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PAPER

Mixed Reality-Supported Interdisciplinary Learning: A Deep Learning Framework for Task-Behavior Prediction

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ABSTRACT

In the rapidly evolving landscape of information technology, mixed reality (MR) technology has been increasingly recognized as a crucial instrument for educational innovation. This technology, which amalgamates elements of virtual reality (VR) and augmented reality (AR), fosters an environment characterized by enhanced interactivity and profound immersion. Such an environment has been instrumental in improving both the efficiency and quality of learning, especially in cultivating students' innovative practice capabilities and facilitating interdisciplinary learning. Despite significant advancements in the application of MR in educational contexts, challenges persist in the precise extraction of task performance and behavioral characteristics of students within MR environments. Furthermore, the integration of interdisciplinary information for effective prediction of learning outcomes remains a complex undertaking. This study conducts a systematic analysis of MR technology's current applications in education, with a focus on strategies that leverage MR technology to support student innovation practices and interdisciplinary learning. Shortcomings in existing research related to the extraction of task performance and behavioral characteristics are identified, and the limitations of conventional predictive models in managing the integration of interdisciplinary information are discussed. To address these challenges, a model based on deep learning for data fusion is proposed. This model is complemented by an end-to-end training approach for task-behavior correlation prediction, with the aim of enhancing both the accuracy of predictions and their practical applicability in educational settings.

KEYWORDS

mixed reality (MR) technology, educational innovation, innovation practice, interdisciplinary learning, task performance, behavioral characteristics, deep learning, data fusion, predictive models

1 INTRODUCTION

With the rapid development of information technology, mixed reality (MR) technology integrating virtual reality (VR), and augmented reality (AR) has attracted increasing attention in education because of its immersive and interactive learning capabilities [1–5]. MR environments can improve students' learning motivation,

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practical abilities, and innovative thinking by providing realistic simulation scenarios. At the same time, MR technology supports interdisciplinary learning through the integration of knowledge from different fields, which contributes to the comprehensive development of students' skills [6–12].

Despite these advantages, current studies on MR-based education still face several limitations. Existing methods remain insufficient in extracting students' task performance and behavioral features, and the prediction of learning outcomes based on interdisciplinary information is still limited in accuracy and effectiveness [13–18]. In particular, the complex relationships between tasks and behaviors in MR learning environments have not been fully explored using deep learning techniques.

This study investigates task performance and behavioral features in MR innovative practice environments and analyzes their relationships with students' learning performances. In addition, a deep learning-based data fusion model with an end-to-end training strategy is proposed to predict task-behavior correlations in interdisciplinary MR learning contexts. The proposed approach is expected to provide practical support for MR-assisted education and interdisciplinary learning research.

2 TASK CHARACTERISTICS IN MIXED REALITY INNOVATIVE PRACTICE

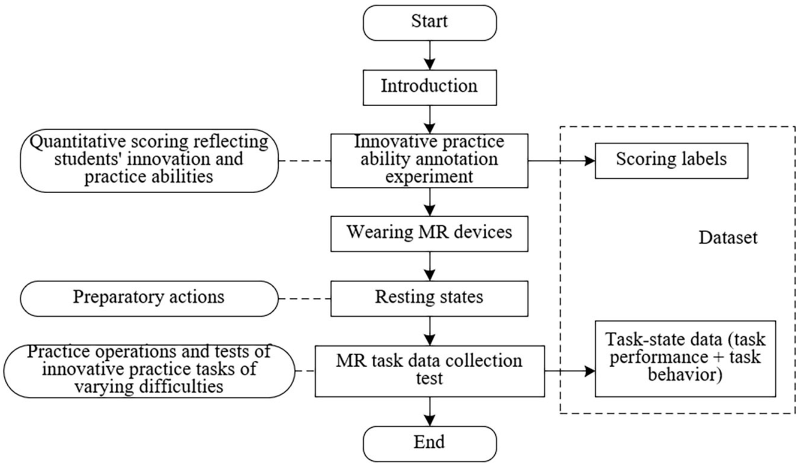


Fig. 1. Data collection process for tasks in MR innovative practice

In MR innovative practice environments, task performance and task behavior are important indicators for evaluating students' learning outcomes and interaction processes. Task performance data mainly reflect the accuracy and efficiency of task completion, while task behavior data describe students' operational patterns and problem-solving processes during task execution. The analysis of these features helps reveal students' learning characteristics and supports the development of more effective and personalized learning models in MR environments. Figure 1 illustrates the data collection process for tasks in MR innovative practice.

