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Learning from Machines: A literature review of AI pattern recognition as a reverse framework for Fashion design pedagogy

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Abstract: *This literature review explores Artificial Intelligence (AI) pattern recognition as a novel teaching-learning model in fashion design education, shifting the traditional perspective by proposing that educators and students learn from machines, rather than solely teaching 'the machines'. It uniquely shifts focus from AI as merely a design tool to its structured logic and refinement, examining how AI's data analysis and pattern extraction can enhance human learning and creativity. It critically analyses current AI uses, particularly generative AI and machine learning, to reveal how their underlying pattern recognition logic can inform novel pedagogical approaches. Drawing from experiential and situated learning theories, it presents AI's systematic pattern analysis as a reverse framework for studio-based pedagogy. A dedicated methodology section explains the systematic study selection. By integrating insights from scholarly and technical literature, this review provides a comprehensive understanding of how learning from machines relates to evolving fashion pedagogy, highlighting opportunities, challenges, and future research areas.*

Keywords: *Artificial Intelligence, Pattern Recognition, Fashion Design Pedagogy, Design Education, Creative Cognition, Learning Models.*

1. INTRODUCTION:

The rapid advancement of Artificial Intelligence (AI) is transforming creative industries, including Fashion design and its educational practices (Anantrasirichai, Zhang & Bull 2025; Balasubramanian & Anderson 2025). Traditionally, Fashion design education has valued intuition, ambiguity, and open-ended exploration over rigid structures (Orr & Shreeve 2019, p. 45). Students often develop original concepts through tools such as mind maps, mood boards, and iterative sketches (Babadoğan 2025, p. 5; Culpepper 2013, p. 25). However, the internal progression from inspiration to conceptualisation frequently remains subjective and difficult to assess through objective frameworks.

In contrast, AI systems rely fundamentally on pattern recognition as a learning mechanism (Bansal 2025, p. 18; Sakovich 2025). Trained on extensive datasets, models like generative neural networks or statistical learners identify structured relationships in data and produce new outputs based on learned patterns (Goodfellow, Bengio & Courville 2016, p. 23; Bommasani et al. 2021; Russell & Norvig 2010, p. 50). A structured review by Peckham et al. (2025, p. 3) highlights a sharp increase in generative design research since 2016, driven by diffusion models, GANs, and automated workflows that enhance diversity and efficiency. These mechanisms offer valuable insights for rethinking how creativity is formed, refined, and evaluated in educational contexts.

This review explores the academic discourse on AI's integration into Fashion design education, with a specific focus on AI's pattern recognition logic as a pedagogical model. It shifts the perspective from AI as a passive design tool to an organised learning framework that mirrors cognitive processes. Drawing from AI's systematic approach to pattern formation, the review identifies embedded logic within creative thinking and proposes a model for analysing studio-based learning. This reoriented approach aligns with future-oriented teaching that integrates creative practice with AI understanding (Kyambade, Namatovu & Ssentumbwe 2025, p. 2) and supports the development of measurable, planned strategies for subjective learning and evaluation (Glickman & Sharot 2024, p. 347).

2. SIGNIFICANCE AND NOVELTY:

This review holds deep implications for fashion design education by consolidating AI advancements, established teaching theories, and their specific applications. Its significance lies in addressing a gap in the literature through critical engagement with existing discussions and linking recent technological developments to foundational learning theories such as experiential learning (Kolb 1984, p. 21) and situated learning (Lave & Wenger 1991, p. 3).

By anchoring the discussion in these established pedagogical frameworks, it contributes to the evolving discourse on how design education can become more adaptive and future-oriented. It supports the integration of creative pedagogy with AI knowledge, a direction aligned with future-ready teaching (Kyambade, Namatovu & Ssentumbwe 2025, p. 2), and connects these insights to recent debates on evaluating subjective learning through quantifiable models (Glickman & Sharot 2024, p. 347).

The novelty of this topic lies in presenting AI pattern recognition not merely as a tool for creative automation, but as a model for reimagining the learning process itself. This review uniquely examines how the epistemological foundations of fashion pedagogy are shifting with the emergence of AI, particularly in understanding AI's logical pattern structures as frameworks for human learning (Educatia 21 Journal 2024). By drawing attention to the structural parallels between machine learning systems and cognitive processes in design thinking, the review proposes a conceptual bridge. It introduces a new perspective for viewing studio-based learning as a pattern-informed, iterative process, revealing hidden cognitive mechanisms that inform creativity and design judgement.

3. RESEARCH QUESTIONS:

This literature review seeks to address the following key questions, which capture the essence and need for this critical examination:

i. How does AI's pattern recognition logic inform our understanding and structuring of human design learning processes?
ii. What parallels exist between AI's systematic learning and human creative synthesis in Fashion design?
iii. How can AI's iterative refinement and feedback mechanisms serve as models for evaluating and enhancing pedagogical approaches in design education?
iv. What challenges and opportunities arise from applying AI pattern recognition as a guiding framework for Fashion design pedagogy?

4. METHODOLOGY:

To ensure a comprehensive and critically informed review of the literature, a systematic and rigorous approach was used for selecting relevant articles. The main goal was to find scholarly works that explore the connection between Artificial Intelligence and Fashion design education. There was a particular focus on how this affects teaching methods, creative processes, and measurable learning outcomes.

