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PAPER

Enhancing Interdisciplinary Learning and Innovative Practice in Students through Mixed Reality: A Deep Learning Approach

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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

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1 INTRODUCTION

In the swiftly evolving landscape of contemporary technology, particularly marked by the information technology revolution, the field of education is undergoing transformative changes [1]. mixed reality (MR), synthesizing virtual reality (VR), and augmented reality (AR) features, has been established as an innovative tool, offering students an immersive learning environment that substantially extends beyond the confines of traditional educational methodologies [2–5]. This study aims to methodically investigate the application of MR technology in augmenting students' capabilities for innovative practice and interdisciplinary learning. Additionally, it focuses on identifying crucial task-state characteristics that facilitate this educational process.

The relevance of MR technology in educational contexts is becoming increasingly pronounced. It serves not only to elevate students' motivation for learning but also to enrich their practical skills and innovative thinking through simulated real-life scenarios [6–8]. Concurrently, as interdisciplinary approaches gain momentum in educational strategies, MR technology emerges as a facilitator for integrating knowledge across various disciplines. This integration fosters a comprehensive enhancement of students' skill sets [9–12]. Therefore, the exploration of strategies to utilize MR technology in promoting innovative practices and interdisciplinary learning among students is of substantial theoretical and practical importance.

However, the research on quantifying students' practical performance and behavioral characteristics within MR environments, as well as predicting learning outcomes from these data, remains underdeveloped [13–15]. Existing methodologies exhibit limitations in extracting task performance and behavioral characteristics comprehensively. Moreover, the models used for predicting interdisciplinary information integration have yet to fully exploit the capabilities of deep learning technology, leading to a lack of precision in understanding and predicting the intricate relationships between tasks and behaviors [16–20].

This paper primarily addresses two research dimensions. The first dimension involves a detailed investigation into the extraction of task-state characteristics within MR's innovative practice environment, categorizing them into task performance and behavior characteristics. Through quantitative analysis, this segment aims to uncover the inherent patterns of student learning performance within MR settings. The second dimension delves into the prediction of task-behavior correlations within the scope of interdisciplinary information integration in MR. For this purpose, a deep learning-based data fusion model is employed, coupled with an end-to-end training approach for correlation prediction, striving for enhanced predictive accuracy and practical applicability. The outcomes of this study are anticipated to offer scientific analytical methods and actionable guidelines for implementing MR technology in educational contexts, thereby establishing a foundation for subsequent studies in this domain.

2 EXTRACTING TASK-STATE CHARACTERISTICS IN MR INNOVATIVE PRACTICE

In the realm of MR innovative practice, task performance and task behavior have been identified as crucial metrics for the assessment of students' learning outcomes and interactive behaviors. The data pertaining to task performance encompasses quantitative indicators such as the accuracy and efficiency of task completion, which are reflective of students' capabilities in executing specific tasks. Concurrently, task behavior data embody students' operational patterns, decision-making processes, and problem-solving strategies during task execution. These insights offer a profound understanding of students' behavioral patterns in navigating complex tasks. The extraction of these two feature categories is essential; accurate analysis of this data enables the development of more personalized and optimized learning models. These models are instrumental in deepening the comprehension of students' interactions, learning processes, and innovation within MR environments, thus augmenting the effectiveness of MR technology in educational contexts and enhancing students' innovative practice capabilities.

2.1 Characteristics of task performance

a) Maximum, minimum, and average values of innovative practice time: The assessment of task performance in MR innovative practice encompasses the evaluation of the maximum, minimum, and average values of time spent in innovative practice activities. These measures provide key dimensions for gauging the efficiency of students' engagements in MR environments. The "maximum value" is characterized as the lengthiest duration a student requires to complete an innovative practice task within a specified assessment period. Conversely, the "minimum value" is identified as the briefest duration required by a student for the same task within the identical timeframe. The "average value" is calculated as the mean duration taken by all students to accomplish the innovative practice task within that assessment period.

b) Number of timely successful attempts: Moreover, the "number of timely successful attempts" is defined as the frequency of a student successfully completing a specific innovative practice task within a predetermined time limit. This metric not only aids educators in comprehending student performance under temporal constraints but also acts as a foundation for refining instructional designs, modifying task difficulty, and fostering students' time management competencies.

