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Are learning preferences really a myth? Exploring the mapping between study approaches and mode of learning preferences

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ABSTRACT
This article tested for the presence of the conversion effect in the mapping related to the strength of students' preferences for receiving information in a visual, auditory, read/write or kinaesthetic modality and the study approaches they adopt when taking notes in class, learning new concepts and revising for exams. The results indicated that the conversion effect is not ubiquitous but is context specific and only present when students seek to learn a new concept and revise for exams. It was present for students with strong visual and read/write preferences but only when attempting to learn a new concept. It was also present for students with a strong auditory preference when revising for exams, while these students preferred to learn a new concept by reading about it. However, the conversion effect did not emerge with kinaesthetic-leaning students in any of the contexts studied, while these students were significantly more likely to utilise auditory input when learning a new concept. Overall, the findings suggest that traditional educational approaches such as lectures and tutorials can be effective in supporting the learning for diverse student groups.

Section: RESEARCH PAPER

Keywords: Learning preferences; VARK; study preferences; study habits; learning

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1. INTRODUCTION

Learning is an essential part of life, and since the acquisition and development of new skills throughout one's career is crucial, scholars are continuing their attempts to identify the factors that influence the effectiveness of learning and the subsequent academic performance. Many instruments have been developed to assess learner engagement and their attitudes and aptitudes at different stages of the learning process or to assess the way in which individuals learn, with the objective of identifying the optimal study strategies that can be adopted by learners at the point of interaction with their learning environment [1]-[3]. While learning can take place in various different contexts, the complex interactions that arise in formal learning sites such as classrooms are of particular interest since the classroom environment provides a unique setting in which exogenous variables can be controlled, thus potentially increasing the effectiveness of the learning process.

A significant number of theories have emerged aimed at explaining the various learning approaches taken by students in the classroom and have been largely embraced by educators. However, various recent meta-analytical studies have failed to support the existence of disparate learning styles [4], [5]. Here, the notion that approaches that are intuitively attractive and highly popular among educators, such as matching the mode of delivery (visual, auditory, read/write or kinaesthetic) to the student's learning preference, can enhance performance has been largely discredited [6]. However, neuroscience-grounded evidence has emerged that indicates that students may, in fact, have an inherent preference for the mode through which they receive information [7]. Specifically, functional magnetic resonance imaging (fMRI) scans have demonstrated that individuals with a strong visual preference have to convert words into pictures when presented with text-based input in order to understand it, while individuals with a strong read/write text preference have to convert pictures into text to help with the comprehension [8]. Further support for the existence of a preference for visual or text-based (read/write) information intake has been provided through psychology-based eye-tracking studies, which demonstrated that visualisers (students with a preference for pictures and diagrams) and verbalisers (students with a preference for text) generally examine the areas on the screen where the information is presented in terms of their specific preference, with visualizers found to be able to focus for longer on information-rich areas of diagrams than verbalisers [9].

These findings suggest that the mode of a student's information input preference could play a role in the speed of the information processing and the way in which they interact with the learning materials. However, empirical research related to the link between students' information-input preferences and their cognitive style and ability within the context of probabilistic reasoning suggests that the interactions between these elements of the learning process are complex and plagued by contradictions, which means that making generalisations and devising practical recommendations regarding the most efficient learning strategy is a highly difficult task [10]-[12].

Furthermore, past research has indicated that students' study strategies and habits, as well as affective factors such as attitudes and self-regulation, can play a significant role in predicting academic performance [13]. Evidence from the fields of educational psychology and educational neuroscience supports these findings and indicates that effective learning takes place when the information taken in by the students is moved to the long-term memory and the behaviour associated with it is automated [14]. In light of these findings, a number of new conceptual learning frameworks have been proposed, explicitly identifying the relationship between the different elements affecting learning proposed by educational neuroscientists and psychologists, such as students' preferred mode of information input (visual, textual) as well as their attitudes, study strategies and the habits they adopt to manage their learning [15], [16]. Despite being grounded in neuroscientific research, the validity of the frameworks is yet to be tested within the context of education-based empirical evidence.

