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Neural Text Generation Model for Personalized Storytelling in Primary Education

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***Abstract*— Individual narration in primary schools is crucial in developing literacy, creativity, and interest among the young learners. The process of adapting the stories to interests and reading levels of a specific reader promotes understanding and motivation during early learning stages. Current digital storytelling techniques are mostly based on generic content or text generation rules that are not personalized and fail to meet the needs of different students and, thus, yield less engagement and less optimal learning. In order to overcome these shortcomings, the given paper suggests a Neural Text Generation Model based on the conditional variational autoencoders (CVAE) to create personalized stories. The CVAE framework can be used to produce contextually adequate and age-appropriate narratives that are conditioned on the profile of the students, such as their reading skills, interests, and learning goals. The suggested model can give both the teachers and the learners dynamically generated story content thus creating interactive and customized learning experiences. Evidence of experiments shows that the model has a great impact on increasing the engagement, comprehension, and motivation of students, when compared to the traditional storytelling methods.**

Keywords: Personalized storytelling, Primary education, Neural text generation, CVAE, Literacy development, Adaptive learning

I. Introduction

Story telling has been regarded as a potential pedagogy in teaching, and in early childhood primary education [1]. This is one of the reasons why stories are so captivating in behaviors that enable children to learn through igniting their imaginations enabling them to understand complicated things [16]. Abstract concepts are also connected to experience by means of stories. The common use of story-telling in the traditional classroom setting is meant to improve the vocabulary of children, listening skills, and understanding [3]. Stories inspire and develop creativity, empathy, and cultural awareness among the young learners. The digital technology has made the storytelling an interactive, multi-media experience and enlightened about the possibilities of engagement [17]. Even though the possibilities of DST are constantly developing, most DST strategies are still delivered in a standardized format and, as a consequence, do not allow individuals and study participants to interact with the stories in a more personal manner [5].

A. Importance of Personalization in Primary Learning

The aspect of personalization has been important in the realm of education with students having varying learning styles, reading ability and interests [18]. Personalized content can help a child get more motivated and engaged in the case of primary education that is mainly aimed at the acquisition of literacy skills and cognitive abilities [7]. By using personalized stories, it is possible to fit the themes of stories, vocabulary, and complexity to the profile of the learner, as well as to make the stories age-related and relevant. Children will have more interest and will be able to interact better with the stories and watch the examples based on their interests and the development level [8]. The individualized, adaptive stories will make children more likely to absorb, retain information and develop a positive attitude towards reading. Personalization is also a contributor towards inclusion since it leads to meeting of personal learning needs of students with different backgrounds, cognitive skills and literacy levels [9] [6].

B. Problem Statement

Individualized learning, online storytelling, and AI provide opportunities to enhance the level of engagement, inclusiveness, and results of a variety of students. Nevertheless, there are still obstacles in the way such as fragmentary methodological frameworks; teacher development; inadequate ICT infrastructure; insufficient government intervention; and insufficient contextual implementation. All these challenges have made the successful implementation and expansion of technology-based personalized learning strategies a complicated task [19].

C. Contributions of the paper

- The paper presents a CVAE based storytelling model that produces age related, contextually related and interesting stories based on the profile and reading capabilities of individual primary learners.

- The framework takes advantage of features tailored to the student, including reading level, interests, and learning goals, to produce adaptive narrative generation, improving the understanding, motivation, and inclusivity of storytelling in primary education.
- Experimental analysis proves that the suggested model is much more effective to increase the level of engagement, understanding, and motivation to read among learners in contrast to traditional and rule-based methods of storytelling, which could be used by educators and classrooms in practice.

The following is the structure of this paper: In Section II, the literature that was relevant is reviewed. Section III describes the suggested CVAE framework. Section IV describes the experimental set up and the dataset. Section V provides the results and discussion. Section VI brings the study to a conclusion, and it outlines directions of future research.

