The COVID-19-Induced Reverse Flynn Effect: A Repeated Cross-Sectional Study of Seventh-Grade Selective School Applicants' Academic Performance in Kazakhstan

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NU GSE Research Approval Decision Letter

53 Kabanbay Batyr Ave.

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October 2022

Dear Diana Kalemeneva,

This letter now confirms that your research project titled: The COVID-19 Pandemic Restrictions Induced Reverse Flynn Effect: A Repeated Cross-Sectional Analysis of Seventh-Grade Selective School Applicants' Academic Performance in Kazakhstan, has been approved by the Graduate School of Education Ethics Committee of Nazarbayev University. The Committee agreed that your research does not involve the participation of human subjects, and therefore you might proceed with your study.

Yours sincerely,

Matthew Courtney

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Abstract

The year 2020 is widely recognized as a historic turning point, marking the emergence of the COVID-19 pandemic and its disastrous impact on all spheres of global and national development. The outbreak of this highly contagious and difficult-to-treat infection put millions of people at risk, which led to the swift imposition of restrictions on various aspects of daily life by governments worldwide. These measures had significant repercussions for the educational sector, affecting the majority of the global student population. Recent statistics provided by UNESCO (2020) indicate that over 90% of the world's students and schoolchildren, which translates to approximately 1.5 billion individuals, had to transition from traditional face-to-face classroom instruction to online "learning" in response to the pandemic. The shift to online learning had a profound effect on the education system, impacting its pedagogical approaches, technological infrastructure, and socio-cultural dynamics, among other effects.

The Republic of Kazakhstan experienced significant modifications to its education system in response to the widespread outbreak of the coronavirus disease. This included school closure from March 2020 to September 2021. With the government having implemented these many restrictions, Kazakhstani scholars now have the opportunity to undertake research on the probable effect of these school closures with a view to inform future governmental policy and practice. Many questions remain unanswered. For example: Did males and female applicants enjoy the same expected advantages in math and languages, respectively? Did student applicants more likely residing in rural areas experience the same level of under-performance for the entire period? And, what was the estimated loss-of-learning for the various subject areas?

In order to recognize the effect of the recent restrictions on the education system in Kazakhstan, this study investigates the trends in academic achievement of applicant students

for one selective school system in the country. The study at hand draws upon two of the most up-to-date datasets provided by the selective school system which monitors applicant performance. Thesis is divided into two separate but related studies.

Study 1 makes use of the student-level data on applicant performance for 2019, 2020, and 2021 for Math, Quantitative Reasoning (QR), Kazakh as a 1st language, Kazakh as a 2nd Language, Russian as a 1st language, Russian as a 2nd Language, and English. For the same seven subjects, Study 2 makes use of aggregated applicant performance data to identify trends in applicant performance from 2013 to 2022. Study 2, RQ2, uses extrapolation techniques to estimate the probable loss-of-learning in the Kazakhstani population due to the COVID-19 disruptions.

For Study 1, findings revealed that student gender and mother tongue (Russian/Kazakh) had a significant influence on applicant performance, as well as school exam location (city/rural). Male students surpass female students in Math and QR, while female students outperformed male students in Kazakh, Russian, and English, according to the report. Furthermore, students who speak Russian as their first language outperform students who speak Kazakh as their first language in all disciplines except for Kazakh language. Study 2 looked at patterns in candidate performance from 2013 to 2022 and utilized extrapolation techniques to predict the loss of learning in the Kazakhstani population as a result of the COVID-19 disruptions. Analysis revealed a COVID-19-induced reverse-Flynn effect on all subjects revealing the extent of the learning loss.

One of the possible solutions to resolving the substantive loss-of-learning is to fund and implement remedial programs, especially in subject areas most affected—Kazakh and Russian literacy skills. In addition, governments should consider the serious developmental and educational costs associated with long-term school closure.

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Keywords: Online learning, Learning Loss, COVID-19 Pandemic, Remedial Learning, Ecological Theory, Flynn Effect

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Аңдатпа

2020 жыл COVID-19 пандемиясының басталуын және оның жаһандық және ұлттық дамудың барлық салаларына апатты әсерін көрсететін тарихи бетбұрыс ретінде кеңінен танылды. Бұл өте жұқпалы және емдеу қиын инфекцияның өршуі миллиондаған адамдарға қауіп төндірді, бұл бүкіл әлем бойынша үкіметтердің күнделікті өмірінің әртүрлі аспектілеріне жылдам шектеулер енгізуіне әкелді. Бұл шаралар білім беру саласына айтарлықтай әсер етіп, бүкіл әлемдегі студенттердің көпшілігіне әсер етті. ЮНЕСКО-ның соңғы статистикасы (2020) әлемдегі студенттер мен мектеп оқушыларының 90%-дан астамы, шамамен 1,5 миллиард адам, пандемияға жауап ретінде дәстүрлі бетпе-бет сыныптан онлайн оқытуға ауысуға мәжбүр болғанын көрсетеді. Онлайн оқытуға көшу білім беру жүйесіне терең әсер етіп, оның педагогикалық тәсілдеріне, технологиялық инфрақұрылымына және әлеуметтік-мәдени динамикасына әсер етті.

Қазақстан Республикасы коронавирустық инфекцияның кең ауқымды өршуіне жауап ретінде өзінің білім беру жүйесінде айтарлықтай өзгерістерге ұшырады. Бұған 2020 жылдың наурызынан 2021 жылдың қыркүйегіне дейін мектептердің жабылуы кірді. Үкімет осы көптеген шектеулерді енгізгендіктен, қазақстандық ғалымдардың Болашақ мемлекеттік саясат пен тәжірибені негіздеу мақсатында осы мектептердің жабылуының ықтимал салдарын зерттеу мүмкіндігі бар. Көптеген сұрақтар жауапсыз қалады. Мысалы: ерлер мен әйелдердің білім алушылары сәйкесінше математика мен тілдерде бірдей күтілетін артықшылықтарға ие болды ма? Ауылдық жерлерде жиі тұратын білім алушылар бүкіл кезең ішінде бірдей үлгерімсіздікті бастан өткерді ме? Әр түрлі пәндер бойынша оқытуда болжамды шығындар қандай болды?

Қазақстандағы білім беру жүйесіне соңғы шектеулердің әсерін түсіну үшін осы зерттеуде елдегі бір Таңдаулы мектеп жүйесіне түсетін оқушылардың академиялық

үлгерімінің тенденциялары қарастырылады. Бұл зерттеуде білім алушылардың үлгерімін бақылайтын іріктеп оқыту жүйесі ұсынған ең заманауи екі деректер жиынтығы пайдаланылады. Диссертация екі бөлек, бірақ өзара байланысты зерттеулерге бөлінеді.

1-зерттеуде математика, сандық ойлау (логика), 1-ші тіл ретінде қазақ тілі, 2-ші тіл ретінде қазақ тілі, 1-ші тіл ретінде орыс тілі, 2-ші тіл ретінде орыс тілі, 2-ші тіл ретінде орыс тілі және ағылшын тілі бойынша 2019, 2020 және 2021 жылдары оқушылар деңгейінде оқуға түсушілердің үлгерімі туралы деректер пайдаланылады тіл. Сол жеті пән бойынша 2-зерттеу 2013 жылдан 2022 жылға дейінгі кандидаттардың үлгерім тенденцияларын анықтау үшін кандидаттардың үлгерімі туралы жиынтық деректерді пайдаланады. 2-зерттеуде COVID-19 жұмысындағы іркілістерге байланысты Қазақстан халқы арасында оқыту қабілетінің ықтимал жоғалуын бағалау үшін экстраполяция әдістері қолданылады.

1-зерттеу нәтижелері оқушының жынысы мен ана тілі (орыс/қазақ) оқушының үлгеріміне, сондай-ақ мектеп емтиханының орналасқан жеріне (қала/ауылдық) айтарлықтай әсер еткенін көрсетті. Есепке сәйкес, ер оқушылар математика және сандық ойлау бойынша әйел оқушылардан асып түседі, ал әйел оқушылар қазақ, орыс және ағылшын тілдерінде ер оқушылардан асып түсті. Сонымен қатар, ана тілі ретінде орыс тілінде сөйлейтін оқушылар қазақ тілін қоспағанда, барлық пәндер бойынша ана тілі ретінде қазақ тілінде сөйлейтін оқушылардан асып түседі. 2-зерттеуде 2013 жылдан 2022 жылға дейінгі кандидаттардың үлгеріміндегі заңдылықтар қарастырылды және COVID-19 салдарынан жұмыс істемеу нәтижесінде Қазақстан халқы арасында Оқу қабілетінің жоғалуын болжау үшін экстраполяция әдістері қолданылды. Талдау барлық субъектілерде Флинннің COVID-19 тудырған кері әсерін анықтады, бұл оқу қабілетінің жоғалу дәрежесін көрсетеді.

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Оқыту қабілетін елеулі жоғалту проблемасының ықтимал шешімдерінің бірі - жағдайды түзету жөніндегі бағдарламаларды қаржыландыру және іске асыру, әсіресе, ең көп зардап шеккен пәндік салаларда-қазақ және орыс тілдеріндегі сауаттылық дағдылары болып табылады. Сонымен қатар, үкіметтер мектептердің ұзақ мерзімді жабылуына байланысты елеулі даму мен білім беру шығындарын ескеруі керек.

Түйін сөздер: Онлайн оқыту, білімнің жоғалуы, COVID-19 пандемиясы, түзету бойынша оқыту, экологиялық теория

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Абстракт

2020 год широко признан историческим поворотным моментом, ознаменовавшим возникновение пандемии COVID-19 и ее катастрофические последствия для всех сфер глобального и национального развития. Вспышка этой очень заразной и трудно поддающейся лечению инфекции подвергла риску миллионы людей, что привело к быстрому введению ограничений на различные аспекты повседневной жизни правительствами по всему миру. Эти меры имели значительные последствия для сектора образования, затронув большинство студентов по всему миру. Последние статистические данные, предоставленные ЮНЕСКО (2020), указывают на то, что более 90% студентов и школьников в мире, что составляет примерно 1,5 миллиарда человек, были вынуждены перейти от традиционного очного обучения в классе к онлайн-обучению в ответ на пандемию. Переход к онлайн-обучению оказал глубокое влияние на систему образования, повлияв, помимо прочего, на ее педагогические подходы, технологическую инфраструктуру и социокультурную динамику.

Республика Казахстан претерпела значительные изменения в своей системе образования в ответ на широкомасштабную вспышку коронавирусной инфекции. Это включало закрытие школ с марта 2020 года по сентябрь 2021 года. Поскольку правительство ввело эти многочисленные ограничения, у казахстанских ученых теперь есть возможность провести исследование вероятных последствий закрытия этих школ с целью обоснования будущей государственной политики и практики. Многие вопросы остаются без ответа. Например: пользовались ли обучающиеся мужского и женского пола одинаковыми ожидаемыми преимуществами в математике и языках соответственно? Испытывали ли обучающиеся, чаще проживающие в сельской местности, одинаковый уровень неуспеваемости в течение всего периода? И каковы были предполагаемые потери в обучении по различным предметным областям?

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Чтобы осознать влияние недавних ограничений на систему образования в Казахстане, в настоящем исследовании рассматриваются тенденции в академической успеваемости учащихся, поступающих в одну выборочную школьную систему в стране. В данном исследовании используются два самых современных набора данных, предоставленных системой выборочного обучения, которая отслеживает успеваемость обучающихся. Диссертация разделена на два отдельных, но взаимосвязанных исследования.

В исследовании 1 используются данные об успеваемости поступающих на уровне учащихся за 2019, 2020 и 2021 годы по математике, количественному мышлению (логике), казахскому языку как 1-му языку, казахскому языку как 2-му языку, русскому языку как 1-му языку, русскому языку как 2-му языку и английскому языку. По тем же семи предметам в исследовании 2 используются агрегированные данные об успеваемости кандидатов для выявления тенденций в успеваемости кандидатов с 2013 по 2022 год. В исследовании 2, используются методы экстраполяции для оценки вероятной потери способности к обучению среди населения Казахстана из-за сбоев в работе COVID-19.

Результаты исследования 1 показали, что пол учащегося и родной язык (русский/казахский) оказали значительное влияние на успеваемость учащегося, а также местоположение школьного экзамена (город/сельская местность). Согласно отчету, учащиеся мужского пола превосходят учащихся женского по математике и количественному мышлению, в то время как учащиеся женского пола превзошли учеников мужского пола по казахскому, русскому и английскому языкам. Кроме того, учащиеся, говорящие на русском языке как на родном, превосходят учащихся, говорящих на казахском языке как на родном, по всем дисциплинам, за исключением казахского языка. В исследовании 2 рассматривались закономерности в успеваемости

кандидатов с 2013 по 2022 год и использовались методы экстраполяции для прогнозирования потери способности к обучению среди населения Казахстана в результате сбоев в работе из-за COVID-19. Анализ выявил вызванный COVID-19 обратный эффект Флинна у всех испытуемых, свидетельствующий о степени потери способности к обучению.

Одним из возможных решений проблемы существенной потери способности к обучению является финансирование и реализация программ по исправлению положения, особенно в наиболее затронутых предметных областях - навыках грамотности на казахском и русском языках. Кроме того, правительствам следует учитывать серьезные затраты на развитие и образование, связанные с долгосрочным закрытием школ.

Ключевые слова: Онлайн-обучение, потеря знаний, пандемия COVID-19, коррекционное обучение, экологическая теория.

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1. Introduction

1.1 Background of the Study

The global outbreak of the coronavirus disease (COVID-19) posed a significant challenge to traditional educational systems worldwide. Within a brief span of two years, the conventional mode of "face-to-face" instruction was disrupted, forcing learners to adopt online and blended learning methodologies. The impact of the pandemic on education was pronounced, as evidenced by the UNESCO Institute for Statistics report that indicated the closure of educational institutions in 41 countries, affecting over 800 million learners as of September 2020. Kazakhstan was not immune to the effects of the pandemic on education, and it was also compelled to shift to alternative modes of instruction to mitigate the spread of the virus.

The COVID-19 pandemic presented a global challenge to education systems, necessitating the rapid adaptation and utilization of diverse online platforms. In order to optimize access and convenience for students, a range of distance learning tools have been actively introduced within the global educational community, including video conferencing tools like Zoom and Google Teams, televised lessons, mobile applications, multimedia lessons posted on dedicated platforms, and materials sent via messaging applications or email.

During the one-and-a-half-year period of distancing/blended learning in Kazakhstan from March 2020 to September 2021, it was reported that the implementation of several associated measures caused significant stress among Kazakh students as a result of the mandatory shift in learning modalities. It was also reported that many students complained of pressure, felt fear of passing exams, and experienced poor assimilation of the curricula material, which led to some instances of burnout for some students in the first half of the year of distance learning in 2020 (Bokayev et al., 2020). According to Bokayev et al. (2020), a significant proportion of Kazakhstan parents, approximately 50.9%, expressed their dissatisfaction with their children's academic performance during the transition to online learning. Furthermore, reports from Kazakhstan indicate that the sudden shift to online learning had adverse effects on students' technical and emotional readiness, thereby negatively impacting their academic performance and generating dissatisfaction with the learning process (UNESCO, 2020). It is, however, noteworthy that these reports lack empirical substantiation.

While online education has its advantages and disadvantages, it is here to stay. Given this, the restrictions imposed by the COVID-19 pandemic provide an opportunity for researchers to identify the effect of a general shift to online learning. Investigating the potential effect of this transition may provide key insights that can inform future transitions, imposed or not, to online modes of learning. The transition to online learning presents a unique opportunity to investigate the potential impact on various academic disciplines, which may offer new insights into how diverse forms of knowledge are acquired and advanced through a range of digital media. Undoubtedly, online learning is no longer just a pandemic-driven phenomenon, but a well-established and pervasive reality with an expanding global community of stakeholders and contributors. Consequently, it is imperative to conduct a comprehensive examination of the effects of online education on students' academic achievement. What might be the loss of learning associated with particular forms of governmental restrictions? Such insights may inform future governmental decision-making vis-à-vis the potential cost of imposing shifts to online and blended learning.

1.2 The Statement of the Problem

While occasional reports on students' experiences during online learning are available, no studies were conducted to systematically measure and compare students' level of academic improvement (or degeneration) under the various forms of restrictive online and blended conditions that were imposed during the pandemic period. In the meantime, in Kazakhstan, the need for alternate online education continues due to inevitable adverse weather conditions and as a means to prepare for potential future unforeseen circumstances such as future pandemics, state-imposed rule-of-law, geopolitical instability, and potential future shortfall in brick-and-mortar school infrastructure. Therefore, there is a growing need to identify the level of disruption and associated costs and benefits associated with the imposition (or shift to) online and blended learning environments on school children and adolescents. The overall of disruption to learning as a consequence of the restrictions is yet to be examined empirically in Kazakhstan.

1.3 Purpose of the Study

The purpose of this quantitative-based study is to analyze the impact of compelled remote and blended learning in Kazakhstan during the COVID-19 outbreak by comparing and tracking the academic performance of Grade 7 student applicants in for selective school system that imposed online learning for approximately 18 months as part of the COVID-19 restrictions.

1.4 Hypothesis

This study is designed to test the hypothesis that the level of COVID-19 related restrictions had a substantive effect on the academic development of students. For Study 1, RQ1, the null hypothesis states that there were no statistically significant differences in student performance for the 2019 to 2021 period based on the four student- and one school-level predictors. For Study 2, the null hypothesis for RQ2 is that there was no expected loss of learning for each of the five subjects under investigation for 2021 and 2022.

1.5 Significance of the Study

The importance of this work is that the current research project will assist policy makers to understand and consider the impact of and potential improvement to current policy and practice vis-à-vis remote and blended learning. It is expected that further monitoring of learning outcomes under different offline/blended/online conditions will be undertaken to further inform educational policy and practice in Kazakhstan. It is expected that this research will serve to fill the research gap in Kazakhstan pertaining to the potential learning loss associated with the imposition of such policies.

1.6 Definition of Key Terms

In order to understand terms used in the proposal, the definitions of central phenomena were provided.

1.6.1 Distance Learning

The United States Distance Learning Association provided a definition of formal and informal distance learning in 1998, as “the acquisition of knowledge and skills through mediated information and instruction, encompassing all technologies and other forms of learning at a distance” (Roblyer & Edwards, 2000). This definition is complemented by Newby et al. (2000), who describe distance learning as “an organized instructional program in which teacher and learners are physically separated” (p.). Collectively, these definitions imply that distance learning encompasses all types of learning that occur remotely, with physical separation between teachers and learners.

1.6.2 Emergency Remote Education

Hodges et al. (2020) conceptualize emergency distance learning (EDL) as a temporary shift to remote instruction in response to crisis situations. This transition involves the complete adoption of distance learning solutions for educational or training purposes that would normally be provided through in-person or hybrid modalities. Once the emergency has passed, the expectation is to return to the original mode of instruction. Kazakhstan has previously experienced instances of EDL, with *e*-learning skills workshops and planning events implemented in 4,135 educational institutions by the end of 2015, in line with the State Program of Education Development in Kazakhstan for 2010-2021 (Kapezovich & Toktarbekovna, 2014).

EDL has become increasingly relevant in recent times due to crises such as natural disasters, political turmoil, and pandemics. Despite its potential to mitigate the negative effects of crisis situations, EDL can pose challenges such as limited technological infrastructure, inadequate teacher training, and difficulties in maintaining student engagement. As such, it is crucial to study the implementation and effectiveness of EDL as an emergency measure to ensure its optimal deployment and minimize potential shortcomings.

1.6.3 Remedial Learning

Remedial learning is a form of education designed to address learning loss or difficulties that students may have experienced. It involves identifying areas where a student is struggling and providing additional support, instruction, and resources to help them improve their knowledge and skills. According to a study published by Alvarez-Marinelli et al. (2021) remedial learning has been shown to be effective in improving student performance and reducing the achievement gap in academic subjects. Another study published in the Quarterly Journal of Economics found that remedial learning can be an effective tool for improving the language and literacy skills of struggling readers (Banerjee et al., 2007). Remedial learning can be delivered in a variety of ways, such as one-on-one tutoring, small group instruction, or specialized classes, and it can be tailored to meet the unique needs of each individual student. The goal of remedial learning is to help students reach their full potential and to ensure that they have the knowledge and skills necessary to succeed in their academic and professional pursuits.

1.6.4 Learning Loss

Learning loss refers to the concept of students experiencing a decrease in knowledge or skills over time, particularly during extended periods away from formal education. According to a recent study published in the Journal of Sociological Science, learning loss can occur during summer breaks, when students are not engaged in formal learning activities, and can result in significant declines in math and reading skills (Workman et al., 2023). The COVID-19 pandemic has also highlighted the issue of learning loss, as many students experienced disruptions to their education due to school closures and the transition to remote learning. A study published by Donnelly et al. (2021) found that students who experienced disruptions to their education during the pandemic were at risk for learning loss and other negative outcomes. Addressing learning loss requires targeted interventions and support, such as remedial learning, to help students catch up and regain lost knowledge and skills.

Based on the purpose of this study, the **main research question** of this research is:

What is the estimated effect of the restrictions during the pandemic on the academic development of Kazakh student applicants in one selective school system in Kazakhstan? This general question is broken down into more specific questions below:

1.7 Research Questions

To explore the role of the COVID-19 Pandemic on students’ academic development, the following two studies aim to provide answer to the following specific research questions:

Study 1

RQ1: What is the effect of student gender, mother tongue, origin, and school exam location on student applicant performance in Math, QR, Kazakh, Russian, and English for the 2019, 2020, and 2021 period?

Study 2

RQ2: What is the estimated loss-of-learning in the Kazakhstani student applicant population due to the imposed COVID-19 restrictions?

