Uncertainty Visualization in Medical Education: Utilizing Novel Teaching Technologies to Enhance Clinical Decision-Making

A.-K. Bernards[1], A. Pippow[1], T. Lang[1] & C. Gillmann[1]

[1]Fraunhofer Institute for Applied Information Technology FIT

Abstract

Uncertainty is an inherent aspect of medical decision-making, influencing diagnostics, treatment planning, and prognosis. While uncertainty visualization can aid clinicians in interpreting probabilistic data and supporting shared decision-making with patients, traditional medical education often overlooks data interpretation and visualization training. This gap can hinder clinicians' ability to navigate and communicate complex medical data, potentially affecting patient care.

To address this challenge, we developed a structured course that integrates new technologies, hybrid learning models, and practical visualization tools based on generative AI to teach uncertainty visualization effectively. By equipping clinicians with these skills, our approach aims to enhance evidence-based decision-making, improve communication of uncertain data, and ultimately foster better clinical outcomes.

CCS Concepts

• ***Social and professional topics*** $\rightarrow$ ***Adult education; Information technology education;*** • ***Human-centered computing*** $\rightarrow$ ***Visualization design and evaluation methods;***

1. Introduction

Uncertainty is an intrinsic aspect of medical decision-making, permeating diagnostics, treatment planning, and prognosis, and is listed as one of ten open problems in medical visualization [GSG*21].

Physicians routinely navigate complex clinical scenarios where data is incomplete, ambiguous, or probabilistic, making definitive statements often unattainable [BYK19]. Embracing and effectively communicating uncertainty is essential for evidence-based practice, enabling clinicians to make informed decisions while managing patient expectations appropriately.

Visualization of uncertain data plays a critical role in this context. By transforming complex statistical information into comprehensible visual formats, uncertainty visualization aids clinicians in interpreting probabilistic data and supports shared decision-making with patients [BYK19, SPS11, GSWS21].

Despite its importance, traditional medical education frequently overlooks training in data interpretation and visualization, particularly concerning uncertain or probabilistic information [WGKH21]. This educational gap can hinder clinicians' ability to fully grasp and convey the nuances of medical data, potentially impacting patient outcomes. Building on the critical importance of uncertainty visualization in medical decision-making and the challenges identified in interpreting uncertain data, we have deliberately designed and structured a course to address fundamental and practical aspects essential for clinicians.

Tackling these challenges with a cutting-edge teaching approach, this paper explores the integration of new technologies, hybrid learning models, and individualized educational approaches to enhance the teaching of uncertainty visualization in medical curricula. By leveraging visualization tools and innovative pedagogical strategies, we aim to equip future clinicians with the competencies to interpret and communicate uncertain data effectively, thereby improving clinical decision-making and patient care.

Therefore, this paper provides a comprehensive and literature-based exploration of recent advances in technologies designed to improve instructional approaches to uncertainty visualization for clinicians. In addition, it contributes to a discussion on how to design effective learning modules on uncertainty visualization.

2. Importance of Uncertainty Visualization for Clinicians and Medical Personnel

Uncertainty visualization is the graphical representation of uncertainty in data or models to help users understand the reliability and variability of the information. It enhances decision-making by ex-

DOI: 10.2312/eved.20251022

plicitly showing the confidence, ambiguity, or potential errors associated with data points, predictions, or outcomes [CHH*14].

Uncertainty influences various aspects of clinical decision-making, including interpreting diagnostic test results, assessing patient risk, and monitoring treatment outcomes. For instance, in breast cancer diagnosis, radiologists must interpret mammograms that may present ambiguous findings. They balance the risks of false positives, which can lead to unnecessary interventions, against false negatives, which may delay critical treatment [SPO18]. Misinterpreting uncertain data in such scenarios can have significant consequences for patient outcomes.

Assessing patient risk involves uncertainty as well. Clinicians use risk assessment tools that provide probabilistic estimates based on population data, which may not fully capture individual patient variations [CA12]. Monitoring treatment outcomes adds another layer of complexity, as patients may respond differently to the same treatment due to genetic, environmental, or lifestyle factors.

Recent studies have highlighted the adverse effects of inadequate handling of uncertain data in medical settings. Skeete et al. (2018) demonstrated that mismanagement of uncertainty in breast cancer diagnosis could lead to significant diagnostic errors, negatively impacting patient care [SPO18]. Another study emphasized that physicians often struggle with statistical concepts, leading to misinterpretation of diagnostic tests and risk estimates [GGKM*07]. These findings underscore the necessity for improved training in uncertainty visualization to mitigate errors stemming from miscommunication or misunderstanding of probabilistic information.

2.1. Unique challenges in visualizing medical uncertainty

Clinicians face unique challenges when interpreting visual data that convey uncertainty. Variability in patient responses, ambiguity in symptom presentation, and limitations in data quality complicate the decision-making process. Clinicians must make rapid yet accurate decisions, especially in high-pressure environments like emergency triage, where time constraints intensify the difficulty of processing uncertain information [PE17].

Traditional visualization techniques may not adequately convey the nuances of uncertainty, potentially leading to overconfidence in the data or misinterpretation. Gillmann et al. (2021) identified uncertainty visualization as one of the ten open problems in medical visualization, highlighting the need for advanced methods that can effectively represent uncertainty without overwhelming the clinician [GSG*21]. Developing such methods is critical for improving clinicians' ability to interpret uncertain data accurately and make informed decisions.