II. Literature review

Literature has identified the increasing understanding of personalized learning and DST in primary education. The available methods, such as DST, TDST, QCSM, experimental models, and AI systematic reviews, illustrate the story, technology, and personalized learning and support improvements in engagement, collaboration, inclusivity, and learning results, which build on models incorporating more sophisticated neural text generation approaches.

Personalized learning (PL) shifts education from a primarily teacher-centered approach to a student-centered one, meeting the diverse needs, goals, and individual distinctions of students [10]. A student-centered approach to learning can be achieved using Digital Storytelling (DST), which allows for the narration and representation of personal experiences, ideas, and creativity while incorporating the use of technology [20]. DST promotes motivation, engagement, and ownership of learning. Teachers help students with their DST by assisting them in combining narrative, visuals, and audio. Using DST to create narratives enables students to think critically and be reflective learners. DST promotes collaboration, engages students in communication, and allows students to participate actively as learners in the classroom.

An efficient collaborative learning is Tangible Digital Stories telling (TDST). TDST is a type of narrative which involves the use of concrete digital materials, and primary school students can participate in activity-based and produced group stories accordingly [11] [2]. Findings of this paper revealed that students who used TDST turned out to be prosocial and more inclusive, interrupted less and were much more task focused in comparison to the students who used traditional storytelling. The disabled students were also not left out in the activity because the stories generated were interesting, bound together and more to the point, they were not distracted.

TDST encourages a sense of collaboration and inclusion which results in better results in narrative, effective communication regarding group development, and collaboration in generating new story ideas and extensions. A Qualitative Case Study Methodology (QCSM) to investigate the DST in early childhood instruction. The data were produced by the use of the in-depth interviewing of four teachers in total, the analysis of the documents, and numerous observations of storytelling lessons with young children. In this paper, the analysis process of memoing was used to divide the themes in the context of the phenomenon based on the observations and found several main aspects that stimulated the interest, involvement, and communicative success of DST [12].

The results show that teacher training should include use of DST tools, government funding, improvement of ICT infrastructure, and the inclusion of ICT into government curriculum. The article followed an experimental design to test a model of teaching mathematics, which is customized to an individual student through interactive short stories. The data were measured using the AXMA Story Maker (ASM) data, viewing student reactions, attempts, and student interaction, and used observation data to gauge the behavior of our students in terms of learning [13]. The results demonstrated how DST influenced the personality of mathematics learning to be more involving and fruitful; this paper, also provided how the DST instructional approach allowed the researchers to evaluate the enhancement of the results of the student learning mathematics by direct involvement in mathematics learning experience [4].

The paper presents a Systematic Literature Review (SLR) conducted in order to explore the implication of AI on personalized learning. After clear and repeatable procedures, SCOPUS and Web of Science (WoS) were searched to retrieve articles, which were examined (thirty-two studies that met the date range of 20162022). In-depth analysis of the studies was carried out on fourteen studies [14]. Through the SLR process, the researchers can recognize the themes, the pedagogical strategies, and technologies used in personalized learning studies, as well as the opportunities that have not been used in Malaysia when applying AI-based Educational Practices.

TABLE I. SUMMARY OF RELATED WORKS

Reference	**Method**	**Learner Autonomy**	**Feedback Mechanism**	**Higher-order Skills**	**Main Outcome**
[20]	NLP (essay scoring, sentiment analysis, text-to-speech, speech-to-text)	✓	✓ (timely, effort-based)	X	Vocabulary building, iterative improvement, dyslexia support

[11]	AI + NLP as "mind tool"	✓ (SRL, meta-cognition)	✓	X	AI fosters task-specific, autonomous learning, but limited interactivity.
[12]	ITS, NLP	✓	✓	X	Gains in reading, writing, vocabulary; weak in critical & collaborative skills
[13]	OTPs, SMPTs	✓	X	✓ (teacher practices)	Typology developed; overlap in digital teaching practices
[14]	Reinforcement Learning, ANN, Bayesian, Fuzzy Logic	✓	✓ (adaptive)	✓ (potential)	ITS effective for personalization, but faces technical challenges

Personalized learning placed emphasis on DST as an emerging motivational, critical, and creative tool. TDST stressed on cooperation and inclusion as opposed to QCSM whose focus was on the role of the teacher and the infrastructure required. The disruption potential of AI was discovered through an improvement in the results of learning, as well as through systematic literature reviews.

