Should Learning Material’s Selection be Adapted to Learning Style and Personality?

Manal Alhathli  
University of Aberdeen  
King’s College  
Aberdeen, UK AB24 3UE  
r01maea@abdn.ac.uk

Judith Masthoff  
University of Aberdeen  
King’s College  
Aberdeen, UK AB24 3UE  
j.masthoff@abdn.ac.uk

Advaith Siddharthan  
University of Aberdeen  
King’s College  
Aberdeen, UK AB24 3UE  
advaith@abdn.ac.uk

ABSTRACT
This paper investigates the influence of learner personality and learning styles on the selection of different styles of learning materials. We considered the five big personality traits (focusing in particular on Extraversion and Openness to Experience) and Felder and Soloman’s Index of Learning Styles instrument (ILS). We found no real impact of learning styles, except for a small effect for the visual/verbal style. We also did not find an impact of personality on the selection of different styles of learning materials.

CCS CONCEPTS
• Human-centered computing → User models; • Applied computing → Computer-assisted instruction;

KEYWORDS
personality; learning material; learning styles; educational recommender; personalization

1 INTRODUCTION AND RELATED WORK
Learning is increasingly no longer confined to the classroom, with a wide variety of learning materials available on-line. We are interested in the adaptive selection of such learning materials (LMS). Many learner and LM characteristics may need to be considered when selecting the best LM for a particular learner. This paper will investigate whether learning style and learner personality need to be considered when selecting a certain style of LM. Of course, an Educational Recommender system would need to also consider the content and the difficulty level of LMs, as well as for example the knowledge, ability, interests, attitudes, motivation, and goals of the learner. However, that is outside the scope of this paper.

1.1 Learning Style
Learning styles have been put forward as an important instrument in education to help teachers understand how learners learn [6], and to be taken into consideration when delivering educational materials [44]. Dunn and Dunn define a learning style as “the way each person begins to concentrate on, process, internalize, and retain new and difficult academic information” [15, 16]. Learning styles can also be considered as learner preferences, and the differences between them are said to matter greatly [2]. Learning style is a wide concept due to the large variety in previous research [43]; 71 different styles were used in the studies reviewed by [8].

The topic of learning styles is highly controversial. On the one hand, there has been research in support of learning styles. Researchers report studies showing that learning style is an essential aspect to understand individual differences and learning achievement [29]. Other studies confirm that developing an on-line learning system which takes into consideration learning style is more efficient than the traditional approach [21]. Furthermore, it is claimed that considering a specific learning style can help to achieve learner goals by reducing learning time, thus enhancing their learning outcomes and comprehension [4, 7, 25, 31, 33]. There has been a lot of work on using learning styles in adaptive e-learning systems, see [39] for a review of 51 studies in this area, many of which reported positive findings. Examples of e-learning systems that use learning styles include eTeacher [34], iWeaver [42], TSAL [40], ilearn [30] and ADAPTAPlan [5].

On the other hand, there is a lot of research pointing out that learning styles are not a valid construct. Learning styles theories have failed to provide scientific evidence, and many other aspects can be used to improve learning, such as a learner’s ability and classroom methods [41]. Prior knowledge and intelligence were found to be the main differences which categorized learners [13].

While there are several learning style tools and methodologies [8], two of them are well known in science and engineering education [17, 37]: Kolb’s Learning Styles Inventory (LSI) [23] and the Felder-Silverman Index of Learning Styles (ILS) [18]. Each instrument classifies learning based on a questionnaire. This paper uses ILS which is available on the Internet and consists of 44 multiple-choice questions designed to identify learning style of an individual [18]. The validity and reliability of ILS has been determined among multiple domains [19], and it tends to be regarded as a more valid construct than other learning styles. The review by [39] of learning styles in adaptive e-learning systems showed that ILS was used in over 70% of the 51 studies reported.

ILS uses four dimensions which are active-reflective, sensory-intuitive, visual-verbal and sequential-global [18]. Cook et al. [9] investigated the validity of ILS constructs. Their study provided evidence for the internal structure validity of the active-reflective, sensing-intuitive and visual-verbal dimensions (with moderate to high test-retest reliability), whilst there was less evidence for the validity of the sequential-global dimension. They also considered
multiple learning style methods and the extent to which their results correlated and found evidence supporting the active-reflective and sensory-intuitive dimensions. Their analysis of whether participants felt the ILS scores reflected their learning style provided support for all ILS dimensions, with active-reflective, sensory-intuitive and visual-verbal scoring high (above 85% agreement) and substantially higher than sequential-global. They also analysed other learning styles (ILS, LSTI, CSA) and concluded LSI was the better one to use. In this paper, we will therefore use LSI, but will keep the relative construct validity of the dimensions in mind when analysing the results.

