

# Integration of Genetic Programming in Healthcare Applications: Opportunities, Challenges, and the Imperative for Explainability

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## INTRODUCTION

The rapid advancement of artificial intelligence (AI) has ushered in a new era of innovation in healthcare, promising transformations in diagnosis, treatment, and patient management. Among the diverse subfields of AI, genetic programming (GP) stands out for its capacity to evolve and optimize complex models and solutions with minimal human intervention. By mimicking evolutionary processes, GP offers unique advantages in dealing with the nonlinearity, high dimensionality, and heterogeneity that characterize medical data. However, as AI systems become more deeply embedded in healthcare workflows, concerns regarding explainability, transparency, fairness, and ethical implementation have come to the fore. These concerns are not merely academic; they carry significant implications for clinical adoption, patient trust, regulatory compliance, and the very safety of care delivery.

This essay critically examines the integration of genetic programming in healthcare applications, focusing on both the transformative potential and the significant challenges that must be addressed. Drawing on recent literature, including systematic reviews of explainable artificial intelligence (XAI) in healthcare and surveys on creative problem solving within AI, the discussion situates GP within the broader context of AI-driven medical innovation. The essay further interrogates the imperative for explainability and fairness in AI-enabled healthcare, integrating perspectives from recent expert-driven studies and contemporary debates around algorithmic bias, transparency, and the ethics of AI deployment. Ultimately, the essay argues that while genetic programming holds great promise for advancing personalized, efficient, and adaptive healthcare, its responsible integration is contingent upon overcoming critical challenges related to interpretability, fairness, and stakeholder collaboration.

## THE PROMISE OF GENETIC PROGRAMMING IN HEALTHCARE

### Genetic Programming: Origins and Mechanisms

Genetic programming is an evolutionary algorithm-based methodology that evolves computer programs or models by simulating the process of natural selection. Unlike traditional optimization techniques, GP explores vast solution spaces by iteratively generating, mutating, and recombining candidate solutions, guided by a fitness function that evaluates their performance on a given task. This paradigm is particularly well-suited to problems characterized by:

- **High dimensionality and complexity:** Medical data often comprise genomic sequences, high-resolution images, clinical records, and sensor streams, which are challenging for conventional algorithms to model.
- **Nonlinear and multifactorial relationships:** Disease phenotypes often emerge from intricate interactions among genetic, environmental, and behavioral factors.
- **Changing and uncertain environments:** Healthcare systems must adapt to evolving disease patterns, emerging therapies, and shifting patient populations.

By leveraging its flexibility and adaptability, GP can discover novel patterns, generate interpretable rules, and optimize treatment protocols in ways that may elude more rigid approaches.

## APPLICATIONS AND CASE STUDIES

GP has been explored in multiple healthcare domains, including but not limited to:

- **Disease Diagnosis and Prognosis:** GP-based models have been used to extract diagnostic rules from clinical data, identify biomarkers in genomics, and predict disease progression trajectories. The capacity to evolve rule-based classifiers makes GP appealing for tasks requiring both accuracy and interpretability.

- **Medical Image Analysis:** In radiology and pathology, GP has been applied to feature selection, image segmentation, and classification, often outperforming traditional machine learning approaches when dealing with heterogeneous image data.
- **Treatment Optimization and Personalized Medicine:** By simulating diverse patient responses and adapting treatment strategies, GP can aid in the design of individualized care pathways and dynamic dosing regimens.
- **Healthcare Process Optimization:** GP has been used to optimize resource allocation, scheduling, and clinical workflows, particularly in complex hospital environments where multiple interacting variables influence outcomes.

