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Design and Application of a Blended Learning Platform for Preschool Education Based on Mobile Internet

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Abstract. *In an era where education is increasingly interfacing with technology, this manuscript introduces EduConnect, an innovative blended learning platform tailored for the evolving landscape of preschool education. Utilizing the pervasive reach of mobile internet and the expansive capabilities of cloud computing (Deep & Cross Network version 2), EduConnect stands at the forefront of personalized learning. At its core, the platform employs the DCN-V2 , an advanced algorithmic model that dynamically adapts content to align with individual learners' profiles. The efficacy of EduConnect is methodically assessed through extensive experimental analyses, employing Area Under the Curve (AUC) and Logarithmic Loss (LogLoss) as primary performance indicators. These evaluations are set against a backdrop of contemporary models to underscore the enhancements in accuracy and user engagement that EduConnect delivers. The results of this study affirm the DCN-V2 model's superiority in predictive performance, validating its deployment within EduConnect as a mechanism to enrich the educational experience. By fostering an interactive and individualized learning environment, EduConnect exemplifies the transformative potential of educational technology to accommodate and stimulate children in their formative years.*
Keywords: Blended Learning, Preschool Education, Educational Personalization, Mobile Internet, DCN-V2, Algorithmic Recommendations.

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1. **Introduction.** The advent of the digital era has profoundly transformed various sectors, with education being one of the most significantly impacted [1-3]. In the sphere of preschool education, this transformation is particularly noteworthy. Traditionally, early childhood education has been characterized by face-to-face interactions and tactile learning experiences. However, the increasing penetration of mobile internet technologies has opened new avenues for learning methodologies. This shift is not a mere addition of digital tools to the existing pedagogical arsenal; it represents a fundamental rethinking of educational delivery mechanisms and their implications on cognitive and developmental aspects of early learners [4,5] .

The current educational landscape, particularly in preschool settings, reveals a significant gap. While there is a general consensus on the importance of integrating technology into education, the practical application of this integration in early childhood settings remains underexplored. This gap is especially evident in the limited research on the effectiveness and implementation of blended learning platforms in preschool education [6].

'EduConnect', the centerpiece of this research, exemplifies this transformation. It is a pioneering blended learning platform that harmoniously integrates traditional educational practices with the advancements of mobile internet technology. The platform is designed with a deep understanding of early childhood educational needs and the capabilities of modern technology. It is a response to the growing demand for educational models that are flexible, accessible, and personalized, catering to the unique learning trajectories of preschool children. EduConnect, therefore, is not just an educational tool; it is a response to this research gap, offering a novel approach to preschool education that aligns with the digital inclinations of contemporary society.

This research aims to extends beyond the technological. It seeks to provide a comprehensive analysis of the platform's efficacy in improving preschool education quality. This analysis is grounded in empirical research, involving a comparative study of EduConnect's performance against traditional educational models. The study employs advanced metrics to evaluate various aspects of the learning experience, including learner engagement, knowledge retention, and developmental progress. Anticipated outcomes of this research are diverse. Primarily, it aims to redefine the standards of personalized, technology-aided preschool education [7]. Furthermore, it seeks to contribute to the broader discourse on the role of sophisticated algorithms in customizing educational content, thus making a significant contribution to the field of educational technology. Finally, the study offers valuable insights for educators, policymakers, and technology developers on the practicalities and potentials of integrating advanced technology into early childhood education.

The structure of this paper is methodically designed to provide a comprehensive understanding of the research. Following this introduction, Section 2 presents a detailed literature review, highlighting previous studies and existing knowledge in the field. Section 3 describes the methodology employed in developing and assessing EduConnect. Section 4 discusses the results of the empirical study, offering critical insights into the platform's effectiveness. Finally, Section 5 concludes the paper with a summary of the findings, implications for future research, and potential applications in the field of preschool education.

2. Literature Review.

2.1. Technological Integration in Preschool Education.

In the realm of preschool education, the integration of technology marks a pivotal shift towards a more dynamic and interactive learning environment. This process of informatization, which encompasses the strategic use of computer and network technology, revolutionizes not only educational management but also teaching methodologies and home-school interactions. As such, digital tools and platforms are increasingly adopted to create personalized and engaging learning experiences for young children, catering to their unique needs and learning styles [8]. This strategic incorporation of technology goes beyond mere convenience; it is an essential step towards the modernization of education, streamlining daily administration and instruction in preschools to enhance overall efficiency and effectiveness [9].

However, the path to technological integration in preschool education is fraught with challenges. A significant concern is the prevalence of outdated core technology, which can impede the effectiveness of educational programs [10]. Furthermore, a noticeable homogeneity among educational products is observed, with many offering basic functionalities that fall short in significantly impacting information management and kindergarten operations [11]. This limitation is compounded by a lack of advanced data mining capabilities, restricting the potential of these products to provide in-depth analyses crucial for effective kindergarten management and child-rearing.

Amidst these challenges, the digital transition in preschool education is gaining momentum, moving from traditional textbook-based teaching methods to more digital and intelligent content. This shift, integrating big data and artificial intelligence, aims not only to enhance teachers' course preparation but also to significantly improve student learning outcomes. Such a transition signifies a critical step in creating an inclusive, interactive, and effective learning environment, capable of adapting to the diverse needs and learning styles of young learners [12].

The integration of technology into preschool education has been significantly influenced by advancements in mobile internet and network communication technologies, particularly with the rise of 5G networks. However, this integration presents several challenges, particularly in terms of security and the effectiveness of the technological applications. Recent studies highlight the importance of secure communication protocols when integrating advanced technologies in educational settings. For instance, Wu et al. discuss the critical role of enhanced authentication protocols in securing drone communications over 5G networks. This emphasis on security can be directly paralleled to the necessity of securing educational data and communications within preschool environments, where sensitive information about young learners must be rigorously protected [13].

In a related study, Wu et al. emphasize the need for robust authenticated key exchange protocols in multi-server architectures. As educational platforms for preschoolers increasingly adopt multi-server and cloud-based architectures, the principles outlined in this study become highly relevant [14]. The security of data transmission between servers is crucial to maintaining the integrity and confidentiality of educational content and communications. Moreover, the practical application of such technologies in preschool education must consider the diverse and dynamic nature of young learners. Kumar et al. [15] demonstrate the use of LSTM networks for transportation mode detection, showcasing how machine learning models can adapt to varied user behaviors. This adaptability is essential in developing personalized educational experiences for preschool children, ensuring that the technology not only supports learning outcomes but also adjusts to the individual developmental stages of each child.

2.2. **Multimedia, Safety, and Administration in the Digital Classroom.** The incorporation of multimedia in the digital classroom has transformed the landscape of early childhood education. Utilizing multimedia tools in preschool settings significantly enhances children's interest in learning and positively influences their language development, imagination, and aesthetic awareness. These tools provide a stimulating and engaging learning environment that encourages active participation and creativity among young learners [16]. Additionally, the advent of augmented reality (AR) and virtual reality (VR) technologies has opened new avenues for interactive and immersive learning experiences in preschool education, further enriching the educational process [17].