This article sets out to address this gap by examining the information input preferences of students and studying their habit behaviour (classified as visual, auditory, read/write and kinaesthetic) in terms of a conversion effect within the context of taking notes in class, learning a new concept and revising for exams. It is expected that students with a strong visual input preference will be more likely to adopt a visual behavioural approach to taking notes in class and learning (e.g. summarising notes as diagrams, or learning a new concept from a diagram), while students with a strong text-based preference (read/write or verbalisers) will be more likely to adopt a corresponding approach (e.g. writing down every word the lecturer says, or learning a new concept by reading about it).

The remainder of the article is organised as follows. Section 2 provides an overview of the proposed conceptual framework linking the preferred learning modality with the study behaviour approaches before section 3 discusses the methodology used to classify the student's information input preferences and study behaviour as visual, auditory, read/write and kinaesthetic as well as the results from the analysis. Section 4 then discusses the implications from the findings within the context of education before the final section summarises the research findings and provides a number of suggestions for further research.

2. FRAMEWORK LINKING INFORMATION INPUT PREFERENCES AND STUDY APPROACHES

Many instruments and models have been designed to assess and describe the approach taken by students when studying [3], while the terms used by academics to reflect the different elements involved in the learning process are not always well defined [17]. Before introducing the learning framework demonstrating the interaction between different aspects of learning, we must first outline the definitions of the different terms used in this paper.

Learning preferences relate to the learner's preference for one method of teaching over another [18] and reflect the way in which a learner prefers to receive information. Conventionally, there are four ways of conveying and absorbing information: visual (via pictures and diagrams), auditory (hearing), read/write (via text) and kinaesthetic (through doing), which together are termed as VARK. The preferences of students for using combinations of information input pathways are generally assessed using VARK-type questionnaires [19]. Meanwhile, the terms 'study habits' and 'study strategies' are used interchangeably in the academic literature and their definitions have evolved over time to encompass a number of different sub-constructs and aspects of study habits or behaviour, covering various different cognitive, affective and behavioural activities [2]. Here, the cognitive factors reflect the approach and techniques used by students to draw inferences from the information, which may include deep, strategic and surface approaches to learning [2], while the affective components are linked to the students' emotions and define their motivation and anxiety as well as their propensity to avoid procrastination [13]. Lastly, behavioural factors include study-related behaviours such as note taking, highlighting and reviewing [20]. The majority of study habits and strategy instruments involve the use of a combination of some, if not all of these sub-scales [2], [3].

However, evidence from empirical neuroscience research suggests that treating study habits and strategies as identical may be an oversimplification. Brain scanning provides further insight into how individuals make decisions, including the way in which students react when finding themselves in a context that may or may not be familiar to them. Here, the attendant research demonstrates that their behaviour is governed by the interactions of two systems in the brain: the reflective *C*-system and the reflexive *X*-system. [21], [22]. The reflective *C*-system is used in situations that are largely unfamiliar and provides a sequential and exacting assessment for the appropriate course of action. Meanwhile, the reflexive *X*-system is used in familiar situations, where actions are automatic and relatively effortless, and involves the use of parallel processing. Within the context of learning, this can be explained in terms of a student who is attending a lecture for the first time and is not sure how to handle the situation versus a student who has attended lectures in the past and automatically 'knows' what to do. Students who consistently use the same study strategies could benefit in the long term by gradually strengthening their decision pathways and shifting from using their reflective system to using the more efficient and less arduous reflexive system. In addition, the repeated actions lead to situational familiarity, which, in turn, is more likely to trigger the same habitual behavioural response [22], further reinforcing the habituation of that specific behaviour. This reinforcing feedback loop could explain how students can become trapped in using inefficient study habits and strategies,