The adaptability of GP makes it a candidate for creative problem solving in medicine, where solutions may need to be dynamically tailored to novel or ill-defined clinical scenarios. As Gizzi et al. observe in their survey on creative problem solving in AI, the ability to manipulate conceptual spaces and discover new solutions is a hallmark of sophisticated intelligence and is increasingly necessary in dynamic healthcare settings.<sup>i</sup>

## SYNERGIES WITH OTHER AI PARADIGMS

Contemporary AI systems frequently integrate GP with other methodologies, such as deep learning, reinforcement learning, and probabilistic graphical models. For example, GP can be used to evolve neural network architectures or feature representations, enhancing the adaptability and performance of hybrid models. In clinical decision support systems, Markov decision processes (MDPs) and dynamic decision networks have been combined with evolutionary strategies to optimize sequential decision-making under uncertainty.<sup>ii</sup> As Bennett and Hauser demonstrate, such frameworks can outperform conventional treatment-as-usual models in both cost and patient outcomes, underscoring the real-world value of advanced AI approaches in healthcare.<sup>iii</sup>

## THE IMPERATIVE FOR EXPLAINABILITY AND TRUSTWORTHINESS

### The Black Box Problem

Despite the promise of AI—and of GP in particular—its widespread adoption in healthcare is hampered by the so-called “black box” problem. Many advanced machine learning models, including those generated via GP, are opaque to end users; their internal logic and decision-making processes are difficult to interpret, audit, or justify. This opacity is especially problematic in medicine, where clinical decisions often carry life-altering consequences and must be explainable to both practitioners and patients.

Bharati et al., in their systematic review of XAI for healthcare, emphasize that explainability is not simply a technical desideratum but a moral and practical necessity. Without transparency, it is impossible to discern whether an AI’s recommendations reflect clinically relevant distinctions or are artifacts of bias, error, or overfitting.<sup>iv</sup> The lack of explainability can erode trust, impede adoption, and expose healthcare providers to legal and ethical risks.

### Explainable AI: Definitions and Taxonomies

Explainable AI refers to methods and techniques that render AI systems’ decisions comprehensible to humans. Bharati et al. distinguish between explainability (XAI)—which addresses why a system made a particular decision—and interpretability (IAI)—which clarifies how the decision was made.<sup>v</sup> Both are essential in healthcare, where clinicians need to understand not only the outcomes but also the underlying rationale to ensure safe, equitable, and effective care.

Bharati et al. synthesize the literature into five categories of XAI methods relevant to healthcare: dimension reduction, feature selection, attention mechanisms, knowledge distillation, and surrogate representations.<sup>vi</sup> GP can contribute to several of these areas, particularly feature selection and surrogate modeling, by evolving transparent rule sets or functional forms that approximate complex models.

### Explainability in Genetic Programming

GP offers unique opportunities for explainability relative to deep neural networks and other black-box models. The outputs of GP—such as decision trees, symbolic expressions, or rule sets—can, in principle, be more interpretable if properly constrained. However, GP-generated models can also become unwieldy or overfit, producing convoluted logic that is difficult for clinicians to parse.

The challenge, therefore, is to balance the expressive power of GP with constraints that promote interpretability. This may involve:

- **Penalizing model complexity** in the fitness function.
- **Imposing domain-specific constraints** that align with clinical knowledge.
- **Integrating human-in-the-loop frameworks**, where experts guide or refine the search process.

Such strategies resonate with the broader thrust in XAI to develop models that are both accurate and transparent, as highlighted by Bharati et al.<sup>vii</sup> The ultimate goal is to produce AI systems whose recommendations can be trusted, audited, and acted upon within the clinical context.

## CREATIVE PROBLEM SOLVING AND THE ROLE OF GENETIC PROGRAMMING

### The Need for Creativity in Healthcare AI

Healthcare is replete with ill-structured, novel, and crisis-driven problems that defy rote solutions. From the COVID-19 pandemic to rare disease diagnosis and disaster response, clinicians are often confronted with scenarios where standard protocols are insufficient. In such contexts, the capacity for creative problem solving (CPS) becomes paramount.

Gizzi et al. define CPS in AI as the ability of an agent to manipulate its current conceptual space to discover new concepts—states, actions, or solutions—not previously represented.<sup>viii</sup> This flexibility mirrors the demands of real-world healthcare, where adaptability and innovation are essential.

