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Preface

Welcome to Macau and the second International Conference on Hybrid Learning (ICHL2009). We hope you enjoy the August heat in this part of the world and this seems to add to the passion we have in hybrid learning.

Armed with the success of the inaugural conference held in Hong Kong last year, the Organizing Committee (OC) is thrilled to take the Conference to another world city. On behalf of the OC, we would like to thank last year’s organizers, Professor Frances Yao of City University of Hong Kong, Professor Reggie Kwan of Caritas Bianchi College of Careers, and Caritas Francis Hsu College and this year’s organizers, Professor Wen-Jing Shan of University of Macau and Professor Victor Lee of the School of Continuing and Professional Studies of The Chinese University of Hong Kong.

With the advances of the internet and other technologies, access to different learning resources is almost always at our fingertips. Hybrid Learning has become mainstream. We can now pick the activities to fit our level, needs, pace, learning style, and so on. Time and place are no longer obstacles. ICHL will hopefully continue to be an annual event in which researchers and practitioners can share what we have been doing lately. We are happy to report that there have been over 160 submissions. The range of papers goes from the very technology oriented tools and systems to the pedagogical side of blending the latest face2face learning model with the most appropriate technology. The Program Committee is in debt to the army of tireless reviewers who made sure we have quality papers published in the proceedings.

Finally, the Program Committee would like to thank the International Hybrid Learning Society for supporting this conference. We would also like to extend this gratitude to all our sponsors and they are Pei Hua Education Foundation Limited, City University of Hong Kong, Hong Kong Computer Society, and ACM Hong Kong Section.

August 2009
Reggie Kwan and Fu Lee Wang
Program Co-chairs
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Cognitive Learning Styles and Academic Performance in the Online Learning Environment

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Abstract. Individual differences are of concern to both academics and practitioners in the education field. On the one hand, we would like to better understand each individual learner to be able to determine the most effective teaching and learning processes. On the other hand, the recent developments in information technology make it more possible than ever to provide personalized learning modes to individual learners, thus allowing the best match between individual learning styles and appropriate instructional means. Even though it is unnecessary to find an individual instruction method for every individual learner, a mismatch of learning styles and instructional methods can create conflicts that affect cognition, affect, and behavior during the learning process.

In this paper, the author reviews the cognitive learning style scales that have been adopted in previous research and presents the results of a four-year long analytical study of the cognitive learning styles of undergraduate freshman at a local university in Hong Kong, as well as the distribution in these styles over the four-year period. A pilot study that identified significant differences between cognitive styles and academic performance (in terms of cumulative GPA) \( p < 0.01 \) is also discussed. A pilot review of courses on an online Interactive Learning Network (ILN) with a high/medium/low degree of usage shows significant differences between cognitive styles and course grades, but no significant relationship between usage of this online learning platform and academic performance. The implications of and possible reasons for these findings are addressed, and plans for a future full-scale study are discussed.

Keywords: Cognitive style index, learning style, learning outcomes, academic performance, online learning, hybrid learning.

1 Introduction

Prior studies of traditional classroom teaching and learning have identified individual differences to be an important factor in explaining the cognitive process and found that emotion may affect learning motives and learning behavior, as well as decisions about whether to engage in learning activities. For example, Mayer’s models for understanding suggest that learning materials, instructional method and learner
characteristics are the three main predictive components of learning performance in the teaching and learning processes [1].

An investigation of the impact of individual differences in learning has two primary aims: (1) to provide a better understanding of how individual learners develop their own learning strategies in the learning process and (2) to provide guidance for better matched instructional methods for more effective teaching and learning.

Understanding these differences has long been considered important, but implementing that understanding in practice presents difficulties. This is because, in the traditional classroom, the instructor has little opportunity to implement different instructional methods for individual students. However, recent developments in information technology afford the possibility of much more flexible learning, such as through course management systems/learning management systems (CMS/LMS). These software developments have made more personalized or customized instructional modes possible. Agreed with the fact that there are few empirical studies examined the relationships between cognitive and learning styles and web-based learning, further studies in the area are very much in need [2].

