Origami as a Means to Assess and Understand Learning Styles

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Abstract. In this research, we model the relationship between a range of sensed metrics and visual-aural-read/write-kinesthetic (VARK) questionnaire metrics and the resulting ability to create aesthetically pleasing origami objects, both at the time of learning and when reproduced at a later date. Results indicate that subjects with a Visual learning preference perform better in this task. We also suggest that subjects who score highly across all VARK categories (Multimodal) tackle the learning task with more mental and physical vigour, leading to better performance in the short and long term. Tackling the learning process with an elevated mental activity, captured by Electroencephalogram (EEG) measurements, appears to be the clearest indicator of success. These results support the common-sense idea that an enthusiastic approach to the problem, which makes use of visual learning support yields better results.

Keywords: Learning Methods · VARK · Sensor-based · EEG · Origami Workshops.

1 Introduction

When studying how people learn, it is important to capture favoured learning styles of the individual, using a set of benchmarked learning tasks and capturing as much environmental and physiological data as possible. If this is successful we can ascertain if any one learning style is favourable and whether different learning styles are more robust to the influence of ambient conditions and favour longer term retention.

It is well understood that each individual has preferences for how they acquire, process and retain information during learning processes [20]. Understanding these differences is essential for optimising teaching methods and designing effective educational tools [22]. Visual, Auditory, Reading, and Kinesthetic (VARK) methods all have a role to play in the learning process for most people [15]. Capturing an individual's learning biases usually involves a questionnaire approach, this yields both a ratio of preference and also some absolute values. For instance, one person may have values of 7, 2, 3, 4 for the 4 VARK categories and another may score 14, 4, 6, 8. Both of these subjects are more Visual learners than any other category, and they favour visual learning in the same proportion, but the second subject has been twice as positive in their responses. This implies that they are more multimodal learners because they are more open to using multiple methods in any learning situations.

Although other learning style models exist, such as Kolb's Learning Style Inventory [11], and Honey and Mumford's Learning Styles Questionnaire [9], the VARK model was selected for this study due to its intuitive classification and its relevance to perceptual and motor-based learning tasks.

Various other environmental and physiological factors can affect how well individuals learn [7]. Because of this, any learning performance can also be standardised against these conditions. Traditional methods for assessing learning styles, such as self-reported questionnaires, can provide useful subjective insights but lack real-time physiological validation [5]. The integration of sensor-based technologies, including heart rate, Galvanic Skin Response (GSR) and Electroencephalography (EEG) can capture biometric signals, which are linked to cognitive load, focus and emotional engagement [21]. Furthermore, ambient temperature and humidity can all have an important influence, and as such, should be captured during the learning process [6].

Origami can provide a compelling medium for investigating the interaction between learning styles and cognitive engagement. Unlike conventional classroom tasks that focus more on passive learning, origami tasks require a high level of spatial reasoning, fine motor skills, and sequential problem-solving, which make it an ideal task for analysing multimodal learning behaviours [16]. In prior research, origami figures have been used as a teaching tool to facilitate learning of skills related to Science, Technology, Engineering and Math (STEM) [3, 4, 10]. For the purposes of this research, we chose a set of origami figures as the assessed learning tasks (Fig. 1). While different designs could be used, we chose these particular models because they offered a balance of complexity, variety in folding techniques, and suitability for the workshop time constraints. During the workshops, participants were taught to fold 4 different designs and then these designs were assessed as a reflection of the successfulness of the learning process.

The primary objective of this study is to examine how individual learning styles, as classified by the VARK model [14], influence task performance and knowledge retention in a hands-on learning activity. Specifically, we investigate whether individuals with a strong visual learning preference perform better in origami-based tasks and whether multimodal learners show greater adaptability in both short-term and long-term recall. Moreover, we analyse the role of physiological engagement, as captured through EEG activity, in determining learning success.