2. Literature Review

2.1 Introduction

The purpose of the literature review is to provide a summary of the scholarship related to the effect of the COVID-19 restrictions on student learning outcomes. This literature review is presented in the following 14 subsections. Subsection 2.2 provides a description of the framework for which the current literature was reviewed and presented herein. Thereafter, subsection 2.3 introduces the policies that were first implemented to transfer to an online education globally. As this juncture, subsection 2.4 sheds light on the readiness of Kazakhstan authorities to respond the COVID-19 emergency situation. Following this, the subsection 2.5 illustrates the eyesight on policies implemented in Kazakhstan for the education sector during the pandemic. The subsection 2.6 provides the insight to Internet access during the pandemic restrictions. The subsection 2.7 provides a review of the educational challenges and opportunities presented by the pandemic, while the subsection 2.8 presents a summary of the novel COVID-19 teacher experience and training necessary for such imposed pandemic situations. Thereafter, subsection 2.9 provides an illustration of the student experience and perceived learning during the pandemic. The subsection 2.10 presents research on the effect of the pandemic on male and female academic performance. The subsection 2.11 revises the influence of students' gender on academic performance. The subsection 2.12 provides a view on the influence of a school type, as well as this, the subsection 2.13 revises the influence of the language of instructions on students' entrance test performance. The subsection 2.14 completes the chapter by detailing research that outlines future planning in a post-COVID world.

2.2 Framework for Review and Presentation of the Literature

Since this study is broken into two studies to provide deeper sight on the effect of student gender, mother tongue, origin, and school exam location, as well as students' potential loss-of-learning due to the COVID-19 restrictions, it was decided to apply constructivist learning theory, and ecological system theory as theoretical frameworks.

The literature review section begins by examining the global changes in education during the COVID-19 crisis with a further inclination to educational policies implemented in Kazakhstan as part of an emergency shift to a remote learning. As well as this, the following subsections describe the educational challenges and opportunities arose during the period. Insofar as possible, this literature review includes certain studies that are relevant to the educational context of Kazakhstan. The research presented in the review was primarily obtained from UNESCO reports and journals ranked by Scopus (as indicated by the Scimago Journal Rank for 2022) as this type of research was considered to be of better quality.

Randolph (2009) offers a guideline for carrying out literature reviews, which entails identifying six features of the literature and suggesting relevant categories for each feature. To comply with this guideline, Table 1 illustrates the chosen categories (indicated by an underline) for the current literature review.

Table 1

Cooper's Taxonomy of Literature Reviews

Characteristic	**Categories**
Focus	Research outcomes Research methods Theories <u>Practices or applications</u>
Goal	Integration Generalization Conflict resolution Linguistic bridge-building Criticism Identification of central issues
Perspective	<u>Neutral representation</u> Espousal of position
Coverage	Exhaustive Exhaustive with selective citation Representative <u>Central or pivotal</u>
Organization	Historical <u>Conceptual</u> Methodological
Audience	Specialized scholars General scholars <u>Practitioners or policy makers</u> <u>General public</u>

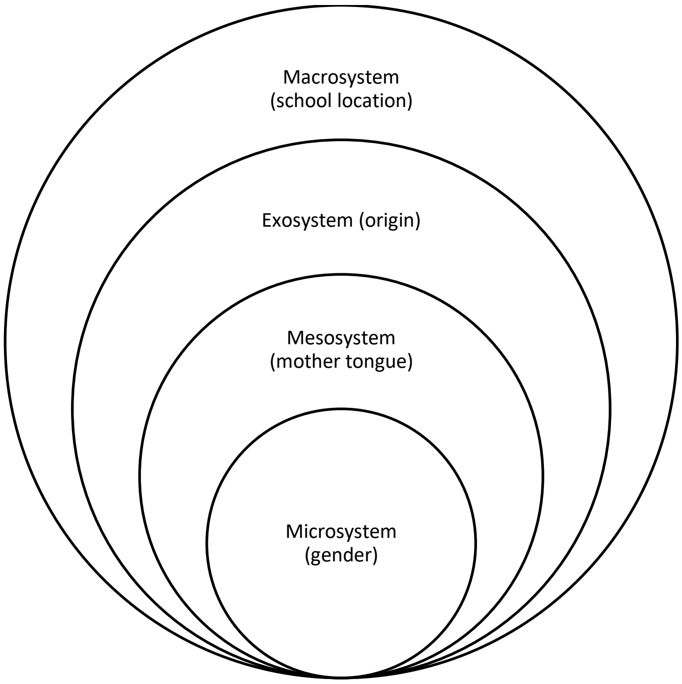
Note. Specific category chosen for teach characteristic is underlined; reprinted from *"A Guide to Writing the Dissertation Literature Review," by J. Randolph, 2009, Practical Assessment,* Research and Evaluation, *14*(13). Copyright 2019. Each selected category relevant to the current literature review is underlined.

Each of the six characteristics will be described sequentially based on the category chosen for it. The focus of the literature review relies on practices or applications and based on examining how the emergency shift to online education affects students' academic development in Kazakhstan, particularly seventh-grade applicants (i.e., young adolescents) of one selective school systems in Kazakhstan. The literature review aims to identify and review various studies and their findings in order understand the potential for students' loss-of-learning during the 18 months of restrictions. The goal of the literature review is to synthesize the studies related to the impact of the COVID-19 restrictions on student development and learning. The perspective of the review is neutral, and the coverage category is limited to only central articles related to the examination of students' academic abilities. Overall, the literature review will systematically present studies that investigate the role of the students' gender, origin, mother tongue, school exam location in terms of remote learning during the pandemic, on their academic performance.

Since the study aims to explain how student's development is influenced by oneself environment and background, the Bronfenbrenner's Ecological Systems Theory (1974) is applied here (Ettekal & Mahoney, 2017). The theory emphasizes the importance of understanding the context in which a person develops and the various relationships and interactions that occur within that context. In essence, the theory highlights the interconnectedness between an individual and their environment and how this dynamic relationship influences their growth and development. Ecological Systems Theory depicts the different levels of the theory as a visual representation of four systems that surround an individual, arranged like a set of concentric circles (see Figure 1).

Figure 1

Bronfenbrenner's Ecological Systems Theory



Note. Adapted from Ettekal & Mahoney (2017), The SAGE encyclopedia of out-of-school learning. Ecological Systems Theory, 230-241.

The ecological systems theory is a useful tool for comprehending how various factors such as a student's gender, origin, mother tongue, and school exam location can affect their growth and academic achievements. These factors can impact the various environments that a student interacts with and the role that these environments play on students' development.

The Ecological Systems Theory can help explain gender differences in mathematical abilities at the microsystem level, which refers to the immediate environment in which individuals live and interact, such as family and school. At the microsystem level, gender differences in mathematical abilities may be influenced by biological and socialization processes, which occur within the immediate environment and involve the transmission of societal norms and values. For instance, in terms of socialization, parents, teachers, and peers may have different expectations and attitudes towards males and females in regards to their mathematical abilities, which can shape their experiences and opportunities.

Similarly, students' mother tongue can affect their academic abilities, especially if they speak a language different than the one taught in school. This may make it difficult to absorb the curriculum and communicate with instructors and classmates, harming academic achievement and impeding social and intellectual growth. The family-school relationships can impact how successfully a student overcomes these problems on a mesosystem level. For instance, parents who are competent in the language of teaching can assist and encourage their kids to better understand and communicate with their instructors and peers. Teachers and institutions can also be important in supporting students who speak another language. They can offer language assistance programs, modify instructional methods, and build a culturally diverse environment.

Furthermore, students' families' socioeconomic status (SES), which is directly related to their origin, can also have an influence on their growth and academic performance at the exosystem level. Students from low-income homes may confront barriers to resources, support networks, and educational opportunities, which can have an influence on their academic performance and social development. Policies relating to education financing, social welfare programs, and economic prospects can all have an influence on the experiences and opportunities accessible to students from various socioeconomic backgrounds at the exosystem level.

Moreover, on an macrosystem level, a school's location might influence a student's access to resources and opportunities in their neighborhood. Students in rural locations, for example, may have less access to extracurricular activities and specialized courses than their urban counterparts. This may have a detrimental influence on their intellectual and social development, as well as limit their options for future education and job pathways. Furthermore, the availability of educational resources, such as libraries, technology, and qualified teachers, might be limited for students depending on the location of the school.

In summary, the Ecological Systems Theory provides a framework for understanding the complex interactions between different environmental systems and how they can impact a student's growth and academic achievements. Schools and policymakers must consider these factors when designing and implementing educational policies and programs to ensure equal access and opportunities for all students.

2.3 Global Crises, Local Consequences

The swift pace of development in the modern world is fueled not only by advancements in technology and high-quality education but also by crises that present unique challenges. One such challenge is the recent COVID-19 pandemic, which has led to a global health emergency of unprecedented proportions. The pandemic has prompted researchers to conduct comprehensive investigations into the impact of the crisis on distance education. As per the Global Education Monitoring Report released by UNESCO (2021), more than 1.6 billion students worldwide have been impacted by the widespread closure of school facilities. Governments have responded to this crisis by offering online education to ensure continuity of learning, enabled by the widespread availability of Internet communication and computer devices. However, the quality and reach of this initiative have been uneven both globally and locally, with many children missing out on academic knowledge, particularly younger and marginalized students. The findings of the report highlight the urgent need to ensure access to high-quality education for all children, irrespective of their background, during crises such as the COVID-19 pandemic.

The COVID-19 pandemic has had a significant impact on the education system, with the closure of schools affecting more than 1.6 billion students worldwide. Governments have attempted to address this issue by introducing online education initiatives, but the quality and effectiveness of these initiatives vary greatly. The United Nations Educational, Scientific, and Cultural Organization (UNESCO) conducted a study on the impact of the pandemic on distance education and has found that younger and marginalized children are at the highest risk of not receiving a high-quality education. This emphasizes the need for effective and equitable online education strategies to mitigate the impact of future crises on education. The OECD study highlights the importance of providing support to students and teachers, ensuring access to technology and internet connectivity, and addressing the socioeconomic factors that may affect online learning. Overall, the COVID-19 pandemic has underscored the need for resilient and adaptable education systems that can effectively respond to crises while ensuring equitable access to education.

2.4 The Pandemic, Kazakhstan, and Student Learning

Based on the research data of the Demoscope Research Group, Kazakhstanis were divided on their opinion about the implementation of online learning during the pandemic (KazTag, 2020). Realizing that these measures were necessary and were introduced to curb the spread of coronavirus, citizens were largely in agreement that they expected authorities to work more effectively. Specifically, results pointed to a large minority, i.e., 43%, who were categorically against the implementation of online distance learning. Similarly, a total 38% of Kazakhstanis were sympathetic to distance learning at that time but believed that the authorities needed to prepare better for the new academic year. However, only 16% of respondents fully supported the online format, considering it a necessary measure. According to the survey, the vast majority of citizens rated the effectiveness of online learning at either average (41% of respondents) or below average (42% of respondents). Perhaps revealing the citizenry's sentiment about the social costs of the shift to online learning, in total, only 12% of respondents highly appreciated this new form of education.

In a recent focus group organized by the PaperLab research community, teachers, students, and educational experts discussed the largely negative consequences due to the COVID-19 restrictions. During the focus group, parents defined the online learning situation as a “profanity”. In support of this sentiment, the World Bank (2020) estimated that the COVID-19 restrictions would create an additional 100,000 15-year-old students defined as functionally illiterate reflecting an overall reduction in 8 PISA scale points. Worryingly, it was projected that the loss would be largely felt among students with low socio-economic backgrounds and those in rural areas, accelerating the achievement gap between the haves and have nots in the country.

The government's measures during a crisis are often evaluated by public sentiment. As the COVID-19 pandemic brought about unprecedented changes in the education sector, it became crucial to understand citizens’ perspectives on the most effective form of education. In Kazakhstan, the public opinion on this matter appears to be split, as approximately half of the respondents viewed online education as the best option, while the other half preferred in-person learning. This finding highlights the need for further research into the factors influencing the preference for one mode of education over the other. Additionally, it is essential to examine the extent to which these preferences align with the actual learning outcomes of students in each form of education, particularly in light of the ongoing pandemic and the potential for future crises. A total 35% of the respondents believe that it is necessary to give people the right to choose the form of education convenient and appropriate to them; 33% of Kazakhstanis were in support of online education, the forced measure imposed; while 29% expressed skepticism about the utility of the online format. In the opinion of the latter group, it was better for students to attend school and university as in the traditional way as they thought that illiteracy was scarier than coronavirus. The findings of a survey conducted by the Demoscope Public Opinion Bureau (2020) indicated that the majority of Kazakhstanis are not well-suited for distance learning mainly due to inadequate material and technical conditions, as well as the unpreparedness of the education system for the upcoming academic year (commencing in September 2020). Moreover, the survey revealed that regional inequality between students has increased significantly, largely attributable to unequal access to the Internet (DEMOSCOPE, 2020). These issues have resulted in students struggling to adapt to online learning, with limited access to the required resources and infrastructure to facilitate their education. As a result, it is crucial to address these issues and ensure that all students have equal opportunities to access education in the wake of the pandemic.

Overall, the results suggested that distance learning may have had a negative impact on the education system, with assessments of student knowledge suggesting stagnation or decline in literacy of 15-year-olds. As well as this, from the perspective of the students' parents, distance learning was not suitable for Kazakhstanis largely due to the lack of material and technical conditions and the unpreparedness of the education system for the forthcoming academic year. Additionally, there was an increase in regional inequality due to differential access to the internet which was expected to have exacerbated previous levels of educational inequality and unequal educational access. The majority of parent respondents believed that people should be given the right to choose a convenient form of education, and some expressed skepticism about online learning, preferring the traditional in-person format. Given the relative dearth of information on the potential learning loss due to COVID-19, just one World Bank study, and the degree to which restrictions were controversial, it is an imperative for further research to be undertaken in this area.

2.5 Educational Policy Shifts for COVID-19

During the sudden shift from in-person instruction to remote learning in emergency situations, policymakers worldwide have implemented various training methodologies to support this transition. To ensure a smooth transition, policymakers prioritized adapting the school curricula, adjusting the school calendar, and creating academic podcasts for TV and radio. Additionally, policymakers have implemented online classroom meetings using digital platforms through both asynchronous and synchronous methods. These measures aimed to provide effective and uninterrupted educational services to students during the crisis. In the face of the pandemic, such approaches played a significant role in maintaining access to education for students worldwide.

In addition, as the data published by UNESCO (2020) suggested, alternative methodologies such as the application of interdisciplinary teaching methods that allow students to master topics using an integrated approach were also adopted. In this case, it could be argued that the adapted curricula provided room for teachers to have more independence in terms of course delivery and teaching. In addition, the development of teachers' interdisciplinary competence and the prioritization of taught content per se should also be regarded highly in such emergency educational contexts. In this way, an integrated approach to teacher training and development for the period was generally developed (UNESCO, 2020). In response to global crises, several countries developed plans to adjust the contextualization of education in order to achieve their goals. These plans included reducing the number of basic learning objectives across various disciplines. For example, Affouneh and Burgos (2021) conducted a study outlining a six-step action plan for emergency response. The study highlighted the significance of the initial decision-making period, analyzing technical support and digital tools, and future reforms as the essential steps for implementing such strategies. The results of the study emphasize the importance of a well-planned response to global crises, with a focus on utilizing digital tools and technical support to enhance the learning process. Furthermore, the study supports the need for continued education reforms to maintain a robust educational system. In conclusion, adapting to global crises through the modification of educational plans and strategies plays a vital role in ensuring a quality education for all learners.

Affouneh and Burgos (2021) suggest that the initial step towards modifying educational structures during crisis situations involves making a decision to adapt the curriculum and transfer it to an online format. This decision-making process should prioritize the timely discussion of a new teacher training plan, where potential risks and the ability of stakeholders to adapt to changes in the usual pace of work are identified at the outset. It is important to note that the study highlights the need to sustain the momentum of progress to ensure the effectiveness of the adaptation process. Additionally, the research recommends the integration of technical support and the utilization of digital tools to enhance the online learning experience. Overall, the study emphasizes the significance of a well-planned approach to curriculum modification and teacher training to ensure the provision of quality education in times of crises.

As it is indicated in UNESCO report (2020), it is necessary to take into account the characteristics of national or subnational curricula, the country's resources and capacities to develop distance learning processes, the levels of segregation and educational inequality in the country, and how much of the school year had elapsed.

In November 2020, the Minister of Education and Science of the Republic of Kazakhstan, Askhat Aimagambetov, announced the decision to extend the spring break by an additional week. The purpose of this extension was to provide policymakers with additional time to prepare for organizing the educational process in the context of non-standard quarantine conditions. Policy makers stated that the extension would create a more favorable academic environment that would ensure the integration of relevant competencies and values in the current context. This integration will help ensure that students are adequately prepared for the challenges they may face in the future. These changes and adaptations were in line with the UNESCO report that suggest that teachers shold prepare students for self-directed study and strengthen their social and emotional skills despite the remote mode of communication (UNESCO, 2020).

As a consequence of the pandemic, school systems, curricula, and teachers around the world have undergone similar, though connected, re-conceptualizations. While the initial period of discussions and negotiations may be a time-consuming process, it is crucial to understand that it should not be delayed, particularly during a crisis. Any delay in decision-making can result in harmful consequences, such as the rapid spread of infections among schoolchildren and staff, as has been observed during the COVID-19 pandemic. Thus, policymakers should prioritize timely decision-making to mitigate the potential risks associated with crises. It is worth noting that the early stage of discussions and negotiations can facilitate the identification of possible challenges and opportunities, which can ultimately aid in creating an effective response plan. Therefore, policymakers should prioritize taking action as soon as possible to ensure the provision of quality education in times of crises. However, it is important for policy makers to consider the potential harm that interventions, such as school closures, might incur.

However, in accordance with the summary of the educational policy shifts for COVID-19 in Kazakhstan, decisions were made based on what was deemed as immediate at the time of the pandemic. Adjustments were made in the interest of creating a favorable academic environment that ensured the balanced integration of competencies and values relevant in the current curriculum, including the preparation for self-directed study and the strengthening of social and emotional skills despite the remote mode of communication. Moreover, further investigations into the loss-of-learning consequent to the pandemic itself may inform future decisions concerning the risks and benefits associated with shifts, especially imposed shifts, to the online learning mode. Such information would, of course, need to be considered alongside potentially harmful consequences, including the spread of infection among schoolchildren and working staff.

2.6 Unequal Access to Education During the Pandemic

Recent epidemiological, political, and social instability in Kazakhstan (Bokayev et al., 2021) has produced apprehensive times for students, parents, and teachers. The recent pandemic and, to some degree, the social unrest (Bloody January, Imamova, 2022) caused paradigmatic shifts in the way in which education was delivered. Any level of upheaval tends to have a disproportionate effect on those in lower socio-economic groups with fewer resources and opportunities. The UNESCO Institute for Statistics database (2020) reported that at the onset of the COVID-19 pandemic, approximately 826 million students globally, which accounted for 50% of the student population, did not have access to household computers or other necessary technical devices. Additionally, 706 million schoolchildren, representing 43% of students worldwide, faced the challenge of not having a stable Internet connection. These statistics highlight the significant digital divide that exists across the globe, which has been further exacerbated by the pandemic. The lack of access to technology and the Internet has had a detrimental impact on students’ ability to continue their education, particularly during times of crisis. Thus, it is imperative that policymakers and educators work towards closing the digital divide to ensure equitable access to education for all students, regardless of their socioeconomic background or geographical location. This effort will require collaborative efforts among various stakeholders to provide necessary resources and support to bridge the gap and ensure that no student is left behind.

COVID-19-INDUCED REVERSE FLYNN EFFECT IN KAZAKHSTAN

This disproportionate effect was mirrored in Kazakhstan. The survey on “Distance education in Kazakhstan” was conducted from the 6th to the 9th of October, 2020. A total 1,100 people took part in 14 regions and cities of republican significance (Nursultan, Almaty, and Shymkent). The data collection for the survey was carried out via telephone calls to landline numbers, using both Kazakh and Russian languages. This method of data collection allowed researchers to reach a wide range of participants, regardless of their geographical location, making it a useful tool for collecting data from a diverse sample population. A total 25% of respondents were men and 75% were women and all were over the age of 18. The sampling frame included households that maintained a subscription to fixed telephone numbers in Kazakhstan. For this sample, the maximum size of the statistical error with a 95% probability does not exceed 3% (DEMOSCOPE, 2020). The data obtained during the survey conducted showed that, geographically, residents of East Kazakhstan, North Kazakhstan, and Zhambyl regions experienced the most technical difficulties with the Internet. Specifically, 44, 39, and 40%, of residents in each region, respectively. Findings from the survey revealed that though nearly half of the surveyed citizens (49%) had an average Internet speed, they still experienced difficulties with online learning. The Kazakhstani-based survey also revealed that a quarter of citizens (25%) had poor Internet quality, meaning that the Internet was always slow in their area. The survey identified that slow Internet speed was noted more than others (varied to 35%) by residents of Almaty, West Kazakhstan, and Karaganda regions. Only 22% of the survey respondents stated that they had a good Internet connection speed, without complaints. The largest percentage of high Internet quality ratings (38%) was in Astana and the Kyzylorda region. Such discrepancies in the speed of the Internet reveal the leveled the inequality in the access to education during the pandemic period (DEMOSCOPE, 2020). The size of disproportionate effect that poor rural internet access had on learning outcomes is therefore an important line of enquiry for Kazakhstan.

2.7 Technological Challenges and Opportunities during the Pandemic

In the context of the COVID-19 outbreak, teachers and students have faced a range of challenges during the transition to online learning, as highlighted by Huang et al. (2020). These challenges include difficulties in finding and adapting suitable online teaching resources, interruptions caused by simultaneous online connections, a lack of e-learning skills and competencies among teachers and students, and a gap in students' adaptation and self-regulation skills. The study by Szpunar et al. (2013) specifically identified the issue of students' inability to effectively self-regulate during online learning, which can lead to procrastination and difficulty concentrating without the guidance of in-person authority figures. These challenges highlight the importance of providing adequate support and training for both teachers and students during emergency transitions to online learning, as well as addressing the digital divide and access to technology and internet connectivity. Additionally, developing strategies to promote self-regulation and motivation in online learning can be beneficial for students' academic success.