1.2 Learner Personality

The most adopted definition of personality is based on five dimensions [10–12]. These so-called Big Five personality traits are usually named extraversion, agreeableness, conscientiousness, neuroticism and openness to experience. Extraversion refers to a higher degree of sociability, energy, assertiveness, and talkativeness. Neuroticism refers to the degree of emotional stability, i.e. someone who is calm and not easily upset. Openness to experience refers to those who are interdependent-minded, and intellectually strong. Conscientiousness refers to being disciplined, organised, and achievement-oriented. Finally, agreeableness refers to being good-natured, helpful, trustful, and cooperative [26].

Several studies have shown the effect of learner personality on the learning process, and it has been shown that certain personality traits consistently correlate with learner achievement and success [24]. Recently published studies from the field of educational psychology found that the Big Five personality traits are a reliable predictor of academic achievement [32].

Our previous work in the language learning domain found that extroverts were more likely to select social and active materials in terms of enjoyment, increasing the learner’s confidence and language skills. However, we also found that the majority of both the extrovert and introvert participants rated social and active as the best materials to recommend [3]. As the learning domain (language learning) could have influenced the results, we have since repeated this study in another domain (mathematics) and found no evidence of an effect of personality in that domain. Some research has taken both personality and learning styles into consideration. For example, learning a wide range of words was associated with both the Openness to Experience personality trait as well as the Intuition learning style [1].

2 STUDY DESIGN: THE INFLUENCE OF PERSONALITY AND LEARNING STYLE

This study aimed to enhance our understanding of the influence of personality and learning style on learning material selection for a learner. The participant’s own personality and learning style was used. To reduce the effort needed from individual participants, the study was split into four, with each group rating 2 LMs.

2.1 Participants

Participants were recruited through a web service called Amazon’s Mechanical Turk [27]. Mechanical Turk allows the creators of tasks (requesters) to recruit participants (workers), and approve or reject completed work before payment. Mechanical Turk holds many statistics on each worker, including their location and acceptance rate. The acceptance rate is a global statistic available to all requesters on Mechanical Turk. Thus if a worker consistently submits poor or incomplete work, their acceptance rate will drop. As requesters usually set a high acceptance rate as as requirement for their tasks, this causes workers to take their acceptance rate very seriously, and to complete the tasks to the best of their ability.

To participate, participants had to pass a Cloze Test [38] for English fluency, have an acceptance rate of 90% on previous Mechanical Turk tasks, and be based in the US. There were 163 participants (73 female, 90 male; 28 aged 18-25, 85 aged 26-40, 47 aged 41-65, 3 over 65). As the project’s focus is on recommendation of on-line learning materials, the wide participant range is not really an issue, given all could be involved in life-long learning.

2.2 Materials

The domain of this study was about learning to create web pages using HTML. We created 8 learning materials (LM1-LM8), trying to match the ILS dimensions which are active/reflective, sensory/intuitive, visual/verbal and sequential/global [18]. The extent to which the LMs aligned with these learning styles was validated during the study.

As we assumed most participants would be new to HTML, the LMs were designed to be very simple, using only very basic HTML tags that were explained to participants at the start of the study.

All LMs were related to the same learning content, to avoid effects due to the content used as much as possible.

Figure 1 shows the LMs used, the learning style characteristic they were designed for, and the characteristics they were used for in the analysis after the validation.

2.3 Procedure

First, participants provided their demographics and completed a short personality test for the Five-Factor Model (FFM) [20], using Personality Sliders, a newly developed personality test [35]. For each trait from the FFM, participants were shown two stories (developed by [14]), one depicting a person that was low for that trait and the other depicting someone who was high. Participants used a slider to indicate which person they were most like, resulting in a value for each trait between 18 and 162. These were validated as accurately measuring the FFM [36].