c) Maximum, minimum, and average values of innovative practice pathways: Furthermore, the "maximum, minimum, and average values of innovative practice pathways" are examined. These refer to the variety of steps and sequences students undertake while completing intricate tasks. The "maximum value" represents the occasion where the student employs the greatest number of steps to achieve the task, denoting extensive methodological exploration and iterative processes indicative of their depth and persistence in addressing intricate challenges. The "minimum value," signifying the least number of steps for task completion, illustrates the student's capacity for direct and effective problem resolution. The "average value," signifying the mean pathway length across all completing students, provides a normative standard, reflecting the prevalent problem-solving approach within the student group.

d) Nearest exploration pathway in student innovative practice: In the context of MR innovative practice, the "nearest exploration pathway" is identified as the sequence of steps executed by students that represents the most direct and efficient approach to seeking innovative solutions. Characterized by the minimal number of steps, shortest distance, or quickest time, this pathway is selected from a range of potential exploration paths. It serves as an indicator of the student's ability to effectively sift through information, swiftly engage in trial and error, and ascertain optimal solutions when confronted with open-ended challenges.

e) Time and path proportions in target areas of student innovative practice: The study also examines the "time and path proportions in the target area of student innovative practice." The former is quantified as the ratio of the duration spent in pivotal sections of a task to the overall task duration, reflecting a student's concentration and efficiency in critical phases of task execution. The latter is calculated as the ratio of the actual pathway traversed by the student to reach their objective compared to the shortest possible path, thereby assessing the student's directness in practice and the optimization of their path selection. The calculation of these metrics involves formulas where *PLSz* and *PLTz* represent the time and path proportions in the target area, respectively, while *TOT*, *PLS*, and *PLT* denote the total pathway length of activities on the innovative practice platform, as well as the duration and path length within specified ranges.

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

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

2.2 Task behavior characteristics

a) Maximum, minimum, and average speeds in student innovative practice: In assessing student innovative practice within MR environments, three key speed metrics are identified: maximum, minimum, and average speeds. The "maximum value" is associated with the highest speed reached by students during practice activities, typically observed when students are highly familiar with the task or under pressing deadlines. Conversely, the "minimum value" denotes the slowest speed in the practice process, usually occurring when students encounter uncertainty or require in-depth reflection. The "average value" is determined as the mean speed across the entirety of the innovative practice, representing the general pace at which students handle tasks. The position coordinates at a given time s_u are represented as (a_u, c_u), with the calculation of the maximum (*NMAX*), minimum (*NMIN*), and average (*NME*) speeds for each practice trajectory formulated as follows:

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

The computation of the average value, *NME*, is conducted using the formula below, where v signifies the number of elements within the speed matrix:

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

b) Standard deviation of student innovative practice speed: The "standard deviation of student innovative practice speed" is quantified as a statistical indicator of the variability in students' speed throughout the practice. This metric assesses the fluctuations or uniformity of students' speeds during innovative practices. For instance, in an MR-based task that involves navigating to and resolving problems at various information points, the standard deviation metric evaluates the variability of movement speeds among these points. A larger standard deviation implies varying durations of stay and movement speeds at different points, while a smaller value suggests more consistent speeds across all locations. The formula for this calculation is presented as follows:

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

c) Normalized variability of student innovative practice speed: In the context of MR-supported student innovative practices, the "normalized variability of student innovative practice speed" is identified as a pivotal task behavior characteristic. This metric is formulated as the ratio between the standard deviation of speed fluctuations and the average speed throughout task execution. It provides an adjusted indicator of speed variability, facilitating more equitable and consistent comparisons across distinct individuals or tasks. The total duration of the task is denoted by *S*, leading to the following computational formula:

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

d) Information entropy in student innovative practice coordinates: The "information entropy in student innovative practice coordinates" in MR-aided student activities is quantified as a measure of the randomness of student movements within virtual spaces. This metric, derived from the distribution of students' positional data during task execution, utilizes the principle of information entropy to evaluate the uncertainty or intricacy of this distribution. In contrast, a systematic movement pattern, following a specific sequence of station visits, would indicate a lower information entropy. The likelihood of occurrence for specific coordinate positions is indicated by $o(a_u)$ and $o(c_u)$, and the calculation is expressed 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: The "initial directional error" within student innovative practice is defined as the deviation between the initial direction chosen by students from the start point to the first target and the optimal pathway. This metric evaluates the precision of students' initial navigational choices in response to initial challenges or tasks. In an MR educational game scenario, the directional vector from the starting point to a position point X is symbolized by f_{ST}, and the vector from the start to the platform center by f_{PL}, leading to the subsequent formula:

