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ЕЖЕМЕСЯЧНЫЙ НАУЧНЫЙ ЖУРНАЛ

Медицинские новости Грузии

საქართველოს სამედიცინო სიახლენი

GEORGIAN MEDICAL NEWS

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GMN: Georgian Medical News is peer-reviewed, published monthly journal committed to promoting the science and art of medicine and the betterment of public health, published by the GMN Editorial Board since 1994. GMN carries original scientific articles on medicine, biology and pharmacy, which are of experimental, theoretical and practical character; publishes original research, reviews, commentaries, editorials, essays, medical news, and correspondence in English and Russian.

GMN is indexed in MEDLINE, SCOPUS, PubMed and VINITI Russian Academy of Sciences. The full text content is available through EBSCO databases.

GMN: Медицинские новости Грузии - ежемесячный рецензируемый научный журнал, издаётся Редакционной коллегией с 1994 года на русском и английском языках в целях поддержки медицинской науки и улучшения здравоохранения. В журнале публикуются оригинальные научные статьи в области медицины, биологии и фармации, статьи обзорного характера, научные сообщения, новости медицины и здравоохранения. Журнал индексируется в MEDLINE, отражён в базе данных SCOPUS, PubMed и ВИНИТИ РАН. Полнотекстовые статьи журнала доступны через БД EBSCO.

GMN: Georgian Medical News – საქართველოს სამედიცინო სიახლენი – არის ყოველთვიური სამეცნიერო სამედიცინო რეცენზირებადი ჟურნალი, გამოიცემა 1994 წლიდან, წარმოადგენს სარედაქციო კოლეგიისა და აშშ-ის მეცნიერების, განათლების, ინდუსტრიის, ხელოვნებისა და ბუნებისმეტყველების საერთაშორისო აკადემიის ერთობლივ გამოცემას. GMN-ში რუსულ და ინგლისურ ენებზე ქვეყნდება ექსპერიმენტული, თეორიული და პრაქტიკული ხასიათის ორიგინალური სამეცნიერო სტატიები მედიცინის, ბიოლოგიისა და ფარმაციის სფეროში, მიმოხილვითი ხასიათის სტატიები.

ჟურნალი ინდექსირებულია MEDLINE-ის საერთაშორისო სისტემაში, ასახულია SCOPUS-ის, PubMed-ის და ВИНИТИ РАН-ის მონაცემთა ბაზებში. სტატიების სრული ტექსტი ხელმისაწვდომია EBSCO-ს მონაცემთა ბაზებიდან.

WEBSITE

www.geomednews.com

К СВЕДЕНИЮ АВТОРОВ!

При направлении статьи в редакцию необходимо соблюдать следующие правила:

1. Статья должна быть представлена в двух экземплярах, на русском или английском языках, напечатанная через **полтора интервала на одной стороне стандартного листа с шириной левого поля в три сантиметра**. Используемый компьютерный шрифт для текста на русском и английском языках - **Times New Roman** (**Кириллица**), для текста на грузинском языке следует использовать **AcadNusx.** Размер шрифта - **12**. К рукописи, напечатанной на компьютере, должен быть приложен CD со статьей.

2. Размер статьи должен быть не менее десяти и не более двадцати страниц машинописи, включая указатель литературы и резюме на английском, русском и грузинском языках.

3. В статье должны быть освещены актуальность данного материала, методы и результаты исследования и их обсуждение.

При представлении в печать научных экспериментальных работ авторы должны указывать вид и количество экспериментальных животных, применявшиеся методы обезболивания и усыпления (в ходе острых опытов).

4. К статье должны быть приложены краткое (на полстраницы) резюме на английском, русском и грузинском языках (включающее следующие разделы: цель исследования, материал и методы, результаты и заключение) и список ключевых слов (key words).

5. Таблицы необходимо представлять в печатной форме. Фотокопии не принимаются. **Все цифровые, итоговые и процентные данные в таблицах должны соответствовать таковым в тексте статьи**. Таблицы и графики должны быть озаглавлены.

6. Фотографии должны быть контрастными, фотокопии с рентгенограмм - в позитивном изображении. Рисунки, чертежи и диаграммы следует озаглавить, пронумеровать и вставить в соответствующее место текста **в tiff формате**.

В подписях к микрофотографиям следует указывать степень увеличения через окуляр или объектив и метод окраски или импрегнации срезов.

7. Фамилии отечественных авторов приводятся в оригинальной транскрипции.

8. При оформлении и направлении статей в журнал МНГ просим авторов соблюдать правила, изложенные в «Единых требованиях к рукописям, представляемым в биомедицинские журналы», принятых Международным комитетом редакторов медицинских журналов - http://www.spinesurgery.ru/files/publish.pdf и http://www.nlm.nih.gov/bsd/uniform_requirements.html
В конце каждой оригинальной статьи приводится библиографический список. В список литературы включаются все материалы, на которые имеются ссылки в тексте. Список составляется в алфавитном порядке и нумеруется. Литературный источник приводится на языке оригинала. В списке литературы сначала приводятся работы, написанные знаками грузинского алфавита, затем кириллицей и латиницей. Ссылки на цитируемые работы в тексте статьи даются в квадратных скобках в виде номера, соответствующего номеру данной работы в списке литературы. Большинство цитированных источников должны быть за последние 5-7 лет.

9. Для получения права на публикацию статья должна иметь от руководителя работы или учреждения визу и сопроводительное отношение, написанные или напечатанные на бланке и заверенные подписью и печатью.

10. В конце статьи должны быть подписи всех авторов, полностью приведены их фамилии, имена и отчества, указаны служебный и домашний номера телефонов и адреса или иные координаты. Количество авторов (соавторов) не должно превышать пяти человек.

11. Редакция оставляет за собой право сокращать и исправлять статьи. Корректура авторам не высылается, вся работа и сверка проводится по авторскому оригиналу.

12. Недопустимо направление в редакцию работ, представленных к печати в иных издательствах или опубликованных в других изданиях.

При нарушении указанных правил статьи не рассматриваются.

REQUIREMENTS

Please note, materials submitted to the Editorial Office Staff are supposed to meet the following requirements:

1. Articles must be provided with a double copy, in English or Russian languages and typed or compu-ter-printed on a single side of standard typing paper, with the left margin of **3** centimeters width, and **1.5** spacing between the lines, typeface - **Times New Roman** (**Cyrillic**), print size - **12** (referring to Georgian and Russian materials). With computer-printed texts please enclose a CD carrying the same file titled with Latin symbols.

2. Size of the article, including index and resume in English, Russian and Georgian languages must be at least 10 pages and not exceed the limit of 20 pages of typed or computer-printed text.

3. Submitted material must include a coverage of a topical subject, research methods, results, and review.

Authors of the scientific-research works must indicate the number of experimental biological species drawn in, list the employed methods of anesthetization and soporific means used during acute tests.

4. Articles must have a short (half page) abstract in English, Russian and Georgian (including the following sections: aim of study, material and methods, results and conclusions) and a list of key words.

5. Tables must be presented in an original typed or computer-printed form, instead of a photocopied version. **Numbers, totals, percentile data on the tables must coincide with those in the texts of the articles.** Tables and graphs must be headed.