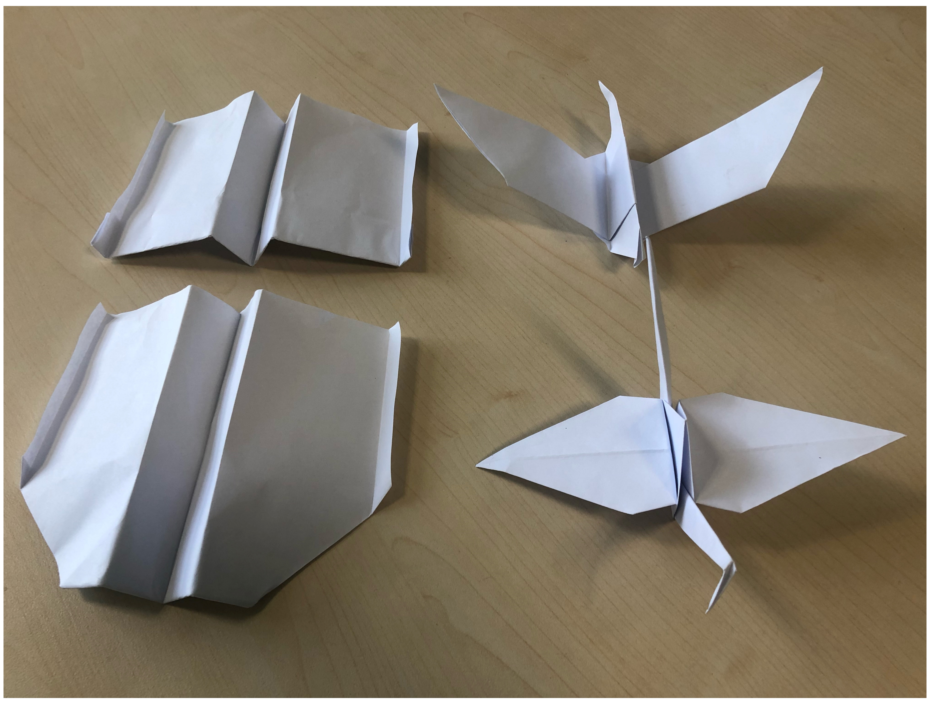


Fig. 1. Examples of the 4 origami tasks

2 Experimental Protocol

2.1 Participants

A total of 88 staff and students voluntarily participated in this study, with 26 completing both phases of the origami submission process. Participants were recruited through open calls within the university, and the sample included both male and female individuals across a wide age range, encompassing students from different year levels and staff from various departments. To encourage participation, a lucky draw was held for those who submitted their second-phase origami work. Before the workshops began, all participants received and signed an informed consent form outlining the study's purpose, data collection procedures, potential risks, and their right to withdraw at any time without consequences. The study was approved by the Ethics Committee of the University of Nottingham Ningbo China.

2.2 Procedure

As shown in the Fig 2, firstly, subjects were asked to complete a VARK questionnaire that captured their learning preferences [14] [8]. This generated a value for each of the four categories. During guided origami sessions, subjects were then connected to a range of sensors and given visual and verbal instructions on how to fold the 4 different origami figures. Participants were informed that these 4 origami figures are progressively more difficult. The sessions began with the simplest origami figure (Fig. 1 - top left) and finished with the most difficult origami figure (Fig. 1 – bottom right). 'Off the shelf' environmental and GSR sensors were used along with an Apple Watch to capture heart rate and a Muse headset [18] to capture Electroencephalogram (EEG) levels. Fig. 3 shows the hardware setup used for capturing environmental and physiological data, which includes the Arduino Uno board, breadboard wiring, Bluetooth module, and connected sensors. In the 20-minute workshop, subjects were encouraged to learn and fold as much as possible. Once time expired, they were asked to stop, and their highest successfully folded origami level was recorded.

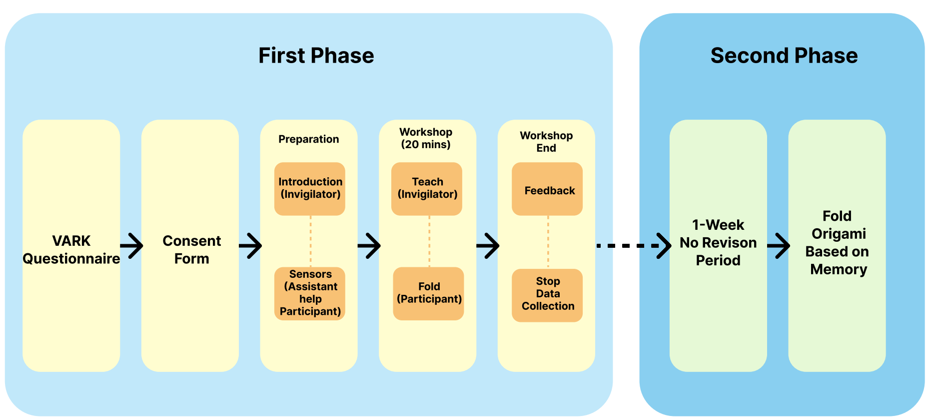


Fig. 2. Flow Chart of Two Phases of Experiment

[8] Permission to use the VARK Questionnaire was obtained from the VARK-Learn Limited

