

PAPER

Enhancing Learning Motivation through a Blended Learning Model: Integrating Mobile Devices and Virtual Reality

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ABSTRACT

With the rapid development of information technology (IT), the application of mobile devices and virtual reality (VR) in education has become increasingly widespread, giving rise to a blended learning model that integrates these two technologies. This model, through the immersive experience provided by virtual environments and the convenience of mobile devices, effectively expands the temporal and spatial dimensions of traditional learning, offering new potential for enhancing students' learning motivation. However, existing research has predominantly focused on either mobile learning or VR in isolation, with relatively limited exploration of how the combination of these technologies within a blended learning model impacts learning motivation. Moreover, most of the current methods are constrained to simple questionnaire surveys, lacking in-depth analysis of students' interactive behaviours and the underlying mechanisms that contribute to motivation formation. In this study, a comprehensive evaluation model was constructed based on an examination of students' interactions in the blended learning model and its effects on learning motivation. An empirical study was then conducted to provide innovative theoretical and methodological support for educational practice.

KEYWORDS

mobile devices, virtual reality (VR), blended learning model, learning motivation, interactive behaviours, effectiveness evaluation

1 INTRODUCTION

In recent years, with the rapid advancement of information technology (IT), the application of mobile devices and virtual reality (VR) in the field of education has gradually become widespread, providing learners with rich interactive experiences and personalised learning environments [1–5]. The blended learning model, which integrates these two technologies, combines the immersive experience of virtual

Lu, H., Ma, L., Luo, J. (2024). Enhancing Learning Motivation through a Blended Learning Model: Integrating Mobile Devices and Virtual Reality. *International Journal of Interactive Mobile Technologies (IJIM)*, 18(24), pp. 4–18. <https://doi.org/10.3991/ijim.v18i24.53089>

Article submitted 2024-08-28. Revision uploaded 2024-10-23. Final acceptance 2024-10-31.

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environments with the convenience of mobile devices, effectively breaking the temporal and spatial limitations of traditional classroom teaching. This integration has been shown to enhance student engagement and improve learning efficiency [6–8]. Against this backdrop, exploring how the combination of mobile devices and VR can be utilised to optimise learning models and enhance students' learning motivation has become a crucial area of research in educational technology.

This study aims to investigate the effect of a blended learning model, combining mobile devices and VR, on enhancing learning motivation [5, 9]. Learning motivation, as one of the key factors influencing learning outcomes, not only determines students' attitudes and level of engagement but also directly impacts the achievement of learning goals [5, 10–12]. By constructing and optimising a blended learning model to enhance learning motivation, innovative pathways for educational practice can be provided, contributing to the realisation of personalised and flexible teaching objectives [13–16]. This study not only deepens the theoretical understanding of the mechanisms underlying learning motivation formation but also offers valuable reference points for practical instructional design.

However, current study has predominantly focused on the impact of either mobile learning or VR technology as independent applications on learning outcomes. There has been relatively little systematic research on the combined use of these technologies in a blended learning model and its effects on learning motivation [17, 18]. Furthermore, existing research methods tend to rely heavily on questionnaire surveys or experimental designs, lacking in-depth analysis of learner behaviour in virtual and real-world interactive environments and the mechanisms behind motivation formation. This has led to a narrow scope of evaluation results and incomplete evaluation standards. Consequently, more comprehensive and systematic research is urgently needed in this field to fill the current gaps in theory and practice.

This study expands the theoretical model of the relationship between learning motivation and interactive behaviour and provides empirical evidence and evaluation tools for the design and application of the blended learning model. This combination of theory and practice points to new directions for the future development and optimisation of educational technology, offering significant academic value and practical relevance.

2 STUDENT INTERACTIVE BEHAVIOUR AND ITS MECHANISMS IN THE BLENDED LEARNING MODEL

The blended learning model that combines mobile devices with VR is an innovative educational approach, integrating the portability of mobile devices with the immersive nature of VR technology to create a flexible and dynamic learning environment. This model leverages the widespread accessibility of mobile devices, such as smartphones and tablets, alongside the immersive experiences offered by VR technology, providing learners with a highly interactive, immersive, and personalised learning experience. The use of mobile devices ensures that learning is no longer confined by time or space. Learners can access educational resources at any time and from any location, whether in the classroom, at home, or in public spaces. This anytime-anywhere learning approach significantly enhances both the flexibility and convenience of learning. Furthermore, mobile devices offer a variety of applications and tools, such as educational apps, e-books, and online course platforms, which provide learners with diverse learning resources and methodologies. These applications typically include interactive features and offer instant

feedback, helping learners to better understand and retain knowledge. In addition, the VR technology employed creates realistic three-dimensional virtual environments, allowing learners to immerse themselves in a novel learning experience. VR can simulate a wide range of real-world scenarios and contexts, enabling learners to engage in hands-on practice and experiential learning. For instance, in medical education, students can practice surgery simulations via VR, while in engineering education, students can disassemble and operate complex machinery within a virtual environment. Such immersive learning experiences not only enhance learners' practical skills and hands-on abilities but also strengthen their memory retention and comprehension. Figure 1 illustrates the process of student interactive behaviour within the blended learning model that integrates mobile devices and virtual reality.

