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Intelligenza artificiale generativa nella formazione medico-umanistica: potenziale dei GPT personalizzati per l'analisi narrativa

Generative Artificial Intelligence in Medical-Humanistic Training: the Potential of Customised GPTs for Narrative Analysis

Enrique Alastor, Inmaculada Martínez-García*

Riassunto: Questo lavoro propone un GPT personalizzato per analizzare le narrazioni di pazienti e professionisti sanitari a fini didattici. Il modello integra la medicina narrativa di Charon, l'analisi narrativa di Labov, modelli di linguaggio generativo e il Design Universale per l'Apprendimento. È stato progettato un GPT che identifica i componenti comunicativi nelle narrazioni cliniche e offre un feedback formativo adattato a diversi livelli. Questo strumento può democratizzare l'accesso alla formazione nelle competenze narrative, personalizzare l'apprendimento secondo i principi dell'inclusione educativa e promuovere la riflessione critica sulle pratiche comunicative in ambito sanitario. I GPT personalizzati rappresentano un'innovazione pedagogica che, con la supervisione umana e le garanzie etiche, può integrare la formazione in medicina narrativa e contribuire a un'istruzione medica più inclusiva e incentrata sulla persona.

Parole–chiave: intelligenza artificiale generativa, medicina narrativa, formazione medica, GPT personalizzato.

* Università di Malaga (Spagna).

Abstract: This paper proposes a customised GPT for analysing narratives from patients and healthcare professionals for educational purposes. The model integrates Charon's narrative medicine, Labov's narrative analysis, generative language models, and Universal Design for Learning. A GPT is designed that identifies communicative components in clinical narratives and offers formative feedback adapted to different levels. This tool can democratise access to training in narrative skills, personalise learning according to principles of educational inclusion, and encourage critical reflection on communication practices in healthcare. Customised GPTs represent a pedagogical innovation that, with human supervision and ethical safeguards, can complement training in narrative medicine and contribute to a more inclusive and person-centred medical education.

Key–words: generative artificial intelligence, narrative medicine, medical education, customised GPT.

1. Introduction

Contemporary medical practice faces a fundamental tension between diagnostic-therapeutic technological advancement and the growing perception of depersonalization in healthcare delivery. This humanization crisis manifests in the reduction of patients to biomedical data, disregarding the narrative, contextual, and existential dimensions of illness experience. In 2001, Rita Charon conceptualized narrative medicine as medicine practiced with narrative competence to recognize, absorb, interpret, and be moved by stories of illness, establishing a framework that integrates medical humanities into clinical training (Charon, 2001). Narrative competence has been demonstrated as fundamental for practicing empathic and person-cantered medicine, with research confirming that narrative medicine improves empathy, strengthens communication, and contributes to professional identity formation among health science students (Milota *et al.*, 2019).

However, traditional teaching of these competencies faces significant limitations related to scarcity of professors specialized in medical humanities, unfavourable student-teacher ratios, and access barriers particularly pronounced in resource-limited contexts. Concurrently, large-scale language models have achieved remarkable capacities for generating and ana-

lysing text with linguistic complexity comparable to humans. ChatGPT, developed by OpenAI, demonstrated the ability to exceed passing thresholds on medical licensing examinations without specialized training (Kung *et al.*, 2023), and in recent studies, oncology patients rated chatbot responses as more empathetic than those of actual physicians (Chen *et al.*, 2025), underscoring both the potential of artificial intelligence and the critical need for human supervision to contextualize and personalize automated outputs.

This convergence raises a fundamental question: can personalized GPTs transform the teaching of narrative competencies in medicine, democratizing access to expert analysis while preserving the irreducibly human dimension of clinical care? This work adopts a critical-propositional position, rejecting both uncritical techno-optimism and technological luddism, to explore the conditions under which generative artificial intelligence can strengthen, rather than erode, medical-humanistic training.

Rita Charon's Narrative Medicine

Charon's narrative medicine framework establishes three core movements that structure how clinicians engage with patient stories. The first, attention, involves full presence through close reading and active listening.

Research by Langewitz *et al.* (2002) demonstrated that 78% of patients complete their initial account within two minutes when allowed to speak without interruption, evidencing the efficiency of narrative-centered approaches. The second movement, representation, involves description and interpretation of experiences through reflective writing and creative expression. Various studies have demonstrated that writing about traumatic experiences improves physiological parameters, including pulmonary function in asthma, decreased pathological activity in rheumatoid arthritis, and enhanced immune response to vaccination (Pennebaker, 2000).

