A Machine Learning Approach to Personalizing Learning by Reading Experiences Based on Individual Cognitive Profiles and Preferences

Hussain Rasheed[1] and Aishath Zahir[2]

[1]Maldives National University, Faculty of Science, Computer Science Department, Rahdhebai Hingun, Malé, Maldives
[2]Villa College, School of Information Technology, Alifu Hingun, Malé, Maldives

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Abstract

Modern educational contexts demand adaptive methods that cater to individual learning styles, cognitive capacities, and preferences. This paper addresses the challenge of personalizing reading experiences for diverse learners by leveraging a machine learning architecture grounded in cognitive psychology and advanced user modeling. The proposed approach systematically captures key cognitive traits, including working memory capacity, information-processing speed, and domain-specific prior knowledge, to tailor reading materials and strategies to each learner's profile. By mapping user interactions with various textual complexities, semantic structures, and contextual cues, the system dynamically adjusts presentation, pacing, and conceptual scaffolding. A rich set of features, encompassing linguistic and psychometric indicators, contributes to building robust user representations. In contrast to purely content-based adaptation, our framework explicitly integrates a cognitive layer that mediates user intentions, engagement levels, and meta-cognitive strategies for comprehension monitoring. A combination of probabilistic modeling and deep learning is employed to infer latent cognitive states, predict performance trajectories, and fine-tune content difficulty. Preliminary evaluations show promising improvements in reading comprehension, engagement, and sustained learning gains, while also revealing the importance of personalization that aligns with fine-grained cognitive profiles. This paper offers a new perspective for adaptive learning systems, guiding future developments toward more inclusive, evidence-based, and cognitively aligned educational technologies.

1 Introduction

The fundamental mission of contemporary educational technologies is to accommodate the diverse range of learners, respecting individual cognitive capacities, preferences, and prior knowledge [1]. Traditional instructional strategies, which were once constrained by static materials and uniform pacing, have gradually evolved toward personalized and adaptive learning solutions [2]. At the heart of this shift lies the recognition that learners exhibit a broad spectrum of capabilities, dispositions, and motivations, prompting the design of systems that can responsively adapt to their evolving needs [3]. Machine learning techniques have played a pivotal role in shaping the field, supplying models capable of ingesting large quantities of interaction data to yield fine-grained inferences about user proficiency [4]. Simultaneously, research in cognitive psychology underscores the influence of working memory, information-processing speed, and other domain-general functions on reading comprehension. This intersection of theory and algorithmic innovation highlights the necessity of integrating psychological constructs into computational frameworks to achieve highly personalized reading experiences. [5]

One of the most compelling arguments for adaptive reading platforms is their potential to improve engagement and long-term retention of knowledge [6]. The reading process itself is a complex phenomenon, entailing not just the decoding of text but also the activation of background knowledge, the interpretation of linguistic structures, and the application of meta-cognitive strategies to monitor comprehension [7]. Different learners may struggle at various stages of this process. For example, a reader with limited working memory might be rapidly overwhelmed by dense paragraphs, whereas a reader with limited domain knowledge may falter when the text assumes a familiarity with specialized concepts or terminologies [8]. Hence, a well-tailored adaptive system must be capable of monitoring user behavior, identifying bottlenecks, and dynamically adjusting content presentation in ways that mitigate cognitive load. [9], [10]

Although a variety of adaptive reading and e-learning platforms have emerged in recent years, many remain limited by their reliance on coarse-grained user models. This constraint arises from oversimplified assumptions that restrict modeling of learner variance to a small set of parameters, often ignoring critical dimensions such as cognitive control, reading fluency in multiple languages, or subtle motivational drivers [11]. More advanced systems incorporate some measure of cognitive traits, but these typically remain partial or loosely integrated. In contrast, the current research aims to develop a unified framework that merges insights from cognitive psychology with advanced machine learning paradigms to create a holistic representation of the learner. [12], [13]

Central to this aspiration is the concept of a cognitive profile—a structured summary of attributes that encapsulates memory capacity, processing speed, metacognitive awareness, and preference for certain reading strategies, among others [14]. By embedding such traits into the model, we facilitate a more nuanced set of adaptations, ranging from reorganizing textual structures to scheduling timed comprehension checks [15]. The synergy between these attributes is captured in a high-dimensional latent space, which is inferred through a combination of user interactions, performance metrics, and psychometric assessments. These are then mapped onto personalized recommendation policies for textual difficulty, complexity of language, and the frequency of summarization prompts. [16]

Another important dimension of personalized reading pertains to the dynamic nature of skill development [17]. As learners gain expertise or their attention levels fluctuate, the optimal difficulty level may shift [18]. A purely static model of learner characteristics fails to capture such trends, often resulting in suboptimal recommendations over time [19]. The present approach addresses this by employing sequential machine learning methods that update user representations in real-time. Data streams such as reading times, accuracy on comprehension questions, and eye-tracking signals serve as features in a predictive model for engagement and learning outcomes [20]. This adaptive cycle, reminiscent of a continuous feedback loop, distinguishes our framework by ensuring that it can respond not only to stable individual differences but also to short-term variations in cognitive and motivational states. [21]

In building such a comprehensive system, various theoretical and technical challenges emerge [22]. First, the extraction of latent cognitive constructs from observable data demands a rigorous modeling approach. Traditional collaborative filtering and matrix factorization techniques are suboptimal if they do not explicitly incorporate cognitive constraints such as working memory limitations or domain knowledge dependencies [23]. Second, bridging the gap between theoretical constructs and algorithmic features requires careful design of data-collection protocols [24]. User logs capturing reading speed, number of regressions to previous text segments, or patterns of question response can be more telling about an individual's cognitive profile than discrete performance metrics in isolation [25]. Finally, the model must reconcile interpretability with predictive power, balancing the complexities of deep neural architectures with simpler parametric forms that can be validated through psychometric tests.

This paper unfolds as follows [26]. First, we lay out the theoretical underpinnings of cognitive profile construction, arguing for the integration of multiple psychological scales and knowledge metrics into a unified model [27]. We then detail the machine learning architecture employed, highlighting the synergy between neural embedding layers, attention mechanisms, and Bayesian components that incorporate priors about cognitive function [28]. Subsequently, we discuss how these models are put into action to adapt reading content in real-time, focusing on the practical algorithms for difficulty calibration and chunking of text [29]. Empirical results from controlled experiments are presented, offering insights into the advantages and limitations of the proposed approach when implemented at scale. Finally, we conclude by reflecting on the broader implications for the design of personalized educational systems and propose directions for future work that incorporate more refined psychological constructs, multi-modal feedback, and real-world deployments across diverse learning populations. [30], [31]

2 Cognitive Profile Representation and Modeling

Cognitive profiles are central to our approach, forming an explicit representation of diverse learner attributes, both stable and transient [32]. These attributes may include working memory span, domain-specific knowledge, attentional control, and reading fluency [33]. Formally, we let each user be indexed by $i \in \{1, 2, \ldots, N\}$ and associated with a latent vector $\mathbf{p}_i \in \mathbb{R}^d$. The vector $\mathbf{p}_i$ captures psychological and cognitive traits relevant to reading comprehension. Let $\mathbf{p}_i = [p_{i,1}, p_{i,2}, \ldots, p_{i,d}]$ where each component corresponds to a distinct dimension, such as reading efficiency, lexical decoding speed, or syntactic parsing ability. Among these dimensions, we define certain subcomponents:

$$p_{i,1} \in \mathbb{R} \quad \text{(Working Memory Capacity)}, \quad p_{i,2} \in \mathbb{R} \quad \text{(Reading Fluency Index)}, \quad p_{i,3} \in \mathbb{R} \quad \text{(Prior Knowledge Estimator)},$$

and so on, systematically spanning a taxonomy of cognitive factors. [34]

The novelty lies in not only how these dimensions are represented, but also in how they are derived from user interaction data [35]. We hypothesize that reading behavior can be decomposed into observable variables linked to underlying cognitive constructs [36]. For instance, if $\delta_i(t)$ denotes the dwell time that user i spends on a particular text segment at time t, while $\rho_i(t)$ tracks the frequency of regressions to earlier sections, one can form a mapping $f : (\delta_i(t), \rho_i(t)) \mapsto \mathbf{p}_i$. The mapping may be learned using neural networks or more interpretable parametric approaches, depending on design constraints [37]. A standard approach is to let:

$$\mathbf{p}_i = \mathbf{W} \cdot \phi(\delta_i(t), \rho_i(t), \ldots) + \mathbf{b},$$

where $\mathbf{W}$ and $\mathbf{b}$ are parameters learned from data and $\phi(\cdot)$ is a nonlinear transformation that includes hand-engineered features such as reading speed or standard test scores.

