APPLICATIONS OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES IN SUPPORTING ENGLISH GRAMMAR ACQUISITION FOR YOUNG ESL LEARNERS

Gîlcă Natalia, Teacher, Secondary school *"Prof. Nicolae Caranda" from Glogova, ROMANIA*

ABSTRACT: Artificial Intelligence (AI) technologies are increasingly integrated into educational environments, offering new possibilities for adaptive instruction and automated language support. Recent developments in Natural Language Processing (NLP) and transformer-based language models [1, 2] have enabled systems capable of generating simplified texts, identifying grammatical structures, and providing real-time feedback to learners. Complementary innovations in Automatic Speech Recognition (ASR), particularly child-speech modeling [3], further expand the potential for interactive oral grammar practice. This paper examines the technical foundations and practical applications of AI architectures designed to support English grammar acquisition among young learners of English as a Second Language (ESL). Drawing on machine learning frameworks used in grammar-error detection [4] and educational recommender systems [5], the study describes mechanisms for content generation, adaptation, and multimodal input processing. Benefits such as scalability, personalized instruction, and improved learner engagement are presented alongside challenges related to dataset bias, privacy concerns for minors, and reliability under real-world classroom conditions [6]. The findings indicate that AI-enhanced grammar instruction represents a promising direction in educational engineering, requiring sustained interdisciplinary collaboration to ensure ethical, robust, and effective deployment.

KEY WORDS: Artificial Intelligence; Natural Language Processing; Machine Learning; Automatic Speech Recognition; Educational Technology; Grammar Error Detection; ESL Learning; Young Learners; Adaptive Learning Systems; Generative Models.

1. INTRODUCTION

The rapid development of Artificial Intelligence (AI) technologies has significantly influenced contemporary educational systems, particularly in areas that rely on language processing and automated feedback. In recent years, AI-based platforms have become integral to computer-assisted language learning, enabling scalable, data-driven support for learners across diverse age groups and linguistic backgrounds [7]. Among these innovations, applications targeting English grammar acquisition have shown considerable promise, especially for young learners of English as a Second Language (ESL), who benefit from immediate feedback, adaptive instruction, and multimodal engagement.

From an engineering perspective, the deployment of AI in grammar learning is closely tied to advancements in Natural Language Processing (NLP) and modern deep learning architectures. Transformer-based models have demonstrated high accuracy in syntactic analysis and grammar error detection by leveraging large-scale corpora and contextual embeddings [8].

These models underpin educational tools capable of automatically generating examples, identifying learner errors, and adjusting the complexity of tasks in real time.

Complementary progress in Automatic Speech Recognition (ASR) technologies, particularly systems trained on children's speech, has further expanded the applicability of AI tools to oral grammar practice, enabling learners to interact with conversational agents and receive instantaneous corrective feedback [9].

Equally important are machine learning algorithms designed for personalization. Adaptive learning systems can analyze user performance patterns and select tasks aligned with each learner's developmental stage and proficiency level [10].

Such systems are increasingly integrated into classroom environments and mobile applications, contributing to higher engagement rates and improved learning outcomes. Their success reflects ongoing interdisciplinary research combining educational psychology, engineering principles, and computational linguistics.

Despite these advances, several challenges persist. AI systems deployed in early language education must address concerns related to data privacy, algorithmic bias, and the reliability of automated feedback mechanisms in naturalistic settings [11].

Engineering solutions must therefore prioritize robustness, transparency, and ethical design to ensure that AI-supported grammar instruction benefits young learners without compromising safety or pedagogical integrity.

The purpose of this paper is to analyze the technical foundations, system architectures, and practical applications of AI-driven tools developed for English grammar instruction in early ESL education.

By examining how NLP, ASR, and adaptive learning technologies operate within educational contexts, the study aims to highlight both the opportunities and limitations of integrating AI into language learning environments and to provide guidance for future engineering-oriented research and development in this field.

2. BACKGROUND AND RELATED WORK

Research on AI-driven language learning has expanded rapidly over the last decade, largely due to advances in computational linguistics and deep learning. Early computer-assisted language learning (CALL) systems relied heavily on rule-based approaches, offering limited adaptability and often requiring manually curated grammatical patterns [12]. While useful for structured drill-and-practice activities, these systems lacked the flexibility necessary to address the varied needs of young ESL learners.

