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USE OF ARTIFICIAL INTELLIGENCE TO IDENTIFY AND CORRECT MISCONCEPTIONS ABOUT RADIATION

Abstract. The expansion of nuclear technologies in various industries, combined with the constant threat of radiation-related incidents, highlights the urgent need for effective radiation education. This study is devoted to an empirical investigation of the effectiveness of artificial intelligence tools (neurological models of artificial intelligence) in detecting and correcting
of artificial intelligence tools (neurological models of artificial intelligence) in detecting and correcting misconceptions about radiation (ionising radiation). We empirically evaluate the effectiveness of artificial intelligence (AI) tools in detecting and correcting these misconceptions among university students, focusing on different cognitive, cognitive-activity, and systemic-axiological levels. A pedagogical experiment was conducted with 168 students of Ukrainian universities using control questionnaires to assess the effectiveness of the selected artificial intelligence tools. The experiment involved presenting students with a series of statements designed to identify misconceptions related to factual knowledge (e.g., radiation units, background levels), conceptual understanding (e.g., the difference between radiation and radioactivity, effects of low-dose exposure), and application/evaluation (e.g., risk assessment, protective measures).
AI tools, including natural language processing models for text analysis and machine learning algorithms for misconceptions classification, were used to provide personalised feedback and targeted corrective information. The results show that AI achieved high accuracy (80-98%) in eliminating misconceptions about factual knowledge. However, the effectiveness decreased for misconceptions requiring deeper conceptual understanding (73-78%) and is much lower for those involving complex knowledge assessment and application (24-36%). These findings indicate that while AI has significant potential to improve basic radiation literacy and provide automated feedback, its current capabilities are limited in addressing more multidimensional and complex misconceptions. Further research is needed to develop more sophisticated AI-based integrations that can effectively target higher-order cognitive skills and promote a more complete understanding of radiation science and its implications. This study contributes to this field by providing empirical evidence on the strengths and weaknesses of AI in radiation education, and offers practical recommendations for the further development and implementation of customised AI-based learning tools.

Keywords: artificial intelligence tools; radiation literacy; radiation safety; radiation awareness; university students

1. INTRODUCTION

The radiation safety of Ukraine in the context of the developed nuclear power infrastructure, as well as the risk of radiation accidents caused by aggression against our country, along with threats of a domestic nature, requires significant attention from the international scientific community. Radiation literacy of the population is one of the key components of comprehensive radiation safety of any state. Radiation literacy is a set of knowledge, understanding and skills related to protection from ionising radiation, which includes the ability to assess the risks associated with radiation and apply appropriate safety measures [1]. An individual who has stable objective cognitive structures regarding radiation safety, effective practical skills in risk prevention and mitigation, and has conscious values regarding safe and responsible use of nuclear energy and radiation technologies will be much more objective in perceiving information on emergencies. That is, people who are free from misconceptions about radiation are less prone to irrational thoughts and actions. "Misconceptions" are defined as stable, well-formed alternative conceptions of students regarding scientific ideas that contradict generally accepted scientific views and are actively employed to explain phenomena [2]. That is, people with a sufficient level of radiation literacy are less prone to panic, have skills of safe behavior in the face of radiation risks, and generally comprehensively assess and objectively perceive information related to radiation.

The problem statement. Today, artificial intelligence (AI) tools are an effective means of learning, understanding complex paradigms, forming and adjusting personal perceptions, which actively facilitate learning. AI tools are neural networks that are saturated by training them through analyzing a large amount of information and generating queries or clarifications from users. In such conditions, artificial intelligence tools can act as both an assistant and a destroyer in the formation of radiation literacy of the population. Therefore, an important issue of pedagogical research is to study the features of AI in identifying and correcting misconceptions about radiation among the public.

Analysis of recent studies and publications. After the Chornobyl and Fukushima accidents, studies on the perception of radiation and related phenomena became quite active. In particular, in the immediate aftermath of the Chornobyl disaster, officials did not disclose the extent of the damage because they (perhaps) did not understand it themselves, using terms such as "x-ray", "zivert", "grey", which were not very clear to a population with a low level of radiation literacy [3]. In the case of Fukushima, the population understood the dangers of radiation but had a rather low level of practical training (low level of communication, lack of understanding of evacuation, special nutrition, etc.), which led to serious consequences for the Japanese population.

Studies on how people perceive radiation risks overwhelmingly show that they hold false and misleading beliefs [4]. A study by P. Slovic shows that a significant proportion of the US population still has misconceptions about radiation risks [5]. Modern tools of the information and digital educational environment have significant potential to optimize the process of studying aspects of radiation safety [6].

According to M. Demirezen, O. Yilmaz, E. Ince, one of the methods of correcting misconceptions related to physical phenomena, including radiation, are AI tools that give the possibility to identify students' misconceptions about the concept of an atom [7]. AI tools allow the construction of individual learning paths and are used by students as a means of informal self-education [8]. It is important that such self-education does not contribute to the formation of false and manipulative ideas, as AI tools analyze a large amount of information regardless of its validity.