As a counter to student procrastination and inattention, some scholars have suggested that there is a need for eye-catching presentations and the integration of dynamic virtual material during lessons as a replacement to ordinary lectures and lessons (Xie et al., 2006). Corbi et al. (2021) proposed the adoption of Learning Management Systems (LMSs) as a potential solution. LMSs are software programs that operate on a server and provide digital learning environments for students. They allow for the distribution of assignments and homework, as well as the downloading of recorded video lectures, posting of class announcements, and sharing of learning materials. LMSs are becoming increasingly popular due to their effectiveness in facilitating distance learning and increasing student engagement.

According to a speech by Askhat Aimagambetov (2020, May 19), in Kazakhstan, 2.4 million schoolchildren utilized online platforms such as “Kundelik,” “Daryn.Online,” and “BilimLand” to continue their education during the COVID-19 pandemic. These platforms provided students with video tutorials that aligned with their curriculum, followed by assignments from their teachers to test their comprehension of the material. In case of any queries, students had the opportunity to revisit the video tutorials and discuss any issues with their teachers. This approach facilitated remote learning and helped students to stay engaged with their academic progress while maintaining social distancing. While these adjustments likely mitigated against the detrimental effects on student learning, the overall size of detrimental effect for the various compulsory school subject areas is yet to be explored.

2.8 Novel COVID-19 Teacher Experience and Training

According to Looi et al. (2021), the outbreak of the pandemic led to a shift in the role of teachers from simply delivering the curriculum to designing effective learning experiences. This involved not only structuring lessons and creating content but also adapting to digital tools and online resources. As pointed out by Lister (2014), teachers had to become adept at using technology to deliver their lessons and ensure that students were engaged and learning effectively.

Additionally, teachers had to take on a new role as mentors, coaches, and motivators, especially with the lack of control they had during the pandemic (Martin, 2020). This was necessary to help students adapt to the new mode of online learning and to ensure their emotional wellbeing. In essence, the pandemic necessitated a reconfiguration of teaching practices to ensure maximum impact on the academic process within a short time frame.

Therefore, training programs for teachers is an imperative in order to ensure that teachers have the skills and knowledge necessary to adapt to the rapidly changing landscape of remote and online teaching (Northcote et al., 2011). The training should include an emphasis on pedagogy over technology, with a focus on the development of collaborative skills that enable teachers to engage in group discussions about teaching design, curriculum development, resource sampling, and methods of content delivery. Furthermore, these training programs should cater to diverse levels of development, allowing teachers to take the lead and recognize emotional issues. By providing teachers with the necessary skills and knowledge, we can ensure that they are better equipped to navigate the complexities of online teaching, and ultimately, provide students with a high-quality education, even during times of crisis.

According to Ni She et al. (2019), the role of modern teachers has evolved from traditional instruction delivery to instructional designers who incorporate interactive technologies in their teaching. Unlike in the physical classroom, online teaching presents challenges such as technological support and ensuring that students remain motivated and engaged in a non-physical social environment. To overcome these challenges, teachers need to adopt innovative approaches while also considering the designer's perspective to create an environment in which students can participate effectively. They also need to use technological tools in a pedagogically sound manner. As such, teachers must possess adaptive experiences to design and deliver online lessons that cater to diverse learning needs. In addition to technological support, they also have to consider the emotional and psychological needs of students and provide support in those areas. Therefore, it is crucial for teachers to receive proper training and support in order to effectively adapt to the evolving demands of the modern teaching environment.

Despite the rapid adoption of online teaching, there are still a significant number of teachers who face challenges in adapting their teaching practices to the online mode. According to Kibaru (2018), this is largely due to their inadequate understanding and experience with online learning methodologies. In order to bridge this gap, it is important for teachers to undergo training programs that can equip them with the necessary skills and competencies required for effective online teaching. This includes training on how to use digital tools and resources, as well as strategies for engaging and motivating students in an online learning environment. Furthermore, ongoing professional development opportunities can help teachers stay up-to-date with the latest trends and innovations in online teaching, and enable them to continuously improve their skills and knowledge.

The following statement was made by the Kazakhstani minister of education and science, Askhat Aimaganbetov:

> At the moment, preparations are underway to provide distance learning courses for teachers in Kazakhstan. It is essential to adopt a scientific approach while designing the course content to cover not just the usage of technical devices but also to address broader concerns such as IT competencies, teaching methodologies, strategies for assigning tasks, and remote system management. To facilitate the professional development of teachers, a specialized module will be created to cover all these competencies in the course. The aim is to equip teachers with the necessary skills and knowledge to carry out online teaching effectively, ensuring the continuation of education during the pandemic and beyond (zakon.kz, 2020)

In the future, according to the Minister, future teachers will initially have to graduate with the knowledge of teaching, both in the traditional form and with distance learning. The minister continues,

> Additionally, it has been communicated to all rectors that universities must also implement a compulsory module on distance learning as part of their preparation. This means that even students who are pursuing their education to become teachers

should acquire knowledge on the use of technology, teaching methods, and various competencies related to distance learning. This measure will ensure that future teachers are adequately equipped to handle the challenges of online teaching and can adapt to new technological advancements. The incorporation of this module will help bridge the gap between traditional teaching practices and digital teaching and will ensure that teachers are well-prepared to teach in both offline and online modes. (zakon.kz, 2020).

Given the statements above, professional training programs during such restrictive periods, should be flexible and allow new and returning employees to participate at any time during the semester, regardless of previous knowledge of the teaching staff. The main task of the state is to inspire teachers to take leadership positions for their professional development. Therefore, professional tutorials should be flexible in terms of time, location, focus, format, and duration. Moreover, employees with lower self-confidence should also be given the opportunity to get together or to make individual consultations. Finally, according to Looi et al. (2021), employees with superior technical and online teaching skills should be encouraged to do the following:

1) exchange ideas, solve problems, and share their teaching methods with other co-workers;

2) browse sample collections;

3) work independently, particularly by using instruction manuals and brochures (Looi et al., 2021).

To sum, it is important to consider the experience and training opportunities for teachers during the COVID-19 pandemic. In the event of necessarily imposed emergency remote education situation in Kazakhstan, providing learning opportunities for teaching management and staff should be made an imperative to offset the potential loss-of-learning among children.

2.9 COVID-19 Student Experience and Learning

Students must focus on self-regulation when studying remotely in order to develop self-directed learning and enhance their e-learning abilities. Students' capacity to work independently is critical in developing procedural skills, which necessitate the integration of many types of information. This occurs when students have to figure out how to solve problems on their own, or use a simulation to understand concepts in practical exercises.

Converting a home setting into a virtual learning environment can be a difficult task, particularly within a limited time frame. It can be even more challenging for families with children of varying ages, each with their own unique set of rules and requirements. During times of emergency online learning, children may need additional support and guidance to manage their learning effectively (Bokayev et al., 2021). According to previous research, parents’ satisfaction with online teaching largely depends on their level of engagement with school activities. To ensure effective online learning, parents need to guide their children in completing homework tasks, participate in virtual meetings, and monitor their academic progress (Beck et al., 2013; Laws & Millward, 2001). However, the level of parents’ involvement may be influenced by their education level and technical skills, as some parents may struggle with navigating the online learning platforms, managing multiple devices, and completing complex registration procedures. Therefore, schools and teachers should provide adequate support to parents to ensure their effective involvement in their children's online learning experience.

The level of support that parents can provide for their children’s online learning varies and this can be observed by teachers. Bokayev et al. (2021) conducted a study that showed that many parents encounter various difficulties when it comes to online learning. For instance, some parents may lack confidence in their ability to fully comprehend the material presented in online classes. Additionally, families with multiple children may struggle to provide enough technological devices for each child to attend their classes simultaneously. Moreover, the lack of access to stable internet connection can pose a significant challenge for students who are learning online. These challenges can lead to negative effects on students academic performance and can cause additional stress for both parents and teachers.

To sum, in Kazakhstan, the 18-month-long period of online schooling during the COVID-19 pandemic has had a significant impact on parents, particularly those with younger children who required more consistent supervision and support. Consequently, many parents had to sacrifice their work duties to meet their children's educational needs. This has had broad educational and economic implications that require further investigation and consideration. It is essential to examine the effects of online learning on parents' work-life balance and economic stability, particularly in families with limited access to technology and reliable internet. Additionally, it is necessary to investigate the impact of online schooling on students' academic performance and their mental and emotional well-being. Moreover, policy-makers and educators must consider the potential long-term effects of online learning on the quality of education and the overall development of the younger generation. Hence, further research is needed to explore the implications of the prolonged online learning regime on the society as a whole.

2.10 The Effect of the Pandemic on Male and Female Academic Performance

As mentioned in subsection 2.4, the World Bank estimated that the loss-of-learning due to COVID-19 restrictions in Kazakhstan was largely felt among underprivileged youth located in rural areas. However, little is known about the level of learning loss in terms of gender. It is not known whether female or male students more disadvantaged as a consequence of the COVID-19 restrictions. International research on the topic suggested has explored the differential effects of COVID-19 on males and females in terms of psychological health and well-being. Specifically, Roma et al. (2021) found that the pandemic affected male and female university students' personal lives equally. However, males consumed more unhealthy food and exhibited less hygienic habits compared with their female counterparts. Little research has been conducted on how the pandemic may have had differential effects on male and female academic performance. One study in based on 300 Pakistani students suggested that females were less likely to support or enjoy eLearning (Ali et al., 2021). While some research suggests that students in rural locations in Kazakhstan may have been severely disadvantaged due to COVID, it is not known whether female students were also disproportionately disadvantaged due to the pandemic restrictions and move to online learning.

2.11 Gender Influence on Academic Performance

Studies have shown that there are persistent gender differences in mathematics and science achievement, with boys tending to outperform girls in these subjects. However, the causes and nature of these differences are still the subject of debate and research. The gender gap in STEM areas, according to Spearman and Watt (2013), may be explained by variations in abilities, attitudes toward STEM, and socialization. International studies, such as the Trends in International Mathematics and Science Study (TIMSS) and the Programme for International Student Assessment (PISA), have consistently found that on average, there are no significant differences in mathematics achievement between boys and girls across countries. While the majority of countries have no substantial gender disparities, boys outperform girls in several circumstances. Numerous academic studies, including those conducted by Alkhateeb (2001), Badr, Morrissey, and Appleton (2012), Bedard and Cho (2010), Guiso, Monte, Sapienza, and Zingales (2008), and Mullis, Martin, Foy, and Arora (2009), have examined the gender gap in mathematical achievement using data from the

Trends in International Mathematics and Science Study (TIMSS) and the Programme for International Student Assessment (PISA). These studies indicate that there is indeed variability in the gender gap in mathematical performance across countries. However, the findings from multiple TIMSS and PISA cycles suggest that gender differences in mathematics achievement are generally not significant in most countries. Moreover, when differences do exist, they tend to favor boys over girls.

Otherwise, girls have greater reading skills than boys, according to research, with girls exhibiting stronger reading comprehension and vocabulary skills in many nations. For example, according to a 2016 PISA assessment, females scored 29 points higher than males in reading literacy across all nations participating in the research. Similarly, an OECD (2015) survey discovered that the gender difference in reading literacy has remained largely steady over the last decade, with girls regularly surpassing boys in the majority of nations.

The causes for gender variations in reading literacy are unclear, although some studies suggest that girls are more driven and engaged in reading and that they may also receive greater support from their families and instructors (OECD, 2019a). Boys, on the other hand, may be less interested in reading and more inclined to participate in other hobbies such as video games or athletics (OECD, 2019a).

While the reasons for these gender differences are complex and multifaceted, they may be due in part to societal and cultural factors that influence girls' and boys' attitudes towards mathematics. These factors may include gender stereotyping, biased teaching practices, and limited role models. Addressing these issues requires a concerted effort by educators, policymakers, and other stakeholders to create a more inclusive and equitable learning environment that supports and motivates all students, regardless of their gender.

2.12 Influence of a School Type on Academic Performance

A school's location can have a substantial influence on pupils' academic success. The location of a school can have an impact on a variety of aspects, including the available resources, the quality of instruction, and the social and economic context in which the school is located. The availability of resources is one of the most important elements influencing academic achievement. Urban schools typically have more resources, such as textbooks, technology, and well-equipped laboratories, which can give students with more opportunity to study and improve their academic performance. Schools in less affluent communities, on the other hand, may have inadequate resources, which might impair kids' academic achievement (Shi, 2020).

The geographical location of a school is a crucial factor that can influence the quality of education it offers. According to Tadesse and Muluye (2020), schools situated in urban or metropolitan areas typically have better access to a wider pool of qualified teachers and instructional resources, which can enhance the overall quality of education. Urban schools may also benefit from closer partnerships with local universities or research institutions, providing opportunities for professional development and access to cutting-edge teaching methodologies.

In contrast, schools located in rural areas may face several challenges in providing a high-quality education. These schools may struggle to recruit and retain qualified teachers due to limited employment opportunities or insufficient compensation. Rural schools may also have limited access to instructional resources and technologies, which can hinder students' learning experiences. Additionally, rural students may face unique socio-economic and cultural challenges that can impact their academic performance and limit their access to educational opportunities.

Furthermore, the social and economic environment in which a school is located might have an effect on academic success. Students attending schools in areas of extreme poverty may face extra stresses, such as a lack of access to basic necessities such as food and shelter, which can have an impact on their academic performance. Similarly, kids attending schools in high-crime regions may suffer dread and anxiety, resulting in low academic performance (UNESCO, 2018).

To summarize, a school's location can have a major influence on the academic achievement of children. Schools in urban areas often have greater resources, higher educational quality, and a more favorable social and economic climate. Schools in less wealthy locations, on the other hand, may struggle to provide the same level of resources and education quality, resulting in inferior academic achievement.

2.13 Influence of Language of Instructions on Academic Performance

The language of instruction plays a crucial role in students' academic success. When students are unable to comprehend and communicate effectively in the language of instruction, it can significantly impact their ability to learn and achieve academic success. In Kazakhstan, a country with two official languages, Kazakh as the native language and Russian as the official language, students who are not proficient in the language of instruction may experience difficulties in reading, writing, and speaking, leading to a reduced capacity to comprehend subject matter and articulate their thoughts effectively. This can negatively impact academic performance, leading to lower grades and reduced academic progress (OESD, 2019a).

Linguistic minorities face additional challenges in their academic pursuits, such as underrepresentation in official assessments like the Programme for International Student Assessment (PISA). This underrepresentation can further exacerbate existing disparities in academic achievement and limit opportunities for linguistic minority students to demonstrate their academic potential. Educational policymakers and stakeholders must develop strategies to support students who face linguistic barriers, such as providing additional language instruction, utilizing bilingual resources, and developing assessment tools that are inclusive and accessible to all students, regardless of their linguistic background. By fostering a more inclusive and supportive learning environment, students from all linguistic backgrounds can have an equal opportunity to achieve academic success.

There is a lack of research on the reading performance of students in bilingual or plurilingual nations, particularly in post-Soviet countries where Russian is widely used at home. Furthermore, the Russian language is more prevalent in metropolitan areas than in rural ones, and some regions of Kazakhstan are more “Russianized” than others. As a result, the purpose of this study is to see if there is a significant difference between students who attend schools where Kazakh or Russian is the central language of teaching.

The language of instruction is a crucial factor that impacts academic performance, as demonstrated by the results of the Unified National Test (UNT) in Kazakhstan. The UNT is an assessment taken by students after completing secondary school to qualify for higher education. According to IAC (2018), there has been a notable difference in UNT performance between students who take the test in Russian versus Kazakh. Historically, before 2016, students who took the test in Russian consistently outperformed their Kazakh-speaking peers. However, there has been a reversal of this trend in recent years. In both 2017 and 2018, students who took the test in Kazakh scored higher on average than those who took it in Russian.

This shift in UNT performance may be attributed to a range of factors, such as changes in the education system, improvements in Kazakh language instruction, or shifts in student demographics. It is also worth noting that UNT results may not necessarily reflect a student's overall academic ability, as the test assesses a specific set of skills and knowledge related to higher education enrollment.

Minority languages are not represented in the UNT, since students can only take the exam in Kazakh, Russian, or English since 2018 (p. 106). While the UNT findings imply that language of study is not a barrier to addressing students' educational requirements, they may be skewed, and a worldwide examination such as PISA may offer a more accurate indicator of educational differences caused by language of instruction in schools. As a result, this study is critical for determining the influence of language on students' academic progress.

Finally, the language employed in schools can have a substantial influence on children's academic success. When pupils are taught in a language in which they are not fluent, their ability to absorb and communicate effectively suffers, resulting in poorer grades and academic accomplishments. When students are taught in a language in which they are proficient, their knowledge and communication abilities improve, enabling higher academic performance.

In this case, to support students in achieving their full academic potential, it is essential to ensure that language barriers do not limit their access to educational opportunities. This may involve providing additional language support and resources for students who are not fluent in the language of instruction, developing inclusive assessment tools that account for linguistic diversity, and promoting multilingualism and language equity in educational policies and practices. By prioritizing linguistic diversity and inclusivity, we can ensure that all students have an equal opportunity to succeed academically, regardless of their language background.

2.14 Future Planning in Post-COVID World

Jaiswal (2020) emphasizes the significance of developing e-learning skills in the 21st century, such as technological literacy and online adaptability, due to the prevalence of the "information age". With the possibility of future global crises, including pandemics, there is a growing need to prepare for a shift to online education as a viable alternative to traditional in-person learning. UNESCO (2020) recommends that online education be viewed as the "new normal" to mitigate the negative impact on education during domestic or international crises. This approach would not only provide a solution to the current crisis but also help to prepare for future potential crises that may disrupt traditional education systems. A recent report by the OECD reads,

> "Real change takes place in deep crisis, you will not stop the momentum that will build. [...] It's a great moment" for learning [...]. All the red tape that keeps things away is gone and people are looking for solutions that in the past they did not want to see. Students will take ownership over their learning, understanding more about how they learn, what they like, and what support they need. They will personalize their learning, even if the systems around them won't." (Anderson, 2020).

Undoubtedly, the incorporation of information and communication technology (ICT) has become increasingly imperative in contemporary classrooms. The employment of sophisticated learning tools such as computers, tablets, and mobile devices can significantly enhance the educational experience by fostering engagement and enjoyment, developing essential twenty-first-century skills, and promoting active collaboration among learners during the learning process. Integrating ICT in educational programs can have a positive impact on student engagement, motivation, and academic performance, ultimately preparing them to thrive in the digital era. By leveraging technological innovations, teachers can cultivate a more dynamic and interactive classroom environment that caters to the diverse learning needs of students. Hence, the integration of ICT in education is a vital step towards fostering a more engaging, effective, and equitable learning experience.

2.15 Summary

The COVID-19 epidemic caused dramatic changes in education throughout the world, with schools closing and students moving to online learning. This transformation caused a number of issues for students, particularly those from low-income households and disadvantaged areas who lacked access to technology and online learning tools. Furthermore, gender has been demonstrated to have an effect on kids' arithmetic and reading skills, with girls frequently surpassing males in reading and boys exceeding girls in math. School location has also been demonstrated to affect academic achievement, with rural pupils frequently having less access to resources and opportunities than their urban counterparts. Furthermore, the language of teaching has been demonstrated to influence academic attainment, particularly in bilingual or plurilingual countries such as Kazakhstan.

All of these aspects are explained by the ecological systems theory, which holds that individuals are impacted by a variety of systems, including microsystems, mesosystems, exosystems, and macrosystems. The microsystem relates to an individual's local surroundings, such as family and school, whereas the mesosystem refers to the interconnections between various microsystems. Exosystems are external systems that have an indirect impact on individuals, such as government legislation, whereas the macrosystem is the greater cultural framework that influences attitudes and values.

In the context of education, ecological systems theory can assist us in understanding how variables such as school location, language of teaching, and gender interact to impact academic success. Students from rural locations, for example, may have difficulties in gaining access to resources and opportunities that their urban peers take for granted. Similarly, pupils in bilingual or multilingual nations may struggle with the language of instruction, especially if their home language is not included in official exams such as PISA. Finally, gender may influence academic success since boys and girls may confront different expectations and opportunities in school.

Overall, ecological systems theory assists us in comprehending the complicated interplay of numerous elements that impact academic success. We may better understand the problems and opportunities that students encounter and devise interventions to enhance their academic performance if we evaluate these elements in the context of an individual's surroundings and culture.

3. Methodology

The main objective of this quantitative research is to explore the effect that the COVID-19 pandemic had on students' academic development in Kazakhstan. Specifically, the research is broken into two studies. Study 1 identifies the role of gender, mother tongue, and exam location on performance in these subjects, while Study 2 draws upon aggregated data to estimate the degree of loss-of-learning on the same five subjects due to the pandemic.

3.1 Research Design

This study employs a quantitative design, which is best for analyzing large datasets, such as entrance exam data. The current study employs a repeated cross-sectional research design (Pan ,2022) as each of the applicant students for each year are unique—it is policy that students cannot re-sit the entrance exam for the selective school in this instance. For repeated cross-sectional designs, the same information is gleaned from the administration of the instruments on independent samples. The advantage of such designs is that comparisons can be made on the level or degree to which the same demographic (i.e., age, gender) exhibit some focal attribute or trait. Therefore, this design is well suited to the current study given that data is provided for both the pre-COVID (2019) and COVID-influenced (2020, onward) educational conditions.

For Study 1, data is provided for each applicant student. In this case, percentage correct scores are provided by the selective school (five subjects x three years). For Study 2, data is provided in aggregate form. In this case, average scale scores are provided for each of the five subject areas for the past ten years (five subjects x 10 years).

3.2 Participants

Participating students for Study 1 included a total 17,485 applicants from 2019, a total 20,084 applicants from 2020, and a total 19,248 applicants from 2021. Table 2 provides a breakdown of the participating students for Study 1. The total sample size was 56,817.

