

## EXPERIENTIAL LEARNING STYLES IN THE AGE OF A VIRTUAL SURROGATE

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### Abstract

*There is a long-held sense in general that the increasing use of computers and digital technology changes how a user experiences and learns about the world, not always for the better. This paper reports on a longitudinal study of 245 architecture and construction students over a two year period which examines the impact that virtual reality technologies have on the learning style preferences of students. A series of controlled experiments tests for the impact that increasing exposure to a proprietary virtual reality system has on the mode of learning and learning style preferences of individuals and particular cohorts. The results confirm that when virtual reality applications are used in teaching and learning, the learning behaviours will favour a more concrete experiential mode of learning and a preference for the Accommodator learning style. However, the results also demonstrate, consistently and for the first time, individual students do not privilege any particular mode of learning or learning style preference to any significant extent but rather engage in all modes and represent all learning styles. Novel visualisation techniques are introduced to examine and discuss this contrast.*

**Keywords:** *Virtual reality, experiential learning model, learning style inventory*

### INTRODUCTION

The widespread use of computers and digital technology is not only changing our lives, but has already become ingrained. The physical world is blending with virtual content and people are living in an extended space enhanced through digital technology. With the growing impact of digital content the experience of learning and teaching in higher education is being changed significantly. Very soon the majority of students entering higher education will have been born during or after 1998, the year Google was launched. Higher education faces a generation of students who have only ever known life with Google and the growing plethora of mobile digital devices. It follows that the ways in which this generation interacts with the world and the things they expect from their learning experiences are likely to be very different from how previous generations have engaged.

There is a long-held sense in general that the increasing use of computers and digital technology changes how a user experiences and learns about the world (Halverson and Shapiro, 2012; White et al., 2014), not always for the better (Margaryan et al., 2011). In architecture education in particular, there is anecdotal concern that the educational experience could become impoverished if creative expression is in some way confined to the use of digital technology. The more general consensus seems to be that digital technology can facilitate learning by at least providing further expressive options. As highlighted by Starkey (2011), the current challenge for teachers is to convert established learning theories into new practices that most effectively leverage and engage the upcoming, digitally literate generation.

Over the past decade and more computer software, most especially Computer-Aided-Design (CAD) software, has been adopted increasingly for architecture and construction teaching and learning. Some argue that the role of digital technology in teaching and learning is now critical (Ham, 2013). Ham and Schnabel (2014) claim that effective learning experiences rely on the

successful acquisition of skills using a combination of digital and physical media. They challenge architecture educators to reposition the role of digital technology in architectural design courses by considering the actual working, learning and engagement styles of students. This paper reports on a study of the impact emerging digital technology is having on the learning styles of architecture and construction students and what that might mean for how those subjects are taught. The study is motivated by developments in virtual reality (VR) technologies that support a more immersive and experiential approach to learning. This locates the study at the developing confluence of VR technology, itself still under development, and the literature specific to experiential learning and learning styles.

## BACKGROUND ISSUES

### VR Technology in Learning

In architecture education the three most fundamental components are knowledge, skill and design, with the teaching of design often regarded as being the most challenging aspect (Chakradeo, 2010). Nabih (2010) argues that there are gaps between the theory and practice of architectural design that require addressing through a problem-based approach to learning rather than a traditional lecture-based format. Chee (2007) highlights the importance of directly engaging students with the experience of architecture. However, the resource and practical difficulties of embedding large student cohorts in actual architectural practice and providing direct experience of key architectural designs are prohibitive. Digital technology is proffered increasingly as a potential alternative to direct experience. VR technology is of particular interest in this regard (Dalgarno et al., 2011).

VR technologies use high performance graphics engines to render moving photo-realistic scenes in real-time and in three-dimensional (3D) perspective combined with associated surround-sound audio and tactile feedback to a user. The user interacts with the virtual environment through a variety of input and output devices. Such virtual environments are considered to be of potential benefit in framing the development of knowledge in architecture education (Yan et al., 2011). However, there is ongoing debate on the most effective role for computers and VR technology as tools in learning and teaching (Margaryan et al., 2011; Starkey, 2011). It is reasonable to assume that with increased realism student engagement with a virtual environment will be improved and learning outcomes will improve as a consequence. However, insufficient evidence is available in the existing literature to confirm those links.

Studies have been conducted on the use of VR technology in architectural design and education. Rahimian et al. (2011) focussed on how a designer interacts with the external design representation to conclude that the use of VR can improve both the cognitive and collaborative activities of designers. Game-like VR interfaces have also been applied within the context of architecture and design education to promote more creative design decision-making (Sampaio et al., 2010; Rahimian et al., 2014). However, according to Abrishami et al. (2015), previous studies of VR applied to architecture and construction have tended to focus on the advanced visualisation potential rather than the broader-based, more blended experiences possible with advanced VR. Certainly the capacity for VR technology to simulate a broader range of performance criteria than just the aesthetic considerations is now being addressed (Leinonen et al., 2003; Goulding et al., 2014). However, the impact on student learning experiences that advanced visualisation and the broader simulation potential of VR could have is not yet clear. Emerging VR technology, for the first time, offers an authentic hyper-immersive learning experience at an affordable price and in a technically feasible format for large cohort teaching. With this watershed it is now timely to investigate how VR might impact the student learning experience in architecture and construction education more directly.

Any application of VR to education must consider the distinction made by Bomsdorf (2005) between a digital learning space and a digital learning context. A digital learning space comprises the particular digital exercises undertaken by a learner, where the context refers to a broader set of circumstances through which sense-making and fundamental understanding are formed. It is a condition of the immersive nature of VR technology that learning space and learning context often become conflated, as the learner is using the virtual environment to achieve particular outcomes and at the same time using the experience to form and test broader experimental hypotheses. For example, the specific properties of a VR simulation also contain the broader situation that renders each learning activity meaningful (Thevenin and Coutaz, 1999). These properties are peripheral to the particular learning exercise, but directly impact the behaviour and learning process of a learner (Cui and Bull, 2005). The blurring of boundaries between learning space and context challenge many established theories of learning. The most significant impact of VR on learning may not be about the technology itself at all, but rather the radically different potential configurations of learning space and context that VR tends to promote (Schwanen et al., 2008)

In the light of the various challenges to established learning theory being wrought by emerging digital technology, traditional theories are being adapted. For example, the active construction of knowledge using 3D environments encourages more exploratory modes of action (de Freitas & Neumann, 2009) and collaboration now includes working collectively at a distance (Bower et al., 2014). However, adaptation may not be sufficient in the case of experiential learning theory, where the transactions between learner and environment are fundamentally changed in a VR context.