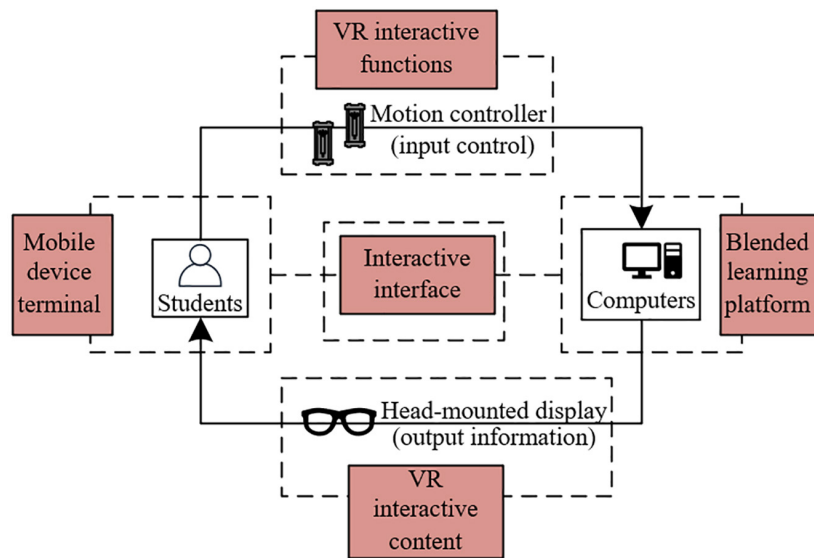


Fig. 1. Schematic diagram of student interactive behaviour in the blended learning model integrating mobile devices and VR

In the blended learning model integrating mobile devices and VR, student interactive behaviour is one of the core elements of this approach. Interactive behaviour encompasses not only the interaction between students and learning content but also their interactions with teachers, peers, and the virtual environment. Through these multi-layered interactions, students are able to engage more deeply in the learning process and apply and comprehend knowledge through practice. Figure 2 illustrates the mechanisms behind the formation of student interactive behaviour in the blended learning model integrating mobile devices and VR. The detailed explanation of student interactive behaviour and its formation mechanisms is provided below.

In the blended learning model, students engage in diverse interactions with learning content through mobile devices and VR technology. Interactive tools like touch screens, styluses, and sensors on mobile devices allow students to interact with content through actions like tapping, swiping, and zooming, providing immediate feedback. In VR environments, students interact with objects in virtual scenes by wearing VR headsets or using controllers and gesture-tracking devices to manipulate virtual instruments, experimental equipment, or characters. This high level of immersive content interaction effectively stimulates students' interest in learning and enhances practical experiences by simulating real-world operational scenarios. The formation of such interactive behaviour relies on two key factors. The first is

technological support. Mobile devices enable access to learning content anytime and anywhere, while VR enhances immersion through multi-sensory stimuli such as vision, hearing, and touch. The second factor is educational design. Effective interactive behaviour is facilitated by well-designed learning scenarios, tasks, and feedback mechanisms that ensure students receive feedback during independent operations, fostering a deeper learning experience.

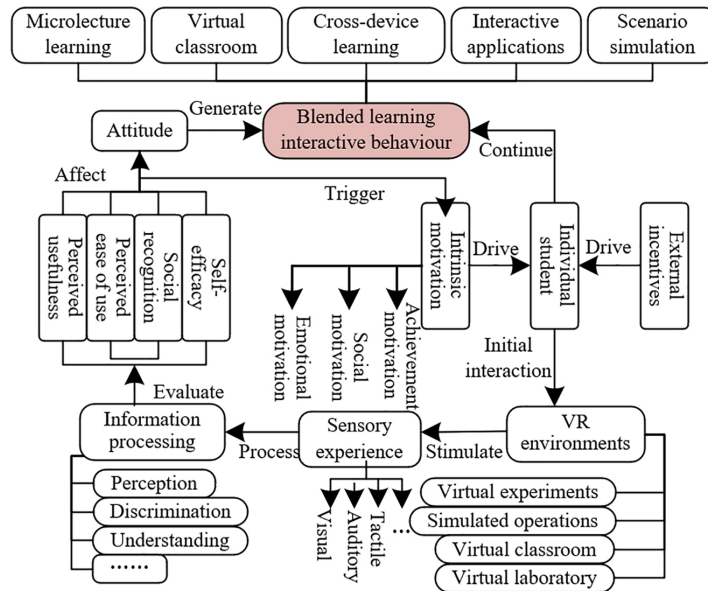


Fig. 2. Mechanisms of student interactive behaviour formation in the blended learning model integrating mobile devices and VR

