







# An Ai-Supported Biostatistics E-Course Based on the Successive Approximation Model: Evaluation in Medical Education

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**Purpose:** The Successive Approximation Model (SAM) provides an iterative framework for developing digital learning resources, while artificial intelligence (AI) may enhance personalization and cognitive support. However, empirical evidence on the combined implementation of SAM and AI in medical education remains limited. This study aimed to evaluate the acceptability and perceived educational effectiveness of a biostatistics e-course developed using the SAM model and supplemented with an AI-supported component.

**Materials and Methods:** A mixed-perspective descriptive study was conducted following the development and implementation of a modular biostatistics e-course based on the SAM at Karaganda Medical University. The course was developed through iterative prototyping, stakeholder feedback, and progressive refinement consistent with the SAM framework. Participants included 215 undergraduate medical students, 73 students involved in the needs assessment phase, and course developers. Questionnaires and descriptive analysis were used to gain staff perceptions of the SAM model of course development, student use of AI, and student evaluation of the quality of the course.

**Results:** Across key evaluation domains, 64.7% of students reported positive perceptions of the course, including improved understanding of biostatistics and greater convenience compared with traditional learning formats, while negative responses remained below 12%. The AI component was used by 56.9% of students, primarily for explanation of theoretical material and analysis of statistical concepts. Among AI users, 82.1% reported improved understanding, and 53.7% reported increased motivation. However, 57.7% encountered errors, and trust in AI remained moderate. Developers positively evaluated the SAM model, particularly its iterative design and flexibility, while highlighting the need for methodological training and institutional support.

**Conclusion:** The integration of SAM-based instructional design and AI-supported learning represents a feasible and acceptable approach to developing adaptive digital courses in medical education. Effective implementation depends on the balanced integration of instructional design, AI-mediated support, and institutional readiness.

**Keywords:** successive approximation model, artificial intelligence in education, medical education, biostatistics education, adaptive learning

## Introduction

In recent decades, higher education has undergone a substantial transformation, shifting from a teacher-centered paradigm toward a learner-centered approach that emphasizes flexibility, individualization, and active engagement. Within this context, modular learning has become a widely adopted organizational model, particularly in medical education.<sup>1</sup> Modular learning structures the curriculum into discrete units that focus on specific competencies and learning outcomes, allowing students to progress stepwise and at an individualized pace.<sup>2</sup>

However, while modular learning provides a structural framework for organizing content, its effectiveness depends largely on how learning materials are delivered and how students interact with them. Traditional implementations of

modular education often rely on static content, limited interactivity, and predefined learning pathways, which may not fully address the diverse cognitive needs of students, particularly in complex disciplines such as biostatistics.

The development of internet connectivity and digital tools has allowed educational institutions to expand access to education beyond the traditional classroom. Some technologies allow students and faculty to interact in real time using tools such as video conferencing. Others enable students to study materials at their own pace using pre-recorded lectures, discussion forums, and other digital resources.<sup>3,4</sup> The demand for reliable solutions for delivering quality education remotely has increased dramatically, leading to the widespread adoption of learning management systems (LMS) and other educational technologies. Open online courses have also gained popularity during this period, offering free or low-cost access to a wide range of subjects.<sup>5</sup> Blended learning, which combines online and offline instruction, has become a flexible model that allows students to benefit from both digital tools and in-person interactions.<sup>6</sup> The introduction of a growing number of educational smartphone apps has also expanded access to materials and overall course participation.<sup>7</sup>

All of these advances in recent years have created a significant challenge in determining which learning models are most effective for delivering online courses, particularly in terms of student engagement, motivation, and overall performance. Models such as ADDIE (Analysis, Design, Development, Implementation, Evaluation), SAM (Successive Approximation Mode), and the Dick & Carey model have become widely used in various educational contexts.<sup>5</sup> A review<sup>8</sup> shows that the effectiveness of learning models depends largely on the specific learning environment in which they are applied. The ADDIE model is linear and structured, ideal for self-paced learning. It provides clear goals, sequencing, and assessment, but is less flexible for rapid change. It is well suited for higher education and corporate training, where stability is needed.<sup>9</sup>

SAM technology is a way to create online courses quickly, flexibly, and with continuous improvement through early drafts and feedback. This is why it is recommended for situations where it is necessary to respond to changes “here and now”.<sup>10</sup>

The Dick & Carey model is a comprehensive model with an emphasis on goals, learner analysis, and formative assessment. It works best in blended environments, balancing online and offline elements. It provides accurate results, but requires more time and resources. While the model’s complexity can pose a challenge in fast-paced learning environments, its thoroughness makes it ideal for situations requiring a deep and well-organized learning process.<sup>11</sup>

In recent years, artificial intelligence has complemented modern teaching methods, particularly adaptive learning systems that deliver content tailored to each student’s expectations, thereby improving the overall educational process.<sup>12,13</sup> Five main areas of application of artificial intelligence (AI) in education are identified: assessment/certification, prediction, AI assistants, intelligent tutoring systems (ITS), and student learning management<sup>14</sup> - each demonstrating potential for innovation in the education sector.