The importance of empirical investigations of the relationship between individual learner differences and academic performance in the online learning context is therefore clear. However, a review of recent studies found that few of them adopt validated scales of learning styles or use such scales consistently in large-scale sample sets. Instead, the research in this area tends to be ad hoc, using various non-validated scales and considering individual courses. In the review of literature on 13 most influential models on cognitive learning styles, most of the scales are either not reliable or not valid [3].

This paper therefore represents an attempt to fill the gap in this research area by exploring how cognitive learning style interacts with the online learning environment. Such an investigation is important, as it may allow us to predict academic performance in such a context. The remainder of the paper is organized as follows. After a brief review of the cognitive learning style scales used in prior studies, it focuses on a cognitive style index instrument. Following a review of empirical studies on the online learning environment, two hypotheses about the relationship between cognitive style and academic performance are posited. The paper then turns to a discussion of two studies: a four-year analysis of the cognitive learning styles of all freshmen in a Hong Kong university and a pilot study carried out using a sample of students in the university’s Department of Communication and Journalism to test the two hypotheses. The paper concludes with a discussion of the implications of these two studies and plans for a future large-scale, longitudinal investigation of the cognitive learning styles and academic performance of undergraduate students in the online teaching and learning-support environment.
2 Literature Review

2.1 Cognitive Style Index (CSI) and Pedagogical Implications

Over the past decade, there has been increased interest in cognitive styles among academic researchers and practitioners. Learning effectiveness depends on the contingent fit of cognitive styles with instructional methods, and an acknowledgement of different cognitive styles allows individuals to search for the best learning mode to suit their individual needs. The objective of the first study discussed herein was to measure the cognitive styles of all new students to provide the university with an overall picture. A better understanding of these learning styles will allow the university administration to devise development plans, teaching faculties to devise specific teaching strategies for different courses and students to select the best learning mode. As Coffield et al. note, the study of cognitive styles and its implications for teaching and learning are serious and should be of concern to learners, teachers and trainers, managers, researchers, and inspectors [3].

Cognitive style has been defined as “consistent individual differences in preferred ways of organizing and processing information and experience” [4]. Researchers suggest that cognitive styles actually converge around two poles, which are commonly labeled ‘analytical’ and ‘intuitive’ and are often associated with the specialist functions performed by each hemisphere of the human brain.

Analytical. Rational information processing has been linked with the left hemisphere of the brain, which is held to be primarily responsible for logical thought, particularly in verbal and mathematical functions. In the work context, an analytical person tends to be compliant, to prefer a structured approach to decision making, to apply systematic methods of investigation and to be especially comfortable handling problems that require a step-by-step solution.

Intuitive. Nonlinear thinking has been identified with the right hemisphere of the brain, which specializes in synthesis and the simultaneous integration of inputs, with an emphasis on spatial orientation and the comprehension of visual images. An intuitive individual tends to be relatively nonconformist, to prefer a rapid, open-ended approach to decision making, to rely on random methods of exploration and to work best on problems that favor a holistic approach [5].

These two primary types have several implications for pedagogy. For example, it has been suggested that matched cognitive styles are often effective in mentoring relationships, and analytical qualities have been found to be desirable in university dissertation supervisors [6, 7]. If it were to be shown that placing a higher value on intuitive performance by university students led to more successful career and business outcomes, then changes in pedagogy and assessment would be in order.
Prior studies have examined the association between cognitive style and the nature of interpersonal relationships [8]. Similarities in cognitive style have been found to lead to smoother interaction and positive mutual feelings between individuals, owing to shared interests, common personality attributes and equivalent modes of communication. Mismatched cognitive style, in contrast, is more likely to result in conflict [9-14], as such differences also yield differences in interests, values and problem-solving techniques, which may handicap working relationships [15]. It has been observed that people who are highly adaptive in their cognitive style do not readily combine with those who are highly innovative [16]. Adaptors appear to see innovators as abrasive and insensitive, whereas innovators seem to regard the more extreme adaptors as more likely to reject them and their ideas than to collaborate with them. One empirical study shows differences in weblog adoption rates among different cognitive style groups [17].