The advantage of using AI is the ability to promptly identify misconceptions, which often arise from an incorrect or incomplete understanding of physical phenomena [9]. On the other hand, the use of AI to combat misconceptions requires consultation with experts in a particular subject area or science, as this allows for more relevant models to be created and misinterpretation of data to be avoided [10]. That is, at this stage of development of information and digital technologies, AI tools require certain supervision and control in order to assess the reliability of their work. For example, N. Bragazzi and S. Garbarino argue that modern AI tools identify about 85% of reliable statements and detect manipulations in complex cognitive constructs even less frequently. Researchers have found that AI tools generate generalized information without resorting to in-depth content analysis of data [11]. A study by L. Messeri and M. Crockett shows that AI is able to process large amounts of data efficiently, but its conclusions can be superficial or inaccurate. At the same time, they see a significant threat to the use of AI in the case of its deep integration into scientific processes, due to the possibility of massive formation of false ideas, especially in narrow specializations [12]. At the same time, AI can automate and improve the accuracy of assessing simple cognitive constructs, with the possibility of personalizing learning. On the other hand, they can generate misconceptions in the absence of a critical assessment of the generated information [13].

Meanwhile, it is necessary to develop strategic approaches that allow for the continuous improvement of the practical application of innovations and ensure the alignment of artificial intelligence principles with fundamental educational values [14]. The explanation for this is that AI analyses and structures radiation-related information quite effectively, but sometimes makes significant cognitive gaps, which can lead to critical errors in important areas [15].

It is important to understand that minimising content gaps in the development of didactic materials using AI tools is possible under the following conditions: cognitive compatibility of educational material in accordance with the capabilities of students, combination of different types of representations, adaptation of educational materials in accordance with feedback [16]. AI primarily acts as a means of individualising learning, as it can analyse students' educational trajectories, and as a result, identify their misconceptions and provide personalised explanations [17].

The effectiveness of AI technologies in detecting and correcting misconceptions and correcting radiation information remains a matter of debate. The potential of AI in recognizing radiation data and correcting it remains uncertain. The degree of accuracy of various AI tools in radiation education remains completely unexplored. The possibility of correcting the generation of objective information about ionizing radiation by the user remains unclear.

Existing approaches to using AI tools in education have certain limitations, especially in terms of correcting complex concepts such as radiation. Firstly, most approaches are based on basic text and keyword analysis (Bragazzi & Garbarino, 2020) Secondly, the personalisation of educational content according to student characteristics is not fully implemented (Messeri & Crockett, 2021). Thirdly, the correction of perceptions of radiation using AI tools should prevent the ‘perception gap’ between the scientific understanding of radiation risks and public opinion (Slovic, 2012; Drottz & Sjöberg, 1990). Fourth, the use of AI tools as basic digital tools does not fully meet the requirements for analysing misconceptions about radiation; it is necessary for AI to act as a tool for in-depth analysis and personalisation (Tymoshchuk, 2023).

It is imperative that a dispassionate evaluation of the risks associated with radiation is facilitated for the purpose of safeguarding public health and civil safety. The propagation of fallacious assumptions pertaining to radiation risks has the potential to engender deleterious consequences, including the formation of misguided fears, the adoption of erroneous decisions and the materialization of adverse social and economic repercussions. In the contemporary age, there exists a pressing imperative to investigate the capacity of artificial intelligence to rectify the issue of the public's misguided perception of radiation risks, a problem that is being exacerbated by the proliferation of information in the digital era.

The research goal.

The purpose of the study is to empirically investigate the effectiveness of artificial intelligence tools in detecting and correcting students’ misconceptions about radiation.

2. THE THEORETICAL BACKGROUNDS

AI tools, namely user query generation systems, have been used in general and in education in particular for about three to five years. Today, AI tools for education are widely studied in scientific circles as tools for improving the development of cognitive skills in a particular subject area, diagnosing the level of knowledge, skills, etc. However, there are currently no clear approaches to assessing the objectivity of AI tools in terms of the accuracy of detecting and correcting misconceptions.

A commonly used methodology for testing the effectiveness of AI tools is to compare analytical reports on a particular topic. In other words, an AI agent is asked to analyze a document or a group of documents and formulate a conclusion (summary), which is subsequently compared with reference sources or expert assessments [18]. Another approach is based on assessing the risks of unreliability of the information generated by AI tools by comparing it with the best practices of diagnostic technologies in a particular area [19]. Generative AI tools pose problems of academic integrity, so researchers at the University of Qatar studied ways to detect plagiarism, i.e. information generated by AI. Despite the fact that the generated information was characterized by significant theoretical soundness, very often unclear classifications and illogical formulations of opinions were found [20]. Thus, the validity of an AI response is determined by comparing it with a certain standard in combination with an analysis of the sequence and logic of the information presentation.

To assess the effectiveness of AI in education, the approach of so-called 'moderator variables' is used to prove or disprove the effectiveness of neural networks in education [21]. Another approach is based on a cross-sectional survey using control questionnaires. A questionnaire with a number of questions is filled in using academic literature and generative AI tools and then compared for data objectivity [22]. Z. Hou proposes a slightly different methodology to assess the quality of AI tools. In his study, he suggests analyzing complex semantic constructs, the analysis of which requires taking into account a significant number of related interpretations, statements, experiences or laws. Despite the fact that AI is very effective in directly answering questions or generating unambiguous queries, it faces significant challenges in solving multidimensional cases [23]. An interesting approach is to evaluate the effectiveness of AI tools in education by generating action algorithms or designing new approaches based on basic theoretical information in a particular subject area. In spite of relatively simple requirements for the generation of certain sequences, AI tools make mistakes much more often than humans, partly by offering illogical solutions [24].