Alongside the educational benefits, the integration of technology in preschool classrooms also addresses the critical aspect of safety. Modern information technology has enabled the implementation of efficient safety monitoring systems. These systems are designed to track students' whereabouts within the educational setting, thereby significantly enhancing the safety and security of young learners [18]. This aspect of technology integration is paramount in assuring parents and educators of a secure learning environment for children.

The digital transformation of education extends to the realm of administration as well. The use of information technology in managing kindergarten operations has streamlined administrative processes, making them more efficient and effective. This modern approach to administration facilitates the better organization of educational resources, smoother communication channels, and a more comprehensive monitoring of educational progress and outcomes [19].

Furthermore, technology has bridged the communication gap between teachers and parents, fostering a more collaborative approach to education. The use of mobile internet and digital platforms facilitates real-time communication, effectively connecting home and school. This synergy between kindergarten and family education ensures a more cohesive and holistic approach to the child's learning journey [20].

2.3. **Blended Learning.** Blended learning, a contemporary educational approach, merges the traditional face-to-face teaching methods with the advancements of e-learning. It is defined as a systematic combination of direct interpersonal interaction and technologically mediated instruction, involving both synchronous (real-time) and asynchronous (flexible-time) methods [21]. This fusion aims to leverage the strengths of both in-person and online learning environments, creating a more versatile and effective educational experience for students. The key components of blended learning include the learning environment, instruction methodologies, and the media used for delivering educational content. The learning environment in a blended learning model is diverse, spanning physical classrooms and virtual spaces. Instruction involves both direct teaching and guidance from educators, along with self-guided learning through digital platforms. The media component comprises various digital tools and resources that facilitate the delivery and reception of knowledge [22].

Flexibility and accessibility are fundamental attributes of blended learning. This approach provides learners the convenience of accessing educational content anytime and anywhere, breaking down the barriers of traditional classroom settings. This accessibility is particularly beneficial in accommodating the diverse needs and schedules of students [23].

The benefits of blended learning extend beyond mere convenience. Research has shown that this approach can lead to improved learning effectiveness, extending the reach of education to a wider audience, and optimizing resource utilization. For students, the advantages are manifold, including the convenience of learning at their own pace, heightened motivation for self-paced learning, and the ability to balance educational commitments with other responsibilities [24].

In terms of learning settings, blended learning can be categorized into various models, including Live Synchronous (LS), Virtual Synchronous (VS), Self-directed Asynchronous (SA), and Collaborative Asynchronous (CA). Each model offers different experiences and benefits. LS involves direct, face-to-face learning activities like lectures and workshops. VS encompasses real-time learning in different locations through digital means like video conferencing. SA allows learners to engage with materials at their own pace and time, supported by digital media such as online courses and simulations. Lastly, CA involves learning at any time or place with others, facilitated by tools like email and online discussion boards, promoting collaborative learning [25].

3. Methodology.

3.1. **System Design.** "EduConnect" is a versatile application designed to bridge the communication and educational gap between parents, teachers, and children in a preschool setting. This application is segmented into three primary user interfaces, each tailored to the specific needs of its users: parents, teachers, and children. User feedback from early testing was instrumental in refining EduConnect. Teachers requested more intuitive tools for tracking student progress, leading to improvements in the Behavioral Analytics module. Parents sought more interactive and real-time updates, prompting the integration of the Home Interaction Module and Remote Surveillance Capability. Children's engagement with content guided adjustments to ensure materials were age-appropriate and engaging.This iterative process ensured that the final product was both functionally robust and aligned with user needs, exemplifying EduConnect's commitment to user-centered design. The design of EduConnect is grounded in the principles of ease of use, interactive learning, and secure communication, ensuring a comprehensive and engaging educational experience.

3.1.1. *Parents' Corner.* Figure 1(a)a presents EduConnect's 'Parents' Corner', a dedicated module within the app designed to engage parents in their child's education. It offers a suite of interactive tools below:

Home Interaction Module: Incorporates a digital class circle for community engagement, detailed behavior logs for child activity monitoring, and updates on family-centered activities and attendance records. Figure 1(b) illustrated the functionalities of this module.

Child Rearing Resources: A repository of high-quality, diverse parenting materials, including an extensive collection of children's literature and multimedia resources. An intelligent recommendation system is embedded to provide tailored parenting advice and resources.

Growth Tracking System: Facilitates collaborative documentation of a child's developmental milestones between parents and teachers, offering digital templates for growth file creation and access to expert developmental insights.

Safety and Health Monitoring: Integrates with the kindergarten's intelligent attendance and health monitoring systems, providing real-time data on children's safety, health checks, and overall well-being. *Remote Surveillance Capability*: Allows for real-time video monitoring of children's activities within the educational setting, offering parents reassurance and transparency.

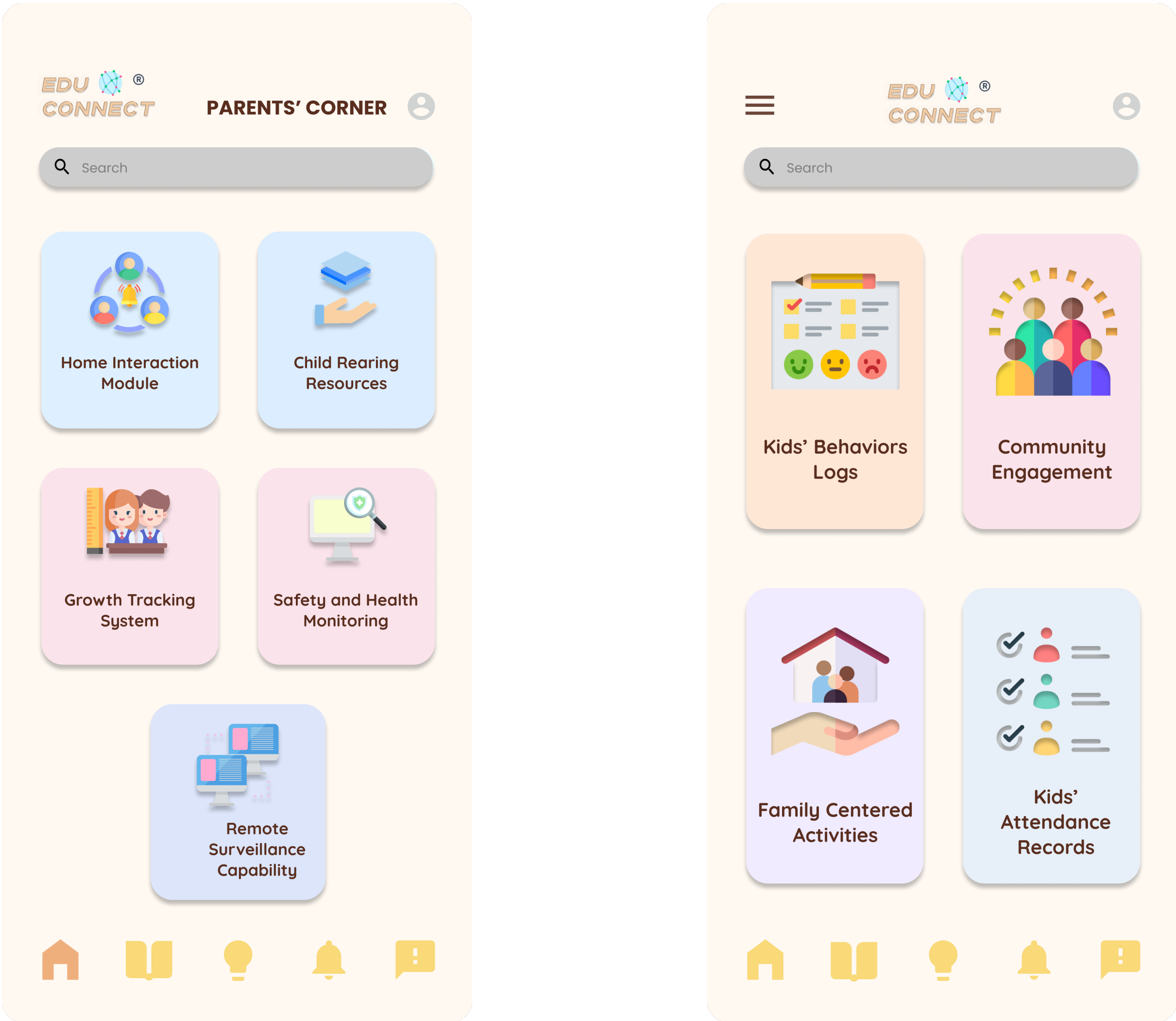
3.1.2. *Teacher's Corner.* Figure 2(a) highlights the 'Teachers' Corner' in the EduConnect app, a feature-rich interface designed to support educators. It includes 'Behavioral Analytics' for tracking and analyzing student engagement and performance, a 'Planner' for organizing lessons and activities, and a 'Library' that provides access to a wealth of educational resources and materials. The detail of each modules was described below :