The third movement, affiliation, refers to the formation of therapeutic alliances and empathic connections across differences, directly addressing the challenge of understanding perspectives of patients from cultural, socioeconomic, or experiential contexts different from the clinician's.

Other publications by Charon emphasize applications of racial justice, pandemic chronicles, and narrative fusion techniques, demonstrating the framework's continued evolution toward urgent contemporary problems (Charon *et al.*, 2021). However, implementation of narrative medicine in medical train-

ing faces structural barriers that limit its scalability and accessibility, generating educational gaps between institutions with different resource levels.

William Labov's Structural Narrative Analysis

Labov's narrative analysis model, originally developed for sociolinguistic studies of personal oral narratives, identifies six structural components present in well-formed accounts: abstract, orientation, complicating action, evaluation, resolution, and coda (Labov & Waletzky, 1967). This framework serves referential functions, anchoring stories in context, and evaluative functions, transmitting meaning. Applied to health narratives, it enables examination of how patients organize and present illness experiences. Identifying where the conflictive core of the patient's story lies, their evaluation of what is happening to them, and their current situation are valuable analytical skills for medical students (Patterson, 2013).

However, other scholars recognize limitations of the Labovian model, including potential exclusion of broader social contexts and demographic specificity challenges, requiring contextualized and critical application. Integration of this framework with artificial intelligence technologies could provide structural scaffolding for students to progressively develop narrative analysis capacity.

Universal Design for Learning

Universal Design for Learning (UDL), developed by CAST, offers practical pedagogical frameworks for inclusive medical education through three core principles: multiple means of representation, multiple means of action and expression, and multiple means of engagement (CAST, 2018). Recent work demonstrates successful applications of UDL in simulation-based education for health professions, creating environments that reduce barriers and foster psychological safety (Doyle *et al.*, 2025). Luke (2021) provides twelve evidence-based tips for implementing UDL in medical curricula, emphasizing the need to anticipate student diversity from initial curricular design.

In the context of medical-humanistic training, UDL justifies the use of artificial intelligence to adapt feedback to diverse learning styles, including students with dyslexia, non-native speakers of the language of instruction, or those with limited prior experience in literary and humanistic analysis.

This perspective reinterprets technology not as a threat to humanization, but as a potential tool for democratizing access to high-quality educational experiences (Alastor & Martínez-García, 2025).

Table 1. UDL Principles Applied to GPT-Mediated Medical-Humanistic Training.

UDL Principle	Barrier in Traditional Training	GPT-Mediated Solution	Reference
Multiple means of representation	Oral explanations only in face-to-face workshop	Text, visual examples, transcripts available 24/7	Luke, 2021
Multiple means of action/expression	Written assessment in single format	Options: written analysis, reflective audio, visual diagrams	Doyle *et al.*, 2025
Multiple means of engagement	Anxiety in group role-play	Private practice with AI reduces social pressure	Masters *et al.*, 2024
Personalization	Generic feedback due to teacher time constraints	Feedback adapted to individual level (basic/advanced)	—
Linguistic accessibility	Non-native students disadvantaged	Clarifications in native language, self-paced	Chen *et al.*, 2024

SOURCE: own elaboration.

2. Personalized GPTs as Narrative Tutors. Current Natural Language Processing Capabilities in Medicine

Natural language processing systems have demonstrated promising results in clinical narrative analysis. MedLEE (Medical Language Extraction and Encoding System) achieved 0.83 recall and 0.89 precision for UMLS concept

extraction from clinical documents (Friedman *et al.*, 2004), demonstrating performance comparable to or exceeding expert human reviewers. These technical advances suggest that computational models can perform specific structural analysis tasks with sufficient reliability for educational applications, provided they operate under appropriate human supervision.

However, it is crucial to distinguish between structured information extraction and deep narrative comprehension. While systems can identify linguistic patterns and clinical entities with high precision, interpretation of the experiential, emotional, and existential meaning of illness narratives requires hermeneutic capacities that transcend statistical processing of textual patterns.

2.1. *Conceptual Design of the Personalized GPT*

A personalized GPT for medical-humanistic training could be configured with structured knowledge in four interrelated domains. The first domain would involve Labovian structural analysis, with automated identification of narrative components in student texts, flagging absent or unclear elements to support improved structuring of their own accounts or more organized understanding of patient stories. The second domain would comprise literary device detection, including recognition of metaphors, analogies, and figurative language in patient narratives. Lakoff and Johnson's (1980) Conceptual Metaphor Theory frames metaphor as a cognitive tool facilitating knowledge transfer from familiar domains, with common health metaphors including military, journey, mechanical, and sports-related. Casarett *et al.* (2010) found that physicians who use appropriate metaphors are perceived as better communicators, although Sontag (1978) warned about risks of obscuring reality and promoting blame, requiring careful contextual application.