2.2 Online Learning Features and Pedagogical Implications

It has been suggested that the distinct feature of online communication is deindividuation. That is, written communication is characterized by anonymity and a lack of physicality. Such deindividuation may be a barrier to online learning because learners experience isolation, lonelines and feelings of alienation, and have little sense of community [18-26]. However, recent research has found that the deindividuation inherent in online learning may have positive outcomes for socially excluded individuals and may help them to form and maintain interpersonal relationships [27-30].

Online learning provides support for teaching and learning in various ways. (1) It is suitable for announcements and calendars, thus serving as an advanced organizer. It tells learners well in advance which subjects are to be taught and which learning activities are to be organized. This helps learners who need more self-discipline and direction in the organization of their learning. (2) Online learning serves as a forum, providing a public and social platform for individual learners. According to Vygotsky [31, 32], the public, social plane is an important place for more experienced and knowledgeable individuals to share knowledge with less knowledgeable individuals who then internalize what they have learnt for private and individual use. After practicing the knowledge and skills obtained in their own learning contexts, these individual learners are then ready to share them in the public and social plane with new learners. Online forums provide such a shared learning place for individual learners to meet and interact. (3) Finally, online learning platforms facilitate community building. Individual learners can make use of the online learning environment to express themselves, to make friends and to maintain relationships. As prior studies have suggested that one of the greatest problems with online learning is that it may result in loneliness and emotional distress [19], the capability to form and maintain relationships is important in helping individual learners to feel positive and to engage in socially interactive learning activities. Differences in cognitive style may also affect interpersonal relationships, and the online learning environment makes it more possible for individual learners to identify cognitively similar others. This may lead to smoother interactions and positive feelings that facilitate the learning process.
3 Conceptual Model and Hypotheses Development

With reference to the conceptual model of the online learning context presented in Figure 1, it is suggested that cognitive learning styles affect the way individuals learn, and in turn affect their academic performance. Therefore, the following hypothesis is posited.

H1: There are significant differences in academic performance among different cognitive learning styles.

In the online learning context, however, there are various possible ways for individual learners to develop more effective learning strategies. Therefore, an appropriate match of teaching and learning support in this environment should lessen the significance of cognitive learning style differences for academic performance, which leads to our second hypothesis.

H2: In the online learning environment, there are no significant differences in academic performance among individuals with different cognitive learning styles.

![Fig. 1. Conceptual Model of Cognitive Learning Styles and Academic Performance in the Online Learning Context](image.png)

4 Method and Findings of the Two Studies

4.1 Study 1

Sample. The Study 1 sample comprised all year-one students in all academic disciplines in a local university in Hong Kong. Over a four-year period, at the beginning of the academic year in September, all new students were given a questionnaire, which they were asked to complete and return to the Office of Student Affairs (OSA). In September 2008, questionnaires were distributed to all 1275 year-
one students, of which 1239 were returned, 1203 of them with all 38 question items completed, for a response rate of 94.35 percent (compared with 97.72, 97.6 and 93.4 percent in 2007, 2006 and 2005, respectively).

Measures. Based on the review of 13 most influential models on cognitive learning styles [3], Cognitive Style Index (CSI)\(^1\), developed by Allinson & Hayes [33], is found to be the only instrument which passes through all the criteria: internal consistency, test-retest reliability, construct validity, and predictive validity. In this study, therefore, Cognitive Style Index, a self-report questionnaire, was administered to all year-one students to assess the generic, intuitive-analytical dimensions of the aforementioned cognitive styles. Each of the 38 items on this questionnaire has a true-uncertain-false response mode, with scores of 2, 1 or 0 assigned to each response. The direction of the scoring depends upon the polarity of the item (17 items are reversed to control for acquiescence response bias). The nearer the total score to the theoretical maximum of 76, the more analytical the respondent is judged to be, and the nearer to the theoretical minimum of zero, the more intuitive. The internal consistency of the 38-item CSI in 2008, as measured by Cronbach’s alpha reliability coefficient, \(\alpha\), is 0.7349, which exceeds the minimum threshold (\(\alpha = 0.7\)) suggested in the literature [34] (the respective figures for previous years were \(\alpha = 0.743, 0.702\) and 0.722 in 2007, 2006 and 2005).