2.2. Example: Conditional probabilities in breast cancer diagnosis

The following scenario illustrates a critical challenge in medical decision-making as visualized in Figure 1.

"For women aged forty who participate in routine screenings, the probability of having breast cancer is 1%. If a woman has breast cancer, there is an 80% chance that she will receive a positive mammography result. Conversely, if a woman does not have breast cancer, there is a 9.6% chance that she will also receive a positive mammography result. If a woman in this age group receives a positive mammography result, what is the probability that she actually has breast cancer?"

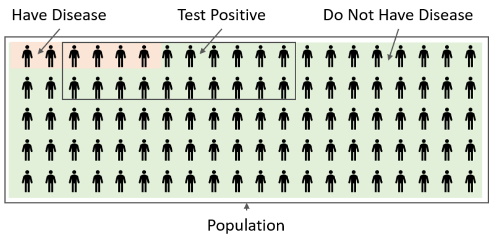

Figure 1: *An example of the proper visualization of conditional probabilities in the diagnosis of breast cancer from [OPH*16].*

This problem is frequently misunderstood due to confusion between statistical concepts, such as the difference between a test's accuracy and the actual likelihood of a condition. Here are two common errors:

- Overestimating Risk Based on Test Accuracy Many people assume that if a test is 80% accurate for detecting cancer, then a positive test result means there is an 80% chance the person has cancer. This ignores the fact that breast cancer is rare in this group, and the relatively high probability of false positives skews the result.
- Neglecting the Rarity of the Condition Another common mistake is to disregard the low prevalence of breast cancer (1%). While the test may be sensitive and specific, the rarity of the disease means that most positive results will actually occur in people who do not have breast cancer. This results in a much lower actual probability than intuition might suggest.

When accounting for the test's accuracy and the rarity of breast cancer in this population, the actual probability that a woman with a positive test result has breast cancer is far lower than expected—around 7.8%. This means that fewer than 1 in 10 women with a positive mammography result in this age group actually have the disease.

Although this seems to be a relatively easy problem, there is evidence that clinical personnel is often not capable of interpreting these results correctly [OPH*16]. This further highlights the need for a course on the visualization of uncertainty in medicine.

3. Novel Teaching Approaches

In this section, theoretical frameworks and concepts and their practical application to uncertainty visualization education are presented.

3.1. Hybrid learning

Hybrid learning, which combines online and face-to-face instruction, offers significant benefits for medical professionals who must balance clinical duties with ongoing education. This approach allows learners to access theoretical content and examples through online modules at their convenience, while in-person sessions focus on hands-on practice and group discussions to reinforce learning [CD04]. Studies have shown that hybrid learning can lead to improved knowledge retention and skill acquisition in medical education compared to traditional methods [LPZ*16].

By adopting a hybrid format, the course provides online modules as well as in-person sessions. The online modules provide interactive lectures, multimedia content, and virtual simulations that cover theoretical aspects of uncertainty visualization. Whereby the in-person sessions focus more on practical workshops, case-based discussions, and collaborative projects that enable learners to apply concepts in real-world scenarios. This blend of asynchronous and synchronous learning maximizes the efficient use of time for busy professionals.

3.2. Use of generative AI

Generative AI (genAI) has the potential to revolutionize medical education by creating personalized learning experiences. In the context of uncertainty visualization, AI can generate customized visualizations, interactive simulations, and adaptive learning content tailored to individual learner needs [WC18]. For example, AI-driven tools can simulate various sources of uncertainty in medical cases, allowing learners to practice interpreting and visualizing uncertain data across a range of clinical scenarios.

Application of genAI in this course includes the creation of personalized visualizations, as AI algorithms can create case-specific visual representations of uncertain data, enhancing comprehension. Additionally, it is used to help students complete tasks and prompts them to ask questions, as shown in figure 3.

By incorporating generative AI, the course can offer a more engaging and effective learning experience that adapts easily to each participant's skill level and supports the use of nudges.

3.3. Digital nudges

Another approach that we want to leverage for the course is digital nudges. Nudge theory, which involves subtle interventions to influence behavior positively, can be effectively applied in educational contexts to enhance engagement and learning outcomes [TS09]. Digital nudges in this course include *reminders*, *gamification* as well as *hints and feedback*. Automated prompts, that serve as reminders encourage learners to complete modules or participate in discussions. Quizzes and tasks in a game-like manner, provide appropriate challenges. Real-time assistance and constructive feedback on common visualization challenges support learners while working on their own. All of these methods help provide a more adaptive learning environment, supporting students' individual needs.

3.4. Self-directed learning

Recognizing the need for flexibility, the course incorporates self-directed learning options. Providing access to resource libraries, case studies, and optional modules allows learners to delve deeper into specific visualization techniques at their own pace. Self-paced learning is particularly beneficial for medical personnel who must fit education around unpredictable patient care schedules [MCYV*10]. The benefits of self-directed learning include flexibility, autonomy, and more thorough learning [AB15, HWL24]. As learners can access materials anytime, accommodating shift work and varying availability, have control over their learning journey, focusing on areas most relevant to their practice. Additionally, they get opportunities for in-depth exploration to foster a deeper understanding of complex concepts.

4. Course Content

In the following, we will describe our course content in general, consisting of three modules. Following that, we will demonstrate an explicit implementation of one of these parts, namely uncertainty visualization approaches, using novel teaching methods.