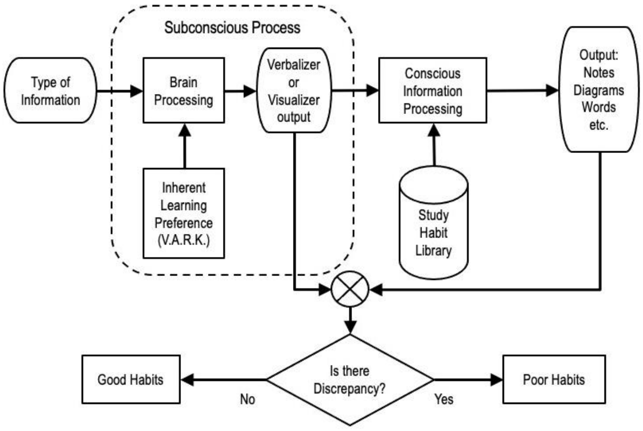

Figure 1. Conceptual framework linking information processing and study approaches.

even when they make a conscious effort to study hard or work efficiently [17].

Therefore, the optimal study strategy would be context-dependent in terms of both the individual's specific information processing preference mode and the mode in which the information is presented to them, which is reflected in the conceptual framework shown in Figure 1. Here, the structure highlights the subconscious information processing carried out to aid comprehension that may lead to an additional information-processing step carried out by learners when presented with information in a mode other than their primary VARK preference. It also illustrates the interaction between the reflective and reflexive decision-making systems by explicitly demonstrating the impact of study habits on the conscious information-processing behaviour learners carry out as part of their learning activities. As can be seen in Figure 1, poor study habits are the result of a discrepancy between the inherent information preference output generated subconsciously to aid understanding and the study related output generated using 'conscious' information processing.

The proposed framework can be used as a tool for identifying the potential for improvement in a student's study behaviour. Specifically, the student's inherent mode of learning preference and the output produced as a result of their study efforts can be compared, with any discrepancy found indicative of potentially poor study habits. The complex interrelationship between learning approaches and information processing may account for some part of the variation in the success of students' learning strategies. Adopting a study strategy that is not optimal (e.g. a visual learner reading their lecture notes over and over again without summarising them into diagrams) could result in a highly inefficient and arduous learning experience and could ultimately lead to discouragement and increased anxiety. While the higher educational system has been deigned to instil good study habits and to encourage students to become independent learners, to the best of our knowledge, no study strategy instrument is aimed at assessing the fit between the student's preference for seeing a specific type of information and their approach to handling it. Of course, if a learner is multi-modal, the impact of the potential discrepancy between actual and optimal behaviour may be small. However, learners with a strong single preference will potentially be most at risk of adopting a suboptimal study strategy, which is supported by empirical findings indicating that learners with a single strong modal learning preference are at a much higher risk of academic failure, compared to their peers with more balanced or multimodal preferences [23]. It is worth noting that the framework focuses on examining the disparities that may exist between a learner's inherent information processing preference and their study habit behaviour in different learning contexts. Study habit behaviour is complex and may be influenced and mediated by other intrinsic factors such as a learner's academic self-efficacy, motivation and optimism as well as external interactions such as formative and/or summative feedback and recommendations by the lecturer [20]. While the impact of these factors on study behaviour may be significant, evaluation of their impact on the interactions between a learner's inherent information processing learning preference and their study habit behaviour in different learning contexts is beyond the scope of this study.

3. MAPPING OF STUDY APPROACHES TO VARK MODALITY PREFERENCES

3.1. Methodology

This research utilises Fleming's updated VARK questionnaire [19] to measure the blend and the strength of students' preferred learning mode. The questionnaire consists of 16 scenarios, each of which includes four options corresponding to a different information input preference, namely, VARK. Users are asked to tick all options that apply to them in a specific situation. The VARK questionnaire's validity has been examined using exploratory factor and Rasch analyses, with the questionnaire confirmed to be suitable as a low-stake diagnostic tool, one that can be used to make study approach recommendations, while

Table 1. Classification of study habits/approaches.

