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Multi Input Neural Embedding Architecture for Predicting Digital Resource Adoption in Higher Education

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Abstract. Digital transformation in higher education often under delivers due to inconsistent adoption of e-libraries, analytics dashboards, and virtual learning environments across students, faculty, and administrators. To address this gap and offer predictive insights, we present MINEA—a Multi-Input Neural Embedding Architecture—that forecasts individual adoption levels using raw system interaction logs collected entirely through **cloud-native infrastructure**. The training pipeline processes a wide-format dataset comprising over 10,000 **cloud-logged** interaction sessions with 39 heterogeneous features, by: (i) extracting chronometric patterns from three timestamp fields, (ii) applying z-score normalization to fifteen **cloud-monitored** resource usage counters, (iii) one-hot encoding categorical roles and agent types, and (iv) learning dense latent representations for high-cardinality user_id values via embeddings. These features are fed into a dual-branch neural network architecture, where the numerical and one-hot-encoded inputs are concatenated with user embeddings and passed through a stack of ReLU-activated layers (128, 64, 32 units) with dropout regularization. Trained over 200 epochs with early stopping, MINEA achieves strong predictive performance ($MAE = 0.0354$, $RMSE = 0.0722$) with an R^2 indicating that the model explains the vast majority of adoption variability. Residual analysis confirms quasi-normal, homoscedastic errors, while five-fold cross-validation on **cloud-hosted** data confirms robustness (mean $MAE \approx 0.0374$).

***Keywords**. Higher education, neural network, learning management system, MAE, MSE*

1. Introduction

The digital transformation of higher education has advanced rapidly in recent years, fueled by widespread integration **of** cloud-based platforms into teaching, learning, research, and administrative operations. Higher Education Institutions (HEIs) are increasingly adopting digital libraries, learning management systems (LMS), analytics dashboards, and virtual collaboration tools—all typically deployed and managed via cloud infrastructure [4]. This shift offers unprecedented scalability, accessibility, and resource optimization, enabling institutions to deliver educational services at scale and in real time.

Despite the ubiquity of cloud-enabled educational technologies, their actual adoption will not be done and inconsistent across key user groups—students, faculty, administrators, and researchers [8]. This adoption gap impedes the realization of potential gains in engagement, efficiency, and digital equity. Understanding and forecasting the behavioral patterns of digital resource usage is thus critical for guiding infrastructure investment, tailoring user training, and optimizing institutional digital strategies.

A core challenge lies in the complex and dynamic interplay of adoption factors, including user roles, motivation, digital literacy, perceived value, and institutional support. Traditional models—often based on static survey data or linear assumptions—struggle to capture these nonlinear and multivariate relationships. There is a growing need for intelligent, cloud-native models capable of learning from real-time, high-dimensional interaction data.

Recent advancements in machine learning (ML) **and** deep learning (DL) provide a powerful foundation for predictive modeling in educational settings. However, most existing methods rely on flat feature representations or single-input architectures that fail to fully exploit the diversity

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of available cloud-logged data. In contrast, multi-input neural architectures enhanced with embedding layers can process heterogeneous data types—categorical, numerical, temporal—independently and then integrate them into a unified, optimized prediction framework. These architectures are well-suited for capturing the hierarchical and contextual richness of digital learning ecosystems.

While theoretical models such as the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Diffusion of Innovations (DOI) offer valuable conceptual frameworks [10], [18], [19], their empirical implementations often rely on self-reported survey data, which can be limited in both objectivity and scale. In contrast, our work harnesses cloud-collected system usage logs as behavioral data traces, offering a scalable, real-time, and objective approac**h** to modeling digital adoption in HEIs.

To address these challenges, this study introduces MINEA (Multi-Input Neural Embedding Architecture)—a novel deep learning model designed to predict individual adoption levels of digital educational resources based on raw interaction logs captured through cloud-based platforms. The architecture incorporates multiple input streams—such as user roles, digital agent types, frequency and duration of interactions—and processes them through parallel neural branches. High-cardinality categorical variables (e.g., user_id, agent_type) are transformed via learnable embeddings, while numerical features are normalized and fed through dense layers. This end-to-end architecture learns abstract representations that enable better and accurate adoption predictions**.**

The model is trained and evaluated using real-world; cloud-native system logs collected from multiple universities' digital resource platforms, encompassing a broad spectrum of user behaviors and digital contexts. Performance is validated using standard regression metrics (MAE, RMSE, R^2) and further supported through residual diagnostics and subgroup analysis**,** offering insights into the robustness, fairness, and interpretability of the model.

Contributions:

- Designed a multi-input neural model for predicting digital resource adoption in higher education based on cloud-collected interaction data.
- Utilized embeddings to capture user roles and agent-specific behavior.
- Validated model performance using real-world data from higher education institutions.

