Bridging minds and machines: AI's role in enhancing mental health and productivity amidst Ukraine's challenges

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Abstract

The article explores the convergence of human intelligence with artificial intelligence, emphasizing its potential to enhance education in the realm of mental health. This synergy is especially crucial in Ukraine, particularly within its educational institutions, following the pandemic and amid wartime conditions. The article delves into the concepts of "digital mental health" and "e-mental health," shedding light on the significance of "mental health technology" and "digital mental health." It also examines the standards for university courses in mental health technologies and introduces a variety of mental health apps, encompassing apps, wearables, platforms, data analytics resources, and other tools. The article underscores the importance of integrating artificial intelligence into both the education and economic sectors. It provides a comprehensive account of an experiment integrated into a standard university curriculum, involving master's psychology students at a pedagogical university. The results and conclusions of this experiment are thoroughly detailed. Moreover, the article investigates the impact of transactional distance on the learning experience of students pursuing mental health technology courses in an online format at Kryvyi Rih State Pedagogical University during the 2023-2024 academic year. Indicators of the transaction distance of the sample are researched and presented in detail. The influence of evaluation, satisfaction and their interaction on the level of transactional distance is analyzed too. Applied logical and statistical tests were used, in particular, using the Pearson test for correlation analysis. The study's findings affirm the critical role of synergizing human and artificial intelligence in addressing pressing challenges, enhancing mental health education, honing data analysis skills, and shaping a brighter future for well-being.

Keywords

human-AI synergy, digital mental health, e-mental health, mental health technology, artificial intelligence in education, transactional distance, online learning, higher education, mental health apps, wearables, data analytics, psychological education, university curriculum, pedagogical innovations, Pearson correlation analysis, wartime education, Ukraine, sustainable well-being, mental health pedagogy, education technology, digital transformation

1. Background context

The fusion of human intellect and artificial intelligence algorithms has ushered in a realm of unsurpassed opportunities for advancing mental health technologies and treatments in an age that is defined by rapid technological progress and data-driven decision-making processes in psychotherapy. This article delves into the vast potential of collaborative synergy between humans and AI that focuses on two key realms: enhancing crisis online counselling education of psychologists in war conditions in Ukraine and data-driven decision making within HEI.

Amidst the backdrop of the Ukrainian conflict from 2022 to 2024, numerous enterprises and institutions operating within Ukraine have been confronted with significant challenges. They not only grapple with adapting to volatile work conditions and employee needs but also contend with the enduring effects

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of the COVID-19 pandemic [1, 2]. The once-prosperous Ukrainian economy of 2021, a driving force behind the nation's growth, has been particularly susceptible to disruptions caused by rolling blackouts, shelling incidents, and labor displacement.

Recognizing the substantial impact of professionals' mental well-being on overall business performance, there arises a critical need for future organizational psychologists to possess skills in monitoring mental health, resilience, and relevant organizational metrics. Addressing these challenges requires an urgent optimization of psychology curricula to align with the demands imposed by the Ukrainian war context.

To tackle these pressing issues, artificial intelligence capabilities come into play. By leveraging AI-based tools, we can overcome hurdles related to tracking and interpreting vital mental health indicators. Moreover, equipping HR and psychologists with practical skills in utilizing psychometric data is essential. This innovative approach not only enhances our understanding of mental health outcomes but also empowers enterprises and institutions to make well-informed decisions crucial for supporting employee well-being and overall efficiency amidst wartime conditions in Ukraine.

2. Literature review

2.1. Mental health technologies for online crisis counselling

Mental health technology is a multi-faceted field that represents the convergence of technology and mental well-being [3]. This broad vision includes various digital innovations carefully designed to support and improve mental health care and overall psychological well-being. At its core, mental health technology is a catchall term that covers a wide range of digital tools, apps and devices, where each of them is strategically designed to serve different aspects of mental health care [3]. These innovations span the entire mental health spectrum [4], from the critical areas of prevention and early intervention to treatment and ongoing support (figure 1) [5].

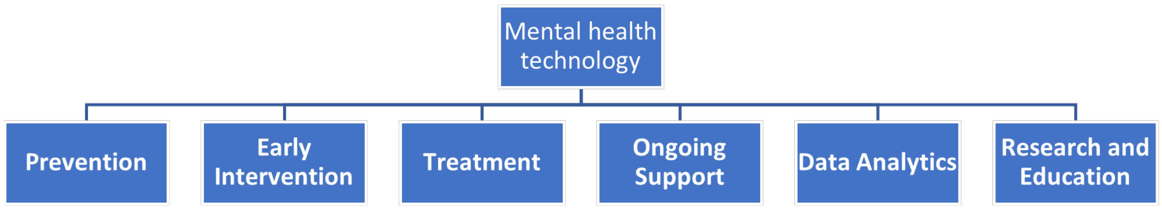

Figure 1: Mental health spectrum of technologies.

Firstly, prevention is at the fore of mental health technology, offering proactive tools and platforms designed to prevent the occurrence of mental health problems [6]. For example, these may be stress-reduction apps, mood-tracking software, and digitally attentive programs that help people build resilience and maintain mental balance. All this tools should supported by statistical analisis and recomendations from psychologist.

Secondly, recognizing the importance of early detection and interference, mental health technologies offer screening and assessment tools that can identify potential mental health problems in their initial stages [7]. These tools enable intervention and access to appropriate resources of support promptly, mitigating the severity of conditions and improving prognosis.

In addition, some researches state that AI can be used as an alternative data source in scientific research, in particular to collect synthesized prior knowledge on the topic under study. Through a research process to study the impact of the global health crisis caused by COVID-19 on education, based on the joint analysis of human intelligence and artificial intelligence [8], it was demonstrated that the use of such technologies can take the process of scientific research a step forward and accelerate the scale and speed of knowledge production for the benefit of humanity [9].

Thirdly, digital mental health solutions offer a variety of options in the treatment space [10]. There are evidence-based digital therapies such as cognitive behavioral therapy (CBT) and dialectical behavior therapy (DBT) delivered through mobile apps and online platforms [11] as well as individual and group therapy zoom-meetings, chat-bots. These solutions allow people to participate actively in treatment and recovery.

Further, after the initial stages of treatment, mental health technology continues to play a decisive role in supporting well-being [12]. Supportive communities and peer networks promote a sense of belonging and reduce feelings of isolation. Wearable devices and monitoring tools can track biometric data, helping individuals and their healthcare teams path progress and make data-driven adjustments to treatment plans [13].

Moreover, the use of big data and advanced analytics is a growing aspect of mental health technology [14]. It becomes possible to identify trends, predict mental health crises and adapt measures on a larger scale with the help of combining and analyzing large data sets. This data-driven approach has the potential to revolutionize mental health care.

Mental health technology also supports research by providing a platform for studying mental health patterns and treatment outcomes [15]. It is a valuable educational resource for both mental health professionals and the general public, offering ideas, guidance, and training materials.

