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ePedagogy Design for Online Instruction by Measuring the Interactive Effects of Cognitive Preference on Performance Outcomes

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ABSTRACT

Researchers are keen to know whether online instruction is effective and whether people learn anything while undertaking an online course. To this end, a research programme was devised to evaluate an ePedagogy, which involves the interactive effects of online instructional strategies enhanced with text-plus-textual metaphors or text-plus-graphical metaphors, and cognitive preference for learning basic programming concepts. The Cognitive Styles Analysis (CSA) program (Riding & Cheema, 1991) was used to identify participants' cognitive preferences. The QUEST Interactive Test Analysis System (Adams & Khoo, 1996) was used to measure cognitive performance, ensuring an absence of error measurement in the programming knowledge testing instruments. Reliability of these instruments was therefore assured through the calibration afforded by the QUEST estimate that provided predictability of the research design. A means analysis of the QUEST data, using the Cohen (1977) approach to size effect and statistical power, further quantified the significance of the findings. The quasi-experimental method adopted for this research links instructional science, cognitive psychology, and objective measurement to provide reliable techniques to enhance cognitive performance evaluation in the education, training and educational technology paradigms. The research outcomes will be of interest to educators, cognitive psychologists, computer science practitioners specializing in human-computer interactions (HCI).

Keywords: ePedagogy, cognitive preference, human-computer interaction, instructional design, computer science, cognitive psychology, web-mediated instruction.

INTRODUCTION

This paper is presenting a study which examined various aspects of a web-mediated instructional system (WMIS). In particular, the research focused on the interactive effects of computer screen-based multimedia instructions and individual characteristics in so far as the way people process the information they receive and whether or not these aspects affect cognitive performance. The cognitive style construct (Riding & Cheema, 1991) was selected as one of the independent variables, among other individual characteristics, due to its significant influence on teaching and learning (Miller, 1987). The term 'cognitive style' refers to the human preferences in perceiving, organising, interpreting and processing information received. It is assumed that cognitive preference is significant due to the learners' need to organise and process information they receive from a hypermedia environment in an efficient manner in order to acquire desired knowledge. Individual performance may be reduced if the instructional format is mismatched with cognitive preferences (Riding & Sandler-Smith, 1992). Conversely, Massa and Mayer (2006) suggest that there is no strong support for the view that verbalisers and visualisers should receive different kinds of multimedia instruction. They state that their findings should not be taken to indicate that instruction should never be designed to suit learners' cognitive preference as a whole. Instead, they question the effectiveness of designing instruction to accommodate individual cognitive differences. Riding and Cheema (1991) define cognitive style as the way in which an individual processes information they receive. According to Riding and Cheema (1991), cognitive preference can be grouped into two basic dimensions: wholist-analytic and verbal-imagery. The wholist-analytic continuum describes "*the way in which an individual interprets or processes the same information, in whole or in parts*", while verbal-imagery refers to a continuum that supports preferences for verbal/visual strategies related to "*how people prefer to represent the information they receive during thinking*" (Riding & Cheema, 1991, p. 210).

The measurement of human performance in the social sciences often lacks rigour in terms of the performance measures used. Researchers frequently rely on statistical measurement to identify the relationships amongst the variables, while the use of measurement models is rarely appreciated. Statistics obviously play an important role in cognitive performance measurement, and vice versa. However, it is important to understand the distinction between statistics and cognitive performance measurement (Fisher Jr, 2010). Therefore, this research study aimed to provide evidence for the value of employing a cognitive performance measurement model that employed both Rasch modeling ('item response theory' (IRT)) and traditional statistical measurement techniques, to investigate the interactions effect between variables. Statistical measures usually use ordinal raw scores in the data analysis, in which case researchers may have a tendency to avoid improving the testing instrument, because any changes to the instruments changes the interpretation of the data. However, measurement models, such as the Rasch model, convert ordinal raw scores into scale scores (Rasch, 1960; Fischer & Molenaar, 1995). Thus, the sense of the data remains constant over instrument reconfiguration which improves the quality of the measures (Fisher Jr, 2010). Moreover, the Rasch model provides an examination of the 'right answer', whereas the more traditional statistical analysis concentrates on the 'wrong answer' (Izard, 2005a, 2005b).

THE STUDY

This research was undertaken to examine the interactive effects of web-mediated instructional strategies and cognitive preferences in the acquisition of introductory computer programming concepts in a Malaysian university. The participants volunteered in this study were defined as 'novice-learners'. This research was guided by the following research question:

Does the interactive effect of web-mediated instructional strategies and a learner's cognitive style preference affect the acquisition of introductory computer programming concepts?

Even though the validity and reliability of the pre- and post-tests was first confirmed in an earlier pilot-study (Mohamad & McKay, 2010), the test-items were again validated in a final-study to strengthen the validity of the inferences drawn. As suggested by Bond and Fox (2007, p. 164), “*it is impossible to measure change with a measure that changes*”. The performance of the test-items in the final-study is therefore reported next.

THE PERFORMANCE OF THE TEST-ITEMS

The test-items in the pre-test were calibrated using the reference or anchor values obtained from the earlier pilot-study. The anchoring or equating strategy intends to establish that two different tests that are measuring the same construct and the scores of these tests are comparable with each other. With an anchoring strategy, test-items that are common to old and new tests could be used as anchored test-items with fixed parameters for conducting a new test analysis. For instance, the pre-test may be harder than the post-test, due to limited existing domain knowledge in the learner’s long-term memory, so without anchoring, examinees would be expected to obtain ‘lower scores’ in the pre-test and ‘higher scores’ in the post-test. Therefore, an anchoring strategy eliminated the effects of the scores due to differences in test form difficulty.