The third domain would center on emotional content inference, with analysis of expressed emotions and underlying concerns. If a patient insists on details about how their illness affects their family, the GPT could flag this significant concern for family wellbeing as a key theme to address in clinical communication. The fourth domain would generate specific formative feedback to improve narratives without writing them for the student, providing suggestions such as considering expanding orientation with information about the patient's work context, or reflective questions that promote critical thinking about implicit meanings in the account.

Table 2. Analytical Domains of Personalized GPTs for Narrative Medicine.

Analytical Domain	GPT Capability	Application Example	Limitations
Structural Analysis (Labov)	Automated identification of narrative components	Flag absence of temporal orientation in patient account	Does not capture contextual meaning of omissions
Literary Device Detection	Recognition of metaphors, analogies	Identify military metaphor ("fighting cancer")	Does not assess cultural appropriateness of metaphor
Emotional Content Inference	Analysis of expressed emotions	Highlight recurring family concern	Lacks genuine experiential understanding
Formative Feedback	Personalized suggestions without drafting	"Consider expanding patient's work context"	Does not substitute individualized human mentorship

SOURCE: own elaboration.

2.2. *Practical Implementation Case*

A concrete implementation illustrates the pedagogical potential of these systems. At the University of Salamanca, Spain, Professor Miguel Marcos developed a ChatGPT-based academic tutor prototype for medical students, trained with complete teaching information on clinical history elaboration. Students upload their texts and the artificial intelligence provides detailed feedback according to official templates and guidelines, marking errors or omissions and suggesting improvements without writing the history for the student. Preliminary reports indicate that students improve their clinical accounts efficiently, while teachers value how artificial intelligence frees time from basic review, allowing them to focus on more subtle aspects of clinical reasoning. This hybrid model, where artificial intelligence handles structural feedback and humans address complex clinical nuances, exemplifies effective pedagogical integration that

respects complementarity between algorithmic capabilities and expert human judgment (Redacción Médica, 2024).

2.3. *Democratization of Access*

Masters *et al.* (2024) published twelve tips in *Medical Teacher* for creating personalized GPTs without programming experience, identifying applications including administrative assistants, online tutors, and virtual patients with integration of personalized knowledge. Chen *et al.* (2024) identify three key democratization factors: general purpose (broad task capacity), ease of use (natural language interaction), and public availability (free or low-cost access fostering experimentation). This addresses traditional barriers including geographical limitations, resource constraints in low-income contexts, scheduling difficulties across time zones, and language barriers that have historically limited equitable access to quality medical-humanistic training.

A pilot study on breaking bad news communication training revealed significant increases in student confidence and greater confidence in ChatGPT as a learning tool following educational intervention (Wang *et al.*, 2025). Randomized controlled trials with 56 medical students comparing GPT-simulated patients versus traditional role-playing demonstrated comparable or superior results with greater motivation, engagement, reduced anxiety, and improved scalability (Chiu *et al.*, 2025). These findings suggest that, when appropriately implemented, generative artificial intelligence technologies can reduce psychological barriers to learning while maintaining or improving educational outcomes, particularly for students experiencing anxiety in high-stakes face-to-face interactions.

3. Pedagogical Advantages and Implementation Models

3.1. *Documented Educational Benefits*

Scalable deliberate practice constitutes a primary advantage of AI-based systems. Students can submit multiple narratives for analysis receiving immediate feedback, impossible if dependent exclusively on limited faculty availability. This iterative practice with instantaneous feedback favors in-

cremental learning: write, revise according to suggestions, rewrite, gradually improving narrative competence. Adaptive personalization represents another significant advantage, with generative models adapting to each student's level, providing basic or advanced advice as appropriate, maintaining motivation and focus in direct alignment with UDL principles of multiple means of action and expression.

Autonomy and self-directed learning is facilitated by availability of a virtual tutor that allows students to explore narratives independently, identifying comprehension gaps without constant instructor dependence. The goal is for students to internalize analytical schemas, becoming more critical and empathic readers without external support. Equity and accessibility constitute central considerations, given that not all medical schools have specialists in narrative or clinical ethics. An AI system trained with best practices would bring expert knowledge to any location, reducing educational gaps that perpetuate inequalities in professional training.