4.1. Scope of the course

Understanding the nature of uncertainty is the foundational step toward effective interpretation and communication. By exploring "What is uncertainty?" and "How can it be classified?", therefore, the course provides participants with a comprehensive framework to identify and categorize different types of uncertainty, such as aleatory (inherent variability) and epistemic (lack of knowledge) uncertainty. This understanding is crucial because recognizing the source and type of uncertainty can significantly influence clinical judgments and patient management strategies [GGKM*07].

The three modules are conceptualized for two days and will utilize a Learning Management System (LMS) for distribution of online materials and access to the genAI assistant.

Module	Content
1	Sources of Uncertainty in the Medical Context
2	Uncertainty Visualization Approaches
3	A Workflow to Apply Uncertainty Visualization

Table 1: *The three building blocks of the presented course.*

4.1.1. Sources of uncertainty in the medical context

First, the course will give a clear definition of uncertainty as the term is often used ambiguously. Therefore, we will make use of the taxonomy of uncertainty events by Gillmann et al. [GMR*23] and will instantiate them to the medical context.

Focusing on sources of uncertainty specific to clinical decision-making ensures that the content is directly applicable to medical practice. Clinicians often encounter uncertainties arising from ambiguous symptoms, variable patient responses, diagnostic test limitations, and probabilistic risk assessments. The course equips medical personnel with the skills to navigate complex clinical scenarios more effectively by addressing these specific sources.

4.1.2. Uncertainty visualization approaches

Given the unique challenges, clinicians face in interpreting visual data that convey uncertainty, it is imperative to provide them with effective visualization and communication strategies [SBR*24, CMKF21]. Traditional methods may not adequately represent the nuances of uncertain information, potentially leading to misinterpretation or overconfidence in the data. This section of the course introduces advanced visualization techniques tailored to medical contexts, enabling clinicians to better comprehend and communicate uncertain data [LSB*21].

Therefore, we will utilize the visualization approaches provided by Jena et al. (2020) [JED*20]. Their interactive browser provides uncertainty visualization approaches that can be filtered by different categories and reviewed interactively.

4.1.3. A workflow to apply uncertainty visualization

As mentioned above, uncertainty visualization is one of the ten open problems in medical visualization, making it especially relevant to medical personnel [LSB*21]. Our course addresses this gap by teaching uncertainty visualization strategies, helping clinicians mitigate risks associated with diagnostic errors and treatment inefficiencies stemming from mismanaged uncertainty.

For practical use, however, it is essential to integrate uncertainty visualization into everyday clinical workflows. Clinicians often operate under time constraints and in high-pressure environments, where quick yet accurate decision-making is crucial. Therefore, this part of the course provides a structured workflow that guides clinicians on how to systematically incorporate uncertainty visualization into their decision-making processes.

By establishing a clear workflow, clinicians can standardize how they interpret uncertain data, leading to more consistent and reliable clinical judgments [MSH*23, MRP*24]. This approach also facilitates better communication within healthcare teams and with patients, as it provides a common framework for discussing uncertain information.

The rapidly evolving landscape of medical education necessitates the integration of new technologies and novel teaching methods to enhance learning outcomes, particularly in complex areas such as uncertainty visualization. By leveraging new approaches, like hybrid learning, generative AI, data-driven nudges, and self-directed learning, educational programs can provide medical professionals with flexible, personalized, and effective training that fits into their demanding schedules.

4.2. Implementation of novel teaching approaches for uncertainty visualization

In order to demonstrate the use of novel teaching approaches in the presented course, while respecting the page limit, we selected one module of the course. We will demonstrate the explicit implementation of this module, which is based on the didactic model of constructivist and active learning [Vyg78]. This means it is designed with evidence-based pedagogical strategies to enhance learning outcomes. For practical tasks, we apply the principles of Self-Determination Theory (SDT) to enhance student motivation [RD02, DR93]. Thus, adapting the difficulty of tasks to match the ability levels of learners, therefore providing challenges that are achievable yet stimulating. An overview of the whole module can be found in figure 2.

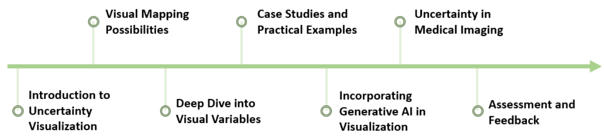

Figure 2: *Implementation of the second module (uncertainty visualization approaches) of the proposed course.*

We begin the chapter by *introducing the concept of uncertainty* in data to underscore its significance in analysis and interpretation. Additionally, there is a short introduction of generative AI to the learners. Teaching students about the inherent uncertainties arising from measurement errors, sampling variability, and model limitations is fundamental because it sets the foundation for all subsequent learning in this area. Emphasizing that all data contain uncertainty encourages students to approach data critically and thoughtfully. Including real-world applications, such as weather forecasting and medical diagnosis, serves to contextualize the abstract concept of uncertainty. By demonstrating how uncertainty visualization impacts decision-making processes in critical fields, we aim to increase student engagement and motivation. This approach aligns with the principles of relevance and contextual learning, which are known to enhance student interest and learning outcomes [HWL23, FS95, JSC22, KN13].