For the final-study reported here, the anchor values obtained from the pilot-study (Mohamad & McKay, 2010) served as a common scale for analysing pre- and post-test items in this final-study. Kolen and Brennan (2004) propose at least four aspects of commonalities between the two tests should be considered. These four aspects involve: inferences; constructs; population; and measurement characteristics. Therefore, according to these four aspects of commonalities in test equating, the pre- and post-tests implemented in this final-study can be concluded to have a ‘high degree of resemblance’.

There were three test-items that were used as the common scale to monitor the development of learners before and after intervention. These test-items have shown stability over time throughout the earlier work (Mohamad & McKay, 2010) and this final-study. The QUEST test-item fit map in Figure 1 demonstrates the ‘unidimensionality’ of the test-items (Adams & Khoo, 1996). In other words, these test-items measure a single construct.

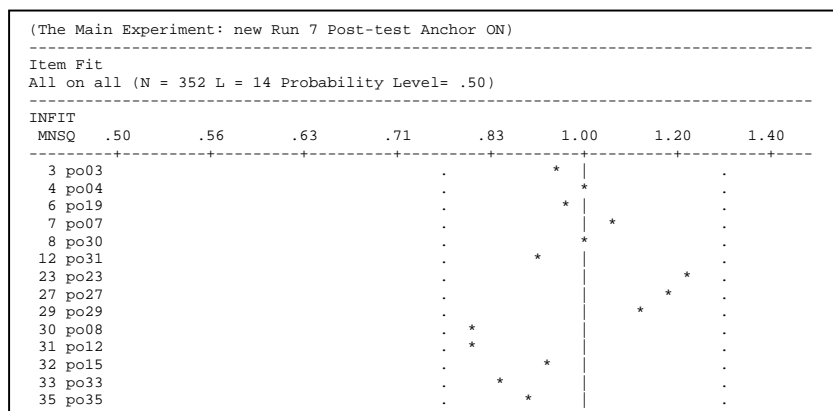


Figure 1: QUEST Item fit map of post-test final-study

The depth of programming knowledge level was tested according to Gagne’s learning capabilities. This research concentrated on the following Gagne’s (1985) learning capabilities: 1. verbal information skills; 2. intellectual skills; 3. cognitive strategies. The learning objectives of the WMIS were designed to develop algorithms and programming which use the WHILE, DO WHILE and FOR control structures using C++ language.

Therefore, in the acquisition of programming concepts, the two types of knowledge acquisition strategies presented were: declarative and procedural (van Merriënboer, 1997). The ‘declarative knowledge’ refers to the knowledge of ‘knowing what’ such as “*computers have three main functions: data input, processing and data output*” (van Merriënboer, 1997). The term ‘procedural knowledge’ refers to the knowledge of ‘knowing how’. For instance, the knowledge about how to write a computer program for checking the input from the user lies in a valid range. A test-items analysis was conducted similar to the test-items analysis process followed in the pilot-study (Mohamad & McKay, 2010). This process was repeated until the final set of test-items satisfied the requirements of the Rasch IRT model; test-items not fitting the model were excluded until a proper ‘fit’ was seen (see Figure 1).

THE COGNITIVE STYLE ANALYSIS RESULTS

The cognitive preference of participants was measured using the Cognitive Style Analysis (CSA) software program, developed by Riding and Cheema (1991). Participants were located on each fundamental preference/style dimension by means of a ratio. Most of the cognitive preference assessment tools measure cognitive preference in a bipolar-like concept of preference. The CSA is one of the available measures that work with continuums of cognitive preference/style and measures the two dimension of preference simultaneously (wholist–analytic and verbal–imagery defined earlier in the introduction section of this paper).

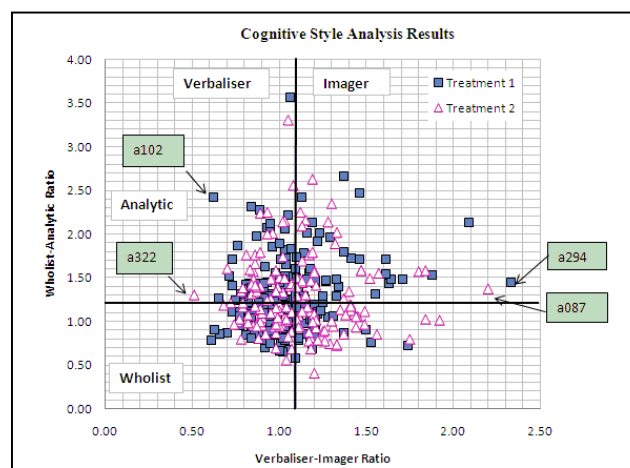


Figure 2: Scatter map of CSA results

In the final-study, the ‘wholist–analytic’ ratio ranged from 0.4 to 3.57 (mean=1.29, sd=0.44) with the cut-off point 1.19. The ‘verbal–imagery’ ratio range from 0.51 to 2.33 (mean=1.08, sd=0.25) with cut-off point 1.04. The cut-off point for ‘wholist–analytic’ is the median value for the intermediate (ranged from 1.02 to 1.35), and the ‘verbal–imagery’ is the median value for bimodal (ranged from 0.98 to 1.09) (Riding, 2005). There were 399 participants seated for the CSA although only 352 participants completed the whole test. The scatter map shown in Figure 2, reveals the 4 x 2 factorial research design for defining the cognitive preferences of students in the final-study. Participants were given either the text-plus-textual metaphor (T1) instructional format or text-plus-graphical metaphor (T2) instructional format.