### Experiential Learning Theory

Vygotsky (1978) claims that learning from experience is the central process of human development. One of the most influential educational theorists of the 20th century, Dewey (1958), provided guiding principles for experiential learning theories. Lewin (1951), although focusing on organizational learning, later established that “learning is best facilitated in an environment where there is dialectic tension and conflict between immediate, concrete experience and analytic detachment”. The development of Lewin’s theory was continued after his death by others such as Festinger (1962), and it has had a profound influence on the practice of adult education, training and organizational development. Another influential theorist was Piaget (1950), whose work focuses on child development and how intelligence is shaped by experience. According to Piaget (1950) intelligence is not an innate internal characteristic of the individual, but rather “a product of the interaction between the person and their environment”.

Kolb and Goldman (1976) established, and Kolb (1984) further developed, an experiential learning model (ELM) based on six propositions drawn from the literature:

- Learning should be conceived of as a process, not in terms of discrete outcomes. Feedback on the effectiveness of an individual’s learning efforts is the best way to improve learning.
- All learning is relearning. Drawing out the beliefs and ideas that a learner already has about a topic enables them to be examined and tested. More refined ideas and knowledge need to be integrated with existing constructs.
- Learning requires the resolution of conflicts between dialectically opposed modes of understanding of the world. The learning process is one in which a learner will “move back and forth between opposing modes of reflection and action and feeling and thinking” (Kolb, 1984).
- Learning is a “holistic process of adaptation to the world, since it involves the integrated functioning of the total person” (Kolb & Kolb, 2005), which includes thinking, feeling, perceiving, and behaving.

- Learning is a result of synergetic transactions between the learner and the environment, a process of assimilating new experiences into existing concepts and projecting existing concepts onto new experiences.
- Learning is a social process of creating individual knowledge created and recreated through the personal knowledge and interactions of individuals.

Having conceptualised experiential learning Kolb and Goldman (1976) went on to develop the learning style inventory (LSI) to measure and identify different learning style preferences. Many researchers have now used this instrument in studies and there have been various critiques and suggestions for improvement of both ELM theory and the LSI. In response, several major updates of LSI have been developed, in 1984, 1991, 1999 and 2005.

Kolb (1984) maintains that learning is one continuous process of knowledge creation and not a series of contained learning outcomes. According to ELM, learning involves four related intellectual processes through which the learner interacts with a learning environment. In one dimension is the process of grasping experience and understanding events based on that experience, where apprehension is the counterpoint to comprehension. In the other dimension is the process of transforming experience into knowledge and understanding, where intention is the counterpoint to extension. Based on these intellectual processes, ELM is defined as a four-stage cycle consisting of four modes – concrete experience, reflective observation, abstract conceptualisation, and active experimentation (See Figure 1). From this theoretical framework Kolb introduced the concept of learning styles (Kolb and Goldman, 1976; Kolb, 1981; Kolb, 1984). Learning styles assess the orientation of an individual towards each of the four learning modes. Kolb (1984) points out that each individual learns differently because of the diversity in cognitive functioning, the scope of the content being focused on and the different sociocultural experiences. Such differences in learning styles ultimately result in different learning experiences.

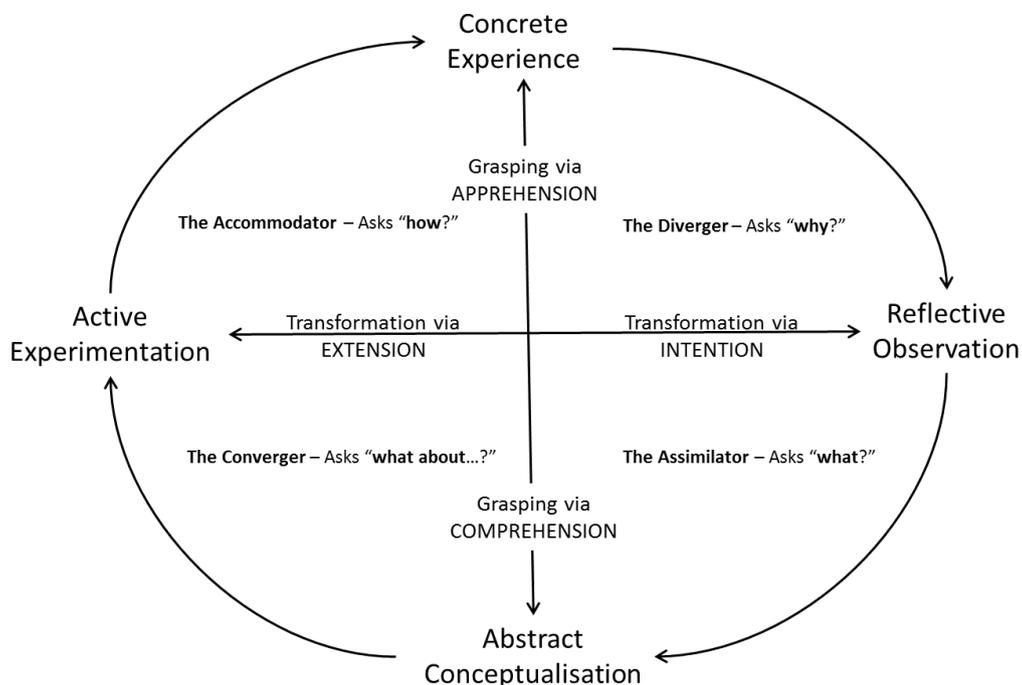


Figure 1: Adapted to summarise a number of separate illustrations relating to Kolb’s Experiential Learning Model (Kolb, 1984)

Experiential learning is then characterised in terms of a four-stage cycle that covers the four learning modes that come from the four intellectual processes described. Figure 1 presents the ELM in terms of the two key dimensions of grasping and transforming. Concrete experience (CE) is a mode in which people grasp experience through apprehension and rely on their feelings to initialise or motivate learning. Abstract conceptualisation (AC) is a mode in which people grasp experience through comprehension and thinking is the main strategy for learning. Reflective observation (RO) is a mode in which people transform experience through intention and during which learners learn by watching others. Active experimentation (AE) is a mode in which people transform experience through extension and during which people learn by doing. Learners go through all four of the learning stages, but each individual learner tends to emphasise one or more of the four modes of the learning process at any given point in their learning activities. This emphasis is claimed to determine the learning style of the individual (Kolb, 1984).

