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Learning Styles of ICT Specialisation Students: Do Differences in Disciplines Exist?

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Within existing ICT degrees there is a widely-held belief that content must be tailored for different 'kinds' of students — often two differing student groups: a technical group requiring detailed Computer Science knowledge and a separate group requiring less technical, more strategic ICT knowledge and skills. Our institution has produced a combined degree that contains both technical and non-technical content taught to a single cohort of students and thus requires a deeper insight into the needs of this diverse group of learners. This paper reports on an assessment of learning styles across our first year students, in order to inform our teaching delivery practices. Our findings, including for example that there are marked preferences for some learning styles over others, inform the development of teaching and assessment materials that better support the diverse needs of students, regardless of their self-selected discipline.

Introduction

The School of Computing and Information Systems (SoCIS) was formed in 2008 and introduced a new Bachelor of ICT as its core undergraduate degree in 2014. After two years of development, this degree is based on industry-standards and international curricula and is strongly focused towards the achievement of career outcomes relevant to today's ICT employers (Herbert et al, 2103; de Salas et al 2013). The degree design commenced with degree learning outcomes, which have been percolated down to the unit learning outcome level (Herbert et al, 2103; de Salas et al, 2013).

SoCIS was formed from the Schools of Information Systems (previously located in the Faculty of Business) and Computing (located within the Faculty of Science). SoCIS was created to provide all Bachelor-level and above ICT-related higher education in the state of Tasmania. Some unit consolidation occurred as a consequence of the creation of the new School, but the majority of units in the two degrees remained separate — in terms of their technical (Computing) or non-technical (Information Systems) focus, the students taking the units, and the staff teaching these units.

Traditionally, due in part to administrative separation, our ICT degrees have been offered to two differing student groups. A technical degree involving detailed Computer Science knowledge and skills has been offered to Science/Engineering students and a separate degree involving less technical, more strategic ICT knowledge and skills has been offered to Business students. The new degree fuses these two traditional offerings. It seeks to consolidate the resources currently spread over the School's two existing degrees, to expose all students to a broader range of technology-related topics, develop a breadth in understanding across all areas of ICT, and allow students to focus on developing a core technical skill that meets their own personal needs and interest areas (Herbert et al, 2103; de Salas et al, 2013). The result will be graduates that are desired by employers, the so-called "T-Shaped" professional (AWPA, 2013) — those with great depth of knowledge and ability in one discipline (the vertical component of the T) with a breadth of understanding in other areas and an ability to collaborate with experts from other fields (the horizontal component of the T).

The new 'unified' degree allows all students to experience both technical and non-technical content and to mix with students from outside their traditional cohort. Unit materials will now have to be relevant and accessible to a mixed cohort, delivery styles will have to support the learning needs of a mixed cohort, and assessment tasks will have to include different opportunities to best demonstrate and assess students' learning across the mixed cohort.

Additionally, within the existing degrees there is a belief that the content suits different 'kinds' of students. The introductory programming unit, KXT101 Programming and Problem Solving, has results which are typically bi-modal with a large portion of the class 'getting it', and another similarly-sized large portion of the class 'not getting it'. This is typical across Australasia (Simon et al 2006) and the wider world (Hudak & Anderson, 1990; Bornat, Dehnadi, & Simon 2008) and it is currently unclear why this occurs despite many studies looking at a multitude of predictors (Wilson & Shrock, 2001; Simon et al 2006),

Learning styles — how learners perceive, interact with, and respond to the learning environment (Keefe, 1979) — have been identified as an important element to understand when developing unit materials, as much research suggests that these characteristics influence a learner's engagement with content, their ability to understand content, and their ability to show their learning through assessment.

Although there are mixed views about the results gained through the application of tests to discern personality types (e.g. Pittenger, 2005) and the implied lack of plasticity in learning styles as identified by tests related to learning style detection, many studies have been completed which have successfully linked results from such tests to career suitability (Raven, Cano, Carton, & Shelhamer, 1993; Capretz, 2003; Wolf & Nikolai, 1997). Many studies have identified that there are significant differences in personality and learner types across higher education discipline cohorts such as Accounting, Engineering, Computing, Design, Economics, Science, Management, and Medicine (Capretz, 2003; Durling, Cross, & Johnston, 1996; Galpin, Sanders, & Chen, 2007; Grasher & Yangarger-Hicks, 2000; Layman, Cornwell, & Williams, 2006; Mupinga, Nora, & Yaw 2006; Pike, 2006; Teague, 1998; Wolk & Nickolai, 1997; Ziegart, 2000). An example of an ICT-specific study is that undertaken by Hudak and Anderson (1990) who found correlation between learning styles — as identified by Kolb's Learning Style Inventory (Kolb, 1985) — and student success in introductory computer programming courses.

In order to be in a position to develop robust, comprehensive, engaging, relevant, and, most importantly, accessible units to students in the new BICT a much clearer understanding about the needs and preferences of our learners is required. The objective of this project therefore was to investigate the differences (if any) in the learning styles of the students in our units. This information would then be used to identify appropriate teaching and assessment practices to best meet the needs of the mixed cohort.

The School of Engineering and ICT

Within the 40 year history of the SoCIS (and its antecedents), three primary disciplines have been core throughout:

- Computer Science/Computing – this core discipline includes knowledge areas of Discrete Structures, Human-Computer Interaction, Programming Fundamentals, Graphics and Visual Computing, Algorithms and Complexity, Intelligent Systems, Architecture and Organization, Information Management, Operating Systems, Social and Professional Issues, Net-Centric Computing, Software Engineering, Programming Languages, and Computational Science (Association for Computing Machinery, 2008). This discipline is very specific and thus rarely draws students outside its own technically focused area, and those of maths and engineering.
- Information Systems – this core discipline includes knowledge areas of Foundations of Information Systems, Data and Information Management, Enterprise Architecture, IS Project Management, IT Infrastructure, Systems Analysis and Design, and IS Strategy, Management, and Acquisition (Association for Computing Machinery and Association for Information Systems, 2010). Given the multidisciplinary derivation of IS as a field of study, this discipline draws students from diverse backgrounds of IT, Management, Accounting, Economics, and Humanities.
- Engineering – this core discipline develops knowledge of science and engineering fundamentals, knowledge and understanding of engineering and technology, knowledge and application of engineering techniques and resources, and general knowledge supporting the nominated fields of engineering practice such as civil engineering, computer systems engineering, electrical power engineering, geotechnical engineering, mechanical engineering and biomedical engineering (Engineers Australia, 2011). Similar to computer science, this discipline is very focused on its own core knowledge areas, and thus primarily draws additional students only from computer science and maths.