Table 2

Demographic of Student Applicants for 2019, 2020, and 2021

Gender		Mother Tongue		Location	
Male *n* (%)	**Female *n* (%)**	**Kazakh *n* (%)**	**Russian *n* (%)**	**Urban *n* (%)**	**Rural *n* (%)**
			2019		
8,750(50.0)	8,735(50.0)	4,746(27.1)	12,739(72.9)	2,468(14.1)	15,017(85.9)
			2020		
9,892(49.3)	10,192(50.7)	5,849(29.1)	14,235(70.9)	2,651(13.2)	17,433(86.8)
			2021		
9.649(50.1)	9,599(49.9)	6,097(31.7)	13,151(68.3)	2,763(14.4)	16,485(85.6)

Note. Percentages of total sample in brackets.

For Study 2, the total number of student applicants for each year were as follows: 2013 = 7,464; 2014 =11, 847; 2015 = 13,558; 2016 = 16, 060; 2017 = 17,362; 2018 = 14,818; 2019 = 17,485 (as above), 2020 = 20,084 (as above), 2021 = 19,248 (as above), and 2022 = 24,045.

In terms of origin status of the applicants, in 2019, 14.11% came from rural locations (villages), in 2020, 13.20% came from rural locations, while in 2021, 14.35% came from rural locations.

3.3 Instruments

For Study 1, applicant data included (1) the school location for which the student sat the exam, (2) the language that the student sat the test in (Kazakh/Russian), (3) the student’s gender (male/female), (4) the location of the school (urban/rural), and individual percentile scores for each of the five subjects.

For Study 2, applicant data was provided for this research project in aggregate form. Specifically, the mean scale scores for each of the ten years for each of the five subjects was provided for this research project by the selective school system. It should be noted that these averages can be compared year-to-year as the exams were comprised of common (link) items and equated via item response theory (IRT). This means that an applicant receiving a scale score of 150 for Math for 2013 could be deemed equivalent to another student receiving a scale score of 150 for Math in 2022, despite each student being subject to only a subset of common link items (Wu, 2010). No demographic data were provided for Study 2.

3.3.1 Dependent Variables

The dependent variables in Study 1 pertained to applicant percentile scores for each of the five subject areas. For Study 2, the dependent variables are the average scale scores for each of the subjects for 2013 to 2022. The exams themselves were designed with the assistance of an international testing body tailored specifically for the Kazakhstani context. All psychometric scaling and equating were undertaken by an international assessment agency. The testing regime and administrative procedures adhered to the highest standards (American Educational Research Association, American Psychological Association, & National Council on Measurement in Education [Eds.], 2014).

3.3.2 Independent Variables

For Study 1, the independent variables include student gender and mother tongue specified at the within-school level, and school exam location (urban/rural) specified at the between school level. For Study 2, the goal is to use historic pre-COVID data (i.e., 2013 to 2019) to project what might have been the average performance for each subject in 2020, 2021, and 2022. Thereafter, the projected performance (based on 2013-2019 trends) could be compared with the actual performance so as to estimate the degree of learning loss experiences by Grade 7 students in 2020, 2021, and 2022. Therefore, the pandemic condition could be conceived as the independent variable for Study 2.

3.3.2.1 Individual – and School-Levels of Data

It should be noted that within each of the schools (or exam locations), applicants varied in terms of gender, mother tongue, and origin location. However, each student's *exam* location varied at the school level. In this instance, multilevel modelling is appropriate so account for the potential for ecological and atomistic fallacies (Roux, 2002). For Study 1, gender is coded male = 2 and female = 1, mother tongue is coded Russian = 2 and Kazakh = 1, and student's origin location is coded urban = 2 and rural = 1, while exam location is coded major city = 2 and minor city = 1 (Astana, Almaty, and Shymkent defined as major metropolis).

3.3 Source of Data

Datasets for Study 1 and Study 2 were both provided by one selective school system in Kazakhstan. All data was anonymized prior to being received by this researcher. In addition, the data itself was kept in a password protected computer due to some level of sensitivity.

3.4 Analysis

For RQ1, pertaining to the degree to which gender, mother tongue, and student origin status, and school exam location predicted applicant performance, multilevel modelling was undertaken with the assistance the misty (Yanagida, 2022) and lme4 (Bates et al., 2015) R packages.

The misty package was used to estimate the intra-class correlation coefficients (ICCs) and associated design effects ($de = 1 + ICC[n_{clus} - 1]$, where n_{clus} = average cluster size). Design effects above 2.00 are consider substantive necessitating multilevel modelling (Lai & Kwok, 2014). While the lme4 package was used to perform the 15 total multi-level models (or single-level models dependent on *de*) required for the analysis (outcomes for five subjects for three years). While is it acknowledged that students may not permanently reside in the school for which they sat the exam, it is expected that applicants would more generally sit the exam in a place more convenient to them across the country and that examination of differences in performance by school location was warranted.

The purpose of RQ2 was to identify the expected learning loss due to the pandemic. Given a generally steady rate of improvement year-to-year in the exam performance of the applicants, simple linear extrapolation is applied to the pre-pandemic data (2013 to 2020) with the assistance of the linear regression (lm function) using base R (R Core Team, 2022). Based on pre-COVID data, a line of best fit would be generated (note that for QR, only the 2019 and 2020 data is used due to the use of a new measurement scale). Thereafter, using the generated intercept and slope details from the linear model, an extrapolation is undertaken for 2021 and 2022. Thereafter, the projected loss-of-learning for each cohort would be estimated by subtracting the expected scale score by the observed scale score. To generate a Cohen's *d* type effect size to measure the magnitude of the loss-of-learning for 2021 and 2022, (1) the projected learning loss for each year will be used as the numerator and (2) the *SD* for the respective year (2021 or 2022) will be used as the denominator. Based on meta-alanyeses of standardized test outcomes, Hattie (2008) has determined that, on average, students gain approximately 0.40 Cohen's *d* per year. Therefore, interpretations of loss-of-learning can be interpreted in a similar way: 0.20 = negligible, 0.20 or above = small, 0.40 or above =

medium (*one year's expected academic development*), and 0.60 or above = large (Hattie, 2008).

3.6 Limitations

According to Cohen et al. (2007), it is indicated that small measurement errors may significantly compound the analysis of outcomes. However, Study 1 deals with estimating general trends in the data. Therefore, while there exists some lack of precision of measurement at the individual level (see Wu, 2010, for an explanation of the mathematics), such imprecision becomes non-significant at the aggregate level.

Another limitation is associated with the idea that the sample applicants are not representative of the population of Kazakhstani population. It is true that applicant students are likely among the top performing academically in the country. Therefore, caution should be made when making generalizations from the current study to the wider population of Grade 7 students. Nevertheless, it is reasonable to assume that a loss-of-learning experienced by top performing students is highly likely to also be felt by students of all levels of the ability spectrum.

Chapter 4. Findings

4.1 Introduction

This chapter presents the findings of a study conducted to assess the impact of the COVID-19 pandemic on the academic performance of Kazakh students in one selective school system in Kazakhstan. Results are presented in accordance with the research questions For RQ1, and results of descriptive statistics for RQ2.

4.2 RQ1: The Role of Student Gender, Mother-Tongue, Origin Status, and Exam Location on Applicant Performance

Prior to undertaking regression-based analysis, it was necessary to estimate the ICCs and design effects due to the school exam location. Table 3 provides all associated information for ICCs and design effects for the seven subjects of interest.

Table 3

Descriptive Statistics and Intraclass Correlation Coefficients/Design Effects for Seven Subjects, 2019-2021

Year	**Math**	**QR**	**Kazakh**	**Kaz(2nd)**	**Russian**	**Rus(2nd)**	**English**
Descriptive Statistics: *M*(*SD*)							
2019	46.01(17.95)	48.99(18.35)	76.83(14.90)	68.12(23.53)	81.18(11.77)	76.07(20.90)	53.49(20.30)
2020	49.70(18.39)	53.08(19.49)	74.99(14.86)	65.65(22.65)	81.63(11.48)	74.46(19.33)	54.06(21.67)
2021	42.72(23.99)	51.68(18.55)	65.47(15.52)	48.98(24.45)	69.22(17.18)	66.02(20.63)	51.57(23.19)
Between-School Random Effects: ICC(*de*)							
2019	.11(97.06)	.10(88.33)	.02(13.72)	.12(29.36)	.08(19.90)	.15(96.39)	.11(97.06)
2020	.09(91.29)	.09(91.29)	.02(15.22)	.14(35.97)	.07(24.32)	.16(107.61)	.09(91.29)
2021	.07(65.09)	.06(55.93)	.04(13.50)	.23(35.72)	.07(24.15)	.15(94.79)	.08(74.25)

Note**.** QR = Quantitative reasoning; ICC = intra-class correlation; *de* = design effect.

Analysis reveals that the standard deviations are generally comparable across years except for Math 2020-2021, and Russian 2020-2021. Findings suggest that there existed very large design effects (over 2.00) due to exam location (schools) for which students sat the exams. Therefore, multilevel modelling was deemed appropriate for the regression-based analysis in order to account for systemic differences between schools.

Table 4 presents the results of the regression analyses for each year (2019-2021) and for each subject. The variance explained due to the predictors at both the within- and between-school exam location is provided in percentile form at the bottom of each set of regression coefficients for each year.

Table 4

Linear Mixed-Effects Multilevel Models for Five Subjects for 2019 to 2020

Intercept/ Effects		Math	QR	Kazakh	Kaz (2nd)	Russian	Rus (2nd)	English
				2019				
Intercept		11.80***	11.31***	76.43***	77.82***	65.61***	55.02***	19.98
Gender(M)		4.57***	6.27***	-3.72***	-5.71***	1.19***	-1.18***	-1.85***
Lang(Rus)		3.62***	4.43***	–	–	–	–	7.38***
Origin(Urban)		6.27***	7.09***	1.08**	-4.78***	6.24***	12.21***	9.94***
Major city[a]		7.92***	6.80***	2.68**	5.67[ns]	1.08[ns]	-0.46[ns]	6.17*
Within-sch	**var**	12.82/281.82	20.16/297.92	3.47/218.26	9.45/500.41	3.18/124.57	19.44/364.73	23.91/358.37
explained		4.55%	6.77%	1.59%	1.89%	2.55%	5.33%	6.67%
Between-sch	**var**	20.32/33.65	18.20/31.83	1.28/5.44	4.53/67.31	1.01/11.07	6.57/63.55	18.74/44.61
explained		60.39%	57.18%	23.53%	6.46%	9.12%	10.34%	42.00%
				2020				
Intercept		13.34***	11.10***	72.57***	79.03***	67.03***	54.79***	21.93***
Gender(M)		5.47***	6.00***	-3.60***	-5.38***	0.49[ns]	0.89**	-2.90***
Lang(Rus)		4.60***	6.96***	–	–	–	–	8.31***
Origin(Urban)		5.68***	6.86***	1.65***	-7.47***	5.80***	11.18***	8.73***
Major city[a]		8.17***	7.89***	3.24***	6.50[ns]	1.55[ns]	-0.39[ns]	6.73***
Within-sch	**var**	16.28/298.87	25.60/338.99	3.40/216.81	10.63/455.77	2.10/122.03	16.19/307.83	25.49/417.63
explained		5.55%	7.55%	1.57%	2.33%	1.72%	5.26%	6.10%
Between-sch	**var**	20.51/30.63	21.67/32.14	2.46/4.68	4.27/72.23	1.43/8.62	3.43/57.04	19.26/40.25
explained		66.96%	67.42%	52.56%	5.91%	16.59%	6.01%	47.85%
				2021				
Intercept		0.80***	16.27***	67.73***	64.66***	54.27***	46.45***	18.58***
Gender(M)		6.75***	5.49***	-4.47***	-4.65***	-1.40***	-0.79*	-2.38***
Lang(Rus)		5.27***	5.07***	–	–	–	–	6.53***
Origin(Urban)		7.00***	6.34***	0.26[ns]	-6.70***	7.05***	12.71***	10.10***
Major city[a]		8.12***	6.13***	2.25[ns]	2.85[ns]	1.88[ns]	-0.56[ns]	6.65**
Within-sch	**var**	24.68/527.37	19.11/317.59	4.88/231.82	8.30/463.00	3.59/272.69	22.59/361.82	24.16/482.21
explained		4.68%	6.02%	2.11%	1.79%	1.32%	6.24%	5.01%
Between-sch	**var**	21.07/39.81	13.15/21.64	0.02/9.18	0.06/130.20	0.86/20.11	3.86/63.37	17.39/43.52
explained		52.93%	60.77%	0.22%	0.05%	4.28%	6.09%	39.96%

Note. QR = quantitative reasoning; origin = original location (urban = 2, rural = 1); [a]predictor modelled at the between-school exam location level; $*p < .05$, $**p < .01$, $***p < .001$; ns = not statistically significant.

Depending upon the outcome subject of interest and year, variance explained for outcomes within-schools ranged between 1.32% (Russian in 2021) and 7.75% (QR in 2020). Likewise, variance explained (due to major city status) for outcomes between-school exam locations ranged between ranged between 0.05% (Kazakh as a second language, 2021) to 67.42% (QR in 2020).

In general coefficients tended to be quite consistent (in terms of size and significance) across the pre-COVID (2019 and 2020) and post-COVID periods. Specifically, the advantages due to gender, Russian language stream students (for Math, QR, and English), and urban origin appeared consistent for the pre-COVID (2019 and 2020) and post-COVID assessment periods.

4.3 RQ2: Projected Loss-of-Learning Due to COVID-19 Disruption

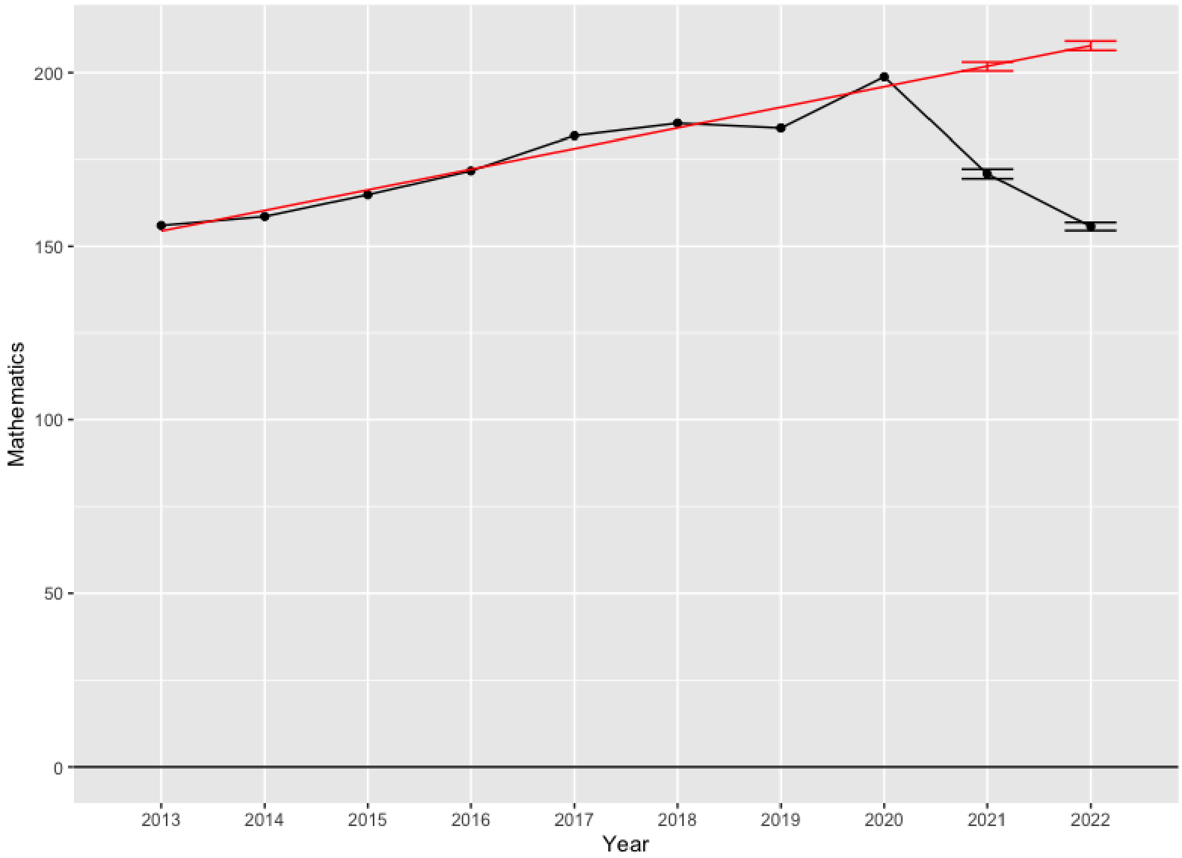
Results are now presented for the projected learning lost due to COVID-19 for each of the five subjects.

4.3.1 Loss-of-Learning for Mathematics

For Mathematics, the projected loss of learning due to COVID-19 interruptions is presented in Figure 2.

Figure 2

Projected Loss-of-Learning in Math Due to COVID-19 Disruptions



Note. Red line represents line of best for 2013 to 2020 only; observed score for 2021 = 170.80 while expected is 201.88 (-31.08 scale score points); observed score for 2022 = 155.60 while expected is 207.83 (-52.23 scale score points); *N*(2021) = 19,248, *SD* = 96.00, 2*seM = 1.38; *N*(2022) = 24,045, *SD* = 91.30, 2*seM = 1.18; seM error bars illustrated in graph.

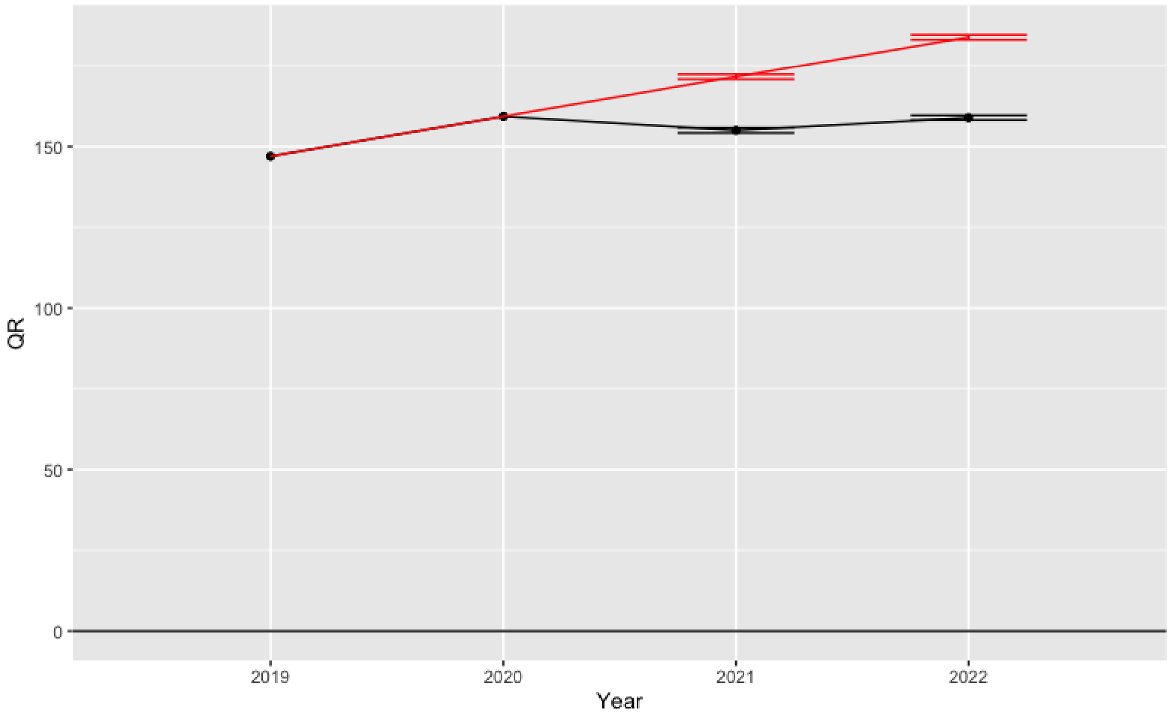
Therefore, projected loss of learning for Mathematics in 2021 was 31.08 scale score points (*d* = -0.32, moderate) and in 2022 was 52.23 scale score points (*d* = -0.57, moderate). This suggests that the COVID-19 pandemic had a substantial negative effect on Grade 7 applicants' mathematical ability.

4.3.2 Loss-of-Learning for Quantitative Reasoning

For QR, the projected loss of learning due to COVID-19 interruptions is presented in Figure 3.

