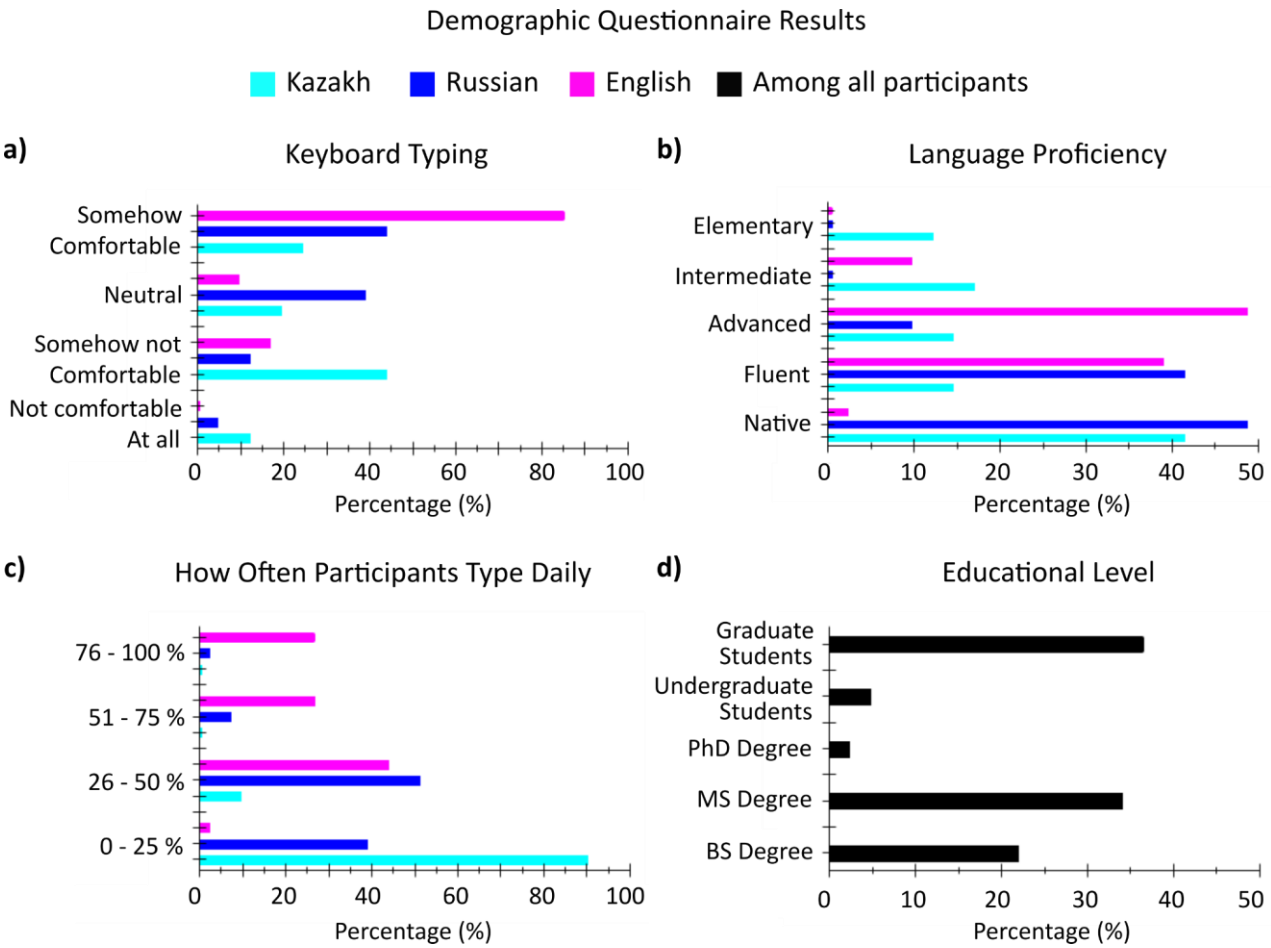

Figure 6 – Demographic questionnaire results expressed in percentage:
a) keyboard typing habits of 41 participants, b) language proficiency in three languages,
c) how often participants type in each of the three languages during the day, and d) educational level of participants

Figure 6c shows how often participants type in each of the three languages in their daily routine. 90.24% of participants use Kazakh language from 0 to 25 % of the time. 51.22% of the participants type in Russian from 26 to 50 %, 43.9% type in English 26-50 % of the time, and only 9.76% type in Kazakh 26-50%. Interestingly, 26.83% of participants type in English 51 -75% of the time and the same number of participants type in English 76-100% of the time. 7.32% and 2.44% of participants indicated that they type in Russian 51-75% and 76-100% of the time in their daily typing routine. None of the participants type in Kazakh more than 51-75% and 76-100% of the time.