We introduce *generative AI* to expose students to cutting-edge technologies that shape the future of data visualization. Teaching about AI applications, such as data augmentation and automated visualization tools, prepares students for the evolving demands of the industry. Discussion of ethical considerations encourages students to critically evaluate the implications of using AI, fostering ethical awareness and responsibility. This component supports the development of digital literacy and critical thinking skills, which are increasingly important in today's data-driven world [WAvSR24, LPTM21]. As seen on Figure 3, we developed a custom GPTbot, based on OpenAI's ChatGPT, to guide students in their learning. The bot itself promts the students to ask questions, like "What insights can we draw from this chart?", supporting students in their initial exploration of visualizations, and supporting them in using the knowledge they have acquired. Additionally, we use this bot for solving tasks and getting practical insights, as described later on. The introduction is designed as an asynchronous chapter.

The next chapter covers various *visual mapping techniques* to provide students with a toolkit for effectively representing uncertainty in data visualizations. Teaching methods such as blurriness, transparency, color saturation, texture, and animation allow students to understand the strengths and limitations of each approach. This knowledge is essential for them to select the most appropriate techniques for different types of data and audiences. Within a synchronous interactive workshop, students are presented with interac-

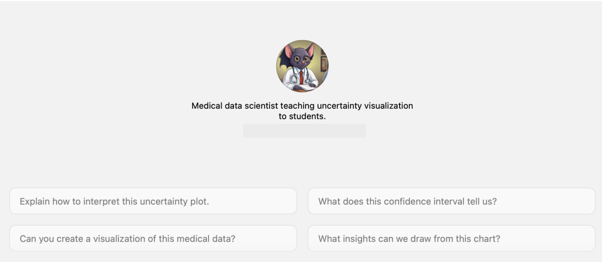

Figure 3: *CustomGPT Bot for Supporting Students in Learning Uncertainty Visualization.*

tive simulations in which they make use of visualization techniques to see their real-time effects on data representation. Studies have shown that interactivity can promote the selection, organization, and integration of relevant content, leading to a deeper understanding of the learning material [LOS14] and also enhancing memory and transfer performance [MC01, BPBH05]. By incorporating examples from bioinformatics and medical contexts, we help students see how these visual variables are applied in professional settings. This practical application supports the transfer of learning [JSC22] and demonstrates the real-world relevance of the content, which can enhance motivation and retention [FS95, MAL13].

This is followed by a deep dive into *visual variables*. Understanding these variables is critical for creating effective visualizations. Here, learners are presented with an asynchronous e-learning that they can engage with on their own. By exploring variables such as position, size, shape, color, and motion, we enable students to grasp how different graphical elements can encode information, including uncertainty. Teaching students how to select and manipulate these variables to represent uncertainty accurately promotes higher-order thinking skills. This section is designed to encourage critical analysis and problem-solving. By engaging with the material at a deeper level, via e-learning and different tasks, students can develop a more comprehensive understanding, which is essential for mastery of complex concepts [BPBH05].

Next, students should get a practical insight into *case studies*. Including case studies and practical examples from experts allows students to apply theoretical knowledge to real-world scenarios. By analyzing different visualization techniques used to represent uncertainty, students can evaluate the effectiveness of each method. This hands-on approach aligns with constructivist learning theories, where learners build new knowledge upon their existing understanding [Vyg78]. Active engagement with the material has been shown to improve learning outcomes and promote long-term retention [RSE*22]. Drawing on SDT, we promote autonomy by allowing students to make choices in their learning, such as selecting datasets for their projects and deciding on visualization techniques. While interactivity is beneficial, too high a level of learner control can lead to disorientation and cognitive overload [Swe88, SAK11]. We developed these tasks with autonomy in mind, while simultaneously providing guidance and structure, ensuring that students remain focused and engaged without becoming overwhelmed.

Thus, we begin with an exploratory stage where learners first independently attempt to create a visualization with the chatbot based on given example data. As we encourage autonomy, students can decide which dataset they want to choose or use their own dataset. For this example, data on systolic blood pressure was used, which is based on fictional and not on actual patient data. This dataset included information on the timestamp, the confidence, and the systolic blood pressure. This initial step allows students to engage with the task without prior instruction, fostering curiosity and active experimentation. For example, students may start by visualizing a dataset of systolic blood pressure over time with confidence intervals, as shown in Figure 4.

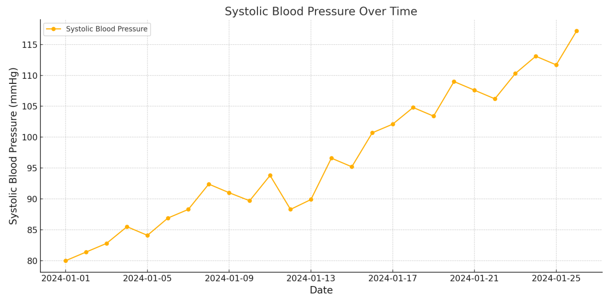

Figure 4: *First visualization output from the customized Chatbot for the Systolic Blood Pressure Dataset Over Time. Confidence Intervals are shown by Glyphs which is not optimal.*

Following their initial attempt, students transition to a guided refinement stage. Here, structured feedback from trainers and peers and tailored instructional support are provided to help learners refine their visualization skills. For example, students may revisit their previous visualization to address specific shortcomings, such as overly complex error bars or unclear labels. Using an improved visualization as a reference, such as Figure 5, instructors offer targeted guidance to illustrate best practices. The guided refinement