Figure 3

Projected Loss-of-Learning in QR Due to COVID-19 Disruptions

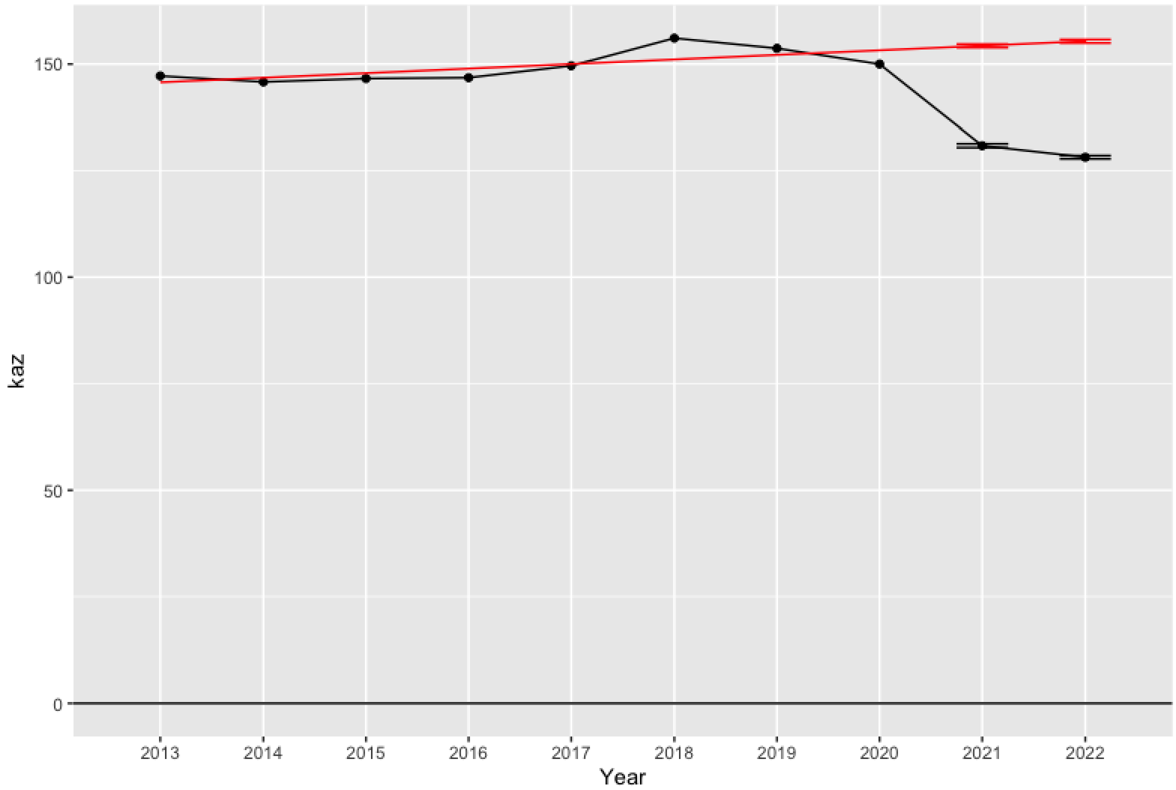


Note. Red line represents line of best for 2019 to 2020 only; observed score for 2021 = 155.0 while expected is 171.60 (-16.60 scale score points); observed score for 2022 = 158.90 while expected is 183.90 (- 25.0 scale score points); *N*(2021) = 19,248, *SD* = 55.60, 2*seM = 0.80; *N*(2022) = 24,045, *SD* = 56.00, 2*seM = 0.72; seM error bars illustrated in graph.

Therefore, the projected loss of learning for QR in 2021 was -16.60 scale score points (*d* = -0.30, small) and in 2022 was -25.0 scale score points (*d* = -0.45, moderate). This suggests that the COVID-19 pandemic had a small to moderate negative effect on students' capacity for quantitative reasoning. Though, as there were only two datapoints to base the extrapolation on, the results should be viewed with some caution.

Figure 4

Projected Loss-of-Learning in Kazakh as a First Language Due to COVID-19 Disruptions



Note. Red line represents line of best for 2013 to 2020 only; observed score for 2021 = 130.90 while expected is 154.32 (-23.42 scale score points); observed score for 2022 = 128.20 while expected is 155.39 (-27.19 scale score points); *N*(2021) = 19,248, *SD* = 31.00, 2*seM = 0.45; *N*(2022) = 24,045, *SD* = 29.70, 2*seM = 0.38; seM error bars illustrated in graph.

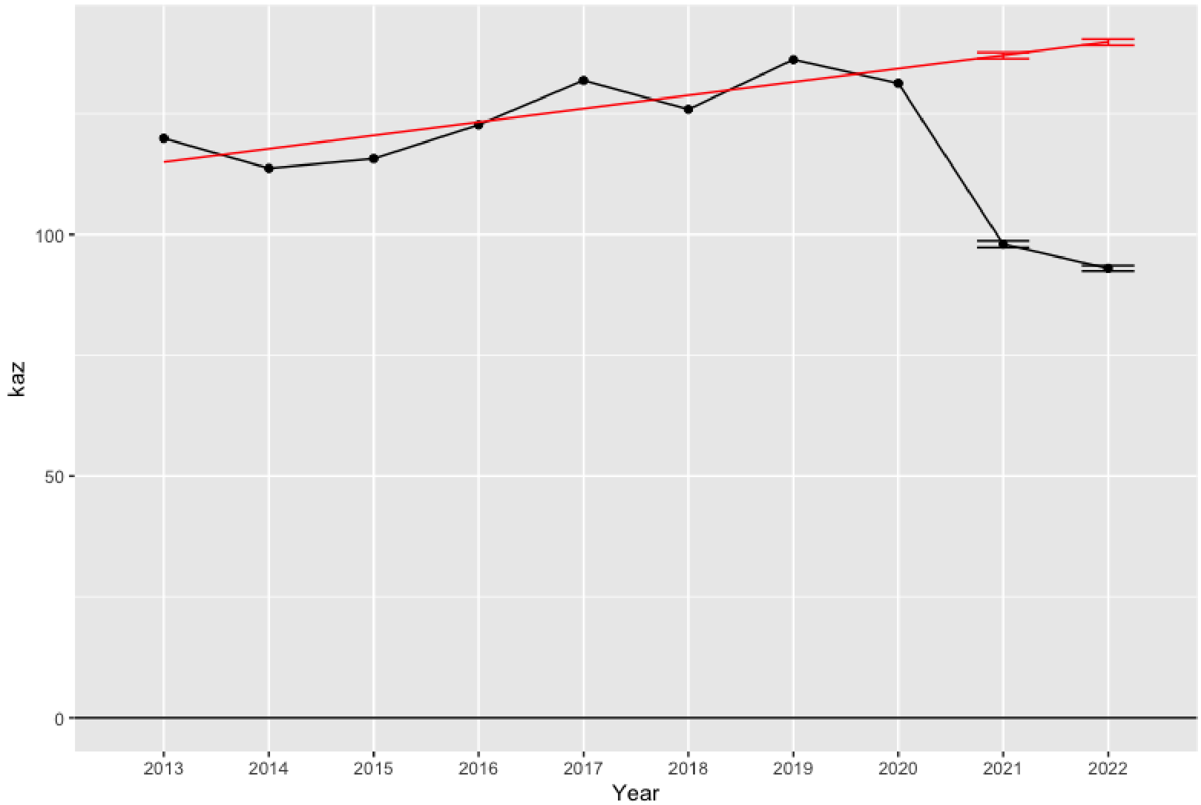
Therefore, projected loss of learning for Kazakh first language performance in 2021 was 23.42 scale score points (*d* = -0.76, large) and in 2022 was 27.19 scale score points (*d* = -0.92, large). This suggests that the COVID-19 pandemic had a large substantial negative effect on Grade 7 applicants' native Kazakh language ability.

4.3.4 Loss-of-Learning for Kazakh as a Second Language

For Kazakh as a second language, the projected loss of learning due to COVID-19 interruptions is presented in Figure 5.

Figure 5

Projected Loss-of-Learning in Kazakh as a Second Language Due to COVID-19 Disruptions



Note. Red line represents line of best for 2013 to 2020 only; observed score for 2021 = 98.00 while expected is 137.10 (-39.10 scale score points); observed score for 2022 = 93.00 while expected is 139.86 (-46.86 scale score points); *N*(2021) = 19,248, *SD* = 48.90, 2*seM = 0.70; *N*(2022) = 24,045, *SD* = 45.00, 2*seM = 0.58; seM error bars illustrated in graph.

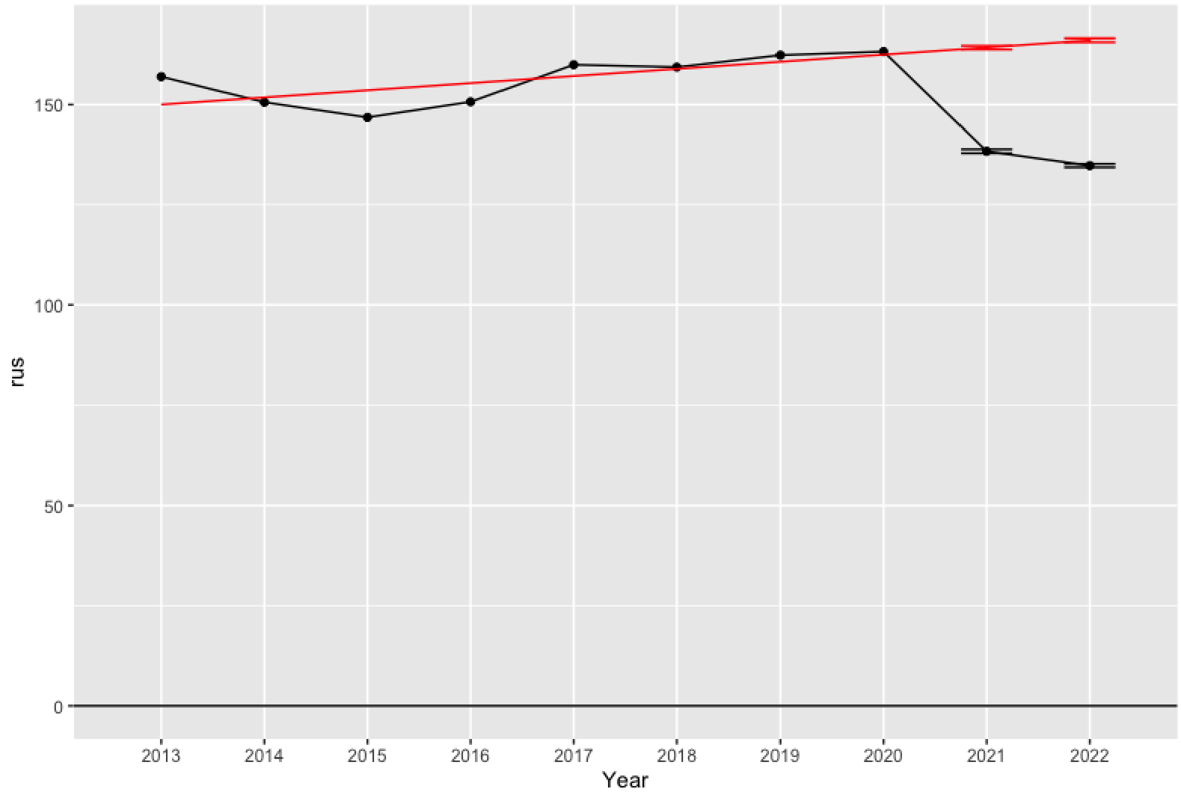
Therefore, projected loss of learning for Kazakh second language performance in 2021 was 39.10 scale score points (*d* = -0.80, large) and in 2022 was 46.86 scale score points (*d* = -1.04, large). This suggests that the COVID-19 pandemic had a large substantial negative effect on Grade 7 applicants' Kazakh second language ability.

4.3.5 Loss-of-Learning for Russian as a First Language

For Russian as a first language, the projected loss of learning due to COVID-19 interruptions is presented in Figure 6.

Figure 6

Projected Loss-of-Learning in Russian as a First Language Due to COVID-19 Disruptions



Note. Red line represents line of best for 2013 to 2020 only; observed score for 2021 = 138.40 while expected is 164.32 (-25.92 scale score points); observed score for 2022 = 134.80 while expected is 166.11 (-31.31 scale score points); *N*(2021) = 19,248, *SD* = 34.40, 2*seM = 0.50; *N*(2022) = 24,045, *SD* = 34.0, 2*seM = 0.44; seM error bars illustrated in graph.

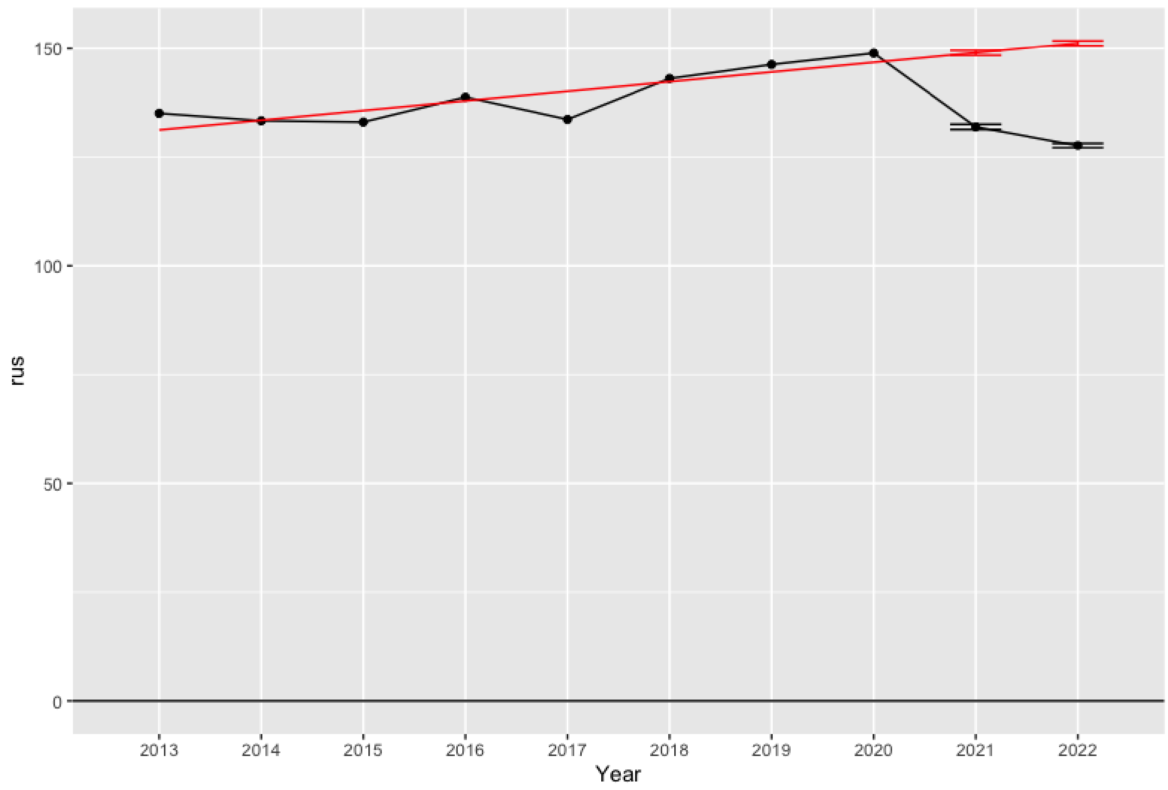
Therefore, projected loss of learning for Russian as a first language performance in 2021 was 25.92 scale score points (*d* = -0.75, large) and in 2022 was 31.31 scale score points (*d* = -0.92, large). This suggests that the COVID-19 pandemic had a large substantial negative effect on Grade 7 applicants' Russian as a first language ability.

4.3.6 Loss-of-Learning for Russian as a Second Language

For Russian as a second language, the projected loss of learning due to COVID-19 interruptions is presented in Figure 7.

Figure 7

Projected Loss-of-Learning in Russian as a Second Language Due to COVID-19 Disruptions



Note. Red line represents line of best for 2013 to 2020 only; observed score for 2021 = 132.00 while expected is 149.01 (-17.01 scale score points); observed score for 2022 = 127.70 while expected is 151.23 (-23.53 scale score points); *N*(2021) = 19,248, *SD* = 41.30, 2*seM = 0.60; *N*(2022) = 24,045, *SD* = 40.20, 2*seM = 0.52; seM error bars illustrated in graph.

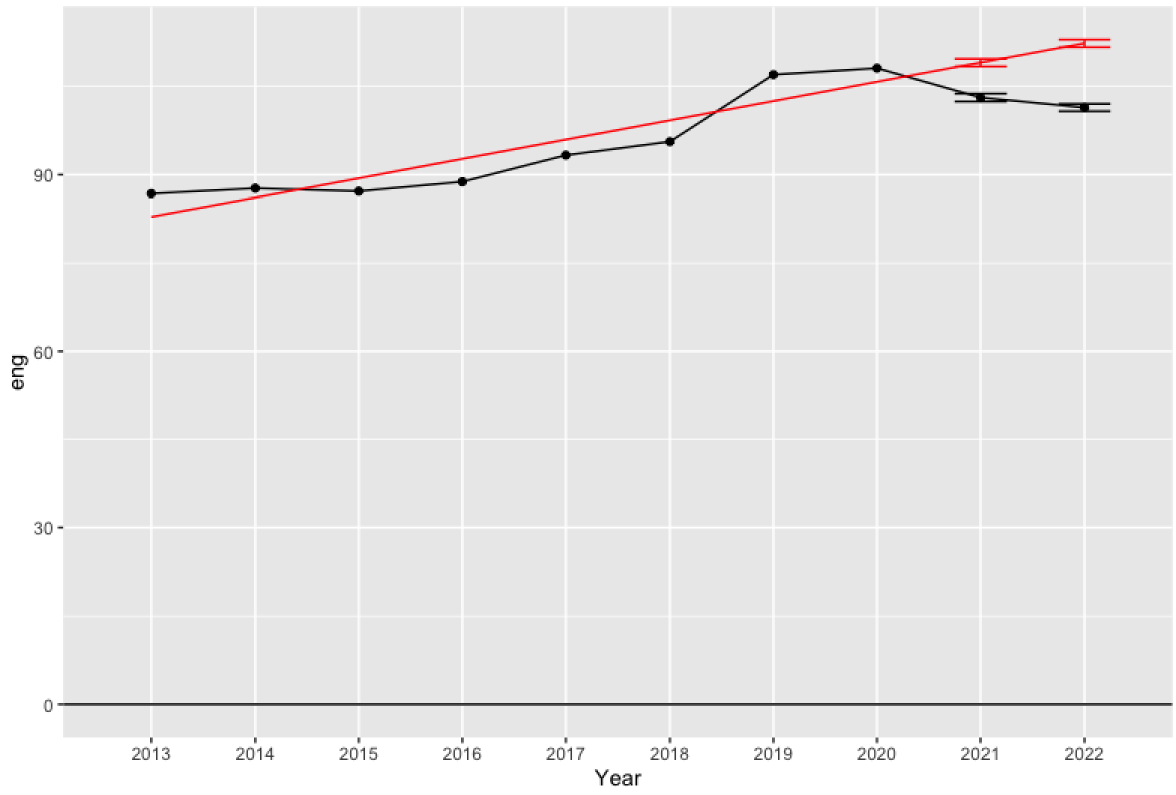
Therefore, projected loss of learning for Russian as a second language performance in 2021 was 17.01 scale score points (*d* = -0.41, moderate) and in 2022 was 23.53 scale score points (*d* = -0.59, moderate). This suggests that the COVID-19 pandemic had a moderate substantial negative effect on Grade 7 applicants' Russian as a second language ability.

4.3.7 Loss-of-Learning for English

For English, the projected loss of learning due to COVID-19 interruptions is presented in Figure 8.

Figure 8

Projected Loss-of-Learning in English Due to COVID-19 Disruptions



Note. Red line represents line of best for 2013 to 2020 only; observed score for 2021 = 103.10 while expected is 109.06 (-5.96 scale score points); observed score for 2022 = 101.4 while expected is 112.34 (-10.94 scale score points); *N*(2021) = 19,248, *SD* = 46.40, 2*seM = 0.67; *N*(2022) = 24,045, *SD* = 48.30, 2*seM = 0.62; seM error bars illustrated in graph.

Therefore, projected loss of learning for English language performance in 2021 was 17.01 scale score points (*d* = -0.13, negligible) and in 2022 was 23.53 scale score points (*d* = -0.23, small). This suggests that the COVID-19 pandemic had a negligible to small negative effect on Grade 7 applicants' English language ability.

4.3.8 Summary

Table 5 presents a summary of the expected loss-of-learning due to COVID-19 for each of the seven subject areas.

Table 3

Summary of Loss-of-Learning Due to COVID for Seven Subject Areas

Year	Observed Scale Score: *M*(*SD*)	Expected Scale Score (*M*)	*d*
	Kazakh (1st)		
2021	98.00(48.90)	137.10	-0.80
2022	93.00(45.00)	139.86	-1.04
	Kazakh (2nd)		
2021	130.90(31.00)	154.32	-0.76
2022	128.20(29.70)	155.39	-0.92
	Russian (1st)		
2021	138.40(34.40)	164.32	-0.75
2022	134.80(34.00)	166.11	-0.92
	Russian (2^{nd})		
2021	132.00(41.30)	149.01	-0.41
2022	127.70(40.20)	151.23	-0.59
	Math		
2021	170.80(96.00)	201.88	-0.32
2022	155.60(91.30)	207.83	-0.57
	QR		
2021	155.00(55.60)	171.60	-0.30
2022	158.90(56.00)	183.90	-0.45
	English		
2021	103.10(46.40)	109.06	-0.13
2022	101.40(48.30)	112.34	-0.23

Note. QR = Quantitative Reasoning; *d* = Cohen's *d* effect size.

The summary suggests that loss-of-learning due to COVID-19 was exhibited the most for first and second language Kazakh speakers, while the least for English and QR.

Chapter 5. Discussion

5.1 Introduction

The previous chapter described the findings from the multilevel regression models on the role of applicants' gender, mother tongue, origin status, and exam location on applicants' performance, based on the total sample of 56,817 students. Accordingly, the chapter also presented the projected loss-of-learning across seven subjects (Mathematics, Quantitative reasoning, Kazakh language, Russian language, and English language).

The study revealed a concerning trend: many students experienced a significant loss-of-knowledge during the pandemic period, which is commonly referred to "remote learning". This loss-of-knowledge will likely have a detrimental effect on students' ongoing academic progress highlighting the importance of finding effective strategies to mitigate this phenomenon.

In this chapter, we will discuss the implications of these findings and suggest potential solutions to address the issue of learning loss. The chapter is organized into multiple subsections. These subsections discuss the COVID-19-induced reverse Flynn Effect across seven studying areas, as well as identifies the influence of such predictors as gender, language of instructions, and school location on the applicants' ability in the different subjects. The chapter concludes by suggesting the implementation of remedial learning into educational process in terms of ecological systems theory. The last subsection presents summary of all subsections mentioned above.