ELM is not the only conceptualisation of learning style possible. There have been many diverse learning-style definitions and models proposed (Curry, 1990). Often the alternative models have strong parallels with ELM, in that they also reference four continuous dimensions but name and describe them differently (see for example, Honey and Mumford, 1982). Other alternatives seek to expand the number of dimensions being considered. For example, the early work of Dunn and Dunn (1992) proposed a far broader-based model that included environmental, emotional, sociological, physiological and psychological elements. Other alternatives again, tend to focus on more specific learning contexts and fields of study, such as early learning development ( ) or engineering (Felder and Silverman, 1988). Several of these alternatives have been widely adopted and tested for reliability and validity (see for example, Felder and Spurlin, 2005), but in general no particular model is without criticism and none has been more widely adopted or as influential as ELM. Furthermore, the alternative models often require extensive questionnaire instruments in order to assess the learning style preferences of individuals (see for example, Dunn et al., 1995).

In contrast to many other models, the ELM is associated with a relatively modest multi-item questionnaire (the LSI) developed to identify and categorise the learning style preferences of individuals. The LSI categories draw from each quadrant of the ELM and classify learning styles in terms of:

- Divergers, who grasp experience through apprehension and transform it via intention – divergers prefer learning by watching and feeling, and tend to ask “why” questions.
- Assimilators, who grasp experience through comprehension and transform it via intention – assimilators prefer learning by watching and thinking, and tend to ask “what” questions.
- Convergers, who grasp experience through comprehension and transform it via extension – convergers prefer learning by doing and thinking, and tend to ask “what about” questions.
- Accommodators, who grasp experience through apprehension and transform it via extension – accommodators prefer learning by doing and feeling, and tend to ask “how” questions.

### Learning Styles

The learning style inventory (LSI) was developed to measure and identify the relative preferences an individual or group of learners have along each dimension of the experiential learning model. The LSI Version 1 (Kolb and Goldman, 1976) contained just nine items/statements, each with four alternative endings that represented each of the four learning styles. In LSI Version 2 (Kolb, 1984), a further three items were included bringing the total number to twelve. Each item in the LSI takes the form of a descriptive sentence with a choice of four alternative endings. Each ending to each sentence represents one and only one of the four learning modes. For example, the sentence beginning “When I learn...” might have the following choice of endings:

“... I like to deal with my feelings.”, CE;

- “... I like to watch and listen.”, RO;
- “... I like to think about ideas.”, AC;
- “... I like to be doing things.”, AE.

Respondents are required to rank each of the endings for every sentence based on how well each one describes how they prefer to learn. The ranking starts with a “4” for the ending that best accords with their learning preference, down to a “1” for the ending that accords least. Each alternative ending must be ranked and all must be ranked differently.

In both Versions 1 and 2 the order in which each ending related to each individual learning style remained constant. In other words, the first ending always aligned with the same learning style and so on for the other three endings. This characteristic was rightly criticised for introducing bias towards those learning styles aligned with the initial response (Ruble and Stout, 1990). LSI Version 3 (Kolb and Kolb, 2005) adjusted the ordering of the endings so that the learning style alignment was more random.

To determine the learning style preference, a total score is calculated for all designated CE, RO, AC, and AE endings. Thus, where a given mode is ranked highest for every one of the twelve sentences the maximum score is  $12 \times 4 = 48$ . As all endings must be ranked the minimum score for any given mode is  $12 \times 1 = 12$ . The overall score should always be  $12 \times (4 + 3 + 2 + 1) = 120$ . Once the totals for all four modes are calculated a location along each of the two dimensions is determined by calculating a balance point between each score on that dimension. For example, the result of [AC – CE] provides a position on the grasping (comprehension/apprehension) dimension, which is then referred as the AC-CE score. The result of (AE – RO) provides a position on the transformation (extension/intention) dimension. A measure of the particular learning style is then provided in two ways: either as a quadrilateral plotted by joining the coordinates of each individual mode total score; or as an individual point to represent the average location (centre) of the quadrilateral thus formed.

### Research Question

There is a long-held sense in general, and in architecture education in particular, that the use of computers conditions (biases) the ways in which an individual learns about the world and that this could be to the detriment of the educational experience (Bandyopadhyay et al., 2010). When virtual reality applications are used in teaching and learning the learning behaviours are expected to favour a more concrete experiential mode of learning and a preference for the Accommodator learning style. Is such an impact observable? If it is not the concrete experiential learning style, then is some other learning style being favoured? Or is a more fundamental change in learning styles evident? There is a definite knowledge gap in this regard.

The research problem is how to investigate emerging virtual reality technologies and how they impact the way people experience the world in a learning context. It is in the nature of emerging technologies that they tend not to be well-embedded already in teaching programs. It is in the nature of human experience that objective measures are difficult to determine. This study takes a broad perspective on VR technology with a focus on a particular implementation (The Situation Engine) specifically developed to support teaching and learning in architecture and construction, and already in use within the teaching programs of several Universities in Australia. The LSI represents a very popular measurement instrument for determining learning style preferences. It has been extensively applied, discussed and developed. Nevertheless, the application of LSI needs to be part of the research consideration in and of itself. It is necessary for the research methodology to consider the research instrument (LSI) just as much as the fundamental research question. Notwithstanding the broader research consideration, the key research question is identified as:

*To what extent is VR conditioning the way people engage in learning and what are the implications for the education process?*

## RESEARCH METHODOLOGY

To address the research question, a two-phase experiment was designed. In both phases of the experiment students were contacted and invited to participate using a class announcement made by the class lecturer. Participation was entirely voluntary on the part of the students and there was no grading associated with the exercise. During the first phase of the experiment the LSI survey was deployed three times: at the beginning; the mid-point; and at the end of the semester, with five weeks interval between each deployment. In the second phase, high-performance computers were provided to run a VR exercise using a proprietary system, The Situation Engine ([www.situationengine.com](http://www.situationengine.com)). The Situation Engine is an application that provides for specific and managed practical building and construction experience to be made available to students using advanced video game technologies (Newton, 2012).