A visual observation of the scatter map in Figure 2 shows two students located at the extreme ‘imager continuum’, one receiving the T1 (a294) and another the T2 (a087). The subsequent QUEST estimate’s results revealed the a294 student experienced negative improvement when given T1. By contrast, a087 shows a positive improvement when learning from T2. The student located at the extreme ‘verbaliser continuum’ and received T1 (a102) shows positive improvement with T1, while the ‘extreme verbaliser’ (a322) with T2 demonstrated even greater improvement. For the ‘wholist–analytic continuum’, the

extreme analytic and wholist experienced higher improvement with T1 compared with T2. The performance of extreme single cognitive preference (SCP) groups is displayed in Figure 3.

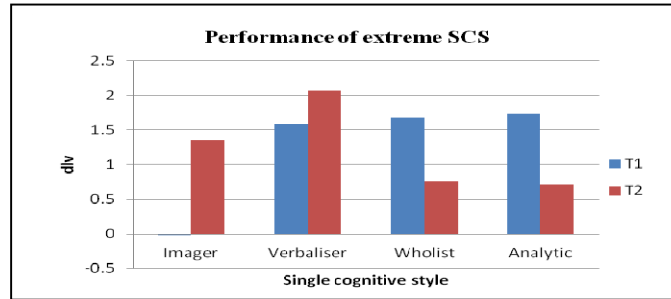


Figure 3: The performance of SCP on T1 and T2

DESCRIPTIVE STATISTICS

A total of (n=399) participants were involved in the final-study; they were second year undergraduate students enrolled in a Malaysian university for a Bachelor of Civil Engineering course. The data from a total of n=47 participants were discarded from the analysis due to incomplete data, such as: the participant did not sit for the CSA test; or pre-test and post-test. Therefore, only (n=352) participants were included in the data analysis as they did complete the whole experiment.

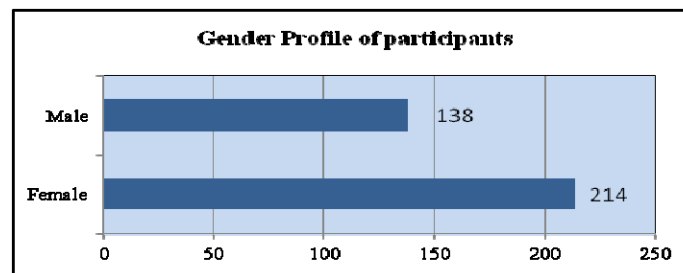


Figure 4: Gender profile of participants

As evident in Figure 4, there were (n=214) female and (n=138) male participants. Increased enrolments of female students reflect the gender distribution in the final-study. The minimum and maximum age of participants was 19 and 27 respectively with a mean age (M=21.63) years. The p -value <0.05 level of significance was used throughout the final-study unless otherwise stated. This means that the probability of falsely rejecting the null hypothesis is smaller than 5%.

PRE-TEST PERFORMANCE

There were 352 participants that successfully completed the pre- and post-tests. Participants with 'zero scores' and 'perfect scores' were excluded from the analysis. This is because the participants with 'zero scores' provided no evidence of whether any learning had occurred. Similarly, the participants with 'perfect scores' were unable to show how much learning had occurred (Izard, 2005b). In the final analysis, only 305 participants were counted for the effect size computation (Cohen, 1977). The pre-test was used to assess students' prior domain knowledge on programming concepts.

Table 1: Average of pre-test estimate logit-value (*prlv*) on the SCP and ICP

Group	Pre-test		
	Mean <i>prlv</i>	n	sd
Single Cognitive Preference/Style (SCP)			
Wholist	-1.67	145	0.87
Analytic	-1.77	160	0.90
Verbaliser	-1.74	158	0.90
Imager	-1.70	147	0.86
Integrated Cognitive Preference/Style (ICP)			
Wholist-verbaliser	-1.74	75	0.83
Wholist-imager	-1.59	70	0.90
Analytic-verbaliser	-1.74	83	0.96
Analytic-imager	-1.81	77	0.82

The cognitive performance of students was measured using the difference between pre- (*prlv*) and post-test (*polv*) estimate logit-value (*dlv*) rather than just post-test results. This practice was to better determine the effects of the treatments (T1 and T2) on cognitive performance outcomes. The variation level of prior domain knowledge based on the single cognitive preference (SCP) and integrated cognitive preference (ICP) is presented in Table 1. The most performed group on the pre-test according to SCP was the ‘wholist’ group with an average performance of all ‘wholists’ being -1.67 (sd =0.87). The average performance of all SCP groups on the pre-test was -1.72 with a standard deviation of 0.04. Meanwhile, by analyzing the data according to the ICS, the ‘wholist–imagers’ performed best in the pre-test (mean =-1.59, sd =0.90).

POST-TEST PERFORMANCE

Figure 5 illustrates the cognitive performance of 352 students on 14 test-items on the pre- and post-tests, the QUEST ‘variable map’ (Adams & Khoo, 1996). The logits scale for both the person (shown on the map as ‘cases’) and test-item ranges between -3.0 and 3.0. The default value of the mean ability and the mean test-item difficulty was set at 0.0 (Adams & Khoo, 1996).