### Genetic Programming as a CPS Engine

GP is inherently suited to CPS tasks due to its evolutionary nature:

- **Exploration of Novel Solutions:** GP searches beyond predefined heuristics, potentially yielding innovative solutions to medical challenges.
- **Adaptation to New Contexts:** By dynamically evolving models, GP can adapt to changing data distributions, emerging diseases, or novel treatment modalities.
- **Integration with Knowledge Representation:** As outlined by Gizzi et al., effective CPS requires robust mechanisms for knowledge representation, manipulation, and evaluation.<sup>ix</sup> GP can encode and evolve such representations in symbolic or rule-based forms.

For example, in complex treatment planning, GP can generate new combinations of therapeutic interventions, simulate their outcomes, and refine strategies based on feedback—a process analogous to the creative improvisation observed in expert clinicians during unprecedented medical crises.<sup>x</sup>

### Challenges in CPS and GP Integration

While GP offers powerful tools for CPS, several obstacles must be addressed:

- **Evaluation of Novelty and Usefulness:** Not all novel solutions are clinically valid or safe. Effective frameworks must incorporate rigorous evaluation criteria, possibly through hybrid human-AI teams.
- **Transferability and Generalization:** Solutions evolved in one context may not generalize to others, necessitating mechanisms for knowledge transfer and adaptation.
- **Transparency and Justification:** Creative solutions must be explainable and justifiable to stakeholders, reinforcing the need for XAI techniques in GP-based systems.

As Gizzi et al. conclude, advancing CPS in AI—and by extension, in healthcare—requires not only technical innovation but also a deep engagement with evaluation, knowledge representation, and ethical considerations.<sup>xi</sup>

## FAIRNESS, BIAS, AND ETHICAL CONSIDERATIONS

### The Risks of Algorithmic Bias

The integration of AI in healthcare raises acute concerns about bias and fairness. AI models, including those generated via GP, are susceptible to inheriting and amplifying biases present in training data. In the context of healthcare, this can lead to disparate treatment recommendations, misdiagnoses, or exclusion of underrepresented populations. As Bulut et al. observe in the context of educational measurement, algorithmic bias can perpetuate inequalities and undermine the validity and reliability of AI-driven assessments.<sup>xii</sup> Similar dynamics operate in healthcare, where the stakes are often higher.

Fenu, Galici, and Marras highlight that AI systems may unintentionally amplify existing inequities unless fairness is explicitly considered at every stage of development and deployment.<sup>xiii</sup> Their expert-driven investigation reveals that challenges such as demographic representation, local context dependencies, and hidden relationships between variables are pervasive and must be systematically addressed.

## Fairness In Genetic Programming

GP's flexibility is a double-edged sword: while it can discover novel solutions, it can also inadvertently optimize for spurious correlations or proxy variables that encode sensitive attributes (such as race, gender, or socioeconomic status). Ensuring fairness in GP-based healthcare applications requires:

- **Diverse and Representative Training Data:** Datasets must reflect the heterogeneity of patient populations to prevent underrepresentation and bias.
- **Fairness-Aware Fitness Functions:** The optimization criteria in GP should include fairness metrics alongside accuracy.
- **Continuous Auditing and Monitoring:** As Fenu et al. advocate, fairness must be assessed at all stages of the pipeline, with mechanisms for detecting and mitigating bias.<sup>xiv</sup>
- **Transparency and Stakeholder Engagement:** Engaging clinicians, patients, and ethicists in the design and evaluation of GP systems can surface blind spots and promote equitable outcomes.

These recommendations align with the broader movement towards responsible AI in healthcare, as articulated by Bharati et al. and other leading scholars.<sup>xv</sup>

## Explainability as a Pillar of Fairness

Explainability and fairness are deeply intertwined. As Bulut et al. note, the opacity of AI decision-making processes can obscure the presence and impact of bias, making it difficult to identify and remediate unfair outcomes.<sup>xvi</sup> In healthcare, where transparency is critical for informed consent and shared decision-making, explainable GP models are essential for surfacing and addressing potential harms.