Study Habit/Approaches	Type of Preference
When taking notes in class I: summarise concepts by drawing pictures and diagrams.	V
When taking notes in class I: write down every word the lecturer says.	R/W
When doing homework, I tend to learn a new concept by: looking at a diagram.	V
When doing homework, I tend to learn a new concept by: having it explained to me.	A
When doing homework, I tend to learn a new concept by: reading about it.	R/W
When doing homework, I tend to learn a new concept by: doing exercises, examples and trying it out.	K
When doing homework exercises, I tend to: read about things first before I try to solve them.	R/W
When doing homework exercises, I tend to: get stuck straight in and try solving them.	K
When revising for exams I: talk to others and discuss the material in my notes.	A
When revising for exams I: read the notes aloud to myself or others.	A
When revising for exams I: read through the notes taken in class.	R/W
When revising for exams I: re-write/re-draw my notes.	K

Table 2. Learning preference sample distribution.

Preference Type	Frequency	Percent	Cumulative Percent
Mild Aural	8	8.7	8.7
Mild Aural, Mild Kinaesthetic	1	1.1	9.8
Mild Aural, Mild Read/Write	1	1.1	10.9
Mild Kinaesthetic	13	14.1	25.0
Mild Read/Write	2	2.2	27.2
Mild Visual	7	7.6	34.8
Strong Visual	7	7.6	42.4
You have no particular preference. You use all 4.	53	57.6	100.0
Total	92	100.0	

more research is required to confirm its suitability as a robust research instrument [24], [25].

To the best of our knowledge, no instrument has been designed to assess the approach taken by students when studying in terms of their VARK modalities. However, a number of study-strategy questionnaires have been proposed with the aim of capturing students' study approaches in different study contexts, such as note taking and revising [20], [26]. The study-strategy questionnaire designed and validated by Nonis and Hudson [20] was used as the basis for developing a questionnaire aimed at eliciting the information-processing approach students adopt (visual, auditory, read/write or kinaesthetic) within three different study contexts, namely, when taking notes in class, doing homework or revising (see Table 1). Each question was allocated to the visual, auditory, read/write or kinaesthetic categories and students were then asked to identify all the study behaviours they may adopt in any specific situation.

The VARK/study approach questionnaire was administered to a convenience sample of 100 postgraduate and undergraduate students, with 92 complete questionnaires gathered electronically. The majority of the respondents were undergraduate students (84 %) and female (57 %), with a mean age of 23 years. The students were from a range of faculties, with the majority studying in the Faculty of Business and Law (57 %), followed by Arts and Social Sciences (20 %) and Science, Engineering and Computing (14 %). The majority of students were classified in terms of 'using all four modes' (57.6 %), followed by students with a single preference (40 %). No students reported using three modes, while only a small number reported utilising two preference modes (2.2 %) (see Table 2). The students in this sample reported slightly weaker preference for Visual study approach overall (see Table 3) and very similar preference strength for Aural, Read/Write and Kinaesthetic approaches. The overall sample mean learning preference strength shown in Table 3 can act as a comparative benchmark when examining the data for statistically significant variations.

The data were analysed using SPSS version 21, with an independent sample t-test used to compare the mean strength of each VARK preference across the different types of study behaviour adopted by the students. Results with statistical

Table 3. Learning preferences strength.

Preference Type	Mean	Standard Deviation
Visual	7.92	3.0
Aural	8.42	2.7
Read/Write	8.13	2.5
Kinaesthetic	8.73	2.6

significance of less than 5 % were also evaluated in terms of practical significance using Cohen's d effect size.

3.2. Results

The behaviour of the students and the strength of their VARK preferences were examined within three different contexts: when taking notes in class, when learning a new concept and when revising for exams.