There have been many amalgamations of these discipline areas and student cohorts over the last 40 years. Not only are these amalgamations structural, they also require substantial integration of teaching and learning practices in order to achieve the economies of scale outcome desired by senior management. This integration can be a challenging prospect, for example in 2008, the existing schools of Computing and Information Systems were merged as a result of a world-wide decrease in ICT education demand (both in Computer Science and Information Systems) (Lewis et al, 2013) and resultant refocus on research outcomes in the higher education sector. Prior to this merge the School of Computing was situated in a broad science faculty and had a traditional attitude to its teaching and learning practices. That is, there was a strong focus on lecture-style delivery as the primary mechanism for relaying content to students, with formal written examinations being the primary mechanism by which knowledge of unit content was assessed (commonly counting towards 70% of the overall assessment).

Conversely, the School of Information Systems was previously situated in a faculty of business and management which had a more progressive approach to its learning and teaching practices. Within this faculty, all staff were actively encouraged to explore innovative ways to deliver unit content and undertake assessment. As a result, this school had a broader focus on interactive workshops as the primary means of class interaction, and more use of online and flexible methods to build theoretical knowledge. Furthermore, the primary methods used to assess content knowledge and application within the school was written reports, rather than an emphasis on formal examinations.

While the merge of these two schools conceptually seemed appropriate based on their joint contributions to knowledge generation in the broader ICT space, bringing together teachers with very different approaches to learning and teaching as well as students from very diverse disciplines caused a range of new challenges. For example, in attempting to obtain economies of scale in teaching, the newly combined school attempted to merge a number of their units into broader topic areas, for example a unit teaching Web Management in the previous School of IS was merged with a unit called Web Development from the previous School of Computing in the hopes of developing one unit that would provide both technical and non-technical elements to all students within the new school.

Despite amalgamation in 2008, units continued to be taught in accordance with the traditional preference of the unit coordinator, with very little real content and style merging or alteration despite the increase in student diversity. There remained a distinct difference in the teaching styles of those staff from the previous schools even after the merger and the attempt at unit integration. The existing practice of teachers had not been updated or informed by current practice, and the school did not have policies in place to facilitate this. For example, Figures 1 and 2 provide an indication that even post merge in 2008, staff from the previous School of Computing retained their traditional orientation towards content delivery and assessment.

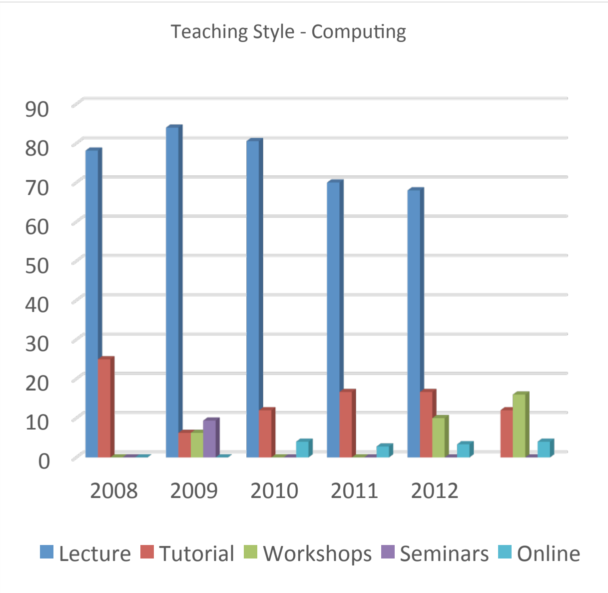

Figure 1: Teaching styles in the Computing discipline.

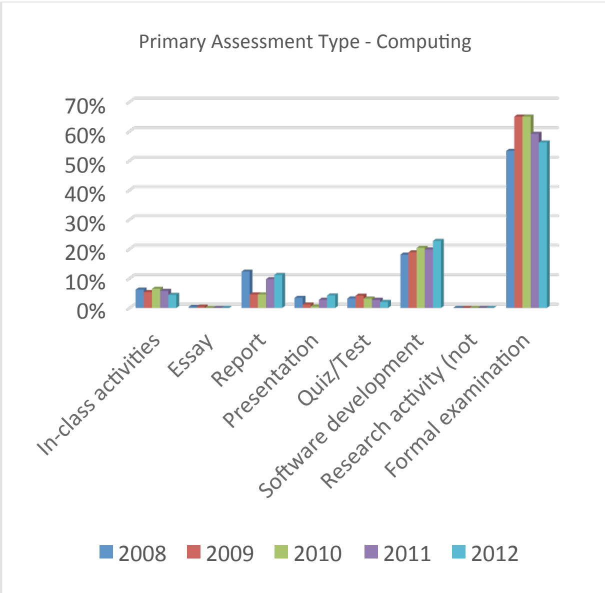

Figure 2: Assessment styles in the Computing discipline.

While Figure 3 and 4 indicate that staff from the previous school of Information Systems maintained their more flexible approach towards content delivery and their focus on written reports for assessment.