Thus, despite the paucity of research on the effectiveness of AI tools in education, there are some proven approaches in current practice. To verify the effectiveness of AI tools in detecting and correcting misconceptions about radiation, we follow the most common approach - comparing generated or analyzed statements with reference samples (control questionnaires). As the analysis of existing approaches has shown, this allows us to analyze basic cognitive constructs (Fig. 1). For a more in-depth analysis of AI tools, we are impressed by the approaches of Z. Hou, who proposes to analyze complex multidimensional phenomena or problems. In our opinion, this allows us to analyze the cause-and-effect relationships in the responses of AI tools and the consistency of his analytical approaches.

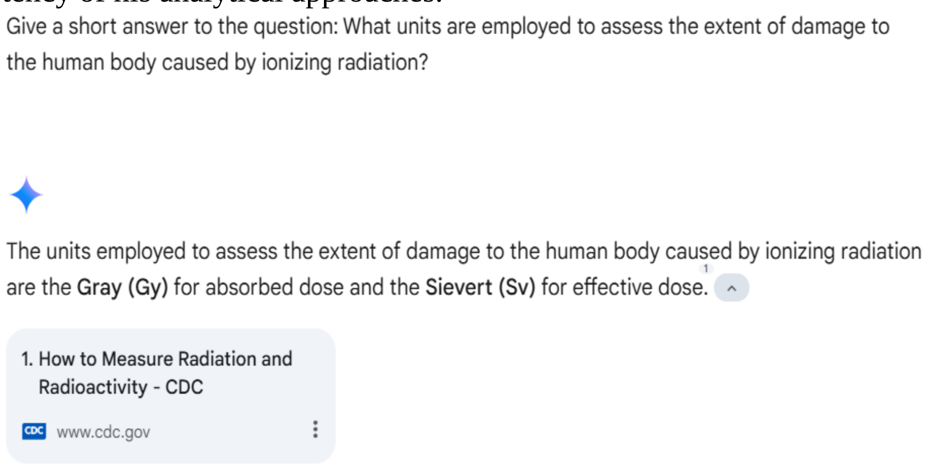
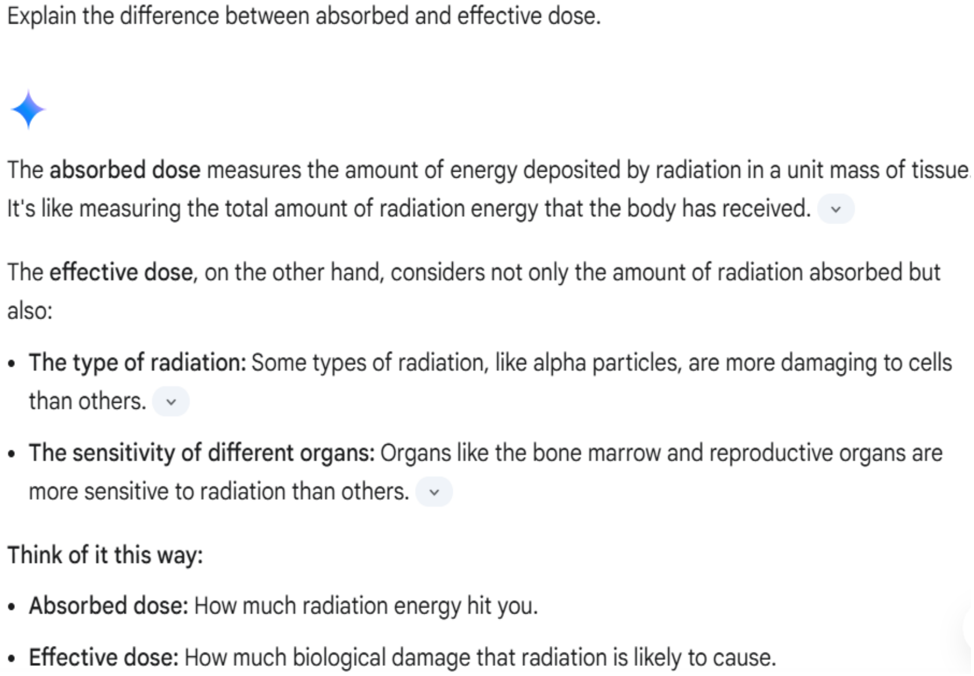


Figure 1. Illustration of basic cognitive patterns in radiation literacy assessment obtained through AI analysis

Our proposal for improving the quality of AI assessment in detecting and correcting misconceptions about radiation is based on a dialogical approach. We believe that since AI generative tools are primarily linguistic neural models, the assessment of their effectiveness should be based on dialogical testing. That is, the answer to a particular question or the interpretation of a particular phenomenon should take place in several iterations through a clarifying dialogue. The effectiveness of generative AI lies in its ability to achieve objective results through clarifying or corrective actions on the part of the user, in our case the student (Fig. 2).


Explain the difference between absorbed and effective dose.