6. Photographs are required to be contrasted and must be submitted with doubles. Please number each photograph with a pencil on its back, indicate author's name, title of the article (short version), and mark out its top and bottom parts. Drawings must be accurate, drafts and diagrams drawn in Indian ink (or black ink). Photocopies of the X-ray photographs must be presented in a positive image in **tiff format**.

Accurately numbered subtitles for each illustration must be listed on a separate sheet of paper. In the subtitles for the microphotographs please indicate the ocular and objective lens magnification power, method of coloring or impregnation of the microscopic sections (preparations).

7. Please indicate last names, first and middle initials of the native authors, present names and initials of the foreign authors in the transcription of the original language, enclose in parenthesis corresponding number under which the author is listed in the reference materials.

8. Please follow guidance offered to authors by The International Committee of Medical Journal Editors guidance in its Uniform Requirements for Manuscripts Submitted to Biomedical Journals publication available online at: http://www.nlm.nih.gov/bsd/uniform_requirements.html
http://www.icmje.org/urm_full.pdf
In GMN style for each work cited in the text, a bibliographic reference is given, and this is located at the end of the article under the title "References". All references cited in the text must be listed. The list of references should be arranged alphabetically and then numbered. References are numbered in the text [numbers in square brackets] and in the reference list and numbers are repeated throughout the text as needed. The bibliographic description is given in the language of publication (citations in Georgian script are followed by Cyrillic and Latin).

9. To obtain the rights of publication articles must be accompanied by a visa from the project instructor or the establishment, where the work has been performed, and a reference letter, both written or typed on a special signed form, certified by a stamp or a seal.

10. Articles must be signed by all of the authors at the end, and they must be provided with a list of full names, office and home phone numbers and addresses or other non-office locations where the authors could be reached. The number of the authors (co-authors) must not exceed the limit of 5 people.

11. Editorial Staff reserves the rights to cut down in size and correct the articles. Proof-sheets are not sent out to the authors. The entire editorial and collation work is performed according to the author's original text.

12. Sending in the works that have already been assigned to the press by other Editorial Staffs or have been printed by other publishers is not permissible.

Articles that Fail to Meet the Aforementioned Requirements are not Assigned to be Reviewed.

ავტორთა საყურადღებოდ!

რედაქციაში სტატიის წარმოდგენისას საჭიროა დავიცვათ შემდეგი წესები:

1. სტატია უნდა წარმოადგინოთ 2 ცალად, რუსულ ან ინგლისურ ენებზე,დაბეჭდილი სტანდარტული ფურცლის 1 გვერდზე, 3 სმ სიგანის მარცხენა ველისა და სტრიქონებს შორის 1,5 ინტერვალის დაცვით. გამოყენებული კომპიუტერული შრიფტი რუსულ და ინგლისურენოვან ტექსტებში - **Times New Roman (Кириллица)**, ხოლო ქართულენოვან ტექსტში საჭიროა გამოვიყენოთ **AcadNusx.** შრიფტის ზომა – 12. სტატიას თან უნდა ახლდეს CD სტატიით.

2. სტატიის მოცულობა არ უნდა შეადგენდეს 10 გვერდზე ნაკლებს და 20 გვერდზე მეტს ლიტერატურის სიის და რეზიუმეების (ინგლისურ, რუსულ და ქართულ ენებზე) ჩათვლით.

3. სტატიაში საჭიროა გაშუქდეს: საკითხის აქტუალობა; კვლევის მიზანი; საკვლევი მასალა და გამოყენებული მეთოდები; მიღებული შედეგები და მათი განსჯა. ექსპერიმენტული ხასიათის სტატიების წარმოდგენისას ავტორებმა უნდა მიუთითონ საექსპერიმენტო ცხოველების სახეობა და რაოდენობა; გაუტკივარებისა და დაძინების მეთოდები (მწვავე ცდების პირობებში).

4. სტატიას თან უნდა ახლდეს რეზიუმე ინგლისურ, რუსულ და ქართულ ენებზე არანაკლებ ნახევარი გვერდის მოცულობისა (სათაურის, ავტორების, დაწესებულების მითითებით და უნდა შეიცავდეს შემდეგ განყოფილებებს: მიზანი, მასალა და მეთოდები, შედეგები და დასკვნები; ტექსტუალური ნაწილი არ უნდა იყოს 15 სტრიქონზე ნაკლები) და საკვანძო სიტყვების ჩამონათვალი (key words).

5. ცხრილები საჭიროა წარმოადგინოთ ნაბეჭდი სახით. ყველა ციფრული, შემაჯამებელი და პროცენტული მონაცემები უნდა შეესაბამებოდეს ტექსტში მოყვანილს.

6. ფოტოსურათები უნდა იყოს კონტრასტული; სურათები, ნახაზები, დიაგრამები - დასათაურებული, დანომრილი და სათანადო ადგილას ჩასმული. რენტგენოგრამების ფოტოასლები წარმოადგინეთ პოზიტიური გამოსახულებით **tiff** ფორმატში. მიკროფოტოსურათების წარწერებში საჭიროა მიუთითოთ ოკულარის ან ობიექტივის საშუალებით გადიდების ხარისხი, ანათალების შეღებვის ან იმპრეგნაციის მეთოდი და აღნიშნოთ სურათის ზედა და ქვედა ნაწილები.

7. სამამულო ავტორების გვარები სტატიაში აღინიშნება ინიციალების თანდართვით, უცხოურისა – უცხოური ტრანსკრიპციით.

8. სტატიას თან უნდა ახლდეს ავტორის მიერ გამოყენებული სამამულო და უცხოური შრომების ბიბლიოგრაფიული სია (ბოლო 5-8 წლის სიღრმით). ანბანური წყობით წარმოდგენილ ბიბლიოგრაფიულ სიაში მიუთითეთ ჯერ სამამულო, შემდეგ უცხოელი ავტორები (გვარი, ინიციალები, სტატიის სათაური, ჟურნალის დასახელება, გამოცემის ადგილი, წელი, ჟურნალის №, პირველი და ბოლო გვერდები). მონოგრაფიის შემთხვევაში მიუთითეთ გამოცემის წელი, ადგილი და გვერდების საერთო რაოდენობა. ტექსტში კვადრატულ ფჩხილებში უნდა მიუთითოთ ავტორის შესაბამისი N ლიტერატურის სიის მიხედვით. მიზანშეწონილია, რომ ციტირებული წყაროების უმეტესი ნაწილი იყოს 5-6 წლის სიღრმის.

9. სტატიას თან უნდა ახლდეს: ა) დაწესებულების ან სამეცნიერო ხელმძღვანელის წარდგინება, დამოწმებული ხელმოწერითა და ბეჭდით; ბ) დარგის სპეციალისტის დამოწმებული რეცენზია, რომელშიც მითითებული იქნება საკითხის აქტუალობა, მასალის საკმაობა, მეთოდის სანდოობა, შედეგების სამეცნიერო-პრაქტიკული მნიშვნელობა.

10. სტატიის ბოლოს საჭიროა ყველა ავტორის ხელმოწერა, რომელთა რაოდენობა არ უნდა აღემატებოდეს 5-ს.