The overall demographic survey questionnaire results show that there is relatively low rating of the typing routine in Kazakh language and relatively low rating of convenience of keyboard typing in Kazakh. The usability of Kazakh language-based digital communication among young individuals in the era of AI can further decrease unless we find out the alternative way of digital communication in Kazakh. One can integrate natural language processing speech applications into LLM systems working in Kazakh to support communication with AI in Kazakh. This class of applications include automatic speech-to-text and text-to-speech conversion technologies for Kazakh and other highly used languages among the Kazakhstani community including Russian and English. Considering how fast AI is integrating into the daily lives of modern people, pronunciation-based input and output systems supporting multiple languages including Kazakh can significantly help to increase the usability of Kazakh language in the country. This would support Kazakh language-based communication with AI, computers and robotic systems. At the same time,

we increase the amount of spoken and written Kazakh language usage in general.

Overall, global innovative AI solutions can benefit usage of highly supported languages, leaving them not very much supported and less popular ones behind. Developing advanced technological and AI solutions operating in Kazakh is very important to save the language from potential distinction in the times of AI. Not all Kazakhstani population have access to learn global world languages such as English or Russian yet. Potentially, this could prevent them from fully utilizing the opportunities brought by AI in their daily life, limiting their competitiveness in the global economy. As a country Kazakhstan needs to have multilingual advanced AI solutions including Kazakh to 1) further promote the accessible and efficient digital communication, 2) support inclusion and digital literacy among locals regardless of their proficiency in global languages, and 3) save the national identity and local language from distinction.

Conclusion

In this paper, we explored keyboard typing speed and accuracy through an experimental study involving 41 participants aged 20 to 40 from the NU community. The study examined how individuals in Kazakhstan type predefined texts in Kazakh, Russian, and English using the Kazakh and Russian Cyrillic keyboard layouts and the English Latin alphabet layout. We also assessed the cognitive load participants experienced after completing typing tasks in each language. At the end of the study, we collected demographic data to evaluate participants' comfort levels when typing in each of the three languages and how frequently they use them in daily life.

The results indicate that the average typing speed for Kazakh is 23.04 ± 6.59 WPM, which is 1.41 times lower than for English and 1.26 times lower than for Russian. Typing accuracy, measured using the CER, further demonstrates the challenges associated with typing in Kazakh. The CER for Kazakh was 1.78 times higher than for English and 1.09 times higher than for Russian, indicating greater difficulty in maintaining accuracy when typing in Kazakh. Furthermore, participants experienced a higher cognitive load when typing in Kazakh using the Cyrillic keyboard layout compared to typing in Russian using the Cyrillic layout and English using the Latin layout.

The demographic survey results confirm that participants find typing in Kazakh significantly less comfortable than typing in English and Russian. 90.24% of participants reported using Kazakh for only 0-25% of their daily typing. In contrast, 43.9% of participants type in English for 26-50% of their daily usage, while 26.83% reported typing in English for 51-75%, and an additional 26.83% use English for 76-100% of their daily typing. These findings highlight the low usability of the Kazakh language in keyboard-based digital communication compared to English and Russian.

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APPENDICES

Appendix A

Table 1 – Age data of 41 participants

	Group A	Group B	Group C
ID_1 – ID_3	28	29	37
ID_4 – ID_6	24	30	37
ID_7 – ID_9	30	23	33
ID_10 – ID_12	30	40	32
ID_13 – ID_15	23	20	26
ID_16 – ID_18	27	23	30
ID_19 – ID_21	22	25	30
ID_22 – ID_24	29	27	27
ID_25 – ID_27	24	22	24
ID_28 – ID_30	22	23	26
ID_31 – ID_33	36	25	20
ID_34 – ID_36	20	21	22
ID_37 – ID_39	21	21	20
ID_40 – ID_41	22	35	
Average	25.57	26	28
Standard Deviation (Std)	5	6	6
Average total	26.49		
Std total	5.36		

Table 2 – Gender data of 41 participants

	Group A	Group B	Group C
ID_1 – ID_3	female	male	female
ID_4 – ID_6	female	female	male
ID_7 – ID_9	male	male	female
ID_10 – ID_12	male	female	male
ID_13 – ID_15	male	male	male
ID_16 – ID_18	male	male	female
ID_19 – ID_21	male	female	female
ID_22 – ID_24	female	female	female
ID_25 – ID_27	male	female	female
ID_28 – ID_30	male	male	male
ID_31 – ID_33	female	male	male
ID_34 – ID_36	male	male	male
ID_37 – ID_39	female	female	female
ID_40 – ID_41	male	female	
Female	5	7	7
Male	9	7	6
Female Total	19		
Male Total	22		