- **Search Strategy and Databases:** The initial search was strategically planned across various academic databases, including broad tools like Google Scholar and specialized journal collections. This involved using specific keyword combinations to ensure relevance and broad coverage, aiming to identify literature that contributes to understanding AI pattern recognition in the context of both machine learning and human learning within design. Beyond traditional scholarly articles, the search also explored relevant academic books (e.g., Bishop 2006; Goodfellow, Bengio & Courville 2016) and reputable online resources (e.g., Loft 2025; Very Engineering Team 2024) to gather foundational and current perspectives on AI and learning.
- **Inclusion and Exclusion Criteria:** Literature was selected based on defined criteria for relevance and academic integrity. Included sources focused on AI in Fashion or design education, were published between 2020-2025, and demonstrated scholarly merit. Foundational works prior to 2020 were retained if contextually or theoretically significant. Accepted materials included peer-reviewed journals, books, theses, conference papers, and reputable online sources in English. Conversely, excluded items were those that lacked methodological rigor, focused solely on general design technology unrelated to AI, or were redundant in concept. Opinion-based articles and those published before 2020 without strong theoretical value, were also removed.
- **Selection Process:** The initial broad search resulted in a large number of findings. To manage this amount and ensure the quality of the chosen literature, a strict two-stage screening process was put in place. In the first stage, titles and abstracts were thoroughly reviewed to check their immediate relevance to the research questions. Articles that were not relevant at this stage were rejected. The remaining articles, having passed the first check,

then underwent a careful full-text review. During this important stage, each article was carefully judged against the defined inclusion rules. Its methods, findings, and overall contribution to the existing body of knowledge were critically assessed. The systematic, multi-stage selection process as detailed in Figure 1, ensured that the final collection of 52 references provided a balanced and critically examined foundation for this literature review.

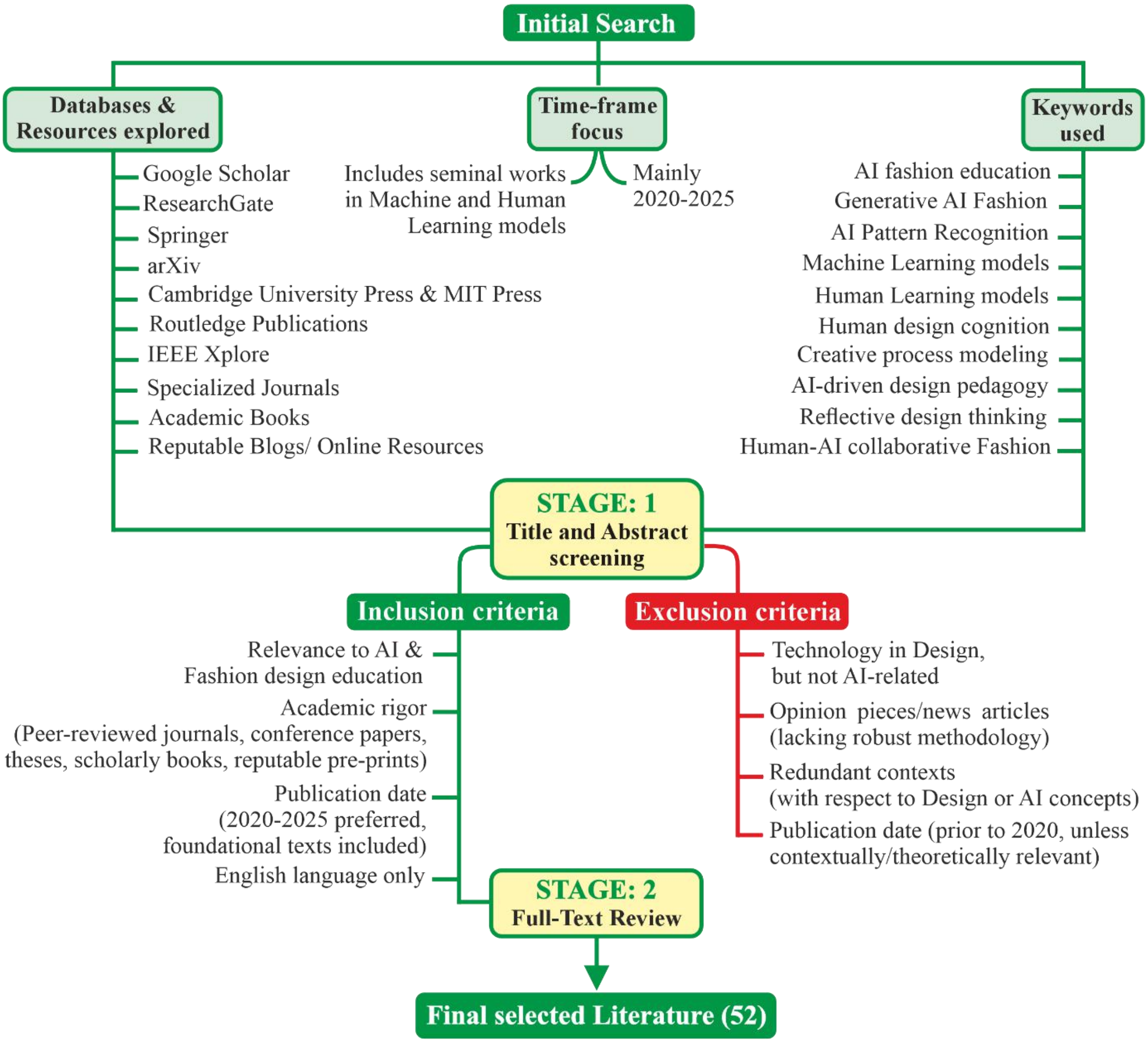

Figure 1. Literature selection flow diagram

5. THEMATIC LITERATURE REVIEW:

This section explores Artificial Intelligence pattern recognition as a parallel framework to human learning in fashion design pedagogy. It begins by examining the core principles behind AI pattern recognition and its structured approach to data, and then transitions into a critical discussion of human learning models in creative disciplines. It culminates in a comparative synthesis, highlighting how AI's logic-driven learning mechanisms can inform pedagogical strategies in design education in general and Fashion pedagogy, in particular.