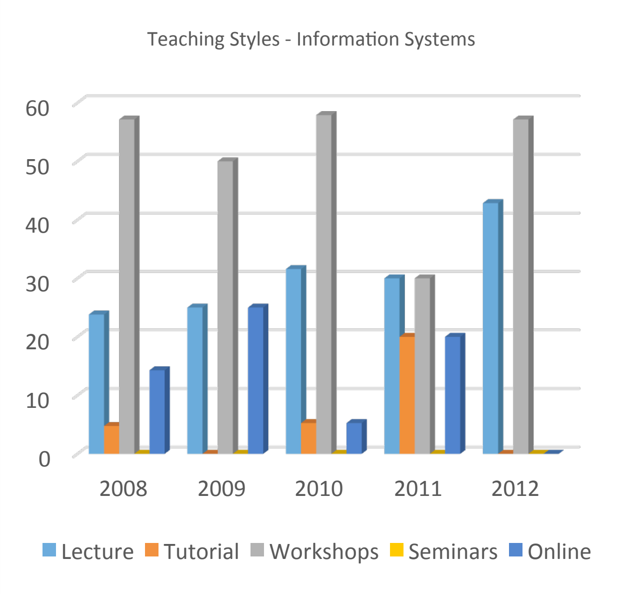

Figure 3: Teaching styles in the Information Systems discipline.

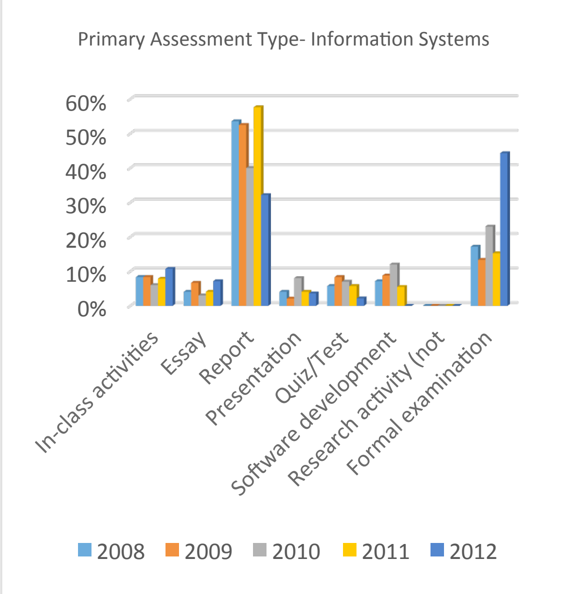

Figure 4: Assessment styles in the Information Systems discipline.

The difference in approach continued to exist due to an anecdotal belief amongst teaching staff that there existed two heterogeneous cohorts within the School – those with a focus on Information Systems (with a strong alignment with business and management and a need for flexible options to support their study) and those with a focus on computing (with a strong alignment with engineering and maths and a preference for more traditional modes of delivery and assessment).

In 2012, the merged School of CIS was reviewed by a panel of external curriculum experts as part of an accreditation review cycle and found to be lacking in its ability to deliver quality undergraduate programs that met the broad needs of students and local employers of our graduates. A primary recommendation of the review was to consolidate the current offerings – a Bachelor of Information Systems and a Bachelor of Computing into one degree that would have a more broad content focus. Throughout 2014 a newly developed Bachelor of ICT was implemented, which includes content relevant to a modern day ICT graduate and draws from a range of disciplines including computer science, software engineering, and Information Systems.

Despite the directive from the review findings to develop a common degree, there still remains the assumption amongst teaching staff that there are distinct student cohorts within the degree that should be taught in distinct ways. The challenge now then is to better understand the learning needs of our students in order to be better informed in our delivery and assessment choices.

Learning Styles

What are learning styles?

People learn in different ways. For many decades researchers have been exploring the ways in which people learn in an attempt to identify better teaching practices. In 1979, Keefe defined a learning style as "characteristic cognitive, affective, and physiological behaviours that serve as relatively stable indicators of how learners perceive, interact with, and respond to the learning environment" (Keefe, 1979). Grasha (1990) further defined learning styles as the "preferences students have for thinking, relating to others, and particular types of classroom environments and experiences" (p. 26). Discovering a student's learning style preference does not prohibit them from learning in other styles; it is merely an indication of the style that would typically be the most efficient, or comfortable, for them.

Why are learning styles important?

It has been suggested that a critical awareness and understanding of student learning styles by both students and educators is important as it could provide valuable insight into what is needed to create meaningful learning experiences, and more effective teaching (Abidin, 2012).

As indicated previously, the School of CIS is currently developing unit content and assessment for a newly developed Bachelor of ICT. According to Zapalska and Dabb (2002) when the curriculum is integrated around a theme with proper attention given to brain compatibility, teaching strategies, and learning styles, learning itself is enhanced. Learners often have different levels of motivation, different attitudes about teaching and learning, and different responses to specific classroom environments and instructional practices. In this context, the more thoroughly instructors understand these differences, the better chance they have of meeting the diverse needs of their learners (Deng, 2011).

Research suggests that differences among learning styles become more striking as our learning communities in higher education become more diverse (Zapalska & Dabb, 2002) and instruction should address individual styles of learning and some students learn best through different approaches. In order to help our students succeed, we must understand how they learn, consider how they perceive, process information, and accommodate their individual differences (Zapalska & Dabb, 2002).

Students have different strengths and preferences in the ways they take in and process information — which is to say, they have different learning styles (Felder & Spurlin, 2005). Some prefer to work with concrete information (facts, experimental data, etc.) while others are more comfortable with abstractions (theories, symbolic information, mathematical models, etc.). Some are partial to visual presentation of information (pictures, diagrams, flowcharts, schematics, etc.) and others get more from verbal explanations. Some like to learn by trying things out and seeing and analysing what happens, and others would rather reflect on things they plan to do and understand as much as they can about them before actually attempting them. When the learning styles of most students in the class and the teaching style of the teacher are seriously mismatched, the students are likely to become uncomfortable, bored and inattentive in class, do poorly in tests, get discouraged about the courses, the curriculum, and themselves (Felder & Spurlin, 2005).