2.1 Characteristics of task performance

a) Maximum, minimum, and average innovative practice time: The maximum, minimum, and average practice times were used to evaluate students' task efficiency in MR environments. The maximum value represents the longest completion time, while the minimum value indicates the shortest completion time. The average value reflects the overall efficiency of students during innovative practice activities.

b) Number of timely successful attempts: The number of timely successful attempts refers to the frequency with which students successfully completed a task within a specified time limit. This metric reflects students' task execution ability and time management performance under constrained conditions.

c) Maximum, minimum, and average innovative practice pathways: The maximum, minimum, and average pathway lengths describe the number of steps students used to complete complex tasks. The maximum value indicates extensive exploration during problem solving, whereas the minimum value reflects a more direct and efficient approach. The average value represents the common problem-solving pattern among students.

d) Nearest exploration pathway: The nearest exploration pathway refers to the shortest and most efficient sequence of steps adopted by students to reach a target solution. This feature reflects students' ability to identify effective solutions through rapid exploration and decision-making.

e) Time and path proportions in target areas: The time proportion in the target area represents the ratio between the time spent in key task regions and the total task duration, while the path proportion represents the ratio between the actual movement path and the optimal shortest path. These indicators evaluate students' concentration and pathway efficiency during task execution. The corresponding calculations are expressed as follows:

$$PLSz = \frac{PLS}{TOS} \tag{1}$$

$$PLTz = \frac{PLT}{TOT} \tag{2}$$

where $PLSz$ and $PLTz$ denote the time and path proportions in the target area, respectively, and TOT, PLS, and PLT represent the total task duration, time spent in the target area, and path length in the target area.

2.2 Task behavior characteristics

a) Maximum, minimum, and average speeds in student innovative practice: The maximum, minimum, and average speeds were used to evaluate students' movement efficiency during MR innovative practices. The maximum speed represents the highest movement speed during task execution, while the minimum speed indicates the slowest movement state. The average speed reflects the overall pace of task completion. Assuming that the position coordinates at time s_u are represented as (a_u, c_u), the maximum ($NMAX$), minimum ($NMIN$), and average (NME) speeds were calculated as follows:

$$n = \frac{\sqrt{(a_{u+1} - a_u)^2 + (c_{u+1} - c_u)^2}}{s_{u+1} - s_u} \tag{3}$$

$$NME = \frac{\sum_{u=1}^{v} n_u}{v} \tag{4}$$

b) Standard deviation of innovative practice speed: The standard deviation of innovative practice speed was used to measure the variability of students' movement speeds during task execution. A larger value indicates greater fluctuations in movement speed, whereas a smaller value reflects more stable behavior. The calculation is expressed as follows:

$$NTsf = \sqrt{\frac{\sum_{u=1}^{v}(n_u - NME)^2}{v-1}} \tag{5}$$

c) Normalized variability of innovative practice speed: The normalized variability of innovative practice speed was defined as the ratio between the speed standard deviation and the average speed. This metric was used to compare speed variability across different students and tasks. The calculation is expressed as follows:

$$VNN = \frac{1}{S|NME|}\sum_{u=1}^{v-1}\left|n_{u+1} - n_u\right| \tag{6}$$

d) Information entropy in innovative practice coordinates: Information entropy was used to evaluate the randomness of students' movement trajectories in MR environments. Higher entropy values indicate more complex and irregular movement patterns. Assuming that the probabilities of coordinate positions are represented by $o(a_u)$ and $o(c_u)$, the entropy was calculated as follows:

$$RSO_a = -\sum_{u=1}^{v} o(a_u)\log_2(o(a_u)) \tag{7}$$

$$RSO_c = -\sum_{u=1}^{v} o(c_u)\log_2(o(c_u)) \tag{8}$$

e) Initial directional error: Initial directional error refers to the deviation between the initial movement direction selected by students and the optimal direction toward the target. This metric reflects the accuracy of students' initial navigation decisions. The directional vectors from the starting point to the target position and platform center are represented by f_{ST}, and f_{PL}, respectively. The calculation is expressed as follows:

$$SD = \beta =< f_{ST,} f_{PL} > \tag{9}$$

3 TASK-BEHAVIOR CORRELATION PREDICTION IN MIXED REALITY

Mixed reality environments provide students with interactive and immersive conditions for interdisciplinary learning and problem-solving. To process complex interdisciplinary information, deep learning methods were adopted because of their strong capabilities in feature extraction and pattern recognition. By constructing interdisciplinary knowledge similarity matrices, the proposed approach identifies relationships among knowledge elements and integrates them through a hierarchical network structure. This process helps reveal the connections between different disciplines and supports the development of students' comprehensive learning and problem-solving abilities.