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

3 INTERDISCIPLINARY INFORMATION FUSION FOR PREDICTING TASK-BEHAVIOR CORRELATIONS IN MIXED REALITY

In MR environments conducive to interdisciplinary learning, students are provided with an enriched setting for interaction, exploration, and problem-solving across various disciplines. Here, the application of deep learning for the fusion of interdisciplinary information is emphasized due to its exceptional capability in feature extraction and pattern recognition, particularly in contexts involving high-dimensional and complex data. Deep learning models facilitate the extraction and identification of pivotal knowledge points and skills from diverse disciplines. This is achieved by constructing matrices that represent similarities in knowledge perspectives and capabilities. The models then adeptly merge these insights through a hierarchically structured network. Such an approach unveils the inherent interconnections between knowledge and skills across disciplines, offering students an integrated pathway for learning. This integration is instrumental in developing a comprehensive knowledge framework and enhancing problem-solving abilities.

3.1 Deep learning-based model for interdisciplinary data fusion

The constructed deep learning-based model for interdisciplinary data fusion comprises an input layer, several intermediate layers, and an output layer. This hierarchical architecture is adept at processing intricate, non-linear relationships between data, rendering it suitable for analyzing and amalgamating complex knowledge structures from various disciplines in MR settings. The input layer is designed to receive an array of interdisciplinary knowledge similarity matrices, which encode the relationships and similarities among knowledge elements from different disciplines. The intermediate layers, equipped with multi-layer neurons, perform the weighted activation and transmission of input data. This step-by-step processing refines and abstracts the data's features, thereby enabling the model to discern the deeper structures and latent linkages within interdisciplinary knowledge. The output layer is responsible for generating a data fusion matrix that encapsulates the consolidated knowledge system, delineated by the model. This matrix serves as a tailored knowledge framework to enrich students' learning experiences in mixed reality.

The mathematical representation of the input interdisciplinary knowledge similarity matrices is denoted as $T = [T_1, T_2, T_s] \in E^{V*V*s}$. 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

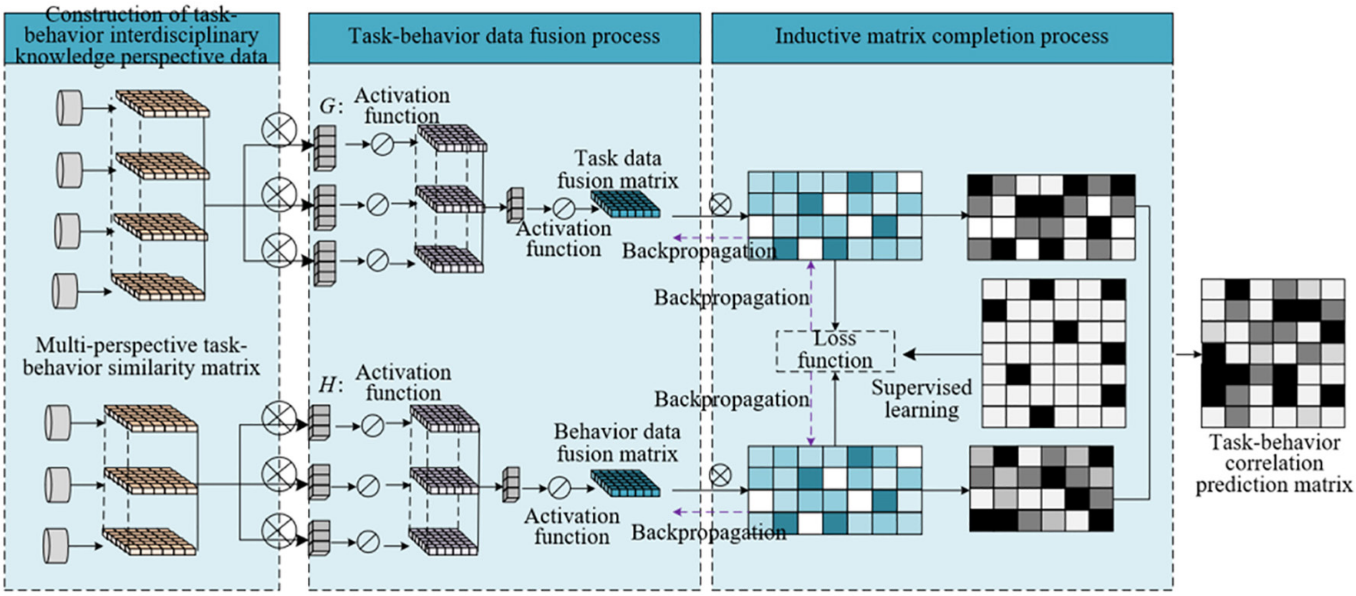

Fig. 1. Comprehensive framework of the MR task-behavior correlation prediction model