The LSI was used as a measure of the learning style preferences of participants. Instructions on how to use the LSI was provided on the first page of the survey booklet. These stressed that “no two endings in a set can be given the same ranking”, and that a score of “4” is the most descriptive of the participant while a score of “1” is the least descriptive of the participant. The instructions also emphasised that there are no right or wrong answers and that the participants should use their first impressions to answer each question as honestly as possible. Completing the full LSI survey usually took no more than five minutes for each participant. Following the suggestion of Ruble and Stout (1990) to avoid set bias, a “scrambled” version of LSI was developed in which the order of the endings were randomly arranged in terms of the learning style each represented. To further avoid the potential bias that one particular randomised version might bring to the results, four different sets of “scrambled” LSI were deployed in each experiment session.

The experiment was undertaken in the Faculty of Built Environment, University of New South Wales (UNSW). 245 undergraduate students at this university were chosen as the sample because they represented a contained and recognised educational cohort in terms of age and other demographics. Three stages of VR technology use were identified in Phase One during the teaching of ARCH1101: Architectural Design Studio – a first semester, first year architecture core course. The first stage was at the beginning of the teaching semester, when participants had minimal (if any) exposure to VR learning contexts. At the beginning of the semester most of the students were just commencing their studies and still transitioning from their experience of high-school study to university life. At this stage it was unlikely that the students would have had previous exposure to teaching and learning using VR, although they may have been exposed to some digital learning technologies such as online search engines and rudimentary online learning management systems.

The second stage was timed at the mid-point of the teaching session for ARCH1101: Architectural Design Studio, when participants had been introduced to VR technology and learning contexts as part of their studies but were yet to use the technology to accomplish a major assignment. During ARCH1101: Architectural Design Studio, students are progressively exposed to a number of 3D modelling systems such as Google SketchUp and Autodesk 3DS Max. They are also introduced to VR by having to complete assessment tasks using real-time interactive game engines to construct virtual worlds. Students have rarely had previous experience in the high-end 3D modelling systems or VR game engines included in this program of study. By the mid-point of the semester students had a reasonable understanding of VR technologies in theory and some basic skills in using VR to learn architectural design. However,

the skill-base was still rudimentary and few students were capable of completing the major assignment task for the subject at this stage.

The third stage was towards the end of the teaching program, when participants had more advanced skills in VR and have substantially completed a significant independent assessment task using the VR technology.

This component of the research was designed to investigate whether student learning style preferences change over the course of study with increasing exposure to VR technology. The same student cohort was surveyed using the same LSI three times during their first semester, 2012. The LSI survey was deployed mainly in a pen-and-paper based format when practical, and the feedback was collected on the same day as participants undertook the experiment in order to ensure high response rates and the currency of responses. Any changes in individual student learning style preferences over the course of the semester as participants progressively learned more about the concepts and skills of VR would be apparent.

To further test whether the VR technology has immediate influence on learning style preferences, in addition to the longitudinal study described above, a lab-based study was also designed as Phase Two of the experiment. In Phase Two, each participant was assigned a small learning task and given a short period of time to accomplish the task in a virtual learning environment, as shown in Figure 2. The aim of the lab-based experiment was to test the immediate influence of VR technology on learning style preferences. In this phase the sample was extended to include participants enrolled in a broader range and variety of subjects within the Faculty of Built Environment, UNSW. Participants in Phase Two were recruited from: ARCH1101: Architectural Design Studio, BLDG1211: Domestic Construction, and ARCH1392: Collaborative Design Studio. These particular courses were selected because the use of The Situation Engine is highly relevant to these courses and either VR teaching technologies were already being used or there is potential to adopt such technologies in these courses in the future. Including a cohort of students from construction in Phase Two provided some diversity to the sample in terms of study background, work experience and familiarity with VR technologies in teaching and learning. These factors are particularly relevant because the learning tasks for the experiments are set in construction contexts where background and experience could play an important role in the learning style preference.



Figure 2: The virtual environment designed for Phase Two of the experiment.

Data from Phase One and Phase Two of the experiment was collected and analysed. The LSI results collected at each of the three stages in Phase One reflect the extent to which VR technology impacts on learning style preferences over time and with increasing exposure to VR. Data collected from Phase Two of the experiment is specific to the immediate impact of VR technology on learning styles. A significant majority of participants in Phase Two had little or no prior exposure to VR technologies. By comparing the results from Phase Two with those from the mid-point testing of Phase One (the closest equivalent in terms of general student progression), it can be determined whether or not VR technology promotes a particular learning style in a short period. Furthermore, any immediate impact can be compared with the longer-term impact found in Phase One.

## RESULTS

The architecture student samples from the first, second and third stages of Phase One are referred to as Group A, Group B and Group C respectively. Also in Phase One (2012), the LSI was administered to a group of construction students enrolled in BLDG1211: Domestic Construction. Those students were taught in a traditional way where VR technology is not used. The sample from the construction cohort is referred to as Group D.

During Phase Two of the experiment (2013), the LSI was administered to a new architecture cohort and a new construction cohort within the same courses as the previous year. However, in 2013 both cohorts experienced learning with VR technology using The Situation Engine. In Phase Two (2013), the LSI was administered to the architecture student sample on two occasions, once in the middle of the teaching semester and once at the end. The architecture student sample recruited in 2013 and surveyed in the middle of semester is referred to as Group E; the construction student sample recruited in 2013 and surveyed in the middle of semester is referred to as Group F; and the architecture student sample recruited in 2013 and surveyed at the end of semester is referred to as Group G.