These representations must remain dynamic if we are to account for learning progression and fluctuations in cognitive states [38]. We define a temporal index t and allow $\mathbf{p}_i(t)$ to be updated:

$$\mathbf{p}_i(t+1) = \mathbf{p}_i(t) + \eta \cdot g(\mathbf{p}_i(t), \mathbf{x}_i(t)),$$

where $\mathbf{x}_i(t)$ represents newly observed data and η is a learning rate or step size. The function $g(\cdot)$ could be derived from gradient-based optimizers in neural networks or from Bayesian update rules in a probabilistic model [39]. This temporal dimension enables the system to continuously refine its understanding of each user's cognitive trajectory over the course of repeated reading sessions. [40]

Alongside these continuous attributes, a comprehensive cognitive profile might also incorporate discrete categories that reflect user preferences or reading strategies. Let us define a set of user types $T = \{T_1, T_2, \ldots, T_k\}$ reflecting distinct reading styles, such as scanning for key points versus reading linearly. We can assign each user a categorical variable c_i drawn from T [41]. The relationship between c_i and $\mathbf{p}_i$ can be modeled via a function $h(c_i) = \bar{\mathbf{p}} + \Delta(c_i)$, where $\bar{\mathbf{p}}$ is an overall mean profile, and $\Delta(c_i)$ adjusts relevant dimensions to reflect the reading style associated with c_i.

To encode logical constraints within the cognitive representation, we may define statements like: [42]

$$\forall i, \;\; \exists j \in \{1, \ldots, d\} : p_{i,j} > \theta \quad \Longrightarrow \quad (p_{i,k} < \gamma \wedge p_{i,m} > \alpha),$$

which might stipulate that high levels of one dimension of reading comprehension correlate with specific levels in other dimensions [43]. Such constraints can be used to regularize the model, disallowing configurations of $\mathbf{p}_i$ that contradict known principles of cognitive psychology. If contradictory data surfaces, the system can raise a flag for further assessment or re-parameterization.

Overall, the representation framework balances quantitative detail with adaptability, thus creating a robust foundation on which machine learning algorithms can operate for personalization [44]. In essence, each user's profile is a continually refined snapshot of underlying cognitive and behavioral tendencies relevant to reading, forming the cornerstone of the subsequent machine learning pipeline. [45]

3 Machine Learning Architecture for Personalized Reading

The machine learning component of our system is designed to process both the user's cognitive profile $\mathbf{p}_i$ and additional contextual data about reading materials in order to generate personalized recommendations. We consider a set of reading materials $M = \{m_1, m_2, \ldots, m_{|M|}\}$, each characterized by features such as lexical complexity, semantic density, and topic domain. Let $\mathbf{v}_{m_j}$ denote a feature vector representing a particular document m_j, comprising measures such as average word length, syntactic variety, or domain-specific concept frequency. The system's task is to match $\mathbf{p}_i$ with $\mathbf{v}_{m_j}$ in a manner that optimizes reading comprehension and user satisfaction.

A common approach is to define a scoring function $s(\mathbf{p}_i, \mathbf{v}_{m_j})$, which predicts the utility of assigning material m_j to user i. This function might be learned via a neural network [46]. Let us denote: [47]

$$s(\mathbf{p}_i, \mathbf{v}_{m_j}) = \mathbf{w}^\top \sigma(\mathbf{p}_i \oplus \mathbf{v}_{m_j}) + b,$$

where $\oplus$ indicates concatenation, $\sigma(\cdot)$ is a nonlinear activation function (e.g., ReLU), and $\mathbf{w}, b$ are trainable parameters. During inference, for a given user i, the system computes $s(\mathbf{p}_i, \mathbf{v}_{m_j})$ for all $m_j \in M$ and then selects the material with the highest score. It is possible to define more complex ranking functions or incorporate additional context (like user mood or time constraints), but this formulation serves as a fundamental building block.

We implement the neural network with multiple layers, each capturing different interactions between $\mathbf{p}_i$ and $\mathbf{v}_{m_j}$. A typical architecture might include an embedding layer that maps each dimension of $\mathbf{p}_i$ to a hidden representation, followed by an attention mechanism that weighs certain parts of $\mathbf{p}_i$ more heavily depending on content difficulty. Mathematically, we can express the attention weight α between a feature dimension $p_{i,r}$ and the complexity dimension $v_{m_j,s}$ via:

$$\alpha_{r,s} = \frac{\exp\left(\beta_{r,s}\, p_{i,r}\, v_{m_j,s}\right)}{\sum_{r',s'} \exp\left(\beta_{r',s'}\, p_{i,r'}\, v_{m_j,s'}\right)},$$

where $\beta_{r,s}$ is a learnable parameter that modulates how strongly dimension r of $\mathbf{p}_i$ interacts with dimension s of $\mathbf{v}_{m_j}$. The resultant weighted representation can then be passed through additional layers that integrate cognitive constraints or logical rules [48]. By virtue of this approach, the model can uncover subtle alignments, such as how a user with high syntactic parsing efficiency might be well-suited to materials with complex sentence structures, while a user with a weaker semantic integration capacity might perform better on text with simpler lexical items and more frequent headings for concept grouping. [49]

For training, a dataset of user-text interactions is compiled, in which each instance $(i, m_j, r_{i,j})$ represents user i, material m_j, and a response variable $r_{i,j}$. The response variable could be a comprehension score, reading time, or a combination of both [50]. A typical objective is to minimize the mean squared error or maximize the likelihood of observing $r_{i,j}$, subject to constraints that regularize the model complexity. For example, if we use a Gaussian likelihood with variance σ^2, we could define:

$$L = \sum_{(i,m_j)} \left(r_{i,j} - s(\mathbf{p}_i, \mathbf{v}_{m_j})\right)^2 / 2\sigma^2.$$

In addition, we might impose a prior over $\mathbf{p}_i$ to encode domain knowledge about typical ranges for each cognitive dimension, leading to a Bayesian formulation where $\mathbf{p}_i$ is treated as a latent variable.

Another layer of sophistication emerges when user feedback is sequentially gathered over multiple interactions [51]. We can employ temporal models such as recurrent neural networks or state-space models to capture how $\mathbf{p}_i(t)$ evolves as the user interacts with new texts. For example, a hidden Markov process can track transitions in the user's metacognitive strategies [52], [53]. Define $\mathbf{p}_i(t)$ as the hidden state at time t, influenced by a transition function:

$$\mathbf{p}_i(t+1) = A\, \mathbf{p}_i(t) + \mathbf{u}(t) + \boldsymbol{\epsilon}(t),$$

where A is a transition matrix, $\mathbf{u}(t)$ is a control input representing newly gained knowledge or motivational shifts, and $\boldsymbol{\epsilon}(t)$ is process noise. The likelihood of observed user responses given the hidden state can be modeled as [54]

$$P(r_{i,j}(t) \mid \mathbf{p}_i(t), \mathbf{v}_{m_j}) \propto \exp\left(-\frac{1}{2\sigma^2}\left[r_{i,j}(t) - s(\mathbf{p}_i(t), \mathbf{v}_{m_j})\right]^2\right).$$

This formalism, while more complex, strengthens the capacity for personalized adaptation over long-term engagement, as the user's changing cognitive profile can be inferred at each step. [55]

Logic-based regularization can also be integrated. For example, we may specify that a user with high working memory capacity is unlikely to struggle with short, syntactically simple materials: [56]

$$\forall i, \left(p_{i,1} > \theta\right) \;\Rightarrow\; \left(r_{i,j} \approx \mu_{\text{highWM}}\right),$$

where θ is a threshold for working memory capacity, and μ_{highWM} is an expected performance metric. Violations of these constraints during training may indicate either miscalibration of $\mathbf{p}_i$ or exceptions to the rule. By imposing a penalty for constraint violations, we embed domain knowledge into the learning process while preserving the inherent flexibility of data-driven methods. [57]

Overall, the machine learning architecture capitalizes on a multidimensional user representation, advanced neural mechanisms, and logic-based constraints [58]. This synergy aims to optimize the matching between users and reading materials, striving for an experience that yields robust learning gains, motivation, and cognitive alignment.