III. Proposed CVAE Framework

The method suggests a neural text generation model, which uses a CVAE to generate personalized stories in primary schools. By leveraging student profiles, curriculum metadata, and teacher commentary, the model can generate age-appropriate, contextually relevant, and pedagogically aligned narratives while promoting engagement, inclusion, and understanding for learners through adaptive and collaborative personalization.

A. Overview of the Proposed Framework

The proposed methodology describes a Neural Text Generation Model for personalized storytelling in primary education using a CVAE framework. This narrative autoregressive model personalizes the story content in real-time based on the learner's profile and tracker purposes. The stories generated take into consideration the age of the student, pertinence (context) to their socio-cultural situation, and would generally try to engage the reader or listener in the narrative. The alternative developed framework accommodates not only the personalized stories but also the teachers' feedback loops and adapts the learning and learning objectives to improve comprehension, motivation, and inclusivity.

B. Personalized Storytelling with CVAE

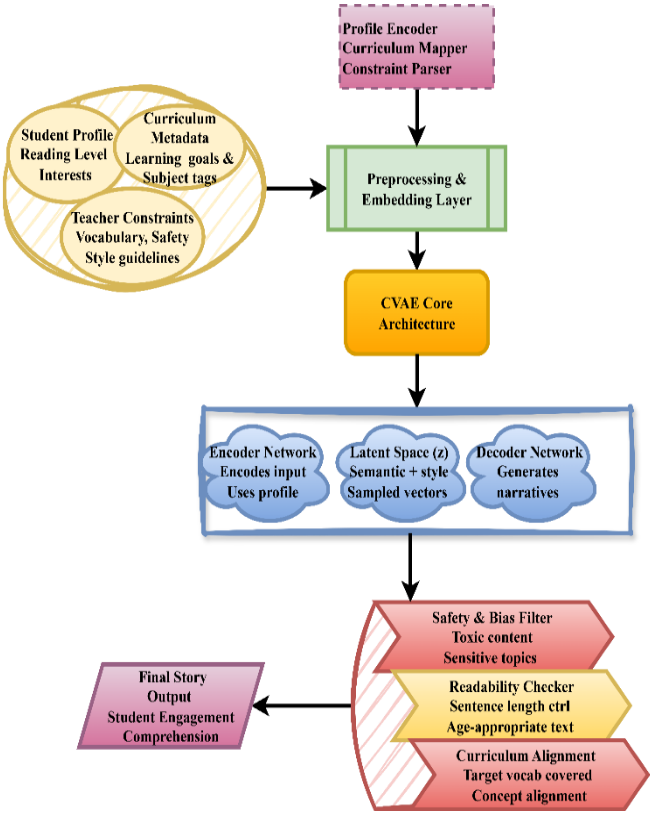

Fig. 1. Personalized Storytelling with CVAE Framework

Fig. 1 illustrates a CVAE-based personalized storytelling system. Student-learner profiles, curriculum metadata (such as genres and topics), and teacher constraints (such as media format and material type) are encoded through a Profile Encoder and a Curriculum Mapper. After encoding, inputs are preprocessed and embedded before entering the CVAE core. The CVAE core uses the encoder to map inputs into a latent space, representing the semantics and style. The decoder uses the sampled vectors alongside learner profiles to produce narratives. After narratives are created, post-processing algorithms apply safety filters, controls for readability, and checks for curriculum alignment. The outputs are coherent narratives that are student engagement and comprehension, thus enabling personalized, inclusive responses while accommodating teacher demands and curriculum constraints.