The integration of human-in-the-loop frameworks, as advocated in both the educational and healthcare domains, is particularly salient. By involving domain experts in the review and refinement of GP-generated models, organizations can better ensure that AI systems are aligned with ethical, clinical, and societal values.<sup>xvii</sup><sup>xviii</sup>

## INTEGRATION FRAMEWORKS AND REAL-WORLD IMPLEMENTATIONS

### Simulation and Decision-Making Frameworks

The translation of GP from theory to practice in healthcare often involves its integration into broader simulation and decision-making frameworks. Bennett and Hauser's work on Markov decision processes (MDPs) and dynamic decision networks exemplifies this approach.<sup>xix</sup> By simulating alternative decision paths and capturing the complex interactions among healthcare system components, such frameworks can optimize treatment policies, explore the consequences of different interventions, and support adaptive clinical AI.

Importantly, these frameworks can operate in partially observable environments, maintaining belief states about patient health and adapting as new data arise. This adaptability is consonant with the strengths of GP in evolving solutions to dynamic and uncertain problems. The integration of GP with MDPs, reinforcement learning, or creative problem solving architectures amplifies the potential for innovation in complex healthcare scenarios.<sup>xxxii</sup>

### Challenges in Real-World Adoption

Despite promising research, the deployment of GP-based systems in clinical practice faces substantial hurdles:

- **Regulatory and Legal Barriers:** The lack of transparency and explainability in AI models can impede regulatory approval and expose institutions to liability.
- **Integration with Clinical Workflows:** AI systems must be seamlessly integrated into existing workflows, electronic health records, and decision support systems.
- **User Acceptance and Trust:** Clinicians and patients must trust AI recommendations, which depends on their ability to understand and interrogate the underlying logic.
- **Continuous Learning and Updating:** Medical knowledge and patient populations evolve; AI systems must be designed for ongoing learning and adaptation without sacrificing safety or fairness.

Bharati et al. emphasize that overcoming these challenges requires active collaboration among physicians, researchers, and technical experts, as well as the development of robust evaluation and auditing mechanisms.<sup>xxii</sup>

## OPPORTUNITIES AND FUTURE DIRECTIONS

### Personalized Medicine and Adaptive Care

The integration of GP into healthcare holds particular promise for advancing personalized medicine. By evolving individualized models based on a patient's genetic, clinical, and behavioral data, GP can support the tailoring of diagnostics and therapeutics to optimize outcomes.

As Bennett and Hauser demonstrate, AI frameworks that incorporate evolutionary algorithms can outperform standard models in both cost and efficacy, paving the way for more efficient, outcome-driven care delivery.<sup>xxiii</sup> The potential to integrate multiple data sources—genomic, clinical, sociodemographic—further enhances the capacity for nuanced, patient-centered decision-making.

### Interdisciplinary Collaboration and Human-in-the-Loop Systems

The complexity of healthcare and the ethical demands of AI deployment necessitate interdisciplinary collaboration. As Bulut et al. and Fenu et al. argue in the context of educational measurement, the involvement of domain experts, stakeholders, and affected communities is critical for ensuring the accountability, fairness, and utility of AI systems.<sup>xxivxxv</sup>

In healthcare, this translates to the development of human-in-the-loop frameworks that balance the creative power of GP with the expertise and judgment of clinicians. Such systems can harness the strengths of both human and machine intelligence, fostering innovation while safeguarding against error and bias.

### Standardization, Auditing, and Governance

The establishment of standards, auditing protocols, and governance structures is imperative for the responsible integration of GP in healthcare. This includes:

- **Clear documentation and transparency** regarding data sources, model logic, and evaluation criteria.
- **Continuous monitoring** for bias, drift, and unintended consequences.
- **Participatory processes** for fairness checking and accountability, as advocated by Fenu et al.<sup>xxvi</sup>
- **Adaptive regulatory frameworks** that can accommodate the rapid evolution of AI technologies while protecting patient safety and rights.