11. რედაქცია იტოვებს უფლებას შეასწოროს სტატია. ტექსტზე მუშაობა და შეჯერება ხდება საავტორო ორიგინალის მიხედვით.

12. დაუშვებელია რედაქციაში ისეთი სტატიის წარდგენა, რომელიც დასაბეჭდად წარდგენილი იყო სხვა რედაქციაში ან გამოქვეყნებული იყო სხვა გამოცემებში.

აღნიშნული წესების დარღვევის შემთხვევაში სტატიები არ განიხილება.

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GENERATIVE AI–ASSISTED DRUG–DRUG INTERACTION CASE SUPPORT AND PHARMACY STUDENTS' COMPETENCE: A MIXED-METHODS STUDY

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Abstract.

Background: Drug-drug interactions (DDIs) significantly contribute to preventable adverse drug events and constitute a vital skill domain in pharmacy education. Recent advancements in generative artificial intelligence (GenAI) have created novel opportunities for enhancing clinical reasoning and medication safety training; however, evidence regarding their educational effectiveness remains limited.

Objective: To evaluate the effect of a generative AI-assisted DDI alert tool on pharmacy students' competence in managing complex DDI cases and to explore students' perceptions of AI-supported clinical reasoning.

Methods: A comparative mixed-methods study was conducted among advanced-level undergraduate pharmacy students in Saudi Arabia during the 2025 academic year. Participants were allocated to either an AI-assisted group (n = 96) or a non-AI group (n = 88). Both groups completed identical case-based assessments involving high-risk DDIs. Objective competence was assessed using a standardized analytic rubric evaluating DDI identification, mechanism assessment, clinical management, and therapeutic justification. Quantitative data were analyzed using descriptive and inferential statistics, while qualitative responses were examined using thematic analysis.

Results: A total of 184 students completed the study. Compared with the non-AI group, students in the AI-assisted group reported significantly higher scores in understanding DDI mechanisms ($p = 0.0089$), confidence in clinical decision-making ($p = 0.0028$), perceived appropriateness of challenge level ($p = 0.0050$), and overall satisfaction ($p = 0.0004$). Objective competence scores were significantly higher among AI-assisted students across all assessed domains, including DDI identification ($p = 0.008$), mechanism assessment ($p = 0.002$), clinical management ($p = 0.005$), and therapeutic justification ($p = 0.004$). The composite competence score was also significantly higher in the AI-assisted group (8.75 ± 1.09 vs. 8.10 ± 1.46; $p = 0.001$). Qualitative analysis identified three overarching themes: clinical relevance and case realism, generative AI as a cognitive support tool, and the need for clearer assessment guidance and additional clinical detail.

Conclusion: Generative AI-assisted DDI support was associated with improved competence, confidence, and overall assessment experience among pharmacy students managing complex clinical cases. The findings suggest that generative AI can serve as an effective educational scaffold that enhances clinical reasoning and therapeutic decision-making when integrated within structured learning environments and supported by appropriate faculty oversight.

Key words. Generative artificial intelligence, drug–drug interactions, pharmacy education, clinical reasoning, case-based assessment, educational technology, mixed-methods research.

Introduction.

Drug–drug interactions (DDIs) are widely recognized as a major contributor to preventable adverse drug events (ADEs), particularly among populations with complex medication regimens such as the elderly and those with chronic comorbidities [1-3]. Numerous studies have shown that DDIs account for a substantial proportion of medication-related hospitalizations, thereby imposing significant clinical and economic burdens on healthcare systems[2]. In light of this, it is essential to equip pharmacy graduates with the competence to identify, assess, and manage DDIs in real-time clinical settings [4].

Despite the inclusion of DDIs in pharmacotherapy curricula, recent evidence has indicated that many pharmacy students lack the applied skills necessary to evaluate interaction risks and make appropriate clinical judgments [5,6]. While these findings do not suggest a failure in knowledge acquisition, they do underscore a persistent gap in translating theoretical content into practice. This has prompted scholars to advocate for instructional approaches that incorporate experiential learning and decision-support tools to bridge this gap [7].

Over the last two years, there has been a marked increase in the integration of artificial intelligence (AI) in healthcare education. In particular, generative AI tools—based on large language models such as GPT-4—have been explored as

potential adjuncts to support clinical reasoning, simulate patient encounters, and generate drug-related explanations [8,9]. Several studies have shown that such models can outperform traditional search methods in generating context-relevant responses and summarizing complex clinical data [9-11].

It has been proposed that the use of AI in pharmacy education may enhance students' ability to manage complex therapeutic scenarios by offering scaffolded support, particularly in identifying clinically significant DDIs [12]. For example, Liu et al. [13] introduced a pharmacy-specific chatbot ("PharmacyGPT") and demonstrated improved diagnostic accuracy among final-year students. Similarly, a comparative study by Li et al. [14] found that generative AI tools varied in their performance but showed potential in helping students resolve clinical pharmacy problems.

Nevertheless, concerns regarding the reliability, transparency, and ethical use of generative AI persist. It has been argued that the use of these tools must be balanced with robust faculty oversight to avoid overreliance and potential propagation of misinformation [15,16]. A recent national survey by Ichikawa et al. [17] showed that while U.S. medical schools are adopting policies and training programs for AI integration, pharmacy education is still in the early phases of structured implementation. Additionally, Patel and Lam [18] emphasized that AI's role in medical documentation—such as discharge summaries—could transform practice but raises questions about accountability and interpretability.

The present study seeks to address this gap by assessing whether the use of a generative AI-assisted DDI alert tool improves pharmacy students' competence in managing high-risk clinical cases. By drawing on mixed-methods design, the study aims to (i) compare student performance in AI-assisted and non-assisted conditions; and (ii) explore students' reflections on the benefits and limitations of AI in clinical decision-making. This research aims to contribute to current debates by providing empirical data on the instructional utility of AI in pharmacy education and by informing the development of AI-integrated curricular strategies. To our knowledge, this is among the first mixed-methods studies to empirically examine the instructional value of generative AI–assisted DDI alerts within undergraduate pharmacy education in KSA.

Methodology.

Study design:

This study employed a comparative mixed-methods design to evaluate pharmacy students' competence in managing complex drug–drug interaction (DDI) cases with and without the assistance of generative artificial intelligence (GenAI). A mixed-methods approach was selected to integrate quantitative comparisons of perceived competence and assessment experience with qualitative insights into students' clinical reasoning processes and reflections on AI-supported learning.

Participants and Setting:

Participants were final-year and advanced-level undergraduate pharmacy students enrolled during the 2025 academic year. This cohort was selected to ensure adequate foundational knowledge of pharmacotherapy, DDIs, and exposure to clinical decision-making relevant to professional practice.

Eligibility criteria included: (1) enrollment in the final year or an advanced stage of the pharmacy program, (2) prior instruction in DDI concepts, and (3) voluntary consent to participate. Students with prior experience using advanced AI tools for clinical decision-making were excluded to reduce potential bias related to AI familiarity.

Sample Size Considerations:

A total sample size of approximately 189 participants was targeted. This sample size provides 80% statistical power at a two-sided significance level of 0.05 to detect a small-to-moderate between-group effect size (Cohen's $d \approx 0.41$) for independent group comparisons between AI-assisted and non-AI conditions. This sample was considered sufficient to support confirmatory quantitative analysis while also enabling meaningful qualitative triangulation.