Given this sampling, if VR is conditioning the way people engage in learning then it should follow that the sequence of Group A, Group B and Group C results will begin to bias a particular mode of learning and learning style preference. It is also the case, because they are drawn from equivalent cohorts at exactly the same stage of study, that the same patterns of learning preference should be presented by Group B and Group E, and by Group C and Group G. The most significant contrast, if exposure to VR in teaching and learning is having any impact, should be between Groups D and F and all other groups.

As described above, to determine the learning style preference a total score is calculated for all designated CE, RO, AC, and AE endings and an average location along each of the two dimensions is determined by calculating a balance point between each score on that dimension. The points are plotted on a two dimensional grid, the LSI grid. The LSI grid mirrors the ELM diagram in Figure 1, and comprises a horizontal AE – RO axis and a vertical AC – CE axis. The position on the AE – RO axis is determined by subtracting the RO score from the AE score. A positive result moves away from the origin along the AE dimension and a negative result moves away from the origin along the RO dimension. The same logic applies to the AC – CE axis location. Each axis is measured from the origin outwards, from 0 to the maximum value. Given the maximum score for any particular learning mode is  $12 \times 4 = 48$  and the minimum score is  $12 \times 1 = 12$ , the most extreme value for either axis will be  $48 - 12 = 36$ . The individual location used to represent the learning style preference is plotted using the derived AE – RO and AC – CE values.

A further consequence of having two dimensions on a single axis is that the scores on each dimension are not absolute. Kolb (1984) has adjusted the axes accordingly. From a review of all available LSI scores, the average location for the total population is calculated and each dimension is then offset by that amount so that the apparent origin is not necessarily (0, 0). For

example, the last review of LSI Version 3 identified 6,977 valid individual LSI scores. The average balance point for each dimension was calculated from those 6,977 surveys as 5.96 on the transformation (AE-RO) dimension (a positive AE-RO value means it is on the AE side), and 6.83 on the grasping (AC-CE) dimension (a positive AC-CE value means it is on the AC side). The convention is then to use this offset datum as the origin of each axis that forms the learning style quadrants. That is, if the balance point of a given learning preference is in the top-left quadrant of the offset point, this identifies an accommodator learner. If the balance point of a given learning preference falls in the bottom-right quadrant of the offset point, this identifies an assimilator learner, and so on.

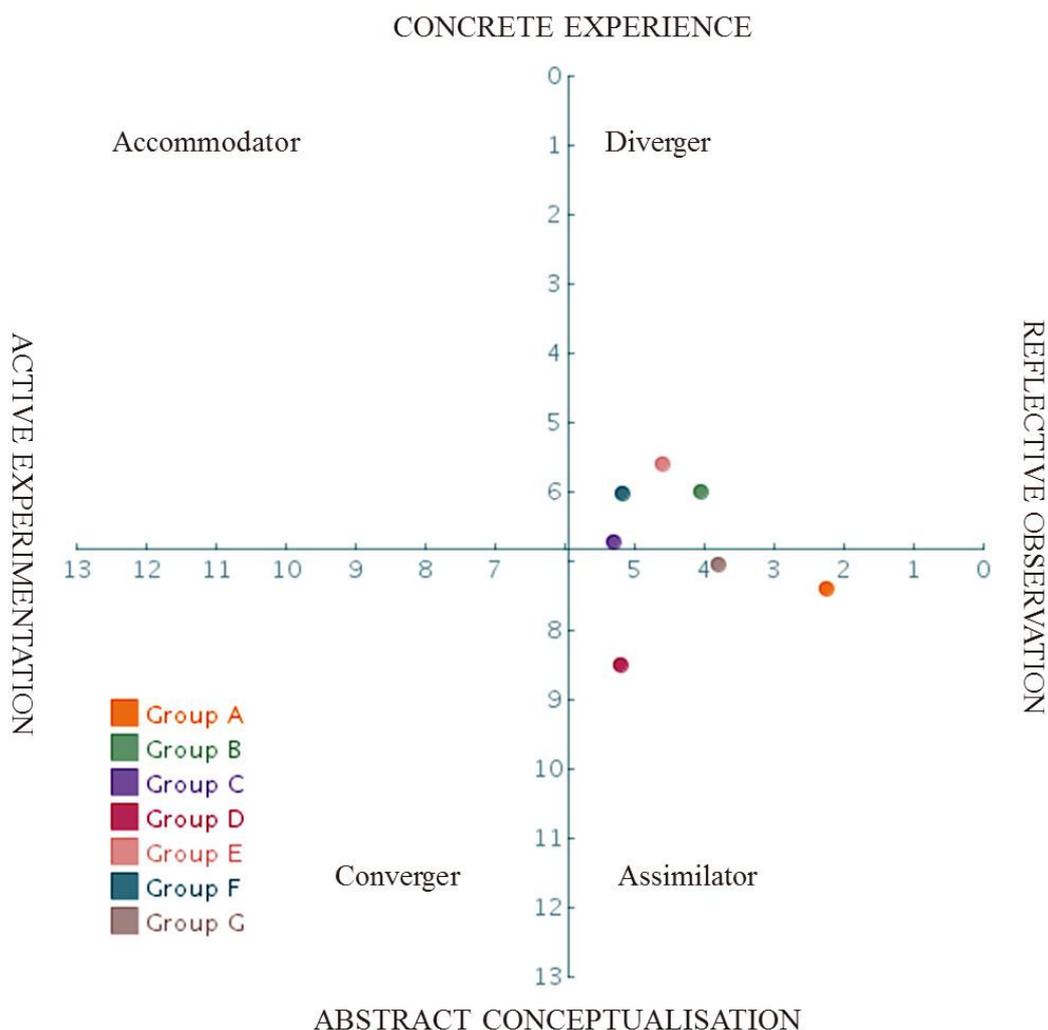


Figure 3: The balance points for each LSI investigation presented on a zoomed-in region with Kolb's offset datum.