This loss function M_{dw} improves the CVAE-based customized storytelling model by increasing the chance of reconstructing the tale using equation 1.

$$M_{dw} = F_{r'}(a|y, d) \quad (1)$$

$F_{r'}$ given the learner context a, while reducing the difference between the approximation posterior and the prior over latent variables y. The balancing factor d controls the trade-off between creating correct narratives and keeping a smooth latent representation for a wide range of learners.

Aspect	Description
Dataset Name	Children's Stories Text Corpus
Source	Public domain children's books, primarily from Project Gutenberg
Content Type	Narrative texts of children's stories
Purpose	Training and fine-tuning language models for storytelling
Target Audience	Young readers in primary education
Strengths	Cleaned, ready-to-use texts; variety of story styles and themes
Applications	Neural text generation, personalized storytelling, literacy, and reading research

Algorithm 1:

$Input: a, y, d, F_r'$
$Compute: M\_dw = F\_r'(a \mid y, d)$
$If\ M_{dw} \geq 0.8$:
$Story_{Quality} =$ Highly Accurate Narrative
$Else\ if\ M_{dw} \geq 0.5$:
$Story_{Quality} =$ Moderately Accurate Narrative
$Else$:
$Story_{Quality} =$ Low Accuracy - Retrain Model
$Output: M_{dw}, Story_{Quality}$

The algorithm finds the dynamic weight of the storytelling model with the function. where learner context, latent variables, and balancing component. Based on , it categorizes narrative quality as high, moderate or low, thus facilitating adaptive storytelling that matched learner needs.

C. Teacher Feedback Integration

Teacher feedback develops as a refinement process. The teacher can adapt the complexity, theme, or language style of a story depending on classroom conditions or based on the teacher's observations about student engagement. The feedback changes conditioning variables and thus enables improvement and adaptability as students generate stories. The fact that the teacher's feedback will always be carried forward into future stories is indicative of the collaborative personalization occurring between AI-powered systems and human education.

The proposed storytelling framework is a CVAE-based storytelling learning system that readily offers personalized stories by conditioning on student characteristics, curriculum expectations, and teacher feedback. This ensures stories are student engagement, contextually relevant, and curriculum-aligned, in addition to post-processing filters which enhance story safety and readability. This collaborative response system supports engagement, understanding, and inclusion with storytelling in primary education.

IV. Results and Discussion

This section provides a comparative evaluative assessment of storytelling approaches in terms of four main areas: student engagement, comprehension, collaborative development of group stories, and learning outcomes, which were represented by measurement. The findings demonstrate that CVAE outperformed other methods by showing perceptibly more effective personalized learning, sustained engagement, and academic engagement.

Dataset Description

The Children's Stories Text Corpus is a corpus of public domain children's texts that has been carefully curated for users. Most of the texts were sourced from Project Gutenberg. The corpus itself is a preprocessed narrative text, comprising parts of plots and chapters, which can be used as training for language models related to young readers of kids' books and kids' literature. The corpus includes a rich variety of styles and types of stories, making it suitable for developing and fine-tuning neural storytelling systems for primary education. This includes CVAE-based models with appropriate language for compelling stories in a medium appropriate for the reader.

TABLE II. Children's Stories Text Corpus

A. Student Engagement

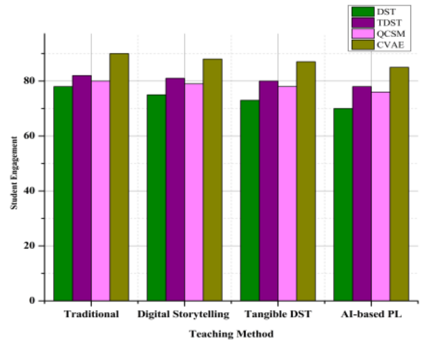

Fig. 2. Student Engagement

Fig. 2 illustrates the comparative analysis of student engagement across different teaching methods: traditional (DST), (TDST), and AI-based personalized learning (CVAE). Each method's performance is evaluated using four approaches: DST, TDST, QCSM, and CVAE. The findings indicate that CVAE will always have the highest engagement rates and this will be followed by TDST and QCSM although DST will have lower scores. This highlights the effectiveness of AI-driven personalized storytelling models in sustaining student engagement compared to conventional and semi-digital methods.