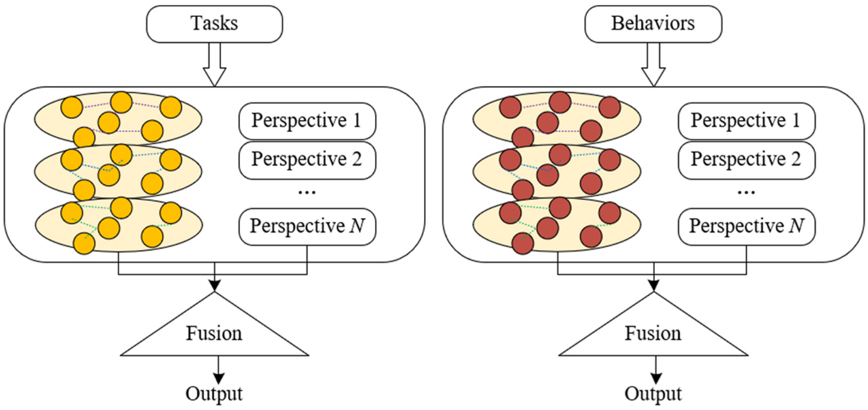

Fig. 2. MR task-behavior interdisciplinary knowledge perspective fusion

Figure 1 delineates the comprehensive framework of the MR task-behavior correlation prediction model. The process initiates with the extraction of task and behavioral data from the MR task history database, leading to the establishment of an interdisciplinary knowledge similarity information matrix. Utilizing a deep learning model, multiple matrices representing knowledge perspectives from different disciplines are inputted. The model undergoes training through both forward and backward propagation, culminating in the output of fused matrices for tasks and behaviors. These matrices are subsequently subjected to an inductive matrix completion method, entailing additional training to enhance the model's ability to address missing or incomplete data. Ultimately, the model outputs a task-behavior correlation prediction matrix, offering quantified insights into the interplay between tasks and student behaviors in interdisciplinary learning contexts.

The methodology employed in this paper for the advanced integration of task and behavior data in MR leverages the inductive matrix completion method (Figure 2). 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 F_u, 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^eG represented as $T_1^eg_1 + T_2^eg_2 + \ldots + T_j^ug_v$, and T_j^uH as $T_1^uh_1 + T_2^uh_2 + \ldots + T_j^uh_j$, leading to the following computation:

$$\begin{aligned} Fe &= MVF(\delta(T_v^eG + y_1)) \\ Fu &= MVF(\delta(T_j^uH + y_2)) \end{aligned} \tag{11}$$

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:

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

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

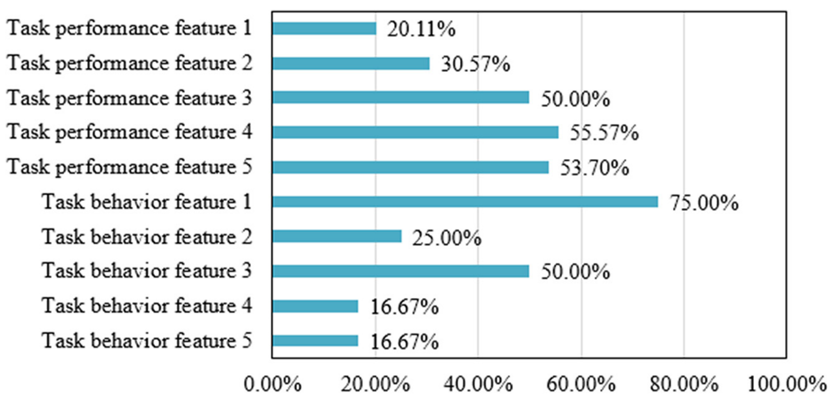

Fig. 3. Proportion of features with significant differences in different innovative ability levels