3.2. *Hybrid Supervised Models*

The literature advocates for hybrid models where artificial intelligence augments, not replaces, human competence. Khan *et al.* (2025) conducted comprehensive reviews demonstrating that artificial intelligence improves traditional analysis methods by automating theme extraction from narrative feedback, while emphasizing contextual limitations and critical need for human supervision. The MedSimAI platform, a collaboration between artificial intelligence, learning science, and medical education experts, uses large language models to provide immediate structured feedback based on validated frameworks, demonstrating effectiveness for deliberate practice in pilot studies. However, multiple sources warn against over-reliance on AI-generated outputs without structured supervision, as it may reduce reflective learning. Mixed pedagogical approaches combining AI-generated feedback with human feedback and critical reflection prove more effective than any isolated modality.

3.3. *Curricular Integration Through KSAVE Framework*

Oftring *et al.* (2024) implemented the KSAVE model (Knowledge, Skills, Attitudes, Values, Ethics) in an innovative five-day course with blended

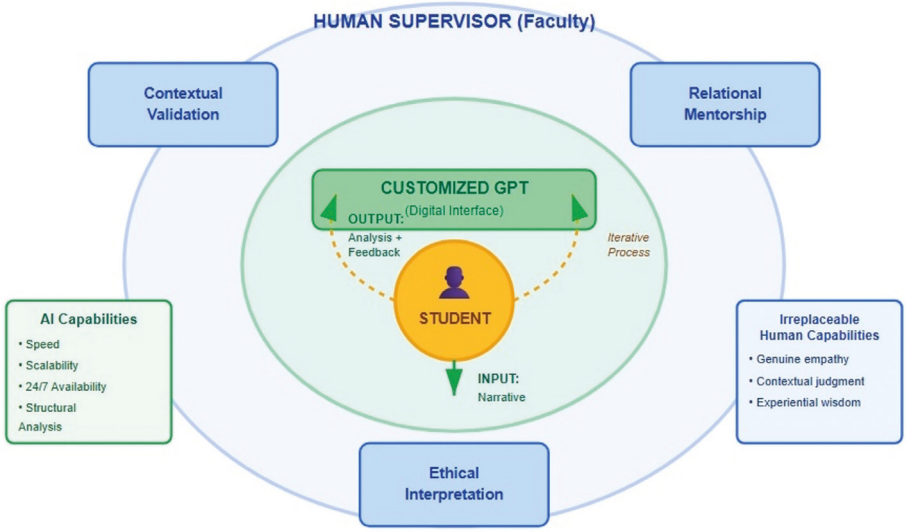


Figure 1. Hybrid Training Ecosystem in Narrative Medicine. *Note.* The model illustrates complementarity between automated analysis and expert human supervision. Bidirectional interactions between student and GPT represent iterative learning cycles, while three human supervisor functions (contextual validation, ethical interpretation, relational mentorship) represent capabilities transcending algorithmic processing.

learning: e-learning, face-to-face workshops, and transfer projects covering artificial intelligence, digital communication, health applications, telemedicine, and augmented virtual reality. Interactive workshops included comparing traditional history-taking with AI chatbots, demonstrating AI-supported imaging for tumor detection, and showing AI pathology analysis. Results from thirty-five participants showed that 100% would recommend the course, with development of nuanced understanding, critical reflection on limitations, and deepened ethical considerations.

This model suggests that successful integration of artificial intelligence in medical-humanistic training requires holistic pedagogical approaches that simultaneously cultivate technical competencies, critical capacities, and ethical sensitivity.

Table 3. KSAVE Framework for Integrating GPTs in Narrative Medicine Education.

KSAVE Component	Training Objective	Activity with GPT	Assessment
Knowledge	Understand narrative structure (Labov)	Analyze 5 example narratives with component identification	Quiz on structural elements
Skills	Draft coherent narrative clinical history	Guided iteration: write → GPT feedback → revise (3 cycles)	Pre-post comparison of narrative quality
Attitudes	Value patient perspective	Written reflection on differences between biomedical and narrative version	Reflective journal evaluated by teacher
Values	Commitment to person-centered medicine	Group discussion on AI limitations vs. human empathy	Participation in ethical debate
Ethics	Identify privacy and bias risks	Case analysis: GPT suggests biased interpretation	Critical essay on necessary safeguards

SOURCE: own elaboration.