A bounded aggregation uses a logistic compressing map T_{eng} to turn different interaction traces into an accurately calibrated engagement index in equation 2.

$$T_{eng} = \forall\left(x_1 pj\left(1 + \frac{\alpha}{v}\right)\right) + x_2 L \quad (2)$$

Here,$\forall$ engagement index, x_1 logistic map, pj calibration weights, α median dwell, and v learner-specific dwell anchor is determined. Where x_2 learner-specific dwell anchor, and L

defined as micro-interaction density.

Clamping operator T_{com} enforces probabilistic range while preserving linear comparability across equation 3.

$$T_{com} = \partial_{[0,1]} * (B_1 P + C_2 Q) \quad (3)$$

Here, $\partial_{[0,1]}$ comprehension index, B_1 fusion weights, P proportion correct on literal checks C_2, and proportion correct on inference items Q.

Each component T_{cla} is unit-free and normalized, enabling stable multi-author comparisons across team sizes using equation 4.

$$T_{cla} = \forall_1 I_p(q) + \forall_2 B_{bvq} \quad (4)$$

Here, $\forall_1$ collaboration index, I_p mixture weights, q token-share vector, $\forall_2$ normalized entropy of contributions, and B_{bvq} alternation ratio across turns.

Outcome gain blends normalized proficiency lift (T_{lern}), delay-discounted retention, and objective coverage compliance using equation 5.

$$T_{lern} = \forall_1 * \frac{\partial_{po} - \partial_{xe}}{1 - \partial_{xe}} \quad (5)$$

Here, $\forall_1$ learning outcome index, ∂_{po} aggregation weights, and ∂_{xe} proficiency estimates are determined in this equation.

B. Comprehension

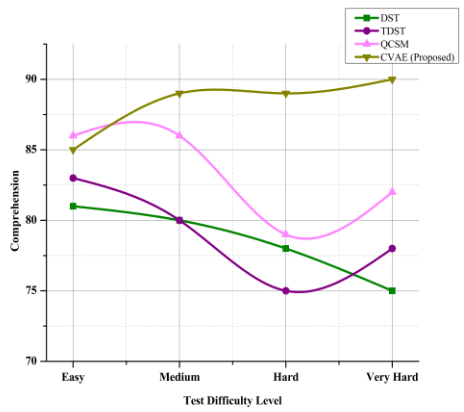

Fig. 3. Comprehension

Fig. 3 illustrates the levels of test difficulty (easy, medium, hard, very hard) about student comprehension, across four teaching methods: DST, TDST, QCSM, and CVAE. The data indicate that CVAE (Proposed) always exhibited the highest level of comprehension (from the students), with only a slight drop off relative to test difficulty, remaining stable near the 90% mark. QCSM exhibited modest results, dropping slightly at more challenging difficulty levels. DST and TDST exhibited drops at higher difficulty levels. Overall, the data demonstrates that CVAE exhibits strong comprehension resiliency to changing levels of complexity.