Group Allocation:

Participants were allocated into two parallel groups based on assessment condition. The non-AI group completed the assessment without access to generative artificial intelligence (GenAI) tools and relied solely on their existing knowledge and clinical reasoning skills. The AI-assisted group completed the same assessment with access to a generative AI–assisted DDI alert tool (ChatGPT, GPT-4 architecture, OpenAI), which provided interaction alerts, explanatory summaries, and suggested management strategies.

Group allocation was conducted using a convenience-based approach while ensuring comparable academic standing across groups. Random allocation was not feasible due to scheduling and logistical constraints associated with the supervised assessment environment and controlled AI access conditions. To reduce the risk of selection bias, both groups were recruited from the same academic cohort, completed identical clinical cases and assessment instruments, and were evaluated under standardized assessment conditions. Baseline comparisons demonstrated no statistically significant differences between groups in age, GPA, sex distribution, or prior exposure to AI tools (Appendix E).

Nature of the Complex Clinical Cases:

The assessment consisted of high-risk, case-based clinical scenarios designed to reflect authentic pharmacy practice. Each case incorporated polypharmacy, multiple comorbidities, and at least one clinically significant DDI requiring interpretation, risk assessment, and clinical management rather than simple identification.

Cases included commonly encountered therapeutic classes such as cardiovascular agents, endocrine therapies, anticoagulants, and antimicrobials. Relevant patient context—including age, renal function, and clinical history—was provided to support realistic decision-making.

All cases were reviewed by academic pharmacy faculty with clinical expertise to ensure content validity, appropriate complexity for final-year students, and alignment with learning outcomes related to medication safety and DDI management.

Operationalization and Scoring of Competence:

Student competence was operationalized across four predefined domains:

(1) identification of clinically significant DDIs,
(2) assessment of interaction severity and underlying mechanisms,
(3) clinical decision-making and selection of appropriate management strategies, and
(4) justification and clarity of therapeutic reasoning.

Each domain was scored on a 10-point standardized scale using a structured analytic rubric developed for this study (maximum composite score = 40). Domain scores were summed to generate a composite competence score, which was subsequently standardized to a mean scale for comparative analysis.

The rubric included explicit performance descriptors for each score level to ensure consistency in evaluation across domains. Responses were independently assessed by trained evaluators who were blinded to group allocation. Scoring discrepancies were resolved through consensus discussion. To minimize the possibility of evaluators inferring AI-assisted status from linguistic patterns, submitted responses were anonymized and assessed using structured rubric criteria emphasizing clinical content and reasoning rather than writing style alone.

Inter-rater reliability was evaluated using a two-way random-effects intraclass correlation coefficient (ICC), reflecting absolute agreement between raters. The observed ICC demonstrated good reliability for educational assessment, supporting the consistency and robustness of the scoring process.

Instrument Development:

The evaluation instrument was developed through a structured multi-step process:

Step 1: Content Specification:

Key competencies related to DDI identification, assessment, and management were mapped to curricular learning outcomes and professional practice expectations.

Step 2: Case and Item Development:

Clinical cases and corresponding open-ended and closed-ended items were designed to assess applied knowledge, reasoning, and decision-making.

Step 3: Expert Review:

The draft instrument was reviewed by a panel of pharmacy education and clinical pharmacy experts to evaluate relevance, clarity, and appropriateness of case complexity. Revisions were made iteratively.

Step 4: Pilot Testing:

The revised instrument was piloted with a group of pharmacy students not included in the final sample to refine wording, timing, and scoring criteria.

Step 5: Reliability and Finalization:

Inter-rater reliability was examined for the scoring rubric, and disagreements were resolved through discussion. The finalized instrument demonstrated acceptable reliability for educational research.

Data Collection:

Participants completed the assessment using an online questionnaire comprising demographic items, case-based questions, Likert-scale perception measures, and open-ended reflection prompts. Students in the AI-assisted group were permitted to consult the GenAI tool during case completion, whereas the non-AI group completed the assessment without AI support.

Data Analysis:

Quantitative data were analyzed using descriptive statistics and inferential tests appropriate to data distribution to compare outcomes between groups. Effect sizes were calculated to estimate the magnitude of observed differences.

Qualitative data from open-ended responses were analyzed using thematic analysis. Two researchers independently coded the data, with codes refined into themes through iterative discussion and consensus.

Ensuring Rigor and Trustworthiness:

Methodological rigor was ensured through standardized scoring procedures, blinded evaluation, and consistent assessment conditions. Qualitative credibility was supported through investigator triangulation and independent coding. Dependability and confirmability were enhanced through maintenance of an audit trail and reflexive discussions within the research team.

Ethical Considerations:

This study was conducted in accordance with the ethical principles of the Declaration of Helsinki for research involving human participants. Ethical approval was obtained from the Ministry of Health Research Committee, Hail City, Kingdom of Saudi Arabia (Approval No. MOH-HL-REC-2025-017).

Participation was voluntary, and written informed consent was obtained from all participants prior to data collection. Students were informed about the study objectives, procedures, and their right to withdraw at any time without academic consequences. Participation or non-participation did not influence course grades or academic standing.

All responses were anonymized prior to analysis, and no personally identifiable information was collected. Data were stored securely on password-protected institutional systems accessible only to the research team.

For the AI-assisted group, only fictional case scenarios were entered into the generative AI system. No real patient data or identifiable health information were used. Participants were informed about the limitations of generative AI systems, including the potential for inaccurate outputs, and were instructed to critically appraise AI-generated information before incorporating it into their clinical reasoning.

Results.

A total of 184 students completed the assessment (AI-assisted group, n = 96; non-AI group, n = 88). Descriptive comparisons of mean Likert-scale scores for perceived competence and assessment experience across the five evaluated domains are presented in Table 1. Overall, students in both groups reported positive perceptions, with mean scores above the midpoint of the scale in all domains.

Across all domains, the AI-assisted group demonstrated higher mean scores than the non-AI group. The largest descriptive differences were observed for overall satisfaction and confidence in clinical decision-making. These trends are visually illustrated in Figure 1.

Inferential Analysis:

Between-group comparisons using Welch's independent samples t-tests are summarized in Table 2.