In other words, the student located on this logits scale has a 50% chance to correctly and incorrectly answer the test-items at the same horizontal level. As shown in Figure 5 (see first column from the left-hand side), all the students are positioned below the 0.0 logits scale on the pre-test except 15 students. However, the students located above the 0.0 logits scale, increased to 80 students in the post-test (see second column from the left-hand side). This result evidenced that their cognitive performance increased in the post-test. The five top performers (*prlv*= 0.83) in the pre-test were: two students from the ‘analytic–imager’ group; one ‘analytic–verbaliser’; one ‘wholist–verbaliser’ and one ‘wholist–imager’. Their performance is graphically illustrated as highlighted AI, AV, WV and WI respectively in Figure 5. The ‘wholist–verbaliser’ who was given T1 achieved perfect score in the post-test and was therefore excluded from the analysis. Both ‘analytic–imagers’ who were randomly given T2, scored considerably higher in the post-test (*polv*= 1.87, *dlv*= 1.04). While the ‘analytic–verbaliser’ who received T2 showed a negative improvement (*polv*=0.32, *dlv* =-0.51). A similar result is reflected by the ‘wholist–imager’ who showed a negative improvement when learning from T2 (*polv*= 0.13, *dlv*= -0.7).

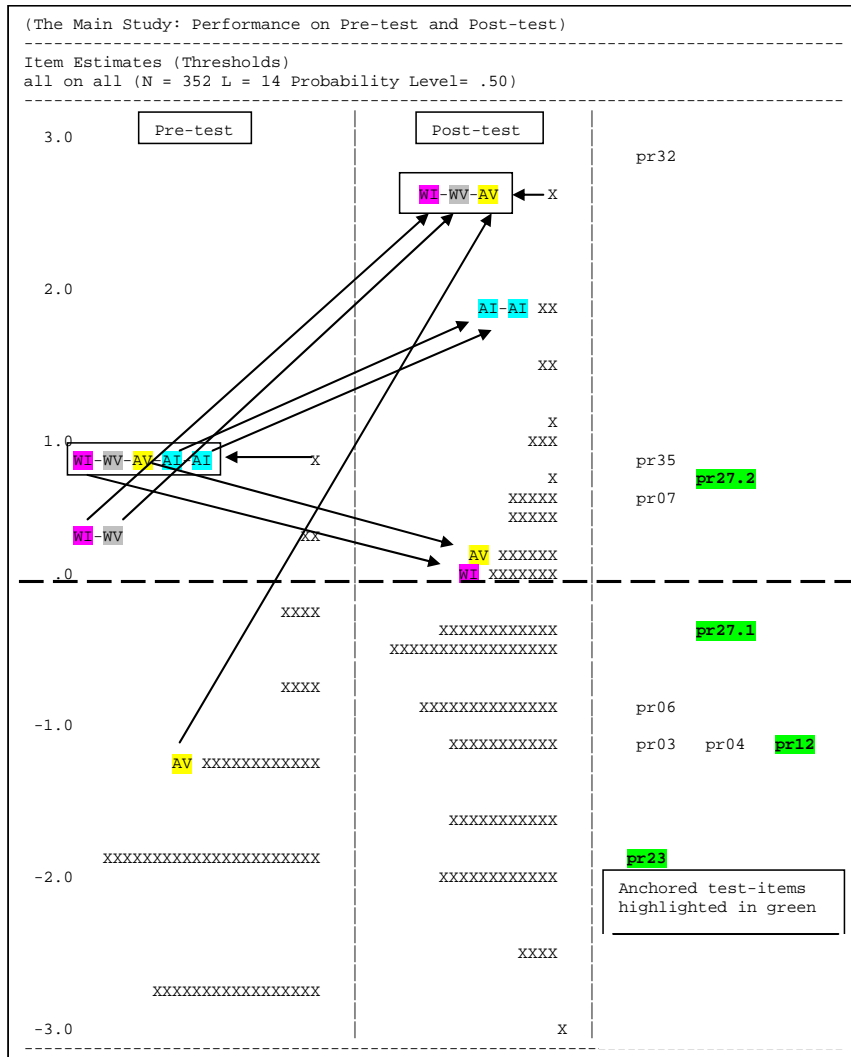


Figure 5: Excerpt of combined QUEST variable map of pre- and post-tests

The performance increased in the post-test with the three top performers located at a 2.57 logits estimate. These students were a 'wholist-imager' who was given T2 ($prlv=0.29$), an 'analytic-verbaliser' with T1 ($prlv=-1.23$) and a 'wholist-verbaliser' who learned with T1 ($prlv=0.29$). However, it was the 'analytic-verbaliser' who made the greatest improvement from the pre- to post-test ($dlv= 3.8$) as presented by the longest arrow in the Figure 5. The average student's ability on the pre-test as computed by the QUEST estimate, is -1.71 ($sd=0.89$). This average value shows that the students found this pre-test as comparatively difficult because their ability is lower. This result is relatively true as the students are expected to have little or no programming domain knowledge. While the average student's ability on the post-test is -0.61 ($sd=1.02$), which indicates that the ability level of the students enhanced with a corresponding increase in programming domain knowledge. The test's difficulty level remained unchanged because it was anchored. In the first column from the right-hand side of the Figure 5 it shows the test-items located based on the logits estimate. The test-items located closer to the bottom of the map are easier to endorse, while the ones further up are more difficult. The probability of the top three performers on the post-test correctly answering the most difficult test-item is less than 50%. However, the test-items were dispersed evenly along the logits scale.

COGNITIVE PERFORMANCE

Here we present the results of cognitive performance of SCP and ICP with the web-mediated instructional treatments (T1 and T2). The null hypotheses were tested using effect size estimates (Cohen, 1977). The cognitive performance of ICP group with the text-plus-textual (T1) and text-plus-graphical format (T2) based on average *dlv*. The detailed information of the analysis is presented in tabular format in Table 2.