Studies have identified that there are significant differences in learner types (reflecting the different skills required) across higher education discipline cohorts such as Accounting, Engineering, Computing, Design, Economics, Science, Management, and Medicine (Capretz, 2003; Durling, Cross, & Johnston, 1996; Galpin, Sanders & Chen, 2007; Grasher & Yangarger-Hicks, 2000; Layman, Cornwell, & Williams, 2006; Mupinga, Nora, & Yaw, 2006; Pike, 2006; Teague, 1998; Wolk & Nickolai, 1997; Ziegart, 2000).

Learning style tools

Coffield, Moseley, Hall, and Ecclestone (2004) identified seventy-one different learning style models with some of the most popular in use being: Myers-Briggs Type Indicator (MBTI)

(Myers et al, 1998), Multiple Intelligences (Gardner, 1993), Kolb's (1985) Learning Styles Theory, Honey and Mumford's (1992) Index of Learning Styles, the Felder-Silverman Learning Style Model (Felder & Silverman, 1998), and VARK (Fleming, 1995) learning styles.

In an attempt to find some clarity amongst this vast number of tools, there have been attempts to group learning style tools by their underlying methodological approach or practical application. Coffield et al (2004) identified five 'families' in which to place seventy-one reviewed tools, whereas Cassidy (2013) (building on work by Curry (1987) and Rayner and Riding (1997)) classified twenty-three tools into eight categories based on the prevailing psychological theory used.

Despite the diversity of models, there are large commonalities between them and many can be considered as equally valid identifiers of differences in learning style. What all these learning style models have in common is that they facilitate the identification of specific learner types for individuals, to enable the provision of suitably tailored material to each learner with the aim of enhancing their overall potential for learning (Deng, 2011).

Methodology

This study employed the Memletic Learning Styles Inventory (2008) a recently developed tool that draws together much of what we know about effective learning and is being increasingly employed (Abidin, 2012; Cooper, 2007; Thurairaj et al, 2013; Kia, 2009) given its ease of application. This inventory is informed by both the MBTI and the Felder-Silverman Learning Style Model (Bocar, Pasok, & Labastin, 2011) and recognises seven different learning styles (Cooper, 2007) that correspond with the intelligence types identified by Gardner (Deng, 2011):

1. Visual (spatial) — learner prefers pictures and images;
2. Aural (auditory/musical) — student prefers sound and music;
3. Verbal (linguistic) — the student has a preference for words;
4. Physical (kinesthetic) — the student is a hands-on learner;
5. Logical (mathematical) — student prefers logic and reasoning system;
6. Social (interpersonal) — the student learns best by working in groups; and
7. Solitary (intrapersonal) — the learner prefers self-study.

In line with previous studies employing the Memletics approach (Abidin, 2012; Cooper, 2007; Thurairaj et al, 2013; Kia, 2009) the entire incoming first year cohort of the school was invited (by email from the Head of School) to complete the 70-question Memletic Styles Quiz (MSQ) via an online survey tool over a two week period. Following the approach of the above research, the participants were required to rate 70 statements by using the following score ratings:

- 0 — the statement is nothing like me;
- 1 — the statement is partially like me; or
- 2 — the statement is very much like me.

Once all statements were rated, the student was provided (via an automatically generated email) with an indication of their relative preference of the seven learning styles, along with an explanation of each learning style.

Discipline self-selection

Rather than dividing student into groups based on their enrolled degree or by some understanding of their individual unit enrolments, students were asked to self-select their discipline of study, as this has been shown to be a better indicator of cohort than artificial administrative groupings (Smyth et al, 2013).

For this study, five relevant disciplines were provided as self-identifying options for the respondents, and a further one to allow for self-selection outside of those directly relevant to ICT. Students were asked to specify which group (with all their associated norms and stereotypes) that they self-identified with as below:

- Computing — Usually highly technical, with a preference for software development;
- Information Systems — Usually less technical in nature than 'Computing', and often seen as the liaison between technology and business;
- Computing and Information Systems — Those students who believed they did not belong to either the group 'Computing' or 'Information Systems' discretely, but instead a combination of these two. Usually preferred to combine technical and non-technical elements of ICT equally;
- Business — Usually less technically oriented than 'Information Systems';
- Engineering — Usually more technical and hardware oriented that 'Computing'; or
- Other — Those students who did not believe they belonged to any of the above five groups. This group may include students from humanities and arts, or more broad sciences.

Findings

215 students responded to the invitation and completed the online survey.

Table 1 indicates the relative percentage of each of the seven mimetic learning styles as the primary learning style, according to each self-identified discipline cohort. As is highlighted in Table 1, the primary preferred learning style for each of the cohorts is as follows:

- Computing — Solitary and Logical (represented equally at 21.3%);
- Information Systems — Solitary (represented at 41.7%);
- Computing and Information Systems — Aural (represented at 25.0%);
- Business — Solitary (represented at 40.0%);
- Engineering — Logical (represented at 29.7%); and
- Other — Social (represented at 33.3%).

Table 1: Frequency of first-preference Learning Styles, by self-identified discipline (highest percentage learning style shaded for emphasis).

	n	**Visual**		**Aural**		**Verbal**		**Physical**		**Logical**		**Social**		**Solitary**	
		Frequency	**%**	**Frequency**	**%**	**Frequency**	**%**	**Frequency**	**%**	**Frequency**	**%**	**Frequency**	**%**	**Frequency**	**%**
Computing	75	8	10.7	12	16.0	13	17.3	4	5.3	16	21.3	6	8.0	16	21.3
Information Systems	12	1	8.3	1	8.3	1	8.3	0	0.0	2	16.7	2	16.7	5	41.7

CIS	36	5	13.9	9	25.0	3	8.3	2	5.6	7	19.4	5	13.9	5	13.9
Business	10	1	10.0	1	10.0	0	0.0	0	0.0	1	10.0	3	30.0	4	40.0
Engineering	64	6	9.4	9	14.1	4	6.3	5	7.8	19	29.7	11	17.2	10	15.6
Other	18	1	5.6	1	5.6	3	16.7	1	5.6	4	22.2	6	33.3	2	11.1

Visualising disciplines

In taking a closer look at each discipline, we can clearly identify a difference in preferred styles of learning across these cohorts. For example, in Figures 5 and 6, while we can see an obvious preference for a Solitary learning style in both Computing and Information Systems, it appears to be much stronger within the Information Systems discipline. The equal highest preference in the Computing discipline is a Logical style, and this style, while also being indicated as a second highest preference for Information Systems, is shared equally with a preference for Social learning. Thus while we can see similarities in preferences across these two core disciplines, the proportions of these highest ranked preferences are quite different.