Although AI offers benefits in academic environments and mental health research, it has evoked a mixture of awe and apprehension among educators and researchers, prompting efforts to understand and potentially mitigate its impact. There are some studies that seek to illuminate the current perceptions of AI in academic literature, exploring its implementations and the perceived risks it may pose to the educational landscape. Disputes about the ethics of using AI have been going on for several years now, and even legal aspects are being discussed. However, its influence continues to grow, with researchers studying both the positive and negative aspects of its use for educational and research purposes [16].

Last but not least, the human brain can acquire knowledge, generate new ideas and make decisions based on internal data and machines, which is known as machine learning [17, 18]. At the same time, neural networks are a tool for their implementation and imitate human skills [19, 20]. Despite the ethical and social impact of rapidly developing AI, it paves the way for more research in a multilingual society [21].

2.2. Standards for university courses of crisis online counselling with implementation mental health technologies

Artificial intelligence is rapidly transforming many fields, including psychology. AI has the potential to improve psychological research, practice, and education. For example, AI can be used to develop new diagnostic tools, create personalized treatment plans, and improve the delivery of mental health services. Notwithstanding, for psychologists to fully embrace AI, they need to be trained in the technology. A recent study found that psychology students are interested in AI, but they need more training in order to use it effectively. The study also found that students are concerned about the ethical implications of AI [22].

In addition to this, in study by Gado et al. [22] developed and tested a new model to explain what factors are relevant to predict psychology students' attitude towards AI and their intention to use it. The study found that perceived usefulness, perceived social norm, and attitude towards AI were significant predictors of intention to use AI. Perceived knowledge of AI was also a significant predictor of intention to use AI, especially for female participants. The study suggests that psychology training programs should focus on fostering a positive attitude towards AI among students by emphasizing its usefulness and ease of use in psychologists' work contexts. Additionally, programs should help students to develop the knowledge and skills they need to use AI effectively.

Another example is the article "Training the next generation of counselling psychologists in the practice of telepsychology" discusses the need for training programs to prepare counseling psychologists for the future of service delivery in psychology, which increasingly includes the use of telepsychology. The authors note that there are few options available for trainees seeking to acquire experience in telepsychology and that guidelines for training programs in this area are virtually non-existent [23].

However, in a study organized by Perle et al. [24], researchers surveyed 782 psychological and medical professionals about their interest in videoconferencing telehealth training and mental health telehealth referral. Results showed that both groups were interested in telehealth training, with psychological professionals more likely to be interested. The most desired training topics were efficacy data, ethical issues, and legal concerns.

Developing comprehensive university standards for online crisis counselling is vital to preparing students for the dynamic demands of this field. Key components and considerations include curriculum design:

1) core courses: cover fundamental topics such as technology integration, ethics, and cutting-edge innovations (figure 2);
2) elective courses: allow specialization in areas like teletherapy, digital interventions, data analytics, or app development.

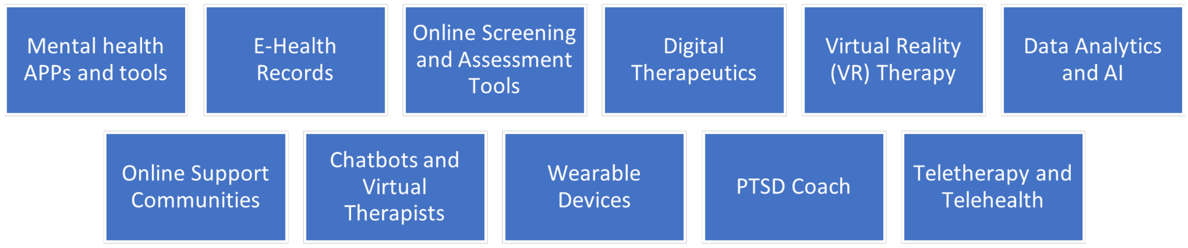

Figure 2: Fundamental topics of mental health technologies for online crisis counselling university courses.

That is why, the online crisis counselling course should adopt an interdisciplinary approach, encouraging cooperation between psychology, computer science, data science, and public health departments to promote a comprehensive view. An integral component of the curriculum focused on ethical foundations, highlighting ethical principles such as safeguarding data privacy, ensuring informed voluntary consent, and the responsible usage of AI in diagnosis and treatment [13].

Additionally, the main attention in course development revolves around development proficiency in the evaluation and application of mental health technologies [25]. This includes the acquisition of required technological skills for evaluation and effective use of an array of mental health apps, including apps, wearables, telehealth platforms, and data analytics resources (figure 2).

First of all, the course should include the specifics of working with mental health apps [15] and digital therapeutics (DTx) [26], virtual reality (VR) Therapy [11] as tools for supporting clients (figure 3). A lot of mobile applications have been created to assist individuals in overseeing their mental well-being. These applications include functionalities like monitoring emotional states, meditation and mindfulness practices, use of cognitive-behavioural therapy (CBT) methods and fostering peer connections for support. It is quite important for psychology students to understand how to use these tools to support community mental health.

VR technology is increasingly used in exposure therapy for PTSD and phobias. It allows individuals to confront and manage their fears in a controlled and immersive environment. As described in the research by Usmani et al. [11], the future of mental health within the metaverse lies in the potential use of immersive digital realms, referred to as the metaverse, for solving mental health issues.

The course should also cover how to use telehealth and teletherapy to support clients specifically. Telehealth and teletherapy platforms have revolutionized the provision of therapeutic and consulting services, enabling individuals to access these vital services remotely through video calls, phone calls, or text messaging. For instance, Miu et al. [27] investigates the impact of the COVID-19 pandemic on psychotherapy, with a specific focus on individuals who have serious mental illness (SMI). These

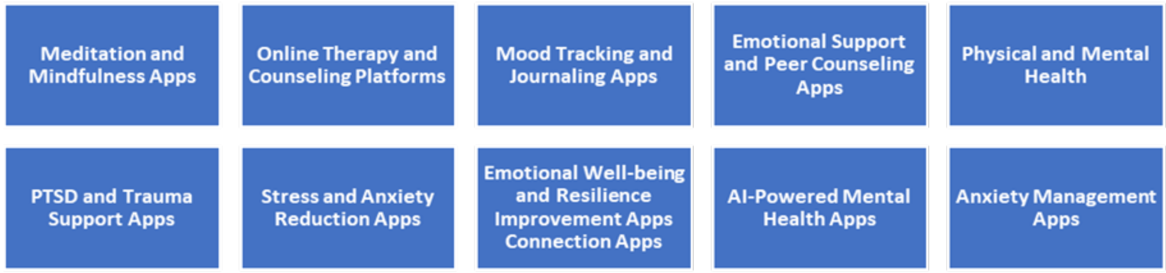

Figure 3: Mental health apps.

findings shed light on the viability and effectiveness of telehealth for individuals with serious mental illness amidst the challenges posed by COVID-19.