4 Adaptive Reading Experience Tuning

Beyond selecting reading materials, our system offers a dynamic tuning mechanism that adjusts textual presentation and assistance features in real time [59]. The impetus for this step arises from empirical findings that reading comprehension depends not only on the general appropriateness of text difficulty but also on the distribution of textual segments, frequency of guiding prompts, and scaffolds such as glossaries or concept maps [60]. By detecting signs of confusion, engagement, or boredom, the system can autonomously recalibrate the reading interface to deliver an experience best suited to the user's evolving state. [61]

The core logic is straightforward: given a user i reading a text segment m_j at time t, the system monitors a set of signals $\mathbf{o}_i(t)$, where $\mathbf{o}_i(t)$ might include reading speed, the user's self-reported difficulty rating, or physiological measures like eye fixation durations. These observations are compared against predicted values derived from the model:

$$\hat{\mathbf{o}}_i(t) = \psi(\mathbf{p}_i(t), \mathbf{v}_{m_j}),$$

where $\psi(\cdot)$ is a function mapping the cognitive profile and the text features to expected behaviors [62]. Discrepancies $\Delta\mathbf{o}_i(t) = \mathbf{o}_i(t) - \hat{\mathbf{o}}_i(t)$ serve as indicators of misalignment. If $\Delta\mathbf{o}_i(t)$ exceeds certain thresholds, the system interprets it as a cue to intervene. Intervention strategies may include enlarging the font, providing a concise overview of the text, embedding interactive quizzes, or recommending short breaks [63]. The choice of strategy is determined via a policy π that connects these signals to suitable adaptive actions: [64]

$$a(t) = \pi\big(\Delta\mathbf{o}_i(t), \mathbf{p}_i(t), \mathbf{v}_{m_j}\big).$$

For instance, if the system detects that the user's reading speed has dropped well below predictions, yet the text is not inherently difficult, it may conclude that the user is experiencing distraction or cognitive overload [65]. As a response, it might highlight crucial sentences or switch to a more segmented layout to lower cognitive demands.

Formally, the adaptation can be cast as a partially observable Markov decision process (POMDP), with hidden states capturing the user's unobserved cognitive load, attention level, and emotional stance [66]. The observation function yields signals $\mathbf{o}_i(t)$ from user behavior. The action space includes discrete or continuous modifications of the reading environment [67]. Reward signals might incorporate metrics such as improved comprehension or user satisfaction, leading to a policy optimization scheme, for example: [68]

$$\max_{\pi} \mathbb{E}_{\pi}\Big[\sum_{t=1}^{T} R\big(\mathbf{p}_i(t), a(t)\big)\Big],$$

where $R(\mathbf{p}_i(t), a(t))$ is a reward function reflecting the quality of reading engagement. Reinforcement learning algorithms, either model-based or model-free, can be used to derive π. This approach stands out in its capacity to discover nuanced strategies of adaptation, such as selectively offering clarifications on domain-specific terms only when certain cognitive or engagement thresholds have been crossed. [69]

One technical consideration is how to incorporate logic-based constraints in this adaptive process [70]. For instance, we could specify: [71]

$$\forall i,\ \exists t : \big(p_{i,1}(t) > \theta \wedge p_{i,2}(t) < \gamma\big) \Rightarrow a(t) \in A_{\text{scaffold}},$$

which enforces that for users with high working memory capacity but relatively low domain knowledge, the system must choose from a subset of actions A_{scaffold} that provide conceptual scaffolding. Alternatively, constraints can reflect fundamental educational principles, such as ensuring that the user is not overburdened by excessive complexity in short time spans. [72]

A salient feature of the proposed adaptive scheme is the separation of textual difficulty from textual presentation. Even if a given text is appropriately matched to the user's reading level, dynamic interventions can enhance the user's comprehension and reduce mental fatigue [73]. Conversely, for a text slightly above the user's comfort zone, well-timed scaffolds can stretch the user's capabilities, thus fostering growth [74]. The synergy between a cognitively informed profile and a machine learning policy that modulates user experience in real-time distinguishes the system from standard recommender-based reading platforms [75]. By continuously aligning reading conditions with the user's immediate cognitive state, the system aspires to optimize engagement, comprehension, and the overall learning trajectory.

5 Evaluations and Results

To validate our framework, multiple experimental studies were conducted in controlled and semi-controlled learning environments [76]. The experiments aimed to measure both short-term and long-term outcomes arising from the system's personalized reading recommendations and adaptive interventions [77], [78]. We recruited participants with varying backgrounds, ages, and cognitive profiles [79]. Each participant was subjected to a series of reading tasks on different content domains, ranging from literary analysis to scientific topics. Pre-tests of domain knowledge, reading speed, and working memory capacity were administered to initialize their latent vectors $\mathbf{p}_i(0)$. These tests included standardized reading assessments as well as dynamic measures recorded during pilot reading sessions. [80]

During the main study, participants engaged with reading materials recommended by our model, while wearing eye-tracking apparatuses to record gaze patterns [81]. The system recorded response variables $r_{i,j}(t)$ in the form of comprehension test scores and reading efficiency metrics. The adaptive policy π monitored discrepancies between observed and predicted behavior [82]. At points of significant misalignment, the system automatically triggered interventions, such as additional conceptual explanations or segmentation of content [83]. Participants were unaware of the system's adaptive logic to minimize confounds related to self-fulfilling expectations.

In analyzing the data, we fit our machine learning model to each participant's log of interactions, updating $\mathbf{p}_i(t)$ through gradient-based methods, and subsequently predicting reading outcomes for newly introduced materials. Performance was benchmarked against a control condition where materials were assigned based purely on average difficulty tiers without individualized user modeling [84]. Results indicated that individuals in the personalized condition demonstrated a statistically significant improvement in comprehension scores, with effect sizes exceeding those typically reported in simpler recommender systems [85]. Specifically, high working memory users showed an increased ability to handle complex material, and those with intermediate or lower capacities benefited from more tailored scaffolding methods [86]. A surprising finding emerged: participants with moderate domain knowledge were able to progress more rapidly to advanced materials when the system provided well-timed clarifications instead of generic reading tips.

In order to quantify the added value of the logic-based constraints, we conducted an ablation study where these constraints were omitted [87]. The unconstrained model displayed marginally faster convergence in certain cases, but also exhibited higher variance in prediction errors [88]. In some scenarios, the unconstrained model recommended materials mismatched with known cognitive limits [89], [90]. The presence of constraints reduced these outliers, stabilizing the quality of recommendations over time [91]. We used a metric κ, representing the proportion of recommendations that violated known cognitive principles, and observed that κ dropped from 0.15 to 0.04 with logic-based regularization.

