Creative Explainable AI Tools to Understand Algorithmic Decision-Making

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ABSTRACT

This doctoral research aims to to design interactive Explainable AI (XAI) tools in response to the challenge of fostering AI literacy among adults without technical expertise. The tools developed thus far focus on edge detection, confidence thresholds, and sensitivity, and were designed based on principles from learning sciences and user-centered design to make AI accessible and ethically reflective. My efforts have resulted in successful design, implementation, and preliminary evaluation. Conducted with 42 adult participants, the study reveals notable improvements in familiarity with and confidence in discussing AI concepts. Qualitative feedback highlights user engagement and enhanced understanding, demonstrating immediate impact and laying a foundation for ongoing work. Looking forward, my work will delve deeper into how non-experts can critically engage with AI's decision-making processes, understand algorithmic trade-offs, and consider how AI can better serve society. This approach broadens AI literacy and leverages cognitive principles for creative and ethical technological interventions.

CCS CONCEPTS

• **Human-centered computing** → **Interactive systems and tools**; *Gestural input*; *Displays and imagers*; **Interaction design theory, concepts and paradigms**; • **Applied computing** → **Interactive learning environments**; **Computer-assisted instruction**; • **Computing methodologies** → Machine learning algorithms; **Computer vision problems**; Cognitive science; • **Social and professional topics** → **Adult education**; **Informal education**; *Computing literacy*.

KEYWORDS

Explainable AI, AI Literacy, AI Transparency, Technology-Mediated Learning, Cognitive Interaction, Interaction Design, Confidence Threshold, Edge Detection, Sensitivity, User Research, Design Theory

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1 INTRODUCTION

The past few years have seen an unprecedented expansion in the public use of artificial intelligence (AI), enhancing everyday experiences and services. However, the complexity and opacity of AI systems often leave users, particularly those without technical backgrounds, in the dark, hindering effective utilization and acceptance [55]. The lack of public understanding surrounding AI introduces significant risks, including the potential for misuse, the propagation of biases, and the undermining of trust in technology [7]. This underscores a critical need for broader *AI literacy*, defined as *"a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace"* [41].

So far, my work has addressed three research questions:

RQ1: How can I design interactive, web-based tools to foster AI literacy via learning-through-doing amongst adult novices?
RQ2: Do the tools I develop lead to improved AI literacy amongst adult novices?
RQ3: What types of dialogue and interaction patterns do adult novices engage in when interacting with the tools?

To date, I have developed and evaluated three interactive tools—*The Art of Edge Detection, Playing with Confidence Scores and Decision Thresholds,* and *Toggling Sensitivity in Machine Learning*—with 42 adult novices. My mixed-methods approach reveals significant enhancements in AI literacy and confidence, alongside emergent interaction patterns that offer insights into adult learning processes with AI.

Moving forward, my research aims to leverage the creative and artistic dimensions as central pillars in the design process, intending to enhance the interaction between non-technical individuals and AI systems. By infusing creativity and the arts, the goal is to demystify AI technologies, making them more relatable and understandable through metaphorical and visual means. This approach aligns with the development of an extensive toolkit of Explainable AI (XAI) systems, which are designed to make the decision-making processes of AI transparent and understandable for all users. Explainable AI refers to techniques and methodologies in artificial intelligence that provide human-comprehensible insights into the machine's decisions, enabling users to understand, trust, and effectively manage AI technologies. My objective is to broaden public understanding of AI's decision-making processes, explore the inherent trade-offs in algorithmic designs, and foster discussions on designing AI systems for societal benefit. This direction not only underscores the critical need for AI literacy but also offers significant contributions to the Creativity & Cognition community, showcasing how design and arts play a pivotal role in making AI education accessible and engaging.

2 RELATED WORK

The need for enhanced AI literacy is particularly acute among adult learners, who often encounter barriers due to a lack of resources tailored to their learning needs, fostering misconceptions and mistrust in AI technologies [18, 22, 29, 61]. Despite the broadening of AI education beyond specialized programs, offerings specifically designed for adults that adhere to principles of relevance and self-direction are still rare [7, 18, 33, 34, 36, 38, 42]. Previous efforts have mainly focused on the K-12 sector, underscoring active exploration and knowledge construction, laying a foundational understanding that my project seeks to extend to adult learners through hands-on, self-guided experiences [17, 18, 63, 70].

Explainable AI (XAI) has emerged as a key area to foster trust and understanding in AI systems among adult users [25, 45, 66]. While XAI seeks to demystify AI algorithms' decision-making processes, existing tools often cater to technically proficient users, limiting accessibility for novices [1, 4, 13, 20, 39]. My approach leverages the pedagogical insights from XAI research and adult learning theories to create interactive tools that enable users to explore AI concepts directly and reflect on their ethical implications [5, 35, 36, 43, 67].