Behavioral Analytics: Assists teachers in recording and evaluating children's progress across various dimensions such as cognitive abilities, social habits, and emotional health, with provisions for instant feedback to parents. Figure 2(b) depicted the functionalities of this module.

Planner: Aids in the organization and promotion of educational activities that enhance the connection between home and kindergarten, fostering a cohesive learning experience.

Library: A comprehensive database of instructional materials, including expert-led courses, training modules for teachers, and a variety of activity guides, all aimed at enriching the instructional process.

3.1.3. *Children Interface.* Figure 3(a) showcases 'Kids' Corner' in the EduConnect app, a vibrant and engaging space designed for children. It features 'Learning Content' with a variety of educational materials tailored to young learners, 'Interactive Applications' that encourage exploration and discovery through play, and personalized elements that check in on the child's well-being, ensuring a holistic approach to learning and development. This section of the app is tailored to make learning fun and interactive, keeping children motivated and eager to learn.



(a) (b)

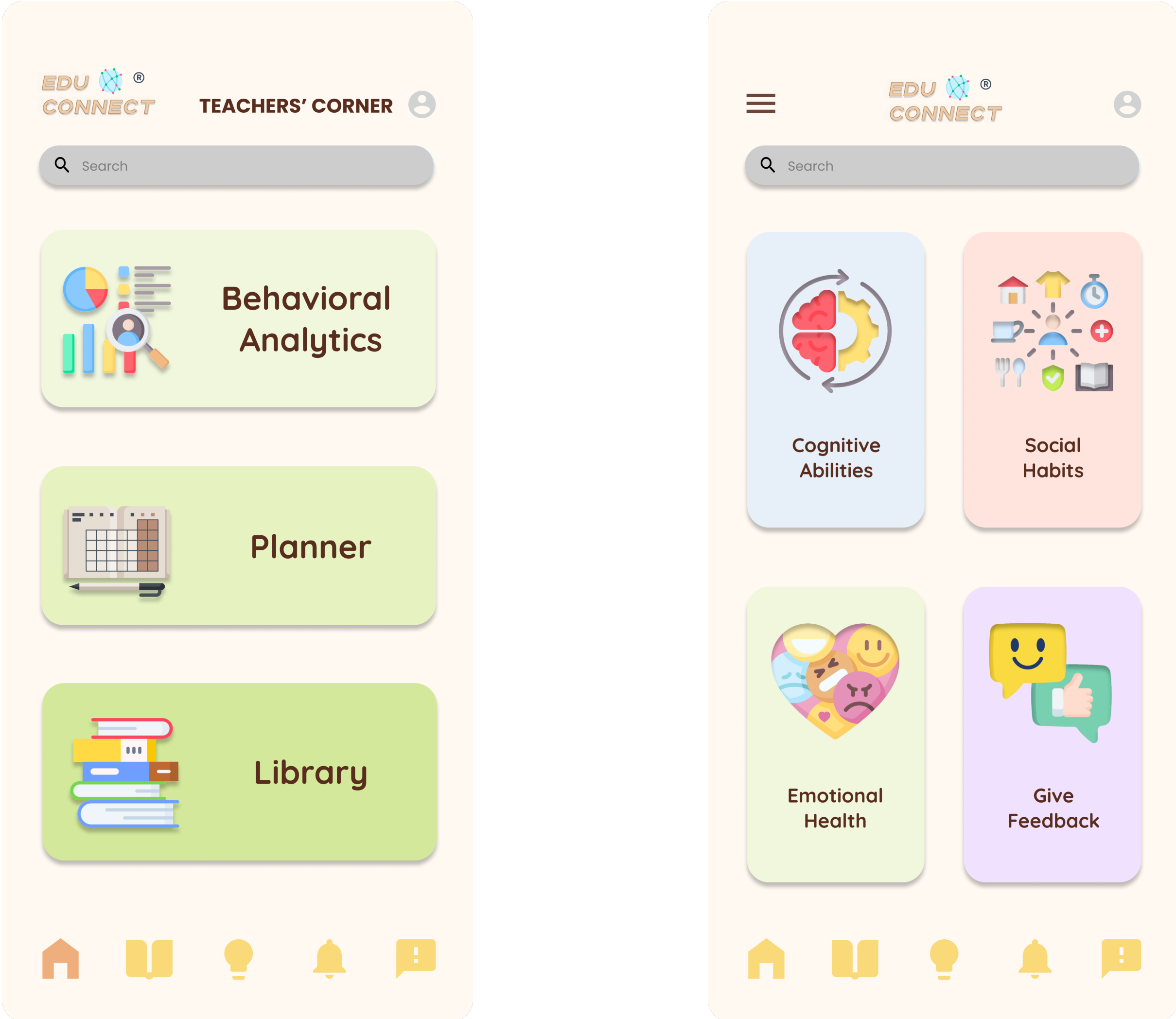
Figure 1. (a) Interface of Parents' Corner in EduConnect; (b) Home Interaction Module

Learning Content: Offers a curated selection of books and educational videos, algorithmically tailored to align with each child's interests and developmental stages.

Interactive Applications: Features age-appropriate educational games that complement the suggested reading and viewing materials, enhancing learning through interactive play.