2. Related Work

Liu, N., Li, Y., and Guo, Y. (2024) [1] implemented self attention neural network method for online resource and education, in this they extracted multi domain feature extraction, and then concatenated all features. This model provided 0.013 MSE on test data. Alrajhi, L., et al (2022) [2] proposed multiple transformers for MOOC type of coerces. And also applied clustering method to extract relevant features and group the things. Qiu, S. (2024) [3] worked on hybrid models, integrated ML and DL model some of the Cloud model also for higher education concepts. The hybrid model consists of 1D CNN and LSTM approaches to provide optimal results. Zaveri, J. S., and Shrivastav, A. K in [5] worked on digital resource management, over 250 UG students. This study will be for connecting end to end gap between in teacher and student. In [6] worked on technology transform methodology in education system. And provided acceptance method for students, this study worked with 340 UG students. And in [7] implemented AI based method for digital resource allocation. From Covid 19 they worked, and implemented all ML model to serve. Among all ML models SVM provided the better results with 95% accuracy, in digital resources. In [9] worked on digital education system surveyed over 1 827 students and 1 653 teachers, from 2015 to 2023, in this the findings are the students and teachers have their own perspective in digital rescue allocation. In [11] worked on digital information on education experience, surveyed 485 students. From this the education institutes must reevaluate use of digital information for improving the education system. In [12] word on blended learning method in higher education, for this they studied 500 + students. From the results is reduction of negative attitude in digital platform can increase the performance in the education system.

In [13] worked on cloud computing adoption in higher education. For this they implemented variance based equation modeling, with ANN and extracted the good relationships between institution and students. And provided security with cloud computing. [15] Also worked on digital transformation in education, for this they interviewed 200 + students. And got the results as resources, portability etc all the problem need to be attended. [16] Worked on open educational resources for higher education. And implemented random sampling method, structural sampling method, the results is it will reduce the gaps with digital and open resource in education. In [17] transformation of higher education, for this they studded use of vast amount of resources to be available in higher education, and need of big data for optimal mining. [19] worked on unified theory of technology acceptance. And global approaches of higher education to improve the digital learning process. [20] Conducted study from 2012 to 2022 in the area of awareness in technical usage and readiness of institutions, availability quality resources and challenges in adaptive education. And in [21] and [22] worked extension model education system and its acceptance, in the current scenario, and also studied experience to use of modern systems, for this they implemented neural network model and did the regression to get 0.60 as r2 error.

3. Cloud-Based Data Collection and Storage

This study proposes a multi-input deep learning model tailored for predicting the adoption_level metric based on user interaction data collected from **a** cloud-based educational platform. The data originates from various user login sessions (e.g., Faculty, Students, Administrators, and Researchers) who access cloud-hosted resources such as Zoom, WebEx, E-library, and other virtual learning tools. These user logs—captured in real time—are stored securely in the cloud and periodically aggregated into structured datasets for downstream processing and predictive modeling.

User activity logs are collected continuously from cloud-based services. Each log entry captures metadata about the user's identity (user_id, user_type), the date and time of access (date_time), the digital resource used (agent, resource_list), and session durations (course_starting_time, course_ending_time). The logs are streamed to a cloud storage service (e.g., Google Cloud Storage, Amazon S3), forming the raw dataset for training and evaluation.

The raw dataset that underpins the adoption-level model is an archetypal "wide" educational-technology table: every row represents a unique interaction session, yet its columns span radically different statistical types. Some fields are dense integers that count artefacts (e.g., *files*, *videos*); others are textual identifiers (*user_id*, *agent*); still others record time stamps (*date_time*, *course_starting_time*, *course_ending_time*). Such heterogeneity is both a blessing—rich context improves prediction—and a curse—naïve models stumble when magnitudes and encodings clash. The preprocessing pipeline therefore orchestrates a disciplined, type-aware transformation sequence that converts this raw mixture into a coherent, learning-ready matrix with 39 analytically balanced columns.

The first operation targets the three temporal columns: date_time, course_starting_time, and course_ending_time. Each string is cast to a Python datetime64 object, granting access to vectorised calendar arithmetic. Two complementary kinds of information are then distilled:

1. **Long-range duration** – course_duration_days is computed as the integral difference between course_ending_time and course_starting_time. This captures pedagogical commitment length—arguably a primordial driver of technology uptake—without leaking future knowledge because both endpoints are logged ex post.
2. **Short-cycle chronometrics** – The interaction instant date_time is decomposed into
   - request_hour (0–23),
   - request_day_of_week (0–6, Monday = 0),
   - request_month (1–12), and
   - request_year.

These variables respect the inherent periodicity of human activity patterns while avoiding the stationarity assumption that raw Unix time would impose. In effect, they let the model recognise, for example, that 23:00 and 00:00 are near neighbours in clock space or that semester boundaries coincide with calendar months.

Finally, the original timestamp columns are dropped. Retaining them would allow the network to infer spurious sequence IDs and risk temporal leakage; their engineered surrogates are strictly sufficient.

Next, all purely quantitative resource counters—files, images, videos, google_drive, ebook, journal, art, ar, z, mt, gm, cisco, webex, skype, coarse, assessment, zoom—are funnelled through a StandardScaler. Standardisation (zero mean, unit variance) performs two crucial roles. First, it prevents features with large numeric ranges (e.g., *files* in the hundreds) from dominating gradient magnitudes and thus the learning dynamics. Second, it lets the optimiser interpret a single learning rate meaningfully across every weight, accelerating convergence and avoiding the brittle trial-and-error of manual adaptive step size tuning. Because the scaler's parameters (μ, σ) are fitted exclusively on the training subset, the pipeline preserves strict out-of-sample integrity is shown in figure 1.