Table 2: Cognitive performance of SCP and ICP groups based on effect sizes.

Cognitive style group	Instructional Strategies						Mean difference	Effect size
	T1			T2				
	Mean	N	SD	Mean	N	SD		
All	1.32	164	0.84	1.16	141	0.85	0.16	0.19
SCP Group								
Wholist	1.28	72	0.89	1.21	73	0.95	0.07	0.08
Analytic	1.35	92	0.81	1.10	68	0.74	0.25	0.32
Verbaliser	1.38	91	0.80	1.12	67	0.79	0.26	0.32
Imager	1.24	73	0.89	1.19	74	0.91	0.05	0.06
ICP Group								
Wholist-verbaliser	1.25	43	0.82	1.23	32	0.87	0.02	0.02
Wholist-imager	1.31	29	0.99	1.19	41	1.02	0.12	0.12
Analytic-verbaliser	1.49	48	0.78	1.03	35	0.71	0.47	0.62
Analytic-imager	1.19	44	0.81	1.18	33	0.76	0.01	0.01

The total of N value for T1 (N=164) in SCP group calculated by adding N values of wholist (N=72) and analytic groups (N=92). While for the ICP group, the total for of N value for T1 is calculated by adding N values of all ICP groups (wholist-verbaliser, N=43; wholist-imager, N=29; analytic-verbaliser, N=48 and analytic-imager, N=44). The first hypothesis (H1), was testing the possibility that one of the cognitive preference groups performed differently according to the treatment they received. For instance, 'wholist-verbalisers' given T1 should have different cognitive performance compared with 'wholist-verbalisers' given T2. Overall, the data in Table 2 shows that web-mediated instructional treatment (T1 and T2) does have a 'small' to 'medium' effect on cognitive performance (Cohen, 1977). The effect sizes between treatments is 'small' ($d=0.19$). As stated in the mean column for all groups, the students, regardless their cognitive preferences performed better with the T1 than T2.

There is an interesting finding in the ICP groups. The 'analytic-verbaliser' group had a significantly higher average on cognitive performance with the T1 than T2. A 'medium' size effect is observed ($d=0.62$). For the 'wholist-imagers', there is a 'negligible' effect size observed ($d=0.12$). There is an even more 'trivial' effect size that is computed for the 'wholist-verbalisers' and 'analytic-imagers' ($d=0.02$ and $d=0.01$ respectively). The data summarised in Table 2 for the SCP groups, indicates that web-mediated instructional treatments (T1 and T2) have 'very small' to 'small' effect on cognitive performance. The 'analytic' and 'verbaliser' cognitive preference have a similar effect size on cognitive performance ($d=0.32$), which indicates that the chance of correctly rejecting the null hypothesis of H1 is approximately 64%. Both 'analytic' and 'verbaliser' groups performed better with T1 than T2. For the 'wholist' and 'imager' groups, the effect sizes are 0.08 and 0.06 respectively, which indicates that there is 12% and 10% chance of correctly rejecting the null hypothesis of H1.

THE INTERACTIVE EFFECTS

This section reports the interactive effects of the ICP and web-mediated instructional format on the cognitive performance in the acquisition of programming concepts. As evidenced in Table 1, no meaningful difference in performance of all groups (SCP and ICP) in the pre-test. Interestingly, as level of ability increased in the post-test, the interactive effects of cognitive preference and web-mediated instructional strategies do exist. Figure 6 shows the interactive of the ICP and web-mediated instructional formats. A practical important effect was found with the 'analytic-verbalisers' who performed best with

the T1 format than the T2 format. The ‘analytic-verbaliser’ group was the top performer, when given T1 (mean $dlv=1.49$) yet their counterpart was the worst performer with T2 (mean $dlv=1.03$). The top performer in T2 was a ‘wholist-verbaliser’ (mean $dlv=1.23$) group.

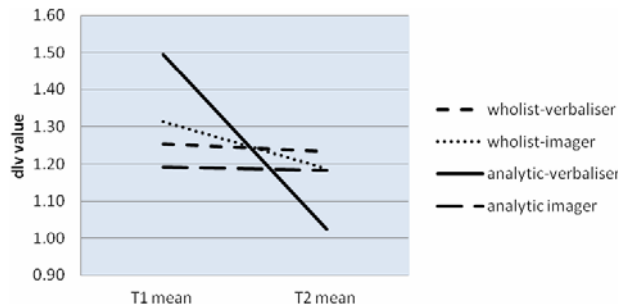


Figure 6: Interactive effects of ICP and web-mediated instructional formats

The ‘wholist-imagers’ performed slightly better in T1 (mean $dlv= 1.31$) than T2 (mean $dlv= 1.19$). Further, there was no practical important effect for ‘wholist-verbaliser’ (mean dlv T1= 1.25, mean dlv T2= 1.23) and the ‘analytic-imager’ (mean dlv T1=1.19, mean dlv T2= 1.18) groups, on both treatments (T1 and T2), as they performed nearly similar with each treatment, yet the cognitive performance of the ‘wholist-verbaliser’ group is better than the ‘analytic-imagers’ on both instructional treatments.

DISCUSSION

In a series of quasi-experiments, the cognitive performance of non-computer science or non-information technology students who have been given web-mediated instructional metaphor formats was investigated (Mohamad & McKay, 2010). The aim was to examine whether cognitive preferences and web-mediated instructional strategies does or does not have an interactive effect on cognitive performance. Several interesting findings were discovered. Some of these findings however are not directly related to the research question and hypotheses; therefore this section will discuss these findings.