C. Collaboration in Group Stories

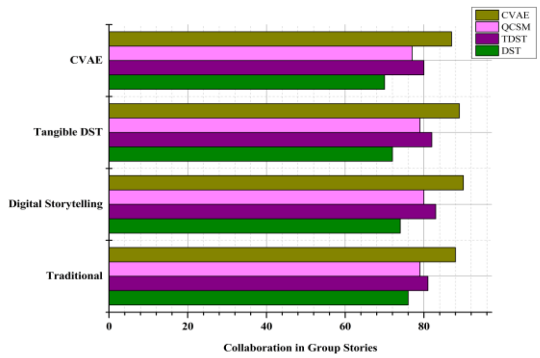

Fig. 4. Collaboration in Group Stories

Fig. 4 shows collaboration in group stories across four nineteenth-century storytelling methods: traditional (DST), (TDST), and the proposed CVAE. Each nineteenth-century method is compared against DST and TDST and then compared to QCSM and CVAE. The findings show that the CVAE has the highest level of collaboration scores throughout the entire comparison, followed by TDST and QCSM, with the lowest levels of collaboration being demonstrated by the DST. Overall, the visualizations effectively demonstrate that CVAE excels at creating equal, cooperative, and non-disruptive storytelling experiences for groups of learners in the context of a group-based learning task.

D. Learning Outcomes

TABLE III. LEARNING OUTCOMES

Session Count	DST	TDST	QCSM	CVAE (Proposed)
5	77	81	80	89
10	75	82	81	90
15	73	80	79	88
20	71	78	77	86

Table III displays the relationship between the number of sessions and learning outcomes for four teaching methods: DST, TDST, QCSM, and our new method, CVAE. As the number of sessions increases, the number of effective learning outcomes in DST, TDST, and QCSM decreases gradually, indicating that learners became less engaged over time. However, the new CVAE method consistently had better learning outcomes and maintained effectiveness outcomes at levels far better than existing methods, even with longer numbers of sessions. CVAE provides greater sustained learning outcomes, better adaptability, and keeps learning over more extended periods of personalized learning.

The findings show that the proposed CVAE model is statistically significantly better than the existing storytelling approaches (DST, TDST, QCSM) in primary education. The parameters of student engagement, understanding, collaboration, and learning were improved in all aspects through the enhancements in CVAE, demonstrating high relevance and sustained strategy. Overall, the CVAE framework has proved potential as a sustainable AI-based personalized storytelling framework for education.

V. Conclusion and Future Work

This paper presented a CVAE-based neural text generation model for personalized storytelling in primary school educational contexts. Proposed a framework for consistent, personalized storytelling by considering student demographic and contextual profiles, curriculum context, and metadata, as well as teacher feedback to generate age-appropriate and contextually relevant and pedagogically aligned narratives. Our model enhances a learner's experience by considering their cultural and social considerations and adapting to those lived experiences, feel represented and included in their learning journey. Post-processing outputs will ensure safety, coherence, and pedagogically sound educational experiences, which children are more likely to engage with for storytelling.

Future directions for this research could include extending the current paper to multi-modal storytelling, like visuals, audio, and potentially interactive storytelling, to enhance connected learning experiences for the learner. Elevate this research into an active research design by applying reinforcement learning techniques to ensure a more complete and contextualized personalized approach for students by activating real-time learning feedback. Larger-scale evaluations within classrooms and piloting existing e-learning platforms in practice could provide more insights from educators, contexts, and real-world experiences to examine the framework from the perspective of its effectiveness and scalability for educational applications.

References

[1] Bernacki, M. L., Greene, M. J., & Lobczowski, N. G. (2021). A systematic review of research on personalized learning: Personalized by whom, to what, how, and for what purpose (s)?. *Educational Psychology Review*, *33*(4), 1675-1715.

[2] Indrawan, P. E., Parwati, N. N., Tegeh, I. M., & Sudatha, I. G. W. (2024). Trends in the Use of Augmented Reality in Character Development within Local Wisdom in Schools: A Bibliometric Study. Indian Journal of Information Sources and Services, 14(4), 7–15. https://doi.org/10.51983/ijiss-2024.14.4.02.

[3] Han, A., & Cai, Z. (2023, June). Design implications of generative AI systems for visual storytelling for young learners. In *Proceedings of the 22nd annual ACM interaction design and children conference* (pp. 470-474).