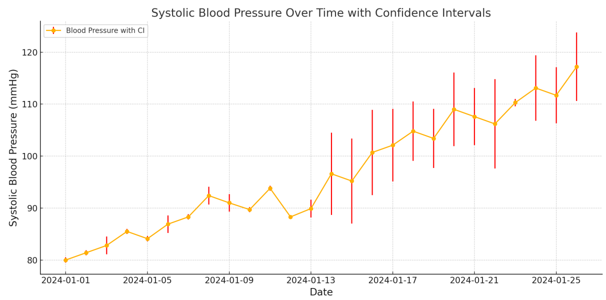

Figure 5: *Refined visualization of the Systolic Blood Pressure Dataset Over Time with explicitly requested confidence intervals.*

stage introduces intermediate complexity by aligning the feedback with the learner's experience. Novices may receive step-by-step instructions, while more advanced learners are encouraged to engage in open-ended revisions. The process is informed by design principles from Cognitive Load Theory, such as the Split-Attention Effect, where textual explanations are integrated with visual examples

Proceedings published by Eurographics - The European Association for Computer Graphics.

to minimize cognitive strain [MM04]. Additionally, the Guidance Fading Effect [SAK11] ensures that learners gradually take greater responsibility for their revisions as their expertise grows.

The final stage focuses on achieving proficiency in uncertainty visualization by synthesizing prior knowledge and demonstrating independence. In this stage, the students are tasked with creating advanced visualizations that explicitly address key uncertainties, such as those shown in Figure 6. This task involves integrating multiple elements—confidence intervals, significant uncertainties, and trends—into a cohesive representation. At this stage, learners are

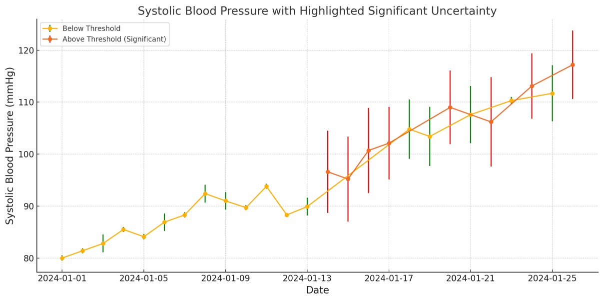

Figure 6: *Second adaptation of visualization of the systolic Blood Pressure over time with highlighted significant uncertainty.*

expected to critically justify their design choices with their peers. For example, they may analyze the trade-offs between simplicity and comprehensiveness or evaluate the effectiveness of highlighting significant uncertainties using distinct visual cues. The goal is to foster deep understanding and flexibility in applying the learned concepts to novel scenarios and collaborate with others to communicate uncertainty visualization effectively. Collaborative projects and peer feedback play a crucial role in refining visualization skills, that clinicians need. By working together on complex cases, learners benefit from diverse perspectives and collective problem-solving. Peer-based learning approaches, such guided discussions that we use here, encourage active engagement and deeper understanding [BM15].

From a cognitive load perspective [Swe88, SAK11], intrinsic load is reduced as learners draw on schemas developed during earlier stages. Extraneous load is minimized through streamlined feedback and focused task objectives, allowing learners to focus on the conceptual aspects of uncertainty visualization. Germane load is maximized by challenging learners to engage in higher-order thinking, such as self-explanation and critical evaluation [Swe88].

This stage not only consolidates learning, but also prepares students for real-world applications, where they must balance clarity, accuracy, and interpretability in their visualizations.

At this stage, students often encounter challenges such as unclear representations of uncertainty or overly cluttered designs. These challenges are crucial learning opportunities, prompting learners to reflect on their decisions and their impact on the clarity and accuracy of the visualization. From a cognitive load perspective, the intrinsic load is moderated by simplifying the initial task—such as limiting the number of variables—while the extraneous load is reduced through user-friendly interfaces. Germane load is encouraged by prompting students to articulate their reasoning and identify areas for improvement.

Focusing on *uncertainty in medical imaging* addresses a specific application area where precision is paramount. Teaching about the challenges and visualization techniques in this field highlights the importance of accurately representing uncertainty in high-stakes environments. This section emphasizes the societal relevance of the subject matter and encourages interdisciplinary learning. By understanding the impact of visualization techniques on patient outcomes, students can appreciate the broader implications of their work.

Assessment and feedback are integral components of the module. Students will get a final project, which requires them to apply what they have learned by creating a visualization that effectively communicates uncertainty. This task encourages the application of knowledge and critical thinking, aligning with Bloom's higher-order cognitive skills [Blo56]. This project will be reviewed by other students. Incorporating peer review allows students to engage in collaborative learning, providing and receiving feedback. This process can enhance understanding and promote reflective learning [RRM01]. Additionally, we provide quizzes and assignments for students to reinforce learning and improve long-term retention of knowledge [RSE*22]. These tools also provide opportunities for self-assessment and immediate feedback.

5. Discussion

Integrating uncertainty visualization including novel learning and teaching methods and generative AI into medical education holds considerable promise, yet requires careful critical reflection. The teaching methods presented in this module — ranging from interactive uncertainty visualization exercises to novel techniques like genAI-assisted data augmentation — must be evaluated against both educational theories and practical constraints. Prior research [MC01, BPBH05, LOS14] has demonstrated that interactivity and appropriate cognitive load management improve comprehension and long-term retention. However, emerging digital tools, especially generative AI, add new layers of complexity and necessitate discussions around accuracy, reliability, and ethical compliance.