Finding-1: Novice-learners performed better with text-plus-textual metaphors (T1) than text-plus-graphical metaphors (T2) regardless of their cognitive preferences. This finding was not only found our main study but also in the pilot-study. The familiarity with the domain knowledge is believed to have a connection with what has previously been constructed and stored in working and long-term memory. As a result, novice-learners are likely facilitated with text-plus-textual metaphor instructional strategy or format, as they have to deal with new complex and novel information. Dealing with such information is difficult for novice-learners. Presenting complex information in a multimedia format may increase extraneous cognitive load because there is too much information and the cognitive manipulations are required simultaneously; thus reducing the resulting cognitive performance (Kalyuga, 2009). These findings may reflect an ‘expertise reversal effect’ as suggested by Kalyuga et al. (2003). They proposed that multimedia formats that are effective for more experienced-learners might not be effective or may even be harmful for novice-learners. This finding conflicts with Mayer’s multimedia principle (Mayer, 2001, 2009) which states that students learn better from learning materials presented to them, using words and pictures than those using words alone. However, this principle is likely to be supported for more experienced-learners as examined in the pilot-study (Mohamad & McKay, 2010). Even though there is no quantifiable variable that can be defined for novice- and experienced-learners, yet the qualities they possess can be identified (Tennyson, 2001). Expert’s knowledge is represented by a hierarchically organized schema, which allows experts to access either a bottom-up or top-down processing mode (Champagne, et al., 1982; Kalyuga, et al., 2003). However, the novice’s chaotic and less-integrated

schema does not allow for such flexibility with their information processing. This effect may be the explanation why more experienced-learners performed better with the text-plus-graphical format. The more experienced-learners have their activated schema ready for constructing their mental representation of the task at hand. Therefore, presenting learning materials with text and graphics assists more experienced-learners to construct a new appropriate mental representation. However, this might be disadvantageous to novice-learners due to their lack of an integrated schema to construct mental representations of high-element interactivity domain knowledge (Kalyuga, et al., 2003).

Finding-2: ‘Analytic–verbalisers’ have performed considerably better in the text-plus-textual metaphors (T1) compared to their counterparts who learned from text-plus-graphical metaphors (T2). This is probably so because the ‘analytic–verbalisers’ have good verbal memories and easily retain information, particularly when presented in a textual (or verbal) format (Riding, 2005). Furthermore, when presented information in a structured verbal format the ‘analytic–verbalisers’ no longer find pictures or graphics very helpful. However, adding some ‘visual signals’ or ‘cues’ does assist learning from textual instruction (Mautone & Mayer, 2001). Such signals in verbal information include: paragraph headings; bolding and italicizing of important words; signals phrases; pointer words and topical overviews written as content preview (Clark, et al., 2006, p. 79; Mayer, 2009). For instance, showing how signals in the tabular form, added to the instructional materials in the text-plus-textual metaphor instructional format for comparing three control structures; ‘while’, ‘do..while’ and ‘for’. This effect might help ‘analytic–verbalisers’ to keep hold of the information presented to them longer, because the purpose of a conceptual ‘signal’ is to draw attention to essential information in the lesson, yet not to add any new information (Mayer, 2009).

Finding-3: The cognitive performance of novice ‘wholist–imagers’ and ‘analytic–imagers’ are almost similar with text-plus-textual metaphor and text-plus-graphical metaphor instructional formats. In other words, the cognitive performance of the ‘imagers’ is not affected by the instructional strategies. Presenting programming concepts in text-plus-graphical metaphor (or multimedia) format did not assist ‘imagers’ in this study because they performed best when the instructional materials can easily be visualised in mental pictures that did not contain any acoustically complex and unfamiliar terms (such as programming language)(Riding, 2005). This finding is contra to what has been found by previous research such as in Riding and Douglas (1993) which discovered that imagers learned better when the materials on motor cars braking systems were presented in a text-plus-illustration format, rather than with text alone. McKay (2000) also found that ‘imagers’ were superior to ‘verbalisers’ with text plus graphical metaphors. Similarly, when tested on college and university students, Smith and Woody (2000) observed that ‘visualisers’ learned better than ‘verbalisers’ when given learning materials in a multimedia format. Further evidence in Lee (2007), revealed that the learning performance of ‘wholist- and analytic-imagers’ is enhanced with a visual metaphor interface. Thomas and McKay (2010) also discovered improvement in learning outcomes when instructional materials matching with students’ cognitive preferences. It is clear from this brief discussion, which focussed on novice and expert students, that the better cognitive performance in the text-plus-textual metaphor instructional format may have been influenced by the level of the learners’ prior domain knowledge. Whereas the novice-learners found that the textual metaphors precisely conveyed the abstract programming concepts, they may prevent misunderstanding of those concepts (Yu-chen, 2007). As a result the novice-learners may construct more accurate mental models when learning from text-plus-textual metaphors compared with the text-plus-graphical metaphor instructional format and thereby, contribute to higher cognitive performance.