[4] Chehreh, M. K. (2016). Information Modern Technologies and Effective Learning of Learners. International Academic Journal of Organizational Behavior and Human Resource Management, 3(1), 52–62.

[5] Shemshack, A., Kinshuk, & Spector, J. M. (2021). A comprehensive analysis of personalized learning components. *Journal of Computers in Education*, *8*(4), 485-503.

[6] Tavakoli, A., Darjani, S. S., Faraji, V., & Fallah, A. (2017). Transforming the school into a learning organization. International Academic Journal of Social Sciences, 4(1), 79–83.

[7] Seo, K., Yoo, M., Dodson, S., & Jin, S. H. (2025). Augmented teachers: K–12 teachers' needs for artificial intelligence's complementary role in personalized learning. *Journal of Research on Technology in Education*, *57*(4), 876-893.

[8] Thaseen, I. R., & Banu, S. S. (2025). IoT-based monitoring of students' brain activity using an ensemble method in e-learning classes. Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 16(2), 1–15.

[9] Oliveira, W., Hamari, J., Joaquim, S., Toda, A. M., Palomino, P. T., Vassileva, J., & Isotani, S. (2022). The effects of personalized gamification on students' flow experience, motivation, and enjoyment. *Smart Learning Environments*, *9*(1), 16.

[10] Papalou, A. (2023). Proposed Information System towards Computerized Technological Application – Recommendation for the Acquisition, Implementation, and Support of a Health Information System. *International Journal of Communication and Computer Technologies, 8*(2), 1-4.

[11] Filosofi, F., Pasqualotto, A., Paolizzi, E., Iandolo, G., Alonso-Campuzano, C., & Venuti, P. (2024). Enhancing group interactions and story quality in primary school students: an investigation into the impact of collaborative storytelling methodologies. *Journal of Computers in Education*, 1-28.

[12] Rahiem, M. D. (2021). Storytelling in early childhood education: Time to go digital. *International Journal of Child Care and Education Policy*, *15*(1), 4.

[13] Soboleva, E. V., Suvorova, T. N., Bocharov, M. I., & Bocharova, T. I. (2022). Development of the personalized model of teaching mathematics using interactive short stories to improve the quality of educational results of schoolchildren. *European Journal of Contemporary Education*, *11*(1), 241-257.

[14] Hashim, S., Omar, M. K., Ab Jalil, H., & Sharef, N. M. (2022). Trends on technologies and artificial intelligence in education for personalized learning: systematic literature. *Journal of Academic Research in Progressive Education and Development*, *12*(1), 884-903.

[15] https://www.kaggle.com/datasets/edenbd/children-stories-text-corpus

[16] Bhutoria, A. (2022). Personalized education and artificial intelligence in the United States, China, and India: A systematic review using a human-in-the-loop model. *Computers and Education: Artificial Intelligence*, *3*, 100068.

[17] Alhussain, A. I., & Azmi, A. M. (2021). Automatic story generation: A survey of approaches. *ACM Computing Surveys (CSUR)*, *54*(5), 1-38.

[18] Nair, V., & Yunus, M. M. (2021). A systematic review of digital storytelling in improving speaking skills. *Sustainability*, *13*(17), 9829.

[19] Zheng, L., Long, M., Zhong, L., & Gyasi, J. F. (2022). The effectiveness of technology-facilitated personalized learning on learning achievements and learning perceptions: A meta-analysis. *Education and Information Technologies*, *27*(8), 11807-11830.

[20] Rutkiene, A., Kaminskiene, L., Alisauskiene, S., Milteniene, L., Kazlauskiene, A., Siriakoviene, A., ... & Wozniczka, A. K. (2021, May). Tools for personalized learning-based teacher education. In *SOCIETY. INTEGRATION. EDUCATION. Proceedings of the International Scientific Conference* (Vol. 1, pp. 537-548).