Addressing adult learners' unique needs, my work emphasizes experiential and self-directed learning outside traditional classroom environments, advocating for learning experiences that are adaptable, relevant, and embedded within the learners' daily contexts [11, 21, 30, 62, 62, 68]. By empowering adults to interact with and understand AI through hands-on tools, I aim to promote a deeper comprehension of AI and encourage ethical engagement with AI technologies [12, 16]. While there is a growing body of interactive explainers designed to help adult learners understand complex AI algorithms [10, 32, 53, 57, 65], my distinctive tools foster an environment where users can directly manipulate AI model parameters, thereby gaining insights into the model's tradeoffs and decision-making process.

3 DESIGN

My interactive AI learning tools, developed using the p5.js library for ease of online embedding and interaction [44], are underpinned by several key principles:

(1) **Creativity-Driven Design:** By allowing users to explore AI concepts in a non-linear fashion and encouraging the generation of unique solutions to presented problems, the tools promote creative engagement with technology. This approach draws upon theories of creativity as a process of exploration and recombination, enabling users to discover novel intersections between AI and their personal or professional interests [60].
(2) **Playful Interaction:** Incorporating elements of play into the learning process, the tools are designed to make the exploration of AI concepts enjoyable and engaging. This aspect of playfulness not only lowers the barrier to entry for novices but also aligns with cognitive theories that suggest play is a powerful mechanism for enhancing cognitive flexibility and fostering a deeper, more meaningful understanding of complex subjects [56].
(3) **Active Learning:** Inspired by constructivist theory [24], these tools engage users in building their understanding through exploration and interaction with AI concepts.
(4) **Collaborative Learning:** Designed for sharing and embedding, my tools facilitate community-based learning and knowledge exchange, aligning with theories on collaborative education [31, 47, 50, 54].
(5) **Explainable AI (XAI) Principles:** With a focus on clear visualizations and interactive elements, my tools demystify AI decision-making processes, leveraging XAI insights [4, 35, 52].
(6) **Critical Engagement:** By encouraging critical thought about AI's functions and societal impacts, my design approach supports deep engagement with AI technologies, drawing on established competencies for accessible AI education [41].

3.1 The Art of Edge Detection

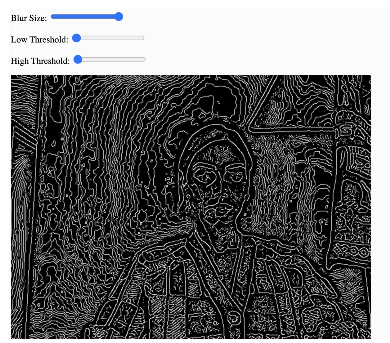


Figure 1: *The Art of Edge Detection* showcases how adjusting the blur size impacts the live camera feed, striking a balance between detail and visual noise in edge detection.

Figure 2: Adjusting the *Low Threshold* and *High Threshold* sliders in *The Art of Edge Detection* tool allows users to refine edge detection sensitivity, balancing edge visibility and noise reduction.

The Art of Edge Detection demystifies a crucial computer vision technique through an interactive visualization widget, focusing on the Canny edge detector, a staple for identifying image boundaries developed by John Canny in 1986 [9]. Employing image smoothing via a Gaussian filter, the tool outlines the edge detection process from smoothing and gradient computation to non-maximum suppression and double thresholding [14, 26, 58]. Users navigate the edge detection mechanism firsthand, enhancing their grasp of the algorithm's intricacies and its practical implications.

3.2 Playing with Confidence Scores and Decision Thresholds

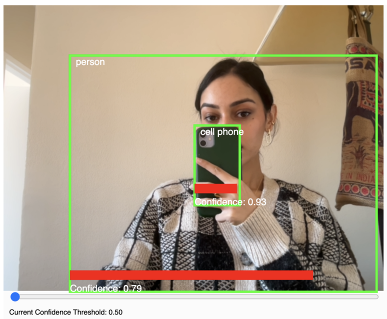


Figure 3: This tool demystifies the role of confidence scores in AI object detection, showing detected objects with bounding boxes and confidence levels in a live feed.

Playing with Confidence Scores and Decision Thresholds is an interactive widget that demonstrates the pivotal role of confidence scores in the realm of AI object detection [49]. It illustrates, in real-time, how objects are detected, classified, and assigned a confidence level, showcasing the AI's accuracy and certainty (Figure 3). This aspect is critical for interpreting the trustworthiness of AI's object recognition outputs and is instrumental in fostering user trust and acceptance of AI systems [51, 69]. By equipping users with the knowledge to understand and assess the reliability of AI systems, this tool contributes to the ethical discourse surrounding AI applications [15, 69].

3.3 Toggling Sensitivity in Machine Learning

Toggling Sensitivity in Machine Learning aims to provide users with a comprehensive understanding of sensitivity in machine learning algorithms, particularly in the context of gesture recognition. This tool, as shown in Figure 4, allows users to play and understand the trade-offs between inclusiveness and precision in machine learning models, a key concept in the field [48].

4 METHODOLOGY

The study evaluated the impact of my AI education tools on 42 adult novices, documenting their learning outcomes and feedback. I recruited participants ages 18 and older from local libraries, ensuring diversity by recruiting in various neighborhoods. Participants used the tools while sharing their thoughts in think-aloud sessions lasting 20 to 50 minutes, concluding with a post-interaction survey. Utilizing a mixed-methods approach, I conducted pre and post-surveys to assess changes in AI knowledge self-efficacy and captured qualitative data through think-aloud sessions and open-ended questions, focusing on participants' comprehension of AI concepts and their applicability to real-life contexts.