3.1 Deep learning-based model for interdisciplinary data fusion

The proposed deep learning-based data fusion model consists of an input layer, multiple hidden layers, and an output layer. This hierarchical structure is used to process nonlinear relationships in interdisciplinary MR learning data. The input layer receives interdisciplinary knowledge similarity matrices that describe the relationships among knowledge elements from different disciplines. The hidden layers perform feature extraction and weighted activation to learn deeper data representations, while the output layer generates a fused data matrix representing interdisciplinary knowledge relationships. The generated matrix provides integrated knowledge information for MR learning environments.

The mathematical representation of the input interdisciplinary knowledge similarity matrices is denoted as $T = [T_1, T_2, \ldots, T_s] \in E^{V*V*s}$. The parameters for each layer are symbolized by $q(s)$, and the feature matrix for the subsequent layer, derived post-activation function (δ) processing, is represented by T'. The bias in the model is indicated by y. The computational process is encapsulated as follows:

$$T^{m+1}(:,k) = \delta\left(\sum_{k,s\in T} T_s^{m}(:,k)\cdot q^{m+1}(s) + y^{m}\right) \tag{10}$$

3.2 End-to-end training method for task-behavior correlation prediction

The proposed end-to-end training method directly learns the relationships between interdisciplinary knowledge and student behaviors from MR task data without relying on manually designed rules or external feature extraction. Historical MR task data were used to construct interdisciplinary knowledge similarity matrices containing task and behavioral information from different disciplines. Through deep learning, the model integrates these features and predicts task-behavior correlations in MR learning environments. Figure 2 shows the overall framework of the proposed prediction model.

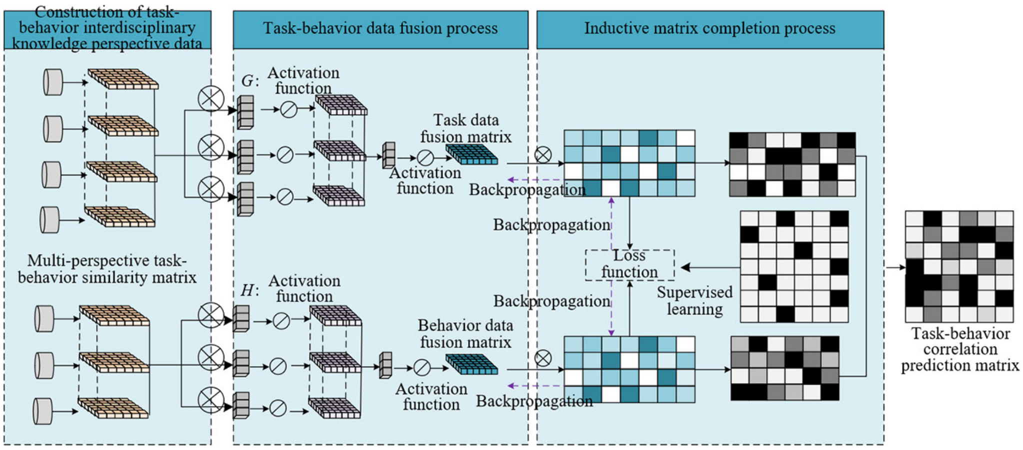


Fig. 2. Comprehensive framework of the MR task-behavior correlation prediction model

The training process begins with extracting task and behavioral data from the MR task database to establish interdisciplinary similarity matrices. These matrices are then input into the deep learning network for feature fusion through forward and backward propagation. The fused task and behavior matrices are further processed using an inductive matrix completion method to improve the model's ability to handle incomplete data and enhance prediction accuracy.

To optimize the prediction performance, the parameters of both the fusion module and the correlation prediction module are updated simultaneously during training. The loss value generated by the inductive matrix completion module is used to measure the difference between predicted and actual results. By minimizing the loss value, the model gradually improves the accuracy of task-behavior correlation prediction. Figure 3 illustrates the interdisciplinary knowledge fusion process used in the proposed model.