4. Ethical Considerations and Fundamental Limitations

4.1. *Privacy and Regulatory Compliance*

Patient narratives contain profoundly sensitive information, and AI models can potentially re-identify patients from anonymized data. The European General Data Protection Regulation adopts strict interpretations of anonymization requiring that organizations prove AI models resist real-world re-identification attacks, particularly concerning for genetic data and rare disease groups. When patient data are employed to train AI systems, pro-

tected health information becomes incorporated into model parameters. Large language models trained with AI-generated content experience a model collapse phenomenon, progressively degrading their accuracy over time, with profound implications for medical record integrity.

Compliance with regulations such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States requires AI developers processing protected health information to establish formal agreements as business associates. However, numerous generative AI tools lack appropriate safeguards, generating risks of unauthorized disclosure. Prescribed technical safeguards include encryption of data both at rest and in transit, robust access controls, comprehensive audit logs, and multi-factor authentication, along with periodic risk assessments (Guillén-Gámez *et al.*, 2024). Under the General Data Protection Regulation (GDPR) framework, primary considerations encompass purpose limitation of processing, data protection by design and implementation from initial development phases, and citizens' rights regarding automated decision-making, aspects with significant implications for AI-assisted medical decisions.

4.2. *Algorithmic Biases and Equity*

More than half of published clinical AI models use datasets from the United States or China with significant overrepresentation of non-Hispanic white patients, causing worse performance for underrepresented groups (Nazer *et al.*, 2023). Imbalanced training datasets cause algorithms to forgo making informative predictions for minority groups, generating clinically meaningless results and perpetuating existing disparities. A widely implemented commercial AI system predicted healthcare costs rather than actual medical need, resulting in African American patients with greater clinical severity receiving care similar to that provided to Caucasian patients with more favourable health states, constituting a demonstration of label bias consequences (Obermeyer *et al.*, 2019).

Mitigation strategies must encompass the complete AI lifecycle. During data collection and preprocessing, maximizing demographic representation and evaluating precision across minority groups using techniques such as decentralized federated learning is essential. In the model development phase, including protected attributes during training, defining group-specific loss functions, and implementing adversarial learning

techniques through specialized tools like the AI Fairness 360 toolkit is fundamental. During validation and deployment stages, establishing performance difference thresholds, enabling systematic surveillance, and implementing continuous algorithmic equity monitoring constitute essential practices for preventing perpetuation of systemic injustices.

4.3. *Limitations of Experiential Understanding*

Fundamental limitations restrict AI interpretation of complex human narratives. Generative AI identifies statistical patterns but fails to appreciate the uniqueness of individual narratives, attributing data rarity to generalized illness narratives and losing unique patient stories central to narrative-based medicine (Schwartz & Lanphier, 2025). Large language model-based AI potentially erodes narrative awareness by ceding comprehensive narration to algorithmic systems, with black box nature preventing transparent interrogation of narrative construction. AI cannot process qualitative and experiential narrative aspects of illness: emotions, fears, hopes, values, and lived experiences essential for person-centered care.

Although GPT and similar models generate convincing text, they lack genuine understanding or human experience. Their analysis is based on statistical patterns, not true empathy or intuition. They may overlook nuances that a sensitive human reader would capture or make inappropriate interpretations when lacking contextual common sense. AI hallucinations—explanations that sound correct but do not align with case reality—represent significant risks particularly in educational contexts where students might internalize incorrect information as validated knowledge.

4.4. *Risk of Dependence and Skills Atrophy*

Constant use of AI to analyze narratives could generate excessive dependence, impeding full development of one's own capacity for analysis and active listening. If students routinely resort to AI to correct clinical histories, they might fall into comfort and cease striving to polish their own narrative skills. This risk demands that faculties implement AI as complement, not substitute, for traditional teaching. Automation bias causes humans to excessively trust computational systems, and in-

creased hours of technological familiarization potentially reduce experience-based training on intuitive physical diagnosis, risking atrophy of clinical intuition and sensory expert knowledge that characterize medical mastery.

5. Ethical Framework and Implementation Recommendations

5.1. *Applied Bioethical Principles*

Ethical frameworks converge around Beauchamp and Childress's four principles of medical bioethics: autonomy (respecting decision-making rights with transparent disclosure), beneficence (ensuring AI improves outcomes while augmenting human capabilities), non-maleficence (preventing harm through rigorous safety standards and bias mitigation), and justice (ensuring equitable access eliminating disparities). The World Health Organization emphasizes protecting human autonomy, promoting wellbeing and safety, ensuring transparency and explicability, fostering responsibility and accountability, ensuring inclusivity and equity, and promoting responsive and sustainable AI (WHO, 2021).