## CONCLUSION

The integration of genetic programming in healthcare applications offers transformative opportunities to enhance diagnosis, personalize treatment, optimize resource allocation, and foster creative problem solving in the face of unprecedented challenges. Its evolutionary approach is uniquely suited to the complexity, heterogeneity, and dynamism of medical data and clinical environments. However, the very power of GP brings with it profound responsibilities: to ensure that AI-driven models are explainable, fair, trustworthy, and ethically aligned with the values of medicine.

This essay has argued that the promise of GP can only be realized through a concerted focus on explainability, fairness, and interdisciplinary collaboration. Drawing on recent systematic reviews and expert studies, it is clear that technical innovation must be matched by robust frameworks for transparency, auditing, stakeholder engagement, and continuous evaluation. Only by addressing the black box problem, mitigating algorithmic bias, and embedding ethical considerations at every stage can the integration of genetic programming in healthcare fulfill its potential to advance human health without compromising the foundational principles of care.

The future of AI in healthcare will be shaped not only by the sophistication of algorithms but by the collective will to ensure that these tools serve all patients equitably, transparently, and safely. In this endeavor, genetic programming is both an engine of innovation and a catalyst for renewed attention to the values that must undergird the digital transformation of medicine.

## BIBLIOGRAPHY

- [1] Gizzi, Evana, Lakshmi Nair, Sonia Chernova, and Jivko Sinapov. "Creative Problem Solving in Artificially Intelligent Agents: A Survey and Framework." arXiv preprint arXiv:2204.10358v1 (2022). <https://arxiv.org/pdf/2204.10358v1>
- [2] Bennett, Casey C., and Kris Hauser. "Artificial Intelligence Framework for Simulating Clinical Decision-Making: A Markov Decision Process Approach." Artificial Intelligence in Medicine (2013). <https://arxiv.org/pdf/1301.2158v1>
- [3] Bharati, Subrato, M. Rubaiyat Hossain Mondal, and Prajyo Podder. "A Review on Explainable Artificial Intelligence for Healthcare: Why, How, and When?" arXiv preprint arXiv:2304.04780v1 (2023). <https://arxiv.org/pdf/2304.04780v1>

[4] Bulut, Okan, Maggie Beiting-Parrish, Jodi M. Casabianca, Sharon C. Slater, Hong Jiao, Dan Song, Christopher M. Ormerod, Deborah Gbemisola Fabiyi, Rodica Ivan, Cole Walsh, Oscar Rios, Joshua Wilson, Seyma N. Yildirim-Erbasli, Tarid Wongvorachan, Joyce Xinle Liu, Bin Tan, and Polina Morilova. "The Rise of Artificial Intelligence in Educational Measurement: Opportunities and Ethical Challenges." arXiv preprint arXiv:2406.18900v1 (2024). <https://arxiv.org/pdf/2406.18900v1>

[5] Fenu, Gianni, Roberta Galici, and Mirko Marras. "Experts' View on Challenges and Needs for Fairness in Artificial Intelligence for Education." arXiv preprint arXiv:2207.01490v1 (2022). <https://arxiv.org/pdf/2207.01490v1>

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[1] Gizzi, Evana, Lakshmi Nair, Sonia Chernova, and Jivko Sinapov. "Creative Problem Solving in Artificially Intelligent Agents: A Survey and Framework." arXiv preprint arXiv:2204.10358v1 (2022). <https://arxiv.org/pdf/2204.10358v1>

[2] Bennett, Casey C., and Kris Hauser. "Artificial Intelligence Framework for Simulating Clinical Decision-Making: A Markov Decision Process Approach." Artificial Intelligence in Medicine (2013). <https://arxiv.org/pdf/1301.2158v1>

[3] Bennett, Casey C., and Kris Hauser. "Artificial Intelligence Framework for Simulating Clinical Decision-Making: A Markov Decision Process Approach." Artificial Intelligence in Medicine (2013). <https://arxiv.org/pdf/1301.2158v1>

[4] Bharati, Subrato, M. Rubaiyat Hossain Mondal, and Prajjoy Podder. "A Review on Explainable Artificial Intelligence for Healthcare: Why, How, and When?" arXiv preprint arXiv:2304.04780v1 (2023). <https://arxiv.org/pdf/2304.04780v1>