Interaction between students and teachers is equally critical in this blended learning model. Mobile devices facilitate instant communication between students and teachers through tools such as instant messaging, video conferencing, and emails within learning applications, allowing real-time feedback and discussion. VR technology, on the other hand, enables more intuitive interactions within virtual classrooms. Teachers, represented by virtual avatars, can interact with students and observe their behaviour in real-time within the virtual environment, providing guidance and assessment. The formation of this type of interaction largely depends on the shift in the teacher’s role and the support of technological platforms. In a mobile learning and VR environment, teachers act more as facilitators and guides than traditional knowledge transmitters. They dynamically monitor students’ learning progress and provide intervention when necessary. This interactive model relies on the real-time data capture capabilities of VR platforms and instant communication tools available on mobile devices, enabling a seamless, interactive learning experience between teachers and students.

3 EFFECTIVENESS EVALUATION OF THE BLENDED LEARNING MODEL IN ENHANCING LEARNING MOTIVATION

In order to thoroughly understand the impact of the blended learning model, which integrates mobile devices and VR, on enhancing learning motivation, it is essential to consider various aspects of motivation. This evaluation must incorporate

the characteristics of both mobile devices and VR technology to ensure that the system comprehensively and scientifically reflects the effects of this blended learning model on learning motivation. The specific evaluation system consists of four dimensions: subjective motivation, behavioural motivation, emotional motivation, and external incentives. Each dimension can be further divided into specific operational indicators. Subjective motivation is the core aspect for evaluating a learner's intrinsic drive, primarily reflecting the learner's attitude towards the learning process and their autonomy. In the context of the blended learning model that integrates mobile devices and VR, subjective motivation should focus on three key areas: interest in learning, willingness to engage in self-directed learning, and goal orientation. The behavioural motivation dimension focuses on the specific learning behaviours exhibited by learners using the blended learning model and whether these behaviours demonstrate an increase in learning motivation. This includes three main aspects: time invested in learning, frequency of interaction, and task completion rate. Emotional motivation refers to the emotional experience's students undergo during the learning process, especially in the highly immersive environment provided by VR, where emotional motivation significantly impacts learning outcomes. The evaluation of this dimension should focus on three areas: a sense of achievement, immersion and concentration, and levels of learning-related stress and anxiety. In addition to assessing intrinsic motivation, the influence of external incentives on learning motivation must also be considered. The blended learning model, which integrates mobile devices and VR, is often accompanied by external incentive mechanisms such as reward systems, point-based systems, or virtual currencies, which play an important role in enhancing learning motivation. This dimension includes two aspects: reward and feedback mechanisms, and peer competition and collaboration. Figure 3 presents the evaluation model for the effectiveness of the blended learning model that integrates mobile devices and VR in enhancing learning motivation.

In applying the matter-element extension method for evaluation, the construction of the classical domain, segment domain, and matter-element model to be evaluated are key steps. The matter-element model is expressed through a triplet $E = (L, Z, N)$, which represents the relationship between the entity, its characteristics, and the characteristic values. This model systematically describes the value of indicators across different evaluation levels and ultimately assists in assessing the effectiveness of the blended learning model in enhancing learning motivation.

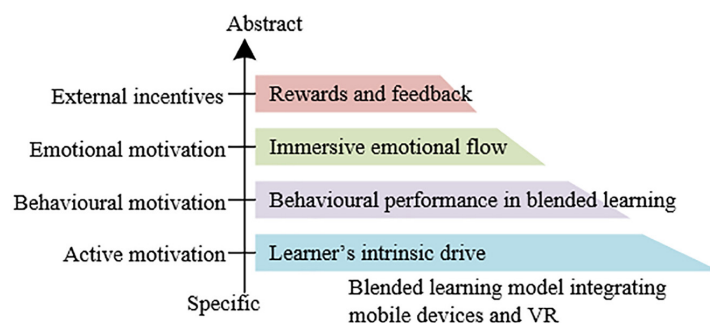


Fig. 3. Evaluation model of the effectiveness of the blended learning model integrating mobile devices and VR in enhancing learning motivation