Figure 4: *Toggling Sensitivity in Machine Learning* showcases the effect of adjusting sensitivity on gesture recognition, showing how the system's responsiveness to hand gestures varies with sensitivity levels. It demonstrates the algorithm's real-time adaptation, balancing between broad inclusivity and precise gesture detection.

4.1 Analysis

Data analysis employed statistical techniques, grading schema, and qualitative analysis, including a paired t-test to measure changes in participants' AI knowledge self-efficacy. Deductive thematic analysis with a codebook strategy [8] explored adult novices' interactions and interpretations of AI tools. This process aided us in identifying distinct participant engagement profiles, leading to the definition of personas reflecting diverse interaction styles and learning preferences.

5 RESULTS

Tables 1 and 2 present the paired sample t-test analysis of pre-survey and post-survey responses to the questions, *"Would you be able to explain the following concepts to another non-technical person?"* and *"How confident would you be in connecting these concepts to things you interact with in the world?"*, respectively, across five different AI concepts. This comparative analysis indicated a statistically significant increase in self-efficacy related to both understanding and applying the identified AI concepts across the board ($p < 0.01$) [23]. The interactive tools appear to be effective at promoting learner confidence and self-perceptions surrounding their knowledge of AI. Cognitive science research illustrates that self-efficacy and learner confidence are instrumental in motivating individuals towards learning [6].

5.1 Demonstrated Understanding of AI Concepts

The outcomes from the graded rubric evaluation of the open-ended questions are shown in Figures 5a & 5b.

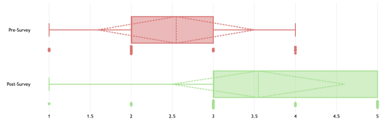
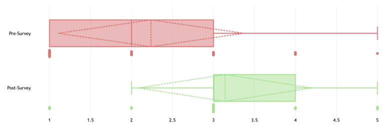
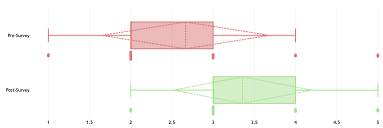
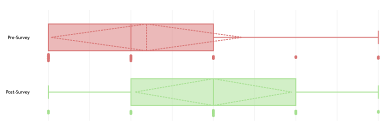
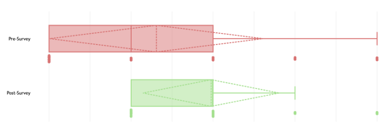
"Would you be able to explain the following concepts to another non-technical person?"	Results
Computer Vision	
Edge Detection	
Confidence Scores	
Decision Thresholds	
Sensitivity Thresholds	

Table 1: Pre-survey (red) and post-survey (green) responses to *"Would you be able to explain the following concepts to another non-technical person?"*

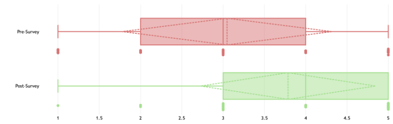
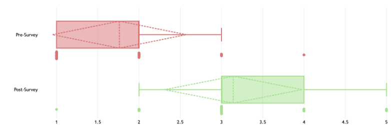
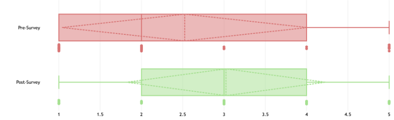
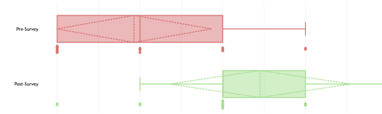
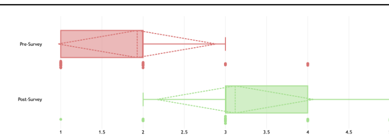
"How confident would you be in connecting these concepts to things you interact with in the world?"	Results
Computer Vision	
Edge Detection	
Confidence Scores	
Decision Thresholds	
Sensitivity Thresholds	

Table 2: Pre-survey (red) and post-survey (green) responses to *"How confident would you be in connecting these concepts to things you interact with in the world?"*

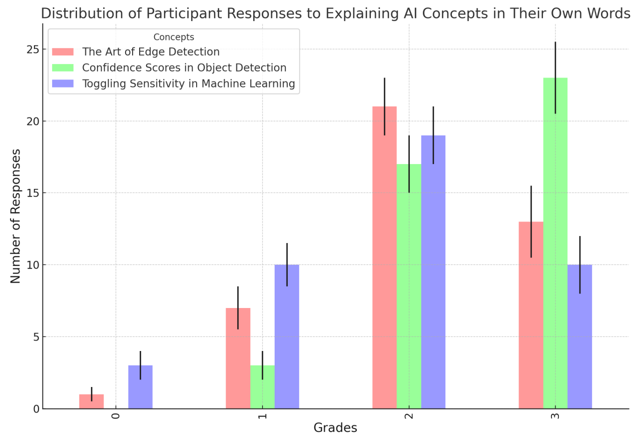
5.2 Themes Describing Participant Interactions with Tools

The thematic analysis sought to identify a set of themes to describe common patterns in participant interactions with the interactive tools. At the outset of the thematic analysis, I defined a codebook of six codes relating to types of participant interactions with the tools.