Table 3 – Educational level of 41 participants

Participants with bachelor's highest (%)	Participants with master's highest (%)	Participants with PhD (%)	Undergraduate Students (%)	Graduate Students (%)
21.95	34.15	2.44	4.88	36.59

Table 4 – Language proficiency in Kazakh, Russian and English of 41 participants

Native			Fluent			Advanced			Intermediate			Elementary		
KAZ (%)	RUS (%)	ENG (%)	KAZ (%)	RUS (%)	ENG (%)	KAZ (%)	RUS (%)	ENG (%)	KAZ (%)	RUS (%)	ENG (%)	KAZ (%)	RUS (%)	ENG (%)
41.46	48.78	2.44	14.63	41.46	39.02	14.63	9.76	48.78	17.07	0.00	9.76	12.20	0.00	0.00

Table 5 – How often people type on the keyboard in Kazakh, Russian and English daily

0 – 25 %			26 – 50 %			51 – 75 %			76 – 100 %		
KAZ (%)	RUS (%)	ENG (%)	KAZ (%)	RUS (%)	ENG (%)	KAZ (%)	RUS (%)	ENG (%)	KAZ (%)	RUS (%)	ENG (%)
90.24	39.02	2.44	9.76	51.22	43.90	0.00	7.32	26.83	0.00	2.44	26.83

Table 6 – How comfortable it is typing in different in Kazakh, Russian and English languages

Not comfortable at all			Somehow not comfortable			Neutral			Somehow comfortable		
KAZ (%)	RUS (%)	ENG (%)	KAZ (%)	RUS (%)	ENG (%)	KAZ (%)	RUS (%)	ENG (%)	KAZ (%)	RUS (%)	ENG (%)
12.20	4.88	0.00	43.90	12.20	17.07	19.51	39.02	9.76	24.39	43.90	85.37

Appendix B

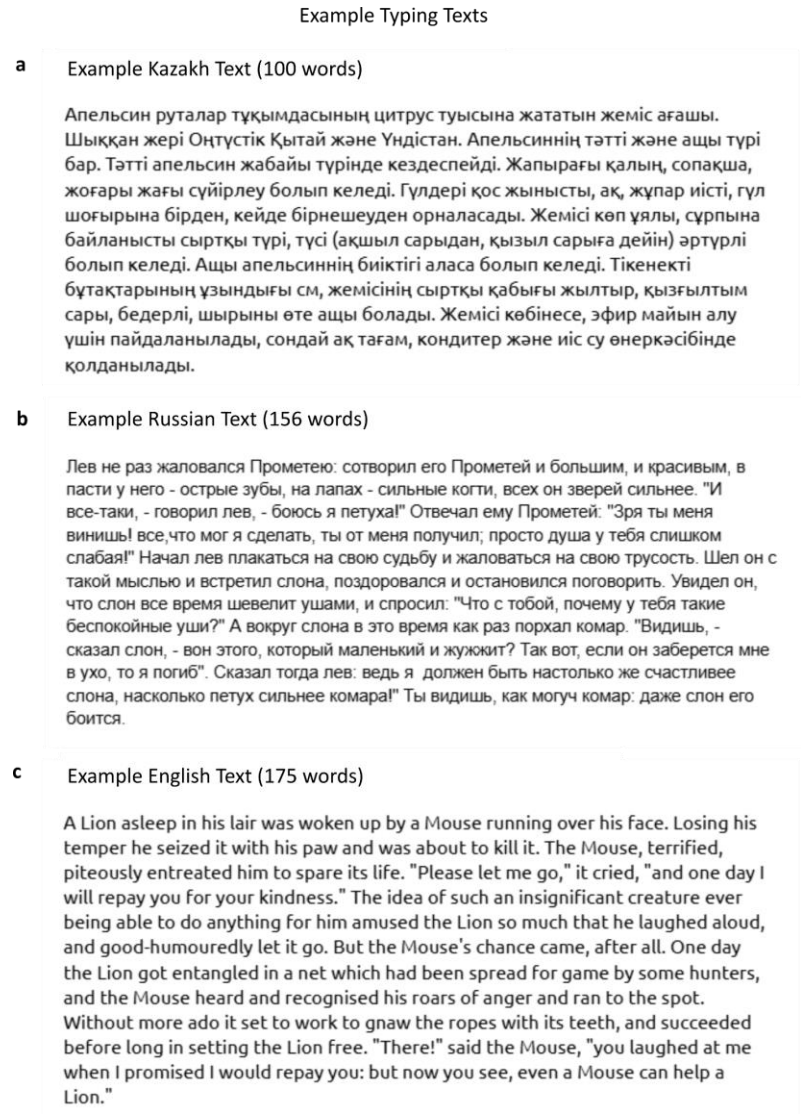

Figure 1 – Example typing texts in Kazakh (a), Russian (b), and English (c) languages