The conversion effect was not present within the context of taking notes in class and no significant difference was observed between the behaviour of students when taking notes in class, when accounting for the strength of their VARK preferences. The students' study behaviour did not change as their respective preference for receiving information in a specific format (visual, auditory, read/write and kinaesthetic) increased. It was hypothesised that perhaps the conversion effect would be present when considering only the students who expressed a strong preference for visual or read/write preferences. However, the sample did not contain any students with a strong read/write preference, thus, the t-test was run for the subgroups of strong visual vs. mild read/write. While, there was no significant difference between the strength of the students' preference scores and their behaviour when summarising notes as diagrams, perhaps somewhat surprisingly, the students with a strong visual preference were significantly more likely to write down every word said by the lecturer when taking notes in class ($M = 12.1$, $SD = 3.03$), compared to students with a lower visual preference, ($M = 3.00$, $SD = 1.41$, $t[7] = 4.001$, $p = 0.005$). Furthermore, Cohen's effect size ($d = 3.18$) suggested the strong practical significance of the above result.

Within the context of learning a new concept, the conversion effect was present for students with strong read/write and visual preferences. Students with a higher read/write preference were significantly more likely to learn a new concept by reading about it ($M = 8.56$, $SD = 2.36$) than those who reported a lower preference ($M = 7.21$, $SD = 2.72$, $t[90] = 2.426$, $p = 0.017$). Here, Cohen's effect size ($d = 0.53$) suggested a moderate practical significance. Similarly, students with a stronger visual preference were more likely to learn a new concept by looking at a diagram ($M = 8.58$, $SD = 2.86$) than those who reported a lower visual preference ($M = 7.08$, $SD = 3.01$, $t[90] = 2.44$, $p = 0.017$), with Cohen's effect size ($d = 0.51$) again suggesting a moderate practical significance.

Again somewhat surprisingly, the conversion effect was not present for students with a stronger auditory preference ($M = 8.84$, $SD = 2.69$), who were far more likely to read about a new concept rather than have it explained to them, compared to their counterparts with a lower auditory preference ($M = 7.52$, $SD = 2.38$, $t[90] = 2.27$, $p = 0.026$). Here, Cohen's effect size ($d = 0.52$) suggested a moderate practical significance. In fact, learning a new concept through having it explained was a behaviour that was also more likely to be adopted by students with higher read/write ($M = 8.73$, $SD = 2.69$) and kinaesthetic ($M = 9.41$, $SD = 2.59$) preferences, with the opposite the case with students with lower read/write ($M = 7.65$, $SD = 2.33$, $t[90] = 2.04$, $p = 0.045$) and kinaesthetic ($M = 8.18$, $SD = 2.54$, $t[90] = 2.31$, $p = 0.023$) preferences. Meanwhile, the effect size for the behaviour of students with a high read/write preference within the context of learning through having concepts explained was found to be moderate to low ($d = 0.43$), which was also the case for students with a high kinaesthetic preference ($d = 0.48$).

Within the context of revision, a conversion effect was present for auditory students, with those with a higher auditory preference ($M = 9.23$, $SD = 2.37$) being more likely to read the notes aloud, compared to students who expressed a lower auditory preference ($M = 7.58$, $SD = 2.70$, $t[90] = 3.13$, $p = 0.002$). Here, Cohen's effect size for the different behaviours of students with high and low auditory preferences was moderate to high ($d = 0.65$). In addition, students with a stronger read/write preference ($M = 8.68$, $SD = 2.21$) were also more likely to read the notes aloud, compared to their counterparts with a lower read/write preference ($M = 7.56$, $SD = 2.76$, $t[90] = 2.16$, $p = 0.03$. Here, Cohen's effect size was moderate to low ($d = 0.45$).

4. DISCUSSION

The results suggest that for this set of students, the convergence between study behaviour and learning preferences was not ubiquitous but context specific.

There was no evidence of such convergence within the context of taking notes in class, with students being equally likely to write down every word said by the lecturer or summarise the ideas using a diagram, irrespective of the strength of their preference for visual, auditory, read/write or kinaesthetic information input. This was somewhat surprising since the evidence from neuroscience suggests that students with a strong visual preference tend to find a summary diagram approach more conducive to their learning, compared to their counterparts with a strong read/write preference [8]. In fact, the converse seems to be true, with students with a strong visual preference being more likely to write down every word the lecturer says. This could possibly be explained by the fact that summarising concepts requires additional processing, which the students may find difficult to achieve within the classroom context while listening at the same time. However, this behaviour could, in fact, be indicative of poor study habits, formed when students do not adopt the approach likely to suit them best. It is worth noting that this finding is based on a very small sample size as the subset of students with a strong visual preference was extremely small and it is thus recommended that further investigations using a larger sample size are undertaken before generalising the conclusions.