The **absorbed dose** measures the amount of energy deposited by radiation in a unit mass of tissue. It's like measuring the total amount of radiation energy that the body has received.

The **effective dose**, on the other hand, considers not only the amount of radiation absorbed but also:

- **The type of radiation:** Some types of radiation, like alpha particles, are more damaging to cells than others.
- **The sensitivity of different organs:** Organs like the bone marrow and reproductive organs are more sensitive to radiation than others.

Think of it this way:

- **Absorbed dose:** How much radiation energy hit you.
- **Effective dose:** How much biological damage that radiation is likely to cause.

Figure 2. Identifying cognitive features with clarifying questions: an example of AI application in radiation literacy research

Thus, the theoretical basis for diagnosing the effectiveness of artificial intelligence in detecting and correcting misconceptions about radiation is a comparative analysis of AI responses to user requests, the need to analyze complex cases, and the need to correct the results through clarifying questions.

3. RESEARCH METHODS

Direct measures of the experimental work are based on the methods of pedagogical experiment [25] and quantitative comparison [26]. The preparation of the experimental activities consisted in the selection of experimental sites - in our case, regionally remote higher education institutions. The assessment of misconceptions was carried out by analytically determining the level of radiation literacy - relevant answers according to cognitive, activity and personal value criteria [27].

The subject of our study is the process of forming and correcting ideas about radiation (radiation literacy) with the help of artificial intelligence tools in university students. We are looking at the effectiveness of different generative AI models in detecting and correcting misconceptions about radiation at different levels of complexity.

The selection of respondents for the general sample was done by randomly selecting students in academic groups studying in different educational programmes. Participants were given an initial survey to identify the most convenient means of generating AI models that they use for self-education. Open access web resources for trend analysis were used as refinement tools.

The following working hypotheses have been formulated for the purposes of this study:

1. AI is able to effectively detect and correct misconceptions about radiation at the basic level.

2. The effectiveness of AI models decreases when analyzing complex cognitive and activity categories.

The theoretical basis for evaluating the efficacy of AI tools is the methodology outlined in Section 2 of this article. The empirical data are classified according to levels or typical characteristics and presented in summary tables. Statements at different levels are employed as control questionnaires to confirm or refute the stated hypotheses.

The statistical and mathematical processing of the empirical data obtained does not entail a comparative analysis. Instead, it is based on descriptive statistics and the establishment of correlations.

The software employed for data processing and analysis included spreadsheet software (MS Excel, WPS Spreadsheets) and statistical data processing packages (SPSS, Statistica).

4. THE RESULTS AND DISCUSSION

4.1. Choosing AI tools to study the detection and correction of misconceptions about radiation

The study of artificial intelligence (AI) tools for the detection and correction of misconceptions about radiation commenced with a review of existing popular resources in this field. To investigate this issue, a survey was conducted among students at universities in Rivne and Kyiv (Ukraine). The general group of respondents included 168 students majoring in the Humanities, Engineering and Pedagogy (i.e. educational programmes not related to the direct use of ionizing radiation sources in professional activities and/or not providing for its deep theoretical foundations). The results are presented in Table 1.

Table 1

Quantitative and percentage distribution of the use of generative artificial intelligence systems by students

No.	Generating system	Number of respondents	Percentage share (%)
1	ChatGPT 3.5 *(AI1)*	84	50
2	Gemini by Google *(AI2)*	62	37
3	Claude AI *(AI3)*	18	10,5
4	Mistral AI *(AI4)*	4	2,5

Based on the survey results, it can be seen that the lion's share of AI tools for educational purposes is represented by ChatGPT 3.5 (AI1) and Gemini by Google (AI2), with slightly lower figures for Claude AI (AI3), and less than 3% for Mistral AI (AI4). To clarify the selection of the above services, we turned to trends.google.com, which largely confirmed the survey results.