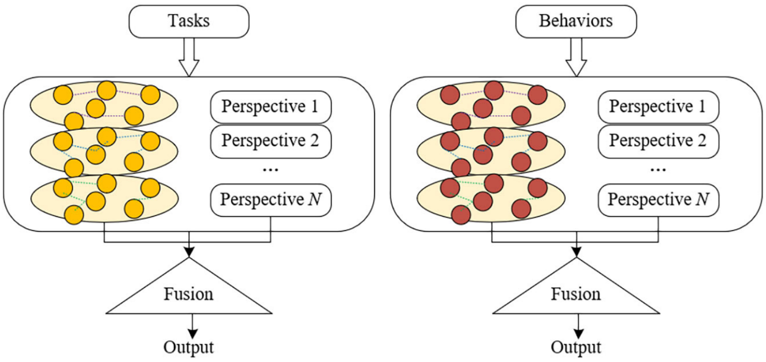


Fig. 3. Mixed reality task-behavior interdisciplinary knowledge perspective fusion

In detail, the approach commences with the transformation of task and behavior data from the historical database into interdisciplinary knowledge perspective similarity matrices. These matrices are subsequently fed into the interdisciplinary knowledge perspective fusion model. Within this model, the internal neural network architecture processes the input matrices, resulting in the production of fused feature matrices for tasks and behaviors. During the training of the task-behavior fusion module, the matrices corresponding to tasks and behaviors, derived from various disciplinary knowledge perspectives, are utilized as feature matrices. The fusion model, denoted by *Fu*, outputs a task fusion matrix *Fe* and a behavior fusion matrix *MVF*(·). The model processes input matrices from multiple disciplinary perspectives, represented as T_v^e for tasks and T_j^u for behaviors. The trained parameter matrices within the model are symbolized by G and H. More specifically, the calculations involve combining these matrices, with $T_v^e G$ represented as $T_1^e g_1 + T_2^e g_2 + \ldots + T_j^u g_y$, and $T_j^u H$ as $T_1^u h_1 + T_2^u h_2 + \ldots + T_j^u h_j$, leading to the following computation:

$$\begin{aligned} Fe &= MVF\left(\delta\left(T_v^e G + y_1\right)\right) \\ Fu &= MVF\left(\delta\left(T_j^u H + y_2\right)\right) \end{aligned} \tag{11}$$

In the concluding segment of the methodology, the inductive matrix completion module plays a pivotal role. Upon receiving the fused matrices, the module engages in completing any missing or uncertain data based on the existing dataset, subsequently calculating the loss value. Utilizing the backpropagation algorithm, this loss value is instrumental in updating the parameters within both the inductive matrix completion module and the interdisciplinary knowledge perspective fusion model. This iterative process fosters self-optimization of both modules. In this context, it is posited that known task-behavior correlations are denoted as T, with non-correlations indicated as T^{-}. The model's training parameter matrices, represented by O and W, are complemented by the inclusion of a negative sample denoted as Fu', a balancing factor β, and a regularization coefficient α. The formulation of the inductive matrix completion method adheres to the following equation:

$$\begin{aligned} &\underset{O,W}{MIN} \sum_{u,k \in t} \frac{1-\beta}{2}(S_{uk} - Fe \cdot OW^S \cdot Fu)^2 + \sum_{u,k \in \bar{t}} \frac{\beta}{2}(S_{uk} - Fe \cdot OW^S \cdot Fu')^2 \\ &+ \alpha\left(\|O\|_D^2 + \|W\|_D^2\right) \end{aligned} \tag{12}$$

This iterative cycle persists until a minimization of the loss value is achieved, signaling the model's capability to deliver precise predictions of task-behavior correlations. Such precision plays a crucial role in providing tailored support and guidance for interdisciplinary learning within MR environments.

4 EXPERIMENTAL RESULTS AND ANALYSIS

In the analysis of experimental results, significant variances were observed in the proportions of task performance and behavior features across different levels of innovative ability, as indicated in Figure 4. The proportion of task behavior feature 1 was found to be the most prevalent at 75.00%, whereas task behavior feature 2 exhibited a relatively lower proportion of 25.00%. For task performance features, both task performance features 4 and 5 accounted for more than half, with 55.57% and 53.70% respectively, underscoring their critical role in assessing students' innovative practices within an MR environment. This quantitative analysis elucidates the intrinsic patterns of student performance in MR settings, highlighting the relevance of specific task performance and behavior features in distinguishing varying levels of innovative practice abilities. The predominance of certain features serves as a key differentiator among students' innovation capabilities, affirming the effectiveness of the proposed feature extraction methodology.