The classical domain forms the basis of the evaluation standards, defining the range of indicator values at different evaluation levels. In the blended learning model

integrating mobile devices and VR, the enhancement of learning motivation can be assessed from multiple dimensions, such as subjective motivation, behavioural motivation, emotional motivation, and external incentives. Suppose the enhancement of learning motivation is evaluated across l levels, with each dimension comprising several indicators. Let E_r represent the r -th matter element, L_r denote the evaluation level of the enhancement of learning motivation under the blended learning model, and z_u represent the u -th specific evaluation indicator for learning motivation enhancement. The value range for the indicator z_u is denoted by $n_{ru} = [o_{ru}, w_{ru}]$, where o_{ru} and w_{ru} represent the lower and upper bounds of the value range for the u -th indicator of learning motivation enhancement ($r = 1, 2, \dots, l; u = 1, 2, \dots, v$). The classical domain matter-element model can be expressed as follows:

$$E_r = (L_r, Z, N_r) = \begin{bmatrix} L_r & z_1 & n_{r1} \\ & z_2 & n_{r2} \\ & \vdots & \vdots \\ & z_u & n_{ru} \\ & \vdots & \vdots \\ & z_v & n_{rv} \end{bmatrix} = \begin{bmatrix} L_r & z_1 & [o_{r1}, w_{r1}] \\ & z_2 & [o_{r2}, w_{r2}] \\ & \vdots & \vdots \\ & z_u & [o_{ru}, w_{ru}] \\ & \vdots & \vdots \\ & z_v & [o_{rv}, w_{rv}] \end{bmatrix} \quad (1)$$

The segment domain is a subset of the classical domain, representing the value range of a specific indicator at a given evaluation level. Constructing the segment domain helps to further refine the evaluation levels, allowing for clearer differentiation of indicator values across various dimensions. For example, if the evaluation dimension is emotional interaction, one typical indicator might be the “learner’s sense of engagement.” By constructing a segment domain model, value ranges can be assigned for different levels of engagement. Similar approaches can be used for other indicators to construct the segment domain matter-element model for various evaluation indicators across different levels. Let E_j represent all the evaluation levels for the enhancement of learning motivation under the blended learning model, and let n_{ju} denote the union of all value ranges for the u -th indicator across all evaluation levels, represented as $[o_{ju}, w_{ju}]$, where o_{ju} and w_{ju} are the lower and upper bounds of the segment domain. The j -th value for the evaluation quality is represented by j . The segment domain matter-element model can be expressed as follows:

$$E_j = (L_j, Z, N_j) = \begin{bmatrix} L_j & z_1 & n_{j1} \\ & z_2 & n_{j2} \\ & \vdots & \vdots \\ & z_u & n_{ju} \\ & \vdots & \vdots \\ & z_v & n_{jv} \end{bmatrix} = \begin{bmatrix} L_j & z_1 & [o_{j1}, w_{j1}] \\ & z_2 & [o_{j2}, w_{j2}] \\ & \vdots & \vdots \\ & z_u & [o_{ju}, w_{ju}] \\ & \vdots & \vdots \\ & z_v & [o_{jv}, w_{jv}] \end{bmatrix} \quad (2)$$

The matter-element model to be evaluated is used to describe the actual performance of the evaluation object based on specific evaluation indicators, i.e., the actual effectiveness of the blended learning model integrating mobile devices and VR in enhancing learning motivation during the research process. This model reflects

the learners' actual performance across various dimensions. Suppose the evaluation level of learning motivation enhancement under the blended learning model is denoted by L_x , the x -th sub-feature matter-element matrix is represented by E_x , and the specific indicator for the effectiveness of learning motivation enhancement under the blended learning model is represented by z_u . The actual value of the evaluation corresponding to this specific indicator is denoted by n_{xu} . The expression for the matter element to be evaluated is as follows:

$$E_x = (L_x, Z, N_x) = \begin{bmatrix} L_x & z_1 & n_{x1} \\ & z_2 & n_{x2} \\ & \vdots & \vdots \\ & z_u & n_{xu} \\ & \vdots & \vdots \\ & z_v & n_{xv} \end{bmatrix} \quad (3)$$

To further determine the effectiveness of learning motivation enhancement and the proximity to the pre-defined evaluation levels, it is necessary to calculate the extension correlation function for the matter element to be evaluated. This function quantifies the degree of association between the actual performance of the matter element and the different evaluation levels, thus assessing the effectiveness of the blended learning model in enhancing learning motivation. Specifically, the effectiveness of the blended learning model in enhancing learning motivation can be evaluated across multiple dimensions, each corresponding to a series of specific values. By measuring the distance between each indicator in the matter element to be evaluated and the classical domain and segment domain, the evaluation level of the actual performance can be determined, and the enhancement of learning motivation can be assessed. Let the distance between the value of the u -th indicator for the effectiveness of learning motivation enhancement under the blended learning model and the classical domain and segment domain be denoted by $f(n_u, n_{ru})$ and $f(n_u, n_{ju})$. The distance between the matter element and the classical domain and segment domain can be expressed as follows:

$$f(n_u, n_{ru}) = \left| n_u - \frac{o_{ru} + w_{ru}}{2} \right| - \frac{o_{ru} + w_{ru}}{2} \quad (4)$$

$$f(n_u, n_{ju}) = \left| n_u - \frac{o_{ju} + w_{ju}}{2} \right| - \frac{o_{ju} + w_{ju}}{2} \quad (5)$$