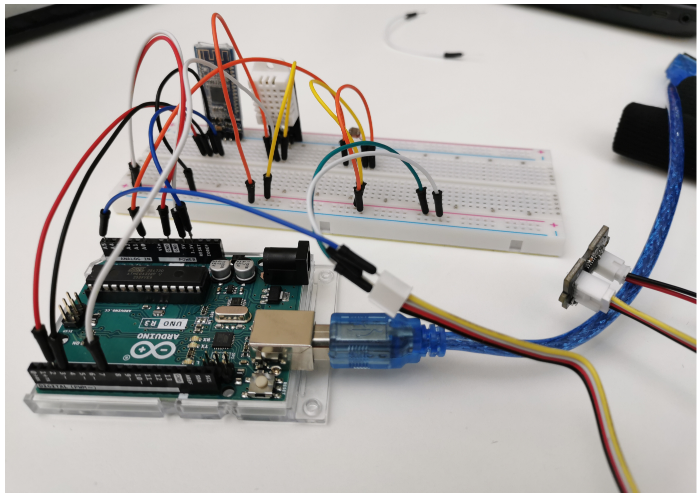


Fig. 3. Experimental Hardware Setup

All guided origami sessions were arranged at the same time of day, and the lighting, the temperature as well as the duration of the sessions are controlled. Folded origami figures were collected at the end of the guided origami sessions, and subjects were instructed not to revise the content over the following week. After the no-revision period, the subjects were asked to submit the most complex origami figure they could recall. Origami assessments were carried out based on visual accuracy and the subjects were not given these values following their guided origami sessions.

13 variables were generated from sensor values [S], questionnaire [Q] or observation [O]. The variables used were as follows:

- Temperature [S]: Mean sensor reading in degree C.
- Humidity [S]: Mean sensor reading in %.
- Light [S]: Mean sensor reading in Lumens.
- Galvanic Skin Response (GSR) [S]: Mean skin measurement in μS.
- Heart Rate (HR) [S]: Mean sensor measurement of subject's heart rate in beats/minute.
- V/A/R/K count [Q]: Amount of positive responses to each VARK related questions. One distinct variable for each category.
- Sum VARK count [Q]: Individual V, A, R and K scores added together.
- Muse Activity [S]: Using a Muse EEG sensor unit [12] as:

$$\frac{\text{EEG active time}}{\text{EEG active time} + \text{EEG calm time}} \tag{1}$$

- Look (initial) [O]: An assessment of the visual accuracy of the origami folded under tuition. This is a sum of 5 people's assessing all 4 origami tasks. This has a maximum value of 200.

– Look (memory) [O]: An assessment of visual accuracy of the origami folded 1 week later, based on memory. This is a sum of 5 people, assessing 1 origami task. This has a maximum value of 50.

To give an idea of visual accuracy scoring, Fig. 4 presents two submitted origami figures from two different subjects following the one week no-revision period (left and middle origami figure) and the original folded by the instructor (right origami figure). The origami on the left received a Look (memory) value of 4, and the origami in the middle received a Look (memory) value of 42.