5.2. *Critical Success Factors*

Five factors are identified from evidence as essential for successful implementation. First, human-in-the-loop supervision must ensure AI augments, not replaces, clinical judgment and mentorship. Second, comprehensive ethical frameworks must be grounded in bioethics principles with attention to privacy protection, algorithmic bias mitigation, and advancement of health equity. Third, blended learning models must combine e-learning, interactive workshops, AI-supported practice, and human mentorship optimizing learning outcomes. Fourth, AI literacy as core competency must prepare practitioners for AI-augmented practice across all levels of medical education. Fifth, strengthening medical humanities education, including narrative medicine, reflective practice, and cultural humility, ensures technology serves humanistic care values.

5.3. *Recommendations for Medical Educators*

Medical educators must reimagine curricula shifting from information acquisition to knowledge management and probability interpretation in contexts of uncertainty. Developing AI competencies including basic understanding of machine learning and ethical decision-making frameworks constitutes a curricular priority. Incorporating medical humanities by strengthening narrative medicine training and emphasizing the irreplaceable value of human connection balances technological emphasis.

Preparing for role evolution by training clinician-as-editor skills and human-AI collaboration while maintaining AI-independent clinical reasoning protects against excessive algorithmic dependence.

5.4. *Future Directions and Necessary Research*

The future trajectory suggests continued rapid technological advancement with enhanced multimodal AI integrating text, image, and voice processing for augmented diagnostic capabilities and more realistic simulations.

Precision medical education leveraging adaptive learning algorithms and personalized pathways will enable competency-based approaches with real-time performance analytics. Interdisciplinary integration between medical humanities and AI will deepen, with narrative medicine frameworks enhanced by natural language processing while maintaining essential focus on contextual understanding of patient stories.

However, successful implementation of personalized GPTs in medical-humanistic training requires rigorous empirical research that is currently pending. Longitudinal studies measuring actual impact using validated metrics such as the Jefferson Scale of Empathy are needed, evaluating improvement in communicative competencies compared to traditional methods. Critical research questions include how to assess GPT feedback quality compared to human tutors, which metrics are most adequate for measuring narrative competency development through AI, how to guarantee privacy and equity in use of these tools particularly in resource-limited contexts, what is the optimal balance between AI-assisted practice and human mentorship to maximize long-term learning retention, and how to prevent excessive dependence while leveraging scalability benefits.

Jacobs *et al.* (2023) developed reliable instruments for objective assessment of narrative feedback quality, evaluating feedback narratives demonstrating that quality improves with education and practice. Rubric-based assessment enables objective self-assessment with multiple sub-items evaluated per feedback response. AI-supported automated OSCE (Objective Structured Clinical Examination) assessment demonstrates high agreement with human evaluators identifying underperforming students using validated frameworks, providing potential for immediate detailed formative feedback although challenges remain in numerical scoring.

Conclusion

The integration of generative artificial intelligence in medical-humanistic training simultaneously represents a transformative opportunity and a significant ethical responsibility. The convergence of Rita Charon's narrative medicine framework with Labov's structural analysis, GPT technologies, and Universal Design for Learning principles creates potential for scalable and accessible platforms that develop essential humanistic competencies, while raising fundamental questions about preserving empathy, critical thinking, and therapeutic relationships central to healing.

Personalized GPTs can democratize access to expert narrative analysis, offering structured, immediate, and adapted feedback that previously required intensive individualized mentorship. Documented applications, from the clinical history tutor in Salamanca to virtual patient systems at international universities, demonstrate technical viability and student acceptance. Evidence shows that, when implemented within hybrid supervised models, these tools can augment confidence, reduce anxiety, and improve engagement with narrative learning, particularly benefiting students with diverse educational needs who encounter barriers in traditional formats.

However, this potential must be balanced with rigorous ethical and technical vigilance. AI limitations, including incapacity for genuine experiential understanding, risk of algorithmic biases perpetuating existing injustices, privacy vulnerabilities threatening confidentiality of sensitive narratives, and potential for excessive dependence atrophying autono-

mous skill development, are not insurmountable obstacles but essential parameters that must guide responsible implementation. Technology must augment, not substitute, the irreducibly human dimension of clinical care and medical education.

The path forward demands interdisciplinary collaboration among computer scientists, clinicians, medical educators, humanists, and bioethicists to ensure AI systems serve person-centered medicine values. It requires robust regulatory frameworks protecting patient and student rights, continuous human supervision contextualizing algorithmic outputs with experiential wisdom, and sustained commitment to empirical research validating or refuting current promises through longitudinal studies with validated metrics of narrative competency development.