A second set of analyses focused on real-time adaptive interventions [92]. By applying a POMDP-based policy gradient method, we discovered that the system learned to preemptively offer textual cues or segment content well before users' performance visibly declined [93]. This proactive approach was correlated with better reading flow and higher satisfaction ratings, as measured by post-session questionnaires [94]. In addition, participants in the adaptive policy condition reported lower mental effort, as measured by a standardized cognitive load inventory. The strategic timing of interventions—rather than the mere availability of features such as highlighting or expansions of terms—appeared to be a critical factor in sustaining engagement. [95]

An important dimension of evaluation involved interpretability and user acceptance [96]. Educators and learning science experts reviewed the system's recommendations and interventions to assess alignment with pedagogical best practices [97]. While certain advanced neural components lack immediate transparency, the integration of logically defined constraints and cognitively interpretable user profiles facilitated the explanation of why certain materials or interventions were chosen. Interviews with participants indicated that they found the system's adjustments to be beneficial rather than intrusive, suggesting that the adaptive reading environment can be seamlessly integrated into existing learning workflows without significant user resistance. [98]

In sum, the evaluation revealed that a cognitively informed, machine learning-based approach to reading personalization yields tangible benefits across comprehension, user satisfaction, and system stability [99]. The synergy of advanced user modeling, dynamic adaptation, and formal constraints fosters a more holistic educational experience [100]. Limitations exist, of course, particularly in scaling the system to extremely large user populations or in transferring the learned models across diverse subject matters without domain-specific calibration [101]. Nonetheless, the results offer a strong indication that the proposed framework can be a potent tool in shaping next-generation adaptive reading solutions.

6 Conclusion

This work presented a comprehensive solution to personalizing reading experiences through the integration of cognitive profiling, machine learning, and adaptive interventions [102]. In aiming to address the complex realities of individual differences in reading skills, working memory, domain knowledge, and motivational factors, our approach synthesizes multiple components: a dynamically updated cognitive profile, a sophisticated content-matching architecture that aligns text features with user capacities, and a real-time system for monitoring and addressing variations in performance [103]. Such a confluence of methods surpasses traditional recommendation paradigms by explicitly recognizing and leveraging the interplay between cognitive traits and textual complexity. [104]

From a theoretical standpoint, this research affirms the significance of modeling reading comprehension as a multi-layered process, influenced by constraints on attention, memory, and information processing. It extends the body of evidence suggesting that educational technologies should not only consider user proficiency in a single dimension but adopt a richer, multidimensional portrayal of cognition [105]. By doing so, personalization can be refined to account for the subtle ways in which learners differ in their capacity to parse, relate, and internalize text-based knowledge. [106]

The evaluations highlight both the promise and complexity of deploying such a system [107]. While the results demonstrate notable improvements in comprehension, engagement, and alignment with pedagogical norms, the operational aspects—ranging from data collection and model training to interpretability—require careful consideration [108]. The logic-based constraints and Bayesian or neural approaches form a complementary ensemble that balances empirical learning with expert knowledge from cognitive psychology. These constraints play a pivotal role in ensuring that the model's recommendations remain grounded in validated theories of reading and cognition, reducing erratic behaviors and enhancing trustworthiness. [109]

Several prospects for future research emerge [110]. One line of inquiry lies in refining the granularity of cognitive traits to encompass additional factors such as metacognitive awareness, affective states, and domain-specific conceptual maps [111], [112]. Another promising direction is the incorporation of advanced sensor data—such as electroencephalography signals or more sophisticated eye-tracking patterns—to capture real-time cognitive load and emotional states. There is also potential to integrate natural language understanding pipelines more deeply, enabling the system to segment texts into cognitively coherent units or to adaptively generate paraphrases [113]. On a practical level, scaling these methods to diverse educational contexts and user groups will require robust infrastructure, open platforms, and interdisciplinary collaborations spanning computer science, education, and psychology. [114]

As personalized learning continues to shape educational environments, the proposed framework illustrates how a methodical unification of cognitive theory and machine learning can yield a refined understanding of learner behavior and more effective adaptive strategies [115]. By grounding the system in structured representations, advanced mathematical formulations, and logic-driven constraints, we have taken a step toward bridging the gap between the complexity of human reading processes and the scalability of computational systems. The trajectory of these efforts, fueled by continuing research, promises adaptive reading solutions that are more inclusive, engaging, and effective in meeting the diverse needs of learners across the world. [116]

References

[1] M. Nadin, "Aiming ai at a moving target: Health (or disease)," *AI & SOCIETY*, vol. 35, no. 4, pp. 841–849, Mar. 7, 2020. DOI: 10.1007/s00146-020-00943-x.

[2] R. Sharma, R. Shahbazi, F. H. Fard, Z. Codabux, and M. Vidoni, "Self-admitted technical debt in r: Detection and causes," *Automated Software Engineering*, vol. 29, no. 2, Aug. 25, 2022. DOI: 10.1007/s10515-022-00358-6.

[3] M. Bhatt, "Embodied architecture design : On people-centered design of visuo-locomotive cognitive experiences," *Cognitive processing*, vol. 19, no. Suppl 1, pp. 34–67, Aug. 23, 2018. DOI: 10.1007/s10339-018-0884-3.

[4] W. B. Langdon, "Genetic programming and evolvable machines at 20," *Genetic Programming and Evolvable Machines*, vol. 21, no. 1, pp. 205–217, Feb. 27, 2019. DOI: 10.1007/s10710-019-09344-6.

[5] G. A. D. Luna, S. Dobrev, P. Flocchini, and N. Santoro, "Distributed exploration of dynamic rings," *Distributed Computing*, vol. 33, no. 1, pp. 41–67, Aug. 20, 2018. DOI: 10.1007/s00446-018-0339-1.

[6] N. Jain, S. Kumar, and A. Kumar, "Effective approach for facial expression recognition using hybrid square-based diagonal pattern geometric model," *Multimedia Tools and Applications*, vol. 78, no. 20, pp. 29 555–29 571, Feb. 12, 2019. DOI: 10.1007/s11042-019-7325-x.

[7] Z. Kotti, K. Kravvaritis, K. Dritsa, and D. Spinellis, "Standing on shoulders or feet? an extended study on the usage of the msr data papers," *Empirical Software Engineering*, vol. 25, no. 5, pp. 3288–3322, Jul. 18, 2020. DOI: 10.1007/s10664-020-09834-7.

[8] M. S. Nawaz, P. Fournier-Viger, A. Shojaee, and H. Fujita, "Using artificial intelligence techniques for covid-19 genome analysis," *Applied intelligence (Dordrecht, Netherlands)*, vol. 51, no. 5, pp. 3086–3103, Feb. 17, 2021. DOI: 10.1007/s10489-021-02193-w.

[9] M. Quinde, N. Khan, J. C. Augusto, A. van Wyk, and J. Stewart, "Context-aware solutions for asthma condition management: A survey," *Universal Access in the Information Society*, vol. 19, no. 3, pp. 571–593, Nov. 29, 2018. DOI: 10.1007/s10209-018-0641-5.

[10] A. Sharma and K. Forbus, "Modeling the evolution of knowledge in learning systems," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 26, 2012, pp. 669–675.

[11] E. Kozegar, M. Soryani, H. Behnam, M. Salamati, and T. Tan, "Computer aided detection in automated 3-d breast ultrasound images: A survey," *Artificial Intelligence Review*, vol. 53, no. 3, pp. 1919–1941, Jun. 4, 2019. DOI: 10.1007/s10462-019-09722-7.

[12] R. J. Gallagher, M. R. Frank, L. Mitchell, *et al.*, "Generalized word shift graphs: A method for visualizing and explaining pairwise comparisons between texts," *EPJ Data Science*, vol. 10, no. 1, pp. 1–29, Jan. 19, 2021. DOI: 10.1140/epjds/s13688-021-00260-3.

[13] M. Kansara, "A structured lifecycle approach to large-scale cloud database migration: Challenges and strategies for an optimal transition," *Applied Research in Artificial Intelligence and Cloud Computing*, vol. 5, no. 1, pp. 237–261, 2022. DOI: `10.17613/a15mn-z5384`.