It is equally important that the course included the specifics of working with online screening and assessment tools [7, 11], wearable devices [28] as tools for client self-diagnosis. Certain wearable fitness trackers and smartwatches are already equipped with functions to monitor stress levels, sleep patterns, and physical activity [28].

Last but not least, data analytics and AI topics should be included in university courses. Advanced analytics and machine learning can help healthcare providers and researchers identify patterns and trends in mental health data. This can lead to more personalized treatment plans and a better understanding of mental health disorders.

While mental health tech is a valuable resource, it should complement, but not replace, professional mental health care. It can provide additional tools for managing mental well-being, but seeking guidance and treatment from trained professionals remains essential for severe or persistent issues. Traditionally, the online crisis counselling course has been perceived as challenging by students due to its reliance on statistical analysis tools and a complex process involving manual decoding of raw survey data, organizing the data, and defining variables using SPSS statistical packages or R coding. These tasks require additional software knowledge and programming skills, which psychology students often find challenging extracurricular tasks.

2.3. Student engagement and satisfaction of online learning

Student engagement and satisfaction are essential to successful online learning. The Zhang Scale of Transactional Distance (RSTD) is a valuable tool for educators to measure and address transactional distance, a key factor influencing student engagement and satisfaction in online online crisis counselling course [29]. Transactional distance refers to the psychological-pedagogical space that separates students from their peers, instructors, course content, and learning interface. This can be caused by various factors, such as:

1. Online students may feel isolated from their peers and professors, leading to decreased engagement and satisfaction [30].
2. Poorly designed or uninteresting online courses can lead to longer distances between transactions. Significant development and widespread adoption of artificial intelligence and no-code software in early 2023 are driving demands for the adoption of AI technologies in course design. Therefore, offering a module that integrates artificial intelligence into online crisis counselling course provides an exceptional opportunity to explore the sought-after convergence of technology and mental well-being. This interdisciplinary approach not only reflects the evolving landscape of mental health support but also gives students additional time to make informed decisions about the data [29, 30].
3. Students may experience technical difficulties accessing course content or using statistical packages purchased by the university, which may also increase the distance between transactions.

However, the developed public platforms are widely available and do not require a presence at the university [31].

RSTD quantifies transaction distance along four key dimensions [32]:

1. transactional distance between students (TDSS) (measures the perceived psychological and educational gap between students in an online learning environment);
2. transactional distance between student and instructor (TDST) (measures the perceived separation and interaction dynamics between students and their instructors in an online course);
3. transactional distance between learners and content (TDSC) (measures the perceived distance or cognitive space between learners and course content or materials);
4. transactional distance between learner and interface (TDSI) (measures the perceived distance between learners and the technology interface or platform used for learning).

In our case, we use RSTD to identify areas for improvement in an online course to evaluate the effectiveness of instructional interventions aimed at reducing transaction distance and increasing student engagement and satisfaction. Given the aforementioned prerequisites, the research inquiry will encompass the following: evaluate the transactional distance encountered by students and their satisfaction levels while utilizing an AI in online crisis counselling course and Data Analytics?

3. Methodology

This study aimed to assess the academic performance and satisfaction of psychology students in their study of the module "Mental Health Technology and AI" in the pilot course "Crisis Online Counselling", explicitly emphasizing the integration of artificial intelligence and machine learning. The research took place in an online format during the 2023-2024 academic year against the backdrop of the ongoing conflict in Ukraine. The research employed a mixed-methods approach to investigate the transactional distance experienced by students enrolled in the course.

3.1. Sampling and procedures

In total, 60 students (table 1) participated in the course. The participants included 80.5% females and 19.5% males. There was no significant difference in the distribution of participants into groups based on gender ($\chi^2(2) = .444, p = .79$). The average age of participants was $M = 20.3$ years ($SD = 2.4$). Most participants were preparing for careers as practical psychologists in educational institutions (53.1%), while the rest aimed to become private (46.9%) psychologists. These two conditions did not significantly differ regarding participants' educational paths ($\chi^2(1) = 1.793, p = .18$).

Table 1
Demographics of the present sample ($N = 60$, mean age = 20.5; $SD = 1.07$).

Variable	Type	Frequency
Gender	Male	12
	Female	48
Age categories	18–24 years old	58
Age categories	25–34 years old	2
Academic status Diploma	BA	60
Department	Psychology	44

Moodle served as the asynchronous platform, while Zoom facilitated synchronous learning and lab work presentations. This approach allowed for a comprehensive exploration of the research problem by combining both quantitative and qualitative data collection and analysis, shedding light on the dynamics of teaching and learning in the specific context of wartime.

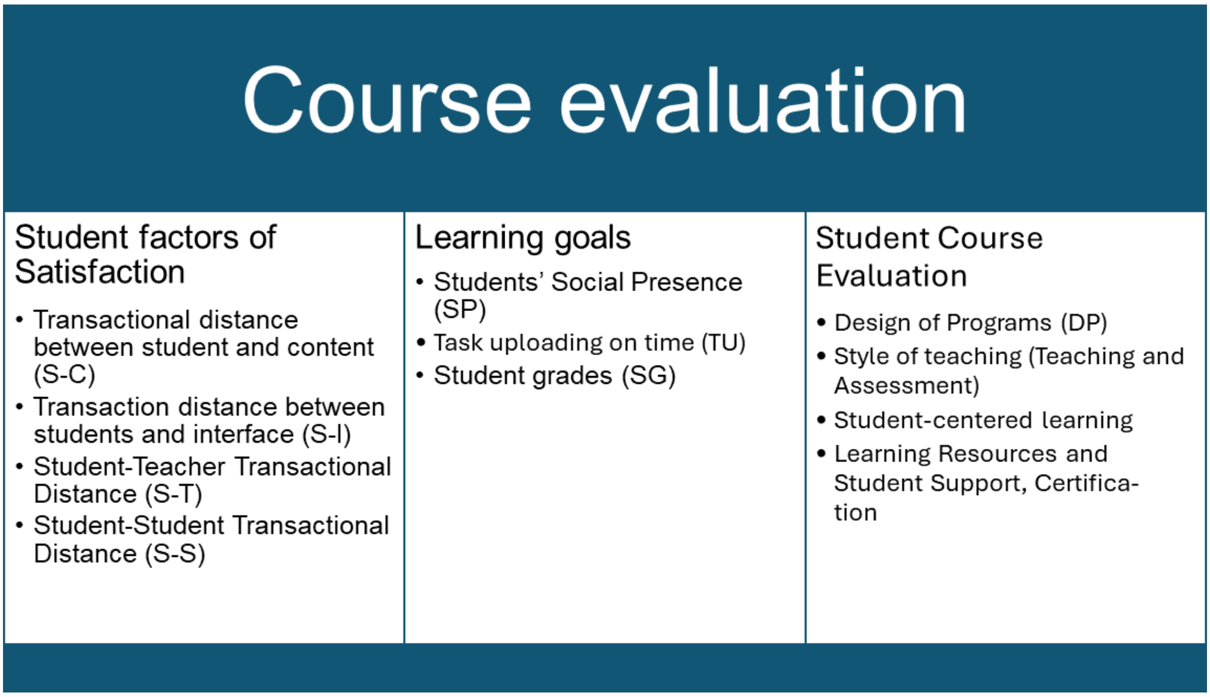

Figure 4: The research model of the study.