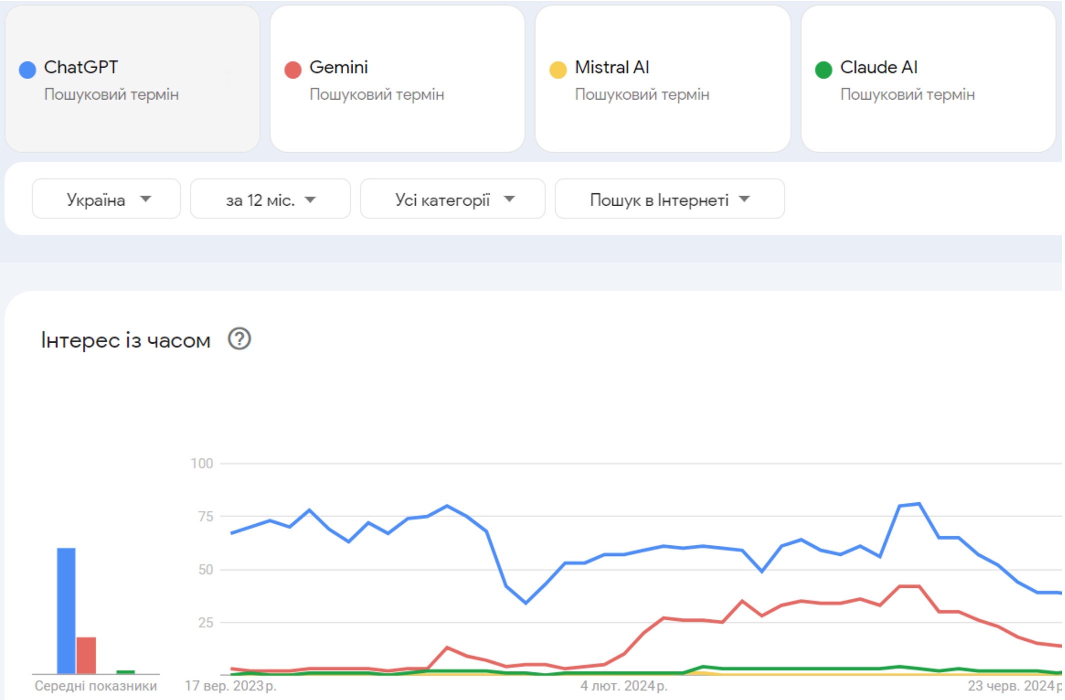


Figure 3. A study of trends in the use of AI tools in Ukraine over the past 12 months (infographic from https://trends.google.com.ua).

In light of the aforementioned considerations, the services that have been identified as the most popular among higher education students have been selected for examination as potential AI tools. To assess the efficacy of these tools in identifying and rectifying misperceptions about radiation, a series of statements have been formulated for use as experimental units. The veracity of these statements will be validated through an empirical investigation, a comparison with the radiation safety guidelines established by the International Atomic Energy Agency (IAEA), and a review of national regulatory documents pertaining to radiation safety.

4.2. Applied AI diagnostic approaches to detect and correct misconceptions about radiation

The experimental statements were differentiated into three levels, namely: basic cognitive, cognitive-activity and systemic-axiological.

The statements of the basic cognitive level include:

– *What units are employed to assess the extent of damage to the human body caused by ionizing radiation?*
– *What level of natural radiation background is considered safe for human exposure?*
– *What measures are taken to disseminate information to the public regarding the potential hazards associated with radiation?*
– *What methods can be employed to safeguard against ionizing radiation?*

The above list of statements is based on publicly available, scientifically based data. The following sources were used to verify the accuracy of AI generation: Radiation Safety Standards of Ukraine [28] and Physics for radiation protection: a handbook, J. Martin [29].

The statements of the cognitive-activity level include the following, which take into account not only theory but also practical skills:

– *Please assess the potential health risks for the local population consuming food grown in the area affected by radiation contamination. Based on your assessment, please suggest appropriate preventive measures.*

- *Please describe the most effective methods for conveying the concepts of 'radiation background' and 'radiation dose' to schoolchildren. Provide practical examples to illustrate these concepts.*
- *Evaluate the effectiveness of diverse materials for radiation protection, with a particular emphasis on alpha, beta, and gamma radiation. Provide examples of their practical applications in various settings.*
- *A comparison of natural and man-made radiation backgrounds should be undertaken, along with an evaluation of the sources of radiation that pose the greatest threat to human health.*

It is important to note that the proposed statements require a comprehensive understanding of the theoretical foundations, as well as the social and ethical implications associated with radiation risks. AI tools should be capable of analyzing and synthesizing data from diverse sources, and subsequently making informed decisions in the form of generated messages. In developing these statements, the IAEA nuclear and radiation safety guidelines and recommendations [30] and those of the State Nuclear Regulatory Inspectorate of Ukraine (SNRIU) [31] were used as a benchmark.

The systemic and axiological statements are intended to evaluate the capacity of AI tools to analyze radiation safety in a comprehensive manner, encompassing its social, ethical and global ramifications. Such assessments transcend mere factual data and necessitate the generation of systemic generalizations, critical insights, value judgements and predictions concerning the implications of radiation risks. Judgements at the systemic and axiological levels are proposed as follows:

- *How did the Chornobyl accident affect the development of global nuclear power? What lessons can be learnt from this tragedy? (the statement requires a retrospective of the events, their consequences and analysis of changes in nuclear power).*
- *How do you assess the balance between the energy needs of society and the risks associated with the use of nuclear energy? (the statement covers the energy needs of modern society, environmental challenges and statistical analysis of the consequences of accidents at nuclear facilities).*
- *Global warming affects radiation safety risks (the statement is based on the need to decarbonize electricity generation, i.e. to stop global warming, it is necessary to stop thermal power plants and develop nuclear power plants instead).*
- *Do you think there is enough scientific evidence to establish a clear linear relationship between low doses of radiation and cancer risk? (the statement requires AI to critically analyze empirical scientific research and synthesize basic academic knowledge).*

The above statements allow us to assess not only the quality of cognitive analysis of AI tools, but also its ability to synthesize and evaluate information in solving complex social problems. As reference sources, it is advisable to use opinions expressed in empirical scientific studies with a high level of recognition and citation. It should be understood that the generated AI response may not have an unambiguous reliable answer, but it should be consistent with the leitmotifs of modern, reliable research.

Therefore, we received 12 statements differentiated into three levels to identify and correct misconceptions about radiation. In other words, the AI received an experimental statement for analysis (1.1 - 1.4, 2.1 - 2.4, 3.1 - 3.4), and then refined it by asking questions separately for each level.