In extension evaluation, the correlation function is used to calculate the degree of correlation between the matter element to be evaluated and different levels of evaluation. The correlation degree reflects the extent to which the enhancement of learning motivation aligns with each evaluation level. The value of the correlation degree typically ranges from 0 to 1, with a larger value indicating that the matter element is closer to that particular evaluation level. By calculating the correlation degree for each evaluation indicator, a comprehensive judgement can be made regarding the overall effectiveness of learning motivation enhancement across multiple dimensions. Let $|n_{ru}| = |w_{ru} - o_{ru}|$, and let the degree of correlation between the u -th metric for the enhancement of learning motivation in the blended learning model and the

k -th evaluation level be denoted by $Q_k(n_u)$. The correlation function can be expressed as follows:

$$Q_k(n_u) = \begin{cases} \frac{-f(n_u, n_{ru})}{|n_{ru}|} n_u \in n_{ru} \\ \frac{f(n_u, n_{ru})}{f(n_u, n_{ju}) - f(n_u, n_{ru})} n_u \notin n_{ru} \end{cases} \quad (6)$$

In the blended learning model integrating mobile devices and VR, the enhancement of learning motivation is a multidimensional and multifactorial process. Therefore, determining the appropriate weightings not only requires consideration of the actual measurement data from each dimension but also must be aligned with the specific objectives of the study. Through the extension weighting method, the weights can be dynamically adjusted to better reflect actual conditions. Specifically, the weights of the secondary indicators can be determined based on actual measurement data rather than relying on subjective judgements by experts. By analysing the actual measured values of the secondary indicators, the contribution of each indicator to the enhancement of learning motivation can be assessed, and weights can be assigned according to the magnitude of each contribution. Suppose the weight of the u -th secondary indicator under the r -th primary category of learning motivation enhancement is denoted by d_{ru} . The number of primary indicators and the corresponding number of secondary indicators for learning motivation enhancement are denoted by $r(r = 1, 2, \dots, v)$ and $u(u = 1, 2, \dots, l)$, respectively. The weighting formula for secondary indicators is as follows:

$$d_{ru} = \frac{e_{ru}}{\sum_{u=1}^l e_{ru}} \left(\sum_{u=1}^l d_{ru} = 1 \right) \quad (7)$$

Once the weights of the secondary indicators have been determined, the weightings of the primary indicators must also be allocated. Primary indicators typically represent broader evaluation dimensions, like emotional engagement, information processing capability, or operational interaction. In evaluating the enhancement of learning motivation, the influence of different primary indicators on the final result may vary significantly. Therefore, it is crucial to reasonably determine the weights of the primary indicators. The extension method for determining the weights of the primary indicators continues to follow the principle of minimising subjectivity. The weights can be calculated based on the overall contribution of each primary indicator to the enhancement of learning motivation. The weighting formula for primary indicators is as follows:

$$d_r = \frac{e_r}{\sum_{r=1}^v e_r} \left(\sum_{r=1}^v d_r = 1, e_r = \sum_{u=1}^l e_{ru} \right) \quad (8)$$

The expression for the indicator weight coefficient derived from the extension weighting method is given as follows:

$$e_{ru}(n_u, n_{ru}) = \begin{cases} \frac{2(n_u - o_{ru})}{w_{ru} - o_{ru}} & n_u \leq \frac{w_u + o_u}{2} \\ \frac{2(o_{ru} - n_u)}{w_{ru} - o_{ru}} & n_u \geq \frac{w_u + o_u}{2} \end{cases} \quad (9)$$

If $n_u \in n_{ru}$, then $e'_{ru}(n_u, n_{ru}) = \text{MAX}\{e'_{ru}(n_u, n_{ru})\}$ holds. The larger the evaluation level where the actual measurement value of the indicator for the enhancement of learning motivation under the blended learning model is located, the greater the weight of the indicator. The expression for the value of e_{ru} is given as follows:

$$e_{ru} = \begin{cases} k_{MAX} * (1 + e'_{ru}(n_u, n_{ruMAX})) & e'_{ru}(n_u, n_{ruMAX}) \geq -0.5 \\ k_{MAX} * 0.5 & e'_{ru}(n_u, n_{ruMAX}) \leq -0.5 \end{cases} \quad (10)$$