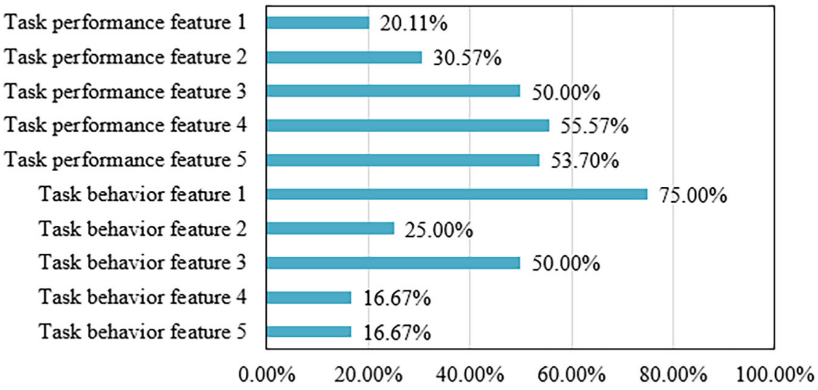


Fig. 4. Proportion of features with significant differences in different innovative ability levels

Further scrutiny of the data proportions in Figure 5 reveals noteworthy disparities in the representation of task behavior and performance features, which correlate with distinct levels of innovative practice ability. In the domain of task behavior features, Features 5, 2, and 1 each accounted for a proportion of 25.00%, while Features 4 and 3 were less influential at 16.67% and 12.31% respectively. Among task performance features, Feature 3 was most prominent at 72.22%, followed closely by Feature 4 at 66.67% and Feature 2 at 52.78%, with Features 5 and 1 being relatively less represented. These findings corroborate the efficacy of the implemented feature extraction method, demonstrating its capacity to effectively discern students' innovative practice abilities in MR contexts. Notably, the substantial representation of task performance features 3 and 4 emerges as a fundamental aspect in the evaluation of students' practice abilities, complemented by task behavior features that offer an auxiliary lens to assess students' behavioral patterns. Through these significantly varied features, educators and researchers are equipped to conduct more precise assessments and enhancements of students' practice capabilities within MR learning frameworks.

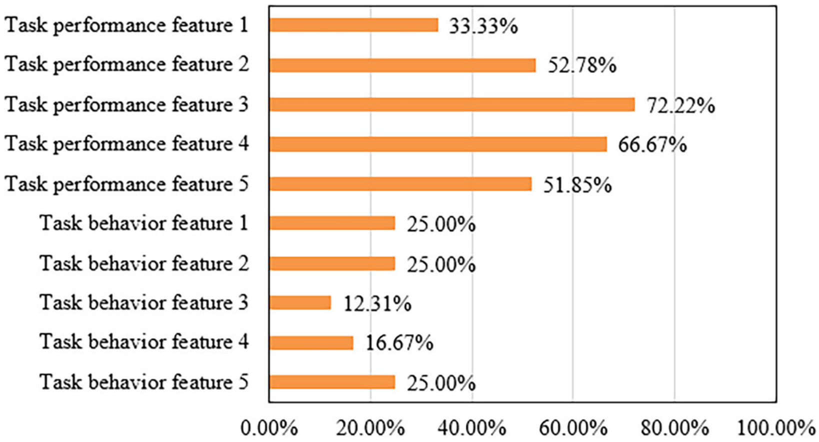


Fig. 5. Proportion of features with significant differences in different practice ability levels

Table 1. Significant feature differences between normal and outstanding groups in comprehensive innovative practice ability

Feature Name	Comprehensive Innovative Practice Ability Level		Significance P
	Normal	Outstanding	
	Mean (Standard Deviation)	Mean (Standard Deviation)	
Task performance feature 1	21.35 (6.89)	12.35 (1.47)	0.015
Task performance feature 2	26.57 (0.84)	23.69 (0.77)	0.015
Task performance feature 3	0.53 (0.13)	0.72 (0.12)	0.009
Task performance feature 4	6.52*E*-04 (4.48*E*-04)	2.78*E*-04 (3.14*E*-04)	0.011
Task performance feature 5	2.14 (0.21)	1.89 (0.21)	0.005
Task behavior feature 1	135.24 (1.58)	114.25 (1.89)	0.013
Task behavior feature 2	11.25 (0.81)	11.48 (0.63)	0.023
Task behavior feature 3	25.21 (0.77)	24.33 (0.51)	0.013
Task behavior feature 4	0.55 (0.14)	0.75 (0.13)	0.005
Task behavior feature 5	132.04 (1.53)	117.61 (1.87)	0.011