Cognitive level statements were checked using such questions as ‘Are there reliable sources to support the statement?’ and ‘Does the statement correspond to the available knowledge and facts?’.

The test was performed by means of queries for each AI tool under study (for each statement, the AI tool received 50 queries from different users and/or at different times). The test results showed the following values for the accuracy of the analysis of experimental statements by AI tools (Table 2).

Table 2

Comparative table for verifying the objectivity of the analysis of experimental statements of the cognitive level by AI

No. AI tool/assertion	Typical answer/comment	Clarifying question number 1	Clarifying question number 2
AI1 - 1.1	94	100	100
AI 1 - 1.2	96	100	100
AI 1 - 1.3	80	92	92
AI 1 - 1.4	88	94	98
AI 2 - 1.1	98	100	100
AI 2 - 1.2	98	100	100
AI 2 - 1.3	86	94	98
AI 2 - 1.4	90	94	100
AI 3 - 1.1	84	90	92
AI 3 - 1.2	88	90	92
AI 1 - 1.3	50	52	68
AI 3 - 1.4	80	84	90

As can be seen from Table 2, the use of artificial intelligence to analyze the experimental cognitive statements showed a high level of accuracy. Sometimes critical errors occurred because unreliable datasets were used to verify the statements, which was mostly the case with AI3.

Cognitive statements were investigated by evaluating the results of the AI's generation of answers to the following questions "Is there a logical sequence in the statement?", "What is the probability that the statement can be true?". The test results are shown in Table 3.

Table 3

Comparative table for verifying the objectivity of the analysis of experimental statements of the cognitive-activity level by means of AI

No. AI tool/assertion	Typical answer/comment	Clarifying question number 1	Clarifying question number 2
AI1 - 1.1	78	80	80
AI 1 - 1.2	76	78	80
AI 1 - 1.3	72	62	70
AI 1 - 1.4	66	68	70
AI 2 - 1.1	80	80	86
AI 2 - 1.2	74	78	84
AI 2 - 1.3	80	88	88
AI 2 - 1.4	64	68	78
AI 3 - 1.1	58	58	70
AI 3 - 1.2	56	62	62
AI 1 - 1.3	64	68	70
AI 3 - 1.4	60	64	78

The results presented in Table 3 are characterized by significantly lower indicators of the objectivity of AI tools. The use of deep learning models, in particular recurrent neural networks, allowed a medium level of accuracy in identifying subtle nuances of radiation safety. The AI tools studied mostly detect typical errors and synthesize information based on theoretical data, statistics and precedents.

The clarification questions at the systemic and axiological level were designed to assess the general theoretical level of the answer, value beliefs and the ability to analyze and synthesize scientific literature. These questions included 'Are there contradictory data or alternative views?', 'Is it possible to conduct an experiment or test the statement?', 'Are there potential biases in the statement? The test produced the following results - Table 4.

Table 4

Comparative table for verifying the objectivity of the analysis of experimental statements of the systemic-axiological level by means of AI

No. AI tool/assertion	Typical answer/comment	Clarifying question number 1	Clarifying question number 2	Clarifying question number 3
AI1 - 1.1	36	36	34	38
AI 1 - 1.2	22	22	22	22
AI 1 - 1.3	24	24	26	30
AI 1 - 1.4	28	28	24	22
AI 2 - 1.1	38	38	22	38
AI 2 - 1.2	24	24	24	23
AI 2 - 1.3	24	26	32	30
AI 2 - 1.4	20	22	22	28
AI 3 - 1.1	26	26	28	32
AI 3 - 1.2	24	24	26	26
AI 1 - 1.3	22	22	18	22
AI 3 - 1.4	20	20	28	30

The data obtained indicate significantly inferior results in the evaluation and correction of experimental statements at the systemic-cognitive level. Initially, it was observed that neural networks, in the process of analyzing intricate concepts pertaining to radiation safety, subsequent to the elucidation of queries, exhibited a reduction in the accuracy of their responses. This phenomenon is attributed to the vast array of scientific data, publications, empirical studies and regulatory documents, which render a comprehensive analysis of experimental statements a challenging endeavor.

4.3. Quantitative summary of AI diagnostic results for detecting and correcting misconceptions about radiation

The results of the effectiveness of generative AI systems were as anticipated, demonstrating superior performance in assessing cognitive statements. This finding aligns with previous studies [15-17]. It is important to note that experimental statements of a cognitive and moral nature are significantly more challenging to analyze using AI tools. In particular, statements related to systemic and axiological issues tend to be the most difficult to process. To assess the effectiveness of artificial intelligence in detecting and correcting misconceptions about radiation among students, we calculated the mean values for each level using Formula 1 for each individual generative system.

$$\underline{x} = \frac{1}{n}\sum \quad x$$

where n is the number of experimental statements, x is the AI performance indicators for each experimental statement, $\underline{x}$ is the average value for each AI tool under study.

The calculation was performed separately for the results of a typical AI response and for the results of corrective/clarifying questions. The results of the averaged indicators (by cognitive, cognitive-activity, and systemic-axiological levels) are presented in Tables 5-7.