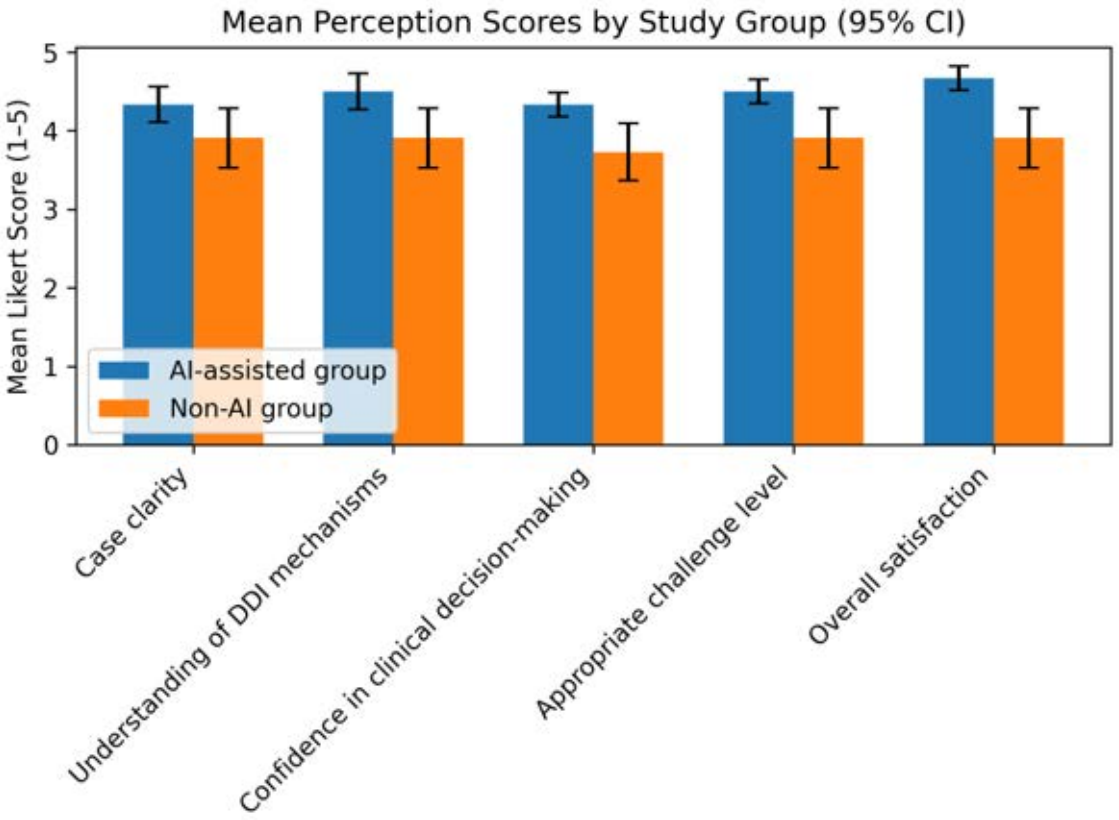

Figure 1. *Mean Perception Scores by Study Group (95% CI).*

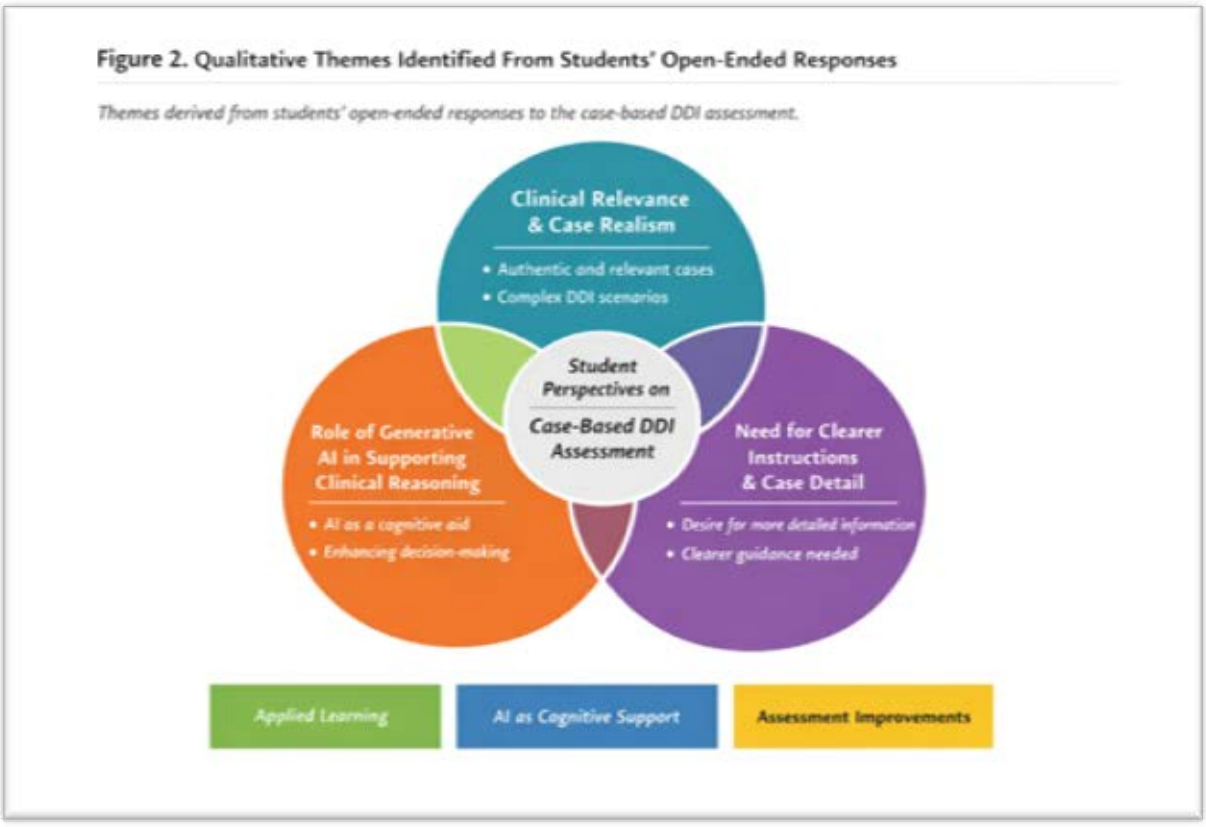

Figure 2. *Qualitative Themes Identified from Students' Open-Ended Responses.*

Table 1. *Mean Likert Scores for Perceived Competence and Assessment Experience by Study Group.*

Domain	AI-Assisted Group (Mean)	Non-AI Group (Mean)
Case clarity	4.33	3.91
Understanding of DDI mechanisms	4.50	3.91
Confidence in clinical decision-making	4.33	3.73
Appropriate challenge level	4.50	3.91
Overall satisfaction	4.67	3.91

Table 2. *Between-Group Comparison of Mean Perception Scores Using Welch's t-Test.*

Domain	AI (n=96) Mean (SD)	Non-AI (n=88) Mean (SD)	Mean diff (AI–Non-AI)	95% CI	p-value	Hedges g
Case clarity	4.33 (1.11)	3.91 (1.79)	0.42	−0.01 to 0.86	0.0582	0.29
Understanding of DDI mechanisms	4.50 (1.12)	3.91 (1.79)	0.59	0.15 to 1.03	0.0089	0.40
Confidence in clinical decision-making	4.33 (0.75)	3.73 (1.72)	0.61	0.21 to 1.00	0.0028	0.46
Appropriate challenge level	4.50 (0.77)	3.91 (1.79)	0.59	0.18 to 1.00	0.0050	0.43
Overall satisfaction	4.67 (0.75)	3.91 (1.79)	0.76	0.35 to 1.17	0.0004	0.56

Table 3. *Student Perceptions of Generative AI Use Among AI-Assisted Participants.*

Domain	n	Mean (SD)	Median	IQR
AI usefulness	96	3.83 (1.68)	5.0	2.0–5.0
Ease of use	96	3.83 (1.68)	5.0	2.0–5.0
Future intention to use AI	96	4.33 (0.95)	5.0	3.0–5.0