In the existing literature, one can find various studies presenting the benefits and uses of AI in different fields of education such as social sciences,<sup>15</sup> engineering,<sup>16</sup> natural sciences,<sup>17</sup> medicine,<sup>18</sup> biological sciences,<sup>19</sup> language acquisition<sup>20</sup> and others.<sup>21,22</sup>

Electronic and blended learning formats are being widely adopted in the teaching of biostatistics and evidence-based medicine, reflecting the overall digital transformation of medical education. Many of the e-courses described are modular in design and include theoretical materials, self-assessment tools, and practical assignments aimed at developing students’ scientific thinking and methodological competence.<sup>23</sup> These approaches improve knowledge retention and student satisfaction.

Similarly, e-learning resources in the field of evidence-based medicine have shown the ability to improve understanding of research methodology and critical evaluation skills for scientific data. They are an effective alternative or supplement to traditional lecture-based learning formats.<sup>24</sup> Typically, such courses rely on asynchronous learning modules, multimedia materials, and formative assessment to reinforce knowledge. However, despite their proven pedagogical effectiveness, these implementations predominantly reflect a content-oriented model of digital learning. In this model, learner support remains static and predetermined.

New trends in biostatistics teaching include active educational strategies such as algorithmic decision-making schemes, analysis of scientific publications, and simulation tasks. These innovations are aimed at increasing engagement and deepening cognitive information processing.<sup>25</sup>

Addressing this gap is essential for understanding how various elements of digital pedagogy can be effectively integrated to improve learning outcomes. In particular, it remains unclear how students perceive such integrated approaches, how AI

tools are actually used in teaching processes, and how developers evaluate the practical implementation of iterative instructional design models in real-world educational settings.

Therefore, this study aims to evaluate an online biostatistics course developed using SAM and supplemented with an AI-based support component, taking into account the perspectives of students, AI users, and course developers.

The study addresses the following research questions:

- To what extent is the e-course in biostatistics, developed using the SAM model, acceptable from the perspective of students and developers?
- How do students perceive the educational utility and limitations of the AI-supported learning component within the course?
- What are the perceived strengths and challenges of integrating SAM-based instructional design with AI tools in medical education?

By addressing these questions, this study contributes to the growing body of research in the field of adaptive digital learning and provides empirical data on the combined application of iterative instructional design and AI-supported educational technologies in the context of medical education.

## Materials and Methods

### Study Design and Setting

A descriptive study with a mixed-perspective approach was conducted to evaluate the implementation of an electronic biostatistics course developed using the Successive Approximation Model (SAM) and supplemented with an artificial intelligence (AI) support component.

The study incorporated both quantitative and qualitative elements, including structured questionnaires, focus group discussions, and analysis of learning analytics.

The study was conducted at Karaganda Medical University (Karaganda, Kazakhstan) within the undergraduate medical education program during the 2024–2025 academic year. The study included three main phases: needs assessment and course development, pilot implementation, and post-course evaluation.

### Participants and Sampling

Participants were recruited using a convenience sampling approach from students enrolled in the biostatistics course and from faculty members involved in course development.

The study included multiple participant groups:

- Needs assessment phase: 73 undergraduate medical students who had previously completed a biostatistics course
- Pilot implementation and evaluation: 215 students enrolled in the course
- Focus groups: groups of 8 students per iteration during the prototyping phase
- Course developers: teaching staff involved in SAM-based instructional design

Inclusion criteria for students were enrollment in the medical program and participation in the biostatistics course. Participation in all study components was voluntary.