Table 5

Performance indicators of AI tools for detecting and correcting misconceptions about radiation at the cognitive level

The symbol represents the AI tool.	Indicators at the basic response stage	Performance after the corrective action stage
AI1	89,5	97,5
AI 2	93	99,5
AI 3	75,5	85,5
AI 4	73,8	79,4

Table 6

Performance indicators of AI tools for detecting and correcting misconceptions about radiation at the cognitive and activity level

The symbol represents the AI tool.	Indicators at the basic response stage	Performance after the corrective action stage
AI1	72	78,7
AI 2	68,7	75,3
AI 3	72	76
AI 4	63,3	73,4

Table 7

Performance indicators of AI tools for detecting and correcting misconceptions about radiation at the systemic and axiological level

The symbol represents the AI tool.	Indicators at the basic response stage	Performance after the corrective action stage
AI1	33,3	36
AI 2	23,3	23,7
AI 3	23,3	27,3
AI 4	22,7	26,7

Figure 4 presents the experimental results in the form of a combined surface diagram.

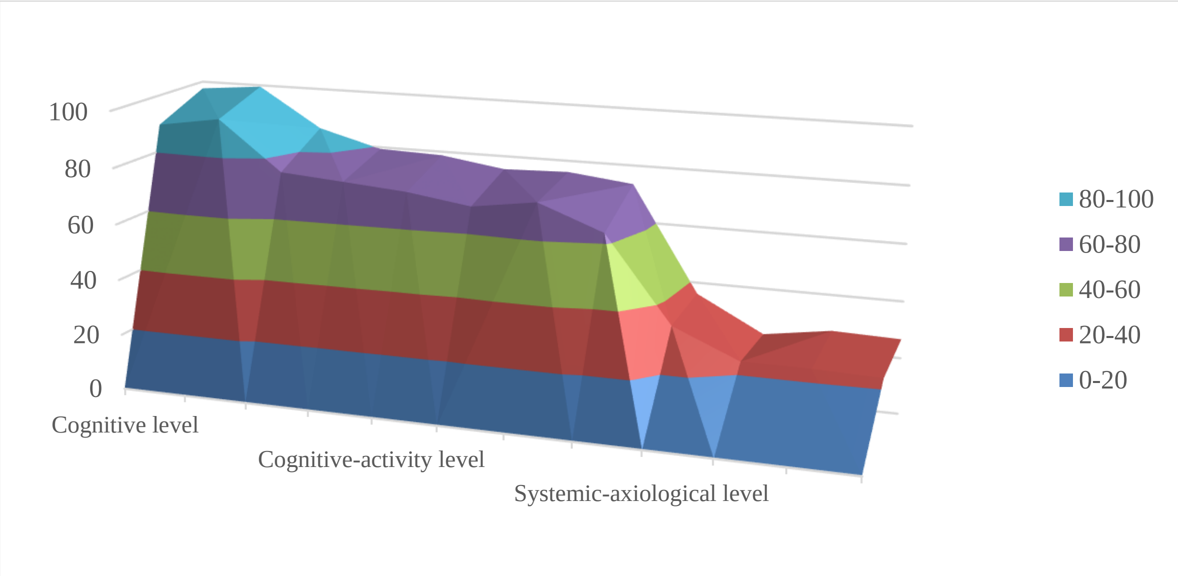


Figure. 4. Effectiveness of AI tools in detecting and correcting misconceptions about radiation by cognitive, cognitive-activity and systemic-axiological levels

The empirical data obtained, along with their subsequent systematization and generalization, permit the identification of a number of trends. Initially, AI tools demonstrate considerable potential for streamlining the process of cultivating radiation literacy among higher education students. Secondly, there is a notable increase in efficiency when solving issues or obtaining information, particularly within the context of general theory. Thirdly, the efficacy of AI tools in addressing specific tasks related to activity aspects is somewhat limited. Fourthly, it has yet to be demonstrated that AI tools are effective in solving value-based problems that require the resolution of complex tasks. Fifthly, all of the AI tools under investigation exhibited comparable characteristics with regard to the identification of misconceptions pertaining to radiation. Sixthly, the following experimental hypotheses were substantiated. Artificial intelligence (AI) is capable of effectively detecting and correcting misconceptions about radiation at a fundamental level. However, the efficacy of AI models declines when analyzing complex cognitive and activity categories. In general, the hypothesis that the effectiveness of different AI models varies in the context of the study was not confirmed, as all the AIs that were studied demonstrated comparable trends in terms of their capacity to detect and correct misconceptions about radiation during the course of the experimental activities.

This study indicates the substantial efficacy of AI algorithms in detecting and rectifying cognitive dissonance pertaining to fundamental concepts in the domain of radiation literacy. Nevertheless, the constrained size of the training sample ($n = 168$), predominantly comprising students, curtails the generalizability of the findings to the broader public. Furthermore, the examination of intricate, multidimensional assessments incorporating value orientations and social contexts unveiled certain constraints within the models. These may pertain to the limited representativeness of the training data.

5. CONCLUSIONS AND PROSPECTS FOR FURTHER RESEARCH

The study examines the current efficacy of artificial intelligence in identifying and rectifying misperceptions about radiation among students. In particular, the study confirms that AI is highly effective in detecting and correcting basic knowledge about radiation safety. Concurrently, AI’s efficacy remains relatively limited, particularly with regard to the capacity to analyze intricate cognitive processes and systemic-axiological elements pertaining to radiation literacy.