Table 4. *Composite Perception Scores by Study Group.*

Group	n	Mean (SD)
AI-assisted	96	4.47 (0.85)
Non-AI	88	3.87 (1.77)

Table 5. *Objective Competence Scores by Study Group.*

Domain	AI-Assisted (n=96) Mean (SD)	Non-AI (n=88) Mean (SD)	Mean Difference (AI–Non-AI)	95% CI	p-value	Hedges g
DDI Identification	8.72 (1.35)	8.11 (1.62)	0.61	0.16 to 1.06	0.008	0.40
Mechanism Assessment	8.85 (1.21)	8.09 (1.70)	0.76	0.29 to 1.23	0.002	0.47
Clinical Management	8.64 (1.29)	8.02 (1.58)	0.62	0.19 to 1.05	0.005	0.43
Justification Clarity	8.78 (1.18)	8.17 (1.64)	0.61	0.19 to 1.03	0.004	0.42
Composite Competence Score	8.75 (1.09)	8.10 (1.46)	0.65	0.27 to 1.03	0.001	0.45

Statistically significant differences were observed in four of the five domains. Compared with the non-AI group, the AI-assisted group reported significantly higher scores for:

- Understanding of DDI mechanisms ($p = 0.0089$)
- Confidence in clinical decision-making ($p = 0.0028$)
- Appropriate challenge level ($p = 0.0050$)
- Overall satisfaction ($p = 0.0004$)

The difference in case clarity approached statistical significance ($p = 0.0582$).

Effect sizes ranged from small to moderate (Hedges $g = 0.29$–0.56), with the largest effect observed for overall satisfaction ($g = 0.56$). These findings indicate a consistent pattern favoring the AI-assisted condition across multiple perception domains.

Perceptions of Generative AI Use:

Students' perceptions of generative AI use are presented in Table 3. Among AI-assisted participants, perceptions were generally favorable.

Mean scores indicated positive views regarding AI usefulness ($M = 3.83$, $SD = 1.68$) and ease of use ($M = 3.83$, $SD = 1.68$). Intention to use AI tools in future assessments demonstrated the highest mean score ($M = 4.33$, $SD = 0.95$). Median scores of 5 across all three items suggest strong agreement among many participants despite variability in responses.

Composite Perception Score:

A composite perception score was calculated by averaging the five primary perception domains for each participant.

As shown in Table 4, the AI-assisted group demonstrated a significantly higher composite score ($M = 4.47$, $SD = 0.85$) compared with the non-AI group ($M = 3.87$, $SD = 1.77$). This difference was statistically significant ($p = 0.005$) and associated with a moderate effect size (Hedges $g = 0.43$).

Objective Competence Outcomes:

Objective competence was evaluated using the structured analytic rubric across four predefined domains: (1) identification of clinically significant DDIs, (2) assessment of interaction severity and mechanisms, (3) clinical decision-making and management selection, and (4) clarity and justification of therapeutic reasoning. Domain scores were aggregated to generate a composite competence score.

Inter-rater reliability for rubric scoring demonstrated good agreement between blinded evaluators (intraclass correlation coefficient [ICC] = 0.82), indicating consistent scoring procedures.

Interpretation:

Across all four competence domains, the AI-assisted group demonstrated significantly higher mean rubric scores compared with the non-AI group. Effect sizes ranged from small to moderate (Hedges g = 0.40–0.47), indicating a consistent advantage associated with AI-assisted case completion.

The largest observed difference was in assessment of interaction mechanisms (g = 0.47), suggesting that AI support may have particularly strengthened mechanistic reasoning and interpretive analysis rather than simple identification alone.

The composite competence score was also significantly higher in the AI-assisted group (p = 0.001; g = 0.45), indicating an overall improvement in objective performance.

Qualitative Results:

Thematic analysis of open-ended responses identified three dominant themes describing students' experiences with the case-based DDI assessment (Figure 2).

1. Clinical Relevance and Case Realism:

Students emphasized the authenticity of the scenarios, particularly the inclusion of polypharmacy and high-risk interactions. Many described the cases as reflective of real-world pharmacy practice and appropriate for final-year training.

2. Generative AI as a Cognitive Support Tool:

Participants in the AI-assisted group reported that generative AI helped structure clinical thinking, clarify interaction mechanisms, and support management decisions. AI was described as a cognitive aid that enhanced explanation and reassurance rather than replacing independent clinical judgment.

3. Need for Clearer Instructions and Additional Clinical Detail:

Across both groups, students suggested improvements in assessment instructions, response expectations, and inclusion of additional contextual data such as laboratory values. This feedback related to assessment design rather than AI use.

Overall, qualitative findings provide contextual depth to the quantitative results, indicating that AI-assisted students experienced enhanced reasoning support and confidence while maintaining independent clinical engagement.

Integration of Qualitative Findings:

Collectively, the qualitative findings provide important context for the quantitative results. While both groups reported positive engagement with the assessment, the qualitative data reveal that generative AI influenced how students approached and reflected on complex clinical reasoning tasks. Students did not report overreliance on AI; rather, AI was viewed as an educational scaffold that supported explanation, validation, and confidence. Additionally, qualitative responses may have been influenced by social desirability bias, whereby students provided favorable perceptions of AI use because they believed such responses aligned with researcher or educational expectations.

These insights reinforce the interpretation that generative AI can enhance the learning experience when integrated thoughtfully into case-based assessments, particularly when paired with clear instructional guidance and faculty oversight.

Discussion.

This study examined the educational impact of a generative AI–assisted drug–drug interaction (DDI) alert tool on pharmacy students' perceived competence and learning experiences when managing complex clinical cases. By integrating quantitative comparisons with qualitative insights, the findings provide empirical evidence on how generative AI may support clinical reasoning and assessment experiences within undergraduate pharmacy education.

In addition to higher perceived competence, objective rubric-based evaluation demonstrated significantly higher performance among AI-assisted students across all competence domains. These findings indicate that AI-assisted support was associated not only with enhanced self-reported confidence but also with measurable differences in clinical reasoning performance. Notably, the largest effect was observed in mechanistic interpretation of drug–drug interactions, suggesting that AI may serve as a scaffold for deeper pharmacological reasoning rather than merely supporting surface-level identification of interactions. This pattern aligns with the interpretation that generative AI functions as a structured cognitive aid, helping students organize and articulate therapeutic reasoning in complex cases.

Quantitative results demonstrated that students in both AI-assisted and non-AI groups reported generally positive perceptions across all evaluated domains, indicating that the case-based assessment design was appropriate for final-year pharmacy students and aligned with curricular expectations. Students who had access to generative AI reported significantly higher scores in four of the five domains, including understanding of DDI mechanisms, confidence in clinical decision-making, perceived appropriateness of challenge level, and overall satisfaction (Table 2 and Figure 1).

The observed effect sizes ranged from small to moderate, which is consistent with prior educational research examining decision-support tools designed to augment, rather than replace, clinical reasoning [12-15]. These findings suggest that generative AI contributes meaningfully to students' learning experiences by enhancing interpretive confidence and engagement with complex clinical tasks. The absence of a statistically significant difference in perceived case clarity indicates that AI support primarily influenced reasoning and decision-making processes rather than basic comprehension of case content.