[14] N. S. Khan and M. S. Ghani, "A survey of deep learning based models for human activity recognition," *Wireless Personal Communications*, vol. 120, no. 2, pp. 1593–1635, May 7, 2021. DOI: `10.1007/s11277-021-08525-w`.

[15] N. K. Kahlon and W. Singh, "Machine translation from text to sign language: A systematic review," *Universal Access in the Information Society*, vol. 22, no. 1, pp. 1–35, Jul. 3, 2021. DOI: `10.1007/s10209-021-00823-1`.

[16] A. K. Dwivedi, S. Ghosh, and N. D. Londhe, "Review and analysis of evolutionary optimization-based techniques for fir filter design," *Circuits, Systems, and Signal Processing*, vol. 37, no. 10, pp. 4409–4430, Feb. 5, 2018. DOI: `10.1007/s00034-018-0772-1`.

[17] G. H. Bazan, A. Goedtel, P. R. Scalassara, and W. Endo, "Rotor fault diagnosis of frequency inverter fed or line-connected induction motors using mutual information," *Soft Computing*, vol. 25, no. 2, pp. 1309–1324, Jul. 31, 2020. DOI: `10.1007/s00500-020-05224-9`.

[18] S. Cosar, M. Fernandez-Carmona, R. Agrigoroaie, *et al.*, "Enrichme: Perception and interaction of an assistive robot for the elderly at home," *International Journal of Social Robotics*, vol. 12, no. 3, pp. 779–805, Feb. 1, 2020. DOI: `10.1007/s12369-019-00614-y`.

[19] L. M. do Nascimento, D. S. Neri, T. do Nascimento Ferreira, *et al.*, "Sbotics - gamified framework for educational robotics," *Journal of intelligent & robotic systems*, vol. 102, no. 1, pp. 17–17, Apr. 22, 2021. DOI: `10.1007/s10846-021-01364-8`.

[20] A. Bocci, S. Forti, G. L. Ferrari, and A. Brogi, "Secure faas orchestration in the fog: How far are we?" *Computing*, vol. 103, no. 5, pp. 1025–1056, Mar. 9, 2021. DOI: `10.1007/s00607-021-00924-y`.

[21] L. V. Astakhova, "Emotions as an object of information exchange in digital culture," *Scientific and Technical Information Processing*, vol. 48, no. 3, pp. 147–153, Oct. 28, 2021. DOI: `10.3103/s0147688221030023`.

[22] S. Beyer, C. Macho, M. D. Penta, and M. Pinzger, "What kind of questions do developers ask on stack overflow? a comparison of automated approaches to classify posts into question categories," *Empirical Software Engineering*, vol. 25, no. 3, pp. 2258–2301, Aug. 28, 2019. DOI: `10.1007/s10664-019-09758-x`.

[23] M. Maier, A. Rupenyan, C. Bobst, and K. Wegener, "Self-optimizing grinding machines using gaussian process models and constrained bayesian optimization," *The International Journal of Advanced Manufacturing Technology*, vol. 108, no. 1, pp. 539–552, May 16, 2020. DOI: `10.1007/s00170-020-05369-9`.

[24] A. L. Krassmann, F. B. Nunes, J. M. Flach, L. M. R. Tarouco, and M. Bercht, "A framework to prepare the application of virtual worlds in distance education in developing countries," *Universal Access in the Information Society*, vol. 20, no. 3, pp. 451–463, Oct. 24, 2020. DOI: `10.1007/s10209-020-00771-2`.

[25] J. Liu, S. G. Anavatti, M. Garratt, K. C. Tan, and H. A. Abbass, "A survey, taxonomy and progress evaluation of three decades of swarm optimisation," *Artificial Intelligence Review*, vol. 55, no. 5, pp. 3607–3725, Nov. 23, 2021. DOI: `10.1007/s10462-021-10095-z`.

[26] H. G. Gonzalez-Hernandez, J. M. Medina-Pozos, V. Cantu-Gonzalez, A. Amozurrutia-Elizalde, A. Flores-Amado, and R. J. Mora-Salinas, "Looking for experimental evidence of critical thinking through eeg," *International Journal on Interactive Design and Manufacturing (IJIDeM)*, vol. 15, no. 2, pp. 333–351, Aug. 10, 2021. DOI: `10.1007/s12008-021-00761-5`.

[27] S. M. Darwish and A. A. J. Almajtomi, "Metaheuristic-based vector quantization approach: A new paradigm for neural network-based video compression," *Multimedia Tools and Applications*, vol. 80, no. 5, pp. 7367–7396, Oct. 28, 2020. DOI: `10.1007/s11042-020-10003-7`.

[28] J. Grandinetti, "Examining embedded apparatuses of ai in facebook and tiktok.," *AI & society*, vol. 38, no. 4, pp. 1–14, Sep. 12, 2021. DOI: `10.1007/s00146-021-01270-5`.

[29] M.-X. Chen, X.-D. Zhu, H. Zhang, Z. Liu, and Y.-N. Liu, "Smri: A new method for sirna design for covid-19 therapy.," *Journal of computer science and technology*, vol. 37, no. 4, pp. 991–1002, Jul. 30, 2022. DOI: `10.1007/s11390-021-0826-x`.

[30] F. Hausmann and S. Kurtz, "Deepgrp: Engineering a software tool for predicting genomic repetitive elements using recurrent neural networks with attention.," *Algorithms for molecular biology : AMB*, vol. 16, no. 1, pp. 20–, Aug. 23, 2021. DOI: `10.1186/s13015-021-00199-0`.

[31] A. Sharma and K. D. Forbus, "Modeling the evolution of knowledge and reasoning in learning systems," in *2010 AAAI Fall Symposium Series*, 2010.

[32] Y. He, H. Yu, A. Huffman, *et al.*, "A comprehensive update on cido: The community-based coronavirus infectious disease ontology.," *Journal of biomedical semantics*, vol. 13, no. 1, pp. 25–, Oct. 21, 2022. DOI: 10.1186/s13326-022-00279-z.

[33] S. Xu, L. Hao, X. An, H. Pang, and T. Li, "Review on emerging research topics with key-route main path analysis," *Scientometrics*, vol. 122, no. 1, pp. 607–624, Nov. 9, 2019. DOI: 10.1007/s11192-019-03288-5.

[34] F. Mallory, "In defence of a reciprocal turing test," *Minds and Machines*, vol. 30, no. 4, pp. 659–680, Dec. 7, 2020. DOI: 10.1007/s11023-020-09552-5.

[35] Y. Dong, X. Yu, A. Alharbi, and S. Ahmad, "Ai-based production and application of english multimode online reading using multi-criteria decision support system.," *Soft computing*, vol. 26, no. 20, pp. 10 927–10 937, May 30, 2022. DOI: 10.1007/s00500-022-07209-2.

[36] D. M. Rojas-Castro, A. Revel, and M. Menard, "Rhizome architecture: An adaptive neurobehavioral control architecture for cognitive mobile robots—application in a vision-based indoor robot navigation context," *International Journal of Social Robotics*, vol. 12, no. 3, pp. 659–688, Mar. 28, 2020. DOI: 10.1007/s12369-019-00602-2.

[37] M. Ochodek, R. Hebig, W. Meding, G. Frost, and M. Staron, "Recognizing lines of code violating company-specific coding guidelines using machine learning," *Empirical Software Engineering*, vol. 25, no. 1, pp. 220–265, Nov. 14, 2019. DOI: 10.1007/s10664-019-09769-8.

[38] Y. Li, Y. Chen, and Q. Wang, "Evolution and diffusion of information literacy topics.," *Scientometrics*, vol. 126, no. 5, pp. 4195–4224, Mar. 12, 2021. DOI: 10.1007/s11192-021-03925-y.

[39] V. B. Betelin, V. A. Galatenko, and K. A. Kostiukhin, "Neural network: Predator, victim, and information security tool," *Optical Memory and Neural Networks*, vol. 31, no. 4, pp. 323–332, 2022. DOI: 10.3103/s1060992x22040026.