Next, participants were introduced to “Alex”, who has a similar personality to them. They were told that Alex is learning HTML and has just attended a class on creating a personal web page. They were given a brief introduction to HTML, explaining what it is for and the basic HTML tags used in the LMs. The virtual learner “Alex” was used to reduce the impact of participants’ possible background knowledge on HTML. This meant participants could rate LMs for this learner who was new to HTML, rather than being influenced by their own knowledge of HTML, which would have influenced how enjoyable and skill enhancing LMs would be for themselves.

Next, participants rated two LMs using 11 criteria. The first 8 criteria investigated to what extent the LMs where aligned with the learning styles. For example, participants rated how textual and visual the LMs were. We used a scale for each aspect, so one for
Follow each step in order to create your first web page:

**Step 1 : Create a new HTML document with a heading**

Open your text editor (Notepad, TextEdit, KEdit, or whatever is your favorite) and type the following:

```html
<html>
<body>
<h1>Hello World</h1>
</body>
</html>
```

**Step 2 : Add some text**

Use the `</p>` tag to define paragraphs, type the following:

```html
<html>
<body>
<p>My first paragraph.</p>
</body>
</html>
```

(a) LM1: Intended to be active; VERBAL

(b) LM2: Intended to be reflective; REFLECTIVE, SENSORY

(c) LM3: Intended to be sensory; REFLECTIVE, SENSORY, VERBAL

Create a web page about yourself just like George did:

```
Hello, My Name is George
This is my new web page.
```

Write your code:

(d) LM4: Intended to be intuitive; VERBAL

(f) LM6: Intended to be verbal; VERBAL, SENSORY

In this code one part is missing, where should `</head>` go:

```
<html>
<head>
<title>Page Title</title>
</head>
<body>
<h1>Hello</h1>
<p>This is my new page</p>
</body>
</html>
```

Choose the correct answer:

- A
- B
- C

Submit

(g) LM7: Intended to be global; REFLECTIVE

(h) LM8: Intended to be sequential; REFLECTIVE, SENSORY

Figure 1: LMs used, the intended characteristic, the characteristics (capitals) they were used for in the analysis
visual and one for verbal rather than putting visual and verbal at the opposite ends of a scale. So, participants rated the extent to which the learning material:

- "Encourages Alex to try things out" (active)
- "Encourages Alex to think" (reflective)
- "Encourages Alex to solve problems" (sensory)
- "Encourages Alex to be innovative" (intuitive)
- "Is visual" (visual)
- "Is textual" (textual)
- "Encourages Alex to focus on details" (sequential)
- "Encourages Alex to focus on the overall structure" (global)

The last 3 criteria investigated the extent to which participants felt the LM (1) "is enjoyable for Alex", (2) "increases Alex’s confidence" and (3) "improves Alex’s skills".

All criteria were rated using a 5-point Likert scale, from not at all to a lot.

Finally, participants answered the 44 questions of the ILS to determine their own learning style.

2.4 Hypotheses

- H1: There will be a significant positive correlation between the extent of a participant’s learning style preference and their appreciation for LMs that support that learning style (or negative for its opposite). Appreciation is measured through enjoyment, increasing confidence, and skills.
  - H1a: Preference for active is positively/negatively correlated with appreciation of active/reflective LMs.
  - H1b: Preference for sensory is positively/negatively correlated with appreciation of sensory/intuitive LMs.
  - H1c: Preference for visual is positively/negatively correlated with appreciation of visual/textual LMs.
  - H1d: Preference for sequential is positively/negatively correlated with appreciation of sequential/global LMs.

- H2: There will be a significant correlation between the participant’s personality and their appreciation for LMs.
  - H2a: Extroversion is positively/negatively correlated with appreciation of active/reflective LMs.
  - H2b: Extroversion is positively/negatively correlated with appreciation of visual/textual LMs.
  - H2c: Openness to Experience is positively/negatively correlated with appreciation of intuitive/sensory LMs.

3 STUDY RESULTS

3.1 Types of learning materials

We first tested whether the LMs did indeed express different types of learning style aspects of the ILS. For the analysis we required subsets of LMs that were: (1) either clearly active or clearly reflective, (2) clearly sensory or clearly intuitive, (3) clearly visual or clearly verbal, (4) clearly sequential or clearly global.