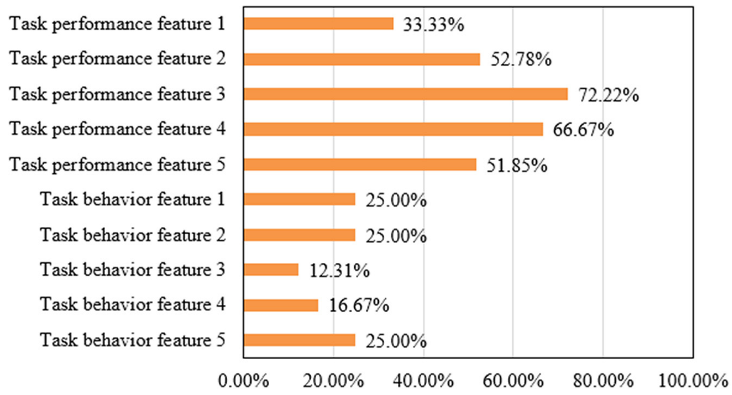

Fig. 4. Proportion of features with significant differences in different practice ability levels

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 3. The proportion of task behavior feature 1 was found to be the most prevalent at 75.00%, whereas task behavior features 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 a 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.

Further scrutiny of the data proportions in Figure 4 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.

In the analysis of experimental outcomes, Table 1 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 a corresponding literature evidence number, which is the 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.

Table 1. 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 investigation of task-behavior correlation changes across different datasets, Figure 5 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 like 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.

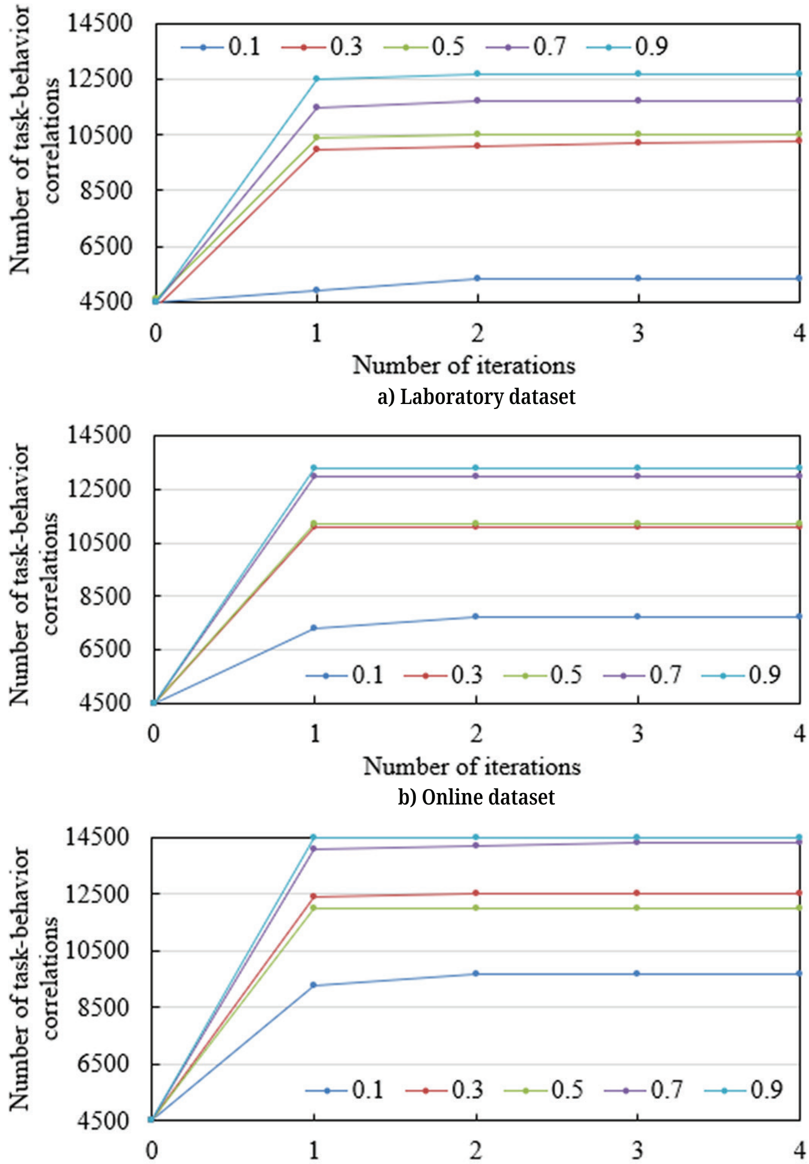

Fig. 5. Changes in the number of task-behavior correlations in different datasets with iteration

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 2). 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 networks (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 2. 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 graph neural networks 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.

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