The procedure for our controlled experiment was conducted as part of the pilot module (1 ECTS) of an "online crisis counselling" course (3 ECTS). The study involved students studying for a BA degree in psychology at a pedagogical university.

Research on the use of student course evaluations has demonstrated a wide range of applications as quality indicators of the system, for enhancing the expansion of students' rights and opportunities, and as tools for measuring educational quality. Accordingly, this study hypothesized that course evaluation is associated with quality of content.

Based on previous research and the development of the model of evaluation, the following hypotheses were formulated, and the proposed research model is illustrated in figure 4.

Here's a breakdown of the procedure:

1. The entire module lasted a total of 4 weeks and consisted of four course topics. Each course topic, "Diagnostics of mental health in technology", "Exploratory Data Analysis (EDA)", "Setting up a chatbot model" and "Evaluation", lasted one week.
   - *The topic "Diagnostics of mental health in technology"* was aimed at studying the analysis of data on mental health for IT companies; we have selected a list of diagnostic tools to analyze the mental health, burnout and resilience of university IT stakeholders ("Mental Health Rating Scale", "Resilience Rating Scale"; individual and organizational stressors, internal and external, as well as 5 open-ended questions about energy demands at work and resilience practices, managerial encouragement, and types of company assistance during war). The SurveyMonkey platform was used to collect mental health data.
   - *The topic "Exploratory Data Analysis (EDA)"* was the data analysis task used several tools: ChatGPT or Bard to code Python commands for data preparation (including raw data cleaning, data quality assurance, anonymization and protection of confidential information for ethical reasons). Also, used Dataiku EDA tools for visual data exploration and descriptive statistics of a sample. The primary goal was to identify patterns, correlations, and potential anomalies in data on mental health, resilience, and stress levels among wartime IT professionals. Next, the goal was to find relevant characteristics or variables that could be useful for analyzing mental health, such as average stress levels, identifying periods of high stress, or classifying employees based on their mental health status.

- *The topic "Setting up a chatbot model"* included content and cluster analysis of open questions (setting up a chatbot model, specifying the context, querying a model with relevant questions, templates based on text data, on which GPT is trained) and skills in using Dataiku for machine learning without coding.
- *The topic "Evaluation"* explained the components of the report and the formulation of conclusions, problems associated with human verification and validation of models.

2. Presentation of course content: students attended lectures and two practical sessions conducted by the same teacher for all students.

3.2. Research design and setting

Research into the utilization of student course evaluations has unveiled a diverse array of applications, serving as barometers of system quality, tools for enhancing student empowerment, and metrics for assessing educational excellence. Consequently, this study posited an association between course evaluations and teaching quality.

Drawing upon prior research and the model, the ensuing hypotheses were formulated. The research model proposed in figure 4 encapsulates these research questions:

- **Research question 1.** How does the utilization of AI tools (AT) influence the factors contributing to student satisfaction in online learning (SfS)?
- **Research question 2.** What is the relationship between student factors of satisfaction in online learning (SfS) and their achievement of learning goals (SS)?

A web-based email surveys were designed for asynchronous data collection to gather feedback through the student evaluation of teaching (SET) [33] that includes Zhang's transactional distance scale and online survey proposed by the National Agency for Higher Education (Methodology of independent, external, on-site evaluation of the quality of legal education in Ukraine) (A and B).

1. The instruments evaluated both student satisfaction with the course and the perceived transactional distance between students and their instructor, as well as between students and course materials. To minimize potential biases, both Zhang's scale and the student satisfaction questionnaire utilized a Likert scale with five response options, ranging from "completely disagree" to "completely agree."
2. Respondents' perceptions regarding the quality of teaching are examined based on four indicators: teaching style, student-centered learning, learning resources and support, certification, and program design. The survey on teaching quality in universities under war conditions, conducted through computer-based Google Forms, comprised 20 questions and 4 statements regarding perceived course benefits, associated factors, and participant behavioral characteristics during the study process. Responses were scored on a 5-point Likert scale from "never true" to "almost always true," and each item was analyzed individually to provide specific insights into its content.
3. Following the completion of the course module, students underwent an online knowledge test. To pass the required knowledge test (Student's graduates) on the Moodle platform, students initially needed a minimum of 50% correct answers on the multiple-choice questions.

Data analysis will be analyzed using Jamovi. Descriptive statistics, including correlation analysis using the Pearson criterion, were used to quantitatively assess the relationship between academic achievement and the effectiveness of Online crisis counseling training, determining the strength and direction of this association. Quantitative data from the Zhang scale will undergo descriptive statistical analysis to uncover patterns and trends in students' perceptions of transactional distance [34]. Inferential statistical tests, correlation analysis, specifically employing the Pearson criterion, was used to determine the relationship between transactional distance scales, and the effectiveness of training quantitatively. This analysis aimed to establish the strength and direction of the association between these variables. [35].

4. Data analysis

The overall satisfaction with the course among participants was notably high, with an average rating of 4.37 and a standard deviation of 0.991, on a scale ranging from 1 to 5 (SS = Student satisfaction "Overall, I am satisfied with this course"). Particularly, students expressed a strong appreciation for the interaction facilitated by the AI tools utilized in the classes (SI = Transaction distance between students and interface, averaging 3.97 with a standard deviation of 0.68) (table 2).

Table 2
Indicators of the transaction distance of the sample ($N = 60$).

Scales	Mean	SE	SD
S-C	3.65	0.0884	0.685
S-I	3.97	0.0750	0.581
S-T	4.00	0.1258	0.974
S-S	4.32	0.1176	0.911
LG	3.93	0.1383	1.071
SS	4.37	0.1279	0.991

However, there was a perceived decrease in student ratings concerning the transactional distance between students and course content, with a mean rating of 3.65 and a standard deviation of 0.68. On the other hand, students rated their transactional distance with teachers and peers relatively high, with average values of 4.00 ($SD = 0.974$) and 4.32 ($SD = 0.911$), respectively (table 2).

Transactional distance is associated with a grade on most dimensions. Post hoc analysis revealed the most significant differences (table 3).

Based on our empirical analysis, we applied logical and statistical tests, particularly using the Pearson criterion for correlation analysis. We tested the quantitative relationships between:

1. Assessment of the quality of the knowledge obtained in the online test and the effectiveness of participation in the course.
2. The total number of timely submitted reports and their correlation with the quality assessment.