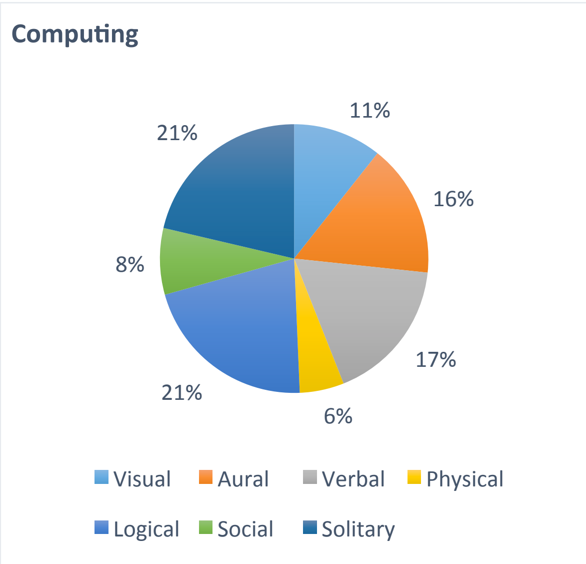

Figure 5: The learning styles preferences of students from the core ICT discipline of Computing.

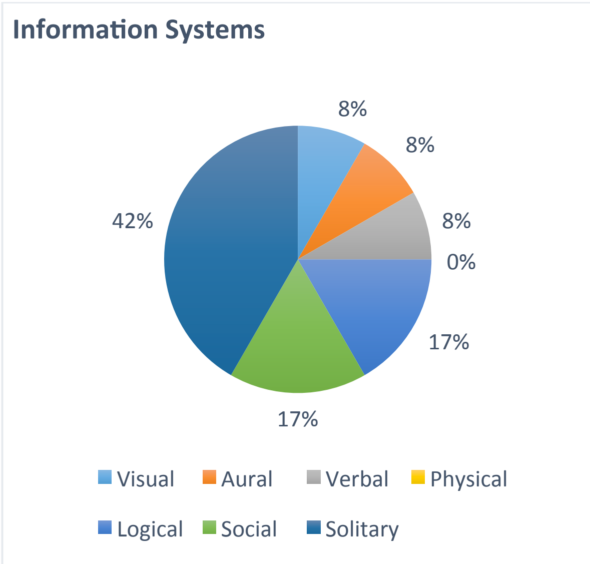

Figure 6: The learning styles preferences of students from the core ICT discipline of Information Systems.

Engineering students are often found to add Computing units to their programs and so it is not uncommon for these students to be co-taught with the Computing cohort. Interestingly, as can be seen in Figure 7, the preferred learning style of Engineering students is Logical, which aligns closely with the secondary preference of the Computing cohort. It can thus be suggested that the combination of Engineering students into Computing units further skews the preferences towards the Solitary/Logical learning styles preferences.

On the other hand, Business students are often found in Information Systems units, given the management orientation of both. As shown in Figure 8, results from this survey indicate that the preferred learning style for Business students is Solitary, with a secondary preference for Social. This aligns with the two top preferences of the Information Systems cohort, thus suggesting that combining these two cohorts skews preferences towards the Solitary/Social preferences.

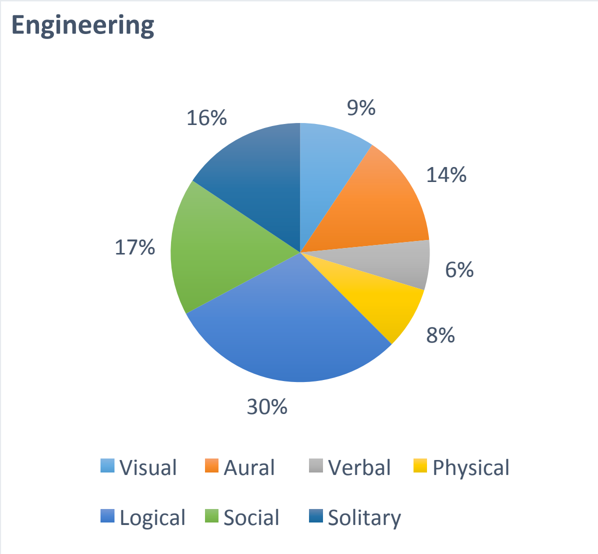

Figure 7: The learning styles preferences of students from the related ICT discipline of Engineering.

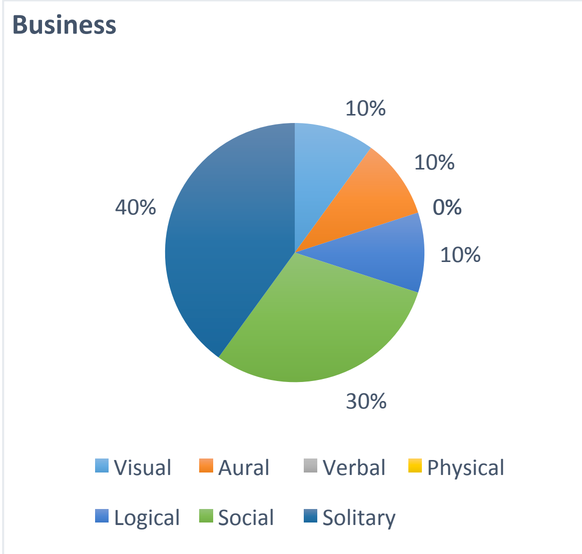

Figure 8: The learning styles preferences of students from the related ICT discipline of Business.