As Charon emphasizes, narrative medicine cultivates three core movements: attention, representation, and affiliation. In the era of medical AI, these movements become more, not less, essential. Technology can help us identify structural patterns in narratives and offer feedback on technical elements of accounts. But only humans can truly be moved by stories of suffering, recognize the irreducible uniqueness of each illness experience, and form therapeutic connections that transcend algorithmic data.

Narrative medicine reminds us that each illness story carries meanings exceeding categorizations, and that clinical encounter is fundamentally an encounter between subjects, not between information processor and dataset.

Successful integration of personalized GPTs in medical-humanistic training will depend on our capacity to maintain this creative tension: leveraging AI's computational power to scale and democratize access to expert analysis, while zealously preserving the human wisdom, empathy, and presence that constitute the heart of narrative medicine. It is not about choosing between humanism and technology, but ensuring that technology serves, and never subverts, the humanistic ends of training technically excellent and profoundly compassionate physicians. The challenge is not technical but moral: to design, implement, and evaluate these tools in ways that strengthen, rather than erode, our commitment to medicine that honors illness stories in all their complexity, uniqueness, and profound humanity.

References

Alastor E., & Martínez-García I., *El uso de la inteligencia artificial en el ámbito educativo [The use of artificial intelligence in education], in E. Sánchez-Rivas*, E. Sánchez Vega, V. Cebrián-Robles & A. Cívico-Ariza (Eds.), *Educación digital: Recursos y estrategias didácticas [Digital Education: Resources and Teaching Strategies]* (pp. 60-73), UMA Editorial, 2025. https://doi.org/10.24310/mumaedmumaed.194

Casarett D., Pickard A., Fishman J. M., Alexander S. C., Arnold R. M., Pollak K. I., & Tulsky J. A., *Can metaphors and analogies improve communication with seriously ill patients?* «Journal of Palliative Medicine», 13(3), 2010, pp. 255-260. https://doi.org/10.1089/jpm.2009.0221

Cast. (2018). *Universal Design for Learning Guidelines version 2.2*. http://udlguidelines.cast.org

Charon R., *Narrative medicine: A model for empathy, reflection, profession, and trust*, «JAMA», 286(15), 2001, pp. 1897-1902. https://doi.org/10.1001/jama.286.15.1897

Charon R., Irvine C., Rivera Colón E., Oforlea A. N., Smalletz C., & Spiegel M., *Racial justice in medicine: Narrative practices toward equity*, «Narrative», 29(2), 2021, pp. 160-177.

Chen A., Liu L., & Zhu T., *Advancing the democratization of generative artificial intelligence in healthcare: A narrative review*, «Journal of Hospital Management and Health Policy», 8, 12, 2024. https://doi.org/10.21037/jhmhp-24-54

Chen D., Chauhan K., Parsa R., Liu Z. A., Liu F. F., Mak E., Eng L., Hannon B. L., Croke J., Hope A., Fallah-Rad N., Wong P., & Raman S., *Patient perceptions of empathy in physician and artificial intelligence chatbot responses to patient questions about cancer*, «*npj Digital Medicine*», 8, 275, 2025. https://doi.org/10.1038/s41746-025-01671-6

Chiu J., Castro B., Ballard I. *et al.*, *Exploration of the Role of ChatGPT in Teaching Communication Skills for Medical Students: A Pilot Study*, «Med. Sci.Educ», 2025. https://doi.org/10.1007/s40670-025-02394-9

Doyle A. J., O'Toole M., Cassidy D., & Condron C. M., *Universal Design for Learning (UDL) in simulation-based health professions education*, «Advances in Simulation», 10, 33, 2025. https://doi.org/10.1186/s41077-025-00361-3

Friedman C., Shagina L., Lussier Y., & Hripcsak G., *Automated encoding of clinical documents based on natural language processing*, «Journal of the American Medical Informatics Association», 11(5), 2004, pp. 392–402. https://doi.org/10.1197/jamia.M1552

Guillén-Gámez F. D., Martínez-García I., Alastor E., & Tomczyk Ł., *Digital competences in cybersecurity of teachers in training*, «Computers in the Schools», *41*(3), 2024, pp. 281–306. https://doi.org/10.1080/07380569.2024.2361614

Jacobs M. M. J., van Son P. M., Scharstuhl A., van Gurp P. J., & Tanck E., *An innovative assessment tool for evaluating narrative feedback quality among Medicine and Biomedical Sciences students*, «International Journal of Medical Education», *14*, 2023, pp. 147-154. https://doi.org/10.5116/ijme.64f6.df43