- **Understanding AI pattern recognition as learning logic:** Pattern recognition is the core mechanism that enables artificial intelligence systems to function and improve over time. It refers to the AI system's ability to detect structures within data and use those structures to make informed classifications, predictions, or generative outputs (Sakovich 2025; Bishop 2006, p. 7). In the context of creative domains like fashion design, pattern recognition allows AI tools to respond to visual input such as color, texture, and form. These tools identify relationships among these features and apply that understanding to generate novel design suggestions or evaluate existing ones. At a technical level, the learning logic in AI involves several distinct stages. Raw data are first pre-processed to remove noise or standardize inputs. This is followed by feature extraction, which breaks down complex visual or numerical information into manageable attributes (Goodfellow, Bengio & Courville 2016, p. 23). The system then enters a training phase where algorithms, particularly neural networks, adjust internal parameters based on feedback received through error measurement. This process is mathematically refined through optimization strategies such as gradient descent (Deisenroth, Faisal & Ong 2020, p. 8; Russell & Norvig 2010, p. 50). Over multiple iterations, the system improves its ability to recognize patterns, and this refinement continues as more data are introduced.

These stages reflect the logic of statistical learning, where model performance improves through feedback-driven optimization of representational accuracy (Hastie, Tibshirani & Friedman 2009, p. 13). According to Bansal (2025, p. 18), such pattern-based abstraction in AI forms a transferable schema for instructional design, offering a systematic, data-driven lens to reimagine how creativity might be scaffolded in design education.

Figure 2 outlines this learning pipeline in AI, helping to contextualize the machine's approach to pattern recognition and refinement.

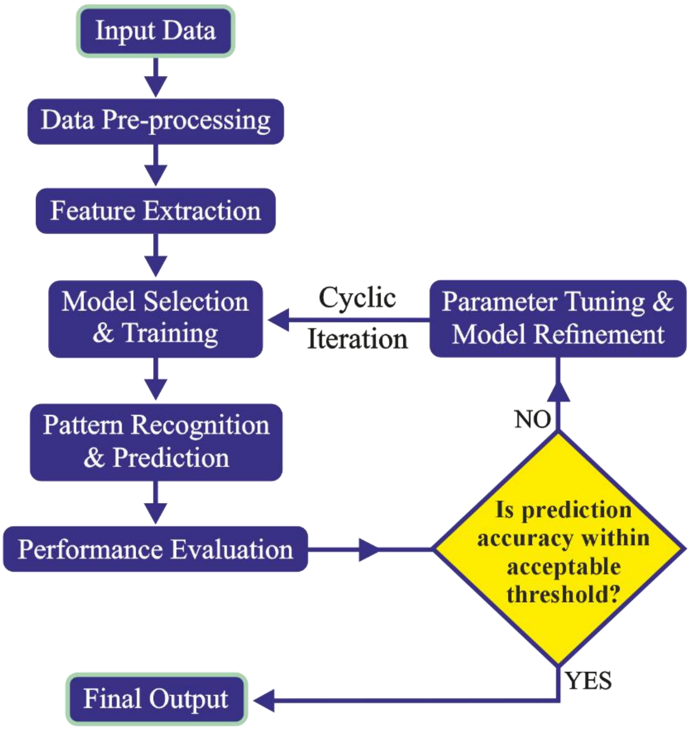

Figure 2. Process flow of AI pattern recognition
Developed based on Sakovich (2025) and GeeksforGeeks (2025)

- **Mapping Human learning in Fashion design- Cognitive and Experiential models:** Learning in fashion design education relies on a complex combination of experience, reflection, intuition, and context. Human learning, particularly in creative disciplines, is shaped by personal and social influences, unlike AI which depends entirely on data and algorithms. To understand this contrast, it is important to explore foundational theories that describe how designers learn, internalize, and apply creative knowledge.

  One influential model is Kolb's theory of experiential learning, which emphasizes a cyclical process involving four stages: concrete experience, reflective observation, abstract conceptualization, and active experimentation (Kolb 1984, p. 21). This model is frequently observed in design studios, where students move from sketching to critique and then revise their work through trial-based prototyping. This aligns with Bransford, Brown and Cocking's (2000, p. 65) emphasis on learning transfer, where students apply abstract knowledge from one context to novel design problems. The process is dynamic and shaped by the learner's reflections and evolving interpretations, which cannot be directly translated into quantifiable data. Masný (2024, p. 7) also highlights how Kolb's model connects with the diverse learning preferences found among design students.

  The situated learning framework by Lave and Wenger (1991, p. 3) reinforces that learning happens in social contexts. In fashion education, this occurs through collaborative practices such as peer feedback, mentor reviews, and real-time critiques. Lave (2008) further explains that these interactions take place within communities of practice, where knowledge transfer involves not only technical skills but also tacit understanding, including aesthetic judgment and stylistic intuition. Babadoğan (2025, p. 2) suggests that visual tools like mind mapping can enhance this by supporting reflective and associative learning in design. Schön's concept of the reflective practitioner highlights how designers make judgments during designing and later reflect to improve future performance (Schön 1987, p. 12).

While AI systems refine outputs based on data accuracy, human learners reflect on intent, context, and meaning. Figure 3 below visualizes the iterative, experiential model of design thinking, demonstrating how human learning operates across emotional, cognitive, and social dimensions.