Qualitative analysis provided important explanatory context for the quantitative results. Students consistently emphasized the clinical relevance and realism of the assessment cases, particularly in relation to polypharmacy and high-risk DDIs. This finding reinforces prior evidence supporting the use of authentic, case-based assessments to strengthen applied competence in pharmacy education [16-18].

A central qualitative theme was the perceived role of generative AI in supporting clinical reasoning. Students in the AI-assisted group described AI as a cognitive aid that helped structure thinking, clarify interaction mechanisms, and validate management decisions. Importantly, AI was not perceived as

replacing clinical judgment. Instead, students viewed AI as a supportive resource that enhanced explanation and reassurance during complex decision-making (Figure 2). This aligns with prior studies demonstrating that generative AI tools can enhance contextual understanding and explanatory depth when used as adjuncts to human reasoning rather than autonomous decision-makers [19-21].

Concerns commonly raised in the literature regarding overreliance on AI and erosion of critical thinking were not substantiated in this study [22-24]. Students did not report diminished independence; rather, AI was perceived as an educational scaffold that supported reflective reasoning and confidence without undermining professional judgment.

The third qualitative theme highlighted the need for clearer instructions and additional case detail, such as laboratory values and explicit expectations regarding response depth. This feedback was expressed across both groups and was related to assessment structure rather than AI exposure, underscoring that effective instructional design remains essential regardless of technological augmentation.

Although no systematic audit of AI-generated inaccuracies was performed, some students reported encountering incomplete or overly generalized interaction explanations during case completion. In several reflections, students described independently verifying AI-generated recommendations against their pharmacotherapy knowledge before finalizing management decisions. These observations reinforce the importance of maintaining critical appraisal and professional oversight when integrating generative AI into pharmacy education.

When considered together, the quantitative and qualitative findings suggest that generative AI primarily influenced how students approached and reflected on complex clinical reasoning tasks rather than simply improving surface-level perceptions. While quantitative results demonstrated higher perceived competence and satisfaction among AI-assisted students, qualitative findings revealed that AI supported reasoning clarity, confidence, and validation without fostering dependence.

This convergence supports the interpretation of generative AI as an educational scaffold, consistent with emerging evidence that AI tools are most effective when embedded within structured pedagogical frameworks and supported by faculty oversight [22-25].

Implications for Pharmacy Education.

The findings have several implications for pharmacy education. First, generative AI–assisted tools may be strategically integrated into case-based assessments to support students' reasoning and confidence when managing complex DDIs. Second, clear guidance on appropriate AI use is essential to mitigate risks associated with automation bias and to reinforce professional accountability [26-28].

Faculty development and institutional policies will play a critical role in ensuring that generative AI is used ethically, transparently, and pedagogically, particularly as adoption increases across health professions education [29-31]. Rather than positioning AI as a standalone solution, educators should embed AI tools within structured learning activities that emphasize justification, reflection, and clinical reasoning.

Limitations and Future Directions.

Several limitations should be considered when interpreting these findings. First, although objective differences in rubric-based competence were observed, the comparative cross-sectional design and convenience-based group allocation preclude definitive causal inference. While both groups were drawn from the same academic cohort, completed identical clinical cases, and demonstrated no statistically significant baseline differences in demographic or academic characteristics, unmeasured factors—such as digital literacy, learning preferences, or informal familiarity with AI systems—may still have influenced performance outcomes.

Second, performance was evaluated within a simulated, case-based assessment environment rather than real-world clinical practice. Although the assessment scenarios were designed to reflect authentic pharmacy workflows involving polypharmacy and clinically significant DDIs, they cannot fully replicate the complexity, time pressures, interprofessional communication, and contextual uncertainty encountered in actual healthcare settings. Consequently, the extent to which AI-assisted improvements translate into sustained clinical performance during experiential training or professional practice remains uncertain.

Third, the study was conducted within a single institutional and educational context, which may limit generalizability to pharmacy programs with different curricular structures, assessment models, technological policies, or student populations. Multi-institutional investigations would strengthen external validity and provide broader insight into contextual influences affecting AI integration within pharmacy education.

Fourth, although the structured analytic rubric demonstrated acceptable inter-rater reliability, rubric-based evaluation may not fully capture all dimensions of higher-order clinical reasoning, particularly adaptive judgment under uncertainty, nuanced prioritization, or real-time therapeutic decision-making. Future research may benefit from incorporating objective structured clinical examinations (OSCEs), simulation-based performance assessments, or longitudinal measures of clinical competence.

Another limitation relates to variability in students' prompt-engineering abilities. Because participants generated their own AI queries without standardized prompting protocols, differences in how students formulated prompts may have influenced the quality, specificity, and clinical relevance of AI-generated outputs. Consequently, part of the observed performance differences may reflect variability in prompt-construction skills in addition to AI-assisted reasoning itself. Although the absence of standardized prompts was intentional to preserve authentic clinical reasoning processes, future studies should examine how prompt quality influences educational outcomes and whether structured prompting guidance improves consistency of AI-supported learning.

Additionally, although evaluators were blinded to group allocation, the possibility of residual detection bias cannot be entirely excluded. AI-assisted responses may have exhibited recognizable linguistic structures or explanatory patterns that could indirectly suggest AI involvement despite anonymization procedures. To minimize this risk, responses were evaluated

using predefined rubric criteria emphasizing clinical reasoning and therapeutic justification rather than writing style alone.

Finally, although students generally described AI as a supportive educational scaffold rather than a replacement for independent reasoning, the study design did not formally assess automation bias, long-term retention of reasoning skills following AI withdrawal, or the extent to which students critically verified AI-generated recommendations. Furthermore, qualitative reflections may have been influenced by social desirability bias, whereby participants expressed favorable perceptions of AI use because they believed such responses aligned with educational or researcher expectations.

Future research should employ randomized or quasi-experimental designs, longitudinal follow-up, and multimodal performance metrics to evaluate the durability, transferability, and educational sustainability of AI-assisted learning effects. Additional investigation into faculty preparedness, institutional governance frameworks, ethical implementation strategies, and structured prompting protocols will be essential to support responsible and pedagogically sound integration of generative AI within pharmacy education [32-34].

Conclusion.

This study demonstrated that the use of a generative AI-assisted DDI support tool was associated with significant improvements in pharmacy students' objective competence, confidence, and overall assessment experience when managing complex medication-related clinical scenarios. Students who received AI assistance achieved higher performance across DDI identification, mechanism assessment, clinical management, and therapeutic justification, while qualitative findings indicated that AI was perceived as a cognitive support tool that facilitated reasoning and decision-making without replacing independent clinical judgment.

The findings support the thoughtful integration of generative AI into pharmacy education as an educational scaffold that complements traditional teaching and case-based learning approaches. Nevertheless, effective implementation requires structured guidance, critical appraisal skills, and ongoing faculty oversight to ensure responsible use and maintain professional accountability. Future research should explore the long-term impact of AI-assisted learning, its transferability to real-world clinical practice, and optimal strategies for sustainable curricular integration.

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Appendix A.

Analytic Rubric for Evaluation of DDI Case Responses:

Each domain was scored on a 0–10 scale using explicit performance descriptors.