Khan S. A., Taiyara J., Zary N., & Otaki F., *Artificial intelligence in narrative feedback analysis for competency-based medical education: A review*, «Studies in Health Technology and Informatics», 327, 2025, pp. 1423-1427. https://doi.org/10.3233/SHTI250637

Kung T. H., Cheatham M., Medenilla A., Sillos C., De Leon L., Elepaño C., Madriaga M., Aggabao R., Diaz-Candido G., Maningo J., & Tseng V., *Performance of ChatGPT on USMLE: Potential for AI-assisted medical education using large language models*, «PLOS Digital Health», 2(2), e0000198, 2023. https://doi.org/10.1371/journal.pdig.0000198

Labov W., & Waletzky J., *Narrative analysis: Oral versions of personal experience*, in J. Helm (Ed.), *Essays on the verbal and visual arts* (pp. 12-44). University of Washington Press, 1967.

Lakoff G., & Johnson M., *Metaphors we live by*, University of Chicago Press, 1980.

Langewitz W., Denz M., Keller A., Kiss A., Rüttimann S., & Wössmer B., *Spontaneous talking time at start of consultation in outpatient clinic: Cohort study*, «BMJ», 325(7366), 2002, pp. 682-683. https://doi.org/10.1136/bmj.325.7366.682

Luke K., *Twelve tips for designing an inclusive curriculum in medical education using Universal Design for Learning (UDL) principles*, «MedEdPublish», 10(1), Article 3784, 2021. https://doi.org/10.15694/mep.2021.000118.1

Masters K., Benjamin J., Agrawal A., MacNeill H., Pillow M. T., & Mehta N., *Twelve tips on creating and using custom GPTs to enhance health professions education*, «Medical Teacher», 46(6), 2024, pp. 752-756. https://doi.org/10.1080/0142159X.2024.2305365

Milota M. M., van Thiel G. J. M. W., & van Delden J. J. M., *Narrative medicine as a medical education tool: A systematic review*, «Medical Teacher», 41(7), 2019, pp. 802-810. https://doi.org/10.1080/0142159X.2019.1584274

Nazer L. H., Zatarah R., Waldrip S., Ke J. X. C., Moukheiber M., Khanna A. K., Hicklen R. S., Moukheiber L., Moukheiber D., Ma H., & Mathur P., *Bias in artificial intelligence algorithms and recommendations for mitigation*, «PLOS Digital Health», 2(6), e0000278, 2023. https://doi.org/10.1371/journal.pdig.0000278

Obermeyer Z., Powers B., Vogeli C., & Mullainathan S., *Dissecting racial bias in an algorithm used to manage the health of populations*, «Science», 366(6464), 2019, pp. 447-453. https://doi.org/10.1126/science.aax2342

Oftring Z. S., Deutsch K., Tolks D., Jungmann F., & Kuhn S., *Novel blended learning on artificial intelligence for medical students: Qualitative interview study*, «JMIR Medical Education», 11, e65220, 2024. https://doi.org/10.2196/65220

Patterson W., *Narratives of events: Labovian narrative analysis and its limitations*, in M. Andrews, C. Squire, & M. Tamboukou (Eds.), *Doing narrative research* (2nd ed., pp. 27-46). SAGE Publications, 2013. https://doi.org/10.4135/9781526402271

Pennebaker J. W., *Telling stories: The health benefits of narrative*, «Literature and Medicine», 19(1), 2000, pp. 3-18. https://doi.org/10.1353/lm.2000.0011

Schwartz D., & Lanphier E., *The new narrative medicine: Ethical implications of artificial intelligence on healthcare narratives*, «Monash Bioethics Review», 2025. https://doi.org/10.1007/s40592-025-00256-z

Redacción Médica, *ChatGPT llega al Grado de Medicina para 'corregir' las historias clínicas* [*ChatGPT arrives at the Medical School to 'correct' clinical histories*], 2024. https://www.redaccionmedica.com/secciones/estudiantes/chatgpt-llega-al-grado-de-medicina-para-corregir-las-historias-clinicas-8914

Sontag S., *Illness as metaphor*, Farrar, Straus and Giroux, New York 1978.

Wang Z., Fan TT., Li ML. *et al, Feasibility study of using GPT for history-taking training in medical education: a randomized clinical trial*, «BMC Med Educ» 25, 1030, 2025. https://doi.org/10.1186/s12909-025-07614-9

World Health Organization, *Ethics and governance of artificial intelligence for health*, 2021. https://www.who.int/publications/i/item/9789240029200