### Structure and Content of the e-Course

The course is implemented on the Moodle platform in Topics format with restricted access (Restrict access by mastery threshold). The course consists of 5 independent modules:

- Statistical characteristics of random variables. Graphical representation of data
- Testing statistical hypotheses. Parametric and nonparametric criteria

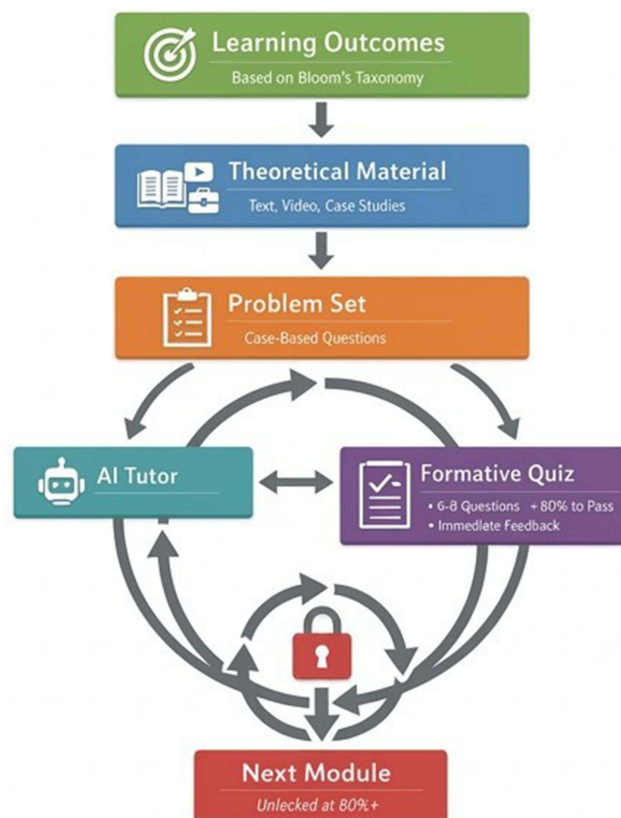
- Analysis of qualitative characteristics
- Correlation and regression analysis
- Survival analysis

The structure of each module is illustrated in Figure 1. This structure reflects the outcomes of the course development process based on the Successive Approximation Model (SAM), which emphasizes iterative design, feedback, and progressive refinement. Each module begins with the formulation of learning outcomes that clearly correspond to Bloom's taxonomy. The theoretical material includes lecture texts, 5–10 minutes videos, tasks to test knowledge of theoretical foundations, and clinical cases. To develop skills in applying biostatistics in real medical practice, each module includes a Problem Set - case-based tasks for individual/group work. The AI consultant option can be used to perform calculations, find critical values or reference (reference) values, construct diagrams, search for errors in interpretation, etc. Upon completion of the module, each student takes a Formative Quiz (10 questions, multiple attempts, immediate feedback, mastery threshold  $\geq 80\%$ ).

Access to the next module is only granted after achieving  $\geq 80\%$  on the previous quiz.

## Course Development Using the SAM Model

Development was carried out using the Successive Approximation Model, which involves short iterative cycles instead of a linear process. The main phases of SAM are: Preparation, Iterative Design (Design  $\rightarrow$  Prototype  $\rightarrow$  Review  $\rightarrow$  Revise), Iterative Development. The final cycle looks like this: Savvy Start (rough mockup)  $\rightarrow$  Alpha prototype (everything is there, but raw)  $\rightarrow$  Refinement  $\rightarrow$  Beta prototype (everything works and has been proofread)  $\rightarrow$  Refinement  $\rightarrow$  Gold master (final version).



**Figure 1** Structure of the biostatistics e-course module.

The model is specifically designed for e-learning projects, where you need to quickly show working results and make adjustments based on real testing. The advantages of this model are that early prototypes appear as early as the design phase, not just at the end, and each iteration improves the product thanks to continuous evaluation and feedback built into each cycle.

## Data Collection

Data were collected using multiple sources:

1. Structured questionnaires administered to:
  - students (course evaluation)
  - students using AI tools
  - course developers
2. Focus group discussions conducted during the prototyping phase
3. Learning analytics obtained from the Moodle platform (eg, completion rates, quiz attempts, time spent)

All questionnaires and focus group protocols are provided in the [Supplementary Materials](#).

## Data Analysis

Quantitative data were analyzed using descriptive statistics, including frequencies, percentages, and confidence intervals. Given the exploratory and descriptive nature of the study and the lack of a control group, inferential statistical analysis was not performed. The primary goal was to assess perception and acceptability, not to test predetermined hypotheses.

Qualitative data from focus group discussions were analyzed using a structured thematic analysis approach. Transcripts and notes were reviewed independently by the researchers, and initial codes were generated based on recurring concepts. These codes were then grouped into broader themes reflecting key aspects of the learning experience, AI usage, and course design.

To enhance reliability, coding and theme development were discussed among the research team until consensus was reached. Representative examples were used to support the identified themes.