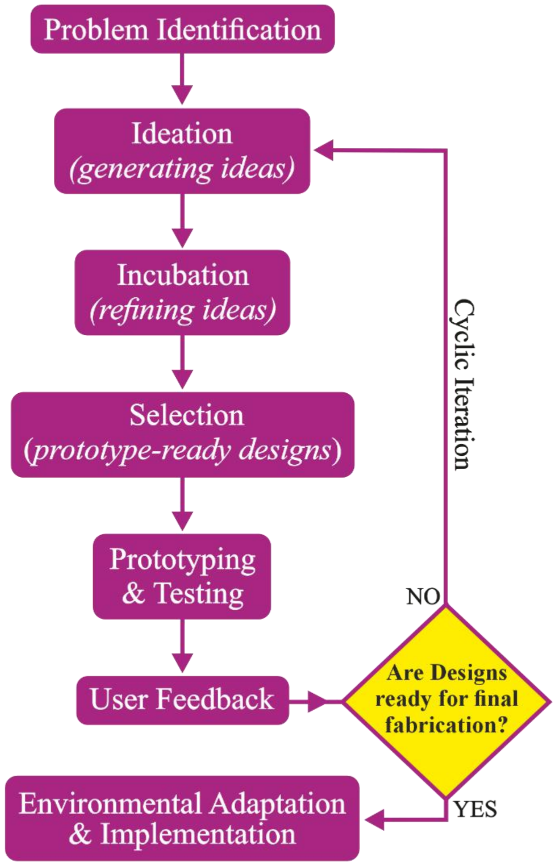

Figure 3. Iterative stages of the creative process
Developed based on Kolb (1984) and d.school (2010)

- **Pattern logic in practice- How AI tools shape fashion design ideation and analysis:** The practical integration of AI into fashion design education offers insights into how pattern recognition functions in creative processes. AI tools such as generative models, design support platforms, and image-based neural networks increasingly contribute to ideation, style forecasting, and material experimentation. These systems follow structured pattern logic, helping learners understand how design decisions evolve from data inputs to visual outputs.
Generative design tools like DALL·E and StyleGAN operate through pattern synthesis, generating novel combinations of form, color, and texture based on trained data. In educational contexts, tools like FashionQ facilitate early-stage ideation by prompting designers with structured visual inputs (Jeon et al. 2021). These tools serve not only as visual generators but as pattern-based ideation aids, guiding students through structured decision spaces rather than open-ended exploration. Selkee (2025, p. 45) highlights how AI-driven innovations actively enhance fashion workflows, enabling designers to explore novel design spaces with greater efficiency and creative control. Samaniego et al. (2024) confirm that pattern-focused ideation enhances divergent thinking when guided by systematic prompts. Balasubramanian and Anderson (2025) argue that such tools support the iterative nature of design through real-time concept validation.
Kim et al. (2025) found that generative AI helped fashion students articulate vague ideas more concretely, especially during mood board and color scheme iterations. Jin et al. (2024) observed AI-supported revisions deepened experimentation in early sketching phases, while Lee (2022, p. 3) emphasizes AI's role in externalizing unstructured ideas into tangible concepts, fostering clarity in ideation.
AI's utility lies in generating suggestions that follow recognizable stylistic patterns. Educators must remain aware of biases, as models trained on dominant design data may reinforce conventional styles or overlook culturally specific aesthetics (Bommasani et al. 2021; Anantrasirichai, Zhang & Bull 2025). Figure 4 illustrates the iterative

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feedback loop between design learners and AI tools, highlighting how students critically engage with AI outputs using aesthetic, contextual, and functional judgments to guide successive iterations.