A key challenge lies in the reliability and trustworthiness of AI-generated outputs. Generative AI models, particularly large language models, are susceptible to several well-documented pitfalls. Among these is the "garbage in, garbage out" phenomenon, a long-standing principle in data processing: if the input data are biased, incomplete, or erroneous, the output will reflect these deficiencies. AI-driven tools in medical education could thus propagate inaccurate information if the underlying training data or prompts are not rigorously vetted. Similarly, the phenomenon of "hallucination," in which AI models confidently produce false or nonsensical information, poses critical risks in a high-stakes domain like medicine [BG-MMS21]. Both educators and learners must be trained not only to use AI tools but also to critically assess the plausibility and validity of machine-generated content. For this course, we evaluated different fictional datasets and how the genAI analyzed the data. Thus far, all of the responses were correct. But as we only used small datasets for these training purposes, there might be hallucination or correctness issues that we have not yet found.

These issues intersect closely with ethical and legal considerations, particularly concerning data protection and privacy regulations. The European Union's General Data Protection Regulation (GDPR) imposes strict requirements on how personal data—including patient records—can be processed, stored, and shared. Incorporating generative AI that may rely on sensitive input data necessitates robust anonymization protocols, encryption, and stringent data governance [JIV19]. Ignoring these legal frameworks risks ethical violations and loss of trust, both among learners and patients. Therefore, no real data is used for this training purpose, and learners are made aware of these issues throughout the module.

Achieving high accuracy and reliability in AI-assisted educational resources also demands carefully curated training datasets and transparent model documentation. Approaches that include expert review, standardized evaluation metrics, and ongoing quality assessment can mitigate some of these risks [Top19]. However, implementing such safeguards is challenging in the dynamic environment of medical education, where resources are often limited and faculty may lack specialized AI literacy. This complexity underscores the importance of integrating foundational digital and data competencies into medical curricula at an international scale. Accrediting bodies and professional associations may need to establish guidelines for the responsible use of AI-driven educational tools, mirroring the calls for digital health literacy from organizations such as the World Health Organization.

Moreover, the principles of Self-Determination Theory [RD02] suggest that learners will be more motivated to engage with these tools if the learning experiences meet their needs for autonomy, competence, and social integration. Allowing learners to choose datasets that reflect their interests or clinical specialties, providing supportive feedback, and encouraging collaborative analysis can enhance motivation and perceived relevance. Equally important is avoiding cognitive overload [Swe88] by carefully scaffolding the introduction of new tools and concepts. Introducing generative AI and uncertainty visualization gradually, supported by interactive demonstrations and structured practice sessions, will likely enhance comprehension and reduce learner frustration.

Despite the potential benefits, the evaluation of these new teaching methods remains underdeveloped. While we have drawn on established pedagogical research to support the theoretical soundness of our approach, the actual impact of this integrative module on learners' performance, retention, and clinical reasoning skills must be empirically tested. Rigorous evaluation studies, employing both quantitative and qualitative methodologies, will be necessary to determine whether the integration of these novel learning and teaching methods truly enhances medical training. Such evaluations might involve pre- and post-course assessments, longitudinal tracking of clinical decision-making outcomes, and learner feedback on usability and trust. Due to page limitation, we focused on the module on uncertainty visualization approaches, disregarding the other two modules in this paper. These modules on "Sources of Uncertainty in the Medical Context" and "Workflow to Apply Uncertainty Visualization" were developed using the same theoretical approach we have used here. The overarching integration of all three modules provides an additional need for further didactical frameworks and techniques, that have been discussed in section 3. Here, e.g. digital nudges are used to remind students to finish tasks between modules and provide them with feedback. This supports students' self-directed learning process within the hybrid setting of the course. Thus, an evaluation of the course will include all three modules as a whole course, not just focusing on a single module.

Finally, embedding these educational strategies into medical training internationally requires careful alignment with curricular frameworks and recognition of regional variations in regulatory landscapes, resources, and learner needs. The relevance for the target audience, namely medical students, clinicians, and related healthcare professionals must be made explicit. This can be achieved by selecting contextually meaningful case studies, such as uncertainty in diagnostic imaging or variable treatment outcomes in population health. By showing how these concepts directly translate into improved diagnostic reasoning, patient communication, and evidence-based decision-making, the perceived value of the course increases, thereby improving its adoption and sustainability. But, the actual integration of this course into medical education, despite the high relevance, might differ due to various factors such as funding or perceived relevance of medical institutions.

6. Conclusion

By integrating modern technologies and evidence-based learning and teaching strategies, our learning modules aim to provide students with a comprehensive understanding of visual uncertainty. Focusing on the rationale behind each topic ensures the content is relevant, engaging, and pedagogically sound. Through this approach, we prepare students to apply these essential skills in their future careers, contributing to better decision-making processes in the medical field.