Even though there is no clear evidence of these mixed findings, it could be speculated that the results from this research was influenced by a level of prior domain knowledge and the learning content. Let us first consider prior domain knowledge; information presented in words or pictures is received through our eyes, organized into a ‘verbal’ or ‘pictorial’ model in our working memory and integrated with prior knowledge into our long-term memory (Mayer, 2005). The meaning of ‘information organizing in working memory’ depends on prior knowledge in long-term memory and determined prior to being stored

in our long-term memory. As discussed previously, working memory is limited in capacity (Miller, 1956). Therefore, the individual's working memory capacity and prior domain knowledge is critical for effective learning. In terms of the 'verbal-imagery' dimension of cognitive preference/style; Riding (2005) states on the one hand, that 'verbalisers' are most affected by working memory capacity because they use an elaborated approach during information processing. While on the other hand, 'imagers' are less influenced because they tend to use a more intuitive approach that requires less working memory capacity (Riding, 2005). When 'imagers' learn from text-plus-graphical metaphor instructional materials, they may create spontaneous mental pictures of representation of the information or of what they may associate with it. Therefore, with insufficient prior domain knowledge in place in their long-term memories, 'imagers' tend to construct inaccurate mental representations of the graphical information in which they may be inclined to misunderstand the concepts presented (Salmerón, et al., 2009). However, when 'imagers' learn from textual materials, the possibilities of constructing irrelevant mental representations is lower, because text (or verbal) descriptions assist learners to organize information and integrate it with their existing knowledge, to build the meaning of information (Kozma & Russell, 1997) yet graphics is worth a thousand words (Mayer & Sims, 1994). It is proposed that, as processing difficult information like abstract programming concepts requires most of our cognitive resources, this may free up some of those resources in our working memory capacity to be devoted to other information processes. Furthermore, Mayer's multimedia principle (Mayer, 2009) suggests that people learn better with text and graphics rather than text alone. Yet this study did not reveal any difference even for the 'imagers'. As Weidenmann (1989) argues, that learners always look at graphical materials as 'easy' and may be only browsed superficially, without understanding the meaning of the information presented. This effect may explain why pictures (or graphics) in this study do not assist 'imagers'.

CONCLUSION

For many of us, knowing how to learn is something that improves as we grow older. For the most part, as we travel along our lifelong learning path, it becomes easier to differentiate which instructional strategies are likely to suit us best. The web-mediated tools of the digital age are redefining pedagogy such that many of us simply cannot keep abreast of the emerging instructional space we are calling ePedagogy in this paper. The difficulties we are likely to face with online instruction may depend upon whether there are suitable instructional strategies to cognitively fast-track the learning tasks. The findings of this study concurs with the research that shows novice learners require the full range of rules and information related to learning something new, whereas an experienced learner might only require a quick revision (Tennyson & Bagley, 1991; McKay, 2008). The earlier researchers clearly demonstrated that beginners or novice learners will respond best to measured amounts of guidance through progressively more complex instructional/learning content with strategic opportunities for interactive practice examples along the way (Merrill 2002a; 2002b). Alternatively, a person possessing a more complete grasp of the task online will likely want to experiment first, preferring to refer to the rules and basic information only when they need assistance. Unfortunately there are many online programmes that do not cater for both modes of learning; therein is the opportunity to design ePedagogies that address the power and complexity of the Internet. When the instructional systems' pedagogy cannot adapt to this important requirement, they run the risk of demotivating both groups of learners (Tennyson & Bagley, 1991). The result may be confusion for novices when the primary rules and examples are not sufficiently explicit, and boredom and frustration for the experienced learner who is forced into following the complete instructional strategy. In seeking answers to the dilemma of how to provide such flexible ePedagogies, our attention should turn to the valuable body of work by Repovs and Baddeley (2006). They say that working memory has proven to be an important part of the human's cognitive system, providing the ability to maintain and manipulate information in the process of guiding and executing complex cognitive tasks.

Our research points out that web-mediated instruction (ePedagogy) should involve flexible screen-based information designed in such a way that people have a choice.