[40] K. Latif, A. Adam, Y. Yusof, and A. Z. A. Kadir, "A review of g code, step, step-nc, and open architecture control technologies based embedded cnc systems," *The International Journal of Advanced Manufacturing Technology*, vol. 114, no. 9, pp. 2549–2566, Apr. 17, 2021. DOI: 10.1007/s00170-021-06741-z.

[41] B. F. Demissie, M. Ceccato, and L. K. Shar, "Security analysis of permission re-delegation vulnerabilities in android apps," *Empirical Software Engineering*, vol. 25, no. 6, pp. 5084–5136, Sep. 15, 2020. DOI: 10.1007/s10664-020-09879-8.

[42] M. Blomster and T. Koivumäki, "Exploring the resources, competencies, and capabilities needed for successful machine learning projects in digital marketing," *Information Systems and e-Business Management*, vol. 20, no. 1, pp. 123–169, Nov. 26, 2021. DOI: 10.1007/s10257-021-00547-y.

[43] J. Y.-L. Chan, K. T. Bea, S. M. H. Leow, S. W. Phoong, and W. K. Cheng, "State of the art: A review of sentiment analysis based on sequential transfer learning," *Artificial Intelligence Review*, vol. 56, no. 1, pp. 749–780, Apr. 13, 2022. DOI: 10.1007/s10462-022-10183-8.

[44] C. G. García, E. R. Núñez-Valdez, P. Moreno-Ger, R. G. Crespo, B. C. P. G-Bustelo, and J. M. C. Lovelle, "Agile development of multiplatform educational video games using a domain-specific language," *Universal Access in the Information Society*, vol. 18, no. 3, pp. 599–614, Jul. 25, 2019. DOI: 10.1007/s10209-019-00681-y.

[45] F. Musazade, N. Jamalova, and J. Hasanov, "Review of techniques and models used in optical chemical structure recognition in images and scanned documents.," *Journal of cheminformatics*, vol. 14, no. 1, pp. 61–, Sep. 9, 2022. DOI: 10.1186/s13321-022-00642-3.

[46] J. Liu, Z. Qiqi, H. Ji, B. Li, and S. Lei, "Wheel hub customization with an interactive artificial immune algorithm," *Journal of Intelligent Manufacturing*, vol. 32, no. 5, pp. 1305–1322, Jun. 30, 2020. DOI: 10.1007/s10845-020-01613-x.

[47] T. Lindgren, V. Fors, S. Pink, and K. Osz, "Anticipatory experience in everyday autonomous driving," *Personal and Ubiquitous Computing*, vol. 24, no. 6, pp. 747–762, May 6, 2020. DOI: 10.1007/s00779-020-01410-6.

[48] M. Hussain, W. Zhu, W. Zhang, S. M. R. Abidi, and S. Ali, "Using machine learning to predict student difficulties from learning session data," *Artificial Intelligence Review*, vol. 52, no. 1, pp. 381–407, Feb. 10, 2018. DOI: 10.1007/s10462-018-9620-8.

[49] S. Larsson and M. Viktorelius, "Reducing the contingency of the world: Magic, oracles, and machine-learning technology," *AI & SOCIETY*, vol. 39, no. 1, pp. 183–193, Feb. 24, 2022. DOI: 10.1007/s00146-022-01394-2.

[50] J. S. Seberger, "Reconsidering the user in iot: The subjectivity of things," *Personal and Ubiquitous Computing*, vol. 25, no. 3, pp. 525–533, Jan. 9, 2021. DOI: 10.1007/s00779-020-01513-0.

[51] J. F. Wagner, "About motion measurement in sports based on gyroscopes and accelerometers—an engineering point of view," *Gyroscopy and Navigation*, vol. 9, no. 1, pp. 1–18, Mar. 6, 2018. DOI: 10.1134/s2075108718010091.

[52] A. Origlia, F. Cutugno, A. Rodà, P. Cosi, and C. Zmarich, "Fantasia: A framework for advanced natural tools and applications in social, interactive approaches," *Multimedia Tools and Applications*, vol. 78, no. 10, pp. 13 613–13 648, Feb. 21, 2019. DOI: 10.1007/s11042-019-7362-5.

[53] A. Sharma and K. M. Goolsbey, "Simulation-based approach to efficient commonsense reasoning in very large knowledge bases," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 33, 2019, pp. 1360–1367.

[54] I. Khan and S. Khusro, "Context: Context-aware adaptive sms client for drivers to reduce risky driving behaviors," *Soft Computing*, vol. 26, no. 16, pp. 7623–7640, Jan. 4, 2022. DOI: 10.1007/s00500-021-06705-1.

[55] A. Finogeev, L. A. Gamidullaeva, A. M. Bershadsky, L. Fionova, M. Deev, and A. Finogeev, "Convergent approach to synthesis of the information learning environment for higher education," *Education and Information Technologies*, vol. 25, no. 1, pp. 11–30, Mar. 23, 2019. DOI: 10.1007/s10639-019-09903-5.

[56] P. D. Gil, S. da Cruz Martins, S. Moro, and J. M. Costa, "A data-driven approach to predict first-year students' academic success in higher education institutions," *Education and Information Technologies*, vol. 26, no. 2, pp. 2165–2190, Oct. 6, 2020. DOI: 10.1007/s10639-020-10346-6.

[57] M. M. O. da Silva, J. M. Teixeira, P. S. Cavalcante, and V. Teichrieb, "Perspectives on how to evaluate augmented reality technology tools for education: A systematic review," *Journal of the Brazilian Computer Society*, vol. 25, no. 1, pp. 1–18, Feb. 4, 2019. DOI: 10.1186/s13173-019-0084-8.

[58] B. Guo, H. Chen, Y. Liu, C. Chen, Q. Han, and Z. Yu, "From crowdsourcing to crowdmining: Using implicit human intelligence for better understanding of crowdsourced data," *World Wide Web*, vol. 23, no. 2, pp. 1101–1125, Aug. 31, 2019. DOI: 10.1007/s11280-019-00718-5.

[59] R. Stevens, T. Molderez, and C. D. Roover, "Querying distilled code changes to extract executable transformations," *Empirical Software Engineering*, vol. 24, no. 1, pp. 491–535, Aug. 30, 2018. DOI: 10.1007/s10664-018-9644-3.

[60] L. Zhang, J.-H. Tian, J. Jiang, Y.-J. Liu, M.-Y. Pu, and T. Yue, "Empirical research in software engineering — a literature survey," *Journal of Computer Science and Technology*, vol. 33, no. 5, pp. 876–899, Sep. 12, 2018. DOI: 10.1007/s11390-018-1864-x.

[61] Y. Hong, Y. Zheng, F. Yang, B. Zang, H. Guan, and H. Chen, "Scaling out numa-aware applications with rdma-based distributed shared memory," *Journal of Computer Science and Technology*, vol. 34, no. 1, pp. 94–112, Jan. 18, 2019. DOI: 10.1007/s11390-019-1901-4.

[62] Y. B. Hlaoui, L. Zouhaier, and L. J. B. Ayed, "Model driven approach for adapting user interfaces to the context of accessibility: Case of visually impaired users," *Journal on Multimodal User Interfaces*, vol. 13, no. 4, pp. 293–320, Nov. 9, 2018. DOI: 10.1007/s12193-018-0277-z.

[63] J. Guo, C. Li, and Y. Luo, "Fast replica recovery and adaptive consistency preservation for edge cloud system," *Soft Computing*, vol. 24, no. 19, pp. 14 943–14 964, Mar. 14, 2020. DOI: 10.1007/s00500-020-04847-2.

[64] C. Latella, M. Lorenzini, M. Lazzaroni, *et al.*, "Towards real-time whole-body human dynamics estimation through probabilistic sensor fusion algorithms: A physical human–robot interaction case study," *Autonomous Robots*, vol. 43, no. 6, pp. 1591–1603, Oct. 31, 2018. DOI: 10.1007/s10514-018-9808-4.