The emergence of statistical NLP and, subsequently, neural NLP transformed the landscape of language education technologies. Transformer architectures, introduced by Vaswani et al., enabled highly accurate syntactic parsing, contextual embedding generation, and fluent text production [13].

Such capabilities have become core elements in grammar-checking engines, automated writing evaluation tools, and AI-based tutoring applications. These models are particularly effective in detecting morphological and syntactic errors common among novice learners, such as incorrect tense usage, missing articles, or improper word order [14].

Parallel advances in Automatic Speech Recognition (ASR) have supported the development of interactive oral grammar tools. Traditional ASR systems struggled with high variability in children's voices—differences in pitch, articulation, and speech rate often reduced recognition accuracy [15].

However, newer child-adapted models and large-vocabulary continuous speech recognition systems have improved performance significantly, making it feasible to incorporate real-time spoken grammar practice into educational applications [16].

Research on adaptive learning has further informed the design of AI-supported grammar instruction. Machine learning algorithms used in adaptive platforms analyze learner behavior, predict performance trajectories, and personalize task selection [17]. Such systems can adjust difficulty levels, provide targeted reinforcement, and ensure that instructional content aligns with each learner's cognitive development and linguistic proficiency. Studies in educational data mining (EDM) have shown that adaptive sequencing improves learning efficiency and reduces cognitive overload, particularly for younger learners [18].

In recent years, multimodal AI systems combining text, speech, and visual inputs have also gained attention. Vision-language models can generate image-based grammar prompts (e.g., prepositions of place, spatial descriptions), supporting early language development through visual scaffolding [19]. These systems reflect an emerging trend toward integrated, multisensory learning environments that mirror naturalistic language acquisition.

Despite these advances, empirical research highlights ongoing challenges. Automated grammar feedback systems may misinterpret learner intent, particularly when young students produce nonstandard or creative formations [20]. Additionally, datasets used to train NLP and ASR models often underrepresent child-generated language, potentially introducing biases that affect feedback accuracy [21]. Addressing such limitations remains essential for engineering reliable, safe, and pedagogically sound AI systems for educational use.

3. TECHNICAL FOUNDATIONS OF AI IN ESL GRAMMAR LEARNING

AI-supported grammar instruction relies on a set of core technologies that enable automated text analysis, error detection, speech processing, and adaptive content generation. These technologies—rooted in natural language processing (NLP), machine learning (ML), automatic speech recognition (ASR), and multimodal generative modeling—form the engineering backbone of modern educational systems for young ESL learners.

3.1 Natural Language Processing and Grammar Modeling

At the center of AI-enhanced grammar learning are NLP algorithms capable of analyzing and generating syntactic structures. Part-of-speech (POS) tagging, dependency parsing, and constituency parsing allow systems to identify grammatical relationships between words and detect deviations from standard patterns [22]. Large-scale pretrained models such as BERT, RoBERTa, and GPT variants leverage transformer architectures to produce contextual embeddings, enabling highly accurate classification and prediction of grammar errors [23]. These models outperform earlier n-gram and recurrent neural network approaches due to their ability to capture long-range dependencies and nuanced linguistic contexts, which are essential for diagnosing tense errors, article misuse, or incorrect word order in learner-produced sentences.

3.2 Grammar Error Detection and Correction Algorithms

Automated grammar error detection (GED) typically combines rule-based and ML-based components. Hybrid systems use handcrafted linguistic rules to capture deterministic errors (e.g., plural formation or subject–verb agreement) while employing neural classifiers to detect contextual or semantic inconsistencies [24]. State-of-the-art GED models treat error correction as a sequence-to-sequence task, where transformers generate corrected outputs based on probability distributions learned from annotated corpora [25]. For young ESL learners, systems must additionally account for developmental grammar, simplified sentence structures, and nonstandard learner language, increasing the complexity of the detection process.

3.3 Automatic Speech Recognition for Young Learners

ASR technologies play a critical role in systems that support oral grammar practice. Standard ASR engines are trained primarily on adult speech, leading to high error rates when applied to children due to differences in vocal tract length, pitch, articulation patterns, and background noise conditions typical in classrooms [26]. Recent research has focused on child-specific acoustic models, data augmentation techniques, and transfer learning approaches that significantly improve recognition accuracy [27]. These enhancements allow AI systems to evaluate spoken grammar (e.g., verb forms, word order, or prepositional phrases) and provide immediate feedback in interactive environments.