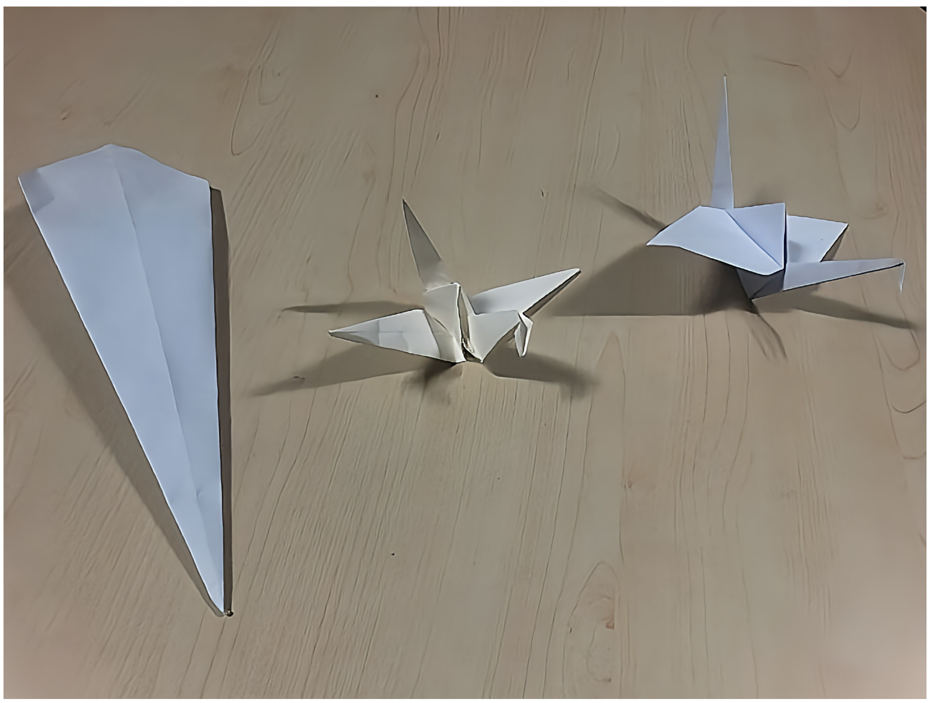


Fig. 4. Low scoring (left), high scoring (middle) and original instructive origami figures

Prior to analysis, all collected data were manually reviewed for completeness and consistency. Incomplete or ambiguous responses were excluded from analysis. Furthermore, all origami submissions were evaluated using a structured scoring process to ensure reliability in performance scoring. Categorical questionnaire responses, for example, VARK preferences, were numerically encoded to enable quantitive analysis. Continuous sensor variables were standardized to ensure comparability across features in the regression models. As shown in Fig. 5, a basic analysis of the data gives an idea of how the degree of correlation between variables.