5.2 RQ1: The Role of Student Gender, Mother-Tongue, Origin Status, and Exam Location on Applicant Performance

Gender disparities in academic achievement have been a longstanding focus of educational research, with the Programme for International Student Assessment (PISA) revealing notable differences between boys and girls across various subjects. Specifically, research shows significant gender gaps in mathematics and science performance, with males outperforming females, while the reverse holds for reading proficiency (Gilleece et al., 2010). The continuing debate over the drivers of these gender differences in academic success encompasses both biological and sociocultural factors, as well as the effectiveness of educational interventions aimed at narrowing these gaps. According to researching data, significant gender imbalances persist across all five subjects (Mathematics, Quantitative Reasoning, Kazakh, Russian, and English) and all three years (2019-2021), with male students generally exhibiting stronger academic performance in Mathematics, Quantitative Reasoning, and Kazakh, while female students tend to excel in Russian and Englishю

5.2.1 The Role of Gender on Applicants' Mathematics and Quantitative Reasoning Performance

Using multiple regression analyses, epy findings show that in 2019, female students displayed better performance in quantitative reasoning skills relative to their male counterparts, as evidenced by a negative standardized beta weight of -0.19 for gender. However, male students outperformed their female peers in both 2020 and 2021, with negative standardized beta weights of -0.17 and -0.15, respectively. These results suggest that the impact of gender on quantitative reasoning ability may vary over time, with gender-based differences emerging in different years. Overall, the analysis indicates that the role of gender in quantitative reasoning skills may be complex and multifaceted, and it may fluctuate over the course of a student's academic journey.

Notably, the COVID-19 pandemic has exacerbated existing gender disparities in math and quantitative reasoning performance. Online learning, which became widespread during the pandemic, may have contributed to a decrease in motivation and participation among female students, due to the lack of in-person support and guidance from instructors. Additionally, the shift to remote learning may have placed students from low-income backgrounds at a disadvantage, as they may not have had access to the necessary equipment or a suitable study environment. These variables are likely to have contributed to the widening gender gap in math and quantitative reasoning skills observed during the pandemic.

5.2.2 The Role of Gender on Applicants' Language Performance

Based on the supplied statistics, female students consistently exhibit stronger language skills than their male counterparts across all three years of study (2019-2021), in all three languages examined (Kazakh, Russian, and English). There are several potential explanations for this gender gap in online language learning. For one, female students may possess greater natural aptitude for language acquisition or be more motivated to pursue language studies than their male peers. Additionally, female students may be more likely to engage in language learning activities that are emphasized in online education, such as collaborative projects, online discussions, and written assignments. Notably, research also indicates that female students tend to be more proficient in using technology for educational purposes than male students, which may be particularly advantageous in the context of online language instruction.

5.2.3 The Role of Language of Instruction on Applicants' Performance

The results of the findings section present that in general, students instructed in Russian perform better in all subjects, with the exception of Kazakh, where students instructed in Kazakh scored slightly higher. These findings suggest that language of instruction is a crucial factor in Kazakhstan in academic achievement among applicants, especially for bilingual study environment. Accordingly, the language of instruction in schools became crucial predictor of students' reading literacy scores and mathematic abilities in PISA 2018, where students with Russian language of instruction outperformed students with Kazakh language of instructions. It is worth noting that the discrepancy in academic achievement between students taught in Russian and Kazakh may be attributed to the location of the schools where these languages are used as the medium of instruction. Russian is predominantly used in metropolitan regions, which are generally associated with higher socioeconomic levels and greater educational resources, while Kazakh is more commonly used in rural areas.

Therefore, addressing the disparities in academic achievement may necessitate a focus on strengthening educational opportunities in rural schools.

5.2.4 The Role of Origin and Exam Location on Applicants' Performance

Based on the analysis, students who took the exam in urban areas demonstrated better academic performance in Math, QR, and English compared to those in rural regions. For instance, the mean Math score for students who took the exam in major cities was 60.33, whereas it was 53.08 for students who took the exam elsewhere. The availability of superior educational resources in urban areas, including access to more instructional materials and well-equipped classrooms, could be a contributing factor to this gap in academic performance. Additionally, peer influence may also play a role, with students in major cities having access to a more diverse and competitive peer group that fosters academic excellence.

It is plausible that the exam may be more challenging for students outside major cities, although this hypothesis is purely speculative. Nonetheless, these findings suggest that students who take exams in major cities have a considerable advantage over those who take exams in other regions, particularly in Math, QR, and English.

5.3 RQ2: Consideration of the Flynn Effect on Projected Loss-of-Learning Due to COVID-19 Disruption

It is necessary to first consider the (reverse) Flynn Effect and how actual changes in Kazakhstani applicants' IQ scores over time might have impacted the expected scale scores for each of the seven subject areas. The Flynn effect suggests that IQ scores tend to increase over time, meaning that students in each grade level should be expected to have higher IQ scores than students in the same grade level in previous years. This could lead to an increase in the expected scale scores for each subject area over time, even without any changes in actual learning. This was, of course, observed for the first eight years for each of the seven subjects (though QR was only 3 years).

However, the projects loss-of-learning, and associated estimated Cohen's *d* effect size for each subject area, suggested that there was a significant decrease in scale scores between 2021 and 2022, indicating that there was indeed a loss-of-learning due to the COVID-19 pandemic. While the Flynn Effect would have likely contributed to an increase in expected scale scores over time, this effect was likely outweighed by the negative impact of the pandemic on student learning.

5.3.1 Loss-of-Learning in Kazakh (1st)

The reverse Flynn Effect on Kazakh (1st) can be observed by comparing the observed scale scores in 2021 and 2022 to the expected scale scores. The loss-of-learning in Kazakh (1st) was equivalent to d = -0.80 in 2021 and d = -1.04 in 2022. This suggests that 2021 applicants were two years behind their projected performance, while the new 2022 cohort of applicants was more than almost three years behind in terms of Kazakh literacy. Given that students generally learn at 0.40 Cohen's *d* per years, it may be that the native Kazakh speaking applicants may have even regressed meaning that their language skills may have become worse. This is especially troublesome given that this is an important language for Kazakhstan and the student applicants would likely have constituted a sub-sample of the Kazakh-speaking Grade 7 student population that was more privileged. Though speculative, the loss-of-learning for less privileged Kazakh-speaking students in Kazakhstan may have been even worse.

5.3.2 Loss-of-Learning in Kazakh (2nd)

The reverse-Flynn effect was also demonstrated in the Kazakh as a second language student applicants. The loss-of-learning in Kazakh (1st) was equivalent to d = -0.76 in 2021 and d = -0.92 in 2022, almost two and two and a half years behind what would be expected. Again, we see evidence here of potential regression. The lack of proficiency in students Russian-native speaking students to communicate in Kazakh has major ramifications for communication domestic communication. While speculative, there is likely less capacity for inter-cultural and inter-ethnic communication among children and young adolescents in the country. Ongoing research on this potential phenomenon is essential.

5.3.3 Loss-of-Learning in Russian (1st)

The reverse Flynn effect was also evident for Russian (1st) with a loss-of-learning equivalent to d = -0.75 in 2021, and -0.92 in 2022. This indicates that, having experienced one and a half years online learning, the 2022 cohort was over two years behind where they might be expected to be in terms of native Russian proficiency. Many teachers had to quickly adapt their teaching methods to accommodate remote learning and that this adaption did not work well. It appears that the adaptions did not function well for students in general leading to a potential regression in language skills. This downward trend was likely associated with the pandemic and its associated disruptions to students’ daily routines and access to educational resources, which likely exacerbated the challenges posed by remote learning. As a result, students whose first language was Russian may not have been receiving the same level of instruction and support as they would have in a normal classroom setting, which may have negative implications for their academic progress and language acquisition.

5.3.4 Loss-of Learning in Russian (2nd)

More recent applicants' performance in Russian (2nd) also showed evidence of the reverse Flynn effect. The loss-of-learning in Russian (2nd) was equivalent to d = -0.41 in 2021, and d = -0.59 in 2022, which indicates that the 2022 cohort was close to a year and a half behind what might be normally expected. The probable lack of exposure to the language in practical, everyday situations may have contributed to the reverse Flynn effect observed in Russian (2nd) proficiency This is because native Kazakh-speaking students were likely not able to supplement their classroom learning with real-life language practice outside the classroom with native Russian speakers. The pandemic has made it difficult for language learners to immerse themselves in the language they are studying, and this could be a contributing factor to the lack of progress in language skills observed among non-native speakers learning Russian as a second language.

5.3.5 Loss-of-Learning in Math

According to Table 5, the reversed Flynn Effect on Math was -0.32 in 2021 and -0.57 in 2022. That means, that learning loss for the 2022 cohort was also approximately one and half behind what might normally had been expected. While some loss has been observed in Math results during the pandemic, the effects have not been as pronounced as initially anticipated (less pronounced that in languages, for example). One possible reason for this is that Math is a subject that is popular among students to have extra classes on, as well as more tutoring hours, which are often held face-to-face. However, due to COVID-19 restrictions, there has been a reduction in the total hours of learning available to students. Despite this, the impact on Math results has been less drastic than observed in the other linguistic-focussed academic subjects. Nevertheless, ongoing efforts are needed to mitigate the effects of the pandemic on students' learning outcomes, particularly in critical subjects such as Mathematics.

5.3.6 Loss-of-Learning in QR

The reverse Flynn Effect was also demonstrated for QR in 2021 (d = -0.30) and 2022 (d = -0. 45). This means that students lost-of-learning in 2022 was close to three quarters of a year. The relative stability in QR for the cohort may be associated with reasoning being more stable in children and less susceptible to change. For example, the study by Strand (2004) suggests that results in QR may be more stable in young children and less susceptible to regression. While the COVID-19 pandemic has disrupted traditional learning environments, the overall IQ level of students may remain relatively stable over time. Speculatively, this is important as regression in QR may be associated with more serious downstream cognitive, developmental, and social effects. While there may be some learning loss due to school closures and remote learning, the stability of IQ levels suggests that any decline is likely to be relatively minor and not significantly impact performance in quantitative reasoning.

5.3.7 Loss-of-Learning in English

According to the table, the reverse Flynn Effect on English seems to be the least severe compared to other subject areas. So, the Cohen's d for the year 2021 was -0.13, while for the year 2022 it was -0,23, which suggests that in 2022, students were only approximately half a year behind their expected performance in terms of English language literacy. This suggests that the impact of school closures and remote learning on their English proficiency may not have been as substantive. It is possible that applicant students in general learned English online anyway through private tutoring or “shadow education”. Furthermore, private tutoring may have played a role in maintaining their English proficiency, as some families may have sought out additional support to ensure their children did not fall behind (Hajar, 2022). Private tutoring has long been a popular option for students seeking additional support in academic subjects in Kazakhstan, and the pandemic may have even increased its prevalence.

5.4 Implementation of Remedial Learning

One of the possible suggestions to mitigate against the loss-of-learning due to COVID-19 disruption is to implement targeted remedial courses and programs. Remedial learning has emerged as a viable strategy for addressing the learning loss that has occurred during the COVID-19 pandemic. This more personalized and targeted approach provides instruction to students who require additional support in specific areas, enabling them to bridge gaps in their knowledge and catch up with their peers (Chen, 2011). To effectively implement remedial learning at the government level, a comprehensive plan must be developed that considers the needs of students across different grade levels and subjects. This plan should include the allocation of additional resources, such as teachers, learning materials, technology, and, importantly, time, to support the delivery of remedial instruction. Moreover, the government can work with schools to identify students who require more extensive remedial support and establish a system for providing personalized instruction, which can take the form of small group sessions or one-on-one tutoring delivered during school hours or during after-school programs. Ensuring the success of remedial learning programs also requires providing training and support to teachers and tutors who will be delivering instruction, through professional development programs and ongoing coaching. Finally, the government can establish monitoring and evaluation systems to track student progress and program effectiveness, allowing for adjustments and improvements to be made as necessary. By taking a coordinated approach and committing to addressing the learning loss, the Kazakhstani government, and other governments experiencing similar levels of loss-of-learning, can help all students to catch up and succeed in their education.

5.5 Application of Bronfenbrenner’s Ecological System Theory

In terms of policy, the Kazakhstani government should carefully consider multiple levels of influence when addressing issues in education. Here are some potential actions that could be taken at each level in accordance with Bronfenbrenner's Ecological Systems theory (1974).

1. Microlevel: Gender issues - Regarding gender variations in mathematical aptitude, it is critical for schools to promote an inclusive and equitable environment for all students. This could include implementing policies and practices that take into account potential differences in how boys and girls learn and process mathematical concepts, providing targeted resources and support for students who may struggle in this subject, and ensuring that all students, regardless of gender, have equal access to educational opportunities.

2. Mesosystem level: Mother tongue - Governments should endeavor to encourage bilingual education programs that value both mother tongue and regional languages, and give opportunity for children to acquire and enhance their language abilities. Investing in language instruction and resources, educating teachers to interact with multilingual kids, and adopting regulations that encourage the use of mother tongue in the classroom are some examples. Certainly, the implementation of the updated curriculum and its new directives and approaches may be useful in this regard (Courtney et al., 2022).

3. Exosystem level: Student origin - Governments can seek to solve systemic concerns affecting students depending on their origin, such as prejudice or a lack of resources. Developing legislation to alleviate socioeconomic inequities, boosting access to educational resources and opportunities, and investing in programs that help students from rural areas and their families are examples of such initiatives.

4. Governments can try to rectify the uneven distribution of resources and opportunities between schools and regions at the macrosystem level. This might involve investing in

underserved areas' schools and infrastructure, adopting policies to alleviate the achievement gap between schools, and providing resources and assistance to schools in rural or isolated locations.

5.6 Conclusion

The findings indicate that there are considerable disparities in academic success across subjects (Math, QR, Kazakh, Russian, and English) among the applicant students throughout the three-year focal period (2019-2021).

In most academic disciplines, male students exhibit higher performance levels than their female counterparts, except in language-based subjects. Gender is a consistently significant predictor of academic success across all three years, with effect sizes that are statistically significant ($p < .001$). Urban students also perform better than their rural peers, with the exception of Kazakh language. The effect size for geographical origin is generally small and lacks statistical significance which actually bodes well for the future, suggestive of less systemic performance gaps between rural and urban students in Kazakhstan (at least for those student applicants). Finally, the location of the exam, whether it takes place in a major city or not, is a predictor of academic performance in specific subjects, with students achieving higher scores in Math, QR, and English when the exam is administered in a major city. Though, more work could be done by the selective school to measure student socio-economic status more comprehensively in the future. This might include mother education level, for example.

Overall, the results suggest that there are both within- and between-school differences in academic achievement across all subjects. The percentage of variance explained by between-school differences is relatively high, indicating that the school a student attends has a significant impact on their academic performance. Though, the key finding of this study is that the loss-of-learning for all seven subjects is not only a concern for those who applied to the one selective school in Kazakhstan but also for all students across the country. More extensive research on the current Grade 4 and 8 national monitoring exam performance of children across the country offers an opportunity to develop an understanding of the loss-of-learning in the general child population. Moreover, students, teachers, and parents invested in preparing for the Unified National Testing (UNT) should also take stock of the current loss-of-learning and implement some level of intervention, ideally remedial. The lack of in-person instruction, reduced access to resources, and the challenges of remote learning have all contributed to the loss-of-learning during the pandemic, which is likely to have long-term implications for students' academic achievements and career prospects. While the economic costs of the pandemic may have been easy to measure, it is hoped that this thesis goes some way to informing all stakeholders about the academic costs that might be incurred as a consequence of imposed online learning.