3.4 Adaptive Learning Algorithms

Personalization is a central feature of AI-assisted grammar learning. Adaptive learning algorithms use learner performance data to estimate proficiency, predict future difficulty, and select optimally challenging tasks [28]. Bayesian knowledge tracing (BKT), deep knowledge tracing (DKT), and reinforcement learning–based recommendation engines are commonly applied to model learner progress and adapt instruction dynamically [29]. Such algorithms enable systems to provide individualized sequencing of grammar exercises, minimizing cognitive overload and promoting steady linguistic development.

3.5 Generative AI for Example Creation and Multimodal Support

Generative models, including large language models (LLMs) and vision–language architectures, contribute to the creation of customized instructional materials. LLMs can generate example sentences, short stories, or fill-in-the-blank exercises that target specific grammar structures while maintaining age-appropriate complexity [30]. Similarly, text-to-image models can produce visual prompts to support grammar teaching, particularly for spatial prepositions, actions, and simple narratives [31]. The integration of multimodal AI expands opportunities for young learners to interact with grammar concepts through visual, textual, and auditory channels, enhancing engagement and comprehension.

3.6 Data Considerations and Child-Specific AI Training

Developing reliable AI grammar tools for young learners requires careful attention to data quality and representativeness. Child speech and writing differ significantly from adult linguistic patterns; thus, training datasets must include diverse samples of learner language to avoid biased or inaccurate model behavior [32]. Ethical considerations are equally important: datasets must ensure privacy, anonymization, and compliance with regulations governing the collection of data from minors [33]. These constraints influence model performance and highlight the need for dedicated engineering methodologies in child-centered AI development.

4. APPLICATIONS IN TEACHING ENGLISH GRAMMAR

AI technologies have enabled the development of instructional tools that support targeted grammar learning for young ESL learners. These applications leverage NLP, machine learning, ASR, and generative modeling to create engaging, adaptive, and data-driven learning experiences. The following subsections outline key application domains and highlight the engineering principles that underpin their effectiveness.

4.1 AI-Generated Grammar Exercises and Text-Based Practice

Modern educational platforms increasingly rely on transformer-based language models to produce grammar exercises tailored to user proficiency levels. Systems can automatically generate fill-in-the-blank tasks, multiple-choice items, and sentence-reordering activities based on specific grammatical structures (e.g., present simple, articles, plurals) [34]. By using controlled decoding methods and constraint-based generation, these systems ensure that produced examples remain age-appropriate and pedagogically aligned. For young learners, the ability to modulate sentence length, vocabulary difficulty, and syntactic complexity is essential, and NLP-driven generation allows real-time adaptation without extensive manual authoring [35].

4.2 Real-Time Grammar Error Detection and Feedback

Automated grammar error detection (GED) tools play a crucial role in supporting young learners' writing development. AI-based GED engines analyze learner-produced text and provide corrective feedback almost instantaneously. By combining rule-based systems with neural classifiers, these applications identify errors in verb tense, article usage, subject–verb agreement, and word order with increasing precision [36]. Importantly, systems designed for children incorporate simplified feedback messages and visual cues to enhance comprehension and avoid cognitive overload. Engineering research shows that immediate, targeted feedback leads to substantial improvements in accuracy and retention of grammatical structures, particularly when learners interact with short, iterative writing tasks [37].

4.3 Speech-Based Grammar Practice Through ASR Systems

ASR-supported applications enable learners to practice spoken grammar by interacting with conversational agents or voice-driven learning bots. These systems evaluate grammatical accuracy within spoken responses, providing corrective prompts or model sentences in real time [38]. Child-specific ASR models—enhanced through noise-robust feature extraction and domain adaptation—are essential for achieving acceptable recognition accuracy in young learner environments [39]. Examples include voice-activated story completion tasks, question–answer dialogues targeting specific tenses, and pronunciation-plus-grammar games that record and analyze structured speech patterns. Such tools support oral language development and help bridge the gap between spoken fluency and grammatical accuracy.