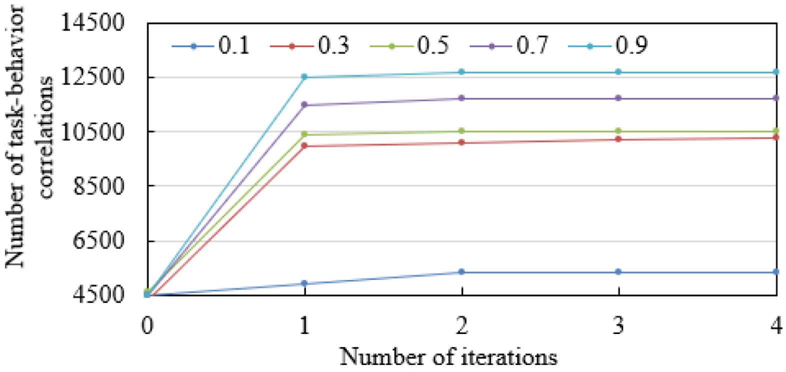
In the examination of the empirical results, Table 1 delineates the discernible differences in features between normal and outstanding groups regarding comprehensive innovative practice ability. The table delineates each feature by name and aligns it with the respective levels of comprehensive innovative practice ability, supplemented by the significance P values. The mean values and standard deviations for each feature are systematically tabulated for both normal and outstanding groups. A meticulous analysis of the data reveals substantial disparities between the two groups across all listed features ($P < 0.05$). Notably, for Task performance feature 1, a significantly lower mean value is observed in the outstanding group compared to the normal group, implying a more concentrated and superior performance level in this feature among the outstanding group. For task performance features 2–5, the outstanding group manifests higher values (Feature 3), reduced variability (Feature 4), or lower mean values (Feature 5), suggesting a correlation of these features with the quality and efficiency of task completion. In the domain of task behavior features, the outstanding group's lower mean values for Features 1 and 5 indicate more efficient or purposeful behavior. Although Features 2 and 3* display significant differences, their mean values are closely aligned, suggesting a less sensitive discernment of group categories compared to other features. Feature 4's significantly higher mean value in the outstanding group relates to the frequency or quality of specific behavioral patterns. In essence, the data in Table 1 illustrates the efficacy of the applied feature extraction method in differentiating student groups based on their comprehensive innovative practice abilities. The significant P values indicate statistical differences between the normal and outstanding groups across these features, directly correlating with students' performance in MR environments. Consequently, these results underscore the validity of the feature extraction method employed in evaluating students' comprehensive innovative practice abilities.

Table 2. Top ten task-behavior correlation prediction results from this experiment

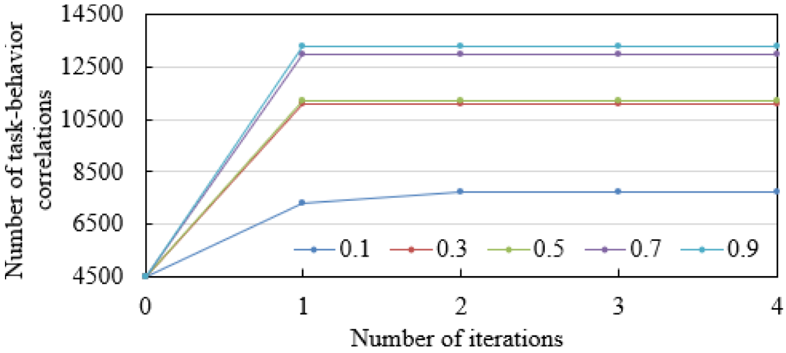
Task	Behavior	Evidence (PMID)
Biochemical molecular simulation and experiment	Simulated experiment	33154795
Environmental science data analysis	Adjusting virtual terrain, and simulating ecological changes	22354875
Physics kinematics exploration	Building and testing virtual structures	32154753
Historical culture recreation	Participating in role-playing	31245867
Mathematical modeling and virtual economic systems	Creating and managing systems	Unconfirmed
Art design and digital exhibition planning	Planning and exhibiting virtual art shows	17542586
Music theory and virtual instrument performance	Playing virtual instruments	31256458
Astrophysics observation and space simulation	Simulating space exploration	Unconfirmed
Psychological behavior research and simulated interaction	Simulating social situations	Unconfirmed
Programming logic and robotics control	Controlling virtual robots	32145785