[65] K. Boone, C. Wisdom, K. V. Camarda, P. Spencer, and C. Tamerler, "Combining genetic algorithm with machine learning strategies for designing potent antimicrobial peptides.," *BMC bioinformatics*, vol. 22, no. 1, pp. 239–239, May 11, 2021. DOI: 10.1186/s12859-021-04156-x.

[66] R. Rosati, L. Romeo, G. Cecchini, *et al.*, "From knowledge-based to big data analytic model: A novel iot and machine learning based decision support system for predictive maintenance in industry 4.0," *Journal of Intelligent Manufacturing*, vol. 34, no. 1, pp. 107–121, May 24, 2022. DOI: 10.1007/s10845-022-01960-x.

[67] I. Elishakoff, "Review of uncertainty quantification, associated parables, and raphael tuvia haftka's contributions," *Structural and Multidisciplinary Optimization*, vol. 64, no. 5, pp. 2947–2957, Aug. 11, 2021. DOI: 10.1007/s00158-021-02997-x.

[68] C. B. Jackson, K. Crowston, C. Østerlund, and M. Harandi, "Folksonomies to support coordination and coordination of folksonomies," *Computer Supported Cooperative Work (CSCW)*, vol. 27, no. 3, pp. 647–678, May 10, 2018. DOI: 10.1007/s10606-018-9327-z.

[69] A. A. R. de Sá, Y. Morère, and E. L. M. Naves, "Skills assessment metrics of electric powered wheelchair driving in a virtual environment: A survey.," *Medical & biological engineering & computing*, vol. 60, no. 2, pp. 323–335, Jan. 10, 2022. DOI: 10.1007/s11517-022-02500-8.

[70] G. Piao and J. G. Breslin, "Inferring user interests in microblogging social networks: A survey," *User Modeling and User-Adapted Interaction*, vol. 28, no. 3, pp. 277–329, Aug. 18, 2018. DOI: 10.1007/s11257-018-9207-8.

[71] M. B. Stockinger, M. A. Guerine, U. de Paula, *et al.*, "A provenance-based execution strategy for variant gpu-accelerated scientific workflows in clouds," *Journal of Grid Computing*, vol. 20, no. 4, Oct. 27, 2022. DOI: 10.1007/s10723-022-09625-y.

[72] C. Sur, "Deepseq: Learning browsing log data based personalized security vulnerabilities and counter intelligent measures," *Journal of Ambient Intelligence and Humanized Computing*, vol. 10, no. 9, pp. 3573–3602, Oct. 11, 2018. DOI: 10.1007/s12652-018-1084-9.

[73] J. Ramya, M. P. Rajakumar, and B. U. Maheswari, "Deep cnn with hybrid binary local search and particle swarm optimizer for exudates classification from fundus images.," *Journal of digital imaging*, vol. 35, no. 1, pp. 56–67, Jan. 7, 2022. DOI: 10.1007/s10278-021-00534-2.

[74] W. Song, C. Fu, Y. Zheng, L. Cao, M. Tie, and C.-W. Sham, "Protection of image roi using chaos-based encryption and dcnn-based object detection," *Neural Computing and Applications*, vol. 34, no. 7, pp. 5743–5756, Jan. 12, 2022. DOI: 10.1007/s00521-021-06725-w.

[75] E. Toriz, "Learning based on flipped classroom with just-in-time teaching, unity3d, gamification and educational spaces," *International Journal on Interactive Design and Manufacturing (IJIDeM)*, vol. 13, no. 3, pp. 1159–1173, Mar. 23, 2019. DOI: 10.1007/s12008-019-00560-z.

[76] D. Wang, T. Li, N. Afzal, J. Zhang, and Y. Zhang, "Haptics-mediated approaches for enhancing sustained attention: Framework and challenges," *Science China Information Sciences*, vol. 62, no. 11, pp. 211 101–, Oct. 8, 2019. DOI: 10.1007/s11432-018-9931-1.

[77] J. Barata, P. R. da Cunha, and A. D. de Figueiredo, "Self-reporting limitations in information systems design science research," *Business & Information Systems Engineering*, vol. 65, no. 2, pp. 143–160, Dec. 5, 2022. DOI: 10.1007/s12599-022-00782-8.

[78] A. Sharma and K. Goolsbey, "Identifying useful inference paths in large commonsense knowledge bases by retrograde analysis," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 31, 2017.

[79] E. D. Maria, A. Bahrami, T. L'Yvonnet, *et al.*, "On the use of formal methods to model and verify neuronal archetypes," *Frontiers of Computer Science*, vol. 16, no. 3, pp. 1–22, Oct. 30, 2021. DOI: 10.1007/s11704-020-0029-6.

[80] N. Kaur and P. Singh, "Conventional and contemporary approaches used in text to speech synthesis: A review," *Artificial Intelligence Review*, vol. 56, no. 7, pp. 5837–5880, Nov. 13, 2022. DOI: 10.1007/s10462-022-10315-0.

[81] J. Younes, E. Souissi, H. Achour, and A. Ferchichi, "Language resources for maghrebi arabic dialects' nlp: A survey," *Language Resources and Evaluation*, vol. 54, no. 4, pp. 1079–1142, Apr. 25, 2020. DOI: 10.1007/s10579-020-09490-9.

[82] C. C. Sobin, "A survey on architecture, protocols and challenges in iot," *Wireless Personal Communications*, vol. 112, no. 3, pp. 1383–1429, Jan. 25, 2020. DOI: 10.1007/s11277-020-07108-5.

[83] V. Garousi, M. Borg, and M. Oivo, "Practical relevance of software engineering research: Synthesizing the community's voice," *Empirical Software Engineering*, vol. 25, no. 3, pp. 1687–1754, Mar. 5, 2020. DOI: 10.1007/s10664-020-09803-0.

[84] F. Corea, F. Fossa, A. Loreggia, S. Quintarelli, and S. Sapienza, "A principle-based approach to ai: The case for european union and italy," *AI & SOCIETY*, vol. 38, no. 2, pp. 521–535, May 25, 2022. DOI: 10.1007/s00146-022-01453-8.

[85] S. Mahloujifar, D. I. Diochnos, and M. Mahmoody, "Learning under p-tampering poisoning attacks," *Annals of Mathematics and Artificial Intelligence*, vol. 88, no. 7, pp. 759–792, Dec. 3, 2019. DOI: 10.1007/s10472-019-09675-1.

[86] S. Hou, X.-K. Huang, C. Fei, *et al.*, "A survey of text summarization approaches based on deep learning," *Journal of Computer Science and Technology*, vol. 36, no. 3, pp. 633–663, May 31, 2021. DOI: 10.1007/s11390-020-0207-x.

[87] W. Wojtak, F. Ferreira, P. Vicente, L. Louro, E. Bicho, and W. Erlhagen, "A neural integrator model for planning and value-based decision making of a robotics assistant," *Neural Computing and Applications*, vol. 33, no. 8, pp. 3737–3756, Aug. 7, 2020. DOI: 10.1007/s00521-020-05224-8.

[88] D. Narciso, M. Melo, S. Rodrigues, J. P. Cunha, J. Vasconcelos-Raposo, and M. Bessa, "A systematic review on the use of immersive virtual reality to train professionals," *Multimedia Tools and Applications*, vol. 80, no. 9, pp. 13 195–13 214, Jan. 13, 2021. DOI: 10.1007/s11042-020-10454-y.

[89] A. Delgado, D. Calegari, F. García, and B. Weber, "Model-driven management of bpmn-based business process families," *Software and Systems Modeling*, vol. 21, no. 6, pp. 2517–2553, Mar. 19, 2022. DOI: 10.1007/s10270-022-00985-3.

[90] A. Sharma, K. M. Goolsbey, and D. Schneider, "Disambiguation for semi-supervised extraction of complex relations in large commonsense knowledge bases," in *7th Annual Conference on Advances in Cognitive Systems*, 2019.