We used Pearson's correlation to illustrate these relationships, recognizing that the correlation coefficient may not reach a perfect. We also applied non-parametric significance tests to establish statistical significance due to the limited distribution information of in the data.

Table 3
Indicators of students' work systematicity on the basis of assignments ($N = 60$).

Assignment title	Number[a]	Correlation[b]	Grade satisfaction[c]
The topic "Diagnostics of mental health in technology"	41	–	0.68
The topic "Exploratory Data Analysis (EDA)"	36	0.67	0.56
The topic "Setting up a chatbot model"	49	0,45	0,62
The topic "Evaluation"	56	0,51	0,63

Note: [a] – number of reports that were uploaded in time; [b] – correlation with the grade for quality (online knowledge test); [c] – correlation with the grade for quality the total number of reports that were uploaded in time.

Based on the provided correlations (table 4), the factors can be ranked from powerful to less powerful associations and organized into groups :

Group 1: Moderately strong

1. Transactional distance between students and content (S-C) correlates positively with:
   - Students' social presence (SP) ($r = 0.61$)
   - Learning goals (LG) ($r = 0.43$)

Table 4
Course evaluation correlations ($N = 60$).

Scales	S-C	S-I	DP	LG	SG	SP
Transactional distance between student and content (S-C)	–	0.31	0.27	0.43	0.39	0.61
Transaction distance between students and interface (S-I)		–	0.33	0.38	0.56	0.36
Design of programs (DP)			–	0.52	0.44	-0.26
Learning goals (LG)				–	0.44	0.45
Student grades (SG)					–	0.56
Students' social presence (SP)						–

- Student grades (SG) ($r = 0.39$)
- Transactional distance between students and interface (S-I) ($r = 0.31$)
- Design of programs (DP) ($r = 0.27$)

2. Transactional distance between students and interface (S-I) correlates positively with:
    - Student grades (SG) ($r = 0.56$)
    - Learning goals (LG) ($r = 0.38$)
    - Design of programs (DP) ($r = 0.33$)

Group 2: Moderately strong relationships

4. Learning goals (LG) show positive correlations with:
    - Student grades (SG) ($r = 0.45$)
    - Students' social presence (SP) ($r = 0.45$)

Group 3: Moderately strong with weaker negative relationship

3. Design of programs (DP) correlates positively with:
    - Learning goals (LG) ($r = 0.52$)
    - Student grades (SG) ($r = 0.44$)
    - but negatively with:
    - Students' social presence (SP) ($r = -0.26$)
5. Student grades (SG) display a positive correlation with:
    - Students' social presence (SP) ($r = 0.56$)

This organization highlights the strengths of associations between different factors, categorizing them into groups based on their correlation values. Here are the definitions for each group based on the revised organization of factors:

Group 1: Strong correlations. This group highlights significant correlations between the transactional distance between students and content (S-C) and both students' social presence (SP) and learning goals (LG). These relationships of factors indicate robust connections, suggesting that when students feel engaged with course content, they are more likely to be socially present and focused on achieving learning objectives.

Group 2: Moderate correlations. Comprising moderate correlations, this group underscores the relationships between Student-Content and various other factors, including student grades (SG), transactional distance between students and interface (S-I), and design of programs (DP). While these relationships are not as strong as those in Group 1, they still suggest moderately strong links between different aspects of the course evaluation.

Group 3: Moderate correlations with a weaker negative relationship. Characterized by moderate associations with a weaker negative relationship, this group reveals the complex interplay between design of programs (DP), learning goals (LG), student grades (SG), and students' social presence (SP). Despite the presence of negative correlations, the overall associations within this group are moderate, indicating nuanced relationships among these factors.

This refined organization provides a comprehensive understanding of the varying strengths of associations among different factors in course evaluations, offering valuable insights for future research and course improvement initiatives.

5. Discussion

Study results highlight the effectiveness of training and the achievement of favorable educational outcomes in the context of integrating artificial intelligence and no-code machine learning for mental health data analysis. Not only does the popularity of discussing these tools ensure that students are involved in studying the subject, but also in conditions of forced online learning against the backdrop of war, it creates a reduction in the distance regarding the use of interfaces and software that does not require the use of programs purchased by the university and stay on campus.

- **Research question 1 aimed to investigate the influence of AI tools (AT) on factors contributing to student satisfaction in online learning (SfS).**

The study found that overall satisfaction with the course was high, with an average rating of 4.37 and a standard deviation of 0.991. Notably, students appreciated the interaction facilitated by AI tools, as indicated by a mean transaction distance between students and interface (SI) of 3.97 with a standard deviation of 0.68 (table 1). However, there was a perceived decrease in ratings for transactional distance between students and course content (S-C), with a mean rating of 3.65 and a standard deviation of 0.68. Conversely, transactional distance with teachers (S-T) and peers (S-S) was rated relatively high, with average values of 4.00 ($SD = 0.974$) and 4.32 ($SD = 0.911$), respectively.

In addition, the study highlights the specific satisfaction of students using learning analytics tools integrated with artificial intelligence. The main objective of the module was to provide psychology students with fundamental competencies to analyze mental health data and solve problems relevant to the ongoing conflict in Ukraine. However, it is critical to understand both the general and specific trends identified in the data set.

Transactional satisfaction distance has also demonstrated a correlation with measures of successful task completion within a given time frame. According to our previous research [33], students who had difficulty meeting assignment deadlines tended to perceive greater transactional distance when interacting with both the course interface and course content, particularly the topic of data ethics. However, their interaction with peers during group assignments remained minimal.

The student research team's primary goal was to identify patterns, correlations, and potential anomalies in a data set related to mental health, resilience, and stress among wartime IT professionals. Deploying trained models into Dataiku enabled real-time predictive analysis. Notably, among students classified as absent, a key factor influencing assignment quality was the presence or absence of strong educational goals. These results are close to the conclusions of research on student motivation [36].

Emphasis during the practicum was on the ethical handling of sensitive mental health data and adherence to confidentiality protocols. However, open-ended responses indicated that students had difficulty completing assignments within the time limits and were only able to engage superficially with ethical considerations. It's close to the results of research [37], where Moodle was found to be ineffective and 92.4% of students considered it a time-wasting tool. Notably, in our research as well as research by Best there were no strong contrary opinions; most respondents were neutral [37].

- **Research question 2 investigated the relationship between student factors of satisfaction in online learning (SfS) and their achievement of learning goals (SS).**

The study found that students with higher grades, such as those in the "B" category, primarily focused on reducing transactional distance related to content, interface, and peer interactions. Conversely, students with lower grades, specifically those in the "C" category, reported dissatisfaction and concentrated efforts on reducing transactional distance associated with content, interface, and teacher parameters.