## Ethical Considerations

The study was conducted in accordance with the principles of the Declaration of Helsinki and was approved by the Local Bioethics Committee of Karaganda Medical University (Protocol No. 5, dated 26 February 2026).

Prior to participation in focus group discussions, all participants were provided with written information about the study, including its purpose, procedures, voluntary nature of participation, confidentiality, and the right to withdraw at any time without consequences. Written informed consent was then obtained from each participant before the start of the focus group sessions.

No personal identifiers were collected, and all responses were anonymized prior to analysis.

## Results

### E-Course Developing Process

#### Preparation

During the Preparation stage, an analysis of the target audience's needs and the learning context was carried out. To this end, 73 medical university students who had previously studied biostatistics completed an anonymous questionnaire ([Supplementary Table 1](#)). The survey included: self-assessment of knowledge level, identification of the most difficult topics, preferences for the format of presentation (video, interactive, clinical cases), and estimation of realistic time per module.

The survey results were used to determine the sequence of modules, the level of difficulty of the theoretical material, and the priority of practical tasks.

The first question concerned students' self-assessment of their knowledge of the subject. 9.8% of respondents rated their level of knowledge as low or very low. The option "moderate" was selected by 30.8%, while 59.6% of students considered themselves to have a good or very good knowledge of the subject. According to the respondents, the most difficult topics are survival analysis (43.7%), p-value and hypothesis testing (30.8%), correlation (30.8%), regression analysis (28%), and interpretation of article results (28%). Descriptive statistics proved to be the least difficult (15.4%). In general, difficulties are concentrated in the areas of probabilistic logic, multidimensional methods, and interpretation of results.

Among the obstacles to studying the discipline, students indicated a large number of formulas (17.3%), a lack of understanding of practical significance (14.5%), and complex terminology (12.6%). Other factors (complexity of calculations, lack of practice, fear of mistakes) were moderately prevalent. Thus, the barriers are primarily cognitive and conceptual in nature, rather than technical. The most popular learning formats were short video lectures with formula analysis (43%), problems with step-by-step analysis (42.5%), and examples using medical data (25.2%). Interest in error analysis and practical assignments was also noted. This indicates a strong demand for explanatory and practice-oriented presentation of the material.

Regarding the time required to complete the module, the following responses were chosen: 45–60 minutes (33.2%), 1–1.5 hours (28%), and up to 30 minutes (25.2%).

39.3% of students supported the idea of moving on to the next section only after successful testing, 27.1% did not support it, and 33.6% were undecided. This indicates a moderate readiness for mastery-based learning.

## Prototyping

The prototyping phase involved creating successive draft versions of each module, followed by testing on students and reflective refinement. For each of the five modules, three to six iterations were carried out according to the following scheme:

Creation of an alpha prototype (basic Topic in Moodle with minimal content).

- Discussion of the module in a focus group of 8 students. The module was discussed according to an approved scenario ([Supplementary Materials, Materials and Methods](#)). During the discussion, a checklist of student responses was completed ([Supplementary Figure 1](#)). All checklists were compiled into a single summary table. The overall frequencies were calculated by topic (eg, "AI assistant: errors mentioned in 12/20 cases"). The top 5 problems and top 5 strengths were identified. Direct quotes (anonymized) were added for illustration. Conclusions were linked to the SAM model: for example, "based on focus group → iteration: improve AI prompts to reduce errors".
- Reflective Revision: making changes based on feedback (simplifying the text, adding visualizations, adjusting the complexity of questions). At this stage, teachers conducted a collective analysis of the feedback and made decisions about improvements. The course authors answer the following key questions: Are students achieving the stated learning outcomes? Which elements cause the most difficulty? Does the complexity of the material correspond to the level of the target audience? Which changes will provide the maximum increase in quality at minimum cost? Is the prototype ready for the next cycle, or does it require significant reworking? The scenario for conducting a focus group of developers is provided in [Supplementary Materials](#), Section 3. After discussing all components, each participant fills out a checklist and gives their assessment for each item on a 5-point scale ([Supplementary Figure 2](#) and [Supplementary Table 2](#)). The average score is then calculated. The criterion for module readiness was a set of conditions:
  - total score  $\geq 80\%$  of maximum possible value
  - no criterion scored below 3
  - no critical technical failures were detected

The process was repeated until an acceptable level of usability and compliance with the stated learning outcomes was achieved. The final versions of the modules were tested on a group of 40–50 students before the course was fully launched.