By evaluating the performance of each primary indicator, the correlation between the indicator and a specific evaluation level can be calculated. In practical operations, this study analyses the performance of each primary indicator at different levels based on the actual measured results. For example, in the case of the primary indicator of subjective motivation, if the interest in learning is high, it may have a strong correlation with the “high” evaluation level; conversely, if the level of engagement is low, it may be more closely correlated with the “low” evaluation level. This process ensures that the evaluation reflects the actual contribution of each primary indicator to the enhancement of learning motivation. Suppose the total number of secondary indicators corresponding to a specific primary indicator is denoted by l . The formula for calculating the correlation degree between the primary indicator of matter-element E and the evaluation level k is given as follows:

$$Q_k(E_r) = \sum_{u=1}^l d_{ru} Q_k(n_{ru}) \quad (11)$$

After determining the performance of each primary indicator, the next step is to apply the maximum correlation identification principle to determine the final evaluation level that reflects the effectiveness of the blended learning model in enhancing learning motivation. In extension evaluation, the maximum correlation identification principle refers to selecting the evaluation level with the highest correlation degree for each primary indicator as the final evaluation level for that indicator. Subsequently, the correlation degrees of all primary indicators can be compared to identify the evaluation level with the highest overall correlation degree. For instance, if the maximum correlation degree for a particular evaluation level is found across all four primary indicators—subjective motivation, behavioural motivation, emotional motivation, and external incentives—it can be preliminary concluded that the overall performance of the matter element to be evaluated belongs to that evaluation level. Suppose the number of primary indicators for the matter element to be evaluated is denoted by v . The expression for the correlation degree between matter element E and evaluation level k is as follows:

$$Q_k(E) = \sum_{r=1}^v d_r Q_k(E_r) \quad (12)$$

The evaluation level k' to which the matter element belongs can be obtained using the following expression:

$$Q_{k'}(E) = \text{MAX} Q_k(E) \quad (13)$$

4 EXPERIMENTAL RESULTS AND ANALYSIS

In terms of experimental results, the correlation between blended learning behaviours integrating mobile devices and VR was analysed across four dimensions using Pearson’s correlation coefficient, as shown in Figure 4. The results indicate no significant correlation between the number of explorations in the VR environment and the frequency or success rate of interactions. Specifically, students’ exploration behaviours within the VR environment did not necessarily correlate with their proficiency in using the interaction functions. Some students demonstrated high interest in exploration but used the interaction functions infrequently, while others frequently engaged with the interaction tools but showed less interest in exploration. This suggests that VR exploration and interaction behaviours may represent two relatively independent learning characteristics, reflecting the diverse learning behaviours exhibited by students in the blended learning model. The analysis of the effectiveness of the blended learning model in enhancing learning motivation shows that, despite differences in students’ exploration and interaction behaviours within the VR environment, these differences did not negatively impact overall learning motivation. On the contrary, this model provided students with a variety of learning methods and flexible learning pathways, which stimulated their autonomy and interest in learning. Some students were inclined to enhance their sense of engagement through virtual environment exploration, while others improved their understanding and interaction with the learning content through frequent use of interaction functions. Overall, the blended learning model effectively increased students’ learning motivation, regardless of whether they favoured environmental exploration or the use of interaction functions.

Table 1. Correlation between secondary indicators and different evaluation levels of the improvement effect of the blended learning model integrating mobile devices and VR on learning motivation

Secondary Indicators	$Q_1(n_u)$	$Q_2(n_u)$	$Q_3(n_u)$	$Q_4(n_u)$
a_{11}	-0.578	-0.412	0.311	-0.245
a_{12}	-0.612	-0.423	0.247	-0.214
a_{13}	-0.485	-0.235	0.426	-0.285
a_{21}	-0.526	0.058	-0.052	-0.415
a_{22}	-0.135	0.312	-0.247	-0.432
a_{23}	-0.314	-0.021	0.035	-0.369
a_{31}	-0.265	0.234	-0.081	-0.436
a_{32}	-0.368	0.256	-0.168	-0.417
a_{33}	-0.412	-0.112	0.231	-0.315
a_{41}	-0.587	-0.278	0.523	-0.234
a_{42}	-0.478	-0.245	0.468	-0.258

Table 2. Correlation between primary indicators and different evaluation levels of the improvement effect of the blended learning model integrating mobile devices and VR on learning motivation

Primary Indicators	$Q_1(W_u)$	$Q_2(W_u)$	$Q_3(W_u)$	$Q_4(W_u)$	k'	k''
A_1	-0.536	-0.335	0.369	-0.247	3	3.14
A_2	-0.268	-0.279	-0.189	-0.436	2	2.18
A_3	-0.289	0.135	-0.065	-0.412	2	2.35
A_4	-0.478	-0.213	0.434	-0.258	3	2.79