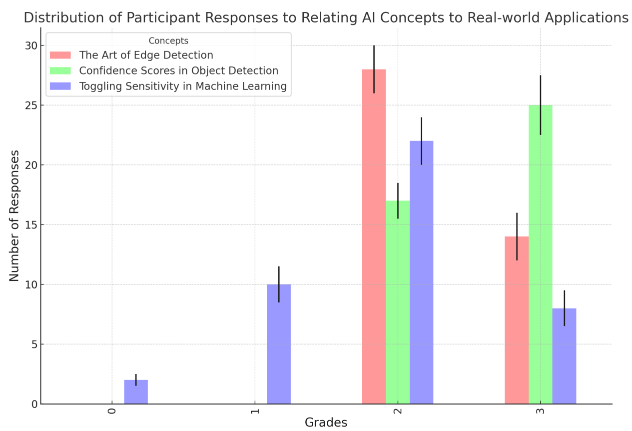
(1) *Exploration:* Participants actively explored the tool, experimenting with features and settings to grasp its functionality.
(2) *Comparison Analysis:* Participants conducted comparative analyses, adjusting settings to discover optimal configurations based on performance and interpretability.
(3) *Root-cause Investigation:* This involved delving into model errors or unexpected outcomes to pinpoint underlying issues.
(4) *Ethical Evaluation:* Participants critically assessed AI decisions for ethical implications, focusing on fairness, bias, transparency, and accountability.
(5) *Real-world Application:* There was a focus on the tool's relevance to real-world scenarios.
(6) *Future Speculation:* Discussions often ventured into future possibilities for the technology.

After applying these codes to the data (see 4 for more detail), I was able to identify four themes describing common patterns in participants' interactions with and dialogue surrounding the tools.

(1) *Critical Thinking* Participants frequently applied critical thinking to dissect AI model predictions, scrutinizing not just the outcomes but the processes leading to these decisions.
(2) *Ethical and Social Considerations* The ethical and social implications of AI were a major concern among participants, who often debated the moral responsibilities of AI developers.
(3) *Practical Application* The connection between AI theories and their practical implications was illustrated through participants' discussions of real-world applications and how



(a) Graded response distribution when asked to explain AI concepts in their own words. Results are shown for three learning tools with error bars for standard deviation.



(b) Graded response distribution when asked to relate AI concepts to real-world applications. Results are shown for three learning tools with error bars for standard deviation.

these concepts relate to real-world applications or their professional lives.

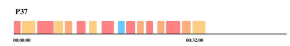
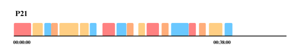
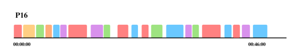
(4) *Future-Oriented Perspective* Anticipation of AI's future developments was a common theme, with participants expressing both excitement and concern.

5.3 Participant Personas and Interaction Trajectories

Analyzing interaction styles revealed distinct personas among participants, corresponding to the coded interaction types. These personas, detailed in Table 3, encapsulate diverse engagement methods with AI tools.

6 DISCUSSION

I return here to the research questions in light of my findings. In response to **RQ1**, I present the design of three tools and findings from a study that indicates learning-by-doing is an effective approach to designing AI literacy interventions for adult learners. My

Personas and Percentage of Participants	Interaction Trajectory
The Tinkerer: Revels in hands-on experimentation across all tools, driven by a "what if" curiosity. **45.2%**	
The Ethical Observer: Focuses on the societal and ethical implications of AI technology. **14.3%**	
The Realist: Grounded in practical applications and real-world relevance. **28.6%**	
The Visionary: Interested in the broader implications and future applications of AI. **11.9%**	

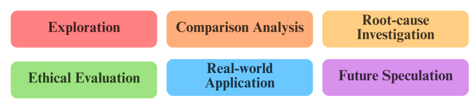


Table 3: Personas and a corresponding interaction pattern from that group

tools increased participants' understanding and confidence in AI – at least in the short-term – answering **RQ2**. In response to **R3**, the thematic analysis of participant dialogue offers a first understanding of how adult learners engage in sensemaking surrounding AI.

The identification of distinct personas among adult learners unveils a spectrum of preferences and interaction styles within AI education tools, providing insights for customizing educational experiences. This persona-based approach suggests that future tools should embrace customization to cater to the diverse needs of learners [3].

My interactive tools have effectively facilitated deep discussions on AI ethics among adult learners, addressing critical issues such as privacy, diversity, bias, transparency, and accountability [28]. This marks a pioneering effort in AI ethics education tailored specifically for adults, contrasting with previous projects focused on children [2, 64]. This work underscores the necessity of incorporating ethical considerations into AI education, aiming to prepare learners for thoughtful, ethical engagement with AI technologies across various contexts [27, 37, 40, 46, 59].