References

[AB15] ALIZADEH L., BARAT P.: Self-directed learning. In *Encyclopedia of the UN Sustainable Development Goals*. Springer, 2015. 3

[BGMMS21] BENDER E. M., GEBRU T., MCMILLAN-MAJOR A., SHMITCHELL S.: On the dangers of stochastic parrots: Can language models be too big? In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (2021), Association for Computing Machinery, pp. 610–623. 6

[Blo56] BLOOM B. S. (Ed.): *Taxonomy of Educational Objectives: The Classification of Educational Goals. Handbook I: Cognitive Domain.* Longmans, Green and Co., New York, 1956. 6

[BM15] BURGESS A., MELLIS C.: Peer learning: Enhancing student engagement through peer learning workshops. *Student Success 6*, 2 (2015), 91–99. 6

[BPBH05] BODEMER D., PLOETZNER R., BRUCHMÜLLER K., HÄCKER S.: Supporting learning with interactive multimedia through active integration of representations. *Instructional Science 33* (2005), 73–95. 5, 6

[BYK19] BRYAN J., YEUNG W., KUMBAMU A.: Uncertainty visualization as evidence-based medicine: towards a visual communication framework. *BMJ Evidence-Based Medicine 24*, 5 (2019), 163–167. 1

[CA12] COLLINS G. S., ALTMAN D. G.: An independent and external validation of qrisk2 cardiovascular disease risk score: a prospective open cohort study. *BMJ 344* (2012), e4181. 2

[CD04] COOK D. A., DUPRAS D. M.: A practical guide to developing effective web-based learning. *Journal of General Internal Medicine 19*, 6 (2004), 698–707. 3

[CHH*14] CHEN M., HAGEN H., HANSEN C. D., JOHNSON C. R., KAUFMAN A. E. (Eds.): *Scientific Visualization: Uncertainty, Multifield, Biomedical, and Scalable Visualization*. Springer, 2014. 2

[CMKF21] COX C. L., MILLER B. M., KUHN I., FRITZ Z.: Diagnostic uncertainty in primary care: what is known about its communication, and what are the associated ethical issues? *Family Practice 38*, 5 (2021), 654–668. 4

[DR93] DECI E. L., RYAN R. M.: Die selbstbestimmungstheorie der motivation und ihre bedeutung für die pädagogik. *Zeitschrift für Pädagogik 39*, 2 (1993), 223–238. 4

[FS95] FRYMIER A. W., SHULMAN G. M.: What's in it for me: Increasing content relevance to enhance students' motivation. *Communication Education 44*, 1 (1995), 40–50. 4, 5

[GGKM*07] GIGERENZER G., GAISSMAIER W., KURZ-MILCKE E., SCHWARTZ L. M., WOLOSHIN S.: Helping doctors and patients make sense of health statistics. *Psychological Science in the Public Interest 8*, 2 (2007), 53–96. 2, 3

[GMR*23] GILLMANN C., MAACK R. G. C., RAITH F., PÉREZ J. F., SCHEUERMANN G.: A taxonomy of uncertainty events in visual analytics. *IEEE Computer Graphics and Applications* (2023). 3

[GSG*21] GILLMANN C., SMIT N. N., GRÖLLER E., PREIM B., VILANOVA A., WISCHGOLL T.: Ten open challenges in medical visualization. *IEEE Computer Graphics and Applications 41*, 5 (2021), 7–15. 1, 2

[GSWS21] GILLMANN C., SAUR D., WISCHGOLL T., SCHEUERMANN G.: Uncertainty-aware visualization in medical imaging-a survey. In *Computer Graphics Forum* (2021), vol. 40, Wiley Online Library, pp. 665–689. 1

[HWL23] HUA M., WANG L., LI J.: The impact of self-directed learning experience and course experience on learning satisfaction of university students in blended learning environments: the mediating role of deep and surface learning approach. *Frontiers in Psychology 14* (2023). 4

[HWL24] HUA M., WANG L., LI J.: The impact of self-directed learning experience and course experience on learning satisfaction of university students in blended learning environments: the mediating role of deep and surface learning approach. *Frontiers in Psychology 14* (2024), 1278827. 3

[JED*20] JENA A., ENGELKE U., DWYER T., RAIAMANICKAM V., PARIS C.: Uncertainty visualisation: An interactive visual survey. In *2020 IEEE Pacific Visualization Symposium (PacificVis)* (2020), pp. 201–205. 4

[JIV19] JOBIN A., IENCA M., VAYENA E.: The global landscape of ai ethics guidelines. *Nature Machine Intelligence 1*, 9 (2019), 389–399. 7

[JSC22] JOHNSTON I. G., SLATER M., CAZIER J.-B.: Interdisciplinary and transferable concepts in bioinformatics education: Observations and approaches from a uk msc course. *Frontiers in Education 7* (2022), 826951. 4, 5

[KN13] KAHU E. R., NELSON K.: Student interest as a key driver of engagement for first-year students. *Studies in Higher Education 38*, 5 (2013), 758–773. 4

[LOS14] LEUTNER D., OPFERMANN M., SCHMECK A.: Lernen mit medien. In *Pädagogische Psychologie: mit Online-Materialien*, Seidel T., Krapp A., (Eds.), 6., vollständig überarbeitete auflage ed. Beltz, Weinheim, 2014, pp. 297–322. 5, 6

[LPTM21] LONG D., PADIYATH A., TEACHEY A., MAGERKO B.: The role of collaboration, creativity, and embodiment in ai learning experiences. In *Proceedings of the Creativity and Cognition Conference (C&C '21)* (2021), ACM, pp. 1–12. 4

[LPZ*16] LIU Q., PENG W., ZHANG F., HU R., LI Y., YAN W.: The effectiveness of blended learning in health professions: systematic review and meta-analysis. *Journal of Medical Internet Research 18*, 1 (2016), e2. 3

[LSB*21] LAWONN K., SMIT N. N., BÜSCHER M., PREIM B., EISEMANN E.: Ten open problems in medical visualization. *Computer Graphics Forum 40*, 6 (2021), 213–234. 4