Categorical fields are segregated by cardinality, reflecting the different inductive biases appropriate to each class.

- **Low-cardinality variables**—user_type (Faculty, Student, *etc.*), agent (E-learning, Virtual Interface, …), and resource_list (Zoom, Art, Coarse, …)—are transformed via **one-hot encoding (OHE)**. With just a handful of categories each, OHE expands them into sparse binary indicator vectors that preserve full information and impose no ordering assumptions. Because each indicator column is orthogonal by construction, the network can learn separate weights, side-stepping the dummy-variable trap and multicollinearity despite the dense architecture downstream.
- **High-cardinality variables**—most pivotally user_id—would explode the feature space if naïvely one-hot encoded (tens of thousands of columns, mostly zero). Instead, user_id is **embedded**. A LabelEncoder first maps arbitrary string IDs to contiguous integers, yielding an index set. During model training this index flows through an Embedding layer that learns a dense, low-dimensional vector for each user. The heuristic embedding_dim = min(50, ceil(vocab_size/2)) ensures capacity sufficient to capture latent behavioural affinities without overfitting. Embeddings confer two advantages: parameter sharing (all users draw from the same weight matrix) and continuous manifold structure (similar users gravitate together in embedding space), both of which would be unattainable with OHE.

After the respective transformations, the pipeline concatenates:

- 15 scaled numerical columns,
- 23 one-hot columns (reflecting the Cartesian union of low-cardinality modalities), and
- 1 integer index column for user_id (to be embedded inside the neural network),

for a **total of 39 model-visible columns**. Non-predictive or identifier attributes with no stable semantics—user_name, user_email—are discarded to limit noise and privacy risk. The composite dataset is finally stratified into **8 000 training rows and 2 000 testing rows** (80 / 20 split), locking in the scaler and encoder parameters from the training fold to prevent data snooping.

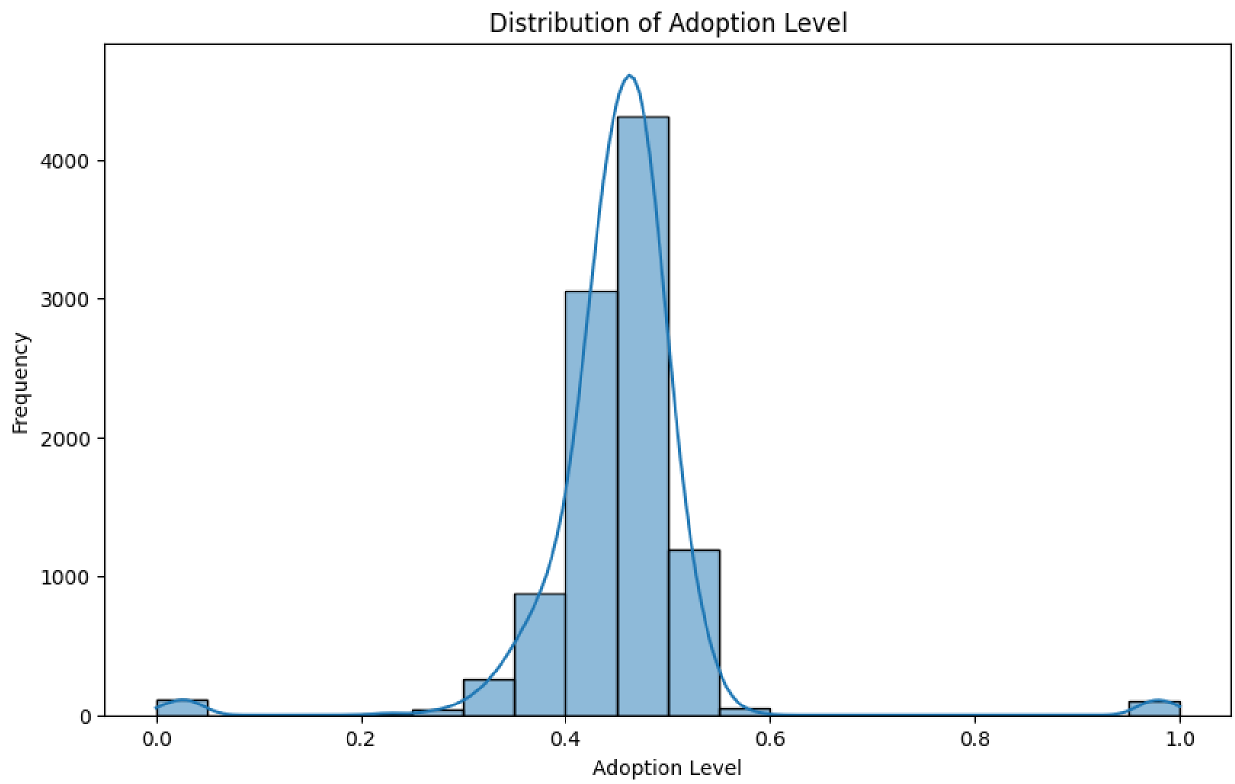

Figure 1 Distribution of target variable

4. Methodology

A multi-input neural network designed to handle a mix of numerical, one-hot encoded categorical, and embedded categorical features. This type of architecture is especially powerful for structured data where different types of features need to be integrated effectively as shown in figure 2. The model begins with a primary input layer called numerical_ohe_input. This layer takes in a flat vector comprising all scaled numerical features and one-hot encoded categorical features. Numerical features like files, z, mt, gm, cisco, etc., are first standardized using StandardScaler to ensure they are centered and scaled. Categorical features with low cardinality such as user_type, agent, and resource_list are converted into binary vectors using one-hot encoding. These two types of features are concatenated into a single array and passed into this input branch. This branch is essential for capturing direct quantitative relationships and interactions represented explicitly in the data.