Figure 3 illustrates the LSI balance points for each group from the seven investigations. The grid shows a zoomed-in region of the total LSI grid. The origin of the grid is set by Kolb's AE – RO : AC – CE scores and the grid is divided by the blue-green lines. When plotted on this grid the pattern of relationships between the groups can be examined. There does appear to be a sequence of results between Group A, Group B and Group C, as each distinctly moves further

along and towards the AE dimension. This would indicate that increasing exposure to VR over time promotes more active experimentation. It is also clear that Group D is an outlier, and that exposure to VR technology in the teaching and learning context appears to move the preferred mode of learning along and towards the CE dimension. Groups D and F both appear towards the AE dimension, suggesting that construction students have a stronger preference for active experimentation. There is some correspondence (closeness) between Groups B and E, and (though less so) between Groups C and G. That would indicate some consistency between equivalent student cohorts from one year to the next. Overall however, the determined learning style preference places Groups A, D and G together as Assimilators and Groups B, C, E and F together as Divergers. There is no apparent underlying explanation for these groupings based on either exposure to VR or to the field of study.

Figure 3 is the classic form of representation for LSI results, and the associations and classifications made about different groups in the previous paragraph are how learning style preferences are typically determined and discussed. However, Figure 4 shows the same results displayed on the full LSI grid. In Figure 4 the distribution of LSI balance points are displayed on an actual LSI grid, with the origin at (0, 0) and the true cross point of the AC – CE and AE – RO axes. In Figure 4, Kolb's offset datum is still represented by the blue-green lines, but from this perspective the results take on a very different complexion. The differences highlighted when zoomed into a specific region pale when placed in the context of a full LSI grid. The immediate impression is how similar and tightly packed the results appear rather than on any differences or spread between them. It is also apparent that from the true origin, all of the groups would have been classified as Convergers.

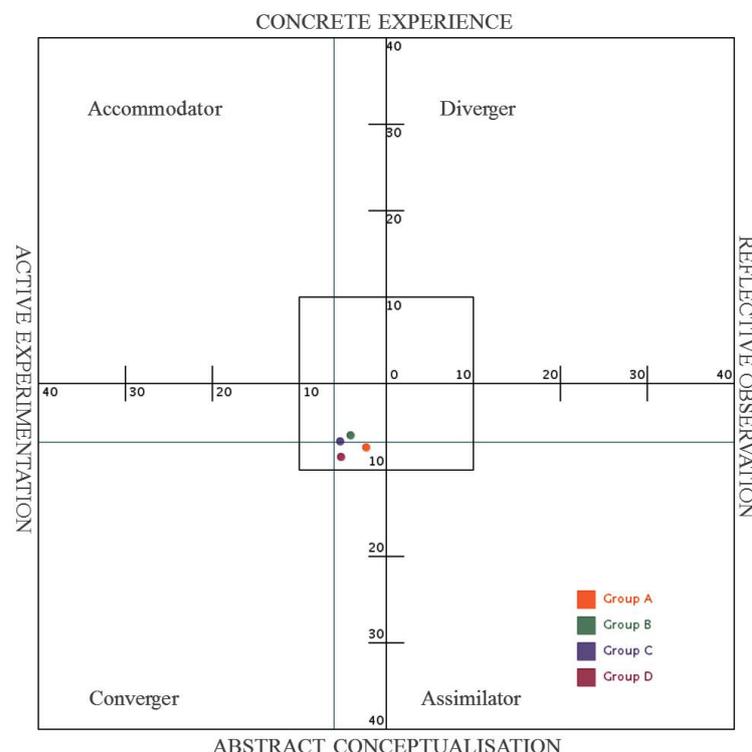


Figure 4: The balance points for each LSI investigation presented on the original/full LSI grid.

This disparity between the zoomed-in representation incorporating Kolb's offset datum and the full LSI grid has been criticised previously (Bergsteiner et al., 2010). The consensus of

opinion however appears to favour the continued use of a zoomed-in grid with Kolb's offset datum (Kayes, 2005). Nevertheless, concern over the use of such a selective representation must be recognised. There is some evidence to support the claims that increasing exposure to VR over time promotes more active experimentation; that exposure to VR technology in the teaching and learning context appears to move the preferred learning style towards concrete experience; and that construction students have a stronger preference for active experimentation. However, that evidence is far from compelling in the broader context. It is certainly the case that specific learning style classifications are not apparent and this aspect requires further investigation.

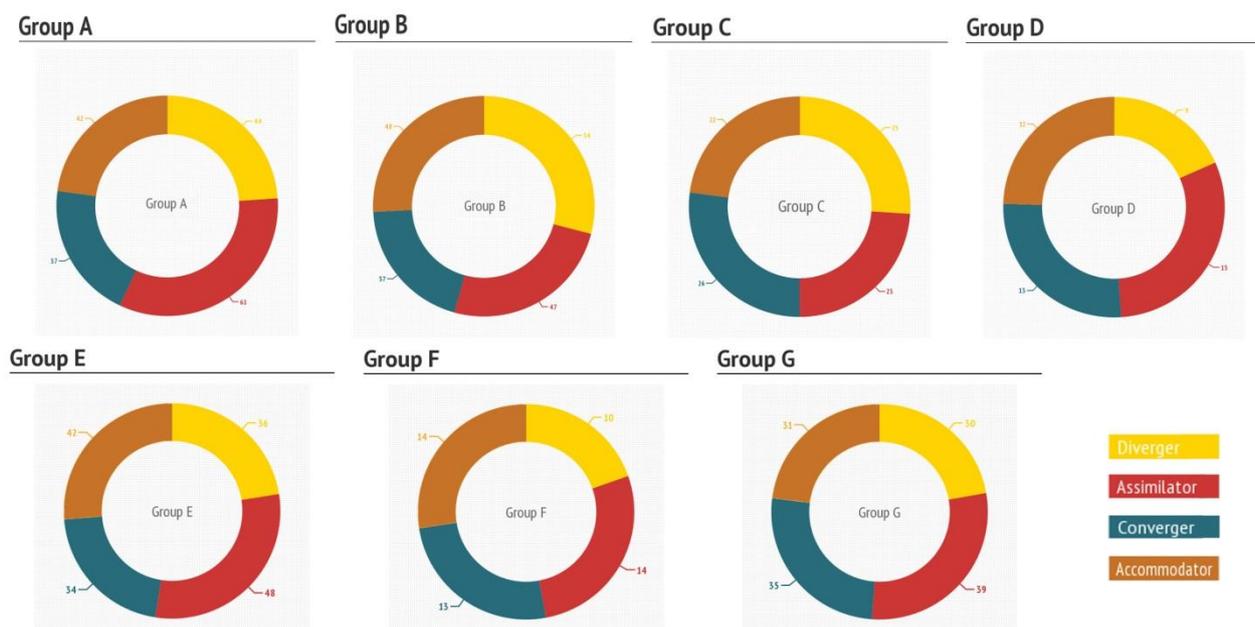


Figure 5: Learning style classifications for each of the seven investigations using a coloured donut representation