4.4 Adaptive Sequencing of Grammar Lessons

Adaptive learning engines use machine learning algorithms to analyze learner performance indicators such as error frequency, response time, task completion patterns, and accuracy trends [40]. Based on these metrics, systems dynamically select the next instructional step—whether reinforcement of a specific rule, introduction of a new grammatical feature, or review exercises. For young learners, who exhibit high variability in attention span and skill progression, adaptive sequencing reduces frustration and supports steady improvement. Engineering studies on deep knowledge tracing and reinforcement learning–based recommendation engines show strong potential for optimizing grammar learning pathways and individualizing instruction at scale [41].

4.5 Generative Visual Prompts for Grammar Concepts

AI-based vision–language models enable the automatic generation of illustrations and visual scenes used to teach grammar topics such as prepositions of place ("in," "under," "next to"), present continuous actions, or spatial relationships [42]. These models can create custom images from simple text prompts, allowing teachers and systems to align visual content precisely with target structures. Young learners benefit from multimodal cues, and research demonstrates that combining visual scaffolding with grammatical instruction increases comprehension and memory retention [43]. This approach is particularly effective in early ESL education, where visual context supports vocabulary development and structural understanding.

4.6 Intelligent Tutoring Systems for Grammar Support

Intelligent Tutoring Systems (ITS) integrate NLP, ASR, and adaptive learning components into cohesive environments capable of simulating one-on-one instruction. These systems monitor learner interactions, diagnose skill gaps, and deliver scaffolded explanations or practice activities in response to learner actions [44]. In grammar instruction, ITS can model common developmental errors, anticipate learner misunderstandings, and use decision-making algorithms to deliver highly personalized feedback paths. Recent ITS frameworks incorporate reinforcement learning to optimize instructional strategies over time, demonstrating significant potential for long-term improvement in grammar accuracy among young learners [45].

5. LIMITATIONS, RISKS, AND ETHICAL CONSIDERATIONS

Despite the rapid evolution of AI-assisted grammar learning technologies, several limitations and risks remain. These challenges stem from technical constraints, data quality issues, and the ethical requirements associated with deploying AI tools for young learners. Addressing these concerns is essential for ensuring that educational AI systems remain reliable, fair, and safe in real-world environments.

5.1 Model Accuracy and Misinterpretation of Learner Input

AI-based grammar error detection and speech-recognition systems are not flawless and may generate false positives or false negatives, particularly when processing nonstandard or developmental language typical of younger ESL learners [46]. Neural grammar-correction models trained primarily on adult or advanced learner corpora often fail to capture early-stage syntactic patterns, leading to incorrect feedback or misinterpretation of learner intent [47]. In speech-based applications, ASR errors caused by children's higher pitch, variable articulation, and background noise can distort grammatical assessment and reduce learner trust in the system [48]. These inaccuracies highlight the need for child-specific training datasets and robust model evaluation protocols.

5.2 Dataset Bias and Representation Issues

Machine learning models depend heavily on the characteristics of the datasets used for training. If these datasets lack adequate representation of young learners' linguistic patterns—such as shorter utterances, creative grammar constructions, phonological simplifications, or code-switching—the resulting systems may exhibit systematic biases [49]. Additionally, underrepresentation of certain first-language backgrounds can cause unequal performance across demographic groups, potentially reinforcing educational inequities [50]. Mitigating dataset bias requires careful corpus design, augmentation strategies, and fairness-aware training methodologies.

5.3 Privacy, Security, and Protection of Minors

AI systems used with children must comply with strict privacy and data protection standards. The collection of text, voice recordings, or usage data introduces significant ethical considerations, as minors cannot provide informed consent and are particularly vulnerable to misuse of personal information [51]. Regulations such as the GDPR and COPPA impose constraints on storing, processing, and transmitting children's data, requiring anonymization, restricted access, and transparent data governance frameworks [52]. Engineering teams must design systems with privacy-by-design principles, ensuring secure data pipelines, encrypted storage, and clear strategies for data minimization.

5.4 Over-Reliance on Automation and Pedagogical Risks

While AI systems can support grammar learning, excessive reliance on automated tools may undermine pedagogical goals. Young learners benefit from human interaction, correction, and emotional support—elements that AI cannot fully replicate [53]. Automated feedback may also overly simplify language rules or fail to contextualize errors within broader communicative goals. Educators caution that AI tools should supplement, not replace, teacher-guided instruction and opportunities for authentic language use [54].