Meanwhile, within the context of learning a new concept, the conversion effect emerged with students who expressed stronger read/write and visual preferences, with the attendant behaviours prioritising reading and looking at diagrams, respectively. This suggests that students intuitively choose the approach that will help them learn more efficiently, which is in line with the findings from neuroscience where the conversion effect was observed [8]. The notion of the conversion effect was also supported by various empirical eye tracking studies related to verbalisers and visualisers, which demonstrated that students with strong visual preferences spend more time looking at diagrams, while those with stronger read/write preferences spend more time looking at text [9]. This finding suggests that in order to effectively support the learning for students with strong read/write and visual preferences, lecturers must ensure that they present balanced materials that contain both visual and read/write content.

Again, somewhat surprisingly, the conversion effect was not present for students with a stronger auditory preference, who were more likely to attempt learning a new concept by reading about it rather than rely on an auditory input, such as an explanation. This convergence was present when students with a stronger auditory preference attempted to revise a concept they had already learned, but not when first attempting to learn it. This implies that auditory students need to reflect on their learning in order to consolidate their understanding and that this happens more effectively when they are revising.

In fact, it is the students with strong read/write and kinaesthetic preferences that would appear to rely on auditory input when learning a new concept, generally in terms of having things explained to them. While the practical effect size for this behaviour was moderate to low, the implication is that traditional lectures or materials with an auditory component will be appropriate for supporting these groups of students. It would appear that students with stronger read/write, auditory and kinaesthetic preferences may adopt learning strategies that do not always align with their expressed learning preferences. This could perhaps be partially explained by the large proportion of multi-modal students in the sample, who, naturally, tend to adopt a range of learning strategies.

As noted above, the conversion effect was found to be present for auditory-leaning students when revising concepts, with students with a stronger auditory preference being more likely to experience it. Somewhat surprisingly, students with a stronger read/write preference were also likely to adopt this behaviour when revising, possibly due to the biased nature of the question, which described behaviour that includes both read/write and auditory aspects.

It is worth noting that students with a strong kinaesthetic preference were the only group that did not support the convergence theory within any of the contexts tested, while they were significantly more likely to adopt an auditory approach when learning a new concept. Further research is required to identify further ways in which the learning of kinaesthetic-leaning students can be supported.

5. CONCLUSIONS

This article examined the presence of a conversion effect between students' preferences for visual, auditory, read/write and kinaesthetic information processing and their study behaviour within the context of taking notes in class, learning a new concept and revising for exams. The results indicated that the conversion effect is not ubiquitous but context specific and is only present when students seek to learn a new concept and revise for exams. The conversion effect was present for students with strong visual and read/write preferences only when they attempted to learn a new concept, which implies that there is a need for including a range of study support materials in lectures and seminars to enhance the students' experience. Meanwhile, the conversion effect was present for students with a strong auditory preference when they revised for exams, while they expressed a preference for learning a new concept by reading about it, suggesting the need for support materials with both auditory and textual components. The conversion effect was not clear with kinaesthetic-leaning students within any of the contexts studied, while the students with a stronger kinaesthetic preference were significantly more likely to utilise auditory input when learning a new concept. Overall, the findings are in line with the research from neuroscience and suggest that traditional educational approaches, such as lectures and tutorials, can be effective in supporting the learning for diverse groups of students. The findings also raise interesting questions regarding the best approaches for supporting peer-to-peer learning within the educational context by creating groups consisting of team members with balanced learning preferences (e.g. students with strong visual or read/write preferences) in order to enhance the learning experience for all students.

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