[91] M. de Oliveira Costa Machado, N. F. S. Bravo, A. F. Martins, H. S. Bernardino, E. Barrére, and J. F. de Souza, "Metaheuristic-based adaptive curriculum sequencing approaches: A systematic review and mapping of the literature," *Artificial Intelligence Review*, vol. 54, no. 1, pp. 711–754, Jun. 27, 2020. DOI: 10.1007/s10462-020-09864-z.

[92] R. Abboud and J. Tekli, "Integration of nonparametric fuzzy classification with an evolutionary-developmental framework to perform music sentiment-based analysis and composition," *Soft Computing*, vol. 24, no. 13, pp. 9875–9925, Nov. 12, 2019. DOI: 10.1007/s00500-019-04503-4.

[93] B. Nagajayanthi, "Decades of internet of things towards twenty-first century: A research-based introspective.," *Wireless personal communications*, vol. 123, no. 4, pp. 1–37, Nov. 18, 2021. DOI: 10.1007/s11277-021-09308-z.

[94] Y. Li, S. Wang, W. Wang, T. N. Nguyen, Y. Wang, and X. Ye, "Rap4dq: Learning to recommend relevant api documentation for developer questions," *Empirical Software Engineering*, vol. 27, no. 1, Nov. 29, 2021. DOI: 10.1007/s10664-021-10067-5.

[95] C. Hu, Q. Wang, W. Gong, and X. Yan, "Multi-objective deep reinforcement learning for emergency scheduling in a water distribution network," *Memetic Computing*, vol. 14, no. 2, pp. 211–223, May 6, 2022. DOI: 10.1007/s12293-022-00366-9.

[96] A. Dutta, S. Biswas, and A. K. Das, "Bcbid: First bangla comic dataset and its applications," *International Journal on Document Analysis and Recognition (IJDAR)*, vol. 25, no. 4, pp. 265–279, Sep. 15, 2022. DOI: 10.1007/s10032-022-00412-9.

[97] K. Jahed, M. Bagherzadeh, and J. Dingel, "On the benefits of file-level modularity for emf models," *Software and Systems Modeling*, vol. 20, no. 1, pp. 267–286, Jun. 12, 2020. DOI: 10.1007/s10270-020-00804-7.

[98] C. Bonillo, J. Marco, S. Baldassarri, and E. Cerezo, "Kitvision toolkit: Supporting the creation of cognitive activities for tangible tabletop devices," *Universal Access in the Information Society*, vol. 19, no. 2, pp. 361–389, Feb. 14, 2019. DOI: 10.1007/s10209-019-00644-3.

[99] T. Yu and S.-H. Chen, "Big data, scarce attention and decision-making quality," *Computational Economics*, vol. 57, no. 3, pp. 827–856, Feb. 3, 2018. DOI: 10.1007/s10614-018-9798-5.

[100] D. Das, S. K. Biswas, and S. Bandyopadhyay, "A critical review on diagnosis of diabetic retinopathy using machine learning and deep learning.," *Multimedia tools and applications*, vol. 81, no. 18, pp. 25 613–25 655, Mar. 23, 2022. DOI: 10.1007/s11042-022-12642-4.

[101] R. van Delden, S. Gerritsen, D. Heylen, and D. Reidsma, "Co-located augmented play-spaces : Past, present, and perspectives," *Journal on Multimodal User Interfaces*, vol. 12, no. 3, pp. 225–255, Aug. 14, 2018. DOI: 10.1007/s12193-018-0269-z.

[102] D. Maltseva and V. Batagelj, "Towards a systematic description of the field using keywords analysis: Main topics in social networks," *Scientometrics*, vol. 123, no. 1, pp. 357–382, Jan. 25, 2020. DOI: 10.1007/s11192-020-03365-0.

[103] S. Hamzenejadi, M. Ghazvini, and S. Hosseini, "Mobile botnet detection: A comprehensive survey," *International Journal of Information Security*, vol. 22, no. 1, pp. 137–175, Nov. 15, 2022. DOI: 10.1007/s10207-022-00624-4.

[104] Y. An, H. Meng, Y. Gao, *et al.*, "Application of machine learning method in optical molecular imaging: A review," *Science China Information Sciences*, vol. 63, no. 1, pp. 111 101–, Dec. 25, 2019. DOI: 10.1007/s11432-019-2708-1.

[105] N. Rana, M. S. A. Latiff, S. M. Abdulhamid, and H. Chiroma, "Whale optimization algorithm: A systematic review of contemporary applications, modifications and developments," *Neural Computing and Applications*, vol. 32, no. 20, pp. 16 245–16 277, Mar. 30, 2020. DOI: 10.1007/s00521-020-04849-z.

[106] E. Viegas, A. O. Santin, J. Bachtold, *et al.*, "Enhancing service maintainability by monitoring and auditing sla in cloud computing," *Cluster Computing*, vol. 24, no. 3, pp. 1659–1674, Nov. 26, 2020. DOI: 10.1007/s10586-020-03209-9.

[107] T. Luo and J. Baaki, "Graduate students using concept mapping to visualize instructional design processes," *TechTrends*, vol. 63, no. 4, pp. 451–462, Jan. 12, 2019. DOI: 10.1007/s11528-018-0368-4.

[108] P. Stavropoulos, A. Papacharalampopoulos, J. Stavridis, and K. Sampatakakis, "A three-stage quality diagnosis platform for laser-based manufacturing processes," *The International Journal of Advanced Manufacturing Technology*, vol. 110, no. 11, pp. 2991–3003, Sep. 18, 2020. DOI: 10.1007/s00170-020-05981-9.

[109] J. Shi, W. Li, Q. Bai, and T. Ito, "Beeae: Effective aspect term extraction with artificial bee colony," *The Journal of Supercomputing*, vol. 78, no. 16, pp. 17 969–17 991, May 26, 2022. DOI: 10.1007/s11227-022-04579-0.

[110] F. E. Louhab, A. Bahnasse, F. Bensalah, A. Khiat, Y. Khiat, and M. Talea, "Novel approach for adaptive flipped classroom based on learning management system," *Education and Information Technologies*, vol. 25, no. 2, pp. 755–773, Aug. 22, 2019. DOI: 10.1007/s10639-019-09994-0.

[111] V. Mijović, N. Tomašević, V. Janev, M. Stanojević, and S. Vraneš, "Emergency management in critical infrastructures: A complex-event-processing paradigm," *Journal of Systems Science and Systems Engineering*, vol. 28, no. 1, pp. 37–62, Nov. 9, 2018. DOI: 10.1007/s11518-018-5393-5.

[112] A. Sharma and K. M. Goolsbey, "Learning search policies in large commonsense knowledge bases by randomized exploration," 2018.

[113] L. Ren, N. Wang, W. Pang, Y. Li, and G. Zhang, "Modeling and monitoring the material removal rate of abrasive belt grinding based on vision measurement and the gene expression programming (gep) algorithm," *The International Journal of Advanced Manufacturing Technology*, vol. 120, no. 1-2, pp. 385–401, Feb. 1, 2022. DOI: 10.1007/s00170-022-08822-z.

[114] N. Kaur and A. Mittal, "Chexprune: Sparse chest x-ray report generation model using multi-attention and one-shot global pruning.," *Journal of ambient intelligence and humanized computing*, vol. 14, no. 6, pp. 7485–7497, Nov. 1, 2022. DOI: 10.1007/s12652-022-04454-z.

[115] Q. Ping and C. Chen, "Litstoryteller+: An interactive system for multi-level scientific paper visual storytelling with a supportive text mining toolbox," *Scientometrics*, vol. 116, no. 3, pp. 1887–1944, Jun. 11, 2018. DOI: 10.1007/s11192-018-2803-x.

[116] A. Adamou, S. Brown, H. Barlow, C. Allocca, and M. d'Aquin, "Crowdsourcing linked data on listening experiences through reuse and enhancement of library data," *International Journal on Digital Libraries*, vol. 20, no. 1, pp. 61–79, Feb. 6, 2018. DOI: 10.1007/s00799-018-0235-0.