REFERENCES

- Adams, R. J., & Khoo, S. T. (1996). *QUEST: The interactive test analysis system*, Vol: 2.1. Melbourne: Australian Council for Educational Research.
- Bond, T., & Fox, C. M. (2007). *Applying the Rasch Model: Fundamental Measurement in the Human Sciences*. 2nd Edition. Lawrence Erlbaum, London.
- Champagne, A., Gunstone, R., & Klopfer, L. (1982). A perspective on the differences between expert and novice performance in solving physics problems. *Research in Science Education*, 12 (1), 71-77.
- Clark, R. C., Nguyen, F., & Sweller, J. (2006). *Efficiency in learning: evidence-based guidelines to manage cognitive load*. J.Wiley & Sons, San Francisco.
- Cohen, J. (1977). *Statistical Power Analysis for the Behavioral Sciences*. Revised Edition. Academic Press, New York.
- Fischer, G. H., & Molenaar, I. W. (Eds.). (1995). *Rasch models : foundations, recent developments, and applications*. Springer-Verlag, New York.
- Fisher Jr, W. P. (2010). Statistics and Measurement: Clarifying the Differences. *Rasch Measurement Transactions*, 23(4), 1229-1230.
- Gagne, R. M. (1985). *The Conditions of Learning and Theory of Instruction*. 4th Edition. Holt, Rinehart & Winston, New York.
- Izard, J. (2005a). Overview of test construction. In K. N. Ross (Editor.), *Quantitative Research Methods in Educational Planning*. International Institute for Educational Planning, Paris.
- Izard, J. (2005b). Trial testing and item analysis in test construction. In K. N. Ross (Editor), *Quantitative Research Methods in Educational Planning* (pp. 84). International Institute for Educational Planning, Paris.
- Kalyuga, S. (2009). Instructional design for the development of transferable knowledge and skills: A cognitive load perspective. *Computers in Human Behavior*, 25 (2), 332-338.
- Kalyuga, S., Ayres, P., Chandler, P., & Sweller, J. (2003). The expertise reversal effect. *Educational Psychologist*, 38 (1), 23-31.
- Kolen, M. J., & Brennan, R. L. (2004). *Test Equating, Scaling and Linking: Methods and Practices*. 2nd Edition. New York: Springer.
- Kozma, R. B., & Russell, J. (1997). Multimedia and understanding: Expert and novice responses to different representations of chemical phenomena. *Journal of Research in Science Teaching*, 34 (9), 949-968.
- Lee, J. (2007). The effects of visual metaphor and cognitive style for mental modeling in a hypermedia-based environment. *Interacting with Computers*, 19, 614-629.
- Massa, L. J., & Mayer, R. E. (2006). Testing the ATI hypothesis: Should multimedia instruction accommodate verbalizer-visualizer cognitive style? *Learning and Individual Differences*, 16 (4), 321-335.
- Mautone, P. D., & Mayer, R. E. (2001). Signaling as a cognitive guide in multimedia learning. *Journal of Educational Psychology*, 93(2), 377-389.
- Mayer, R. E. (2001). *Multimedia Learning*. Cambridge University Press, Cambridge.
- Mayer, R. E. (2005). Cognitive theory of multimedia learning. In R. E. Mayer (Editor), *The Cambridge Handbook of Multimedia Learning* (pp. 31-48). Cambridge University Press, New York.
- Mayer, R. E. (2009). *Multimedia Learning*. 2nd Edition. Cambridge University Press, Cambridge.
- Mayer, R. E., & Sims, V. K. (1994). For whom is a picture worth a thousand words? Extensions of a dual-coding theory of multimedia learning. *Journal of Educational Psychology*, 86 (3), 389-401.
- McKay, E. (2000). *Instructional Strategies Integrating Cognitive Style Construct: A Meta-Knowledge Processing Model*. Deakin University, Melbourne.
- McKay, E. (2008). *The Human-Dimensions of Human-Computer Interaction: Balancing the HCI Equation*. 1st Edition. Vol: 3. IOS Press, Amsterdam.
- Merrill, M. D. (2002a). First principles of instruction. *ETR&D*, 50 (3), 43-59. from <http://www.indiana.edu/~tedfrick/aect2002/firstprinciplesbymerrill.pdf>
- Merrill, M. D. (2002b). Effective use of instructional technology requires educational reform. *Educational Technology*, 42 (4), 13-16.
- Miller, G. A. (1956). The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, 63 (2), 81-97.
- Miller, G. A. (1987). Cognitive Styles: an integrated model. *Educational Psychology*, 7 (4), 251-268.
- Mohamad, M. and McKay, E., (2010). A test instrument calibration study: The Rasch model approach to investigate web-mediated instructional outcomes. In *Proceeding of the Global Learn Asia Pacific 2010* (Abas, Z.W., Jung, I., and Luca, J. Ed.), p. 4253-4262. AACE: Penang, Malaysia

- Rasch, G. (1960). *Probabilistic Models for Some Intelligence and Attainment Tests*. Danish Institute for Educational Research, Copenhagen.
- Repovs, G., & Baddeley, A. (2006). The multi-component model of working memory: explorations in experimental cognitive psychology. *Neuroscience*, 139 (1), 5-21 from <http://www.ncbi.nlm.nih.gov/pubmed/16517088#>.
- Riding, R. J. (2005). *Cognitive Styles Analysis Administration: Learning and Training Technology*, Birmingham.
- Riding, R. J., & Cheema, I. (1991). Cognitive styles -an overview and integration. *Educational Psychology: An International Journal of Experimental Educational Psychology*, 11 (3-4), 193-215.
- Riding, R. J., & Douglas, G. (1993). The effect of cognitive style and mode of presentation on learning performance. *British Journal of Educational Psychology*, 63, 297-307.
- Riding, R. J., & Sandler-Smith, E. (1992). Type of instructional material, cognitive style and learning performance. *Educational Studies*, 18 (3), 323-340.
- Salmerón, L., Baccino, T., Cañas, J. J., Madrid, R. I., & Fajardo, I. (2009). Do graphical overviews facilitate or hinder comprehension in hypertext? *Computers & Education*, 53 (4), 1308-1319.
- Smith, S. M., & Woody, P. C. (2000). Interactive effect of multimedia instruction and learning styles. *Teaching of Psychology*, 27 (3), 220-223.
- Tennyson, R. D. (2001). Defining core competencies of an instructional technology. *Computers in Human Behavior*, 17 (4), 355-361.
- Tennyson, R. D., & Bagley, C. A. (1991). Structured versus constructed instructional strategies for improving concept acquisition by domain-experienced and domain-novice learners. *Paper presented in the symposium, Perspectives on higher order knowledge and problem solving, at the annual meeting of the American Education Research Association*, Chicago, April.
- Thomas, P. R., & McKay, J. B. (2010). Cognitive styles and instructional design in university learning. *Learning and Individual Differences*, 20(3), 197-202.
- van Merriënboer, J. J. G. (1997). *Training complex cognitive skills: a four-component instructional design model for technical training*: Educational Technology Publications.
- Weidenmann, B. (1989). When good pictures fail: An information processing approach to the effect of illustrations. In H. Mandl & J. R. Levin (Eds.), *Knowledge acquisition from text and pictures* (pp. 157-171). Amsterdam: Elsevier.
- Yu-Chen, H. (2007). The effects of visual versus verbal metaphors on novice and expert learners' performance. In J. A. Jacko (Ed.). *Human-Computer Interaction Part IV HCII 2007* (pp. 264-269). Berlin-Heidelberg: Springer-Verlag.