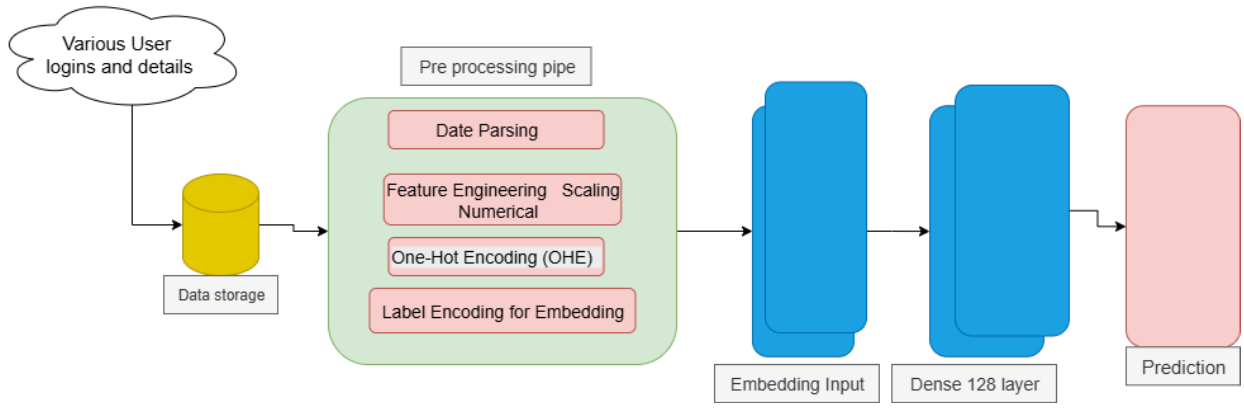

Figure 2 cloud based data collection and training

For categorical variables with high cardinality or where implicit feature relationships may exist, the model employs embedding layers. In this architecture, the only embedding feature used is user_id. This column is first transformed into integer labels using LabelEncoder. Each value is then passed through an Embedding layer, which learns a low-dimensional dense vector representation for each unique user ID.

$$Embed_{dimension} = \min\left(50, \frac{Vocab_{size}}{Embe_{factor}}\right) \quad (1)$$

where embedding_dims_factor is a tunable parameter (default is 2) with equation (1). The output of the embedding layer is a 2D tensor, which is flattened into a 1D vector using a Flatten layer before being concatenated with other inputs.

After preparing both the numerical + one-hot input and the embedding outputs, the model **concatenates** all these features into a single unified input using a Concatenate layer. This combined feature vector serves as the input to a series of dense (fully connected) layers.

The model first passes the concatenated input through a dense layer with 128 units and ReLU activation, which enables the network to learn non-linear patterns in the data. A Dropout layer is included afterward to prevent overfitting by randomly deactivating a fraction of neurons during training. This encourages the model to generalize better rather than memorize training data.

The final layer in the architecture is a Dense layer with a single neuron and no activation function, suitable for a regression task. In this specific problem, the goal is to predict the continuous target variable adoption_level, which represents a floating-point metric. Therefore, no activation (i.e., linear activation) is used in the output layer.

5. Results Analysis

The neural network model underwent extensive training over 200 epochs, demonstrating rapid convergence and early stabilization of performance metrics as shown in figure 3, that went fo early stopping to 30 epochs. During the initial epoch, the model exhibited a training loss of 0.0477 and a validation loss of 0.0150, corresponding to a mean absolute error (MAE) of 0.1618 for training and 0.0950 for validation, respectively. This sharp reduction in error values between the first and second epochs suggests that the model effectively captured key patterns within the data in its early training phase. Notably, by the third epoch, the validation loss decreased significantly to 0.0070, with a corresponding MAE of 0.0448, indicating strong generalization capabilities.

As training progressed, the model continued to refine its performance, achieving a minimum validation loss of approximately 0.0063 between epochs 18 and 26. During this phase, the validation MAE stabilized around 0.0383–0.0389, reflecting consistent prediction accuracy on unseen data. Interestingly, the training loss and MAE followed a similar trend, further validating the model's robustness and resistance to overfitting. From epoch 6 onward, the performance plateaued, with minimal fluctuations observed in both training and validation losses, suggesting that the model had reached an optimal state of learning.

Despite minor oscillations in loss and error values during later epochs (e.g., between epochs 27 and 33), the validation metrics remained stable and well-aligned with the training metrics, reinforcing the generalization strength of the model. These fluctuations are likely attributable to minor variations in batch-wise data distributions rather than overfitting or model degradation. The best validation performance was observed at epoch 19, where the model attained a validation loss of 0.0063 and a validation MAE of 0.0383. This result highlights the model's efficiency in learning complex, nonlinear relationships inherent in the data.