[5] Bharati, Subrato, M. Rubaiyat Hossain Mondal, and Prajjoy Podder. "A Review on Explainable Artificial Intelligence for Healthcare: Why, How, and When?" arXiv preprint arXiv:2304.04780v1 (2023). <https://arxiv.org/pdf/2304.04780v1>

[6] Bharati, Subrato, M. Rubaiyat Hossain Mondal, and Prajjoy Podder. "A Review on Explainable Artificial Intelligence for Healthcare: Why, How, and When?" arXiv preprint arXiv:2304.04780v1 (2023). <https://arxiv.org/pdf/2304.04780v1>

[7] Bharati, Subrato, M. Rubaiyat Hossain Mondal, and Prajjoy Podder. "A Review on Explainable Artificial Intelligence for Healthcare: Why, How, and When?" arXiv preprint arXiv:2304.04780v1 (2023). <https://arxiv.org/pdf/2304.04780v1>

[8] Gizzi, Evana, Lakshmi Nair, Sonia Chernova, and Jivko Sinapov. "Creative Problem Solving in Artificially Intelligent Agents: A Survey and Framework." arXiv preprint arXiv:2204.10358v1 (2022). <https://arxiv.org/pdf/2204.10358v1>

[9] Gizzi, Evana, Lakshmi Nair, Sonia Chernova, and Jivko Sinapov. "Creative Problem Solving in Artificially Intelligent Agents: A Survey and Framework." arXiv preprint arXiv:2204.10358v1 (2022). <https://arxiv.org/pdf/2204.10358v1>

[10] Gizzi, Evana, Lakshmi Nair, Sonia Chernova, and Jivko Sinapov. "Creative Problem Solving in Artificially Intelligent Agents: A Survey and Framework." arXiv preprint arXiv:2204.10358v1 (2022). <https://arxiv.org/pdf/2204.10358v1>

[11] Gizzi, Evana, Lakshmi Nair, Sonia Chernova, and Jivko Sinapov. "Creative Problem Solving in Artificially Intelligent Agents: A Survey and Framework." arXiv preprint arXiv:2204.10358v1 (2022). <https://arxiv.org/pdf/2204.10358v1>

[12] Bulut, Okan, Maggie Beiting-Parrish, Jodi M. Casabianca, Sharon C. Slater, Hong Jiao, Dan Song, Christopher M. Ormerod, Deborah Gbemisola Fabiyi, Rodica Ivan, Cole Walsh, Oscar Rios, Joshua Wilson, Seyma N. Yildirim-Erbasli, Tarid Wongvorachan, Joyce Xinle Liu, Bin Tan, and Polina Morilova. "The Rise of Artificial Intelligence in Educational Measurement: Opportunities and Ethical Challenges." arXiv preprint arXiv:2406.18900v1 (2024). <https://arxiv.org/pdf/2406.18900v1>

[13] Fenu, Gianni, Roberta Galici, and Mirko Marras. "Experts' View on Challenges and Needs for Fairness in Artificial Intelligence for Education." arXiv preprint arXiv:2207.01490v1 (2022). <https://arxiv.org/pdf/2207.01490v1>

[14] Fenu, Gianni, Roberta Galici, and Mirko Marras. "Experts' View on Challenges and Needs for Fairness in Artificial Intelligence for Education." arXiv preprint arXiv:2207.01490v1 (2022). <https://arxiv.org/pdf/2207.01490v1>

[15] Bharati, Subrato, M. Rubaiyat Hossain Mondal, and Prajjoy Podder. "A Review on Explainable Artificial Intelligence for Healthcare: Why, How, and When?" arXiv preprint arXiv:2304.04780v1 (2023). <https://arxiv.org/pdf/2304.04780v1>