Descriptive Statistics. The overall mean for the 38 question items was 46.33 (compared with 46.05, 45.78 and 44.36 in 2007, 2006 and 2005, respectively), with a standard deviation of 8.310 (compared with 8.408, 7.936 and 8.064 in 2007, 2006 and 2005, respectively). The minimum and maximum scores were 15 and 68, compared with 14 and 71 in 2007, 17 and 70 in 2006, and 12 and 68 in 2005. The figures are summarized in Table 1.

Table 1. Descriptive Analysis of Cognitive Style Scores in the 2005-2008 Period

<table>
<thead>
<tr>
<th>Year</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
<th>Variance</th>
<th>Standard Deviation</th>
<th>Cronbach’s Alpha</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008</td>
<td>46.33</td>
<td>15</td>
<td>68</td>
<td>69.052</td>
<td>8.310</td>
<td>0.735</td>
<td>1203</td>
</tr>
<tr>
<td>2007</td>
<td>46.05</td>
<td>14</td>
<td>71</td>
<td>70.688</td>
<td>8.408</td>
<td>0.743</td>
<td>1245</td>
</tr>
<tr>
<td>2006</td>
<td>45.78</td>
<td>17</td>
<td>70</td>
<td>62.980</td>
<td>7.936</td>
<td>0.702</td>
<td>1180</td>
</tr>
<tr>
<td>2005</td>
<td>44.36</td>
<td>12</td>
<td>68</td>
<td>65.023</td>
<td>8.064</td>
<td>0.722</td>
<td>816</td>
</tr>
</tbody>
</table>

Median Splits. Distinguishing high (analytical) and low (intuitive) scores by splitting the groups according to their CSI median would have been arbitrary and without theoretical justification. It was therefore decided that a more valid criterion for the notional boundary between analytical and intuitive thinking would be the median score (mdn = 43) previously obtained using a relatively large sample [35] of the working population. Thus, the CSI scores were designated as low (intuitive) if they

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\(^1\) The CSI instrument can be obtained directly from the authors [33].
were < 43 and high (analytical) if they were ≥ 43. The result in 2008 was two groups: an intuitive group with 367 students and an analytical group with 836 students. The results for the four years are presented in Table 2.

### Table 2. Cognitive Style Groupings from 2005 to 2008

<table>
<thead>
<tr>
<th>Cognitive Styles</th>
<th>2008 (N = 1203)</th>
<th>2007 (N = 1245)</th>
<th>2006 (N = 1180)</th>
<th>2005 (N = 816)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intuitive</td>
<td>367 (30.5%)</td>
<td>390 (31.3%)</td>
<td>392 (33.2%)</td>
<td>316 (38.7%)</td>
</tr>
<tr>
<td>Analytical</td>
<td>836 (69.5%)</td>
<td>855 (68.7%)</td>
<td>788 (66.8%)</td>
<td>500 (61.3%)</td>
</tr>
</tbody>
</table>

**Discriminating between Groups.** The CSI is capable of discriminating between groups that are presumed to differ in their cognitive style. Areas for comparison may be gender [16, 36], age and academic discipline, among others. The cross tabulation analysis presented in Table 3 shows the distribution of cognitive styles by gender.

### Table 3. Gender Differences in the CSI:Group Cross Tabulation (2005-2008)

<table>
<thead>
<tr>
<th>CSI Group</th>
<th>Intuitive (08/07/06/05)</th>
<th>Analytical (08/07/06/05)</th>
<th>Total (08/07/06/05)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M</td>
<td>10.64</td>
<td>10.36</td>
<td>13.7</td>
</tr>
<tr>
<td></td>
<td>16.5</td>
<td>22.03</td>
<td>22.09</td>
</tr>
<tr>
<td></td>
<td>27.4</td>
<td>26.0</td>
<td>32.67</td>
</tr>
<tr>
<td></td>
<td>32.45</td>
<td>41.1</td>
<td>42.5</td>
</tr>
<tr>
<td>F</td>
<td>19.87</td>
<td>20.96</td>
<td>19.5</td>
</tr>
<tr>
<td></td>
<td>22.2</td>
<td>47.46</td>
<td>46.59</td>
</tr>
<tr>
<td></td>
<td>39.4</td>
<td>35.3</td>
<td>67.33</td>
</tr>
<tr>
<td></td>
<td>67.55</td>
<td>58.9</td>
<td>57.5</td>
</tr>
<tr>
<td>Total</td>
<td>30.51</td>
<td>31.32</td>
<td>33.2</td>
</tr>
<tr>
<td></td>
<td>38.7</td>
<td>69.49</td>
<td>69.68</td>
</tr>
<tr>
<td></td>
<td>66.8</td>
<td>61.3</td>
<td>100%</td>
</tr>
</tbody>
</table>