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Appendix

Thesis coding

```
##############################################################################################################
#                                              Thesis coding                                                 #
##############################################################################################################


rm(list=ls())
# setwd("C:/Users/?????/Desktop/Thesis codings")
setwd("/Users/user/Desktop/Masters Students/Diana")


# Packages
library(pacman)
library(ggplot2)
library(car)
library(haven)
library(CTT)
library(readxl)
library(psych)
library(lme4)
library(misty)
```

```
library(sjPlot)

library(lme4)


citation("misty")

citation("lme4")


############################################### INTRO ###################################################

dir()

df <- readxl::read_xlsx("file_for_M.xlsx")

str(df)

df <- as.data.frame(df)

str(df)


dim(df)                           # 56817, 16 variables


table(df$year)

# 2019  2020  2021

# 17485 20084 19248


tapply(df$math, df$year, FUN = function(x)mean(x))

#     2019     2020     2021
```

```
# 183.9520 198.7976 170.7644 : math is lower in 2021 compared to 2019.


tapply(df$qr, df$year, FUN = function(x)mean(x))

#     2019     2020     2021

# 146.9610 159.2529 155.0338 : Qr is higher in 2021 compared to 2019.


tapply(df$kaz, df$year, FUN = function(x)mean(x))

#     2019     2020     2021

# 148.9273 144.5420 120.4955 : kaz is lower in 2021 compared to 2019


tapply(df$rus, df$year, FUN = function(x)mean(x))

#     2019     2020     2021

# 150.6444 153.0918 134.0732 : rus is lower in 2021 compared to 2019


tapply(df$eng, df$year, FUN = function(x)mean(x))

#     2019     2020     2021

# 106.9787 108.1262 103.1434 : eng is lower in 2021 compared to 2019


str(df)

df <- as.data.frame(df)

str(df)
```

```
####################################################################################################
###################################### 2019: PRE-COVID #############################################


df.2019 <- df[df$year == "2019", ]
dim(df.2019)                                              # 17485 applicants
table(df.2019$lang)                                       # kaz 12739, rus 4746

apply(df.2019, 2, FUN=function(x)str(x))

table(df.2019$year)     #17485

table(df.2019$nis)
str(df.2019$nis)
df.2019$nis <- as.numeric(df.2019$nis)
str(df.2019$nis)

table(df.2019$school)
```

```
str(df.2019$ID)


# Language

str(df.2019$lang)

table(df.2019$lang)

df.2019$lang <- car::recode(df.2019$lang, " 'kaz' = 1; 'rus' = 2")

table(df.2019$lang)

table(df.2019$lang)/nrow(df.2019)

#      1     2

#   4746 12739


# Gender

str(df.2019$gender)

table(df.2019$gender)

df.2019$gender <- car::recode(df.2019$gender, " 'female' = 1; 'male' = 2")

table(df.2019$gender)

table(df.2019$gender)/nrow(df.2019)

#   1    2

# 8750 8735


# Residence
```

```
str(df.2019$mestnost)

table(df.2019$mestnost)

df.2019$mestnost <- car::recode(df.2019$mestnost, " 'city' = 2; 'notcity' = 1")

table(df.2019$mestnost)

#    1     2

# 2468 15017

table(df.2019$mestnost)/nrow(df.2019)




# Math performance

str(df.2019$math)

psych::describe(df.2019$math)      # mean 183.95, sd = 71.82, skew = 0.56 (not larger than +- 2.00)

hist(df.2019$math)


# Quantitative Reasoning

str(df.2019$qr)

psych::describe(df.2019$qr)      # mean 146.96, sd = 55.03, skew = 0.43 (not larger than +- 2.00)

hist(df.2019$qr)


cor(df.2019$math, df.2019$qr)         # 0.8513601
```

```
# Cross tabs for school and location

table(df.2019$nis, df.2019$mestnost)

tapply(df.2019$mestnost, df.2019$nis, FUN = function(x)sd(x))   # Applicants vary by region inside each school


# Kaz lang

str(df.2019$kaz)

psych::describe(df.2019$kaz)      # mean 148.93, sd = 36.17, skew = -0.97 (not larger than +- 2.00)

hist(df.2019$kaz)


# Rus lang

str(df.2019$rus)

psych::describe(df.2019$rus)      # mean 150.64, sd = 38.4, skew = -1.32 (not larger than +- 2.00)

hist(df.2019$rus)


# Eng lan

str(df.2019$eng)

psych::describe(df.2019$eng)      # mean 106.98, sd = 40.61, skew = 0.35 (not larger than +- 2.00)

hist(df.2019$eng)


####################################################################################################
```

```
# Multi-level Modelling: Null model (finding the amount of variation in performance due to different schools)


misty::multilevel.icc(df.2019$math, df.2019$nis)       # 0.1066809,  1.6% of the variation in math scores can be attributable to the schools
      where the students did the test

misty::multilevel.icc(df.2019$qr, df.2019$nis)         # 0.09653674, 9,6% of the variation in qr scores can be attributable to the schools where
      the students did the test

misty::multilevel.icc(df.2019$kaz, df.2019$nis)        # 0.04034574, 4%

misty::multilevel.icc(df.2019$rus, df.2019$nis)        # 0.139929,   1.3%

misty::multilevel.icc(df.2019$eng, df.2019$nis)        #0.1107031,   1,1%


round(misty::multilevel.icc(df.2019$math, df.2019$nis),2)

round(misty::multilevel.icc(df.2019$qr, df.2019$nis), 2)

round(misty::multilevel.icc(df.2019$kaz, df.2019$nis), 2)

round(misty::multilevel.icc(df.2019$rus, df.2019$nis), 2)

round(misty::multilevel.icc(df.2019$eng, df.2019$nis), 2)


ICCS <- c(0.11, 0.10, 0.4, 0.14, 0.11)

length(table(df.2019$school))

avg.size <- nrow(df.2019)/20

round(1 + (ICCS*(avg.size -1)), 2)


####################################################################################################
```

```
# Multilevel modelling

colnames(df.2019)

table(df.2019$mestnost)


# Check variance of rural/urban by school

names(table(df.2019$school))

sort(tapply(df.2019$math, df.2019$school, FUN = function(x)mean(x)), decreasing = F)


major.city <- car::recode(df.2019$school, "

            'Актау ХБН' = 1;

            'Актобе ФМН' = 1;

            'Алматы ФМН' = 2;

            'Алматы ХБН' = 2;

            'Атырау ХБН' = 1;

            'Караганда ХБН' = 1;

            'Кокшетау ФМН' = 1;

            'Костанай ФМН' = 1;

            'Кызылорда ХБН' = 1;

            'Нур-Султан НИШ' = 2;

            'Нур-Султан ФМН' = 2;

            'Павлодар ХБН' = 1;
```

```
            'Петропавловск ХБН' = 1;

            'Семей ФМН' = 1;

            'Талдыкорган ФМН' = 1;

            'Тараз ФМН' = 1;

            'Уральск ФМН' = 1;

            'Усть-Каменогорск ХБН' = 1;

            'Шымкент ФМН' = 2;

            'Шымкент ХБН' = 2")


table(major.city)

df.2019 <- cbind.data.frame(df.2019, major.city)

head(df.2019)


round(misty::multilevel.icc(df.2019$mestnost, df.2019$nis), 2)  # 0.05


tapply(df.2019$mestnost, df.2019$school, FUN = function(x)sd(x))



####################################################################################################

colnames(df.2019)

head(df.2019)
```

```
df.2019[,c(9,11,13,14,15)] <- apply(df.2019[,c(9,11,13,14,15)], 2, FUN = function(x)as.numeric(x))

df.2019[,c(13,14,15)] <- apply(df.2019[,c(13,14,15)], 2, FUN = function(x)x/2)

apply(df.2019[,c(9,11,13,14,15)], 2, FUN = function(x)psych::describe(x))


####################################################################################################

# Descriptives

table(df.2019$lang)   # (1)native Kaz 12739 (2)Native Russians, 4746


# Kaz first

psych::describe(df.2019$kaz[df.2019$lang == 1])

round(misty::multilevel.icc(df.2019$kaz[df.2019$lang == 1], df.2019$school[df.2019$lang == 1]), 2) # .02

12739/20

1 + (0.02*(636.95-1))  # 5.73


# Kaz second

psych::describe(df.2019$kaz[df.2019$lang == 2])

round(misty::multilevel.icc(df.2019$kaz[df.2019$lang == 2], df.2019$school[df.2019$lang == 2]), 2) # .12

4746/20

1 + (0.12*(237.3-1))  # 29.36


# Rus first
```

```
psych::describe(df.2019$rus[df.2019$lang == 2])

round(misty::multilevel.icc(df.2019$rus[df.2019$lang == 2], df.2019$school[df.2019$lang == 2]), 2) # .08

4746/20

1 + (0.08*(237.3-1))  # 51.876


# Rus second

psych::describe(df.2019$rus[df.2019$lang == 1])

round(misty::multilevel.icc(df.2019$rus[df.2019$lang == 1], df.2019$school[df.2019$lang == 1]), 2) # .15

12739/20

1 + (0.15*(636.95-1))  # 96.39



######################################### Math ####################################################

# Null Model

colnames(df.2019)

summary(df.2019$`math%`)

hist(df.2019$`math%`)

mod1 <- lme4::lmer(`math%` ~ 1 + (1 | school), data = df.2019)

summary(mod1)


# With fixed indiivdual and group predictor
```

```
colnames(df.2019)

mod2 <- lme4::lmer(`math%` ~ gender + lang + mestnost + major.city + (1 | school), data = df.2019)

summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)


########################################## QR ######################################################

# Null Model

colnames(df.2019)

mod1 <- lme4::lmer(`qr%` ~ 1 + (1 | school), data = df.2019)

summary(mod1)


# With fixed indiivdual and group predictor

colnames(df.2019)

mod2 <- lme4::lmer(`qr%` ~ gender + lang + mestnost + major.city + (1 | school), data = df.2019)

summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)
```

```
print(coefs)


###################################### Kaz First ###################################################

# Null Model

colnames(df.2019)

summary(df.2019$kaz)

mod1 <- lme4::lmer(kaz ~ 1 + (1 | school), data = df.2019[df.2019$lang == "1",])

summary(mod1)


# With fixed indiivdual and group predictor

colnames(df.2019)

mod2 <- lme4::lmer(kaz ~ gender + mestnost + major.city + (1 | school), data = df.2019[df.2019$lang == "1",])

summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)


######################################## Kaz 2nd ###################################################

# Null Model

colnames(df.2019)
```

```
summary(df.2019$kaz)

mod1 <- lme4::lmer(kaz ~ 1 + (1 | school), data = df.2019[df.2019$lang == "2",])

summary(mod1)


# With fixed indiivdual and group predictor

colnames(df.2019)

mod2 <- lme4::lmer(kaz ~ gender + mestnost + major.city + (1 | school), data = df.2019[df.2019$lang == "2",])

summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)


########################################## Rus 1st ################################################

# Null Model

colnames(df.2019)

summary(df.2019$rus)

mod1 <- lme4::lmer(rus ~ 1 + (1 | school), data = df.2019[df.2019$lang == "2",])

summary(mod1)


# With fixed indiivdual and group predictor
```

```
colnames(df.2019)

mod2 <- lme4::lmer(rus ~ gender + mestnost + major.city + (1 | school), data = df.2019[df.2019$lang == "2",])

summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)


########################################## Rus 2nd #################################################

# Null Model

colnames(df.2019)

summary(df.2019$rus)

mod1 <- lme4::lmer(rus ~ 1 + (1 | school), data = df.2019[df.2019$lang == "1",])

summary(mod1)


# With fixed indiivdual and group predictor

colnames(df.2019)

mod2 <- lme4::lmer(rus ~ gender + mestnost + major.city + (1 | school), data = df.2019[df.2019$lang == "1",])

summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))
```

```
rownames(coefs)

print(coefs)




########################################## Eng ######################################################

# Null Model

colnames(df.2019)

summary(df.2019$rus)

mod1 <- lme4::lmer(eng ~ 1 + (1 | school), data = df.2019)

summary(mod1)


# With fixed indiivdual and group predictor

colnames(df.2019)

mod2 <- lme4::lmer(eng ~ gender + lang + mestnost + major.city + (1 | school), data = df.2019)

summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)


####################################################################################################
```

```
####################################################################################################
############################################## 2020 - COVID ########################################


df.2020 <- df[df$year == "2020", ]
dim(df.2020)              #20084 applicants

apply(df.2020, 2, FUN=function(x)str(x))

table(df.2020$year)

table(df.2020$nis)
str(df.2020$nis)
df.2020$nis <- as.numeric(df.2020$nis)
str(df.2020$nis)

table(df.2020$school)

#Laguage
```

```
str(df.2020$lang)

table(df.2020$lang)

df.2020$lang <- car::recode(df.2020$lang, " 'kaz' = 1; 'rus' = 2")

table(df.2020$lang)

table(df.2020$lang)/nrow(df.2020)

#     1     2

#   5849 14235


#Gender

str(df.2020$gender)

table(df.2020$gender)

df.2020$gender <- car::recode(df.2020$gender, " 'female' = 1; 'male' = 2")

table(df.2020$gender)

table(df.2020$gender) / nrow(df.2020)

#    1     2

#  9892  10192


#City

str(df.2020$mestnost)

table(df.2020$mestnost)

df.2020$mestnost <- car::recode(df.2020$mestnost, "'city' = 2; 'notcity' = 1")
```

```
table(df.2020$mestnost)

table(df.2020$mestnost)/nrow(df.2020)

#    1     2

#   2651 17433


# Math performance

str(df.2020$math)

psych::describe(df.2020$math)      # mean 198.8, sd = 73.57, skew = 0.53 (not larger than +- 2.00)

hist(df.2020$math)


# Quantitative Reasoning

str(df.2020$qr)

psych::describe(df.2020$qr)      # mean 154.04, sd = 56.7, skew = 0.36 (not larger than +- 2.00)

hist(df.2020$qr)


cor(df.2020$math, df.2020$qr)  #0.8801216


table(df.2020$nis, df.2020$mestnost)

tapply(df.2020$mestnost, df.2020$nis, FUN = function(x)sd(x))


# Kaz
```

```
str(df.2020$kaz)

psych::describe(df.2020$kaz)      # mean 144.54, sd = 35.99, skew = -0.78 (not larger than +- 2.00)

hist(df.2020$kaz)


# Rus

str(df.2020$rus)

psych::describe(df.2020$rus)      # mean 153.09, sd = 35.43, skew = -1.26 (not larger than +- 2.00)

hist(df.2020$rus)


# Eng

str(df.2020$eng)

psych::describe(df.2020$eng)      # mean 108.13, sd = 43.33, skew = -0.9 (not larger than +- 2.00)

hist(df.2020$eng)


####################################################################################################


# Multi-level Modelling: Null model


misty::multilevel.icc(df.2020$math, df.2020$nis)       # 0.09297291, 9.3% of the variation in math scores can be attributable to the schools
      where the students did the test

misty::multilevel.icc(df.2020$qr, df.2020$nis)         # 0.08660664, 7.5% of the variation in qr scores can be attributable to the schools where
      the students did the test
```

```
misty::multilevel.icc(df.2020$mestnost, df.2020$nis)   # 0.03839991, 3.8% of the variation in student rural/urban split is attributable to
      schools

misty::multilevel.icc(df.2020$kaz, df.2020$nis)        # 0.03931545, 3.9%

misty::multilevel.icc(df.2020$rus, df.2020$nis)        # 0.1425071,  1.4%

misty::multilevel.icc(df.2020$eng, df.2020$nis)        # 0.08789943, 8.7%

misty::multilevel.icc(df.2020$gender, df.2020$nis)     # 0.01734989



round(misty::multilevel.icc(df.2020$math, df.2020$nis),2)

round(misty::multilevel.icc(df.2020$qr, df.2020$nis), 2)

round(misty::multilevel.icc(df.2020$kaz, df.2020$nis), 2)

round(misty::multilevel.icc(df.2020$rus, df.2020$nis), 2)

round(misty::multilevel.icc(df.2020$eng, df.2020$nis), 2)



ICCS <- c(0.09, 0.09, 0.4, 0.14, 0.09)

length(table(df.2020$school))

avg.size <- nrow(df.2020)/20

round(1 + (ICCS*(avg.size -1)), 2)



####################################################################################################

# Multilevel modelling

colnames(df.2020)
```

```
table(df.2020$mestnost)


# Check variance of rural/urban by school

names(table(df.2020$school))

sort(tapply(df.2020$math, df.2020$school, FUN = function(x)mean(x)), decreasing = F)

length(table(df.2020$school))


major.city <- car::recode(df.2020$school, "

            'Актау ХБН' = 1;

            'Актобе ФМН' = 1;

            'Алматы ФМН' = 2;

            'Алматы ХБН' = 2;

            'Атырау ХБН' = 1;

            'Караганда ХБН' = 1;

            'Кокшетау ФМН' = 1;

            'Костанай ФМН' = 1;

            'Кызылорда ХБН' = 1;

            'Нур-Султан НИШ' = 2;

            'Нур-Султан ФМН' = 2;

            'Павлодар ХБН' = 1;

            'Петропавловск ХБН' = 1;
```

```
            'Семей ФМН' = 1;

            'Талдыкорган ФМН' = 1;

            'Тараз ФМН' = 1;

            'Уральск ФМН' = 1;

            'Усть-Каменогорск ХБН' = 1;

            'Шымкент ФМН' = 2;

            'Шымкент ХБН' = 2")


table(major.city)

df.2020 <- cbind.data.frame(df.2020, major.city)

head(df.2020)


round(misty::multilevel.icc(df.2020$mestnost, df.2020$nis), 2)  # 0.04


tapply(df.2020$mestnost, df.2020$school, FUN = function(x)sd(x))



####################################################################################################

####################################################################################################


colnames(df.2020)
```

```
head(df.2020)

df.2020[,c(9,11,13,14,15)] <- apply(df.2020[,c(9,11,13,14,15)], 2, FUN = function(x)as.numeric(x))

df.2020[,c(13,14,15)] <- apply(df.2020[,c(13,14,15)], 2, FUN = function(x)x/2)

apply(df.2020[,c(9,11,13,14,15)], 2, FUN = function(x)psych::describe(x))


####################################################################################################

# Descriptives

table(df.2020$lang)   # (1)native Kaz 14235 (2)Native Russians, 5849

length(table(df.2020$school)) # 20


# Kaz first

psych::describe(df.2020$kaz[df.2020$lang == 1])

round(misty::multilevel.icc(df.2020$kaz[df.2020$lang == 1], df.2020$school[df.2020$lang == 1]), 2) # .02

14235/20

1 + (0.02*(711.75-1))  # 15.215


# Kaz second

psych::describe(df.2020$kaz[df.2020$lang == 2])

round(misty::multilevel.icc(df.2020$kaz[df.2020$lang == 2], df.2020$school[df.2020$lang == 2]), 2) # .14

5849/20

1 + (0.12*(292.45-1))  # 29.36
```

```
# Rus first

psych::describe(df.2020$rus[df.2020$lang == 2])

round(misty::multilevel.icc(df.2020$rus[df.2020$lang == 2], df.2020$school[df.2020$lang == 2]), 2) # .07

5849/20

1 + (0.08*(292.45-1))  # 24.32


# Rus second

psych::describe(df.2020$rus[df.2020$lang == 1])

round(misty::multilevel.icc(df.2020$rus[df.2020$lang == 1], df.2020$school[df.2020$lang == 1]), 2) # .16

14235/20

1 + (0.15*(711.75-1))  # 96.39



####################################################################################################

######################################### Math #####################################################

# Null Model

colnames(df.2020)

summary(df.2020$`math%`)

hist(df.2020$`math%`)

mod1 <- lme4::lmer(`math%` ~ 1 + (1 | school), data = df.2020)
```

```
summary(mod1)


# With fixed indiivdual and group predictor

colnames(df.2020)

mod2 <- lme4::lmer(`math%` ~ gender + lang + mestnost + major.city + (1 | school), data = df.2020)

summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)


########################################## QR ######################################################

# Null Model

colnames(df.2020)

mod1 <- lme4::lmer(`qr%` ~ 1 + (1 | school), data = df.2020)

summary(mod1)


# With fixed indiivdual and group predictor

colnames(df.2020)

mod2 <- lme4::lmer(`qr%` ~ gender + lang + mestnost + major.city + (1 | school), data = df.2020)

summary(mod2)
```

```
coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)


########################################## Kaz 1st #################################################

# Null Model

colnames(df.2020)

summary(df.2020$kaz)

mod1 <- lme4::lmer(kaz ~ 1 + (1 | school), data = df.2020[df.2020$lang == "1",])

summary(mod1)


# With fixed indiivdual and group predictor

colnames(df.2020)

mod2 <- lme4::lmer(kaz ~ gender + mestnost + major.city + (1 | school), data = df.2020[df.2020$lang == "1",])

summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)
```

```
########################################## Kaz 2nd #################################################

# Null Model

colnames(df.2020)

summary(df.2020$kaz)

mod1 <- lme4::lmer(kaz ~ 1 + (1 | school), data = df.2020[df.2020$lang == "2",])

summary(mod1)


# With fixed indiivdual and group predictor

colnames(df.2020)

mod2 <- lme4::lmer(kaz ~ gender + mestnost + major.city + (1 | school), data = df.2020[df.2020$lang == "2",])

summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)


########################################## Rus 1st #################################################

# Null Model

colnames(df.2020)

summary(df.2020$rus)

mod1 <- lme4::lmer(rus ~ 1 + (1 | school), data = df.2020[df.2020$lang == "2",])
```

```
summary(mod1)


# With fixed indiivdual and group predictor

colnames(df.2020)

mod2 <- lme4::lmer(rus ~ gender + mestnost + major.city + (1 | school), data = df.2020[df.2020$lang == "2",])

summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)


########################################## Rus 2nd #################################################

# Null Model

colnames(df.2020)

summary(df.2020$rus)

mod1 <- lme4::lmer(rus ~ 1 + (1 | school), data = df.2020[df.2020$lang == "1",])

summary(mod1)


# With fixed indiivdual and group predictor

colnames(df.2020)

mod2 <- lme4::lmer(rus ~ gender + mestnost + major.city + (1 | school), data = df.2020[df.2020$lang == "1",])
```

```
summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)


########################################## Eng ######################################################

# Null Model

colnames(df.2020)

summary(df.2020$rus)

mod1 <- lme4::lmer(eng ~ 1 + (1 | school), data = df.2020)

summary(mod1)


# With fixed indiivdual and group predictor

colnames(df.2020)

mod2 <- lme4::lmer(eng ~ gender + lang + mestnost + major.city + (1 | school), data = df.2020)

summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)
```

```
####################################################################################################

####################################################################################################
############################################## 2021 - Post COVID ###################################

df.2021 <- df[df$year == "2021", ]
dim(df.2021)              #19248 applicants

apply(df.2021, 2, FUN=function(x)str(x))

table(df.2021$year)

table(df.2021$nis)
str(df.2021$nis)
df.2021$nis <- as.numeric(df.2021$nis)
str(df$nis)

table(df.2021$school)

str(df.2021$ID)
```

```
#Language

str(df.2021$lang)

table(df.2021$lang)

df.2021$lang <- car::recode(df.2021$lang, " 'kaz' = 1; 'rus' = 2")

table(df.2021$lang)

table(df.2021$lang)/nrow(df.2021)

#     1     2

#   6097  13151


#Gender

str(df.2021$gender)

table(df.2021$gender)

df.2021$gender <- car::recode(df.2021$gender, " 'female' = 1; 'male' = 2")

table(df.2021$gender)

table(df.2021$gender) / nrow(df.2021)

#    1     2

# 9649    9599


#City

str(df.2021$mestnost)
```

```
table(df.2021$mestnost)

df.2021$mestnost <- car::recode(df.2021$mestnost, " 'city' = 2; 'notcity' = 1")