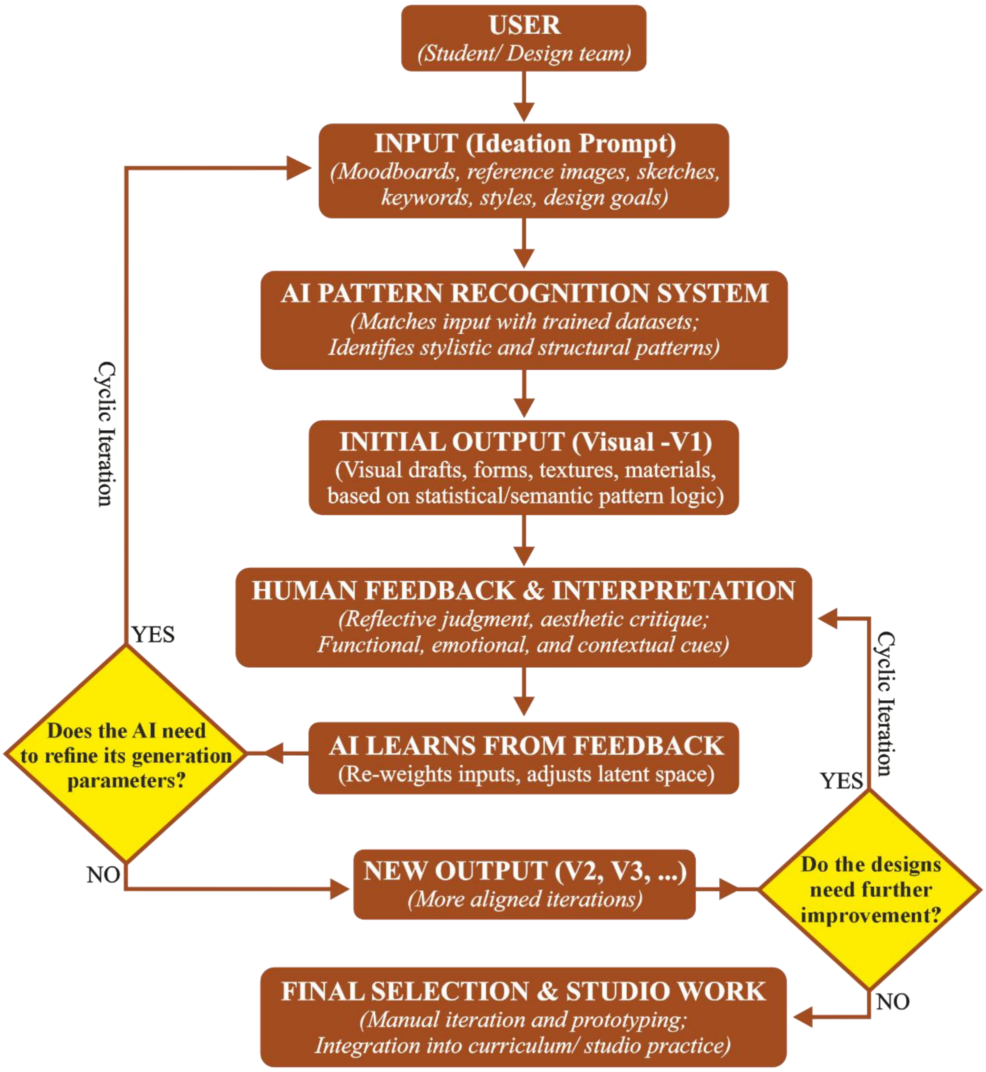

Figure 4. AI-Supported ideation loop in Fashion design education
Developed based on Jeon et al. (2021) and Kim (2024)

- **Parallel systems- comparing human creative cognition and AI pattern recognition:** While human creativity and artificial intelligence operate under fundamentally different paradigms, comparing their internal logic reveals pedagogically valuable insights. Both systems rely on prior inputs, interpretive strategies, and iterative feedback to improve outputs. However, they diverge in purpose, context, and adaptability. These differences are not merely technological; they reflect contrasting cognitive frameworks that influence how knowledge is produced, applied, and evaluated (as shown in Table 1).
  Human cognition in design is rooted in abstraction, ambiguity, and often intuitive leaps. Designers frequently engage in associative thinking, draw from emotional memory, and adapt to social or cultural cues. Gardner's theory of multiple intelligences (1983) highlights that creative learning involves spatial, interpersonal, and intrapersonal dimensions, capacities that are currently beyond AI systems. Similarly, Schön (1987, p. 12) emphasized reflection-in-action as central to human creativity, a process involving subjective judgments and context-specific adjustments.
  In contrast, AI operates through calculable logic. Its creativity, such as in generative design or predictive modelling, is dependent on mathematical transformations of existing data. As Bengio, Courville and Vincent (2012) describe, deep learning achieves abstraction through layered representation learning, but it remains bound by training data and statistical inference. According to Bansal (2025, p. 18), AI systems follow fixed patterns to improve results, not to explore meaning.
  Even within these constraints, reinforcement learning demonstrates trial-and-error behaviors comparable to human experiential learning (Kaelbling, Littman and Moore 1996, p. 237). Additionally, as von Luxburg and

Schölkopf (2008, p. 3) note, statistical learning theory underpins many AI decision-making models, making AI highly proficient at pattern optimization but less adaptive to novelty without retraining.

COGNITIVE FEATURE	HUMAN CREATIVITY	AI PATTERN RECOGNITION
Processing Method	Intuitive, associative, emotion-influenced	Statistical, rule-based, data-driven
Learning Mechanism	Experience, reflection, context sensitivity	Training on labelled/unlabelled datasets, pattern generalization
Flexibility and Novelty	High flexibility, emergent ideation	Constrained by prior data and algorithmic boundaries
Feedback Cycle	Internalized, situational judgment	External error correction, weight tuning
Source of Originality	Cultural memory, emotion, identity	Novel recombination of existing data
Evaluation Criteria	Aesthetic value, purpose, social context	Statistical accuracy, performance metrics

Table 1. Comparative features of human creative cognition and AI pattern logic
Developed based on Schön (1987) and Bengio et al. (2012)

While the distinctions are clear, some AI capabilities still parallel aspects of human cognition. Feedback loops in AI resemble Schön's reflection cycles (Schön 1987, p. 12), albeit stripped of emotional or cultural context (Happer 2025; Loft 2025). Additionally, reinforcement learning mimics the trial-and-error processes found in experiential pedagogy (Kaelbling, Littman & Moore 1996, p. 237). These parallels suggest a promising model for introducing more logic and systematic approaches to design thinking and process in Fashion design pedagogy.

- **Toward a machine-inspired pedagogy in Fashion design education:** Reframing artificial intelligence not as a tool but as a pedagogical reference offers new ways to design fashion education. Traditional studio-based models are often nonlinear, intuitive, and mentor-driven. However, integrating the logic of AI pattern recognition introduces an opportunity to develop more structured, self-aware learning strategies. Rather than treating machines as passive engines for generating output, educators can study their learning systems and apply this understanding to shape how students think, reflect, and iterate.

The integration of AI into fashion design education is fundamentally changing the nature of creativity and the learning process. While concerns persist about AI replacing human imagination, an increasing body of academic literature emphasizes its augmentative potential by encouraging novel design approaches and improving learning outcomes (Cunningham, Radvansky and Brockmole 2025, p. 3; Ok 2025, p. 1).

At the center of machine learning is structured feedback. AI systems improve by comparing predictions to outcomes and adjusting internal parameters (Goodfellow, Bengio and Courville 2016, p. 23; Mohri, Rostamizadeh and Talwalkar 2012, p. 44). In fashion design, this mirrors how students improve through critique, though human feedback often lacks consistency. Educators can model feedback loops on AI systems to help students recognize growth patterns, mistakes, and stylistic preferences (Loft 2025; Happer 2025), aligning with statistical learning frameworks (James et al. 2013, p. 9). Visual tools like mind mapping can clarify the design process into stages of development and abstraction (Babadoğan 2025, p. 6). Kim et al. (2025, p. 15) further emphasize that AI-based creativity tools interact differently with various designer creativity types, suggesting pedagogical approaches must adapt to individual learning styles for optimal support.