Child-Friendly User Interface: Designed with an intuitive, visually engaging interface to encourage independent exploration by children.

3.2. **Methodology for Personalized Learning Implementation.** This section explores the design orientation of Personalised Learning Content for children, which is a fundamental aspect of our EduConnect application. Central to this design is the implementation of the Deep & Cross Network version 2 (DCNv2) model, renowned for its efficacy in learning intricate feature interactions in large-scale data sets. The choice of DCNv2 is predicated on its proven capability to capture complex, non-linear relationships inherent in user data, which is crucial for tailoring educational content to individual learning patterns and preferences of children. User interaction data is processed through an embedding layer, converting inputs into dense vectors for analysis. The model's stacked and



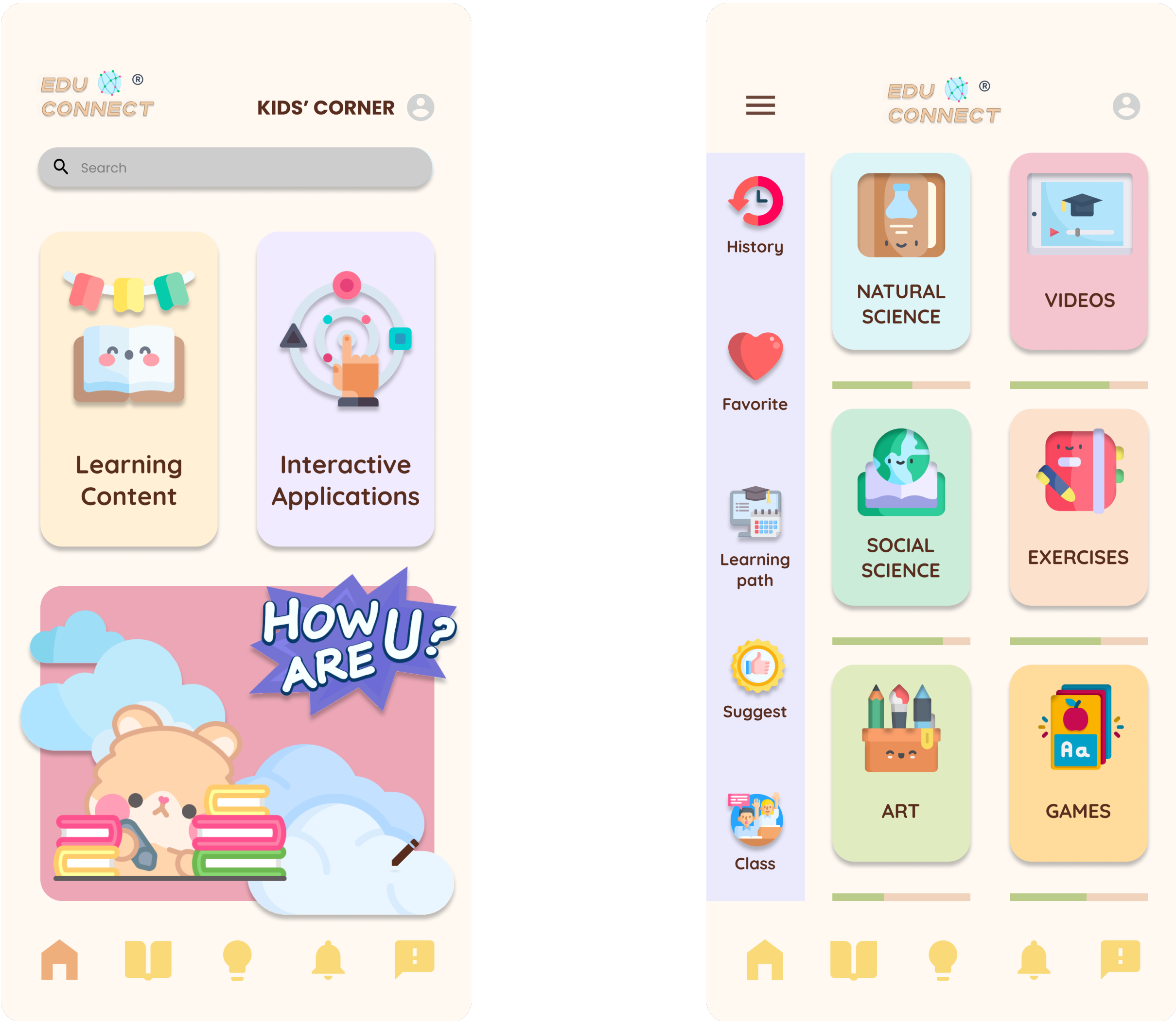
(a) (b)

Figure 2. (a) Interface of Teachers' Corner in EduConnect; (b) Behavioral Analytics Module

parallel structures then capture both explicit and implicit high-order interactions, refining content recommendations. These recommendations are integrated with EduConnect's content management system, which dynamically adjusts educational materials based on the model's outputs. Using a microservices approach, the DCN-V2 model processes large data volumes in real-time, ensuring immediate feedback and content adaptation as children interact with the platform.

To validate the effectiveness and adaptability of the DCNv2 model in the context of content personalization, we conducted rigorous performance testing using the Criteo dataset. This dataset, known for its voluminous and diverse user interaction records, serves as an ideal testing ground to evaluate the model's proficiency in generating accurate and relevant content recommendations. The subsequent analysis aims to demonstrate how the DCNv2 model can be leveraged to revolutionize the personalization aspect of digital learning platforms, ensuring that each child receives a learning experience that is not only engaging but also aligned with their unique developmental needs.

3.2.1. *Proposed Model.* Figures 4(a) and 4(b) illustrate the proposed DCNv2 architectures for the EduConnect platform: the stacked structure processes inputs through embedding,



(a) (b)