To decide which LMs were suitable, we conducted one sample t-tests to investigate for each learning style aspect whether the mean significantly differed from the mid-point of the scale (i.e. 3). Based on this, four LMs were found to be more reflective (LM2, 3, 7, 8), and four verbal (LM1, 3, 4, 6). Results for selected LMs are shown in Table 1 and the LMs used are indicated in Figure 1. We did not find a suitable subset of LMs for sequential-global, so excluded this from the subsequent analysis and no longer investigate H1d. As we noted in the literature review, there is less evidence of the validity of the sequential-global construct, which may be one reason for our difficulty in constructing learning materials to express this dimension.

<table>
<thead>
<tr>
<th>LMs Style</th>
<th>LM</th>
<th>Active</th>
<th>Reflective</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reflective</td>
<td>LM2</td>
<td>3.07 (1.19)</td>
<td>3.81 (1.01)* **</td>
</tr>
<tr>
<td></td>
<td>LM3</td>
<td>3.23 (1.23)</td>
<td>3.60 (1.05)**</td>
</tr>
<tr>
<td></td>
<td>LM7</td>
<td>2.81 (1.01)</td>
<td>3.45 (0.86)**</td>
</tr>
<tr>
<td></td>
<td>LM8</td>
<td>3.29 (1.29)</td>
<td>4.02 (0.81)**</td>
</tr>
<tr>
<td>Sensory</td>
<td>LM2</td>
<td>3.64 (1.16)**</td>
<td>2.51 (1.17)**</td>
</tr>
<tr>
<td></td>
<td>LM3</td>
<td>3.60 (1.05)**</td>
<td>2.45 (1.15)**</td>
</tr>
<tr>
<td></td>
<td>LM6</td>
<td>3.71 (1.94)**</td>
<td>2.86 (1.09)**</td>
</tr>
<tr>
<td></td>
<td>LM8</td>
<td>3.95 (1.05)**</td>
<td>2.86 (1.42)**</td>
</tr>
<tr>
<td>Verbal</td>
<td>LM1</td>
<td>3.05 (1.26)</td>
<td>4.19 (1.80)**</td>
</tr>
<tr>
<td></td>
<td>LM3</td>
<td>2.98 (1.23)</td>
<td>4.05 (1.03)**</td>
</tr>
<tr>
<td></td>
<td>LM4</td>
<td>2.23 (1.25)**</td>
<td>3.83 (1.21)**</td>
</tr>
<tr>
<td></td>
<td>LM6</td>
<td>2.76 (1.22)</td>
<td>4.36 (0.79)**</td>
</tr>
</tbody>
</table>

*p<.05, **p<.01, ***p<.001

One conclusion we draw from these results is that it is possible to produce LMs that vary on these aspects (with the exception of global-sequential), but that it is difficult to do so deliberately. The LMs seldom portrayed the aspects we had tried to design into them.

One could argue that our LMs are not extreme enough on the learning style dimensions. As shown in Table 1, there is on average less than 1 scale point difference between the Reflective and Active ratings for the same LMs, though all these LMs are rated significantly above the mid point for reflective whilst being at the mid point for active. However, it is hard to imagine how we could have produced an LM on this topic that was even less active than for example LM7, which only provided information and did not require the learner to do more than consider it. The difference between sensory and intuitive is a bit larger at around 1 scale point. Again, it is hard to see how for instance LM6 and LM8 could be made less intuitive (given there is absolutely no creativity involved in these).

The difference between Visual and Verbal is larger (1.6 for LM4 and LM6), showing that incorporating this dimension may be easier to do, though with a topic such as HTML, a textual component is hard to avoid. However, again, the example of LM1 which is only really textual or clearly intuitive (given there is absolutely no creativity involved in these).

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3.2 Correlations of learning styles

The ILS questionnaire asked 11 questions for each of the 4 learning style aspects. To investigate hypothesis H1, we calculated the extent to which the participant’s learning style was active, sensing, and visual, by counting how often the participant picked the active, sensing and visual options in the questionnaire. This results in levels for each learning style aspect between 0 and 11.2

Table 2 shows the results of the correlations between the selected LMs that had been validated as expressing a certain learning style, and the learning style preference of the participants.