## Level of Mastery of the Material

All 215 students completed all five modules, as progression required achieving a minimum score of 80%. The mean scores differed across modules, with higher performance observed in earlier modules (Module 1: 97.5%) and lower performance in later modules (Module 5: 88.6%), which may reflect increasing complexity of the material. The average number of attempts per quiz was 2.4 (SD = 0.9). The average time to complete one module was 1.7 hours. The average final exam score in biostatistics was 79.6% (SD = 3.7%).

## Students' Perception of the Educational Effectiveness of the Course

215 students were surveyed regarding the effectiveness of the developed course ([Supplementary Table 3](#)).

Most students evaluated the developed course positively and noted that it contributed to a better understanding of biostatistics ([Figure 2](#)). 64.7% of respondents agreed or strongly agreed with this statement. The share of negative assessments was 8.4%, while 27% of students chose a neutral response option.

The training format, in which students must achieve an 80% threshold to move on to the next module, was positively evaluated by 60.4% of students. A negative perception of this element was demonstrated by 12.1% of participants, while 27.4% found it difficult to evaluate.

Those who rated the e-course as more convenient than traditional lectures and textbooks accounted for 60% of respondents. In this context, 12% of respondents gave a negative assessment, and 27.9% gave a neutral assessment.

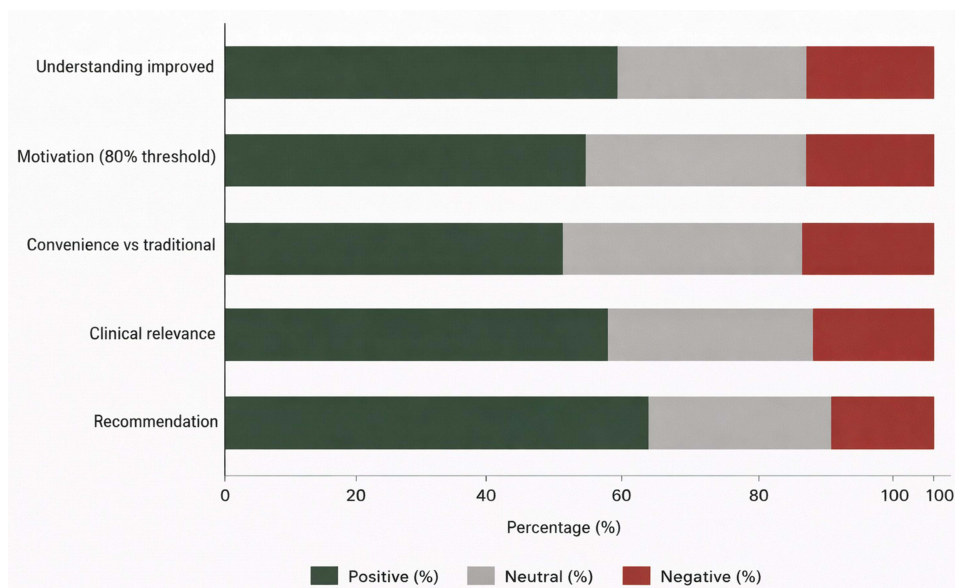
60% of students gave a positive assessment of the applicability of the module materials for clinical practice and exam preparation, while 32.1% chose a neutral response option. The share of negative assessments did not exceed 8%.

More than half of the students (61.9%) expressed their willingness to recommend this course to other students, 28.8% of respondents did not have an opinion on this, and 9.3% gave a negative answer.

Overall, the share of positive responses ranged from 60% to 65% across all indicators, with a consistently low share of negative responses (8% to 12%).

## Students' Assessment of the AI Component in the Structure of an e-Course

A separate survey was conducted among students on the effectiveness of using AI consultants when studying biostatistics ([Supplementary Table 4](#)).



**Figure 2** Distribution of student responses to key evaluation items of the biostatistics e-course.

It should be noted that most students (56.9%) reported periodically using AI, while 43.1% did not use it at all in the learning process (Table 1). Only 13% of respondents reported regular use of AI, indicating that the integration of AI into learning activities was predominantly episodic.

The most common function of AI was to help explain theoretical material (52%) and analyze formulas and statistical indicators (47.2%). AI was less commonly used to solve problems (33.3%), prepare for tests (27.6%), and interpret statistical results (24.4%). Thus, AI was used primarily as a tool for cognitive support and clarification of concepts. When assessing the educational benefits, 83.7% of respondents gave ratings from 3 to 5, similarly. Similarly, 82.1% of students reported an improvement in their understanding of statistical methods. According to the students, the use of AI increases motivation to learn (53.7%), but there are those who found it difficult to evaluate (28.5%). At the same time, it should be noted that only 2.4% of participants completely trust the explanations received from the AI assistant, ie, trust was moderate - 83.7% expressed partial or general trust. More than half of the students (57.7%) encountered errors or incorrect explanations from the AI.