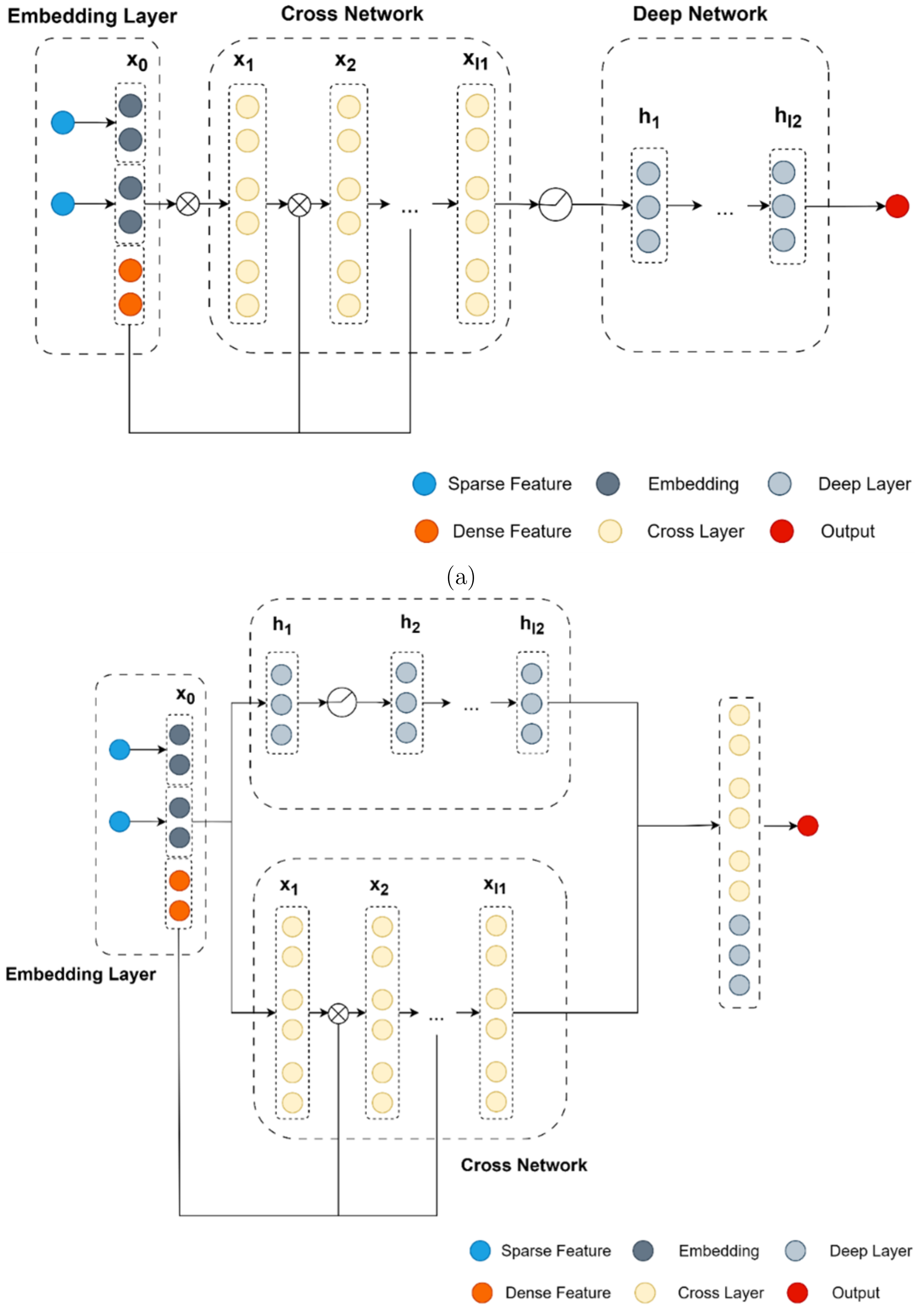
Figure 3. (a) Interface of Kids' Corner in EduConnect; (b) Learning Content Module

cross, and deep layers in sequence for a compounded feature interaction, while the parallel structure feeds the embedding layer output concurrently to cross and deep networks, merging their outputs for a diverse feature analysis. These designs optimize the recommendation system by exploiting different aspects of data representation and interaction modeling.

3.2.2. *Embedding Layer.* In the DCNv2 model, the embedding layer plays a crucial role in processing the input features, which consist of both categorical (sparse) and continuous (dense) variables. The primary function of this layer is to transform the high-dimensional sparse representation of each categorical feature into a lower-dimensional, dense embedded vector. This transformation is achieved through a learned projection matrix $W_{embed,i}$ for the i-th categorical feature. The transformation can be mathematically expressed as

$$x_{embed,i} = W_{embed,i} e_i \tag{1}$$

where e_i is a binary vector in $\{0,1\}^{v_i}$ representing the categorical feature, and $x_{embed,i}$ show the resulting dense embedded vector in $\mathbb{R}^{e_i}$. Here,v_i and e_i denote the vocabulary size and the embedding size of the i-th feature, respectively.



(a)

(b)

Figure 4. Proposed framework of DCN-V2 (a) Stacked ; (b) Parallel

For features that are multivalent, the final embedded vector is derived as the mean of all embedded vectors. The output from this layer, x_0, is a concatenated vector comprising all the dense embedded vectors and the normalized dense features, expressed as

$$x_0 = [x_{\text{embed},1}; \dots ; x_{\text{embed},n}; x_{\text{dense}}] \tag{2}$$

A distinct advantage of the DCNv2 model is its flexibility in handling varying embedding sizes, contrary to many related works which require uniform embedding dimensions across all features. This flexibility is particularly beneficial in industrial recommender systems where the vocabulary sizes can range significantly. Additionally, the model is not restricted to the embedding method described above; it can also incorporate alternative embedding techniques such as hashing, enhancing its adaptability and applicability in diverse scenarios.

3.2.3. *Cross Network.* Center of the DCN-V2 architecture is its cross network, specifically engineered for creating explicit feature crosses. The functionality of each cross layer, beginning from the $(l+1)$-th layer, is encapsulated in the following equation:

$$x_{l+1} = x_0 \odot (W_l x_l + b_l) + x_l \tag{3}$$

In this equation, $x_0 \in \mathbb{R}^d$ represents the base layer, typically the embedding layer, containing the original first-order features. The terms x_l and x_{l+1} in $\mathbb{R}^d$ denote the input and output of the $(l+1)$-th cross layer, respectively. The learned weight matrix $\mathbf{W}_l \in \mathbb{R}^{d\times d}$ and bias vector $\mathbf{b}_i \in \mathbb{R}^d$ facilitate the feature crossing process.

Each cross layer operates by interacting the base feature vector $\mathbf{x}_0$ with the transformed feature vector from the previous layer, effectively capturing the explicit interactions between features. In a cross network composed of l layers, the highest attainable polynomial order is $l+1$, encompassing all feature crosses up to this order. For a deeper exploration of this concept, particularly from bitwise and feature-wise perspectives. Notably, if $\mathbf{W}$ is set as $1 \times w^T$, where $\mathbf{1}$ is a vector of ones, the DCN-V2 model reverts to the standard DCN. It's important to note that the cross layers in DCN-V2 are primarily designed to reproduce polynomial function classes of a bounded degree, with more complex function spaces being only approximable.

3.2.4. *Deep Network.* In DCN-V2, the functioning of the l-th deep layer can be described by the formula

$$h_{l+1} = f(W_l h_l + b_l) \tag{4}$$

Here, $h_l \in \mathbb{R}^{d_l}$ and $h_{l+1} \in \mathbb{R}^{d_{i+1}}$ represent the input and output of the l-th deep layer, respectively. The weight matrix $W_l \in \mathbb{R}^{d_l \times d_{l+1}}$ and bias vector $b_l \in \mathbb{R}^{d_{l+1}}$ are integral to the layer's transformation process. The function $f(\cdot)$ is an element-wise activation function, for which ReLU is typically employed in this model, although other activation functions can also be utilized as per the requirements.

3.2.5. *Deep and Cross Combination.* In DCN-V2, two structures are commonly adopted to merge the cross network and the deep network: stacked and parallel. The choice between these structures is often dependent on the specific characteristics of the data.

Stacked Structure (Figure 4(a)): Here, the initial input x_0 is first processed through the cross network, then passed to the deep network. The final output x_{final} is obtained from the last layer of the deep network, denoted as

$$x_{final} = h_{L_d} \tag{5}$$

with $h_0 = x_{L_c}$. This structure effectively models the data using $f_{deep} \circ f_{cross}$.