table(df.2021$mestnost)

table(df.2021$mestnost)/nrow(df.2021)

#    1     2

#  2763 16485


# Math performance

str(df.2021$math)

psych::describe(df.2021$math)      # mean 170.76, sd = 95.97, skew = 0.66 (not larger than +- 2.00)

hist(df.2021$math)


# Quantitative Reasoning

str(df.2021$qr)

psych::describe(df.2021$qr)      # mean 155.03, sd = 55.64, skew = 0.37 (not larger than +- 2.00)

hist(df.2021$qr)


cor(df.2021$math, df.2021$qr)  # 0.8405231


table(df.2021$nis, df.2021$mestnost)

tapply(df.2021$mestnost, df.2021$nis, FUN = function(x)sd(x))
```

```
# Kaz

str(df.2021$kaz)

psych::describe(df.2021$kaz)      # mean 120.5, sd = 40.64, skew = -0.44 (not larger than +- 2.00)

hist(df.2021$kaz)


# Rus

str(df.2021$rus)

psych::describe(df.2021$rus)      # mean 134.07, sd = 39.32, skew = -0.6 (not larger than +- 2.00)

hist(df.2021$rus)


# Eng

str(df.2021$eng)

psych::describe(df.2021$eng)      # mean 103.14, sd = 46.38, skew = 0.35 (not larger than +- 2.00)

hist(df.2021$eng)



####################################################################################################


# Multi-level Modelling: Null model
```

```
misty::multilevel.icc(df.2021$math, df.2021$nis)       # 0.07020114, 7.0% of the variation in math scores can be attributable to the schools
      where the students did the test

misty::multilevel.icc(df.2021$qr, df.2021$nis)         # 0.0638056,  6.3% of the variation in qr scores can be attributable to the schools where
      the students did the test

misty::multilevel.icc(df.2021$mestnost, df.2021$nis)   # 0.03688245, 3.6%

misty::multilevel.icc(df.2021$kaz, df.2021$nis)        # 0.09780773, 0,9%

misty::multilevel.icc(df.2021$rus, df.2021$nis)        # 0.1163566,  1,1%

misty::multilevel.icc(df.2021$eng, df.2021$nis)        # 0.08277332, 0,8%

misty::multilevel.icc(df.2021$gender, df.2021$nis)



round(misty::multilevel.icc(df.2021$math, df.2021$nis),2)

round(misty::multilevel.icc(df.2021$qr, df.2021$nis), 2)

round(misty::multilevel.icc(df.2021$kaz, df.2021$nis), 2)

round(misty::multilevel.icc(df.2021$rus, df.2021$nis), 2)

round(misty::multilevel.icc(df.2021$eng, df.2021$nis), 2)



ICCS <- c(0.07, 0.06, 0.10, 0.12, 0.08)

length(table(df.2021$school))

avg.size <- nrow(df.2021)/21

round(1 + (ICCS*(avg.size -1)), 2)
```

```
####################################################################################################

# Multilevel modelling

colnames(df.2021)

table(df.2021$mestnost)


# Check variance of rural/urban by school

names(table(df.2021$school))

sort(tapply(df.2021$math, df.2021$school, FUN = function(x)mean(x)), decreasing = F)

length(table(df.2021$school))


major.city <- car::recode(df.2021$school, "

            'Актау ХБН' = 1;

            'Актобе ФМН' = 1;

            'Алматы ФМН' = 2;

            'Алматы ХБН' = 2;

            'Атырау ХБН' = 1;

            'Караганда ХБН' = 1;

            'Кокшетау ФМН' = 1;

            'Костанай ФМН' = 1;

            'Кызылорда ХБН' = 1;

            'Нур-Султан НИШ' = 2;
```

```
            'Нур-Султан ФМН' = 2;

            'Павлодар ХБН' = 1;

            'Петропавловск ХБН' = 1;

            'Семей ФМН' = 1;

            'Талдыкорган ФМН' = 1;

            'Тараз ФМН' = 1;

            'Уральск ФМН' = 1;

            'Усть-Каменогорск ХБН' = 1;

            'Шымкент ФМН' = 2;

            'Шымкент ХБН' = 2;

            'Туркестан ХБН' = 1")


table(major.city)

df.2021 <- cbind.data.frame(df.2021, major.city)

head(df.2021)


round(misty::multilevel.icc(df.2021$mestnost, df.2021$nis), 2)  # 0.04


tapply(df.2021$mestnost, df.2021$school, FUN = function(x)sd(x))
```

```
####################################################################################################


####################################################################################################

####################################################################################################

colnames(df.2021)

head(df.2021)

df.2021[,c(9,11,13,14,15)] <- apply(df.2021[,c(9,11,13,14,15)], 2, FUN = function(x)as.numeric(x))

summary(df.2021[,c(9,11,13,14,15)])

df.2021[,c(13,14,15)] <- apply(df.2021[,c(13,14,15)], 2, FUN = function(x)x/2)

apply(df.2021[,c(9,11,13,14,15)], 2, FUN = function(x)psych::describe(x))


####################################################################################################

# Descriptives

table(df.2021$lang)   # (1)native Kaz 13151  (2)Native Russians, 6097

length(table(df.2021$school)) # 21


# Kaz first

psych::describe(df.2021$kaz[df.2021$lang == 1])

round(misty::multilevel.icc(df.2021$kaz[df.2021$lang == 1], df.2021$school[df.2021$lang == 1]), 2) # .04

13151/21

1 + (0.02*(626.2381-1))  # 13.50476
```

```
# Kaz second

psych::describe(df.2021$kaz[df.2021$lang == 2])

round(misty::multilevel.icc(df.2021$kaz[df.2021$lang == 2], df.2021$school[df.2021$lang == 2]), 2) # .23

6097/21

1 + (0.12*(290.3333-1))  # 35.72


# Rus first

psych::describe(df.2021$rus[df.2021$lang == 2])

round(misty::multilevel.icc(df.2021$rus[df.2021$lang == 2], df.2021$school[df.2021$lang == 2]), 2) # .07

6097/21

1 + (0.08*(290.3333-1))  # 24.15


# Rus second

psych::describe(df.2021$rus[df.2021$lang == 1])

round(misty::multilevel.icc(df.2021$rus[df.2021$lang == 1], df.2021$school[df.2021$lang == 1]), 2) # .15

13151/21

1 + (0.15*(626.2381-1))  # 94.79


######################################### Math ####################################################
```

```
# Null Model

colnames(df.2021)

summary(df.2021$`math%`)

hist(df.2021$`math%`)

mod1 <- lme4::lmer(`math%` ~ 1 + (1 | school), data = df.2021)

summary(mod1)


# With fixed indiivdual and group predictor

colnames(df.2021)

mod2 <- lme4::lmer(`math%` ~ gender + lang + mestnost + major.city + (1 | school), data = df.2021)

summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)


########################################## QR ######################################################

# Null Model

colnames(df.2021)

mod1 <- lme4::lmer(`qr%` ~ 1 + (1 | school), data = df.2021)

summary(mod1)
```

```
# With fixed indiivdual and group predictor

colnames(df.2021)

mod2 <- lme4::lmer(`qr%` ~ gender + lang + mestnost + major.city + (1 | school), data = df.2021)

summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)


####################################### Kaz first ##################################################

# Null Model

colnames(df.2021)

summary(df.2021$kaz)

mod1 <- lme4::lmer(kaz ~ 1 + (1 | school), data = df.2021[df.2021$lang == "1",])

summary(mod1)


# With fixed indiivdual and group predictor

colnames(df.2021)

mod2 <- lme4::lmer(kaz ~ gender + mestnost + major.city + (1 | school), data = df.2021[df.2021$lang == "1",])

summary(mod2)
```

```
coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)


####################################### Kaz 2nd ##################################################

# Null Model

colnames(df.2021)

summary(df.2021$kaz)

mod1 <- lme4::lmer(kaz ~ 1 + (1 | school), data = df.2021[df.2021$lang == "2",], REML = F)

summary(mod1)


# With fixed indiivdual and group predictor

colnames(df.2021)

mod2 <- lme4::lmer(kaz ~ gender + mestnost + major.city + (1 | school), data = df.2021[df.2021$lang == "2",], REML = F)

summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)
```

```
########################################## Rus 1st #################################################

# Null Model

colnames(df.2021)

summary(df.2021$rus)

mod1 <- lme4::lmer(rus ~ 1 + (1 | school), data = df.2021[df.2021$lang == "2",])

summary(mod1)


# With fixed indiivdual and group predictor

colnames(df.2021)

mod2 <- lme4::lmer(rus ~ gender + mestnost + major.city + (1 | school), data = df.2021[df.2021$lang == "2",])

summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)


########################################## Rus 2nd #################################################

# Null Model

colnames(df.2021)

summary(df.2021$rus)

mod1 <- lme4::lmer(rus ~ 1 + (1 | school), data = df.2021[df.2021$lang == "1",])
```

```
summary(mod1)


# With fixed indiivdual and group predictor

colnames(df.2021)

mod2 <- lme4::lmer(rus ~ gender + mestnost + major.city + (1 | school), data = df.2021[df.2021$lang == "1",])

summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)




########################################## Eng ######################################################

# Null Model

colnames(df.2021)

summary(df.2021$rus)

mod1 <- lme4::lmer(eng ~ 1 + (1 | school), data = df.2021)

summary(mod1)


# With fixed indiivdual and group predictor
```

```
colnames(df.2021)

mod2 <- lme4::lmer(eng ~ gender + lang + mestnost + major.city + (1 | school), data = df.2021)

summary(mod2)

coefs <- data.frame(coef(summary(mod2)))

coefs$p.z <- 2 * (1 - pnorm(abs(coefs$t.value)))

rownames(coefs)

print(coefs)


####################################################################################################

#                             EXPECTATIONS AND PROJECTED LEARNING LOSS                             #

############################### Expectations for Mathematics #######################################

rm(list=ls())

# Input all datapoints

Mathematics <- c(155.9, 158.5, 164.8, 171.7, 181.8, 185.4, 184.0, 198.8, 170.8, 155.6)

Math.SD <- c(60.8, 66.7, 65.7, 69.9, 72.2, 72.0, 71.8, 73.6, 96.0, 91.3)

Year <- c(2013:2022)

tmp <- cbind.data.frame(Mathematics, Math.SD, Year)


# Find geo mean

exp(mean(log(Math.SD)))  # 73.31
```

```
# Run model
mod <- lm(Mathematics ~ Year, data = tmp[1:8,])
intercept <- mod$coefficients[1]
slope <- mod$coefficients[2]

# Build linear model with missing values too
expectations <- intercept + (2013:2022*slope)

# Integrate standard errors of the mean (observed)
two.se.2021 <- (Math.SD[9]/sqrt(19248))*2                    # 19248 is sample size for 2021
print(two.se.2021)
er.2021.min <- Mathematics[9] - two.se.2021
er.2021.max <- Mathematics[9] + two.se.2021

two.se.2022 <- (Math.SD[10]/sqrt(24045))*2                   # 24045 is sample size for 2021
er.2022.min <- Mathematics[10] - two.se.2022
er.2022.max <- Mathematics[10] + two.se.2022
print(two.se.2022)

y.min <- c(rep(NA, 8), er.2021.min, er.2022.min)
y.max <- c(rep(NA, 8), er.2021.max, er.2022.max)
```

```
# Integrate standard errors of the mean (expected)
y.mine <- expectations - two.se.2021
y.maxe <- expectations + two.se.2022
y.mine[1:8] <- NA
y.maxe[1:8] <- NA

# Graph initial results
ggplot(tmp, aes(x = Year, y=Mathematics)) +
  geom_line() +
  geom_point() +
  geom_hline(aes(yintercept=0)) +
  geom_line(aes(y = expectations), color="red") +
  scale_x_discrete(limits=c(2013:2022)) +
  geom_errorbar(aes(ymin=y.min, ymax=y.max), width=.5, col = "black") +
  geom_errorbar(aes(ymin=y.mine, ymax=y.maxe), width=.5, col = "red")

# Expectations minus observation
learn.loss <- c(170.8, 155.6) - expectations[9:10]
print(learn.loss)  # -31.08214 -52.23095
```

```
round(learn.loss/ Math.SD[9:10], 2)


################################### Expectations for QR ######################################

# Input all datapoints

QR <- c(128.9, 129.4, 130.6, 123.5, 126.6, 131.4, 147.0, 159.3, 155.0, 158.9)

QR.SD <- c(8.7, 8.9, 8.7, 8.0, 10.4, 11.2, 55.0, 58.5, 55.6, 56.0)

Year <- c(2013:2022)

tmp <- cbind.data.frame(QR, QR.SD, Year)


# Run model

mod <- lm(QR ~ Year, data = tmp[1:8,])

intercept <- mod$coefficients[1]

slope <- mod$coefficients[2]


# Build linear model with missing values too

expectations <- intercept + (2013:2022*slope)


# Graph initial results

ggplot(tmp, aes(x = Year, y=QR)) +

  geom_line() +

  geom_point() +
```

```
  geom_hline(aes(yintercept=0)) +
  geom_line(aes(y = expectations), color="red") +
  scale_x_discrete(limits=c(2013:2022))

# Expectations minus observation
learn.loss <- c(155.0, 158.9) - expectations[9:10]
print(learn.loss)  # 4.003571 4.257143

round(learn.loss/ QR.SD[9:10], 2)

############################## Expectations for QR (corrected) #####################################
# Input all datapoints
QR <- c(147.0, 159.3, 155.0, 158.9)
QR.SD <- c(55.0, 58.5, 55.6, 56.0)
Year <- c(2019:2022)
tmp <- cbind.data.frame(QR, QR.SD, Year)

# Run model
mod <- lm(QR ~ Year, data = tmp[1:2,])
intercept <- mod$coefficients[1]
slope <- mod$coefficients[2]
```

```
# Build linear model with missing values too
expectations <- intercept + (2019:2022*slope)

# Integrate standard errors of the mean (observed)
two.se.2021 <- (QR.SD[3]/sqrt(19248))*2                    # 19248 is sample size for 2021
print(two.se.2021)
er.2021.min <- QR[3] - two.se.2021
er.2021.max <- QR[3] + two.se.2021

two.se.2022 <- (QR.SD[4]/sqrt(24045))*2                    # 24045 is sample size for 2021
er.2022.min <- QR[4] - two.se.2022
er.2022.max <- QR[4] + two.se.2022
print(two.se.2022)

y.min <- c(rep(NA, 2), er.2021.min, er.2022.min)
y.max <- c(rep(NA, 2), er.2021.max, er.2022.max)

# Integrate standard errors of the mean (expected)
y.mine <- expectations - two.se.2021
y.maxe <- expectations + two.se.2022
```

```
y.mine[1:2] <- NA

y.maxe[1:2] <- NA


# Graph initial results

ggplot(tmp, aes(x = Year, y=QR)) +

  geom_line() +

  geom_point() +

  geom_hline(aes(yintercept=0)) +

  geom_line(aes(y = expectations), color="red") +

  scale_x_discrete(limits=c(2019:2022)) +

  geom_errorbar(aes(ymin=y.min, ymax=y.max), width=.5, col = "black") +

  geom_errorbar(aes(ymin=y.mine, ymax=y.maxe), width=.5, col = "red")


# Expectations minus observation

learn.loss <- c(155.0, 158.9) - expectations[3:4]

print(learn.loss)  # -16.6 -25.0


round(learn.loss/ QR.SD[3:4], 2)


################################## Expectations for Kaz 1st lang ###################################

# Input all datapoints
```

```
kaz <- c(147.2, 145.8, 146.6, 146.8, 149.6, 156.1, 153.7, 150.0, 130.9, 128.2)

kaz.SD <- c(32.3, 32.3, 31.6, 31.5, 29.6, 27.6, 29.8, 29.7, 31.0, 29.7)

Year <- c(2013:2022)

tmp <- cbind.data.frame(kaz, kaz.SD, Year)


# Run model

mod <- lm(kaz ~ Year, data = tmp[1:8,])

intercept <- mod$coefficients[1]

slope <- mod$coefficients[2]


# Build linear model with missing values too

expectations <- intercept + (2013:2022*slope)


# Integrate standard errors of the mean (observed)

two.se.2021 <- (kaz.SD[9]/sqrt(19248))*2                          # 19248 is sample size for 2021

print(two.se.2021)

er.2021.min <- kaz[9] - two.se.2021

er.2021.max <- kaz[9] + two.se.2021


two.se.2022 <- (kaz.SD[10]/sqrt(24045))*2                         # 24045 is sample size for 2021

er.2022.min <- kaz[10] - two.se.2022
```

```
er.2022.max <- kaz[10] + two.se.2022
print(two.se.2022)


y.min <- c(rep(NA, 8), er.2021.min, er.2022.min)
y.max <- c(rep(NA, 8), er.2021.max, er.2022.max)


# Integrate standard errors of the mean (expected)
y.mine <- expectations - two.se.2021
y.maxe <- expectations + two.se.2022
y.mine[1:8] <- NA
y.maxe[1:8] <- NA


# Graph initial results
ggplot(tmp, aes(x = Year, y=kaz)) +
  geom_line() +
  geom_point() +
  geom_hline(aes(yintercept=0)) +
  geom_line(aes(y = expectations), color="red") +
  scale_x_discrete(limits=c(2013:2022)) +
  geom_errorbar(aes(ymin=y.min, ymax=y.max), width=.5, col = "black") +
  geom_errorbar(aes(ymin=y.mine, ymax=y.maxe), width=.5, col = "red")
```

```
# Expectations minus observation
learn.loss <- c(130.9, 128.2) - expectations[9:10]
print(learn.loss)  # -23.41786 -27.19405

round(learn.loss/ kaz.SD[9:10], 2)



################################## Expectations for Kaz 2nd lang ###################################
# Input all datapoints
kaz <- c(119.9, 113.7, 115.7, 122.7, 131.9, 125.9, 136.2, 131.3, 98.0, 93.0)
kaz.SD <- c(52.6, 48.8, 48.6, 45.8, 46.4, 46.5, 47.1, 45.3, 48.9, 45.0)
Year <- c(2013:2022)
tmp <- cbind.data.frame(kaz, kaz.SD, Year)

# Run model
mod <- lm(kaz ~ Year, data = tmp[1:8,])
intercept <- mod$coefficients[1]
slope <- mod$coefficients[2]

# Build linear model with missing values too
```

```
expectations <- intercept + (2013:2022*slope)


# Integrate standard errors of the mean (observed)

two.se.2021 <- (kaz.SD[9]/sqrt(19248))*2                           # 19248 is sample size for 2021

print(two.se.2021)

er.2021.min <- kaz[9] - two.se.2021

er.2021.max <- kaz[9] + two.se.2021


two.se.2022 <- (kaz.SD[10]/sqrt(24045))*2                          # 24045 is sample size for 2021

er.2022.min <- kaz[10] - two.se.2022

er.2022.max <- kaz[10] + two.se.2022

print(two.se.2022)


y.min <- c(rep(NA, 8), er.2021.min, er.2022.min)

y.max <- c(rep(NA, 8), er.2021.max, er.2022.max)


# Integrate standard errors of the mean (expected)

y.mine <- expectations - two.se.2021

y.maxe <- expectations + two.se.2022

y.mine[1:8] <- NA

y.maxe[1:8] <- NA
```

```
# Graph initial results

ggplot(tmp, aes(x = Year, y=kaz)) +

  geom_line() +

  geom_point() +

  geom_hline(aes(yintercept=0)) +

  geom_line(aes(y = expectations), color="red") +

  scale_x_discrete(limits=c(2013:2022)) +

  geom_errorbar(aes(ymin=y.min, ymax=y.max), width=.5, col = "black") +

  geom_errorbar(aes(ymin=y.mine, ymax=y.maxe), width=.5, col = "red")


# Expectations minus observation

learn.loss <- c(98.0, 93.0) - expectations[9:10]

print(learn.loss)  # -23.41786 -27.19405


round(learn.loss/ kaz.SD[9:10], 2)



################################## Expectations for Rus 1st lang ##################################

# Input all dataoints

rus <- c(157.0, 150.6, 146.8, 150.7, 160.0, 159.4, 162.4, 163.3, 138.4, 134.8)
```

```
rus.SD <- c(28.6, 29.9, 32.4, 29.2, 25.0, 23.8, 23.5, 23.0, 34.4, 34.0)

Year <- c(2013:2022)

tmp <- cbind.data.frame(rus, rus.SD, Year)


# Run model

mod <- lm(rus ~ Year, data = tmp[1:8,])

intercept <- mod$coefficients[1]

slope <- mod$coefficients[2]


# Build linear model with missing values too

expectations <- intercept + (2013:2022*slope)


# Integrate standard errors of the mean (observed)

two.se.2021 <- (rus.SD[9]/sqrt(19248))*2                           # 19248 is sample size for 2021

print(two.se.2021)

er.2021.min <- rus[9] - two.se.2021

er.2021.max <- rus[9] + two.se.2021


two.se.2022 <- (rus.SD[10]/sqrt(24045))*2                          # 24045 is sample size for 2021

er.2022.min <- rus[10] - two.se.2022

er.2022.max <- rus[10] + two.se.2022
```

```
print(two.se.2022)


y.min <- c(rep(NA, 8), er.2021.min, er.2022.min)

y.max <- c(rep(NA, 8), er.2021.max, er.2022.max)


# Integrate standard errors of the mean (expected)

y.mine <- expectations - two.se.2021

y.maxe <- expectations + two.se.2022

y.mine[1:8] <- NA

y.maxe[1:8] <- NA


# Graph initial results

ggplot(tmp, aes(x = Year, y=rus)) +

  geom_line() +

  geom_point() +

  geom_hline(aes(yintercept=0)) +

  geom_line(aes(y = expectations), color="red") +

  scale_x_discrete(limits=c(2013:2022)) +

  geom_errorbar(aes(ymin=y.min, ymax=y.max), width=.5, col = "black") +

  geom_errorbar(aes(ymin=y.mine, ymax=y.maxe), width=.5, col = "red")
```

```
# Expectations minus observation

learn.loss <- rus[9:10] - expectations[9:10]

print(learn.loss)  # -25.92143 -31.30952


round(learn.loss/ rus.SD[9:10], 2)


################################## Expectations for Rus 2nd lang ##################################

# Input all dataoints

rus <- c(135.1, 133.4, 133.1, 138.8, 133.7, 143.1, 146.3, 148.9, 132.0, 127.7)

rus.SD <- c(43.4, 44.3, 45.8, 40.6, 43.8, 41.4, 41.8, 38.7, 41.3, 40.2)

Year <- c(2013:2022)

tmp <- cbind.data.frame(rus, rus.SD, Year)


# Run model

mod <- lm(rus ~ Year, data = tmp[1:8,])

intercept <- mod$coefficients[1]

slope <- mod$coefficients[2]


# Build linear model with missing values too

expectations <- intercept + (2013:2022*slope)
```

```
# Integrate standard errors of the mean (observed)
two.se.2021 <- (rus.SD[9]/sqrt(19248))*2                          # 19248 is sample size for 2021
print(two.se.2021)
er.2021.min <- rus[9] - two.se.2021
er.2021.max <- rus[9] + two.se.2021

two.se.2022 <- (rus.SD[10]/sqrt(24045))*2                          # 24045 is sample size for 2021
er.2022.min <- rus[10] - two.se.2022
er.2022.max <- rus[10] + two.se.2022
print(two.se.2022)

y.min <- c(rep(NA, 8), er.2021.min, er.2022.min)
y.max <- c(rep(NA, 8), er.2021.max, er.2022.max)

# Integrate standard errors of the mean (expected)
y.mine <- expectations - two.se.2021
y.maxe <- expectations + two.se.2022
y.mine[1:8] <- NA
y.maxe[1:8] <- NA

# Graph initial results
```

```
ggplot(tmp, aes(x = Year, y=rus)) +
  geom_line() +
  geom_point() +
  geom_hline(aes(yintercept=0)) +
  geom_line(aes(y = expectations), color="red") +
  scale_x_discrete(limits=c(2013:2022)) +
  geom_errorbar(aes(ymin=y.min, ymax=y.max), width=.5, col = "black") +
  geom_errorbar(aes(ymin=y.mine, ymax=y.maxe), width=.5, col = "red")

# Expectations minus observation
learn.loss <- rus[9:10] - expectations[9:10]
print(learn.loss)  # -17.01429 -23.52857

round(learn.loss/ rus.SD[9:10], 2)



######################################## Expectations for Eng ######################################
# Input all dataoints
eng <- c(86.8, 87.7, 87.2, 88.8, 93.3, 95.6, 107.0, 108.1, 103.1, 101.4)
eng.SD <- c(40.0, 40.9, 41.5, 41.7, 42.6, 41.5, 40.6, 43.3, 46.4, 48.3)
Year <- c(2013:2022)
```

```
tmp <- cbind.data.frame(eng, eng.SD, Year)


# Run model

mod <- lm(eng ~ Year, data = tmp[1:8,])

intercept <- mod$coefficients[1]

slope <- mod$coefficients[2]


# Build linear model with missing values too

expectations <- intercept + (2013:2022*slope)


# Integrate standard errors of the mean (observed)

two.se.2021 <- (eng.SD[9]/sqrt(19248))*2                           # 19248 is sample size for 2021

print(two.se.2021)

er.2021.min <- eng[9] - two.se.2021

er.2021.max <- eng[9] + two.se.2021


two.se.2022 <- (eng.SD[10]/sqrt(24045))*2                           # 24045 is sample size for 2021

er.2022.min <- eng[10] - two.se.2022

er.2022.max <- eng[10] + two.se.2022

print(two.se.2022)
```

```
y.min <- c(rep(NA, 8), er.2021.min, er.2022.min)

y.max <- c(rep(NA, 8), er.2021.max, er.2022.max)


# Integrate standard errors of the mean (expected)

y.mine <- expectations - two.se.2021

y.maxe <- expectations + two.se.2022

y.mine[1:8] <- NA

y.maxe[1:8] <- NA


# Graph initial results

ggplot(tmp, aes(x = Year, y=eng)) +

  geom_line() +

  geom_point() +

  geom_hline(aes(yintercept=0)) +

  geom_line(aes(y = expectations), color="red") +

  scale_x_discrete(limits=c(2013:2022)) +

  geom_errorbar(aes(ymin=y.min, ymax=y.max), width=.5, col = "black") +

  geom_errorbar(aes(ymin=y.mine, ymax=y.maxe), width=.5, col = "red")


# Expectations minus observation

learn.loss <- eng[9:10] - expectations[9:10]
```

```
print(learn.loss)  # -17.01429 -23.52857


round(learn.loss/ eng.SD[9:10], 2)
```