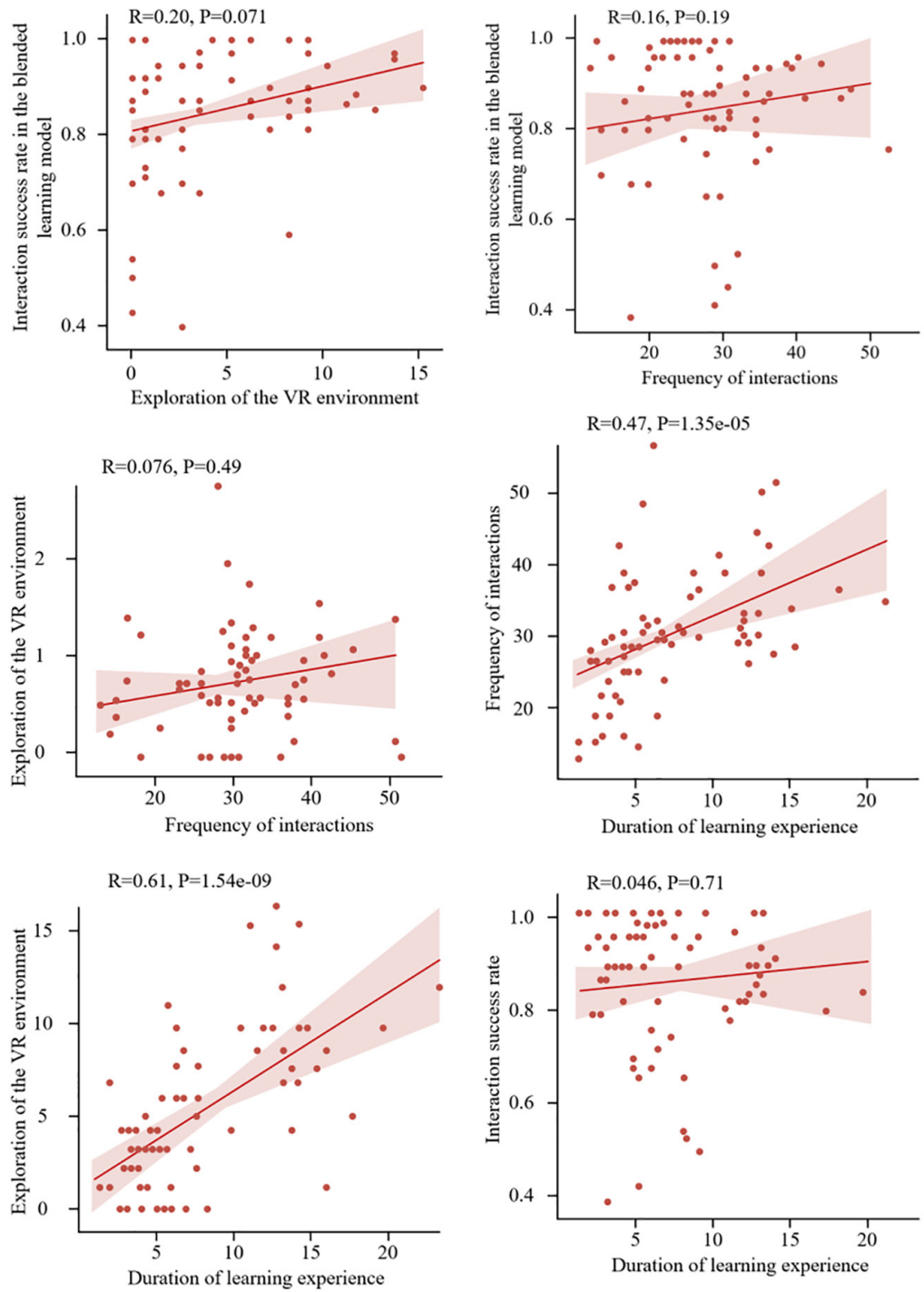


Fig. 4. Correlation analysis of blended learning behaviours integrating mobile devices and VR

Table 3. Correlation between the overall objective and different evaluation levels of the improvement effect of the blended learning model integrating mobile devices and VR on learning motivation

Overall Objective	$Q_1(W_u)$	$Q_2(W_u)$	$Q_3(W_u)$	$Q_4(W_u)$	k'	k''
A	-0.369	0.002	0.079	-0.354	3	2.48

The results in Table 1 demonstrate variations in the correlation between secondary indicators and the four evaluation levels of learning motivation within the blended learning model integrating mobile devices and VR. At the subjective motivation level, learning interest (a_{11}), willingness for self-directed learning (a_{12}), and goal orientation (a_{13}) showed positive correlations with Q_3 (mid-high level), particularly with goal orientation showing the highest positive correlation (0.426). However, negative correlations were observed for Q_1 , Q_2 , and Q_4 , indicating that subjective motivation enhancement is most evident at mid-high levels. For behavioural motivation, time invested in learning (a_{21}) and interaction frequency (a_{22}) showed positive correlations with Q_2 , with interaction frequency having the strongest positive correlation at this level (0.312). However, task completion (a_{23}) exhibited no significant positive correlation at any level, reflecting that behavioural motivation is most enhanced at moderate levels. Regarding emotional motivation, a sense of achievement (a_{31}) and immersion and concentration (a_{32}) were positively correlated with Q_2 , while learning pressure and anxiety (a_{33}) showed a weak positive correlation with Q_3 (0.231), indicating that the blended learning model had some effectiveness in enhancing emotional motivation at moderate levels. In the external incentives dimension, the reward and feedback mechanisms (a_{41}) and peer competition and collaboration (a_{42}) showed the highest correlations with Q_3 , at 0.523 and 0.468, respectively, demonstrating that external incentives had a significant effect on mid-high level motivation enhancement.