7 PLANNED TRAJECTORY OF FUTURE WORK

In light of the initial successes and learnings from my doctoral research into creating interactive Explainable AI (XAI) tools for adult novices, my future work aims to significantly expand and deepen this trajectory. This next phase seeks not only to broaden the scope of AI concepts accessible to non-experts but also to foster a more nuanced understanding and ethical engagement with AI technologies. Specifically, here are my goals:

(1) **Fostering Ethical AI Design:** Recognizing the critical importance of ethics in AI, future tools will aim to educate users on how to design and evaluate AI systems from an ethical standpoint. This includes understanding and mitigating biases, ensuring transparency, and evaluating the societal impact of AI applications.
(2) **Exploring Trade-offs in AI:** An important aspect of AI literacy is understanding the inherent trade-offs in AI system design, such as between accuracy and explainability or between model complexity and interpretability. Future tools will enable users to experiment with these trade-offs, providing insights into how different priorities can shape AI system development and deployment. In exploring the trade-offs inherent in AI system design, a significant aspect of this work will be to investigate from a cognitive perspective how individuals understand and evaluate these trade-offs, contributing to a deeper comprehension of decision-making in AI.
(3) **Engaging in Speculative Design:** A forward-looking component of my work will involve engaging users in speculative design [19] exercises related to the future of XAI. This will include imagining future applications of XAI, considering how evolving technologies could impact society, and designing conceptual tools or systems that address future ethical, social, or technical challenges in AI.

The existing literature lacks comprehensive studies on how cognitive processes affect learning and understanding AI, especially regarding AI trade-offs. My future research will fill this gap, enhancing AI literacy and enabling adult novices to approach AI critically, ethically, and creatively. This effort aligns with the Creativity & Cognition community's focus on innovative, ethically-informed technology education.

8 CONCLUSION

My doctoral journey thus far has set the groundwork for demystifying the complex domain of artificial intelligence (AI) for adult novices. Through the design, development, and preliminary evaluation of interactive Explainable AI (XAI) tools, this research aims to foster AI literacy by making AI concepts accessible and engaging. The initial findings from working with adult participants highlight the potential of hands-on, interactive learning experiences to enhance understanding and confidence in discussing and engaging with AI technologies.