Figure 5 shows the proportions of each learning style in the seven investigations as a series of coloured donuts. The proportions are determined by the number of students in each cohort that preference a given learning style. The coloured donuts provide a novel way to visualise the learning style classifications specially developed for this research. The size of each colour on each donut in Figure 5 represents the proportional distribution of the four learning styles for each of the seven data groups. For consistency, each of the four colours representing the four different learning styles is located in the same quadrant/position as on the ELM grid (see Figure 1). This new form of representation makes it relatively simple to identify the majority and minority learning styles for each group. For example, in Figure 5 it is immediately apparent that for Group A the dominant learning style is Assimilator (red) and the minority is Converger (green). It is also relatively simple to make comparisons between groups. For example, in Figure 5 it is immediately apparent that Group B has the strongest representation of Diverger (yellow) learning style preferences of all seven of the groups. Most strikingly however, in all groups there is some degree of balanced distribution of learning style preferences. In other words, whilst there may be a bias towards the Assimilator learning style, this is not a significant bias. On the contrary, all learning styles are strongly preferred in all groups.

It is also apparent that no sequencing of Groups A, B and C is apparent; Groups B and E and Groups C and G are no more similar than any of the groups; and there is no apparent contrast with Groups D or F. This strongly indicates that exposure to VR technology, whether

impacted over time or impacted immediately, does not appear to promote any radically particular learning style preference. On the contrary, the learning style classification is relatively evenly spread across all learning style preferences for all cohorts, regardless of exposure to VR or field of study.

If there is a relatively even spread of learning style classification, is there any more revealing spread of balance points for the individuals in each cohort? In this case the focus is on whether the spread of balance points reveals particular sub-groups within each cohort. In other words, are the individuals within a group clustered into specific learning style preferences or more evenly spread, and is the overall spread relatively tight or more dispersed. Clustering would suggest that other parameters are playing a significant role in the learning style preference. A tight overall spread would suggest that either the LSI instrument is failing to differentiate preferences or that there is actually little difference between individuals.

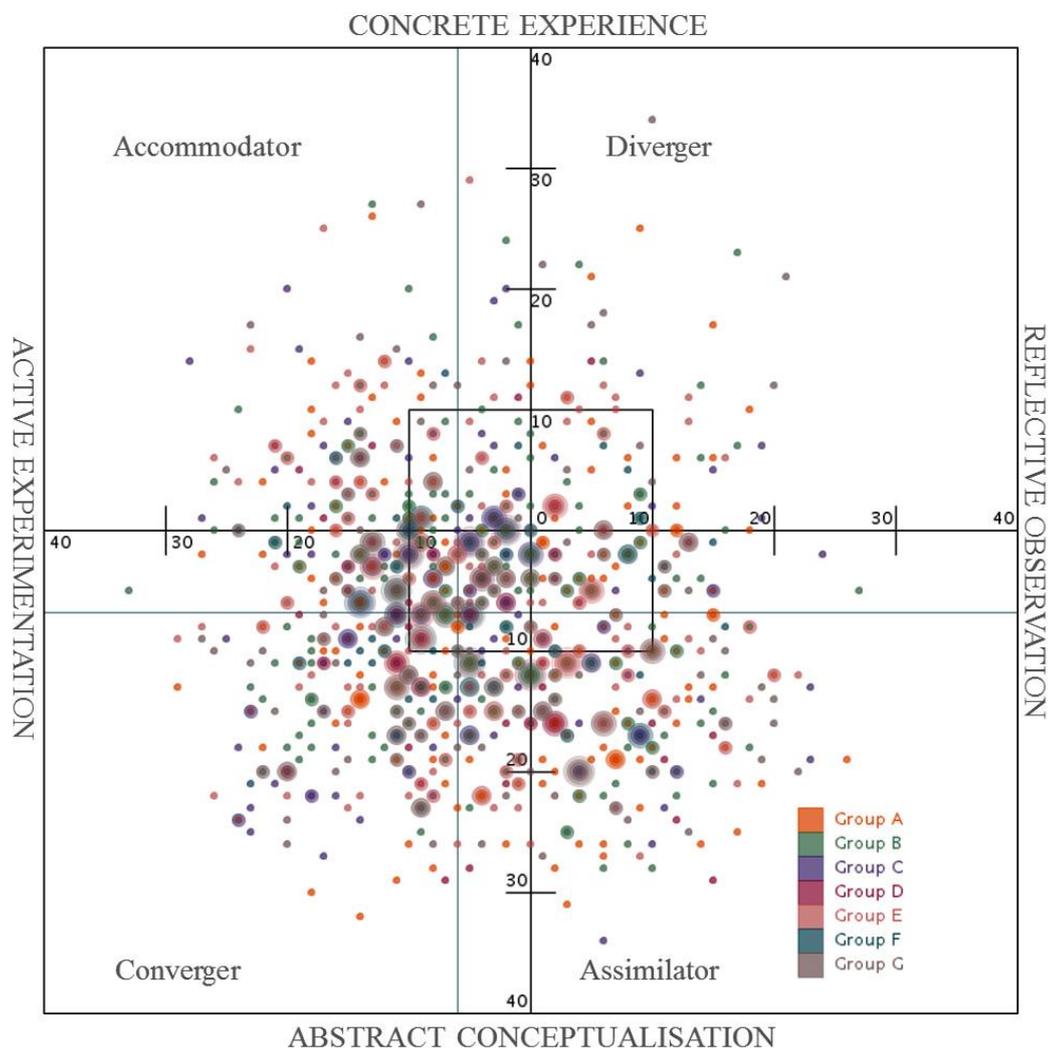


Figure 6: Individual balance points for all groups resented on a full LSI grid

Figure 6 shows the distribution of all individual balance points across the entire experiment presented on the full LSI grid with Kolb's offset datum indicated in blue-green lines. Each dot represents the learning style result for a particular participant. Where more than one participant is located at exactly the same position on the LSI grid, the dot size is increased. All dots are colour-