We can thus see that Computing students, with strong preferences for Solitary and Logical styles are often joined by Engineering students who also exhibit a preference for a Solitary style, thus creating a cohort with a dominance of this style (see Figure9). Furthermore, we can see that Information Systems students, with a preferred Solitary learning style, closely followed by Social and Logical preferences are often joined by business students who also exhibit a preference for Solitary and Social styles, thus creating a cohort with a high proportion of Social/Solitary styles (see Figure 10).

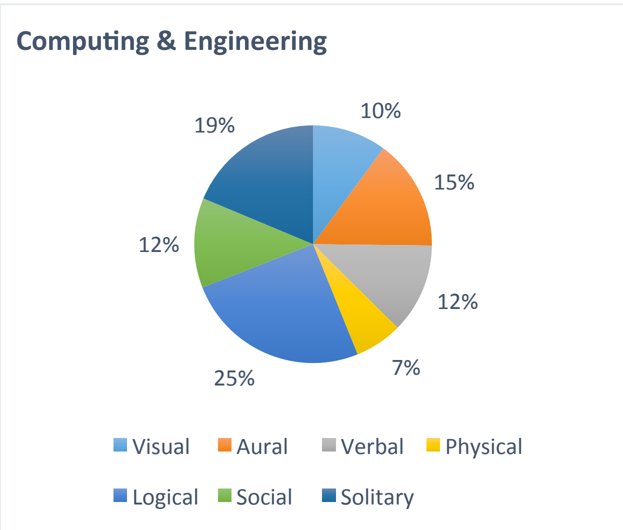

Figure 9: The learning styles preferences of students from the related ICT discipline of Engineering.

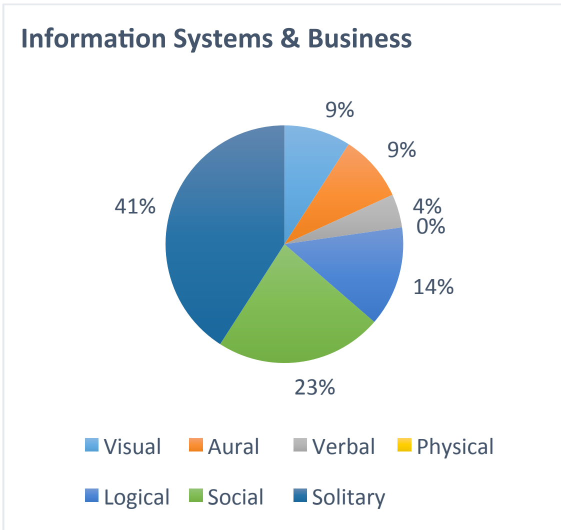

Figure 10: The learning styles preferences of students from the related ICT discipline of Business.

Visualising learning styles

In looking across the seven Memletic learning styles, we can identify some interesting findings with regard to learning preferences.

Firstly, with regard to the Visual learning style, as shown in Figure11, we can see that the highest preference for this style was identified within the Computing and Information Systems (CIS) discipline. This self-identified discipline consists of students who undertake studies in ICT, drawing from each of the separate Computing and Information Systems disciplines, thus attaining a broader ICT focus in their study than would be provided by either discipline alone. Interestingly, while only 11% of Computing students and 8% of Information Students identified the Visual learning style as their preference, those students choosing to combine these disciplines indicated a higher preference for this style, namely 14%.

Similarly, the Aural learning style, as shown in Figure12. was also rated as the highest amongst students in the combined CIS discipline, at 25%, whereas the Computing and Information disciplines rated this style at 16% and 8% respectively.

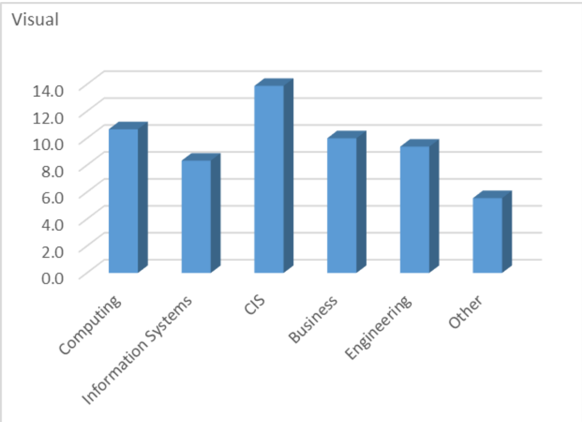

Figure 11: The preferences for the Visual style across the self-identified disciplines.

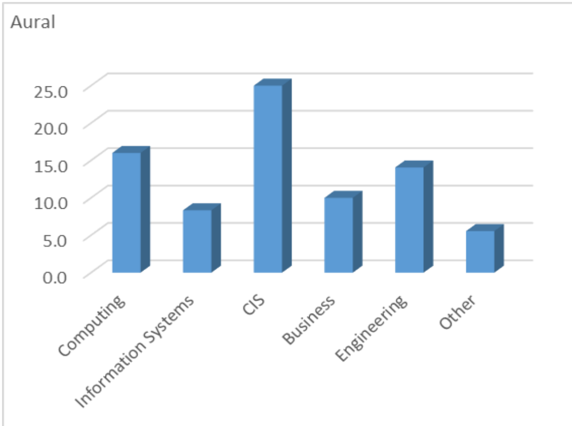

Figure 12: The preferences for the Aural style across the self-identified disciplines.

Interestingly, we can see that while students in the individual Computing and Information Systems disciplines indicated strong preferences for Solitary learning, students self-identifying across these two combined disciplines show the highest preferences for both Visual and Aural styles.