Most respondents agreed that AI contributed to the development of independence in solving problems (79.7% completely or mostly agree). 76.4% of students used AI to analyze the material, rather than simply copying answers. As noted by 74% of respondents, this led to a decrease in the need for teacher consultations. Technical difficulties arose rarely: 88.7% of students indicated that there were none. AI also performed a navigational function, helping students to orient themselves in the course structure completely or partially.

As a result, 79.7% of students reported an increase in academic performance (30.9% - significant) when the course was built using AI, while 17.9% did not note any changes. The vast majority of students (83.8%) found the use of AI components in electronic textbooks acceptable, but 44.7% believe that the use of AI should be limited when completing test and exam assignments.

## Teachers' Opinions on the Process of Creating an e-Course Using SAM Technology with AI

A survey was conducted among the teachers who participated in the development of the e-course to assess their awareness and understanding of the SAM model (Supplementary Table 5). Respondents answered a series of questions, which are presented in Supplementary Materials. Only 22.2% of participants expressed a complete understanding of SAM, while 44.4% took a neutral position. A similar pattern of responses was observed with regard to understanding the principles of interactive design, where neutral (44.4%) and moderately positive (44.4%) assessments prevailed. The responses show that teachers do not have sufficient information about the application of this model. In other words, when preparing to develop the course, the developers were only partially familiar with the technology. However, as a result, most respondents agreed with the positive impact of the model on the quality of electronic textbooks (77.7% rated it 4–5). The iterative approach was particularly highly rated, with 88.9% of developers noting that it allows errors to be corrected in a timely manner. 55.6% of participants pointed to an improvement in the structure of the teaching material, although a relatively high proportion of neutral responses (44.4%) remained slightly more than half of the developers (66.7%) agreed that the institutional conditions for implementing SAM at the university are in place, but noted a lack of

**Table 1** Use and Perception of AI Component

Indicator	%
AI used	56.9
Improved understanding	82.1
Increased motivation	53.7
Encountered errors	57.7
Trust (partial/general)	83.7

methodological training (66.7%), technical difficulties (66.7%), and the need for additional training for teachers (77.8%). The majority (77.8%) recognized the advisability of introducing SAM in the higher education system and expressed a desire to recommend it to colleagues (66.6%). However, only 55.5% of the participants themselves expressed a willingness to apply SAM, while 33.3% took a neutral position.

The survey participants noted the most significant advantages of the model. These included: iterative development (66.6%), flexibility in making changes (77.8%), improvement in the quality of the final product (66.6%), time savings due to early detection of shortcomings (66.6%), and adaptation of materials to the needs of learners (66.7%). The developers attributed less significance to the speed of feedback and the reduction of the risk of methodological errors, where moderate assessments prevailed.

## Discussion

### Main Finding

This study evaluated an online course in biostatistics developed using the Sequential Approximation Model (SAM) and supplemented with an artificial intelligence-supported learning component. Three main findings emerged. First, the course demonstrated generally positive acceptability among students: approximately 64.7% of respondents gave positive ratings on key parameters, including understanding, ease of use, and perceived relevance. Second, the AI component was primarily used as a tool for conceptual clarification and cognitive support, with most users noting perceived benefits alongside moderate trust and frequent identification of inaccuracies. Third, developers rated the SAM model positively, particularly its iterative and flexible nature, while also identifying methodological and institutional challenges related to its implementation.

These results suggest that the integration of iterative learning design and AI-supported learning is feasible and acceptable in medical education. However, the results should be interpreted with caution due to the descriptive nature of the study, reliance on self-reported outcomes, and the absence of a control group.

### Students' Perceptions of the Online Course

The pre-course survey provided a better understanding of the conditions under which the electronic course on biostatistics was implemented. The survey results showed that the self-assessment of students who had already studied biostatistics most often remained at an average level. This is consistent with the situation observed in medical education, where students have basic experience in studying the discipline but do not feel confident in their statistical skills.

The structure of the difficulties was quite predictable: the greatest difficulties were caused by topics requiring probabilistic thinking, working with multidimensional methods, and interpreting research results. This shows once again that the main problem in studying biostatistics is not so much the performance of calculations as the understanding of the statistical logic and meanings behind the formulas. The analysis of obstacles also demonstrated the predominance of cognitive factors. Students noted the complexity of terminology, the formalized nature of the material, and the lack of obvious practical significance of the discipline. It is particularly telling that some students have difficulty understanding how biostatistics will be used in their future professional activities - a problem well known in medical education and related to the insufficient integration of statistical concepts into the clinical context.