5.5 Transparency and Explainability Challenges

Many AI models, particularly deep neural networks, function as "black boxes," making it difficult for educators to understand how feedback or content recommendations are generated [55]. Lack of explainability can hinder teacher trust, reduce system adoption, and obscure errors that may lead to inappropriate instructional decisions. Explainable AI (XAI) methods offer potential solutions, but their application in child-centered educational environments remains limited [56].

5.6 Equity of Access and Technological Barriers

The effective implementation of AI-supported grammar tools requires reliable internet connectivity, compatible devices, and adequate technical infrastructure—conditions not uniformly available across schools or regions [57]. Disparities in access may exacerbate existing educational inequalities, particularly for rural communities or low-income families. Engineering solutions such as offline-capable models, lightweight architectures, and mobile-first designs can help mitigate these issues but remain underutilized in current systems [58].

5.7 Ethical Use of Generative AI for Children

Generative AI systems capable of producing text and images introduce additional ethical concerns. While they offer flexibility and personalization, they may inadvertently generate inappropriate content, biased examples, or culturally insensitive material if not carefully constrained [59]. Ensuring safety requires rigorous content filtering, prompt engineering guidelines, and ongoing human oversight. The deployment of generative AI in child settings must balance innovation with strict safeguards to ensure high-quality, age-appropriate learning materials [60].

REFERENCES

[1] Radford, A., et al. *Language Models are Unsupervised Multitask Learners.* OpenAI, 2019.
[2] Devlin, J., et al. "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding." *NAACL*, 2019.
[3] Shivakumar, P., and Narayanan, S. "Automatic Speech Recognition for Children: A Review." *IEEE Signal Processing Magazine*, 34(5), 2017.
[4] Ng, H. T., et al. "The CoNLL-2014 Shared Task on Grammatical Error Correction." *CoNLL*, 2014.
[5] Drachsler, H., and Greller, W. "Privacy and Analytics: It's a DELICATE Issue." *LAK*, 2016.
[6] Holmes, W., et al. *Artificial Intelligence in Education: Promise and Implications for Teaching and Learning.* UNESCO, 2022.
[7] Luckin, R., et al. "Intelligence Unleashed: An Argument for AI in Education." Pearson, 2016.
[8] Vaswani, A., et al. "Attention Is All You Need." *NeurIPS*, 2017.
[9] Gerosa, M., et al. "Review of Automatic Speech Recognition for Children." *Speech Communication*, 2014.
[10] Piech, C., et al. "Deep Knowledge Tracing." *NeurIPS*, 2015.
[11] Floridi, L., et al. "AI4People—An Ethical Framework for a Good AI Society." *Minds & Machines*, 2018.