coded to indicate the reference group of the individual. Equivalent plots for individual groups were also produced to confirm the consistency of the results. It is immediately apparent from Figure 6 that there is no significant clustering or stratification in the results. This suggests that the balanced classification revealed in Figure 5 is representative of each group and no hidden factors appear to be at play. It is also apparent that the spread of individual learning style preferences is widely dispersed. There are different individuals who represent extreme preferences (maximum scores of 36) along all four dimensions of the LSI grid. There are different individuals who represent extreme examples of each learning style classification (approaching maximum scores on two dimensions). This indicates that the LSI instrument is successful in differentiating both preferences and classifications of learning styles effectively at the level of each individual. Whilst there are different overall distributions of individual balance points for each group, the strongest and most consistent feature is well indicated in Figure 5, and that is the wide and evenly dispersed spread of individual learning style preferences.

## CONCLUSION

Are there any grounds to support the long-held sense that the use of computers in general and VR in particular will condition (bias) the learning experience?

The findings of this research demonstrate that using a standard, zoomed-in representation of the LSI grid incorporating Kolb's offset datum (Figure 3), the longitudinal study of an architecture cohort in Phase One (2012) reveals that increasing exposure to VR over time promotes a progressive movement along and towards a preference for active experimentation. More broadly, Group D compared with all other groups reveals that exposure to VR technology in the teaching and learning context appears to move the preferred mode of learning along and towards a preference for concrete experience. Combined together, these trends indicate that use of VR will condition the learning experience towards an Accommodator learning style preference. This confirms the expectation that when virtual reality applications are used in teaching and learning, the learning behaviours will favour a more concrete experiential mode of learning and a preference for the Accommodator learning style.

Whilst any particular conditioning of learning style preference has the potential to stifle key aspects of a rounded learning experience, the promotion of concrete experience and active experimentation fit comfortably with the nature of professional degree programs such as architecture and construction. If the conditioning evident in Figure 3 is genuine, then the impact on learning and teaching in architecture and construction can most reasonably be taken to be a positive outcome for the use of VR. The key implication of this is that the introduction of VR technology into professional education programs of study can be encouraged because it promotes relevant learning styles.

In the broader picture of Figure 4, the classification of learning styles in Figure 5 and the individual distribution of balance points in Figure 6, the impression is far more of a balanced distribution of learning modes and learning style preferences. The wide spread of individual balance points evident in Figure 6 indicates that the LSI instrument is providing an effective representation of learning style preferences. The primary conclusion to be drawn from these findings is that all cohorts, whether exposed to VR or not and whatever the field of study, represent a relatively even balance on all four modes of learning and all four learning style preferences. Rather than conditioning the learning experience in any particular direction or conflicting with any existing learning style preference, exposure to VR technology supports a diversity of approaches and learning experiences. This is particularly noteworthy, as it contrasts with the implications drawn from Figure 3 and challenges any suggestion that existing architecture and construction cohorts adopt or prescribe a characteristic or particular approach to learning. Architecture and construction students do not privilege any particular mode of learning

or learning style preference to any significant extent, but rather engage in all modes and represent all learning styles. The implication of this is that professional education students actually preference all styles of learning and all styles of learning should be supported and encouraged.

More particular to the study of experiential learning itself, several findings from this study are of significance. Whilst the consensus is still in support of using a zoomed-in LSI grid, magnifying differences can lead to questionable classifications and differentiation of learning styles between cohorts when considered in broader perspective. More significantly, the widespread practice of using a balance point to represent the averaged learning style preferences of a group can be considered utterly flawed. When the same data is presented using the novel visualisation techniques of Figure 5, very different conclusions can be drawn. When this is complemented with the display of individual balance points in Figure 6 it is very apparent that any differences in the balance points of group averages is inconsequential when compared to the differences/spread in the balance points of the individuals comprising those groups. In every cohort the spread of individual balance points were substantially greater than any spread between the group averages. The strong implication of this is that more judicious use of balance points is required, and wider use of visual representations such as Figures 5 and 6 is necessary. This is the first study to utilise the visualisation in Figure 5 and, apart from D'Amore et al. (2012), it is the only study to utilise the visualisation in Figure 6 to contrast individual with average group balance points.

## LIMITATIONS AND FUTURE WORK

The subject of the research is specific to architecture and construction higher education at a single institution in Australia, and most participants were first year undergraduate students enrolled in these programs. All participants had therefore met a common, minimum entry standard including English language competency and regular academic requirements. From one perspective the fact that all participants were drawn from the same institutional context reduces the risk of variation in, for example, learning environment and teacher factors. On the other hand, limiting the source of participants homogenizes the population and the range of factors available for study. Future studies would usefully extend and contrast the sample population.

Although using this specific sample has certain benefits in terms of reducing the scope for independent variables, the use of broader and different samples in the future will enrich the scope and the depth of the research findings. For example, people from the architecture and construction industry with years of practical experience might have different learning style preferences, as could students from a different field of study. The representation of participants with different first languages and from different age groups in this study is also limited and further work in that regard would be relevant. Comparing participants across national and cultural boundaries could also reveal significant factors.

VR technology is itself still under development, and neither the definition of VR used in this research nor the particular implementation of the technology (The Situation Engine) are stable or comprehensive demonstrations of VR today or into the future. As alternative VR technologies emerge and VR becomes more deeply embedded in teaching and learning programs, studies of learning style preferences will be more representative than a single technology used in a particular way. The use of a single contrast group (Group D) to represent students with no exposure to VR is very limited, but the similarity of findings between all groups suggests that further studies should confirm a similar balance of learning style preferences. A primary focus for future research then needs to be on how learning and teaching can most effectively accommodate and support a variety of learning style preferences. This is perhaps where VR technology will not merely avoid promoting a single learning style, but positively accommodate and promote a full complement of learning experiences. The use of a virtual surrogate for

experiential learning in the future might far better address the broad learning style preferences of our students.

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