REFERENCES

[1] Ashraf Abdul, Jo Vermeulen, Danding Wang, Brian Y Lim, and Mohan Kankanhalli. 2018. Trends and Trajectories for Explainable, Accountable and Intelligible Systems: An HCI Research Agenda. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–18.
[2] Safinah Ali, Blakeley H Payne, Randi Williams, Hae Won Park, and Cynthia Breazeal. 2019. Constructionism, ethics, and creativity: Developing primary and middle school artificial intelligence education. In *International workshop on education in artificial intelligence k-12 (eduai'19)*, Vol. 2. 1–4.
[3] Farshid Anvari, H. Tran, Deborah Richards, and M. Hitchens. 2019. Towards a Method for Creating Personas with Knowledge and Cognitive Process for User Centered Design of a Learning Application. In *2019 IEEE/ACM 12th International Workshop on Cooperative and Human Aspects of Software Engineering (CHASE)*. IEEE. https://doi.org/10.1109/CHASE.2019.00037
[4] Alejandro Barredo Arrieta, Natalia Díaz-Rodríguez, Javier Del Ser, Adrien Bennetot, Siham Tabik, Alberto Barbado, Salvador García, Sergio Gil-López, Daniel Molina, Richard Benjamins, et al. 2020. Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion* 58 (2020), 82–115.
[5] Azlan Abdul Aziz, Intan Nur Hafawati Adam, Jamaluddin Jasmis, S. J. Elias, and S. Mansor. 2021. N-Gain and System Usability Scale Analysis on Game Based Learning for Adult Learners. *IEEE* (2021). https://doi.org/10.1109/ICRAIE52900.2021.9704013
[6] Albert Bandura. 1997. *Self-efficacy: The exercise of control.* W.H. Freeman and Company, New York, NY.
[7] Dawn Branley-Bell, Rebecca Whitworth, and L. Coventry. 2020. User Trust and Understanding of Explainable AI: Exploring Algorithm Visualisations and User Biases. In *International Conference on Human-Computer Interaction*. Springer, –. https://doi.org/10.1007/978-3-030-49065-2_27
[8] Virginia Braun and Victoria Clarke. 2023. Toward good practice in thematic analysis: Avoiding common problems and be(com)ing a knowing researcher. *International Journal of Transgender Health* 24, 1 (2023), 1–6. https://doi.org/10.1080/26895269.2022.2129597
[9] J. Canny. 1986. A Computational Approach to Edge Detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence* PAMI-8, 6 (1986), 679–698.
[10] Michelle Carney, Barron Webster, Irene Alvarado, Kyle Phillips, Noura Howell, Jordan Griffith, Jonas Jongejan, Amit Pitaru, and Alexander Chen. 2020. Teachable machine: Approachable Web-based tool for exploring machine learning classification. In *Extended abstracts of the 2020 CHI conference on human factors in computing systems*. 1–8.
[11] S. Cornelius, Carole Gordon, and Aileen Ackland. 2011. Towards flexible learning for adult learners in professional contexts: an activity-focused course design. *Interactive Learning Environments* 19, 5 (2011), 467–484. https://doi.org/10.1080/10494820903298258
[12] K. Crawford and R. Calo. 2016. There is a blind spot in AI research. *Nature* 538 (2016), 311–313. https://doi.org/10.1038/538311a
[13] Aba-Sah Dadzie, Laura Benton, Asimina Vasalou, and Russell Beale. 2014. Situated design for creative, reflective, collaborative, technology-mediated learning. In *Proceedings of the 2014 Conference on Designing Interactive Systems* (Vancouver, BC, Canada) *(DIS '14)*. Association for Computing Machinery, New York, NY, USA, 83–92. https://doi.org/10.1145/2598510.2598527
[14] Guang Deng and L.W. Cahill. 1993. An adaptive Gaussian filter for noise reduction and edge detection. *Proc. of Nuclear Science Symposium and Medical Imaging Conference* 3, 1615 – 1619 vol.3. https://doi.org/10.1109/NSSMIC.1993.373563
[15] Shipi Dhanorkar, Christine T. Wolf, Kun Qian, Anbang Xu, Lucian Popa, and Yunyao Li. 2021. Who needs to know what, when?: Broadening the Explainable AI (XAI) Design Space by Looking at Explanations Across the AI Lifecycle. In *Proceedings of the 2021 ACM Designing Interactive Systems Conference* (Virtual Event, USA) *(DIS '21)*. Association for Computing Machinery, New York, NY, USA, 1591–1602. https://doi.org/10.1145/3461778.3462131
[16] Nicholas Diakopoulos. 2016. Accountability in Algorithmic Decision Making. *Commun. ACM* 59, 2 (jan 2016), 56–62. https://doi.org/10.1145/2844110
[17] Stefania Druga. 2018. *Growing up with AI: Cognimates: from coding to teaching machines*. Ph. D. Dissertation. Massachusetts Institute of Technology.
[18] Stefania Druga, Nancy Otero, and Amy J. Ko. 2022. The Landscape of Teaching Resources for AI Education. *Proceedings of the 2022 ACM Conference on International Computing Education Research* (2022). https://doi.org/10.1145/3502718.3524782
[19] Anthony Dunne and Fiona Raby. 2013. *Speculative Everything: Design, Fiction, and Social Dreaming*. The MIT Press. JSTOR, http://www.jstor.org/stable/j.ctt9qf7j7.
[20] Upol Ehsan and Mark O Riedl. 2019. Human-centered Explainable AI (HCXAI): Beyond opening up the black-box of AI. In *Proceedings of the 24th International Conference on Intelligent User Interfaces*. Association for Computing Machinery, New York, NY, USA, 1–2.
[21] John H Falk, Scott Randol, and Lynn D Dierking. 2012. Mapping the informal science education landscape: An exploratory study. *Public Understanding of Science* 21, 7 (2012), 865–874.
[22] F. Faruqe, R. Watkins, and L. Medsker. 2021. Competency Model Approach to AI Literacy: Research-based Path from Initial Framework to Model. *Advances in Artificial Intelligence, Machine Learning, and Computational Intelligence* (2021). https://doi.org/10.54364/aaiml.2022.1140
[23] A. Field. 2013. *Discovering Statistics Using IBM SPSS Statistics* (4th ed.). SAGE Publications.
[24] C. T. Fosnot. 2005. *Constructivism: Theory, Perspectives, and Practice, Second Edition*. Teachers College Press.
[25] F. O. Giuste et al. 2021. Explainable Artificial Intelligence Methods in Combating Pandemics: A Systematic Review. *IEEE Reviews in Biomedical Engineering* 16 (2021), 5–21.
[26] Rafael C. Gonzalez and Richard E. Woods. 2018. *Digital Image Processing* (4 ed.). Pearson, New York, NY, USA.

[27] Thilo Hagendorff and D. Danks. 2022. Ethical and methodological challenges in building morally informed AI systems. *AI and Ethics* (June 2022). https://doi.org/10.1007/s43681-022-00188-y

[28] Alexa Hagerty and Igor Rubinov. 2019. Global AI Ethics: A Review of the Social Impacts and Ethical Implications of Artificial Intelligence. *CoRR* abs/1907.07892 (2019). arXiv:1907.07892 http://arxiv.org/abs/1907.07892

[29] Julie Henry, Alyson Hernalesteen, and Anne-Sophie Collard. 2021. Teaching Artificial Intelligence to K-12 Through a Role-Playing Game Questioning the Intelligence Concept. *KI - Künstliche Intelligenz* (2021). https://doi.org/10.1007/s13218-021-00733-7

[30] Yan Yin Ho, Eun-Young Yeo, and Dhaniah Suhana Binte Mohammad Wijaya. 2023. Turning Coffee Time into Teaching Moments Through Bite-Sized Learning for Adult Learners. *Journal of Continuing Higher Education* 71, 2 (2023), 123–134. https://doi.org/10.1080/07377363.2021.2024000

[31] Henry Jenkins et al. 2006. Confronting the Challenges of Participatory Culture: Media Education for the 21st Century. *An Occasional Paper on Digital Media and Learning* (2006). http://tinyurl.com/2uztw4

[32] Minsuk Kahng, Nikhil Thorat, Duen Horng Chau, Fernanda B Viégas, and Martin Wattenberg. 2018. Gan lab: Understanding complex deep generative models using interactive visual experimentation. *IEEE transactions on visualization and computer graphics* 25, 1 (2018), 310–320.