Parallel Structure (Figure 4(b)): In this setup, the input x_0 is simultaneously fed to both the cross and deep networks. The outputs from the last layers of these networks x_{L_c} and h_{L_c} , are then concatenated to form the final output layer, expressed as

$$x_{final} = [x_{L_c}; x_{L_d}] \tag{6}$$

This approach models the data as $f_{cross} + f_{deep}$.
The prediction $\hat{y}_i$ is calculated using the logistic function:

$$\hat{y}_i = \sigma\left(w_{\log it} x_{final}\right) \tag{7}$$

Where $w_{\log it}$ is the weight vector for the logistic regression and $\sigma(x) = \frac{1}{1+e^{-x}}$ .The DCN-V2 model employs Log Loss, a common choice for learning-to-rank systems, particularly with binary labels . The loss is defined as:

$$loss = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] + \lambda \sum_j ||W_j||_2^2 \tag{8}$$

In this equation $\hat{y}_i$ are the predictions, y_i are the true labels, N is the total number of inputs, and λ is the L2 regularization parameter. It's noteworthy that DCN-V2 is agnostic to both the prediction task and the loss function, offering flexibility in its application.

3.3. **Real-Life Use of EduConnect.** EduConnect seamlessly integrates into the daily routines of children, teachers, and parents, enhancing the educational experience. Children use EduConnect to engage with interactive learning activities, like games and multimedia lessons, during school or at home. The platform adapts content to their progress, promoting independent learning. Teachers utilize the platform's Behavioral Analytics to monitor student engagement and adjust lessons accordingly, while the Planner feature helps organize daily activities and align them with curriculum goals.

Parents stay informed through the Home Interaction Module, receiving updates on their child's progress and participating in community forums. The Remote Surveillance feature provides real-time classroom monitoring, strengthening the connection between home and school.

4. **Experiment Results.**

4.1. **Dataset.** The Criteo dataset, renowned for its use in click-through rate (CTR) prediction, serves as an invaluable asset for refining the recommendation algorithms underpinning the EduConnect platform. Comprising tens of millions of user-ad interaction records from a week-long period, the dataset provides a rich tapestry of anonymized categorical features alongside numerical features, each entry labeled with a binary indicator of ad click outcome. EduConnect utilizes the Criteo dataset to enhance its personalized content delivery system, leveraging the dataset's vast and varied feature set to fine-tune the predictive accuracy of its algorithms. The dataset's complexity and volume offer a realistic backdrop for testing and improving the DCNv2 model's capability to discern nuanced user preferences and deliver educational content that aligns with individual user engagement patterns.

Criteo dataset includes information about each ad's display and the corresponding user click feedback. This dataset is extensively utilised for evaluating CTR models. The Criteo dataset consists of 26 categorical fields and 13 continuous feature fields, all of which are anonymous. The instances are divided randomly into three sets: training, validation, and test, with a ratio of 8:1:1. The statistics of the evaluation datasets are presented in Table 1.

Table 1. Statistics of the Criteo datasets

Datasets	Instances	Fields	Features
Criteo	45M	39	30M

4.2. **Experiment Metric.** In assessing the performance of predictive models within EduConnect, particularly for tasks akin to CTR prediction, two widely recognized metrics are employed: Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) and Logarithmic Loss (LogLoss). These metrics provide robust measures of model accuracy and reliability.

a. AUC

The AUC is a fundamental metric for evaluating binary classification models. It represents the probability that the model ranks a random positive example more highly than a random negative example. The AUC metric ranges from 0 to 1, where an AUC of 1 denotes perfect prediction, 0.5 suggests no discriminative power (equivalent to random guessing), and 0 indicates complete misclassification. To calculate AUC, the Receiver Operating Characteristic (ROC) curve was plotted by varying the threshold for classification and then measuring the True Positive Rate (TPR) against the False Positive Rate (FPR) at each threshold. The area under this curve was then computed using numerical integration, typically with the trapezoidal rule, to provide a single scalar value ranging from 0 to 1, where higher values indicate better model performance. The formula to calculate AUC is as follows:

$$AUC = \int_0^1 TPR(t)d\left(FPR(t)\right) \tag{9}$$

where TPR is the true positive rate, FPR is the false positive rate, and t is the threshold. A higher AUC value correlates with a better model performance, capable of distinguishing between the positive and negative classes.

b. LogLoss

LogLoss, or logarithmic loss, quantifies the accuracy of a classifier by penalizing false classifications. It measures the uncertainty of the probability estimates by comparing the predicted probability distribution with the true distribution. Lower values of LogLoss indicate models with probabilities closer to the true labels. The LogLoss for binary classification is defined as

$$LogLoss = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)\right] \tag{10}$$

In this formula, N is the number of observations, y_i is the true label of the i-th observation, and $\hat{y}_i$ is the predicted probability that the i-th observation is positive. A LogLoss of 0 implies perfect log-likelihood, representing a model with predictions that exactly match the observed data.

These statistical methods were implemented using Python's data analysis libraries, ensuring accurate and replicable calculations. By detailing the AUC and LogLoss computations, the study ensures transparency and allows other researchers to replicate the results in similar contexts.

4.3. **Experiment environments.** Our experimental evaluation was carried out on a robust computational platform configured with an AMD Ryzen 9 5950X CPU, known for its multitasking prowess and efficiency in processing complex operations. The graphical computations were powered by an NVIDIA GeForce RTX 3080 Ti GPU, selected for its advanced architecture optimized for machine learning workloads. The hardware was complemented by 32GB of high-bandwidth DDR4 RAM, ensuring smooth data flow and multitasking efficiency during the processing of voluminous datasets and demanding algorithms. On the software front, we employed Python 3.9, which is highly favored in the scientific community for its comprehensive suite of data analysis and machine learning tools. The machine learning models were developed and evaluated using Pytorch 1.8, recognized for its flexible, user-friendly API, and strong community support, enabling robust model development and efficient training.

4.4. **Experiment setup.** The experimental evaluation of the EduConnect platform was conducted to assess its effectiveness in personalizing educational content for preschool children. The study involved 278 preschool children aged 3 to 6 years, drawn from diverse educational institutions across various regions. The sample was balanced by age and gender, with an equal distribution of male and female participants. Participants were selected from urban, suburban, and rural areas to ensure diverse socioeconomic representation. Parental involvement and the frequency of digital device use at home were recorded to analyze their impact on the children's interaction with EduConnect. Ethical guidelines were strictly followed, with informed consent obtained from all participants' parents or guardians. The data collected was anonymized and securely stored.

4.5. **Experimental Results and Analysis.**

4.5.1. *Performance Analysis.* The efficacy of the DCN-V2 model within the EduConnect platform was meticulously analyzed to ensure optimal performance in delivering personalized educational content. This section presents the main discoveries derived from the performance analysis, with a specific emphasis on ROC curves and parameter investigations related to dropout tuning and variations in activation functions.

