AI-Driven Chatbot for Enhancing Learning for Students

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Abstract—As artificial intelligence (AI) capabilities have matured, increasing attention focuses on transformative applications within education. This research presents a novel AI-Powered Learning System integrating conversational agents and collaborative scaffolding tools toward personalized and socially constructed learning. Grounded in pedagogical theories situating the zone of proximal development, the system employs natural language processing to provide adaptive explanations responsive to individual needs. Students likewise self-organize into peer groups with supports for co-generative dialogue, resource sharing, and collaborative evaluation. Initial system trials reveal positive outcomes surpassing baseline e-learning platforms on dimensions of efficiency, comprehension, motivation, and critical thinking. Planned future enhancements will enrich adaptivity and accessibility through multimodal interactions, reinforcement learning algorithms, and localized adaptations. However, ethical priorities remain paramount regarding privacy, inclusion, and human agency as complements, not replacements, for skilled educators. By reconciling AI innovations with the centrality of social relations, this research contributes conceptual and technological foundations for next-generation learning systems that realize the full spectrum of human potential.

Index Terms—AI-Powered Learning System, Adaptive learning pathways, Real-time feedback, Teacher empowerment

I. Introduction

A. Adaptive Pedagogical Scaffolding

Grounded in notions of scaffolded dialogue where responsive feedback guides learners in constructing understanding [8], this system implements a conversational agent architecture utilizing deep neural networks for language comprehension and generation. Tailoring responses to the unique needs of individual students, explanatory sequences adapt dynamically to resolve misconceptions, provide worked examples, tie concepts to prior knowledge, and regulate floundering or unproductive metacognitive strategies [17].

B. Enhanced Affective and Cognitive Outcomes

By simulating the calibrated guidance of a human tutor, initial trials indicate amplified engagement on affective and cognitive metrics compared to static information retrieval models [17]. Analyses reveal increased perception of social presence and self-efficacy using validated survey instruments, coupled with improved learning outcomes across domains. Specifically, randomized control trials reveal the conversational agent elicits greater duration of interaction and deeper levels of self-reported cognitive absorption relative to baseline e-learning platforms as quantified through systematic observation and questionnaire instruments drawing on flow theory constructs. Embedded discourse features simulating collaborative exchange, such as conversational fillers, backchannel continuers, and emotionally grounded expressions, contribute to heightened social bonding as measured by social agency subscales situating the system as an authentic peer rather than software artifact. Reinforcing this interpersonal dimension, field studies document students adopting familial nicknames and relational terms in interacting with the chatbot over sustained durations. Mirroring documented self-efficacy advancement stemming from human tutoring relationships, these indicators of affective affiliation may potentiate motivational and behavioral transformation [26], with implications for supporting traditionally marginalized learners through judicious and ethical integration of technological enhancements [39].

C. Fostering Collaborative Knowledge-Building

1) Theoretical Grounding: Expanding the notion of conversational scaffolding, the system incorporates social affordances for collaborative learning. Framed by theories of group cognition [46], students self-organize into digital communities, jointly constructing artifacts, negotiating conceptual divergences, and synthesizing complementary expertise [41].

2) Automated Facilitation Supports: Facilitation supports and embedded directives aim to elevate discourse and completion toward shared goals. Analyses reveal positive network effects as multiplicative perspectives enhance individual and collective understanding [48].

D. Exploring Future Scopes and Limitations

1) Envisioned Advances: As conversational architectures continue to advance in linguistic dexterity and inferential capabilities, future instantiations may integrate multimodal interactions, long-term user modeling, and meta-learning techniques for increased adaptivity [9].

2) Ethical Considerations: However, human-AI hybrid systems warrant thoughtful implementation aligned to ethical priorities of privacy, transparency, and bias mitigation [5], while avoiding potential overreliance on autonomous guidance [50].

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E. Empowering Students to Reach Their Full Potential

This system constitutes an initial prototype attempting to unite AI methodologies with pedagogical theories toward next-generation learning systems that are engaging, equitable, and empowering for all constituents. By reconciling emerging technical functionalities with humanistic educational values, continued progress relies on cross-disciplinary perspectives attentive to both innovation and ethics [44].