Table 2: Correlations between participants’ preferences for learning style and appreciation of LMs

<table>
<thead>
<tr>
<th>LMs</th>
<th>Preference</th>
<th>Enjoyable</th>
<th>Confidence</th>
<th>Skills</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reflective</td>
<td>Active</td>
<td>.104</td>
<td>.051</td>
<td>-.033</td>
</tr>
<tr>
<td>Sensory</td>
<td>Sensory</td>
<td>-.043</td>
<td>-.072</td>
<td>-.032</td>
</tr>
<tr>
<td>Verbal</td>
<td>Visual</td>
<td>-.088</td>
<td>-.176*</td>
<td>-.186*</td>
</tr>
</tbody>
</table>

*p<.05

There were no significant correlations between the extent of the participants’ learning style preference being active and their ratings for the reflective LMs (LM2, 3, 7, 8). Similarly, there were no significant correlations between the extent of the participants’ learning style being sensory and their ratings for the sensory LMs (LM2, 3, 6, 8). In fact, in both cases, the very small correlations are even almost always in the wrong direction.

So, H1a and H1b were clearly not supported. This means that the extent of the participants preferring active or sensory LMs is not related at all with their appreciation (enjoyability, increasing confidence, increasing skills) of the reflective and sensory LMs.

To investigate H1c, we considered the correlations between the extent of the participants’ learning style being visual and their ratings for the verbal LMs (LM1, 3, 4, 6). We found small significant correlations for Confidence and Skills, in the expected direction. So, there is some support for H1c, though the correlations are quite small. This means that there is some evidence that the extent of the participants preferring visual LMs is negatively related to their appreciation (increasing confidence and skills) of the verbal LMs.

3.3 Correlations with personality

Table 3 shows the results of the correlations between the selected LMs that had been validated as expressing a certain learning style, and the personality of the participants.

Table 3: Correlations between participants’ personality and appreciation of LMs

<table>
<thead>
<tr>
<th>LMs</th>
<th>Personality</th>
<th>Enjoyable</th>
<th>Confidence</th>
<th>Skills</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reflective</td>
<td>Extroversion</td>
<td>-.022</td>
<td>.020</td>
<td>.046</td>
</tr>
<tr>
<td>Verbal</td>
<td>Extroversion</td>
<td>.071</td>
<td>.003</td>
<td>.088</td>
</tr>
<tr>
<td>Sensory</td>
<td>Openness to Exp.</td>
<td>-.118</td>
<td>-.041</td>
<td>-.083</td>
</tr>
</tbody>
</table>

*Given the way the ILS works, the extent to which a learner is for instance reflective will be 11 - the extent to which they are active, so in the analysis we only considered one aspect for each style.

There were no significant correlations between the extent of the participants’ extroversion and their ratings for the reflective LMs, nor for the verbal LMs. Similarly, there were no significant correlations between the extent of the participants’ openness to experience and their ratings for the sensory LMs. For Extroversion and Verbal and for Openness to Experience and Sensory, the correlations are indeed in the expected direction, but very small.

So, H2a, H2b, and H2c were not supported, and if there is a potential impact of personality it is very small.

4 CONCLUSIONS

Whilst many people have argued that learning styles are important to adapt to when selecting learning materials, we found no clear benefit of doing so. The only exception is for the Visual/Verbal dimension, where there was a small correlation. We also investigated the impact of personality, and did not find any evidence for adapting the selection of learning style inspired material to personality.

In our study, we kept the learning topic the same for all LMs. It is possible that learning style may play a larger role for certain kinds of learning topics than others. This could be investigated further, and also whether more extreme versions of LMs could be produced for another topic. It may also be interesting to investigate whether learning styles should influence the selection of topics, rather than the selection of a LM for a particular topic.

In our study, we measured participants’ perception of how much a LM would build confidence, improve skills and be enjoyable. More research is needed to investigate what the actual effect of LMs would be on the learner. This could also involve considering learners with different levels of knowledge.

In our study, we did not consider the participants’ level of interest in the particular learning topic presented (HTML). We tried to minimize the impact by using an indirect study, where participants decided for another learner who resembled their personality, but this could still have had an impact. The study could be repeated with learners who had an interest in the topic.

In our study, each participant rated only two LMs to reduce the time required. It may be interesting to investigate the impact of a wider range of LMs from the perspective of an individual participant.

Despite the fact that much recent research has focussed on learning style, there is a strong tendency to move away from this theoretical perspective, as it is hard to characterise learners by a specific learning style [22]. Another possibility for future work is to investigate the impact of other learner characteristics on LM selection, such as cultural differences. An overview of other learner characteristics that may be relevant is provided in [28].

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