Based on the provided correlations (table 4), the factors were organized into groups based on their correlation values. In Group 1, characterized by moderately strong associations, transactional distance between students and content (S-C) showed positive correlations with students' social presence (SP), learning goals (LG), student grades (SG), transactional distance between students and interface (S-I), and design of programs (DP). Group 2 highlighted moderately strong relationships, with learning goals (LG) positively correlating with both student grades (SG) and students' social presence (SP). Group 3, displaying moderately strong associations with a weaker negative relationship, revealed that the design of programs (DP) correlated positively with learning goals (LG) and student grades (SG) but negatively with students' social presence (SP). Additionally, student grades (SG) in Group 3 displayed a positive correlation with students' social presence (SP).

This organization provides valuable insights into the strengths of associations between different factors, allowing for a clearer understanding of their relationship with student satisfaction and achievement of learning goals in online learning environments.

6. Conclusion

This research explores the potential of AI to improve mental health education and data analysis learning, demonstrating the significant benefits it can bring to individuals and organizations. As technology advances, the synergy between human intelligence and artificial intelligence will play a key role in shaping the future of work and well-being. The results of this study provide information about the influence of relevance of course content on student perception.

The hypothesis, that the declining transactional distance between student-content and interface correlates with their grade (academic performance) while utilizing an AI in Mental Health Tech and Data Analytics, was supported. This finding suggests that active participation in the course, coupled with understanding how artificial intelligence tools can be applied in a psychological context, can positively influence students' career intentions. This emphasizes the role of practical experience and practical application in shaping students' professional trajectories.

Conducting this study in an online format during the conflict in Ukraine adds a unique dimension to the research. This reflects the adaptability and resilience of students and teachers in the face of difficult circumstances. The findings emphasize that even under these conditions, effective teaching strategies can make a significant difference in students' learning experiences and outcomes.

7. Significance and consequences

The research is particularly noteworthy for several reasons. For educators, this highlights the value of incorporating real-world relevance into curriculum development and providing students with opportunities to work with emerging technologies. Conducted during the 2022-2023 academic year amidst the ongoing conflict in Ukraine, this study navigates the unique challenges presented by the online format. This context adds relevance and urgency to understanding student engagement and achievement in such conditions. The study addresses the complexity associated with the subject matter, which students often consider challenging. This complexity stems from the reliance on statistical analysis tools and the need for skills in decoding raw data, data organization, and using statistical packages. Investigating how students cope with these demands is of substantial significance. By examining how students perceive the relevance of course content and their intentions to apply artificial intelligence tools in their future careers, this research sheds light on the effectiveness of educational approaches in preparing students for the evolving demands of their field.

8. Ethical considerations

Students were assured anonymity and that survey responses wouldn't affect their course assessment. Before the survey, participants consented to data use, including knowledge test scores. Two months post-data collection, participants received a thorough debrief with initial findings. This process ensured ethical and systematic experiment execution in the university course context.

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Declaration on Generative AI: During the preparation of this work, the author) used GPT-4o in order to: Improve writing style, Content enhancement. After using this tool, the author(s) reviewed and edited the content as needed and takes full responsibility for the publication's content.

References

[1] M. Velykodna, Psychoanalysis during the COVID-19 pandemic: Several reflections on countertransference, Psychodynamic Practice 27 (2021) 10–28. URL: https://doi.org/10.1080/14753634.2020.1863251.

[2] V. Tkachuk, Y. Yechkalo, S. Semerikov, M. Kislova, Y. Hladyr, Using Mobile ICT for Online Learning During COVID-19 Lockdown, in: A. Bollin, V. Ermolayev, H. C. Mayr, M. Nikitchenko, A. Spivakovsky, M. Tkachuk, V. Yakovyna, G. Zholtkevych (Eds.), Information and Communication Technologies in Education, Research, and Industrial Applications, volume 1308 of *Communications in Computer and Information Science*, Springer International Publishing, Cham, 2021, pp. 46–67. URL: https://doi.org/10.1007/978-3-030-77592-6_3.

[3] J. Brassey, A. Güntner, K. Isaak, T. Silberzahn, Using digital tech to support employees' mental health and resilience, 2021. URL: https://www.mckinsey.com/industries/life-sciences/our-insights/using-digital-tech-to-support-employees-mental-health-and-resilience.

[4] E. B. Hiland, Therapy Tech: The Digital Transformation of Mental Healthcare, University of Minnesota Press, 2021. URL: http://www.jstor.org/stable/10.5749/j.ctv1xp9q3t.

[5] L. Bollaert, A manual for internal quality assurance in higher education: With a special focus on professional higher education, Eurashe, Brussels, 2014.

[6] J. R. Olson, M. Lucy, M. A. Kellogg, K. Schmitz, T. Berntson, J. Stuber, E. J. Bruns, What Happens When Training Goes Virtual? Adapting Training and Technical Assistance for the School Mental Health Workforce in Response to COVID-19, School Mental Health 13 (2021) 160–173. URL: https://doi.org/10.1007/s12310-020-09401-x. doi:10.1007/s12310-020-09401-x.

[7] L. Balcombe, D. De Leo, Psychological Screening and Tracking of Athletes and Digital Mental Health Solutions in a Hybrid Model of Care: Mini Review, JMIR Form Res 4 (2020) e22755. URL: https://doi.org/10.2196/22755. doi:10.2196/22755.

[8] O. M. Haranin, N. V. Moiseienko, Adaptive artificial intelligence in RPG-game on the Unity game engine, in: A. E. Kiv, S. O. Semerikov, V. N. Soloviev, A. M. Striuk (Eds.), Proceedings of the 1st Student Workshop on Computer Science & Software Engineering, Kryvyi Rih, Ukraine, November 30, 2018, volume 2292 of *CEUR Workshop Proceedings*, CEUR-WS.org, 2018, pp. 143–150. URL: http://ceur-ws.org/Vol-2292/paper16.pdf.

[9] T. Karakose, M. Demirkol, N. Aslan, H. Köse, R. Yirci, A Conversation with ChatGPT about the Impact of the COVID-19 Pandemic on Education: Comparative Review Based on Human–AI Collaboration, Educational Process International Journal 12 (2023). URL: https://doi.org/10.22521/edupij.2023.123.1. doi:10.22521/edupij.2023.123.1.

[10] S. Scott, V. Knott, A. L. Finlay-Jones, V. O. Mancini, Australian Psychologists Experiences with Digital Mental Health: a Qualitative Investigation, Journal of Technology in Behavioral Science 8 (2023) 341–351. URL: https://doi.org/10.1007/s41347-022-00271-5. doi:10.1007/s41347-022-00271-5.