[33] Maria Kasinidou. 2022. Promoting AI Literacy for the Public. *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (2022). https://doi.org/10.1145/3545947.3573292

[34] Maria Kasinidou. 2023. AI Literacy for All: A Participatory Approach. *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (2023). https://doi.org/10.1145/3587103.3594135

[35] Anna Kawakami, Luke Guerdan, Yang Cheng, Anita Sun, Alison Hu, Kate Glazko, Nikos Arechiga, Matthew Lee, Scott Carter, Haiyi Zhu, and Kenneth Holstein. 2022. Towards a Learner-Centered Explainable AI: Lessons from the learning sciences. arXiv:2212.05588 [cs.HC]

[36] Malcolm S. Knowles. 1984. *Andragogy in Action: Applying Modern Principles of Adult Education*. Jossey-Bass, San Francisco, CA.

[37] T. Köhler. 2021. Didactic modeling of a digital instrument for the perception, construction and evaluation of ethical perspectives in AI systems. *2021 IEEE 10th International Congress on Information Science and Technology (CiSt)* (July 2021). https://doi.org/10.1109/IIAI-AAI53430.2021.00030

[38] Valentin Kuleto, Milena P. Ilić, Mihail-Alexandru Dumangiu, M. Ranković, Oliva M. D. Martins, D. Păun, and Larisa Mihoreanu. 2021. Exploring Opportunities and Challenges of Artificial Intelligence and Machine Learning in Higher Education Institutions. *Sustainability* 13, 18 (2021), 10424. https://doi.org/10.3390/su131810424

[39] Qianyang V Liao, Daniel Gruen, and Sarah Miller. 2020. Questioning the AI: Informing Design Practices for Explainable AI User Experiences. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–15.

[40] Daria Loi, Christine T. Wolf, Jeanette L. Blomberg, Raphael Arar, and Margot Brereton. 2019. Co-designing AI Futures: Integrating AI Ethics, Social Computing, and Design. In *Companion Publication of the 2019 on Designing Interactive Systems Conference 2019 Companion* (<conf-loc>, <city>San Diego</city>, <state>CA</state>, <country>USA</country>, </conf-loc>) *(DIS '19 Companion)*. Association for Computing Machinery, New York, NY, USA, 381–384. https://doi.org/10.1145/3301019.3320000

[41] D. Long and B. Magerko. 2020. What is AI literacy? Competencies and design considerations. In *CHI Conference on Human Factors in Computing Systems*.

[42] Duri Long, Jessica Roberts, Brian Magerko, Kenneth Holstein, Daniella DiPaola, and Fred Martin. 2023. AI Literacy: Finding Common Threads between Education, Design, Policy, and Explainability. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems* (<conf-loc>, <city>Hamburg</city>, <country>Germany</country>, </conf-loc>) *(CHI EA '23)*. Association for Computing Machinery, New York, NY, USA, Article 329, 6 pages. https://doi.org/10.1145/3544549.3573808

[43] Celestin Mayombe. 2020. Adult learners' perception on the use of constructivist principles in teaching and learning in non-formal education centres in South Africa. *International Journal of Lifelong Education* (2020). https://doi.org/10.1080/02601370.2020.1796834

[44] L. McCarthy, C. Reas, and B. Fry. 2015. *Getting started with p5.js: Making interactive graphics in JavaScript and Processing*. Maker Media, Inc.

[45] C. Meske and E. Bunde. 2020. Transparency and Trust in Human-AI-Interaction: The Role of Model-Agnostic Explanations in Computer Vision-Based Decision Support. *Interacción* (2020).

[46] T. Miletić. 2020. *Military Medical Enhancement and Autonomous AI Systems: Requirements, Implications, Concerns*. Springer. https://doi.org/10.1007/978-3-030-36319-2_11

[47] Seymour Papert and Idit Harel. 1991. *Situating Constructionism*. Ablex Publishing, Norwood, NJ, USA.

[48] S. S. Rautaray and A. Agrawal. 2015. Vision based hand gesture recognition for human computer interaction: a survey. *Artificial Intelligence Review* 43, 1 (2015), 1–54.

[49] J. Redmon et al. 2016. You only look once: Unified, real-time object detection. *IEEE CVPR* (2016).

[50] Mitchel Resnick, John Maloney, Andrés Monroy-Hernández, Natalie Rusk, Evelyn Eastmond, Karen Brennan, Amon Millner, Eric Rosenbaum, Jay Silver, Brian Silverman, and Yasmin Kafai. 2009. Scratch: Programming for All. *Commun. ACM* 52, 11 (2009), 60–67.