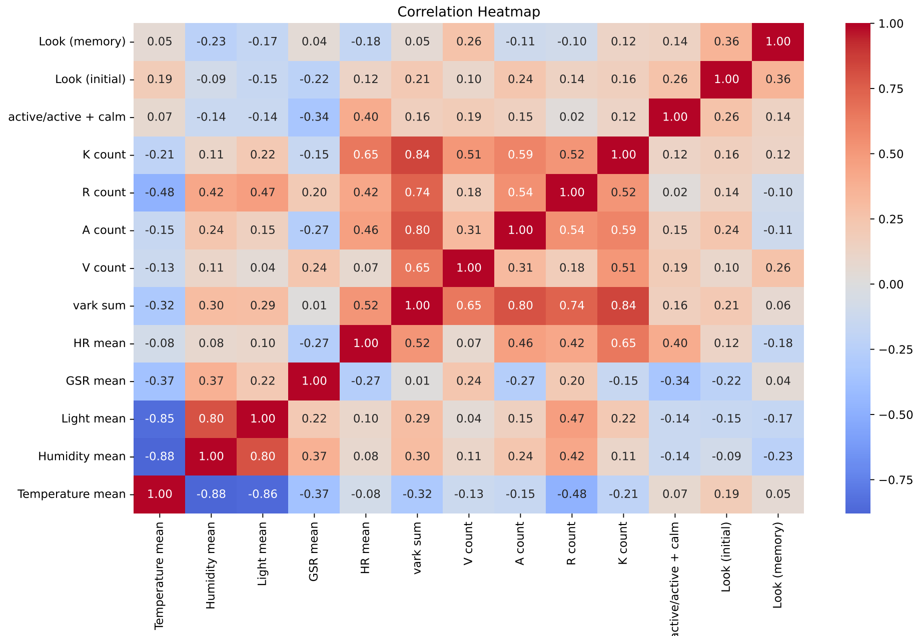


Fig. 5. Cross correlations of variables

3 Results

Table 1. CORRELATIONS

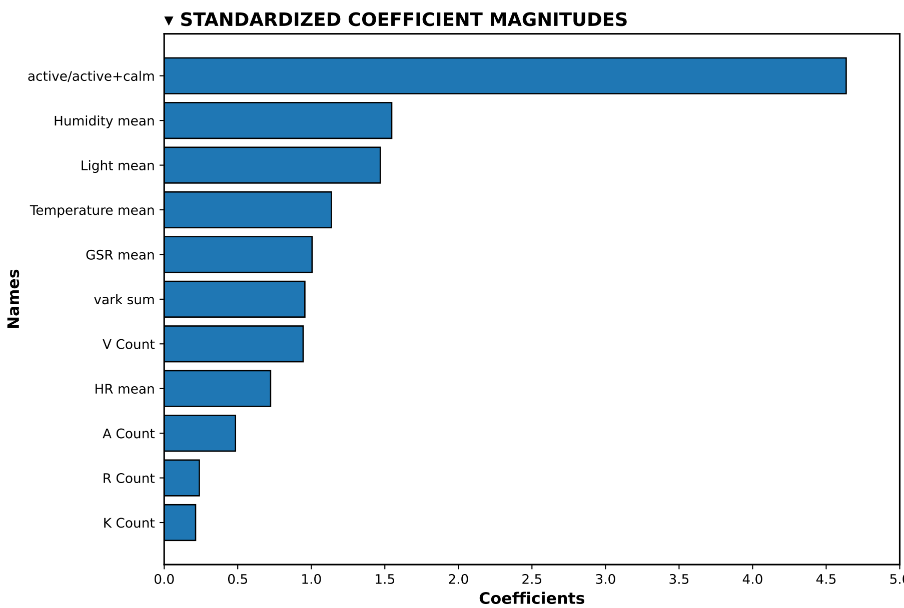
	First Measurement	Second Measurement	Coeff
1	Mean Heart Rate	Sum VARK values	0.52
2	Appearance (initial)	Appearance (memory)	0.36
3	Mean Heart Rate	Muse activity (%)	0.4
4	GSR mean	Muse activity (%)	-0.34

There are some high correlations present in the matrix (Table 1), some possible explanations for these are:

- *Initial appearance and appearance after 1 week.* People who learn well during the training period retain more of that learning over time.
- *Heart rate and proportion of Muse active time.* Mental activity may be related to physical activity. A harder working brain increases heart rate.

One correlation that is difficult to explain is the relationship between heart rate and sum VARK values. As such, this would be an interesting topic for further study. It is possible that people who answer the VARK questionnaire enthusiastically also put more physical and mental enthusiasm into the learning procedure.

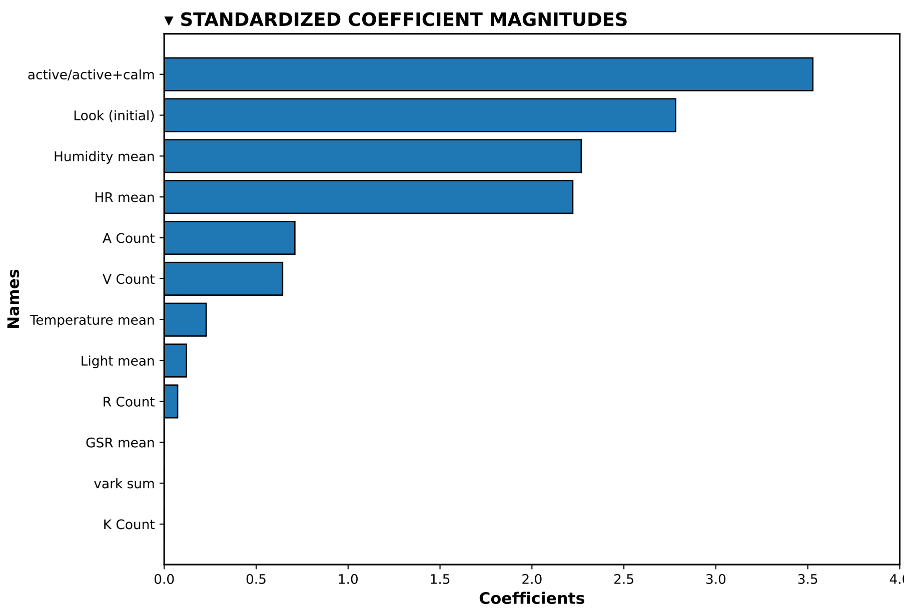
Single variable correlations can yield some interesting relationships, for instance, a coefficient of 0.52 equates to a p value of 0.013 meaning there is a good possibility that there is a significant relationship between heart rate during learning and the sum VARK score variable. To get a deeper understanding of how different variables impact on the learning model, a generalised linear model was built. This approach uses a least squares approach corresponding to the Gaussian model [17]. The model is fitted by solving the least squares problem, which is equivalent to maximising the likelihood.