Concurrently, the efficacy of AI tools in identifying and rectifying misperceptions about radiation, as delineated by the cognitive activity level, falls within the range of 73.4% to 78.7%. This evidence suggests that AI tools are effective in detecting and correcting basic radiation information, but less so in analyzing more complex concepts that require a deep understanding of the context and combined application of knowledge and skills. In other words, despite their significant efficiency, AI tools do not fully assess the context and consequences of decision-making.

The results of testing the effectiveness of AI tools in detecting and correcting misconceptions about radiation based on statements of a systemic and axiological nature indicate a range of 23.7-36%. This again indicates that while AI tools are highly effective at detecting and correcting simple errors, their capabilities are limited when analyzing complex, context-dependent tasks that require a comprehensive understanding of the subject matter.

These results indicate that AI tools do not yet have properties similar to human intuition and critical analysis. This is because they analyze expert opinions and statements rather superficially. The results show that AI cannot completely replace human intelligence, as it is not capable of empathy and synthesis of optimal solutions.

In light of the findings of the study, it can be stated that, at this stage of technological advancement in the domain of identifying and rectifying misconceptions about radiation, AI tools are an efficacious instrument for attaining theoretical knowledge, fundamental practical abilities, analyzing voluminous data sets, and discerning potential issues pertaining to radiation. Concurrently, it is not yet feasible for AI to wholly supplant human intelligence, as it may be susceptible to axiomatic bias intrinsic to generally accepted educational and theoretical data. Moreover, AI tools demonstrate a limited capacity to address issues pertaining to ethical considerations and moral principles. In other words, despite the notable efficacy of AI tools, the pivotal role in decision-making concerning radiation risks remains with an individual who possesses the capacity to comprehensively evaluate factors of diverse natures.

The analysis of the results showed that there are limitations in the use of AI to develop complex cognitive and value aspects of radiation literacy. This highlights the importance of integrating AI tools into a broader didactic paradigm. Further research should focus on developing the potential of AI to support analytical thinking, critical evaluation, and consideration of the moral and ethical dimensions of radiation safety in the educational process.

The study will contribute to a comprehensive understanding of the specific characteristics of the utilization of AI tools in the educational process of developing radiation literacy among diverse segments of the population. The use of AI in optimizing the formation of radiation literacy remains in its infancy and only partially meets the didactic goals of radiation education. The subsequent direction of the research will be to substantiate methodological approaches to the use of AI in different stages of studying radiation education. This will be followed by the creation of individual AI consultants, whose role will be to contribute to the qualitative individualization of training and improve the remote interaction of the subjects of the educational process. In addition, future research will focus on the development and testing of models for integrating artificial intelligence into the process of forming radiation literacy of science teachers in a digital educational environment.

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ВИКОРИСТАННЯ ШТУЧНОГО ІНТЕЛЕКТУ ДЛЯ ВИЯВЛЕННЯ ТА КОРЕКЦІЇ ПОМИЛКОВИХ УЯВЛЕНЬ ПРО РАДІАЦІЮ

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Анотація. Представлене дослідження висвітлює емпіричне дослідження ефективності засобів штучного інтелекту (нейронних мовних моделей штучного інтелекту) у виявлені та корекції помилкових уявлень про радіацію (іонізуюче випромінювання). Радіаційна грамотність здобувачів освіти вищих навчальних закладів дуже важлива у контексті негативного «радіаційного» досвіду України, потужної інфраструктури ядерних енергогенеруючих станцій, загрози використання ядерного озброєння з боку країни-агресора. Проведений аналіз літературних джерел засвідчує, що проблеми формування радіаційної грамотності та використання засобів штучного інтелекту користуються значною увагою серед представників міжнародного наукового співтовариства.
Для дослідження було проведено опитування серед 168 здобувачів освіти українських університетів щодо використання ними засобів штучного інтелекту для самоосвітніх цілей. У результаті було обрано ряд засобів ШІ, котрі використовувались для оцінки їхньої ефективності у виявленні та корекції помилкових уявлень про радіацію.
Аналіз ефективності засобів ШІ виконувався шляхом аналітичної перевірки експериментальних тверджень за базовим когнітивним, когнітивно-діяльнісним та системно-аксіологічним рівнями.
Кількісні результати систематизації та узагальнення отриманих емпіричних даних дозволили засвідчити/спростувати ефективність засобів ШІ для виявлення та корекції помилкових уявлень про радіацію. Зокрема ШІ демонструють високу ефективність аналізу та корекції помилкових уявлень експериментальних тверджень когнітивного характеру (80-98%). Значно меншу ефективність ШІ спостережено при аналізі експериментальних тверджень когнітивно-діяльнісного (73-78%) та системно-аналітичного (24-36%) характеру.
Нині засоби ШІ є ефективним інструментом для отримання теоретичних знань, базових практичних навичок, аналізування великих обсягів даних, виявлення потенційних проблем пов’язаних з радіацією, однак поки не здатні повністю замінити людський інтелект, оскільки можуть бути схильними до аксіоматичної упередженості, яка закладена в загальноприйнятих навчально-теоретичних даних.

Ключові слова: засоби штучного інтелекту; радіаційна грамотність; радіаційна безпека; радіаційна обізнаність; здобувачі вищої освіти