The ROC curve in Figure 5 displayed here illustrates the performance of the DCN-V2 model. The curve itself, which charts the TPR against the FPR, showcases the model's capability to distinguish between classes. With an AUC score of 0.8269, the DCN-V2 model demonstrates a strong discriminative ability.

Observing the curve, the steep ascent towards the upper left corner signifies that the model achieves a high TPR with a relatively low FPR for a considerable range of threshold values. This characteristic is indicative of a model that is highly effective at identifying relevant educational content for users, which is crucial for the user engagement goals of EduConnect.

In addition to the ROC analysis, a parameter study was conducted to optimize the DCN-V2 model further. Two key aspects were considered: dropout tuning and the impact of different activation functions.

Figures 6(a) and 6(b) display the impact of dropout rate adjustments on the DCN-V2 model's performance in the EduConnect system, measured by AUC and LogLoss metrics. A optimal point is observed at a dropout rate of 0.5, where the AUC reaches its peak, indicating optimal discrimination between classes, and the LogLoss reaches its lowest point, denoting high accuracy in predictions. Any deviation from this rate, whether it is higher or lower, results in a decrease in the model's performance. This emphasises the need for a careful balance in regularisation to avoid overfitting while still allowing the model to effectively learn from the data.

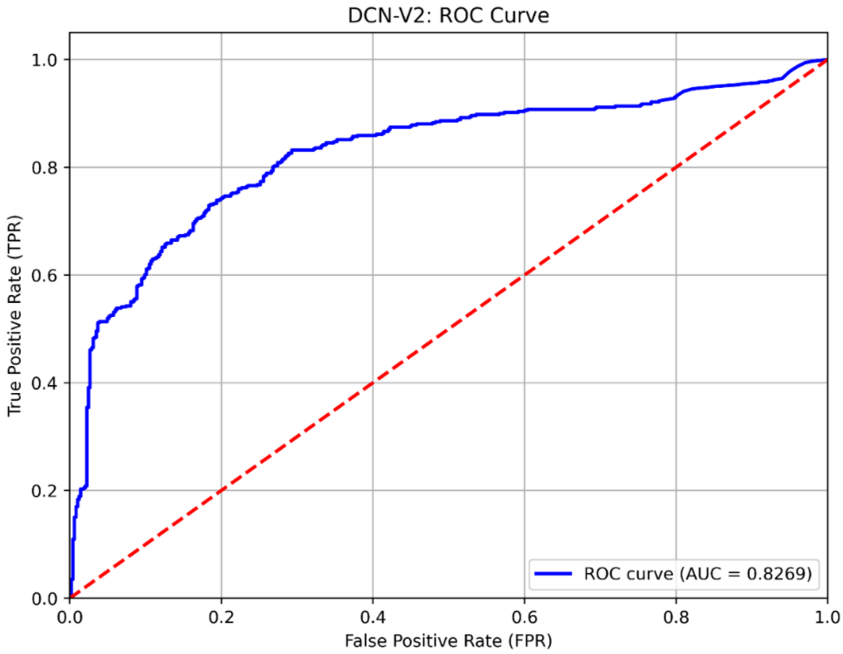
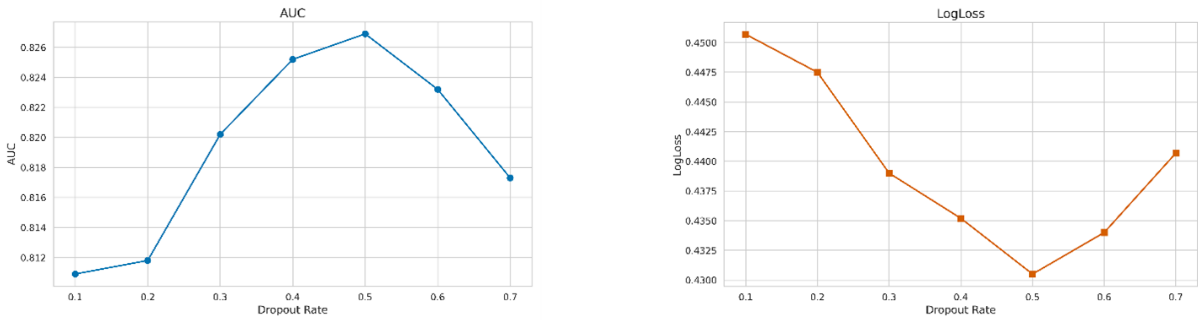


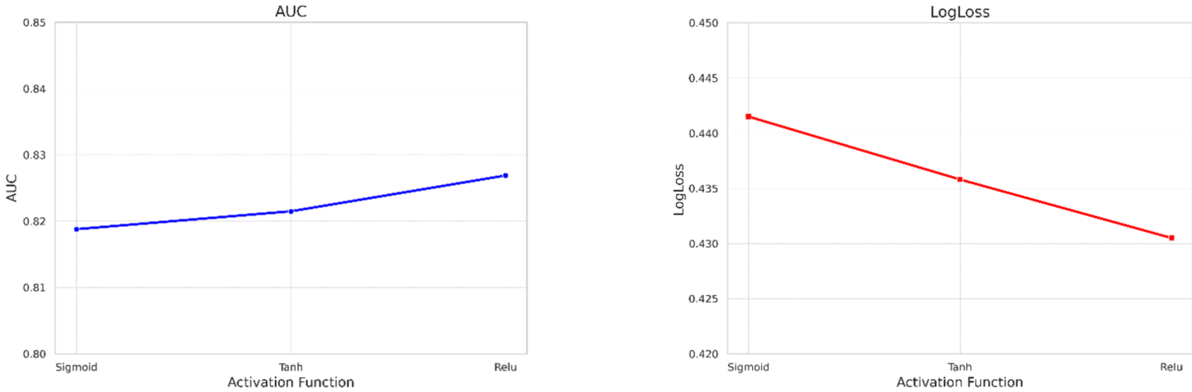
Figure 5. ROC Curves of DCN-V2



(a) (b)

Figure 6. Performance of DCN-V2 on Dropout tuning

Figures 7(a) and 7(b) illustrate the impact of different activation functions - sigmoid, tanh, and Relu - on the EduConnect DCN-V2 model's performance. The AUC graph shows a progressive improvement from sigmoid to Relu, highlighting Relu's superior capability in handling non-linear data patterns. Correspondingly, the LogLoss graph confirms this trend, with Relu achieving the lowest score, indicative of the most accurate predictions. These results clearly establish Relu as the optimal choice for EduConnect, enhancing both the accuracy and reliability of the content recommendation system.



(a) (b)

Figure 7. Performance of DCN-V2 on different Activation functions

4.5.2. *Comparing with differrent model.* In the pursuit of rigorously assessing the DCN-V2 model's capabilities within EduConnect, we will conduct a comparative analysis with several contemporary models that represent the latest advancements in recommendation systems. This will allow us to directly benchmark the performance of DCN-V2 against the cutting-edge models recently introduced to the field, providing a clear perspective on its relative effectiveness and efficiency. Such a comparison is essential to demonstrate the value DCN-V2 brings to EduConnect in the context of modern, data-driven recommendation tasks. Below, we introduce several baseline models that are used for comparison.