Variable	Relative Importance	Scaled Importance	Percentage
active/active+calm	4.6360	1.0000	0.3471
Humidity mean	1.5467	0.3336	0.1158
Light mean	1.4691	0.3169	0.1100
Temperature mean	1.1368	0.2452	0.0851
GSR mean	1.0053	0.2168	0.0753
vark sum	0.9563	0.2063	0.0716
V Count	0.9446	0.2038	0.0707
HR mean	0.7233	0.1560	0.0542
A Count	0.4847	0.1046	0.0363
R Count	0.2390	0.0516	0.0179
K Count	0.2135	0.0461	0.0160

Fig. 6. Linear regression coefficients when predicting origami quality (Elastic Net regularisation (alpha = 0.5, lambda = 2.5))

This model approximated the 'Look' metric to a 5 fold cross validation accuracy of greater than 90% for both the initial training origamis and the remembered origami one week after the learning phase. When we examine the standardised coefficients of this model with the Muse activity quotient (Equation 1) as being at least three times more important than any other metric, for predicting the visual quality of the folded origami on the day of learning. As shown in Fig. 6, various other metrics appear to have some importance, with the V score in the VARK questionnaire generating the highest coefficient out of the 4 learning preferences.



Variable	Relative Importance	Scaled Importance	Percentage
active/active+calm	3.5275	1.0	0.2805
Look (initial)	2.7816	0.7885	0.2212
Humidity mean	2.2681	0.643	0.1803
HR mean	2.222	0.6299	0.1767
A Count	0.7106	0.2014	0.0565
V Count	0.6439	0.1825	0.0512
Temperature mean	0.2284	0.0647	0.0182
Light mean	0.1213	0.0344	0.0096
R Count	0.0731	0.0207	0.0058
GSR mean	0.0	0.0	0.0
vark sum	0.0	0.0	0.0
K Count	0.0	0.0	0.0

Fig. 7. Linear regression coefficients when predicting origami quality on memory (Elastic Net regularisation (alpha = 0.5, lambda = 1.8))

As shown in Fig. 7, when we look at the predictive task of estimating the quality of the origami folded one week after the learning process, the Muse EEG quotient still appears most important but to a lesser extent than during the learning session. This is mainly because the initial quality of the origami during training, "Look (initial)", is also a good predictor. Subjects scoring higher on the Visual learning metric of the VARK questionnaire again appear related to the ability to retain the folding skills.

4 Discussion

In this work we use the process of teaching subjects to fold origami objects as a proxy for learning. This brings with it some possible biases. It may be that this type of learning is more visual and tactile than many other types of learning, so may inherently favour subjects who enjoy Visual learning. Accepting this, we still feel it is a useful example of a learning process and the results point to some interesting features.

Firstly, there appears to be a strong correlation between the 'positivity' when users fill in the VARK questionnaire and the enthusiasm captured by the heart rate and Muse activity during the learning task. If this persists across a range of experiments, this would be an interesting observation with significant implications for learning strategies and engagement metrics. The VARK questionnaire is a self-authored tool whereby users assess their own learning styles and if there is a key link between how open minded ("I enjoy and am able to learn in all ways"), subsequent performance and activity during the learning process, this would point to a useful learning strategy for students.

When analysing the predictive task of estimating the origami quality, we find an important role, via linear regression coefficients, of the Muse headset activity. This is a threshold degree of EEG activity as captured by the headset. There seems a clear short term and long term benefit of learning in a way that creates detectable EEG activity. This may be useful to learners in that if they train themselves to get into the active EEG state during learning, both their short and long term learnt ability may increase.

4.1 Limitations and Future Work

While this study provides valuable insights into learning styles, cognitive engagement, and physiological responses, there are several limitations to consider. Firstly, the final sample of 26 participants who completed both phases may not be sufficiently large or diverse to generalize findings to broader populations. Future studies should aim for a larger and more representative sample to enhance reliability. Secondly, the origami task primarily relies on visual-spatial skills and may inherently favour visual and kinaesthetic learners. Other learning tasks, such as verbal reasoning or mathematical problem-solving, might yield different correlations between learning styles and physiological engagement.

Furthermore, while this study employs a linear regression model to analyse the relationship between learning engagement (measured via EEG activity and heart rate) and learning performance, we acknowledge that the underlying relationship may be non-linear. Many cognitive and physiological processes exhibit complex, non-linear interactions [1], which may not be fully captured by a linear approach. However, the choice of a linear model was made due to its interpretability and computational efficiency, which allows for easier identification of key contributing factors. Future research could explore non-linear modelling techniques, such as generalized additive models (GAMs) [8], neural networks [13], or support vector regression [19], which have been used for capturing complex patterns in physiological and cognitive data [2].

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