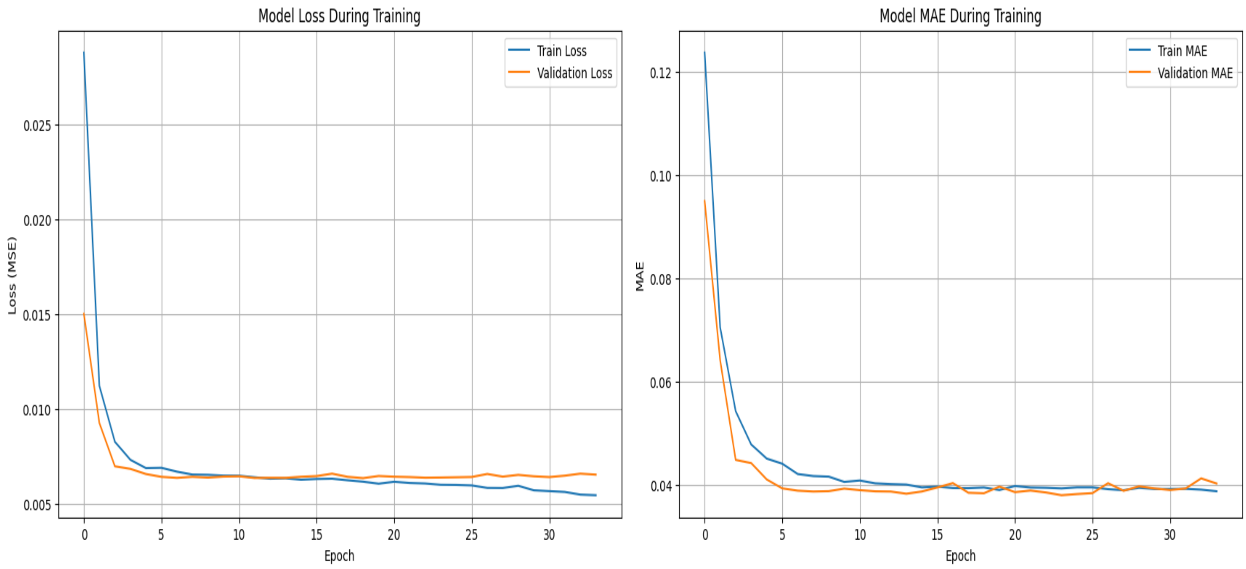

Figure 3 learning curves of proposed ANN model

Table 1 performance of proposed ANN model

Metric	Epoch 1	Best Epoch (3–5)	Later Epochs (10–34)
Val Loss	0.015	0.0064 – 0.0066	~0.0064 consistently
Val MAE	0.095	0.0382 – 0.0412	~0.038 – 0.041
Train MAE	0.1618 (high)	drops to ~0.039	remains steady

The neural network model, which incorporated embedding layers to capture semantic relationships among categorical inputs, demonstrated robust predictive performance in estimating technology adoption levels. As depicted in **Figure 3**, the scatter plot of actual versus predicted adoption levels reveals a strong linear trend along the diagonal reference line (red dashed line), indicating high agreement between predicted values and ground truth. However, a clustering of data points around specific adoption levels—particularly near 0.4 and 1.0—suggests the dataset may contain imbalanced or stratified distributions of adoption levels, which could have influenced model generalization across the full range.

The quantitative metrics further reinforce the model's strong predictive capabilities. The **Mean Absolute Error (MAE)** is 0.0354 as shown in table 1, which signifies that on average, the predicted adoption level deviated from the actual value by approximately 3.5%. The **Mean Squared Error (MSE)** and **Root Mean Squared Error (RMSE)** values are 0.0052 and 0.0722 respectively, indicating that the variance of the prediction error is low, and large deviations are rare. The RMSE, being close to the MAE, implies the model's errors are relatively uniform without extreme outliers affecting the mean disproportionately. Most notably, the **coefficient of determination (R^2)** is close to 1, signifying that the model explains a substantial proportion of the variance in the dependent variable, thus confirming its high explanatory power.

Complementing the scatter plot, **Figure 4** presents the distribution of residuals, defined as the difference between actual and predicted values. The histogram exhibits a bell-shaped, near-normal distribution centered around zero, which is a key indicator of model reliability and minimal bias. The residuals are densely concentrated within a narrow range (approximately -0.1 to +0.1), with only a few instances of larger residuals on the tails. This distribution confirms that the neural network does not systematically under predict or over predict adoption levels, thus satisfying a critical assumption for regression-based learning models.