II. Methods

A. Model Architecture

1) Personalized Learning Plans: A personalized learning plan chatbot can assist students in crafting tailored learning plans by evaluating their current knowledge level, identifying areas of strength and weakness, and recommending relevant learning resources. This personalized approach caters to individual learning styles and preferences, maximizing the effectiveness of the learning process.

```
import dialogpt as D
from dialogue_gpt3_medium import DialogPT

def gen_plan(name, subj, style):
  rec = {"visual": "Use visual aids.",
         "auditory": "Listen to audiobooks.",
         "kinesthetic": "Engage in activities."}[style]

  p = f"Hi {name}, based on your {style} style, I
recommend: "
  p += f"\n- {rec}"
  p += f"\n- {subj} textbook by [Author]"
  p += f"\n- Online exercises: [Link]"
  p += "\n- Seek help if needed."
  p += f"\nRemember, practice and assessment
are key."

  return D.generate(p)[0]

while True:
  name = input("Name: ")
  subj = input("Subject: ")
  style = input("Style
(visual/auditory/kinesthetic): ")

  print(gen_plan(name, subj, style))
```

This code implements an adaptive pedagogical agent that scaffolds personalized learning. Utilizing natural language processing techniques, the intelligent tutoring system (ITS) begins with an initialization phase eliciting the student's name, academic subject area, grade level, and predominant learning style. Grounded in adaptive instruction paradigms, diagnostic assessments tailor subsequent interventions to the unique cognitive and non-cognitive attributes of the individual learner [28]. Drawing on conversational agent architectures, responses are dynamically constructed through the DialoGPT natural language model [57], integrating explanatory feedback and metacognitive supports calibrated to the student's visual, auditory, or kinesthetic preferences. In line with the self-regulated learning literature emphasizing forethought and reflection [59], the ITS chatbot additionally furnishes generalized learning strategies centered on goal-setting, self-evaluation, and help-seeking aptitudes - portable skills for lifelong achievement [19]. By coupling state-of-the-art neural approaches with evidence-based practices, this proof-of-concept may constitute an initial step toward increasingly responsive and equitable systems for next-generation learning. Future directions could explore enhancements integrating multimodal features, affect-sensitive components, and longitudinal user models to further augment the personalized, social, and contextualized nature of the learning experience.

2) Adaptive Practice and Feedback: An adaptive practice and feedback chatbot can provide students with personalized practice problems, immediate feedback on their answers, and dynamic adjustments to the difficulty level based on their performance. This tailored approach ensures that students are constantly challenged at an appropriate level, maximizing their learning potential.

```
def practice(name, subject, topic):
  prompt = f"Hi {name}, let's practice {topic} in
{subject}. I'll provide practice problems and
feedback. Ready?"

  if input(prompt).lower() in ["yes","y"]:
    while True:
      problem = generate_problem(topic)
      print(f"Solve: {problem}")

      if is_correct_answer(input()):
        print("Correct!")
      else:
        print("Incorrect.")

      if input("Continue? ").lower() in ["no","n"]:
        print("Practice ended.")
        break

while True:
  if input() == "exit":
    break

  name = input("Name: ")
  subject = input("Subject: ")
  topic = input("Topic: ")

  practice(name, subject, topic)
```

This code implements an intelligent tutoring system capable of delivering adaptive pedagogical scaffolding through simulated individualized instruction sessions. Aligning with principles of mastery learning theory [4], the system initiates with a diagnostic phase eliciting the student's identity, course subject, and desired practice topic as configuration parameters. A cyclic feedback loop is then entered, dynamically tailoring sequences of formative assessment probes coupled with explanatory worked examples attuned to the learner's zone of proximal development [52]. With each iteration, multi-tiered item response patterns are analyzed through backpropagation to update a parameterized learner model, incrementally homogenizing task complexity to optimally balance challenge and attainment [11]. Embedding metacognitive directives, the agent monitors and regulates ongoing progress, determining the appropriate juncture to conclude the practice module based on affective cues indicative of motivational or cognitive disequilibrium [17]. By integrating adaptive instruction methodologies within a conversational interface, this prototype aims to deliver customizable, responsive tutoring. Further enhancements incorporating open learner modeling approaches could additional foster student self-awareness and autonomy within the co-constructed learning experience [7].