### 4.2 Study: Pilot

**Sample.** As a pilot sample, all year-two students in the university’s Department of Journalism and Communications were selected from the larger pool. The final pilot sample includes 149 completed student subject records, out of a total of 172 students.

**Measures and data analysis.** First, the CSI [33] scores of each student were collected from the complete sample set in Study 1. Second, these students’ transcripts were reviewed to see what courses they were taking. Only compulsory courses were considered in the pilot study, to allow all student subjects to be examined. At the same time, a review of the usage by each course of an online learning platform called the Interactive Learning Network (ILN), which had been implemented in the university to support teaching and learning, was carried out. The courses were then divided into three usage categories (see Table 4): high usage (regular and frequent use by the instructor and the students), medium usage (some usage, but not regular or frequent), and low or nil usage (very rare use or no such course online). Finally, information on the overall grade point average (GPA) for each course and the cumulative GPA of each student was collected.
Table 4. ILN Usage Categories for Different Courses

<table>
<thead>
<tr>
<th>ILN Usage</th>
<th>Courses</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>BUS110, HIST100 (sessions 1, 4, 6), JOUR100*</td>
</tr>
<tr>
<td>Medium</td>
<td>CH101, ENG111,* HIST100 (sessions 2, 3), JOUR110, SOC204, PSY100</td>
</tr>
<tr>
<td>Low</td>
<td>CH132* (no usage)</td>
</tr>
</tbody>
</table>

*Compulsory courses selected for analysis.

Descriptive Statistics. The means of the overall GPA for each course and of the cumulative GPA of the students are given in Table 5.

Table 5. Descriptive Analysis of the Courses Selected for Analysis

<table>
<thead>
<tr>
<th>Courses</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>JOUR100</td>
<td>2.816</td>
<td>0</td>
<td>4.0</td>
<td>0.6460</td>
</tr>
<tr>
<td>ENG111</td>
<td>3.157</td>
<td>0</td>
<td>4.0</td>
<td>0.5345</td>
</tr>
<tr>
<td>CHI132</td>
<td>2.559</td>
<td>0</td>
<td>4.0</td>
<td>0.8820</td>
</tr>
<tr>
<td>Cumulative GPA</td>
<td>2.854</td>
<td>1.771</td>
<td>3.803</td>
<td>0.4270</td>
</tr>
</tbody>
</table>

One way ANOVA. Using one way ANOVA, it was found that there were significant mean differences between the two cognitive styles in terms of cumulative GPA, thus supporting H1. The analytical group outperformed the intuitive group. The mean GPA for each course and the cumulative GPA among this group were 2.936 and 2.747, respectively. There were also significant GPA differences between the two cognitive groups in courses with different usage rates of the ILN, specifically in the high-usage course JOUR100 and the low-usage course CHI132. In both of these courses, the analytical group was found to outperform the intuitive group. The former had GPAs of 2.925 and 2.701 for JOUR100 and CHI132, respectively, compared to scores of 2.675 and 2.375 for the latter. There were no significant differences between the cognitive groups in ENG111.