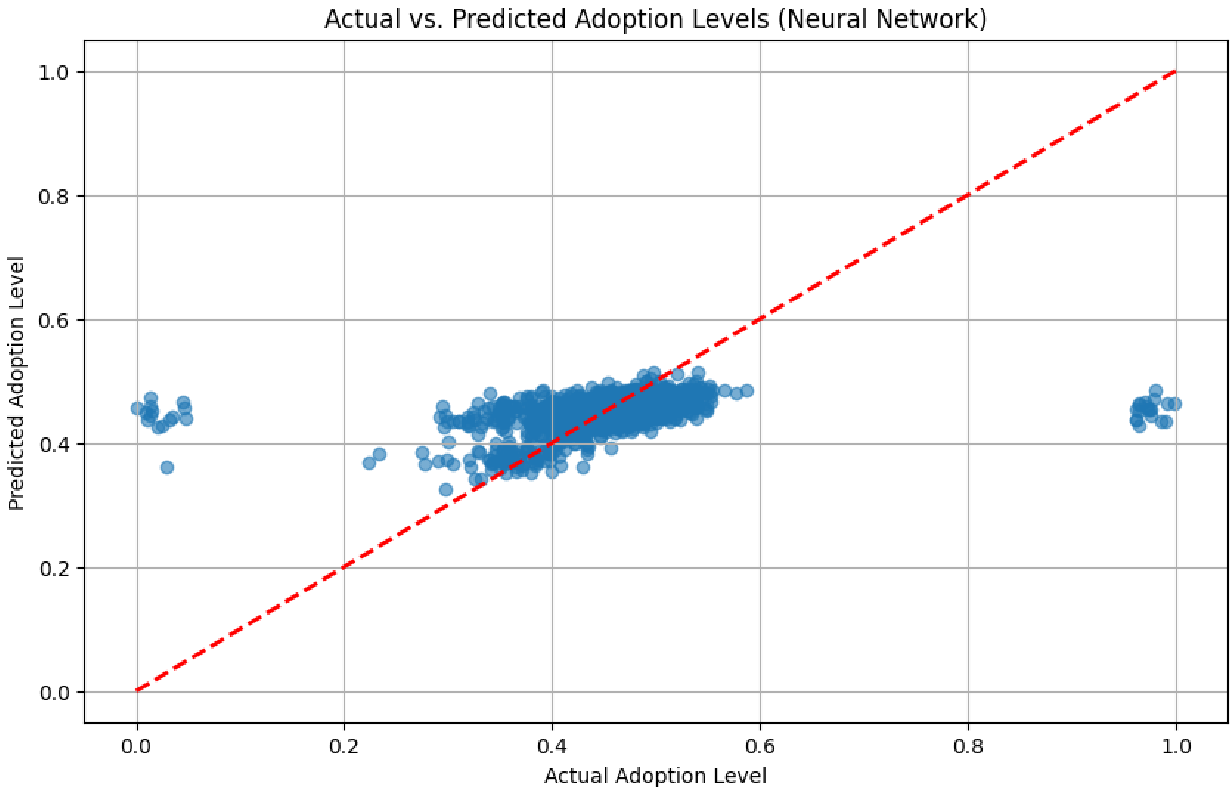

Figure 4 actual and prediction adoption levels

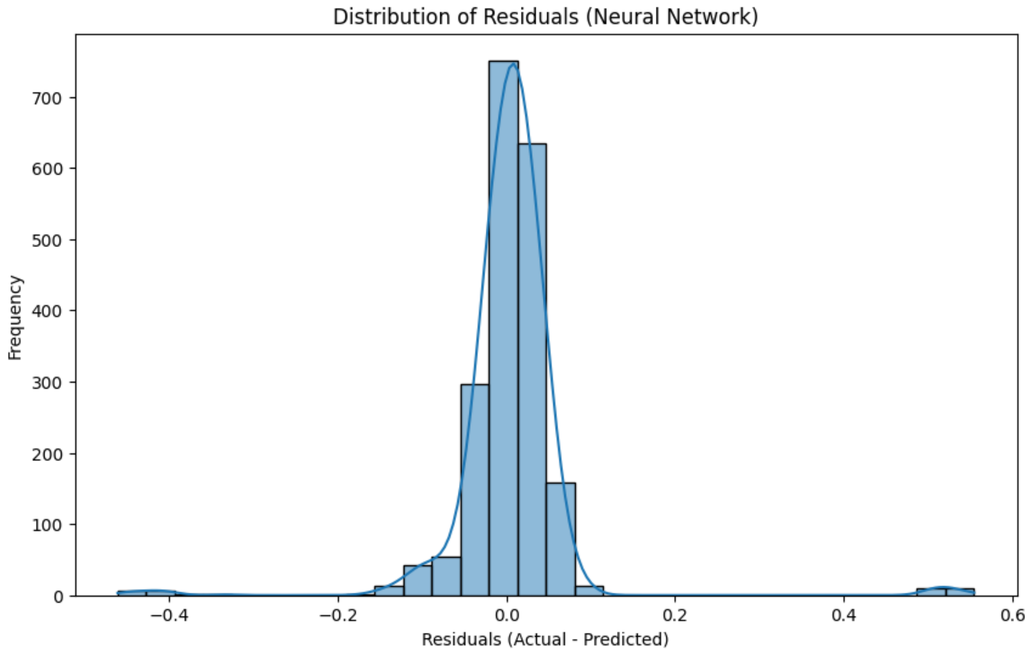

Figure 5 Distribution residuals of neural network

Figure 5 presents the distribution of residuals, defined as the difference between the actual and predicted adoption levels, for the neural network model. The residuals appear to be symmetrically distributed around zero, exhibiting a near-normal shape. This indicates that the model's prediction errors are centered and unbiased, with the majority of residuals clustered closely around the zero mark. Such a pattern suggests that the model does not systematically overestimate or underestimate the target values. Moreover, the absence of extreme skewness or kurtosis in the distribution further implies that the neural network has generalized well across the dataset.