Table 2 presents cues drawn from AI logic that encourage reflective, data-aware, and iterative learning, not to replace studio methods, but to complement them.

AI FEATURE	EDUCATIONAL CUE FOR FASHION DESIGN
Iterative feedback refinement	Encourage structured self-critique and revision checkpoints
Representation learning	Teach students to break down ideas into core visual components
Transparent performance metrics	Develop clear rubrics to track creative progress
Optimization through error	Embrace failure as feedback in design development
Pattern-based abstraction	Guide students in identifying recurring approaches in their design thinking

Table 2. Pedagogical cues inspired by AI learning frameworks
Developed based on Goodfellow et al. (2016) and Mohri et al. (2012)

The ultimate aim is not to replicate machine learning, but to study its principles to build a more conscious, process-oriented fashion design pedagogy. Learning from machines, in this view, becomes a method for teaching humans better.

6. CHALLENGES AND FUTURE DIRECTIONS:

While the transformative potential of AI in Fashion design education, particularly as a model for pattern recognition and learning, is undeniably vast, several significant challenges are discussed in the literature that must be thoughtfully addressed to ensure its effective, ethical, and equitable implementation. These challenges span crucial technological, pedagogical, and ethical considerations.

- **Technological limitations and accessibility:** Despite the breathtaking pace of advancements, current AI models still possess inherent limitations in their pattern recognition. Issues like bias embedded within datasets can lead to AI generating designs that perpetuate stereotypes or lack genuine novelty, reflecting flawed learned patterns (Prince 2024; Ok 2025). Moreover, the accessibility of advanced AI tools remains a concern for educational institutions with limited financial or technological resources. Ensuring equitable access to sophisticated software and robust computational power is crucial to prevent a digital divide in design education, which could hinder AI adoption as a pedagogical model (Bengio, Courville & Vincent 2012).
- **Pedagogical adjustments and faculty training:** The meaningful integration of AI into the fashion curriculum demands deliberate pedagogical change. As Md Khairulanwar and Jamaluddin (2025, p. 5) emphasize, educators must move beyond passive adoption and reframe AI as a collaborative thinking partner. This requires comprehensive faculty development programs to build competence in AI theory, pattern logic, and creative co-design practices. Gkintoni et al. (2025) adds that educational neuroscience combined with AI tools can enhance cognitive efficiency and reduce mental load in design learning environments.
  Additionally, AI literacy must be embedded in curriculum design, including topics such as bias detection, interpretability of AI output, and responsible human-AI collaboration. Sweller (1988, p. 267) emphasizes the role of minimizing unnecessary complexity during problem solving, and Oakley (2014) reinforces this through techniques like chunking and spaced learning, which support better retention in AI-integrated education. Babadoğan (2025, p. 6) advocates for mind mapping to organize visual ideation effectively, and Marku (2023) underscores that these tools should enhance, not constrain, student creativity.
- **Ethical considerations and the future of human creativity:** Ethical implications of AI in creative fields raise concerns about authorship, intellectual property, and the devaluation of human artistry (Cunningham, Radvansky & Brockmole 2025, p. 5). Educators must foster critical thinking on AI's responsible use, helping students distinguish AI-generated output from authentic human creativity. Emphasis should be on AI's pattern recognition as a tool to enhance human potential, not replace it, since 'AI-learning' focuses on optimization, not genuine understanding (Zhang 2024, p. 3). It is vital to assess how frequent interaction with AI-generated content influences students' originality and their ability to recognize refined iterations versus authentic authorship.
  Future research should examine AI's long-term effects on design thinking and problem-solving, particularly how its pattern logic shapes these processes. Longitudinal studies on early AI exposure and standardized integration frameworks are needed. Predictive modelling for student engagement (JITE 2015) suggests such frameworks can inform adaptive pedagogy. Understanding the symbiotic 'learning-by-thinking' in natural and artificial minds is key, recognizing the uniqueness of human learning compared to AI. Future studies should develop collaborative systems where AI aids pattern discovery and adapts to the fluidity of human creativity, fostering hybrid innovation models (Lombrozo 2024, p. 2; Lave & Wenger 1991, p. 3; Masný 2024, p. 7; Kaelbling, Littman & Moore 1996).

7. CONCLUSION:

This literature review highlights the strong potential of AI pattern recognition as a reverse framework that can reshape fashion design education. By exploring how machines detect and respond to patterns, it consolidates emerging discussions on AI's structured approach to interpreting complex visual and contextual information. These systems offer insights into how human creativity can be re-evaluated and taught more analytically. The review demonstrates how AI's feedback-based logic parallels human iterative design processes and presents a model for improving pedagogy through structured reflection and refinement. Although challenges remain, including technological access, faculty preparedness, and ethical concerns around authorship and bias, the future of fashion education lies in fostering a reciprocal learning environment. In such contexts, students engage critically with AI-generated outputs, learning from machine logic rather than merely teaching it. Emphasizing ethical engagement and critical thinking will allow future designers to merge human intuition with computational insight, creating a progressive and adaptive design education model for a rapidly evolving industry.