At the same time, these results should not be interpreted as evidence of objective educational effectiveness. The study design does not allow for causal inferences regarding improved learning outcomes compared to traditional teaching methods. Instead, the results reflect perceived usefulness and acceptability.

Students' preferences in learning formats indicate a clear demand for a more visual and explanatory presentation of the material. Short video lectures, step-by-step analysis of tasks, and examples based on medical data proved to be the most popular. This combination of formats is consistent with modern approaches to teaching quantitative disciplines, which are focused on reducing cognitive load and increasing the comprehensibility of the material.<sup>26,27</sup> Students' expectations regarding the duration of classes show that a module lasting about one hour is perceived as optimal, which confirms the advisability of a compact modular structure for the e-course.

Attitudes toward the mastery approach were mixed: some students supported the idea of sequential mastery of material through testing, but a significant proportion found it difficult to evaluate. This is probably due to the limited experience of students working in such formats and possible concerns about increased requirements. This highlights the need for the gradual introduction of mastery logic and its accompaniment by clear explanations for students. Overall, the results of the pre-course survey show that students want biostatistics training that is more adaptive, understandable, and practice oriented. It was this educational demand that became one of the key reasons for developing an e-course based on an iterative design model and supplemented with comprehension support tools aimed at overcoming the identified difficulties.

The post-course results demonstrate a predominantly positive perception of the e-course in biostatistics among undergraduate students. The share of positive ratings in all analyzed domains exceeded 60%, with a consistently low level of negative responses. These data indicate the acceptability of the implemented educational model and the absence of significant resistance from students. However, a significant proportion of neutral responses (27–32%) requires further interpretation. This distribution pattern may reflect students' moderate subjective confidence in their own statistical competencies. International studies have repeatedly shown that medical students and practicing physicians often experience statistics anxiety and demonstrate limited confidence in interpreting quantitative data.<sup>28</sup> Low levels of statistical self-efficacy can lead to cautious or neutral responses even when knowledge has actually improved.<sup>29</sup>

The issue of clinical relevance deserves special attention. A higher proportion of neutral ratings on this item may be related to the continuing gap between the perception of statistics as a theoretical discipline and its practical role in clinical decision-making. A number of studies emphasize that some students and healthcare professionals view biostatistics as an auxiliary rather than a fundamental component of medical education.<sup>28–31</sup> Some studies even note a sceptical attitude toward the mandatory study of statistics in the early stages of training, especially when clinical examples are not sufficiently integrated.<sup>30</sup>

International literature convincingly demonstrates that statistical literacy is a key element of evidence-based medicine (EBM) and is directly related to the quality of clinical decisions.<sup>31</sup> Insufficient understanding of statistical concepts is associated with difficulties in interpreting the results of clinical studies and an increased risk of errors in the evaluation of medical evidence.<sup>28</sup> Consequently, a moderate subjective assessment of the relevance of the course may reflect not so much shortcomings in content as a broader problem of professional identity formation, in which statistical competence is not yet fully integrated into students' clinical thinking. The positive perception of the mastery approach ( $\geq 80\%$ ) also deserves discussion. Despite the potentially higher workload, most students rated this format positively. This is consistent with research showing that structured feedback and clear criteria for achieving competencies contribute to increased academic responsibility and improved learning outcomes.<sup>32</sup> However, the presence of a small proportion of negative ratings indicates the need for a balance between academic rigor and a comfortable educational environment.

## Interpretation of AI-Related Results

Analysis of AI use showed that it was accepted by most students and served primarily as a support tool. The most common tasks were explaining theoretical material and analyzing statistical indicators, confirming the role of AI as a consultant for understanding complex material. The high proportion of students who reported an improvement in their understanding of statistical methods and an increase in academic performance indicates the potential of the AI component as a means of personalized learning support. At the same time, a moderate level of trust and frequent reports of identified errors indicate the formation of a critical stance among users. This observation is consistent with emerging literature highlighting the dual nature of generative AI in education, which offers both significant opportunities for personalized learning and potential risks associated with misinformation and overreliance.<sup>33</sup>

This combination can be considered pedagogically beneficial, as it reduces the risk of uncritical use of generative systems. The impact of AI on learning behavior was manifested in increased student independence and reduced need for teacher consultation, reflecting a redistribution of educational support functions. At the same time, significant support for pedagogical control and restrictions on the use of AI in exam situations demonstrates students' awareness of the need to balance technological capabilities and academic integrity.