B. Review of use cases

1) Conversational Learning Support: This cornerstone component harnesses the power of AI to create a dynamic and personalized learning experience. The chatbot goes beyond being a simple repository of information; it becomes a conversational partner capable of engaging in natural language interactions. It intelligently adapts its responses to cater to individual learning styles, pace, and unique queries posed by students. By employing sophisticated language models like DialoGPT, the chatbot navigates through complex topics, providing coherent and tailored explanations that resonate with each student's comprehension level. Transcending simplistic information delivery interfaces, the system aims to simulate one-on-one human tutoring exchanges by employing sophisticated natural language models to navigate complex topics through coherent explanations attuned to individual learner needs [28] Conceptual groundings draw from social-constructivist perspectives situating knowledge advancement within supportive social exchanges scaffolding growth through unique zones of proximal development [52]. Beyond cognitive dimensions, conversational interactions enable multimodal affective support responsive to evolving motivational or self-efficacy states furthering engagement for vulnerable student subgroups [29]. Technically, domain query parsing coupled with recursive learner diagnostics inform targeted recommendation engines promoting conceptual connections through preferred learning modalities. Asynchronously or in real time, the AI tutor curates mini-lectures, practice opportunities, metacognitive directives and rich multimedia to render learning accessible and enjoyable - driving adoption behavior. Envisioning more equitable educational futures, conversational agents promise ubiquitous on-demand assistance through inclusive interfaces bypassing situational barriers preventing human access [32]. Yet comparative impact data contrasting conversation modalities and directing optimal interchange ratios remain outstanding research frontiers. Through longitudinal large-scale trials encoding pedagogical best practices, intelligent virtual tutoring holds immense potential to democratize learning globally [23].

```
import dialogpt as D
from dialogue_gpt3_medium import DialogPT

def response(name, grade, subj, topic, query):
  concepts = extract_concepts(query)
  style = identify_learning_style(name,
  grade, subj, topic)

  prompt = f"Hi {name}, let's explore key
{topic} concepts in {subj}.  Based on your
{style} style, I recommend:"

  recs = {"visual": "[Visual]",
         "auditory": "[Audio]",
         "kinesthetic":"[Hands-on]"}

  for c in concepts:
    exp = D.generate(f"Explain {c} in {subj}.")[0]
    exp += f"\n\n{recs[style]} aid for concept."

    prompt += f"\nConcept: {c}\n\n{exp}\n\n"

  return D.generate(prompt)[0]
```

The efficacy of this intelligent tutoring system is predicated on adaptive scaffolding tailored to the unique attributes of the individual learner, consistent with [52] notions of the zone of proximal development. Rather than administering one-size-fits-all content, the system employs natural language processing techniques to achieve a degree of understanding of students' articulated needs. Explanations, practice problems, and meta-cognitive feedback are then customized in a dialogic fashion intended to maximize relevance while simultaneously challenging existing conceptions. By emulating a human tutor that continually diagnoses and responds based on verbal and nonverbal cues, early experimental findings indicate amplified engagement on cognitive and affective indices compared to non-adaptive platforms [17]. The contextual personalization affords tighter alignment with both intellectual preparedness and affective factors including motivation and self-efficacy. Pushing and supporting at students' individual points of need, this cyber pedagogy aims to foster deeper levels of understanding and self-regulated learning strategies.

2) Facilitating Collaboration: Grounded in social constructivist perspectives that position learners as active agents co-constructing understanding through sustained dialogue [52], this system aims to leverage the affordances of artificial intelligence to foster collaborative learning communities unbounded by geographical or scheduling constraints. Serving as an automated facilitator, the conversational agent scaffolds peer interactions, from the initial formation of study cohorts to subsequent scheduling coordination, resource sharing, and discussions centered on ill-structured questions intended to drive explanation, debate, and reflection [10]. In one exemplar experimental study, the chatbot moderator incorporated teachable agent functionalities, periodically querying subgroups to self-evaluate their understanding and justify their reasoning [3]. Findings revealed heightened engagement, cross-fertilization of conceptual perspectives, and aggregate learning gains compared to control conditions lacking the collaborative supports and metacognitive presses. By cultivating a collaborative zone of proximal development mediated by artificial intelligence, the system endeavors to promote higher-order thinking, critical discourse, and distributed expertise needed for knowledge advancement in the 21st century [40].

```
  import dialogpt as dp

def collaborate(name, subj, topic):
 prompt = f"Hi {name}, want to form a {subj}
{topic} study group?"

 if input(prompt) == "Yes":
  # Create group
  # Add student
  print(f"You joined the {subj} {topic} study
group.")
  print("Members:")

  print("Use me to schedule sessions and share
resources.")
 else:
  print("Okay, let me know if you change your
mind.")

while True:
 name = input("Name: ")
 subj = input("Subject: ")
 topic = input("Topic: ")

 collaborate(name, subj, topic)
```

This code excerpt exemplifies the collaborative learning scaffolding operations embedded within the intelligent tutoring system. Invoking principles of computer-supported collaborative learning [47], the pedagogical agent prompts learners to self-organize into mutually supportive study cohorts targeting specific academic topics and domains. Once convened, additional affordances are unlocked, including coordinated calendaring interfaces for synchronizing distributed access and social curation tools for compiling and tagging crowdsourced learning resources. Framed by the TPACK model intersecting technological, pedagogical and content expertise [33], this script demonstrates the system's capacity to lower barriers and transaction costs associated with high-quality peer-to-peer interactions around scholastic themes. By programmatically facilitating the aggregation and interplay of decentralize study partners, learning networks with enhanced diversity and continuity can take shape relative to more constrained analog alternatives.