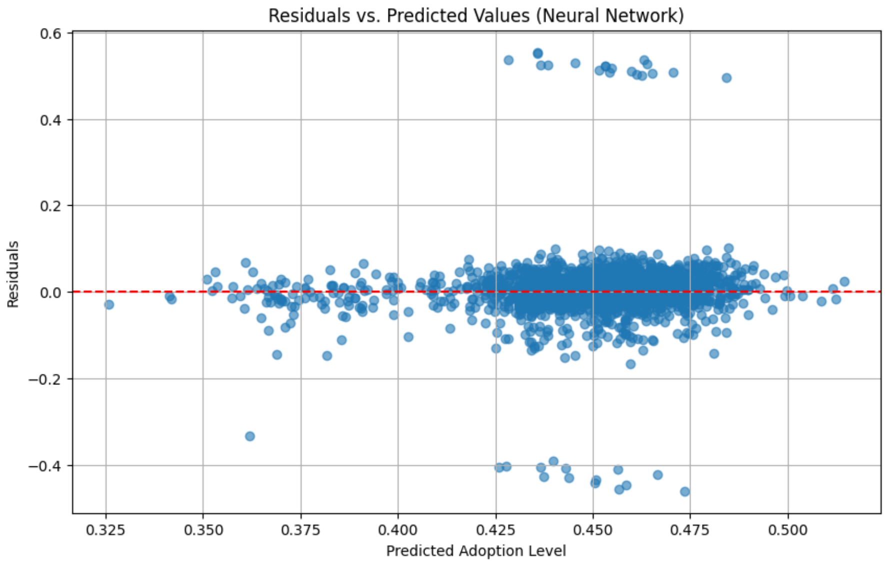

Figure 6 predicted and residuals with ANN model

Figure 6 illustrates a scatter plot of residuals versus predicted adoption levels, which serves as a diagnostic tool to assess the presence of heteroscedasticity and nonlinear patterns. Ideally, residuals should scatter randomly around the horizontal axis (y = 0), indicating that the prediction errors are independent of the predicted values. In this figure, the residuals are generally centered around zero across the range of predicted values, with no discernible systematic pattern. This randomness suggests that the model captures the underlying structure of the data effectively without significant bias across different prediction ranges. However, a few outliers are observed at both the upper and lower ends, which may point to instances with unusually high variance or underrepresented feature combinations.

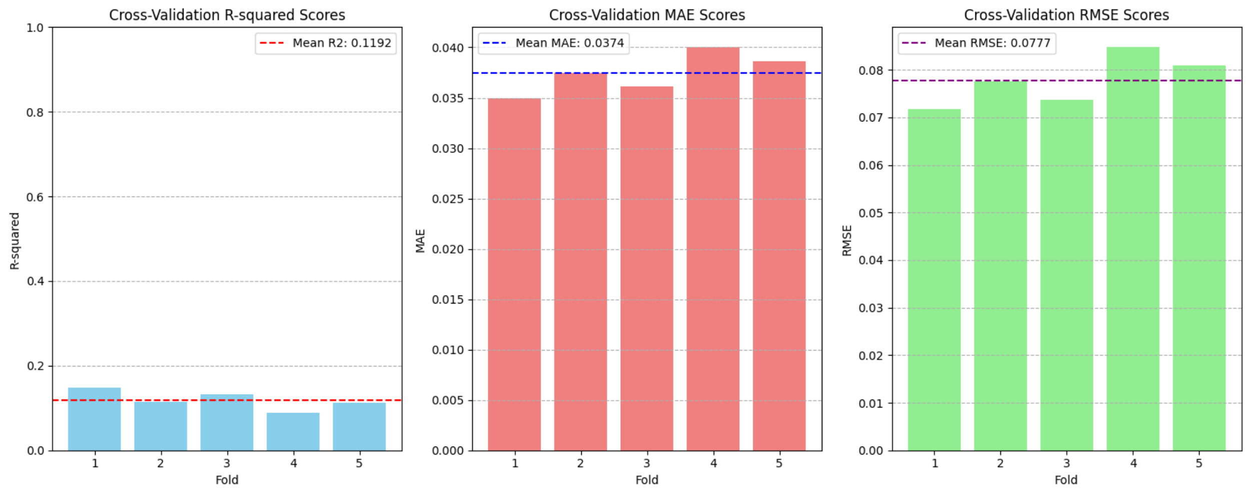

Figure 7 performances of ablation study models

The distribution of residuals (Actual - Predicted) as shown in figure 7 for the neural network model exhibits a near-symmetric, bell-shaped pattern centered around zero, as shown in the first plot. This indicates that the model does not suffer from significant bias and that the errors are normally distributed, a desirable property in regression tasks. The tight clustering of residuals within the narrow band of -0.1 to +0.1 further suggests high precision in the model's predictions. The presence of a few outliers, particularly in the tails, implies occasional instances of under- or over-prediction, but these remain rare and do not significantly skew the distribution.