In the analysis of experimental outcomes, Table 2 elucidates the top ten task-behavior correlation predictions, ascertained through the deployment of a deep learning-based data fusion model subjected to end-to-end training. Each task-behavior pair in the list is substantiated by corresponding literature evidence number, which is PubMed Unique Identifier (PMID), underscoring the empirical foundation of these predictions. The array of tasks spans diverse academic disciplines, encompassing biochemistry, environmental science, physics, history, mathematics, art, music, astrophysics, psychology, and computer science. This diversity attests to the broad applicability of interdisciplinary information fusion within the domain of MR technology. The table indicates that for most task-behavior duos, there exists literature evidence corroborating their interrelation, affirming the predictive method's capacity to discern authentic, scientifically grounded associations. However, certain pairs, such as mathematical modeling and virtual economic systems, astrophysics observation and space simulation, and psychological behavior research and simulated interaction, are marked as "unconfirmed." This designation implies that these specific predicted correlations have not yet been substantiated by existing scholarly works, thereby highlighting potential avenues for future research endeavors. The findings demonstrate the efficacy of the employed deep learning-based data fusion model and the end-to-end training methodology within the scope of this study. Notably, the predicted correlations between tasks and behaviors, which are supported by scientific literature, can serve as valuable guides for educators in structuring effective pedagogical tasks in MR settings. Moreover, these insights can significantly aid students in comprehending the interconnections among various academic disciplines, thereby fostering their interdisciplinary learning.

In the investigation of task-behavior correlation changes across different datasets, Figure 6 delineates the variations observed in the number of these correlations in laboratory, online, and field datasets over successive iterations. This part of the study provides a comparative analysis of the model's performance across varying data environments. At the outset (iteration zero), a uniform starting point is evident across all datasets for each balancing factor setting, establishing an equitable baseline for subsequent comparisons. As iterations progress, an increase in the number of task-behavior correlations is observed across all settings, indicative of the model's deepening training and enhanced capacity to predict more extensive task-behavior associations. Notably, with an increment in the balancing factor, a corresponding rise in correlation numbers is observed, particularly pronounced in later iterations. For instance, settings with higher balancing factors, such as 0.7 and 0.9, demonstrate a greater increase in correlations compared to lower factors such as 0.1 and 0.3. This pattern suggests the pivotal role of the balancing factor in modulating the task-behavior correlation prediction model, especially pertinent to addressing imbalances in varied data categories. Following a certain number of iterations, the growth in the number of correlations stabilizes, indicating the model's convergence after sufficient training, with the predicted correlation numbers reaching a steady state. The results from this phase of the study affirm the efficacy of the proposed MR task-behavior correlation prediction methodology across diverse datasets and under various balancing factor settings. The observed increases and subsequent stabilization in correlation numbers reflect the model's learning and generalization capabilities. Moreover, the introduction of the balancing factor effectively aids the model in adapting to different data distributions, enhancing its predictive power in scenarios of data imbalance.

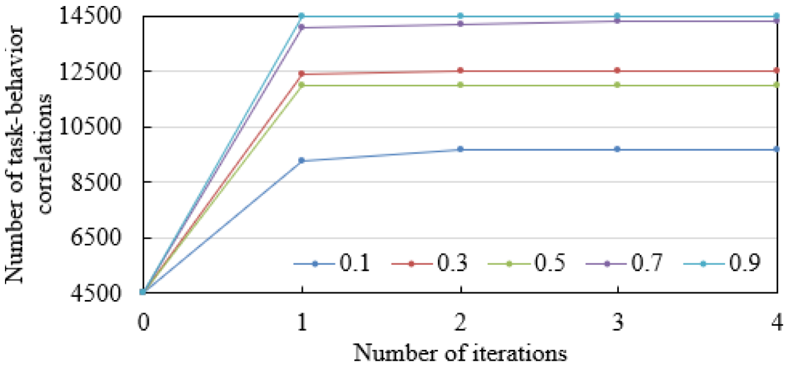


a) Laboratory dataset



b) Online dataset

Fig. 6. *(Continued)*



c) Field dataset

Fig. 6. Changes in the number of task-behavior correlations in different datasets with iteration