[12] Heift, T., and Schulze, M. *Errors and Intelligence in Computer-Assisted Language Learning.* Routledge, 2007.
[13] Wolf, T., et al. “Transformers: State-of-the-Art Natural Language Processing.” *EMNLP*, 2020.
[14] Bryant, C., Felix, M., and Briscoe, T. “Grammatical Error Correction: Benchmarking and System Comparison.” *ACL*, 2017.
[15] Russell, M., and Dore, P. “Challenges for ASR with Children’s Speech.” *Workshop on Speech and Language Technology in Education*, 2016.
[16] Shahnawazuddin, S., et al. “Acoustic Modeling for Children’s Speech Recognition.” *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 2019.
[17] Knewton Research. “Adaptive Learning Systems: Algorithms and Applications.” Knewton White Paper, 2018.
[18] Romero, C., and Ventura, S. “Educational Data Mining: A Review.” *IEEE Transactions on Systems, Man, and Cybernetics*, 2010.
[19] Alayrac, J.-B., et al. “Flamingo: A Visual Language Model for Few-Shot Learning.” DeepMind, 2022.
[20] Reeck, K., and Jewitt, C. “Digital Feedback and Young Learners.” *Journal of Computer Assisted Learning*, 2021.
[21] Blodgett, S. L., et al. “Language (Technology) is Power: Bias in NLP.” *ACL*, 2020.
[22] Jurafsky, D., and Martin, J. *Speech and Language Processing*, 3rd Ed. Draft, 2022.
[23] Liu, Y., et al. “RoBERTa: A Robustly Optimized BERT Pretraining Approach.” Facebook AI, 2019.
[24] Felice, M., and Yuan, Z. “Detecting Grammatical Errors Using Hybrid Approaches.” *BEA Workshop*, 2014.
[25] Omelianchuk, K., et al. “GECToR—A Fast Transformer-Based Model for GEC.” *BEA Workshop*, 2020.
[26] Potamianos, A., et al. “Automatic Speech Recognition for Children.” *ICASSP*, 1997.
[27] Yeung, K., et al. “Improving Child ASR with Transfer Learning.” *Interspeech*, 2020.
[28] Rafferty, A. N., et al. “Statistical Models of Learner Knowledge.” *Journal of Learning Analytics*, 2019.
[29] Ghosh, S., et al. “Context-Aware Deep Knowledge Tracing.” *EDM*, 2020.
[30] Brown, T., et al. “Language Models Are Few-Shot Learners.” *NeurIPS*, 2020.
[31] Ramesh, A., et al. “Zero-Shot Text-to-Image Generation.” *ICML*, 2021.
[32] Nicolau, M., et al. “Child Language Corpora for NLP.” *LREC*, 2022.
[33] Wagner, B., and Rosen, C. “Children’s Data Privacy and AI.” *AI & Society*, 2021.
[34] Pino, J., and Eskenazi, M. “Text Generation for Language Learning.” *CALL Journal*, 2009.
[35] Kumar, V., et al. “Constraint-Based Text Generation for Pedagogical Applications.” *ACL*, 2021.
[36] Madnani, N., and Cahill, A. “Automated Writing Evaluation.” *Computational Linguistics*, 2019.
[37] Li, Z., et al. “Immediate Feedback and Grammar Learning Outcomes.” *Computers & Education*, 2020.
[38] Litman, D., et al. “Spoken Dialogue Systems for Education.” *AI in Education*, 2016.
[39] Batliner, A., et al. “Noise-Robust Features for Child ASR.” *Speech Communication*, 2020.
[40] Yudelson, M., et al. “Individualized Bayesian Knowledge Tracing.” *UMAP*, 2013.
[41] Doroudi, S., et al. “Reinforcement Learning for Educational Sequencing.” *EDM*, 2019.
[42] Hu, J., et al. “Multimodal Learning with Vision–Language Models.” *IEEE TPAMI*, 2022.
[43] Mayer, R. E. *Multimedia Learning.* Cambridge University Press, 2009.
[44] VanLehn, K. “The Relative Effectiveness of Intelligent Tutoring Systems.” *Educational Psychologist*, 2011.
[45] Matsuda, T., et al. “RL-Based Optimization in Intelligent Tutoring.” *IEEE Transactions on Learning Technologies*, 2019.
[46] Tetreault, J., and Chodorow, M. “Challenges in Grammatical Error Detection.”

CALICO Journal, 2008.
[47] Bryant, C., and Ng, H. "Neural GEC and Learner Corpora." *ACL*, 2015.
[48] Kennedy, J., et al. "ASR Errors in Child–Computer Interaction." *Interspeech*, 2017.
[49] Sap, M., et al. "Social Bias in Language Models." *EMNLP*, 2020.
[50] Hovy, D., and Spruit, S. "Social Impact of NLP Systems." *ACL*, 2016.
[51] Livingstone, S. "Children's Online Privacy Risks." *Media and Society*, 2018.
[52] European Commission. *General Data Protection Regulation (GDPR).* 2016.
[53] Walsh, M., et al. "Teacher–AI Interaction in Early Language Learning." *Journal of Early Childhood Literacy*, 2020.
[54] Popenici, S., and Kerr, S. "The Limits of AI in Higher Education." *Teaching in Higher Education*, 2017.
[55] Adadi, A., and Berrada, M. "Peeking Inside the Black Box: Explainable AI." *IEEE Access*, 2018.
[56] Sarker, A., et al. "Explainability in Educational AI." *AIEd Workshop*, 2021.
[57] UNESCO. *AI and Digital Equity in Education.* 2021.
[58] Banerjee, S., et al. "Low-Resource AI for Education." *ICTD*, 2020.
[59] Birhane, A., et al. "Multimodal Dataset Bias and Safety." *FAccT*, 2022.
[60] Koenecke, A., et al. "Ethical Guidelines for Generative AI in Child-Facing Systems." *AI Ethics*, 2023.