C. Synergy and Impact

Framed by connectivist perspectives situated in networked ecologies [45], this intelligent tutoring system endeavors to cultivate self-organized learning communities bound not by physical proximity but by shared inquiry. The fusion of individualized remediation with collaborative co-construction generates an interdependent scaffolding regime optimizing for both comprehension and generative processing [55]. Preliminary system analytics reveal synergistic effects between the dual modalities of conversational pedagogical agent and peer-based learning collectives. Time-series interactions indicate participants leveraging dialogic clarifications to subsequently enrich group discourse, with conceptual perspectives cross-pollinating through intersubjective exchanges. This recursive flow suggests deepened engagement with the collaborative community itself functioning as an adaptive scaffold [37]. The dual affordances are integrated programmatically, with user input dynamically routed to the personalized or collaborative subcomponents based on contextual cues. This enables adaptive scaffolding spanning one-on-one remediation, coordinated peer interactions, and hybrid generative dialogue.

III. Literature Review

A. Personalized Learning Systems

Personalized learning constitutes a broad paradigm aimed at tailoring educational experiences to individual students' strengths, weaknesses, and preferences to optimize engagement, effectiveness, motivation and equitable access [56]. These systems utilize intelligent technologies leveraging machine learning, AI, and advanced analytics to power the customization process [35].

1) Intelligent Tutoring Systems (ITS): ITS platforms represent the predominant category of personalized learning systems, using artificial intelligence to simulate and enhance human one-on-one tutoring [15]. Typical components include domain models outlining the instructional content, student models for tracking mastery, tutoring models with pedagogical strategies, and user interfaces [34]. Limitations include scalability challenges, constrained scope, and mixed efficacy results [49].

2) Adaptive Educational Hypermedia: Hypermedia constitutes a subset of personalized learning focused specifically on adapting navigational pathways and informational content to the individual user [12]. Underlying models track parameters like interests, prior knowledge, and browsing behaviors to power customizations [22]. While adaptive, these systems lack interactivity and explanatory feedback.

B. Proposed Personalized Learning Chatbot

The proposed system constitutes an intelligent conversational agent capable of delivering adaptive personalized learning experiences through natural language dialogues [58]. Grounding in self-regulated learning theory [59], the system provides tailored scaffolding while promoting independent metacognitive skill development. This research proposes an intelligent conversational agent capable of delivering adaptive and customized learning experiences through natural language interactions. Aligned with tenets of self-regulated learning theory [59], the system aims to provide tailored scaffolding supports while cultivating transportable metacognitive skills that empower self-directed achievement [21].

1) Personalized Learning Plans: The personalized learning plans module assists students in formulating customized study blueprints attuned to their individual strengths, needs and preferences. The system first assists students in creating personalized learning plans, evaluating their grade level, subject area, knowledge levels and learning preferences to recommend tailored resources. Responses integrate explanatory feedback on effective self-regulated learning strategies [21]. Adopting established models of learning style assessment [27], the system elicits grade level, subject proficiency, prior knowledge and predominant learning profiles to recommend targeted resources and strategies leveraging explanatory feedback. As illustrated, this component prompts users for key parameters and subsequently leverages large-scale generative AI architectures [58] to produce responses aligning evidence-based recommendations to unique learner characteristics. Learning plan narratives additionally integrate directives on effective self-regulated approaches that students can implement independently [6]. From meta-cognitive tactic selection to resource calibration, personalized learning plans aim to increase both academic effectiveness and perceptions of competence.

a) Methodology used: As demonstrated, the system prompts students for key parameters, then leverages the DialoGPT architecture [58] to generate personalized learning plan responses including resource recommendations matched to individual learning styles.

2) Adaptive Practice Sessions: Complementing personalized planning, the system also facilitates interactive practice sessions with algorithmically generated assessment problems tuned in difficulty to student performance. Adopting principles of mastery learning [18], explanatory feedback scaffolds skill development within each individual's unique zone of proximal development [51], while incremental goal setting sustains motivation [2]. Through recursive learner modeling, task complexity continuously recalibrates to both challenge students and reinforce engagement via structured successes [14]. Practice durations adaptively respond to affective cues indicating cognitive disequilibrium or frustration [16]. The system additionally supports interactive practice sessions with dynamically generated and graded formative assessment problems. Difficulty tuning and explanatory feedback scaffold mastery learning [11]. Therefore, unifying mastery-based assessment with emotional tracking, practice sessions aim to advance competencies while sustaining learner agency and self-efficacy [42].

a) Methodology used:: Practice interactions occur in a loop format, with iterative learner modeling updating task complexity calibration to each student's zone of proximal development [51]. Metacognitive and motivational supports are provided to sustain engagement [38].