[11] S. S. Usmani, M. Sharath, M. Mehendale, Future of mental health in the metaverse, General

Psychiatry 35 (2022) e100825. URL: https://doi.org/10.1136/gpsych-2022-100825. doi:10.1136/gpsych-2022-100825.
[12] S. R. Pendse, D. Nkemelu, N. J. Bidwell, S. Jadhav, S. Pathare, M. De Choudhury, N. Kumar, From Treatment to Healing:Envisioning a Decolonial Digital Mental Health, in: Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems, CHI '22, Association for Computing Machinery, New York, NY, USA, 2022. URL: https://doi.org/10.1145/3491102.3501982. doi:10.1145/3491102.3501982.
[13] E. G. Lattie, C. Stiles-Shields, A. K. Graham, An overview of and recommendations for more accessible digital mental health services, Nature Reviews Psychology 1 (2022) 87–100. URL: https://doi.org/10.1038/s44159-021-00003-1. doi:10.1038/s44159-021-00003-1.
[14] H. A. Eyre, A. B. Singh, C. Reynolds III, Tech giants enter mental health, World Psychiatry 15 (2016) 21–22. URL: https://doi.org/10.1002/wps.20297.
[15] K. Moon, M. Sobolev, J. M. Kane, Digital and Mobile Health Technology in Collaborative Behavioral Health Care: Scoping Review, JMIR Ment Health 9 (2022) e30810. URL: https://doi.org/10.2196/30810. doi:10.2196/30810.
[16] Z. H. İpek, A. I. C. Gözüm, S. Papadakis, M. Kallogiannakis, Educational Applications of the ChatGPT AI System: A Systematic Review Research, Educational Process International Journal 12 (2023) 26–55. URL: https://doi.org/10.22521/edupij.2023.123.2. doi:10.22521/edupij.2023.123.2.
[17] S. Semerikov, D. Zubov, A. Kupin, M. Kosei, V. Holiver, Models and Technologies for Autoscaling Based on Machine Learning for Microservices Architecture, in: V. Lytvyn, A. Kowalska-Styczen, V. Vysotska (Eds.), Proceedings of the 8th International Conference on Computational Linguistics and Intelligent Systems. Volume I: Machine Learning Workshop, Lviv, Ukraine, April 12-13, 2024, volume 3664 of *CEUR Workshop Proceedings*, CEUR-WS.org, 2024, pp. 316–330. URL: https://ceur-ws.org/Vol-3664/paper22.pdf.
[18] H. B. Danylchuk, S. O. Semerikov, Advances in machine learning for the innovation economy: in the shadow of war, in: H. B. Danylchuk, S. O. Semerikov (Eds.), Proceedings of the Selected and Revised Papers of 10th International Conference on Monitoring, Modeling & Management of Emergent Economy (M3E2-MLPEED 2022), Virtual Event, Kryvyi Rih, Ukraine, November 17-18, 2022, volume 3465 of *CEUR Workshop Proceedings*, CEUR-WS.org, 2023, pp. 1–25. URL: https://ceur-ws.org/Vol-3465/paper00.pdf.
[19] S. Semerikov, H. Kucherova, V. Los, D. Ocheretin, Neural Network Analytics and Forecasting the Country's Business Climate in Conditions of the Coronavirus Disease (COVID-19), in: V. Snytyuk, A. Anisimov, I. Krak, M. Nikitchenko, O. Marchenko, F. Mallet, V. V. Tsyganok, C. Aldrich, A. Pester, H. Tanaka, K. Henke, O. Chertov, S. Bozóki, V. Vovk (Eds.), Proceedings of the 7th International Conference "Information Technology and Interactions" (IT&I-2020). Workshops Proceedings, Kyiv, Ukraine, December 02-03, 2020, volume 2845 of *CEUR Workshop Proceedings*, CEUR-WS.org, 2020, pp. 22–32. URL: https://ceur-ws.org/Vol-2845/Paper_3.pdf.
[20] S. Semerikov, I. O. Teplytskyi, Y. V. Yechkalo, O. M. Markova, V. N. Soloviev, A. Kiv, Computer Simulation of Neural Networks Using Spreadsheets: Dr. Anderson, Welcome Back, in: V. Ermolayev, F. Mallet, V. Yakovyna, V. S. Kharchenko, V. Kobets, A. Kornilowicz, H. Kravtsov, M. S. Nikitchenko, S. Semerikov, A. Spivakovsky (Eds.), Proceedings of the 15th International Conference on ICT in Education, Research and Industrial Applications. Integration, Harmonization and Knowledge Transfer. Volume II: Workshops, Kherson, Ukraine, June 12-15, 2019, volume 2393 of *CEUR Workshop Proceedings*, CEUR-WS.org, 2019, pp. 833–848. URL: https://ceur-ws.org/Vol-2393/paper_348.pdf.
[21] S. Athanassopoulos, P. Manoli, M. Gouvi, K. Lavidas, V. Komis, The use of ChatGPT as a learning tool to improve foreign language writing in a multilingual and multicultural classroom, Advances in Mobile Learning Educational Research 3 (2023) 818–824. URL: https://doi.org/10.25082/AMLER.2023.02.009.
[22] S. Gado, R. Kempen, K. Lingelbach, T. Bipp, Artificial intelligence in psychology: How can we enable psychology students to accept and use artificial intelligence?, Psychology Learning & Teaching 21 (2022) 37–56. URL: https://doi.org/10.1177/14757257211037149. doi:10.1177/