However, interpreting these results requires caution. Although a significant proportion of students reported improved comprehension and increased motivation, these results are based on subjective self-assessment and do not constitute objective evidence of improved academic performance. Therefore, the AI in this study should be viewed as a tool that

helps students understand the material, rather than as evidence that it actually improves learning. Effective integration of AI into medical education requires not only technical implementation but also clear pedagogical guidelines regarding appropriate and responsible use.<sup>34</sup>

## Developers' Views on the SAM Model

The results of the developer survey showed a positive perception of the pedagogical value of SAM, especially with regard to the iterative nature of development and the possibility of timely error correction. These data confirm that the key conceptual advantages of the model have been realized in practice. At the same time, the high level of uncertainty in understanding the model and readiness to apply it indicates that the methodological competence of developers is only partially formed. This situation is typical for the early stages of implementing innovative instructional design approaches, when practical experience outpaces theoretical reflection.

The barriers noted by the developers - lack of methodological training, technical difficulties, and the need for additional training - emphasize the systemic nature of the conditions for successful SAM implementation. These results allow us to consider the implementation of the model as an organizational innovation that requires institutional support, not just individual initiative. In this regard, this study extends the existing literature by demonstrating that the adoption of an instructional design model does not necessarily imply a commitment to its sustainable application.<sup>35</sup>

## Implications for Medical Education

The integration of data from the three groups of respondents shows a consistent picture of the course's implementation. The positive assessment by developers of SAM's interactivity and flexibility correlates with the course's sustained acceptability among students, which indirectly confirms the effectiveness of the chosen development model. In turn, the use of the AI component enhanced the educational effect of the course, providing an additional level of cognitive support and personalization of learning. A characteristic feature was that both students and developers generally perceived the technology positively, but at the same time noted its limitations. This combination indicates a fairly mature attitude toward innovation and the absence of uncritical perception. Taken together, the results allow us to consider the implementation of the electronic biostatistics course as an example of multi-level educational innovation, in which the instructional design model, digital technology, and educational context interact to form a complex effect. The data obtained confirm that the successful implementation of such projects depends not only on the quality of the educational product, but also on the readiness of the participants in the educational process, institutional conditions, and the level of digital pedagogical competence.

## Limitations

Despite the meaningful results obtained, the study has a number of limitations that should be taken into account when interpreting the findings.

First, the study design was descriptive and based primarily on self-reported data from respondents. Subjective assessments of satisfaction, perceived usefulness, and willingness to use technology may not fully reflect objective changes in learning outcomes and professional competencies.

Second, the study was conducted within a single educational institution, which limits the external validity of the results and the possibility of directly generalizing them to other educational contexts, disciplines, and institutional environments.

Third, the sample of developers was relatively small, which is due to the specifics of the project team, but this reduces the statistical stability of the assessments and increases the width of the confidence intervals.

Fourth, the study did not include a control group that was trained without using the SAM model or the AI component, which limits the possibility of causal interpretations regarding the effectiveness of individual elements of the innovation.

Fifth, the analysis did not cover long-term educational effects, including knowledge retention, the transfer of statistical competencies to clinical practice, and the impact of the course on students' academic trajectories.

## Conclusion

The results of this study demonstrate that integrating a successive approximation model (SAM) and AI-assisted learning is a feasible and acceptable approach to developing biostatistics e-learning courses in medical education. However, the results should be interpreted with caution as they are based on a descriptive design and self-report data.

From a practical perspective, the study demonstrates that AI can be used as a tool to support understanding of complex concepts, provided its use is guided by clear pedagogical recommendations and appropriate limitations, particularly in the context of assessment. Furthermore, the implementation of iterative learning design models such as SAM can improve course development processes but requires methodological training and institutional support.

Future research should focus on assessing the impact of such approaches on objective learning outcomes, including knowledge acquisition, retention, and application in a clinical context, as well as on developing effective strategies for integrating AI into medical education in a pedagogically sound manner.

## Data Sharing Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

## Ethics Approval and Informed Consent

The study was conducted in accordance with the Declaration of Helsinki and approved by the Local Commission on bioethics of NJSC “Karaganda Medical University”, Protocol №5 dated 26.02.2026. The study included anonymous surveys and focus group discussions. Survey participation was voluntary and anonymous, and completion implied consent. Informed consent was obtained from all focus group participants.

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## Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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