REFERENCES:

1. Anantrasirichai, N., Zhang, R., & Bull, D. (2025). Artificial intelligence in creative industries: Advances prior to 2025. *arXiv*. https://arxiv.org/pdf/2501.02725v1
2. Balasubramanian, M., & Anderson, R. (2025). Generative artificial intelligence in fashion curriculum accentuates design process. *International Textile and Apparel Association Annual Conference Proceedings, 81*(1). https://doi.org/10.31274/itaa.18763
3. Orr, S. & Shreeve, A. (2019). *Art and design pedagogy in higher education: Knowledge, values and ambiguity in the creative curriculum*. 1st ed. London: Routledge. https://www.routledge.com/Art-and-Design-Pedagogy-in-Higher-Education-Knowledge-Values-and-Ambiguity-in-the-Creative-Curriculum/Orr-Shreeve/p/book/9780367192501
4. Babadoğan, M. C. (2025): Mind mapping as a learning tool: A course design example for higher education. *Psycho-Educational Research Reviews*, 14(1), 1-14. https://doi.org/10.52963/PERR_Biruni_V14.N1.01
5. Culpepper, M. K. (2013). *The telling line: The relationship between cognitive style and fashion design sketching* (Master's thesis, State University of New York, College at Buffalo). https://digitalcommons.buffalostate.edu/creativetheses/20
6. Bansal, P. (2025). AI pattern recognition and its features. *International Journal of Engineering and Advanced Technology, 14*(3), 18. https://doi.org/10.35940/ijeat.C4562.14030225
7. Sakovich, N. (2025). Pattern recognition in AI: A comprehensive guide. *SaM Solutions*. https://sam-solutions.com/blog/pattern-recognition-in-ai/
8. Goodfellow, I., Bengio, Y. & Courville, A. (2016). *Deep learning*. Cambridge, MA: The MIT Press. https://www.deeplearningbook.org
9. Bommasani, R., Yu, T., Jain, S., et al. (2021). On the opportunities and risks of foundation models. *Stanford Institute for Human-Centered Artificial Intelligence*. https://arxiv.org/abs/2108.07258
10. Russell, S. & Norvig, P. (2010). *Artificial intelligence: A modern approach*. 3rd ed. Upper Saddle River, NJ: Prentice Hall. https://aima.cs.berkeley.edu/
11. Peckham, O., Smith, J., & Nguyen, T. (2025). Artificial intelligence in generative design: A structured review of trends and opportunities in techniques and applications. *Designs*, 9(4), 79. https://doi.org/10.3390/designs9040079
12. Kyambade, M., Namatovu, A.N. & Ssentumbwe, A.M. (2025). Exploring the evolution of artificial intelligence in education: From AI-guided learning to learner-personalized paradigms. *Cogent Education*, 12(1), 2505297. https://doi.org/10.1080/2331186X.2505297
13. Glickman, M. & Sharot, T. (2024). How human-AI feedback loops alter human perceptual, emotional and social judgements. *Nature Human Behaviour*, 9(2), 345-359. https://doi.org/10.1038/s41562-024-02077-2
14. Kolb, D.A. (1984). *Experiential learning: Experience as the source of learning and development*. Englewood Cliffs, NJ: Prentice-Hall. https://books.google.com/books/about/Experiential_Learning.html?id=zXruAAAAMAAJ
15. Lave, J. & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation*. Cambridge: Cambridge University Press. http://dx.doi.org/10.1017/CBO9780511815355
16. Educatia 21 Journal. (2024). Epistemological foundations of fashion pedagogy: Investigating knowledge and emerging issues. *Educatia 21 Journal*. https://educatia21.reviste.ubbcluj.ro/data/uploads/article/2024/ed21-no28-art02.pdf
17. Bishop, C.M. (2006). *Pattern recognition and machine learning*. New York: Springer. https://www.microsoft.com/en-us/research/wp-content/uploads/2006/01/Bishop-Pattern-Recognition-and-Machine-Learning-2006.pdf
18. Loft, G. (2025). How AI uses feedback loops to learn from its mistakes. *Zendesk*. https://www.zendesk.com/in/blog/ai-feedback-loop/
19. Very Engineering Team (2024). Machine learning vs neural networks: Understanding their differences. *Very Technology*. https://www.verytechnology.com/insights/machine-learning-vs-neural-networks
20. Deisenroth, M.P., Faisal, A.A. & Ong, C.S. (2020). *Mathematics for machine learning*. Cambridge: Cambridge University Press. https://www.cambridge.org/9781108470049