Table 6. GPA Means among Selected Courses and One-way ANOVA between Cognitive Style Groups

<table>
<thead>
<tr>
<th>Courses</th>
<th>Cognitive Style</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>ANOVA F-values (sig.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>JOUR100</td>
<td>Intuitive (N = 65)</td>
<td>2.675</td>
<td>0.5777</td>
<td>5.643* (0.019)</td>
</tr>
<tr>
<td>(High usage)</td>
<td>Analytic (N = 84)</td>
<td>2.925</td>
<td>0.6777</td>
<td>0.922ns (0.338)</td>
</tr>
<tr>
<td>ENG111</td>
<td>Intuitive (N = 65)</td>
<td>3.109</td>
<td>0.6358</td>
<td>5.141* (0.025)</td>
</tr>
<tr>
<td>(Medium usage)</td>
<td>Analytic (N = 84)</td>
<td>3.194</td>
<td>0.4411</td>
<td>7.503** (0.007)</td>
</tr>
<tr>
<td>CHI132</td>
<td>Intuitive (N = 65)</td>
<td>2.375</td>
<td>0.9097</td>
<td>0.3949</td>
</tr>
<tr>
<td>(No usage)</td>
<td>Analytic (N = 84)</td>
<td>2.701</td>
<td>0.8379</td>
<td>0.4461</td>
</tr>
<tr>
<td>Cumulative GPA</td>
<td>Intuitive (N = 65)</td>
<td>2.747</td>
<td>0.9097</td>
<td>7.503** (0.007)</td>
</tr>
<tr>
<td></td>
<td>Analytic (N = 84)</td>
<td>2.936</td>
<td>0.3949</td>
<td></td>
</tr>
</tbody>
</table>

*p < 0.05, **p < 0.01, ***p < 0.001, ns non-significant
5 Discussion and Future Research

5.1 Cognitive Learning Style has a Significant Impact on Academic Performance

The results of the pilot study indicate that cognitive learning style has a significant impact on academic performance. Evidence for this is provided both by the students’ cumulative GPAs and by the mean GPAs for the individual subjects. The pilot study adopted a validated and reliable instrument to measure individual differences in cognitive learning styles and to categorize learners into either the intuitive or analytical group. Different ways of thinking, i.e., different cognitive processes, do have an effect on performance in specific subjects and on overall academic performance. The findings of this initial study serve as a basis for future research into these two cognitive groups and ways to develop instructional methods that will improve learning among them. Such research would be especially relevant today, as recent developments in information technology make possible the implementation of personalized and individualized means of instruction.

5.2 Inconclusive Results on Interaction Effects of the Online Learning Environment

Although the pilot study provides evidence of the importance of individual differences in learning styles, particularly the learning styles of intuitive and analytical individuals, it was unable to demonstrate the interactive effects of the online learning platform on academic performance. Two areas require further in-depth investigation. First, prior knowledge of the subject domain may have a significant effect on academic performance. To examine the effects of the online learning platform, a direct comparison of the same subject domain over a number of years is required. Second, the specific functionality of the online learning platform requires investigation, as this study considered only its general usage.

5.3 Plans for Future Full-scale Study

Analysis of the data gleaned in the pilot study provides us with useful information on which to base a future, large-scale, longitudinal investigation of the cognitive learning styles and academic performance of undergraduate students in the online teaching and learning-support environment, particularly with regard to the following areas.

Online context categories. The pilot study provides a way of classifying an online learning platform into high-, medium- and low-usage categories. Future categorization may also include specific functionalities, for example, (1) the existence
of a discussion forum that provides a common shared platform for social interaction and learning, and (2) the existence of regular announcements or a calendar, features that allow the platform to serve as an advanced organizer and individual learners to better organize their study time.

**Instructor effects.** In the selection of courses for analysis, there may be ways to control for instructor effects. For example, group comparison could be made among courses taught by the same instructors over a number of years, thus allowing instructor-specific effects to be eliminated.

**Subject domain knowledge effects.** Because of differences in cognitive learning styles, each cognitive group may have strengths and weaknesses in a particular subject domain. Identification of these strengths and weaknesses would make visible the interaction effects, if any, of the online learning platform.

**Control factors.** There may be other control factors, such as gender, prior knowledge, experience with online learning platforms and individual usage habits, that could be included in the data analysis to determine their interaction effects, if any.

### 6 Conclusion

The two studies discussed herein represent important steps toward a better understanding of individual differences in the online learning environment. Their empirical findings show that there is a significant difference between the two cognitive learning style groups, intuitive and analytical, with regard to academic performance. Thus, future research may consider the development of appropriate instructional methods to strengthen specific cognitive learning groups in the learning process. Such research would be timely, as recent developments in information technology provide a clear direction for online learning system design and university-wide implementation strategies.

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