Domain 1: Identification of Clinically Significant DDIs (0–10).

Score Range	Descriptor
0–2	Fails to identify major clinically significant interaction(s)
3–5	Identifies interaction(s) but misses clinical significance or relevance
6–8	Correctly identifies major interaction(s) with minor omissions
9–10	Accurately identifies all clinically significant interactions with clear prioritization

Domain 2: Assessment of Interaction Severity and Mechanisms (0–10).

Score Range	Descriptor
0–2	No mechanistic explanation or incorrect reasoning
3–5	Partial or superficial explanation of mechanism
6–8	Accurate explanation of pharmacokinetic or pharmacodynamic mechanism
9–10	Comprehensive mechanistic explanation integrated with clinical context

Domain 3: Clinical Decision-Making and Management Strategy (0–10).

Score Range	Descriptor
0–2	Inappropriate or unsafe recommendation
3–5	Partially appropriate management plan
6–8	Clinically appropriate management strategy
9–10	Evidence-based, context-sensitive, patient-specific recommendation

Domain 4: Justification and Clarity of Therapeutic Reasoning (0–10)

Score Range	Descriptor
0–2	No justification provided
3–5	Minimal or unclear reasoning
6–8	Clear justification supported by rationale
9–10	Well-structured, logically coherent, and clinically grounded explanation

Appendix B.

Standardized AI Access Protocol.

Generative AI Tool and Access Conditions:

Students in the AI-assisted group were provided access to a generative artificial intelligence tool powered by a large language model (ChatGPT, GPT-4 architecture, OpenAI) through the standard web-based interface. Access was provided during the scheduled assessment period only. Students used their own devices under supervised academic conditions. The AI tool was used exclusively as a decision-support aid during completion of the case-based DDI assessment. Internet searches outside the AI platform were not permitted.

Standardized Instructions Provided to Students:

To ensure consistency of AI use across participants, the following written guidance was provided:

1. The AI tool may be used to assist in identifying potential drug–drug interactions.
2. Students must independently interpret AI-generated information in the context of the provided case.
3. Final answers must reflect the student's own clinical reasoning and justification.
4. AI-generated text must not be copied verbatim into the submitted response.
5. Students are responsible for verifying the clinical appropriateness of any AI-generated suggestions.

Students were reminded that generative AI systems may produce incomplete or inaccurate information and that professional accountability remains with the user.

Scope of Permitted AI Queries:

Students were informed that AI queries may include:

- Identification of potential interactions between listed medications
- Explanation of pharmacokinetic or pharmacodynamic mechanisms
- Assessment of clinical severity and risk stratification
- Suggested evidence-based management strategies

Students were encouraged to frame queries clearly and to refine prompts iteratively if clarification was needed.

No standardized or pre-scripted prompts were supplied to avoid constraining authentic clinical reasoning processes.

Assessment Integrity Safeguards:

To preserve assessment validity:

- All students completed identical case scenarios.
- The AI-assisted group had access to the AI tool only during case completion.
- Submitted responses were evaluated solely on the basis of rubric criteria.
- AI outputs were not graded directly; only student-submitted responses were assessed.
- Evaluators were blinded to group allocation.

Students were informed that AI assistance would not automatically result in higher scores and that clear justification of reasoning was required to achieve high rubric ratings.

Data Handling and Ethical Considerations:

No identifiable patient information was entered into the AI system. All clinical scenarios were fictional and developed for educational purposes.

Students were informed of the experimental nature of AI-assisted assessment and provided informed consent prior to participation. Participation did not affect academic grading outside the study context.

Rationale for AI Integration:

The AI tool was integrated as a structured cognitive support mechanism rather than an autonomous decision-maker. The protocol was designed to:

Encourage critical appraisal of AI-generated information
Maintain student accountability for clinical judgment
Minimize automation bias
Preserve assessment rigor

Appendix C.

Perceived Competence and Assessment Experience Scale.

Response Format:

All items were measured using a 5-point Likert scale:
1 = Strongly disagree
2 = Disagree
3 = Neutral
4 = Agree
5 = Strongly agree
Higher scores indicate stronger agreement with the stated item.

Core Perception Items (Administered to All Participants):

Participants in both AI-assisted and non-AI groups responded to the following five items:

1. The case scenarios were clearly presented.
2. I understood the mechanisms underlying the identified drug–drug interactions.
3. I felt confident in my clinical decision-making.
4. The level of challenge was appropriate for my training level.
5. I was satisfied with the overall assessment experience.

These items were designed to evaluate perceived clarity, mechanistic understanding, clinical confidence, appropriateness of difficulty, and overall satisfaction with the assessment.

AI-Specific Perception Items (AI-Assisted Group Only):

Participants in the AI-assisted group additionally responded to the following items evaluating their experience with the generative AI tool:

6. The AI tool was useful in supporting my clinical reasoning.
7. The AI tool was easy to use.
8. I would consider using similar AI tools in future clinical assessments.

These items assessed perceived utility, usability, and future behavioral intention regarding AI-assisted learning.

Composite Score Calculation:

The primary composite perception score was calculated by computing the mean of Items 1–5 for each participant. Higher composite scores reflect more positive perceived competence and assessment experience.

AI-specific items (Items 6–8) were analyzed descriptively and were not included in the primary composite perception score.

Appendix D.

Qualitative Coding and Thematic Analysis Framework.

Analytical Approach:

Qualitative responses were analyzed using reflexive thematic analysis through the following steps:

1. Familiarization with data via repeated reading.
2. Independent open coding by two researchers.
3. Code comparison and reconciliation through consensus discussion.
4. Grouping of codes into categories.
5. Development and refinement of overarching themes.
6. Maintenance of an audit trail documenting analytic decisions.

Examples of Initial Codes:

- "Realistic clinical scenario"
- "Helped organize my thoughts"
- "Clarified interaction mechanism"
- "Provided reassurance"
- "Wanted more lab values"
- "Instructions not detailed enough"

Final Themes

Theme 1: Clinical Relevance and Case Realism

Participants described scenarios as authentic and aligned with real-world pharmacy practice.

Theme 2: AI as a Cognitive Support Tool

AI was perceived as structuring reasoning, clarifying mechanisms, and reinforcing management decisions without replacing independent judgment.

Theme 3: Need for Clearer Assessment Guidance

Students suggested improvements in instructions and inclusion of additional clinical data.

Trustworthiness Measures

- Independent dual coding
- Investigator triangulation
- Audit trail documentation
- Reflexive memoing

Appendix E.

Baseline Participant Characteristics by Study Group.

Table E1. Baseline Characteristics

Characteristic	AI-Assisted (n = 96)	Non-AI (n = 88)	p-value
Mean age, years (SD)	23.8 (0.9)	23.7 (1.0)	0.48
Female, n (%)	62 (64.6%)	55 (62.5%)	0.77
Mean GPA (SD)	4.21 (0.32)	4.18 (0.35)	0.54
Prior AI exposure, n (%)	28 (29.2%)	24 (27.3%)	0.79

Statistical Notes

- Independent samples t-tests were used to compare continuous variables (age, GPA).
- Chi-square tests were used to compare categorical variables (sex, prior AI exposure).

No statistically significant baseline differences were observed between groups (all $p > 0.05$).