Furthermore, as shown in Figure 13, in reviewing the preference for learning styles, we can see that while the disciplines of Computing, CIS, Engineering, and Other all indicted some preference for the Physical learning style, this style was entirely absent amongst students self-identifying as Information Systems or Business Students.

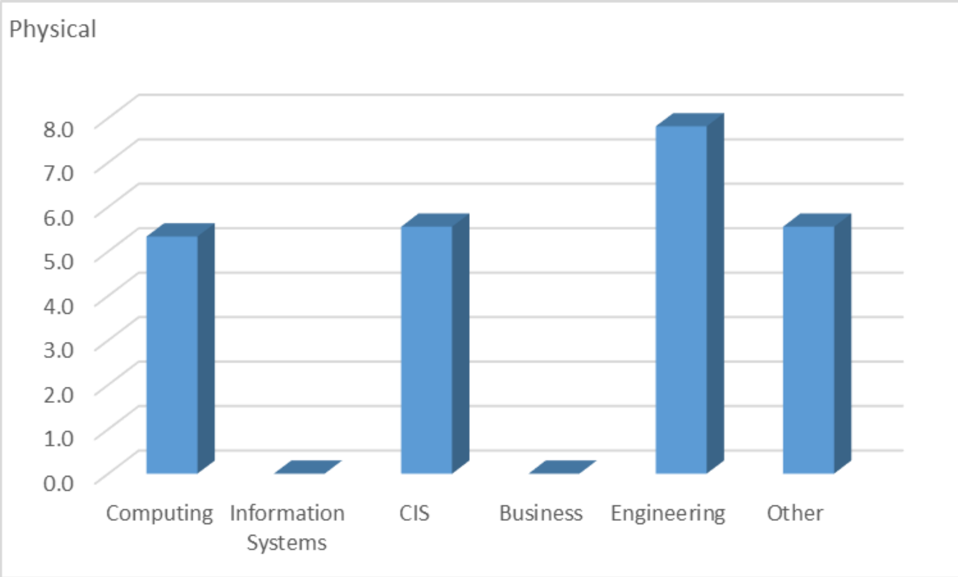

Figure13: The preferences for Physical style across the self-identified disciplines.

In looking across all learning styles (see Figure 14), we can see that the disciplines indicating the strongest preference for each style. The Visual style exhibits itself most strongly among CIS students, as does the Aural style. The Verbal style is preferred more frequently within the Computing discipline amongst all others, and the Physical learning style is indicated more highly by Engineering students than any others, with a notable lack of any preference for this style by Information Systems and Business Students included in this study.

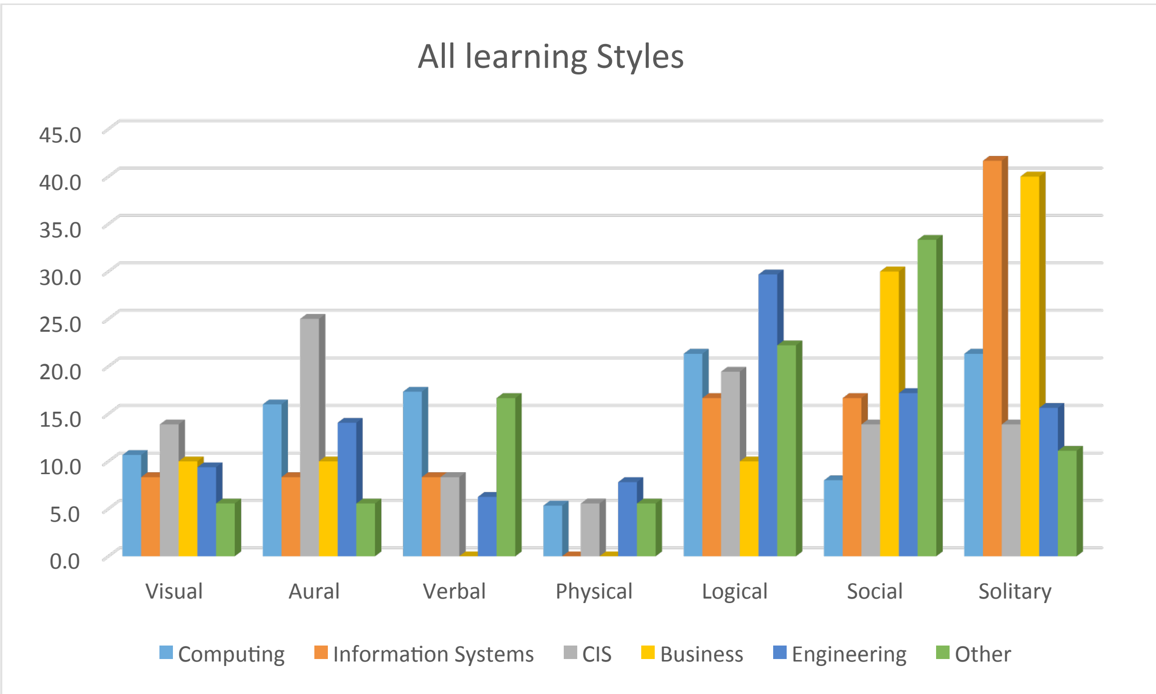

Figure14: The preferences for all styles across the self-identified disciplines.

The Logical style features highly amongst a number of self-selected disciplines, but most highly for Engineering students.

Interestingly, the Social style is strongly preferred by those students not directly-aligned to any of the ICT-related disciplines. The highest incidence of this learning style preference was indicated by students who did not self-identify in the five ICT-related disciplines, but rather saw themselves outside. These students may either have either been better represented as Humanities of general Science students, however we are not able to substantiate this based on our data. Most interesting however is the highest preference for the Solitary learning style being exhibited by the Information Systems students, followed closely by Business.

Statistical significance of the findings

While, the above diagrams highlight apparent differences between learning styles across disciplines, statistical testing was undertaken to determine if these results were truly significant.