[51] Marco Túlio Ribeiro, Sameer Singh, and Carlos Guestrin. 2016. "Why Should I Trust You?": Explaining the Predictions of Any Classifier. *CoRR* abs/1602.04938 (2016). arXiv:1602.04938 http://arxiv.org/abs/1602.04938

[52] Lorena Sánchez Chamorro, Kerstin Bongard-Blanchy, and Vincent Koenig. 2023. Ethical Tensions in UX Design Practice: Exploring the Fine Line Between Persuasion and Manipulation in Online Interfaces. In *Proceedings of the 2023 ACM Designing Interactive Systems Conference* (<conf-loc>, <city>Pittsburgh</city>, <state>PA</state>, <country>USA</country>, </conf-loc>) *(DIS '23)*. Association for Computing Machinery, New York, NY, USA, 2408–2422. https://doi.org/10.1145/3563657.3596013

[53] Benjamin Sanchez-Lengeling, Emily Reif, Adam Pearce, and Alexander B Wiltschko. 2021. A gentle introduction to graph neural networks. *Distill* 6, 9 (2021), e33.

[54] David W. Shaffer and Mitchel Resnick. 1999. "Thick" Authenticity: New Media and Authentic Learning. *Journal of Interactive Learning Research* 10, 2 (1999), 195–216.

[55] Donghee Shin and Yong Jin Park. 2019. Role of fairness, accountability, and transparency in algorithmic affordance. *Computers in Human Behavior* (2019). https://doi.org/10.1016/j.chb.2019.04.019

[56] Dorothy G. Singer and Jerome L. Singer. 2009. Play and cognitive development. *Encyclopedia on Early Childhood Development* (2009).

[57] Daniel Smilkov, Shan Carter, D Sculley, Fernanda B Viégas, and Martin Wattenberg. 2017. Direct-manipulation visualization of deep networks. *arXiv preprint arXiv:1708.03788* (2017).

[58] Milan Sonka, Vaclav Hlavac, and Roger Boyle. 2014. *Image Processing, Analysis, and Machine Vision*. Cengage Learning, Stamford, CT, USA.

[59] K. Sorbán. 2021. Ethical and legal implications of using AI-powered recommendation systems in streaming services. *Információs Társadalom* (June 2021). https://doi.org/10.22503/inftars.xxi.2021.2.5

[60] Robert J. Sternberg. 1999. *Handbook of Creativity*. Cambridge University Press, Cambridge.

[61] A. Tlili, J. Zhang, Z. Papamitsiou, S. Manske, R. Huang, Kinshuk, and H. Hoppe. 2021. Towards utilising emerging technologies to address the challenges of using Open Educational Resources: a vision of the future. *Educational Technology Research and Development* (2021). https://doi.org/10.1007/s11423-021-09993-4

[62] Curtis L. Todd, K. Ravi, H. Akoh, and Vance Gray. 2021. *Engaging Adult Learners Online Through Technology, Andragogy, and Flexible Course Design*. https://doi.org/10.4018/978-1-7998-8598-6.ch055

[63] David Touretzky, Christina Gardner-McCune, Fred Martin, and Deborah Seehorn. 2019. Envisioning AI for K-12: What should every child know about AI?. In *Proceedings of the AAAI conference on artificial intelligence*, Vol. 33. 9795–9799.

[64] Benjamin Walsh, Bridget Dalton, Stacey Forsyth, and Tom Yeh. 2023. Literacy and STEM teachers adapt AI ethics curriculum. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 37. 16048–16055.

[65] Zijie J Wang, Robert Turko, Omar Shaikh, Haekyu Park, Nilaksh Das, Fred Hohman, Minsuk Kahng, and Duen Horng Polo Chau. 2020. CNN explainer: learning convolutional neural networks with interactive visualization. *IEEE Transactions on Visualization and Computer Graphics* 27, 2 (2020), 1396–1406.

[66] K. Weitz et al. 2019. "Do you trust me?": Increasing User-Trust by Integrating Virtual Agents in Explainable AI Interaction Design. In *ACM IVA*.

[67] L. Wells and T. Bednarz. 2021. Explainable AI and Reinforcement Learning: A Systematic Review of Current Approaches. *Frontiers in Robotics and AI* 8 (2021), 550030. https://doi.org/10.3389/frai.2021.550030

[68] Mette Wichmand and Ditte Kolbaek. 2021. Collective Memory Work: A Method for Turning Adult Learners' Work-Life Experiences Into a Rich Collective Knowledge Resource in Higher Education. *Adult Learning* 32, 3 (2021), 117–127. https://doi.org/10.1177/10451595211004767

[69] Y. Zhang, Q. V. Liao, and R. K. E. Bellamy. 2020. Effect of confidence and explanation on accuracy and trust calibration in ai-assisted decision making. *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (2020). https://doi.org/10.1145/3351095.3372852

[70] Xiaofei Zhou, Jessica Van Brummelen, and Phoebe Lin. 2020. Designing AI learning experiences for K-12: Emerging works, future opportunities and a design framework. *arXiv preprint arXiv:2009.10228* (2020).