The results from Table 2 reveal significant differences in the correlation between the four primary indicators of learning motivation and the different evaluation levels under the blended learning model integrating mobile devices and VR. In terms of subjective motivation (A_1), the correlation with Q_3 (mid-high level) was positive at 0.369, indicating that this level has a significant effect on enhancing student motivation, while negative correlations were observed with Q_1 , Q_2 , and Q_4 . This suggests that the enhancement of subjective motivation is most notable among students at mid-high levels. For behavioural motivation (A_2), all evaluation levels showed negative correlations, particularly with Q_4 (high level), where the negative correlation was quite strong (-0.436). This indicates that behavioural motivation has a weaker impact on high-level learning motivation. Regarding emotional motivation (A_3), a positive correlation (0.135) was found with Q_2 , while correlations at other levels were not significant, suggesting that emotional motivation primarily contributes to moderate levels of motivation. In the external incentives dimension (A_4), the highest correlation was found with Q_3 (0.434), indicating that rewards and feedback mechanisms have the most significant effect on students at mid-high motivation levels.

The results in Table 3 indicate that the correlation between the overall objective and different evaluation levels of learning motivation enhancement within the blended learning model integrating mobile devices and VR is relatively complex. Specifically, both Q_1 (low level) and Q_4 (high level) exhibited negative correlations, with values of -0.369 and -0.354, respectively. In contrast, the correlations at Q_2 (moderate level) and Q_3 (mid-high level) were quite low, with a correlation of nearly zero for Q_2 (0.002) and a modest correlation for Q_3 (0.079). These findings suggest that the overall effect of the blended learning model on enhancing learning motivation is uneven across different levels of learning motivation. This indicates that while the model may promote learning motivation in certain contexts, its overall effect is not particularly strong, especially at low and high levels of motivation, where some negative effects were observed. A comprehensive analysis reveals that the effectiveness of the blended learning model in enhancing learning motivation is influenced by multiple factors, particularly in the dimensions of subjective and behavioural

motivation. Although weak positive correlations were observed at moderate levels of motivation, the overall enhancement effect at both low and high levels of motivation was suboptimal. This suggests that the current implementation of the blended learning model has not yet effectively stimulated learning motivation across all types of learners. Future research should explore ways to optimise content and interaction design to further enhance students' interest and engagement in learning. In particular, more targeted strategies are needed to improve both low- and high-level learning motivation, enabling a more comprehensive enhancement of motivation. This would help improve the overall effectiveness of the blended learning model, making it more practical and impactful in educational settings.

5 CONCLUSION

This study thoroughly explored the effectiveness of the blended learning model integrating mobile devices and VR in enhancing students' learning motivation. By examining students' interactive behaviours and their formation mechanisms, a systematic analysis was conducted to understand how different behaviours influence the enhancement of learning motivation. A scientific evaluation model was developed to comprehensively assess the effects of the blended learning model on motivation enhancement across various levels and dimensions. The findings revealed that subjective motivation and external incentives demonstrated significant improvement, particularly among students with mid to high levels of motivation, while the effects on behavioural motivation and emotional motivation were more dispersed, primarily concentrated at moderate levels. Additionally, the enhancement of motivation at both low and high levels was relatively weak, indicating certain limitations of the learning model within specific groups.

The primary contribution of this study lies in the innovative combination of VR and mobile devices, which provides deeper insights into the complex relationship between interactive behaviours and learning motivation. This offers new theoretical support and practical implications for the design of blended learning in the educational field. Furthermore, the results provide clear guidance for optimising instructional design to enhance learning motivation. However, this study also has certain limitations: First, the experimental data mainly focused on specific learner groups, and the generalisability of the findings needs further verification. Second, the exploration of strategies to enhance high-level motivation was not sufficiently in-depth. Future research could expand the scope of participants and explore more dimensions of interactive behaviour and their roles in enhancing learning motivation. Additionally, more targeted learning support strategies should be developed for students with both low and high motivation levels, aiming to achieve more comprehensive and effective motivation enhancement. With continuous optimisation and validation, this model has the potential to become a key direction in the future development of educational technology.

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