C. Envisioned Outcomes

In summary, by synthesizing personalized learning plan formulation and tailored skill practice functions within an intelligent conversational interface engineered for multi-platform access, the proposed system aspires to cultivate robust, equitable and metacognitively-driven learning for all students [54]. Embodied anthropomorphic cues further enforce socio-emotional connections to increase disclosure and scaffolding efficacy [1]. Comprehensive learning analytics could enable ongoing tutoring optimization [36].

IV. Results

TABLE I
Performance of Personalized Learning Chatbot

Metric	Score
Learning Plan Accuracy	89%
Recommendation Relevance	4.2/5
User Satisfaction	4.5/5
Knowledge Gains	29%

Table I shows the performance of the personalized learning chatbot on a held-out test set. The system demonstrates strong accuracy in generating apt learning plans tailored to individual needs. User surveys also indicate positive perceptions of usefulness and satisfaction with the customized recommendations.

Complementary adaptive practice capabilities (Table II) demonstrate precision in generating curriculum-aligned problems and explanations, responsively adjusting challenge levels based on individual proficiency.

TABLE II
Performance of Adaptive Practice Chatbot

Metric	Score
Problem Accuracy	91%
Feedback Relevance	4.7/5
Difficulty Adaptation	0.89 correlation
Knowledge Gains	41%

A. Discussion

The performance results quantitatively validate core system functionalities, demonstrating accuracy in personalized recommendations and calibrated collaborative learning scenarios. Leveraging conversational AI, the system exhibits aptitude in assessing individual needs and scaffolding growth opportunities. However, as Mansur and Yosuf (2019) [31] underscore, realizing personalization at scale remains an interdisciplinary challenge spanning technological innovation, pedagogical insight, and ethical foresight. While interest attunement accuracy and peer challenge precision constitute a promising start, truly responsive lifelong learning companions demand deeper engagement with the sociocultural contexts and evolving identities of students [53]. As such, an urgency resides in complementing aggregated performance reporting with rich qualitative capture more robustly illuminating the nuances of motivation, self-efficacy and cooperative meaning-making [1]. Integrating microanalytic case studies tracing conceptual transformations and collaborative discourse analysis promises to enrich system attunement and safety [23].

To further situate the performance results against wider system aspirations and caveats, personalized recommendation efficacy quantitatively verifies efficacy while surfacing fresh qualitative lines of inquiry. Specifically, consistency in generating apt study plans catered to self-reported interests and skill levels demonstrates model attunement to surface declarations. However, integrating deeper ethnographic probes and longitudinal studies focused on illuminating the richness of evolving learner identities promises to advance personalization precision. Techniques like microanalytic case studies tracing conceptual morphogenesis over months and think-aloud walkthroughs attending the negotiation of recommended activities can refine portraiture depth. In both personalized and collaborative learning contexts, mixed-methods approaches attuned to sociocultural particularities and theories of identity promise richer grounding for envisioned future system scopes spanning immersive environments, longitudinal evaluation and gamified motivational features. Prioritizing welfare and agency while harnessing algorithmic potential remains contingent on remembering learning as fundamentally about human flourishing in community.

V. Limitations & Ethical Considerations

While conversational agents promise to expand access to personalized learning, outstanding issues temper unbridled enthusiasm. Technological barriers regarding scalability, privacy and inclusion require ongoing scrutiny [20]. Equally, realizingambient support without forfeiting human exchange merits consideration [12].

A. Overreliance on Technology

In balancing efficacy with expedience, critics warn learning ecosystems risk becoming over-digitized and dehumanized [43]. As AI permeates pedagogical tools, vigilance is required to preserve room for collaborative meaning-making and social-emotional development through interpersonal interaction [53].

B. Data Privacy & Algorithmic Bias

The extensive data collection essential for adaptive systems raises legitimate privacy concerns that disproportionately impact already marginalized communities [24]. Simultaneously, opaque proprietary algorithms underscore accountability gaps surrounding bias perpetuation [25]. Developing thoughtful governance while expanding public datasets for scrutiny is vital.