[16] Bulut, Okan, Maggie Beiting-Parrish, Jodi M. Casabianca, Sharon C. Slater, Hong Jiao, Dan Song, Christopher M. Ormerod, Deborah Gbemisola Fabiyi, Rodica Ivan, Cole Walsh, Oscar Rios, Joshua Wilson, Seyma N. Yildirim-Erbasli, Tarid Wongvorachan, Joyce Xinle Liu, Bin Tan, and Polina Morilova. "The Rise of Artificial Intelligence in Educational Measurement: Opportunities and Ethical Challenges." arXiv preprint arXiv:2406.18900v1 (2024). <https://arxiv.org/pdf/2406.18900v1>

[17] Bulut, Okan, Maggie Beiting-Parrish, Jodi M. Casabianca, Sharon C. Slater, Hong Jiao, Dan Song, Christopher M. Ormerod, Deborah Gbemisola Fabiyi, Rodica Ivan, Cole Walsh, Oscar Rios, Joshua Wilson, Seyma N. Yildirim-Erbasli, Tarid Wongvorachan, Joyce Xinle Liu, Bin Tan, and Polina Morilova. "The Rise of Artificial Intelligence in Educational Measurement: Opportunities and Ethical Challenges." arXiv preprint arXiv:2406.18900v1 (2024). <https://arxiv.org/pdf/2406.18900v1>

[18] Fenu, Gianni, Roberta Galici, and Mirko Marras. "Experts' View on Challenges and Needs for Fairness in Artificial Intelligence for Education." arXiv preprint arXiv:2207.01490v1 (2022). <https://arxiv.org/pdf/2207.01490v1>

[19] Bennett, Casey C., and Kris Hauser. "Artificial Intelligence Framework for Simulating Clinical Decision-Making: A Markov Decision Process Approach." Artificial Intelligence in Medicine (2013). <https://arxiv.org/pdf/1301.2158v1>

[20] Bennett, Casey C., and Kris Hauser. "Artificial Intelligence Framework for Simulating Clinical Decision-Making: A Markov Decision Process Approach." Artificial Intelligence in Medicine (2013). <https://arxiv.org/pdf/1301.2158v1>

[21] Gizzi, Evana, Lakshmi Nair, Sonia Chernova, and Jivko Sinapov. "Creative Problem Solving in Artificially Intelligent Agents: A Survey and Framework." arXiv preprint arXiv:2204.10358v1 (2022). <https://arxiv.org/pdf/2204.10358v1>

[22] Bharati, Subrato, M. Rubaiyat Hossain Mondal, and Prajjoy Podder. "A Review on Explainable Artificial Intelligence for Healthcare: Why, How, and When?" arXiv preprint arXiv:2304.04780v1 (2023). <https://arxiv.org/pdf/2304.04780v1>

[23] Bennett, Casey C., and Kris Hauser. "Artificial Intelligence Framework for Simulating Clinical Decision-Making: A Markov Decision Process Approach." Artificial Intelligence in Medicine (2013). <https://arxiv.org/pdf/1301.2158v1>

[24] Bulut, Okan, Maggie Beiting-Parrish, Jodi M. Casabianca, Sharon C. Slater, Hong Jiao, Dan Song, Christopher M. Ormerod, Deborah Gbemisola Fabiyi, Rodica Ivan, Cole Walsh, Oscar Rios, Joshua Wilson, Seyma N. Yildirim-Erbasli, Tarid Wongvorachan, Joyce Xinle Liu, Bin Tan, and Polina Morilova. "The Rise of Artificial Intelligence in Educational Measurement: Opportunities and Ethical Challenges." arXiv preprint arXiv:2406.18900v1 (2024). <https://arxiv.org/pdf/2406.18900v1>

[25] Fenu, Gianni, Roberta Galici, and Mirko Marras. "Experts' View on Challenges and Needs for Fairness in Artificial Intelligence for Education." arXiv preprint arXiv:2207.01490v1 (2022). <https://arxiv.org/pdf/2207.01490v1>

[26] Fenu, Gianni, Roberta Galici, and Mirko Marras. "Experts' View on Challenges and Needs for Fairness in Artificial Intelligence for Education." arXiv preprint arXiv:2207.01490v1 (2022). <https://arxiv.org/pdf/2207.01490v1>