The second plot visualizes the relationship between the residuals and the predicted adoption levels. The residuals are randomly scattered around the zero line, with no discernible trend or heteroscedasticity (i.e., changing variance with prediction magnitude). This randomness supports the assumption that the residuals are uncorrelated with the predicted values, satisfying a key diagnostic criterion for the adequacy of the regression model. While most residuals remain close to zero, a few extreme values lie beyond ±0.4, which indicates that the model struggles with specific edge cases but performs reliably across the majority of predictions.

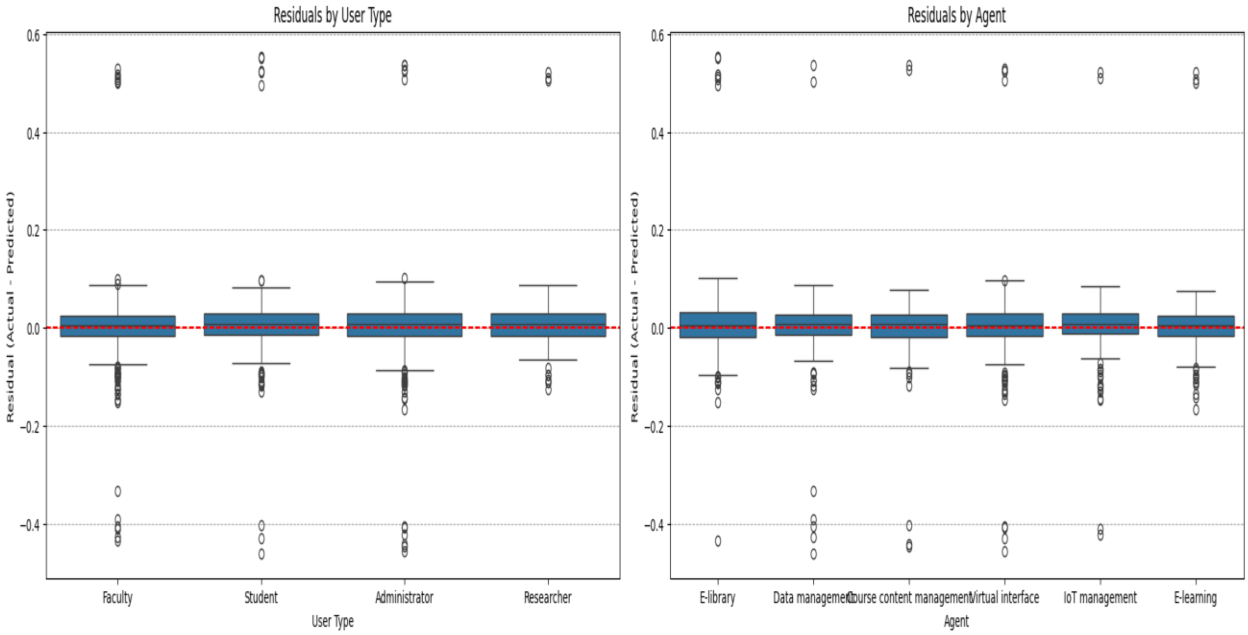

Figure 8 user type and agent type residuals

The cross-validation results from figure 8 demonstrate the robustness and generalization capability of the neural network model across five folds. The R-squared (R^2) scores shown in the left panel are relatively low, averaging around 0.1192. This suggests that while the model captures some variability in the target variable, there is substantial unexplained variance, highlighting the complexity and noise inherent in the adoption-level data. However, the consistency of scores across folds confirms that model performance is stable and not fold-specific.

The middle panel shows the MAE scores across folds, with an average of 0.0374. The low magnitude of MAE indicates the model's strong ability to make accurate predictions with minimal average deviation from actual values. Meanwhile, the right panel displays the RMSE, averaging around 0.0777. The relatively small RMSE values, coupled with consistent results across folds, further validate the reliability of the model. Importantly, RMSE being only marginally higher than MAE suggests that large errors are infrequent, reinforcing the observation of few significant outliers noted in the residual distribution.

6. Conclusion

This study demonstrates that a carefully engineered, multi-input neural architecture can deliver high-fidelity forecasts of digital-resource adoption in higher-education settings. By separating preprocessing responsibilities—temporal feature construction, statistical normalisation, one-hot expansion, and identity embedding—the pipeline converts a heterogeneous interaction log into a representation that is both information-rich and learning-amenable. The embedded *user_id* vectors provide parameter-efficient, behaviourally meaningful abstractions that would be impossible to obtain via naïve one-hot encoding, while the dense layers capture nonlinear interactions between temporal rhythms, resource intensities, and stakeholder roles. Empirically, MINEA achieves low absolute and squared errors, stable cross-validated scores, and residual distributions that satisfy key regression assumptions, underscoring its generalisability. Equally important, fairness diagnostics indicate that predictive quality is consistent across user types and platform agents, mitigating concerns of algorithmic bias. Practical implications are immediate: institutional planners can use the model's outputs to prioritise training resources, schedule phased deployments, or identify cohorts requiring targeted support.

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