AFM [26]: AFM (Attentional Factorization Machine) is a highly sophisticated model that excels in capturing second-order feature interactions. It expands the functionality of FM (Factorization Machine) by incorporating the attentional mechanism to differentiate the varying significance of second-order combinatorial features.

xDeepFM [27]: xDeepFM is an enhanced iteration of Wide & Deep that incorporates a CIN (Compressed Interaction Network) layer to explicitly create feature combinations of finite order.

FiBiNET [28]: The FiBiNET model is a predictive model for CTR that combines the importance of features and the interaction between features using bilinear methods.

AFN [29]: AFN (Adaptive Factorization Network) is introduced for adaptive eigennorm estimation without the need for parameters. It has been demonstrated that this method yields significant results.

SELNN [30]: SELNN model leverages an attention mechanism and logarithmic transformations to refine CTR predictions, achieving notable accuracy gains with efficient computational performance on benchmark datasets.

Table 2. Comparison outcomes of experiments.

Model	AUC	LogLoss
FiBiNET [23]	0.7434	0.4621
AFN [24]	0.7465	0.4608
AFM [25]	0.7962	0.4541
xDeepFM [26]	0.8072	0.4474
SELNN [27]	0.8146	0.4352
Our	**0.8269**	**0.4305**

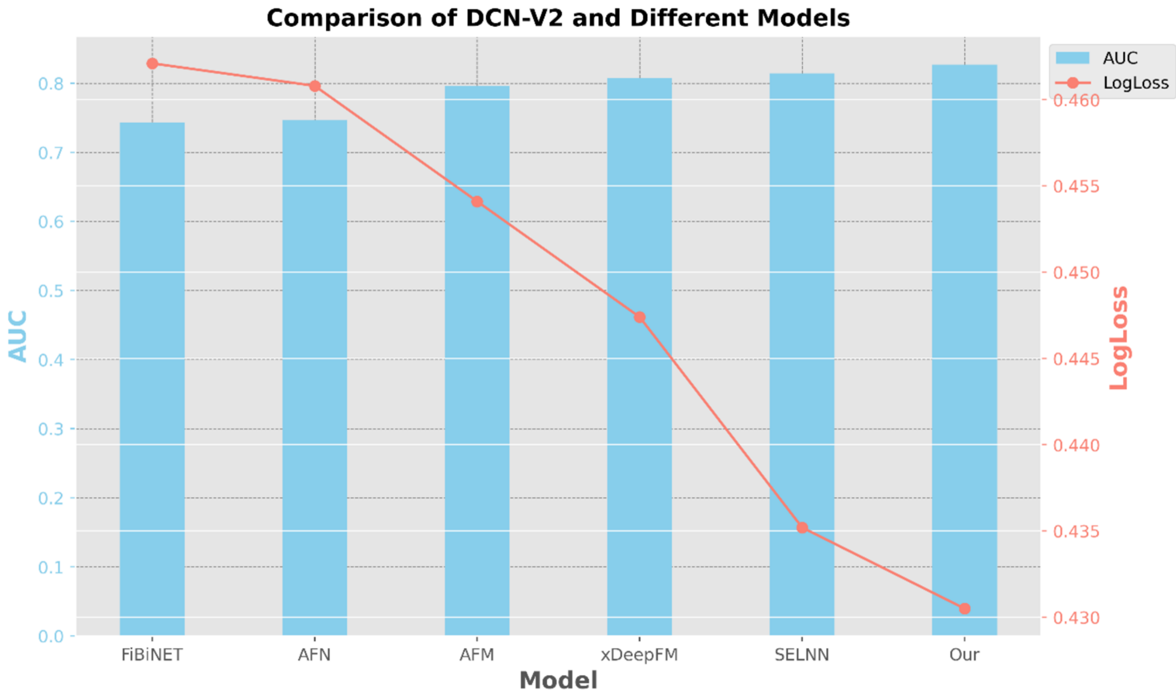


Figure 8. Comparison of DCN-V2 and different models

The findings are displayed in Table 2 and Figure 8. The DCNv2 model outperforms other models, achieving the highest AUC and the lowest LogLoss, indicating superior predictive accuracy and reliability. Our DCNv2 model showcases the highest AUC at 0.8269, indicating a superior true positive rate with minimal false positives, and the lowest LogLoss at 0.4305, suggesting the most accurate predictions among the models tested. Other models, such as xDeepFM and SELNN, demonstrate competitive performance with AUCs of 0.8072 and 0.8146, and LogLoss values of 0.4474 and 0.4352, respectively. Models like FiBiNET and AFN, while effective, display relatively lower AUC and higher LogLoss, indicating a modest performance in comparison. The data indicate that while contemporary models like xDeepFM and SELNN offer substantial improvements in recommendation system accuracy, the DCNv2 model outperforms them, setting a new benchmark for EduConnect's personalized content delivery.

While these models excel in certain areas, they also exhibit specific limitations that EduConnect, through its integration of the DCN-V2 model, is designed to overcome. Firstly, models like AFM and FiBiNET are highly effective in capturing second-order feature interactions, but they often struggle with higher-order interactions that are crucial for accurately modeling the complex relationships in educational data. EduConnect addresses this limitation by leveraging the cross-network capabilities of DCN-V2, which can efficiently model both explicit and implicit high-order feature interactions, leading to more accurate content recommendations tailored to individual learning needs.

Secondly, models such as xDeepFM and SELNN incorporate sophisticated mechanisms like CIN layers and attention mechanisms to enhance feature interaction modeling. However, these models can be computationally expensive and less flexible when dealing with large, dynamic datasets, such as those found in educational environments. EduConnect's DCN-V2 model, with its stacked and parallel structures, offers a more adaptable and computationally efficient approach, ensuring that the platform can scale effectively while maintaining high accuracy in content personalization.

Furthermore, while adaptive models like AFN are designed to estimate feature interactions dynamically, they can be limited by their reliance on fixed architecture and parameter settings, which may not fully capture the diverse learning trajectories of preschool children. EduConnect overcomes this by implementing a flexible embedding layer and a deep network capable of adapting to varying data inputs, ensuring that the learning experience remains personalized and responsive to each child's development.

5. **Conclusion.** This study demonstrates that the implementation of the DCN-V2 model within the EduConnect platform significantly enhances personalized educational experiences for preschool children, leading to improved short-term engagement and learning outcomes. Key findings indicate that EduConnect effectively adapts to individual learning needs, providing a robust framework for personalized education in early childhood settings. However, the long-term impact of EduConnect on learners' developmental trajectories and overall educational outcomes warrants further investigation. Future research should focus on examining the longitudinal effects of sustained EduConnect use, particularly in how it influences cognitive, social, and emotional development, as well as long-term academic performance. Understanding these effects will be crucial for refining EduConnect and ensuring its effectiveness in fostering not only immediate learning outcomes but also long-term developmental success. These insights will also have important implications for educational practice, particularly in designing and implementing technology-driven personalized learning solutions that support the diverse needs of young learners.

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