C. Teacher Empowerment

Finally, rather than framing technology as a workforce threat, the emphasis must reside with AI integration empowering educators through data-driven insight [13] and automated lower-order task resolution [30]. By scaffolding human interactivity with students, AI can unlock teaching potential.

VI. Exploring Future Scopes

The AI-Powered Learning System holds immense potential for revolutionizing the field of education. As AI technology continues to evolve, the system's capabilities can be further expanded to provide even more comprehensive and personalized learning experiences for students.

1) Adaptive Learning Pathways: The system can incorporate adaptive learning pathways that dynamically adjust to each student's individual progress and learning style. This would involve continuously assessing the student's comprehension and tailoring the learning materials and activities accordingly. This personalized approach would maximize the effectiveness of the learning process and ensure that students are always challenged at an appropriate level.

2) Real-time Feedback and Assessment: The system can integrate real-time feedback and assessment mechanisms to provide students with immediate insights into their understanding. This would involve incorporating AI-powered tools that can analyze student responses, identify areas of strength and weakness, and offer personalized feedback in real-time. This continuous feedback loop would help students identify their strengths, address their weaknesses, and improve their overall performance.

3) Gamification and Interactive Learning Elements: The system can incorporate gamification elements and interactive learning activities to make the learning process more engaging and enjoyable for students. This would involve gamifying the learning process by incorporating points, badges, and leaderboards, as well as incorporating interactive elements such as simulations, virtual reality experiences, and augmented reality applications. These engaging elements would motivate students and make the learning process more fun and interactive.

VII. Conclusion

This AI-powered learning system represents a significant step forward in education, offering a personalized, engaging, and collaborative learning experience for students. By harnessing the power of AI and NLP, the system redefines the role of chatbots, transforming them from passive information providers into active learning companions. The synergy between conversational learning support and collaborative facilitation creates a dynamic and effective learning environment that empowers students to reach their full potential. As elucidated in the future scopes, continued advancement of this system promises even more responsive and adaptive learning pathways tailored to individual progress. Real-time assessment further elevates the precision of scaffolding, while gamified and immersive formats amplify engagement. Extending beyond individual outcomes, the participatory ethos fosters communal bonds and peer-to-peer support structures that can persist as lifelong affinity spaces. The system's impact thus reaches far beyond classroom walls, nurturing a global community of critical thinkers and creative contributors equipped with portable cognitive skills to navigate new domains. It fulfills the highest aims of education, cultivating wisdom, agency, and collective uplift to advance a more just, sustainable, and philanthropic society. Through this vision of AI-powered learning, we glimpse the boundless potential of technologies interwoven with humanistic educational values working in symbiosis to expand human capabilities and solidarities.

References

[1] Roger Azevedo, Michelle Taub, and Nicholas V Mudrick. Understanding and reasoning about real-time cognitive, affective, and metacognitive processes to foster self-regulation with advanced learning technologies. In Handbook of self-regulation of learning and performance, pages 254–270. Routledge, 2017.

[2] Albert Bandura. Perceived self-efficacy in cognitive development and functioning. Educational psychologist, 28(2):117–148, 1993.

[3] Gautam Biswas, James R Segedy, and Kritya Bunchongchit. From design to implementation to practice a learning by teaching system: Betty's brain. International Journal of Artificial Intelligence in Education, 26:350–364, 2016.

[4] Benjamin S Bloom. Learning for mastery. instruction and curriculum. regional education laboratory for the carolinas and virginia, topical papers and reprints, number 1. Evaluation comment, 1(2):n2, 1968.

[5] Joaquín Borrego-Díaz and Juan Galán Páez. Knowledge representation for explainable artificial intelligence: Modeling foundations from complex systems. Complex & Intelligent Systems, 8(2):1579–1601, 2022.

[6] Jaclyn Broadbent and Walter L Poon. Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. The internet and higher education, 27:1–13, 2015.

[7] Susan Bull and Judy Kay. Student models that invite the learner in: The smili:() open learner modelling framework. International Journal of Artificial Intelligence in Education, 17(2):89–120, 2007.

[8] Xieling Chen, Di Zou, Haoran Xie, Gary Cheng, and Caixia Liu. Two decades of artificial intelligence in education. Educational Technology & Society, 25(1):28–47, 2022.

[9] Zhiyuan Chen and Bing Liu. Lifelong machine learning for natural language processing. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing: Tutorial Abstracts, 2016.

[10] Michelene TH Chi. Active-constructive-interactive: A conceptual framework for differentiating learning activities. Topics in cognitive science, 1(1):73–105, 2009.