[MAL13] MALAU-ADULI B. S., LEE A. Y. S.: Retention of knowledge and perceived relevance of basic sciences in an integrated case-based learning (cbl) curriculum. *BMC Medical Education 13*, 1 (2013), 139. 5

[MC01] MAYER R. E., CHANDLER P.: When learning is just a click away: Does simple user interaction foster deeper understanding of multimedia messages? *Journal of Educational Psychology 93*, 2 (2001), 390–397. 5, 6

[MCYV*10] MURAD M. H., COTO-YGLESIAS F., VARKEY P., PROKOP L. J., MURAD A. L.: The effectiveness of self-directed learning in health professions education: a systematic review. *Medical Education 44*, 11 (2010), 1057–1068. 3

[MM04] MAYER R. E., MORENO R.: Split-attention effect in multimedia learning: Evidence for dual processing systems in working memory. *Journal of Educational Psychology 96*, 3 (2004), 425–434. 6

[MRP*24] MAACK R. G., RAITH F., PÉREZ J. F., SCHEUERMANN G., GILLMANN C.: A workflow to systematically design uncertainty-aware visual analytics applications. *The Visual Computer* (2024), 1–14. 4

[MSH*23] MAACK R. G., SCHEUERMANN G., HAGEN H., PEÑALOZA J. T. H., GILLMANN C.: Uncertainty-aware visual analytics: scope, opportunities, and challenges. *The Visual Computer 39*, 12 (2023), 6345–6366. 4

[OPH*16] OTTLEY A., PECK E. M., HARRISON L. T., AFERGAN D., ZIEMKIEWICZ C., TAYLOR H. A., HAN P. K. J., CHANG R.: Improving bayesian reasoning: The effects of phrasing, visualization, and spatial ability. *IEEE Transactions on Visualization and Computer Graphics 22*, 1 (2016), 529–538. 2

[PE17] PATTERSON R. E., EGGLESTON R. G.: Systematic methodology for designing data visualizations to support cognitive work at different stages of decision making. *Journal of Cognitive Engineering and Decision Making 11*, 1 (2017), 42–62. 2

[RD02] RYAN R. M., DECI E. L.: Overview of self-determination theory: An organismic-dialectical perspective. In *Handbook of Self-Determination Research*, Deci E. L., Ryan R. M., (Eds.). University of Rochester Press, Rochester, NY, 2002, pp. 3–33. 4, 7

[RRM01] REINMANN-ROTHMEIER G., MANDL H.: Unterrichten und lernumgebungen gestalten. In *Pädagogische Psychologie*, Krapp A., Weidenmann B., (Eds.). Beltz Psychologie Verlags Union, Weinheim, 2001, pp. 601–646. 6

[RSE*22] ROELLE J., SCHWEPPE J., ENDRES T., LACHNER A., VON AUFSCHNAITER C., RENKL A., EITEL A., LEUTNER D., RUMMER R., SCHEITER K., VORHOLZER A.: Combining retrieval practice and generative learning in educational contexts: Promises and challenges. *Zeitschrift für Entwicklungspsychologie und Pädagogische Psychologie 54*, 4 (2022), 142–150. 5, 6

[SAK11] SWELLER J., AYRES P., KALYUGA S.: The guidance fading effect. In *Cognitive Load Theory*. Springer, 2011, pp. 117–130. 5, 6

[SBR*24] SIDDIQUI F., BROUWERS H. B., RUTTEN G.-J., HÖLLT T., VILANOVA A.: Effect of white matter uncertainty visualization in neurosurgical decision making. *IEEE Computer Graphics and Applications* (2024), 1–16. 4

[SPO18] SKEETE D. A., PALERMO C., O'DWYER P. J.: The impact of uncertainty in medical decision making: a breast cancer diagnosis case study. *Journal of Surgical Education 75*, 4 (2018), 885–890. 2

[SPS11] SPIEGELHALTER D. J., PEARSON M., SHORT I.: Visualizing uncertainty about the future. *Science 333*, 6048 (2011), 1393–1400. 1

[Swe88] SWELLER J.: Cognitive load during problem solving: Effects on learning. *Cognitive Science 12*, 2 (1988), 257–285. 5, 6, 7

[Top19] TOPOL E. J.: High-performance medicine: the convergence of human and artificial intelligence. *Nature Medicine 25* (2019), 44–56. 7

[TS09] THALER R. H., SUNSTEIN C. R.: *Nudge: Improving Decisions About Health, Wealth, and Happiness*. Penguin Books, 2009. 3

[Vyg78] VYGOTSKY L. S.: *Mind in Society: The Development of Higher Psychological Processes*. Harvard University Press, Cambridge, MA, 1978. 4, 5

[WAvSR24] WOLTERS A., ARZ VON STRAUSSENBURG A. F., RIEHLE D. M.: AI Literacy in Adult Education — A Literature Review. In *Proceedings of the 57th Hawaii International Conference on System Sciences (HICSS)* (2024), pp. 6888–6897. 4

[WC18] WARTMAN S. A., COMBS C. D.: Medical education must move from the information age to the age of artificial intelligence. *Academic Medicine 93*, 8 (2018), 1107–1109. 3

[WGKH21] WOOD G., GADD K., KAYE L. K., HULIN J.: Teaching and assessing data literacy in a medical school curriculum: a pilot study. *BMC Medical Education 21*, 1 (2021), 443. 1