In order to determine the statistical significance between the learning styles of disciplines, a Mann-Whitney U test (a non-parametric t-test equivalent) was run between each specific discipline. From these analyses, only the following statistically significant differences were noted:

- Computing and Other for the Social learning style ($p = 0.009$);
- Computing and Engineering for the Verbal learning style ($p=0.022$);
- Computing and Business for the Social learning style ($p=0.025$);
- Computing and Information Systems and Business for the Solitary learning style ($p=0.020$);
- Business and Engineering for the Solitary learning style ($p=0.026$); and
- Business and Other for the Solitary learning style ($p=0.036$).

If we consider the technical disciplines (Computing and Engineering) as one cohort and the non-technical disciplines (Information Systems and Business) to be another, results indicate a statistically significant difference only for the Solitary learning style ($p=0.037$).

However, with the application of a Bonferroni correction to counteract the problem of multiple comparisons, each of these apparent significant p-values cease to be significant under the greater p-value requirements.

Implications for learning and teaching

While the differences between disciplines cannot be determined to be statistically significant, descriptively, there are still marked preferences for some learning styles over others. Again, Computing and Engineering students exhibit a stronger preference for Solitary and Logical styles, while Information Systems and Business students exhibit stronger preferences for Solitary and Social styles. In reviewing these, then, we can see that there might indeed be differences in teaching style that better suit these students, for example:

- Solitary learners enjoy learning on their own. While they can work well one-on-one, they do not function well in groups. Self-study and self-reflection are their strengths which allow them to learn most successfully. These students need step-by-step goals and detailed lists that keep them on track. Using a journal helps with any questions they may have. Writing it out can help them solve many academic problems, or keep them ready for the tutor or teacher. In order to provide a supportive learning environment for these learners, instructors create a connection between new material and subjects the students already know, as these learners gain understanding by finding their similarities. Furthermore, as Solitary learners are challenged by social learning, instructors might avoid such requirements and instead provide opportunities watching how-to-videos and reading to learn new things (Neidorf, 2012).

- Logical learners thrive on reasoning and systems. Logical learners are forever making lists and agendas and enjoy exploring questions of 'why?'. People with mathematical logical learning styles learn best when taught using visual materials, computers, statistical and analytical programs, and hands on projects. They prefer structured, goal-oriented activities that are based on math reasoning rather than less structured, creative activities with inexact learning goals. Mathematical Logical learners would find a statistical study more appealing than analysing literature or keeping a journal. In order to support this learning style, it is suggested that instructors provide deep resources to allow these learners to explore issues extensively, and develop whole system simulations to test theories (Neidorf, 2012).
- Social Learners, on the other hand thrive on interpersonal communications and learn best in a group atmosphere. The Social learner can communicate with others verbally and non-verbally very easily. They also tend to listen and collaborate easily with peers and teachers/instructors. They also like to help others that seem to need a little extra help, so they would be great in-class tutors for their peers. These learners can use group associations, role-playing, brainstorming with others, and social games and puzzles in which to learn. Instructors are encouraged to teach to this learning style through role playing, group projects, volunteering, service projects, and debates. Students should be encouraged to engage with others, facilitate discussions, and encourage collaboration (Neidorf, 2012).

On the basis of this descriptive analysis, we could now take these findings and formulate teaching strategies in the hopes of better supporting these three learning types. However, what needs to be recognised, is that while 21% of Computing respondents and 42% of Information Systems respondents identified Solitary as their preferred learning style, there still remains 79% and 58% respectively that did not. As a result, we must be careful in drawing solid conclusions about specific teaching strategies and instead, focus on the diversity of styles across these cohorts. In again reviewing the results, we can see that each of the seven Memletic learning styles is present in each of the self-selected disciplines, with the exception of the Physical style in the Information Systems and Business disciplines.

What we can then determine is that while there indeed exists some difference in the proportion of preferred learning style within each of the self-identified disciplines, this difference is not statistically significant and the range of all styles is represented in most disciplines, and in that regard, there is little difference across cohorts. Therefore, rather than developing teaching strategies that support the dominant strategy according to the mistaken belief that each cohort exhibits only one preference, we need rather, to develop teaching strategies that support the complex mix of learning styles within the one cohort. In doing so, we will better support the real needs of our diverse cohorts, not because of a belief that each is different, but due to the realisation that they are the same in that they all consist of individuals with different preferences, all of which need to be supported.

Conclusions and Future Work

This finding allows us now to commence the development of teaching and assessment materials that better support the diverse needs of our students, despite their self-selected discipline. We can now recognise that while we may have delivered materials to Computing students through lectures and assessed their work via written examination based on the belief that that was their preference, and delivered materials to Information Systems students through workshops and assessed via written reports based on what we believed their preferences required, we can now see that all units require a combination of approaches to support all learning styles.

Indeed, the discipline of ICT is broad and in developing graduates with the capacity to fulfil the variety of entry-level roles (such as Business Process Modeller Systems Analysts, Data Modeller Network Analysts, Database Administrator Security Specialists, Systems Administrator Software Designers, Information Management Specialist Software Developers, Graphic Designer Multimedia Developers, Games Developer Multimedia Designers, Web Developer Testing Managers, or Project Support Officer ICT Researchers (Herbert et al, 2014)) requires developing a broad set of skills including strategy and architecture, business change, solution development and implementation and service management (SFIA, 2013). Only a combination of delivery approaches will best support the variety of students required by the ICT industry into the future.

With regard to the data set available for this study, the small sample sizes for the non-technical cohorts (n=12 and n=10 for Information Systems and Business respectively) reflect the current population of students, but also likely reduces the possibility of discovering statistically significant differences between the cohorts.

In future work we will add to our sample size with the inclusion of 1st year enrolments at UTAS in subsequent years, as well as extending the sampling to include cohorts from similar ICT degree programs at other Universities in order to gain further insights.

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