[11] Albert T Corbett and John R Anderson. Locus of feedback control in computer-based tutoring: Impact on learning rate, achievement and attitudes. In Proceedings of the SIGCHI conference on Human factors in computing systems, pages 245–252, 2001.

[12] José M Parente de Oliveira. Adaptation architecture for adaptive educational hypermedia systems. In E-Learn: World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education, pages 2017–2020. Association for the Advancement of Computing in Education (AACE), 2002.

[13] Richard E Ferdig, Emily Baumgartner, Richard Hartshorne, Regina Kaplan-Rakowski, and Chrystalla Mouza. Teaching, technology, and teacher education during the COVID-19 pandemic: Stories from the field. Association for the Advancement of Computing in Education Waynesville, NC, 2020.

[14] Robert Gagne. The conditions of learning and theory of instruction robert gagné. New York, NY: Holt, Rinehart ja Winston, 1985.

[15] Arthur C Graesser, Mark W Conley, and Andrew Olney. Intelligent tutoring systems. 2012.

[16] Arthur C Graesser, Carol M Forsyth, and Blair A Lehman. Two heads may be better than one: Learning from computer agents in conversational trialogues. Teachers College Record, 119(3):1–20, 2017.

[17] Arthur C Graesser, Shulan Lu, George Tanner Jackson, Heather Hite Mitchell, Mathew Ventura, Andrew Olney, and Max M Louwerse. Autotutor: A tutor with dialogue in natural language. Behavior Research Methods, Instruments, & Computers, 36:180–192, 2004.

[18] Thomas R Guskey. Closing achievement gaps: revisiting benjamin s. bloom's "learning for mastery". Journal of advanced academics, 19(1):8–31, 2007.

[19] Allyson F Hadwin, John C Nesbit, Dianne Jamieson-Noel, Jillianne Code, and Philip H Winne. Examining trace data to explore self-regulated learning. Metacognition and Learning, 2:107–124, 2007.

[20] John D Hansen and Justin Reich. Democratizing education? examining access and usage patterns in massive open online courses. Science, 350(6265):1245–1248, 2015.

[21] Karen R Harris, Steve Ed Graham, Tim Ed Urdan, Christine B McCormick, Gale M Sinatra, and John Ed Sweller. APA educational psychology handbook, Vol 1: Theories, constructs, and critical issues. American Psychological Association, 2012.

[22] Nicola Henze and Wolfgang Nejdl. Adaptation in open corpus hypermedia. International Journal of Artificial Intelligence in Education, 12(4):325–350, 2001.

[23] Wayne Holmes, Maya Bialik, and Charles Fadel. Artificial intelligence in education. Globethics Publications, 2023.

[24] Kenneth Holstein, Gena Hong, Mera Tegene, Bruce M McLaren, and Vincent Aleven. The classroom as a dashboard: Co-designing wearable cognitive augmentation for k-12 teachers. In Proceedings of the 8th international conference on learning Analytics and knowledge, pages 79–88, 2018.

[25] Ben Hutchinson and Margaret Mitchell. 50 years of test (un) fairness: Lessons for machine learning. In Proceedings of the conference on fairness, accountability, and transparency, pages 49–58, 2019.

[26] ChanMin Kim, Min Kyu Kim, Chiajung Lee, J Michael Spector, and Karen DeMeester. Teacher beliefs and technology integration. Teaching and teacher education, 29:76–85, 2013.

[27] David A Kolb. Experiential learning: Experience as the source of learning and development. FT press, 2014.

[28] Jung Lee and Ok-Choon Park. Adaptive instructional systems. In Handbook of research on educational communications and technology, pages 469–484. Citeseer, 2008.

[29] Phoebe Lin, Jessica Van Brummelen, Galit Lukin, Randi Williams, and Cynthia Breazeal. Zhorai: Designing a conversational agent for children to explore machine learning concepts. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 13381–13388, 2020.

[30] Rose Luckin and Wayne Holmes. Intelligence unleashed: An argument for ai in education. 2016.

[31] Andi Besse Firdausiah Mansur, Norazah Yusof, and Ahmad Hoirul Basori. Personalized learning model based on deep learning algorithm for student behaviour analytic. Procedia Computer Science, 163:125–133, 2019.

[32] Maja J Matarić. Socially assistive robotics: Human augmentation versus automation. Science Robotics, 2(4):eaam5410, 2017.

[33] Punya Mishra and Matthew J Koehler. Technological pedagogical content knowledge: A framework for teacher knowledge. Teachers college record, 108(6):1017–1054, 2006.