In the presented study, experimental results regarding task-behavior correlation prediction were obtained for various data fusion models, assessed using the Hits@1 metric (refer to Table 3). This metric reflects the precision of the model's foremost prediction. It was discerned that models founded on deep learning principles, namely recurrent neural network (RNN), hypergraph convolutional network (HGCN), hierarchical attention mechanism network (HMAN), deep belief networks (DBN), graph neural networks (GNN), attribute graph neural network (AttrGNN), and the model proposed within this study, uniformly surpassed those based on conventional algorithms in terms of Hits@1 values. This pattern was consistent across both original and preprocessed datasets, thereby underscoring the proficiency of deep learning models in addressing the complexities inherent in correlation prediction tasks. A noteworthy observation from the results is the enhanced performance of most models on preprocessed datasets compared to original datasets, implying that preprocessing procedures substantially augment predictive accuracy. Of all models evaluated, the model introduced in this study recorded the highest Hits@1 scores in each comparative set, particularly achieving a notable accuracy rate of 91.56% on the preprocessed dataset. This outcome indicates not only the model's adeptness in dealing with intricate correlation prediction tasks but also its heightened responsiveness to the nuances of data preprocessing. Within the spectrum of traditional models, the Dempster-Shafer theory demonstrated superior performance. Meanwhile, in the domain of deep learning models, both GNN and the model developed in this study emerged as prominent. This observation suggests that the task-behavior correlation prediction in MR environments benefits significantly from graph-structured data representation and the advanced feature learning capabilities inherent in deep learning models. To encapsulate, the MR task-behavior correlation prediction methodology proposed in this paper exhibits a marked superiority in predictive accuracy, particularly when applied to preprocessed datasets. These findings underscore the method's efficacy in comprehensively understanding data structures and correlation patterns within MR learning contexts. The potential applicability of this approach extends to enhancing interdisciplinary learning, elevating educational quality, and refining personalized learning recommendation systems, as suggested by the experimental outcomes.

Table 3. Task-behavior correlation prediction experimental results for different datasets

Type of Data Fusion Model Employed	Model Name	Original Dataset		Preprocessed Dataset	
		Hits@1	Hits@1	Hits@1	Hits@1
Based on traditional algorithms	*Kalman filter*	31.25	62.14	23.47	51.24
	Particle filter	41.27	71.25	37.21	68.23
	Dempster-Shafer theory	62.38	81.23	61.58	78.54
	Bayesian networks	41.47	72.85	41.23	71.21
Based on deep learning	*CNN*	4256	73.26	35.69	68.69
	RNN	64.89	85.46	62.47	82.33
	HGCN	73.21	84.52	67.89	77.45
	HMAN	55.68	84.23	52.31	82.13
	DBN	72.86	84.97	71.45	82.47
	GNN	78.95	81.25	75.69	87.52
	AttrGNN	73.21	85.87	71.45	81.23
	Proposed model	83.58	89.36	82.56	91.56

5 CONCLUSIONS

In this study, the emphasis has been placed on the utilization of MR technology to facilitate interdisciplinary learning among students. The study has been primarily focused on the prediction and optimization of task-behavior correlations using data fusion models. It aimed at uncovering the innovative practice abilities of students within MR learning environments through quantitative analysis and augmenting the precision of task-behavior correlation predictions with deep learning methodologies. This approach is intended to foster the creation of individualized learning pathways and the refinement of educational techniques.

The experimental segment of the study involved the identification and extraction of critical task performance and behavior characteristics that influence students' capacity for innovative practice. A quantitative analysis of the distribution of these characteristics revealed a significant association between specific features and the level of students' innovative abilities. The results have validated the effectiveness of the feature extraction method employed in this study in differentiating between varying levels of innovative ability. Additionally, the study investigated the performance variations of the MR task-behavior correlation model across diverse datasets and under different settings of balancing factors. It was observed that as the balancing factors and the number of iterations increased, the quantity of correlations predicted by the model expanded and eventually stabilized. This phenomenon underscores the vital role of balancing factors in managing data imbalances during the model's training phase. The comparative analysis of various data fusion models, encompassing both traditional algorithms and deep learning methodologies, was conducted on both original and preprocessed datasets. The deep learning models, particularly GNNs and the model proposed in this study, demonstrated superior performance in comprehensive prediction tasks. These findings highlight the strengths of deep learning models in navigating complex correlation prediction challenges, with the model introduced in this study achieving the highest accuracy on the preprocessed dataset.

For future research, several pathways are suggested. First, expanding the testing to include a broader array of MR learning scenarios would further ascertain the generalization capabilities of the model. Second, an exploration into the adaptability of the model across different cultural and educational contexts is recommended. Lastly, integrating real-time feedback mechanisms and adaptive learning algorithms could enhance the effectiveness of personalized teaching approaches within MR learning environments. This exploration would potentially yield significant advancements in the field of educational technology and contribute to the evolution of learning methodologies.

6 ACKNOWLEDGMENTS

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