21. Hastie, T., Tibshirani, R. & Friedman, J. (2009). *The elements of statistical learning: Data mining, inference, and prediction*. 2nd ed. New York: Springer. https://books.google.com/books/about/The_Elements_of_Statistical_Learning.html?id=eBSgoAEACAAJ
22. GeeksforGeeks (2025). Flowchart for basic Machine Learning models. *GeeksforGeeks*. https://www.geeksforgeeks.org/machine-learning/flowchart-for-basic-machine-learning-models/
23. Bransford, J. D., Brown, A. L., & Cocking, R. R. (2000). Learning and transfer. In *How people learn: Brain, mind, experience, and school* (Expanded ed., pp. 63–84). National Academy Press. https://nap.nationalacademies.org/read/10067/chapter/7
24. Masný, A. (2024). *Learning styles: VARK, Kolb, Honey and Mumford comparison* [Unpublished research paper]. *Trnava University in Trnava, Pedagogy Faculty*. https://www.academia.edu/118663127
25. Lave, J. (2008). Situating learning in communities of practice. In *Ecology of design*. https://ecologyofdesigninhumansystems.com
26. Schön, D.A. (1987). *Educating the reflective practitioner: Toward a new design for teaching and learning in the professions*. San Francisco, CA: Jossey-Bass. https://web.eecs.umich.edu/~mjguz/csl/home.cc.gatech.edu/allison/uploads/4/schon1987c.pdf
27. d.school. (2010). *An introduction to design thinking: Process guide*. Hasso Plattner Institute of Design at Stanford University. https://s3-eu-west-1.amazonaws.com/ih-materials/uploads/Introduction-to-design-thinking.pdf
28. Jeon, Y., Jin, S., Shih, P.C. & Han, K. (2021). FashionQ: An AI-driven creativity support tool for facilitating ideation in Fashion design, In CHI Conference on Human Factors in Computing Systems. https://www.researchgate.net/publication/345324055
29. Selkee, C. (2025). *AI-driven innovation in fashion: Enhancing the design process through technology* (Bachelor's thesis, University of Lapland). https://lauda.ulapland.fi/bitstream/handle/10024/66758/Selkee_Charlotta.pdf
30. Samaniego, M., Usca, N., Salguero, J. & Quevedo, W. (2024): Creative thinking in art and design education: A systematic review. *Education Sciences*, 14(2), 192. https://doi.org/10.3390/educsci14020192
31. Kim, M., Joo, Y., & Han, K. (2025). Understanding the differences in an AI-based creativity support tool between creativity types in fashion design. *International Journal of Human-Computer Interaction*. https://doi.org/10.1080/10447318.2024.2448484
32. Jin, Y., Yoon, J., Self, J. & Lee, K. (2024): Understanding Fashion designers' behavior using generative AI for early-stage concept ideation and revision. *Archives of Design Research*. https://www.researchgate.net/publication/382942142
33. Lee, Y.K. (2022): How complex systems get engaged in Fashion design creation: Using artificial intelligence. *Thinking Skills and Creativity*, 44, 101005. https://doi.org/10.1016/j.tsc.2022.101005
34. Kim, S.J. (2024): Generative artificial intelligence in collaborative ideation: Educational insight from Fashion students. *IEEE Access*. https://doi.org/10.1109/ACCESS.2024.3382194
35. Gardner, H. (1983). *Frames of mind: The theory of multiple intelligences*. New York: Basic Books. https://books.google.com/books/about/Frames_of_Mind.html?id=ObgOAAAAQAAJ
36. Kaelbling, L.P., Littman, M.L. & Moore, A.W. (1996). Reinforcement learning: A survey. *Journal of Artificial Intelligence Research*, MIT Press. https://doi.org/10.48550/arXiv.cs/9605103
37. von Luxburg, U. & Schölkopf, B. (2008). Statistical learning theory: Models, concepts, and results. *Springer*. https://doi.org/10.48550/arXiv.0810.4752
38. Bengio, Y., Courville, A. & Vincent, P. (2012). Representation learning: A review and new perspectives. *Foundations and Trends in Machine Learning*. https://doi.org/10.48550/arXiv.1206.5538
39. Happer, C. (2025). Creating feedback loops between human experts and AI systems. *ResearchGate*. https://www.researchgate.net/publication/391398367_CREATING_FEEDBACK_LOOPS_BETWEEN_HUMAN_EXPERTS_AND_AI_SYSTEMS
40. Cunningham, C. V., Radvansky, G. A., & Brockmole, J. R. (2025). Human creativity versus artificial intelligence: Source attribution, observer attitudes, and eye movements while viewing visual art. *Frontiers in Psychology, 16*. https://doi.org/10.3389/fpsyg.2025.1509974
41. Ok, E. (2025). Comparing Human Creativity and AI-Generated Image Design. https://www.researchgate.net/publication/388849201_Comparing_Human_Creativity_and_AI-_Generated_Image_Design
42. Mohri, M., Rostamizadeh, A. & Talwalkar, A. (2012). *Foundations of machine learning*. Cambridge, MA: MIT Press. https://mitpress.mit.edu/9780262039406

43. James, G., Witten, D., Hastie, T. & Tibshirani, R. (2013). *An introduction to statistical learning: With applications in R*. New York: Springer. https://www.stat.berkeley.edu/~rabbee/s154/ISLR_First_Printing.pdf

44. Prince, S. (2024). *Understanding deep learning*. Cambridge, MA: MIT Press. https://anthology-of-data.science/resources/prince2023udl.pdf

45. Md Khairulanwar, A.B. & Jamaluddin, K.A. (2025): *Artificial Intelligence in Fashion Design Education: A Phenomenological Exploration of Certificate-Level Learning*. *International Journal of Academic Research in Business and Social Sciences*, 15(3), 313–331. https://doi.org/10.6007/IJARBSS/v15-i3/24604

46. Gkintoni, E., Antonopoulou, H., Sortwell, A. & Halkiopoulos, C. (2025): Challenging cognitive load theory: The role of educational neuroscience and artificial intelligence in redefining learning efficacy. *Brain Sciences*, 15, 203. https://doi.org/10.3390/brainsci15020203

47. Sweller, J. (1988): Cognitive load during problem solving: Effects on learning. *Cognitive Science*, 12(2), 257-285. https://mrbartonmaths.com/resourcesnew/8.%20Research/Explicit%20Instruction/Cognitive%20Load%20during%20problem%20solving.pdf

48. Oakley, B. (2014): Learning how to learn. [online course]. https://www.coursera.org/learn/learning-how-to-learn

49. Marku, E. (2023). AI-Artificial Intelligence and the growth of the creative potential of designers in the Fashion industry. *Forum A+P*. https://www.researchgate.net/publication/379573623

50. Zhang, J. (2024). Artificial intelligence vs. human intelligence: Which excels where and what will never be matched. *UTHealth Houston McWilliams School of Biomedical Informatics*. https://sbmi.uth.edu/blog/2024/artificial-intelligence-versus-human-intelligence.htm

51. JITE (2015). A Systematic Review of Machine Learning Techniques for Predicting Student Engagement in Higher Education Online Learning. *Journal of Information Technology Education: Research*, 24, 1-20. https://www.jite.org/documents/Vol24/JITE-Rv24Art005Chong10955.pdf

52. Lombrozo, T. (2024): Learning by thinking in natural and artificial minds. *Trends in Cognitive Sciences*, 28(11). https://doi.org/10.1016/j.tics.2024.07.007