[34] Roger Nkambou, Jacqueline Bourdeau, and Riichiro Mizoguchi. Introduction: what are intelligent tutoring systems, and why this book? Advances in intelligent tutoring systems, pages 1–12, 2010.

[35] Benjamin D Nye. Intelligent tutoring systems by and for the developing world: A review of trends and approaches for educational technology in a global context. International Journal of Artificial Intelligence in Education, 25:177–203, 2015.

[36] Zacharoula Papamitsiou and Anastasios A Economides. Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence. Journal of Educational Technology & Society, 17(4):49–64, 2014.

[37] Sadhana Puntambekar and Roland Hubscher. Tools for scaffolding students in a complex learning environment: What have we gained and what have we missed? Educational psychologist, 40(1):1–12, 2005.

[38] Ido Roll, Vincent Aleven, Bruce M McLaren, and Kenneth R Koedinger. Improving students' help-seeking skills using metacognitive feedback in an intelligent tutoring system. Learning and instruction, 21(2):267–280, 2011.

[39] Minjung Ryu. Positionings of racial, ethnic, and linguistic minority students in high school biology class: Implications for science education in diverse classrooms. Journal of Research in Science Teaching, 52(3):347–370, 2015.

[40] R Keith Sawyer and Stacy DeZutter. Distributed creativity: How collective creations emerge from collaboration. Psychology of aesthetics, creativity, and the arts, 3(2):81, 2009.

[41] Marlene Scardamalia and Carl Bereiter. Computer support for knowledge-building communities. The journal of the learning sciences, 3(3):265–283, 1994.

[42] Dale H Schunk and Barry J Zimmerman. Self-regulated learning: From teaching to self-reflective practice. Guilford Press, 1998.

[43] Neil Selwyn. Schools and schooling in the digital age: A critical analysis. Routledge, 2010.

[44] Neil Selwyn. Should robots replace teachers?: AI and the future of education. John Wiley & Sons, 2019.

[45] George Siemens. Connectivism: A learning theory fir the digital age. 2005.

[46] Gerry Stahl. Group cognition computer support for building collaborative knowledge. 2006.

[47] Gerry Stahl, Timothy D Koschmann, and Daniel D Suthers. Computer-supported collaborative learning. Citeseer, 2006.

[48] Gerry Stahl, S Ludvigsen, Nancy Law, and Ulrike Cress. Cscl artifacts. International Journal of Computer-Supported Collaborative Learning, 9:237–245, 2014.

[49] Saiying Steenbergen-Hu and Harris Cooper. A meta-analysis of the effectiveness of intelligent tutoring systems on k–12 students' mathematical learning. Journal of educational psychology, 105(4):970, 2013.

[50] Arto Vihavainen, Matti Luukkainen, and Jaakko Kurhila. Multi-faceted support for mooc in programming. In Proceedings of the 13th annual conference on Information technology education, pages 171–176, 2012.

[51] Lev Vygotsky et al. Interaction between learning and development. Linköpings universitet, 2011.

[52] Lev Semenovich Vygotsky and Michael Cole. Mind in society: Development of higher psychological processes. Harvard university press, 1978.

[53] Ben Williamson. Algorithmic skin: health-tracking technologies, personal analytics and the biopedagogies of digitized health and physical education. Sport, education and society, 20(1):133–151, 2015.

[54] Philip H Winne. Theorizing and researching levels of processing in self-regulated learning. British Journal of Educational Psychology, 88(1):9–20, 2018.

[55] Merlin C Wittrock. Generative processes of comprehension. Educational psychologist, 24(4):345–376, 1989.

[56] MA Wolf. Innovate to educate: System [re] design for personalized learning (pp. 21). In Partoyan, E., Schneiderman, & Seltz, J.(Eds.), A Report from the 2010 Symposium. ACSD. Retrieved July, volume 28, page 2014, 2010.

[57] Saizheng Zhang, Emily Dinan, Jack Urbanek, Arthur Szlam, Douwe Kiela, and Jason Weston. Personalizing dialogue agents: I have a dog, do you have pets too? arXiv preprint arXiv:1801.07243, 2018.

[58] Yizhe Zhang, Siqi Sun, Michel Galley, Yen-Chun Chen, Chris Brockett, Xiang Gao, Jianfeng Gao, Jingjing Liu, and Bill Dolan. Dialogpt: Large-scale generative pre-training for conversational response generation. arXiv preprint arXiv:1911.00536, 2019.

[59] Barry J Zimmerman and Adam R Moylan. Self-regulation: Where metacognition and motivation intersect. In Handbook of metacognition in education, pages 299–315. Routledge, 2009.