14757257211037149.
[23] C. E. McCord, J. J. Saenz, T. W. Armstrong, T. R. Elliott, Training the next generation of counseling psychologists in the practice of telepsychology, Counselling Psychology Quarterly 28 (2015) 324–344. URL: https://doi.org/10.1080/09515070.2015.1053433. doi:10.1080/09515070.2015.1053433.
[24] J. G. Perle, J. Burt, W. J. Higgins, Psychologist and Physician Interest in Telehealth Training and Referral for Mental Health Services: An Exploratory Study, Journal of Technology in Human Services 32 (2014) 158–185. URL: https://doi.org/10.1080/15228835.2014.894488. doi:10.1080/15228835.2014.894488.
[25] L. Valentine, S. D'Alfonso, R. Lederman, Recommender systems for mental health apps: advantages and ethical challenges, AI & SOCIETY 38 (2023) 1627–1638. URL: https://doi.org/10.1007/s00146-021-01322-w. doi:10.1007/s00146-021-01322-w.
[26] J. Lutz, E. Offidani, L. Taraboanta, S. E. Lakhan, T. R. Campellone, Appropriate controls for digital therapeutic clinical trials: A narrative review of control conditions in clinical trials of digital therapeutics (DTx) deploying psychosocial, cognitive, or behavioral content, Frontiers in Digital Health 4 (2022). URL: https://doi.org/10.3389/fdgth.2022.823977.
[27] A. S. Miu, H. T. Vo, J. M. Palka, C. R. Glowacki, R. J. Robinson, Teletherapy with serious mental illness populations during COVID-19: telehealth conversion and engagement, Counselling Psychology Quarterly 34 (2021) 704–721. URL: https://doi.org/10.1080/09515070.2020.1791800. doi:10.1080/09515070.2020.1791800.
[28] H. Tikkanen, K. Heinonen, A. Ravald, Smart Wearable Technologies as Resources for Consumer Agency in Well-Being, Journal of Interactive Marketing 58 (2023) 136–150. URL: https://doi.org/10.1177/10949968221143351. doi:10.1177/10949968221143351.
[29] R. C. Paul, W. Swart, A. M. Zhang, K. R. MacLeod, Revisiting Zhang's scale of transactional distance: refinement and validation using structural equation modeling, Distance Education 36 (2015) 364–382. URL: https://doi.org/10.1080/01587919.2015.1081741. doi:10.1080/01587919.2015.1081741.
[30] J. Weidlich, T. J. Bastiaens, Technology Matters – The Impact of Transactional Distance on Satisfaction in Online Distance Learning, The International Review of Research in Open and Distributed Learning 19 (2018). URL: https://doi.org/10.19173/irrodl.v19i3.3417.
[31] F. G. Karaoglan-Yilmaz, K. Zhang, A. B. Ustun, R. Yilmaz, Transactional distance perceptions, student engagement, and course satisfaction in flipped learning: a correlational study, Interactive Learning Environments 32 (2024) 447–462. URL: https://doi.org/10.1080/10494820.2022.2091603. doi:10.1080/10494820.2022.2091603.
[32] L. Goel, P. Zhang, M. Templeton, Transactional distance revisited: Bridging face and empirical validity, Computers in Human Behavior 28 (2012) 1122–1129. URL: https://doi.org/10.1016/j.chb.2012.01.020.
[33] K. Bondar, O. Shestopalova, V. Hamaniuk, V. Tursky, Ukraine higher education based on data-driven decision making (DDDM), CTE Workshop Proceedings 10 (2023) 346–365. URL: https://doi.org/10.55056/cte.564. doi:10.55056/cte.564.
[34] J. Fox, S. Weisberg, B. Price, D. Adler, D. Bates, G. Baud-Bovy, B. Bolker, S. Ellison, D. Firth, M. Friendly, G. Gorjanc, S. Graves, R. Heiberger, P. Krivitsky, R. Laboissiere, M. Maechler, G. Monette, D. Murdoch, H. Nilsson, D. Ogle, B. Ripley, T. Short, W. Venables, S. Walker, D. Winsemius, A. Zeileis, R-Core, CRAN: Package car, 2023. URL: https://cran.r-project.org/package=car.
[35] jamovi - open statistical software for the desktop and cloud, 2022. URL: https://www.jamovi.org/.
[36] F. Dübbers, M. Schmidt-Daffy, Self-determined motivation for data-based decision-making: A relevance intervention in teacher training, Cogent Education 8 (2021) 1956033. URL: https://doi.org/10.1080/2331186X.2021.1956033. doi:10.1080/2331186X.2021.1956033.
[37] B. Best, S. C. O. Conceição, Transactional Distance Dialogic Interactions and Student Satisfaction in a Multi-Institutional Blended Learning Environment, European Journal of Open, Distance and E-Learning 20 (2017) 139–153. URL: https://doi.org/10.1515/eurodl-2017-0009.

A. Student course evaluation "Survey on the quality of teaching disciplines"

Instruction: *"Dear Student! The University Administration invites you to take part in a survey on the level and quality of teaching disciplines. Your answers will help to improve the educational process and improve the quality of education at the university. The survey is conducted anonymously. Thank you in advance for participating in the survey!"*

Zhang's scale of transactional distance

ST = Transactional distance between students and teacher

1. The instructor generally answers the student's questions
2. The instructor pays no attention to me
3. I receive prompt feedback from the instructor on my academic performance
4. The instructor was helpful to me
5. The instructors are available to answer my questions
6. The instructor can be turned to when I need help in the course

SC = Transactional distance between student and content

7. The content of this course is of great interest to me
8. I don't know why I have to learn this
9. The examinations in this course have challenged me to do my best work
10. This course emphasized SYNTHESIZING and organizing ideas, information, or experiences into new, more complex interpretations and relationships
11. This course emphasized MAKING JUDGEMENTS about the value of information, arguments, or methods such as examining how others gathered and incorporated data and assessing the soundness of their conclusions
12. This course emphasized APPLYING theories and concepts to practical problems or in new situations

SS = Transactional distance between students and students

13. I learned a lot from observing the interactions among the students
14. The students in this online class challenged me to do my best work
15. I get along well with my classmates
16. I feel valued by the class members in this online class
17. My classmates in this online class value my ideas and opinions very highly
18. My classmates respect me in this online class
19. I am good at working with the other students in this online class
20. I feel a sense of kindred spirit with my fellow classmates
21. The class members can be turned to when I need help in the course
22. There are students I can turn to in this online class
23. The class members are supportive of my ability to make my own decisions

SI = Transactional distance between students and interface

24. It is difficult to pay attention to the instructor in the web environment
25. I have adequate access to the web resources I need
26. The fact that I am online does not inhibit my class participation
27. An efficient system is provided for students and instructors to exchange materials
28. I am comfortable using the computer
29. I hate using the web
30. It was easy for me to use the technology involved with this online class
31. The technology used in this course is difficult to learn and use

SL = Student learning

I have learned a great deal in this online class
LG = Learning goals
I have made tremendous progress towards my goal in the subject area of this course
SS = Student satisfaction
Overall, I am satisfied with this course
Please give 3 recommendations to improve course design

B. Student course evaluation "Survey on the quality of teaching disciplines"

Instruction: *"Dear Student! The University Administration invites you to take part in a survey on the level and quality of teaching disciplines. Your answers will help to improve the educational process and improve the quality of education at the university. The survey is conducted anonymously. Thank you in advance for participating in the survey!"*

20 questions on a 5-point scale, 3 questions with answer options, and 1 open-ended question. For all psychological variables, respondents gave answers on a 5-point Likert scale from "(1) never true" to "(5) almost always true" in Google Forms.

Design of programs:
1.1. I need discipline for my future professional activity.
1.2. The discipline contains useful material.
1.3. The discipline is logically connected with other disciplines.
1.4. The discipline contributes to the formation of skills and abilities.
1.20. In general, it was interesting for me to master this discipline.
Style of teaching (teaching and assessment):
1.6. The professor is fluent in educational material and modern scientific information;
1.7. The professor motivates students to independently search for information in depth;
1.8. The professor clearly formulates the goals and the training plan;
1.9. The educational material is presented in an accessible and interesting way;
1.10. The professor uses the latest interactive teaching methods.
Student-centered learning:
1.12. I have the desire to continue studying with this teacher (other disciplines, coursework, qualification work);
1.13. The teacher is open and friendly with students;
1.14. I always had the opportunity to turn to the teacher for clarification or advice;
1.16. The teacher is tactful and knows how to establish contact with students.
Learning resources and student support, certification:
1.5. The discipline is provided with the necessary textbooks and teaching materials.
1.11. The teacher clearly defines the criteria for assessing students' knowledge.
1.17. The professor always conducts classes on time and according to the schedule.
1.18. Distance learning was well organized by the professor.
1.19. But, in my opinion, it would be more correct to teach the discipline personally.