What the malleability of Kolb's learning style preferences reveals about categorical differences in learning

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Notwithstanding the neuromyth controversy, the malleability of learning style preferences impacts the validity of the measurement instrument and the effectiveness of the associated model of learning. This study investigates the test-retest reliability and underlying dynamics of Kolb's Learning Style Inventory (KLSI). It surveys 245 college-level students in Australia, over three rounds of data collection at 7-week intervals. Results show that over 75% of participants are incorrectly categorised, and more than 50% materially changed their category of learning style between rounds. The study reveals that individuals roam freely, rapidly, and extensively across learning style categories. Thus, the categorical differences measured by the KLSI lack meaningful purpose. Whether or not learning styles are a neuromyth, this study indicates that the act of learning, as an act of agency, is fluid with potentiality and choice. The more meaningful focus for teaching and learning practice would then be on student commonalities, not categorical difference.

Keywords: neuromyth; agency; potentiality; learning style inventory; test-retest; emancipation

Introduction

A category is typically considered to comprise a set of entities that share a common representation or concept (Pommerening and Bisang 2017). The ability to categorise is a powerful cognitive tool that helps make sense of an otherwise amorphous world by grouping entities and allowing causal inferences to be made about that group of entities as a whole (Sloman 2005). For example, the capacity to identify and associate a group of learners with important shared learning characteristics, would enable teachers to tailor their curricula more specifically for that group, even across changing contexts (Van den Bossche et al. 2011). However, just as categorisation seeks to group individuals with shared learning characteristics and make teaching more tractable, it will also, and often more emphatically, differentiate between groups of learners and potentially prejudice group members at the boundaries of each category (Liberman et al. 2017).

The strong possibility is for certain forms of categorisation to misrepresent and pigeon-hole individual learners (Cuevas 2015). This possibility is becoming all the more significant as the conceptual models that define some of the more popular learning categorisations are questioned (see for example, Willingham et al. 2015). That challenge to the prevailing conceptual models that define distinct categories of learners, and the differentiations they promote, is being fuelled by growing educational emphasis on the likes of learner equality (Säfström 2020), individual agency (Lewis 2018), and potentiality (Sellar 2015). All aspects of the growing broader call for an emancipation of education (Hooley 2021). An emancipation that questions all forms of prescriptive categorisation, but naturally and most especially those forms of categorisation where the defining conceptual model is contested or lacks credible supporting evidence.

This study seeks to examine arguably one of the most widely applied and influential categorisations of learning, Kolb's Learning Style Inventory (KLSI), and the conceptual model from which it is derived, namely: the Kolb Experiential Learning Model (KELM) (Kolb 1974; Kolb 2015; Kolb and Kolb 2017). In particular, the malleability of learning style preferences over time, as measured by the KLSI, is analysed. The nature and extent of that malleability reveals important implications for the emancipation of education in general, and the utility of the KELM in particular.

Background

The notion of 'learning styles' was developed in the second half of the 20th century, by proponents such as Kolb (1974). The two most popular learning styles currently are derivatives of either: the Visual-Auditory-Kinaesthetic (VAK) set of learning modalities, as originated by Barbe and Milone (1981); or, the KELM experiential learning theory of Kolb (1974). The use of learning style models continues to be promoted practice across school, higher education and workplace settings, globally (Dandy and Berndersky 2014; Dekker et al. 2012; Ferrero et al. 2016; Papadatou-Pastou et al. 2017; Simmonds 2014). A comprehensive review of learning styles publications in the higher education literature reported a strong endorsement of their use (Newton 2015).

This continuing engagement with learning styles comes despite a significant lack of clear empirical evidence to support the use of learning styles in many of the ways they are promoted – most especially perhaps, that instruction tailored to student learning style preferences will benefit students (Pashler et al. 2009). Indeed, there is now a widely held consensus (most especially in educational psychology and neuroscience) that the whole concept of learning styles should be considered as a 'neuromyth' (Dekker et al. 2012; Howard-Jones 2014; Kirschner 2017). Note however, that a recent review of educational neuromyth research by Sullivan et al. (2021), identified a series of potential shortcomings in the framing of items used to measure the prevalence of such neuromyth misconceptions. Strong endorsement of learning styles also continues (Felder 2020).

Despite the controversy, the KELM itself continues to evolve – from the basic premise that effective learning requires a two-fold process of grasping and transformation. A 'grasping' of concrete experience (CE) through abstract conceptualisation (AC), and a 'transformation' of that experience into understanding through reflective observation (RO) and active experimentation (AE). Kolb (1974) proposed that learners develop and naturally settle on a preference for a particular combination of one experience-grasping approach and one experience-transforming approach. Each combination identifies a specific category of learning style:

Accommodator (CE+AE); Converger (AC+AE); Diverger (CE+RO); and Assimilator (AC+RO). Each learning style is then claimed to provide a relatively stable categorisation of distinctive learning style preference for individuals, although it is acknowledged that this preference may change over the longer term, lifetime of an individual (Kolb and Kolb 2018).

An effective measure of individual learning style preferences remains key to the majority of benefits claimed for any learning styles model. Categorising individual learning style preferences is intended to help target training and development efforts, motivate teams and make best use of individual capabilities (Kolb and Kolb 2013). According to Kolb and Kolb (2013), there have been only two noteworthy test-retest reliability studies of the KLSI, both of which found the test-retest reliability to be reasonable (Ruble and Stout 1991; Veres et al. 1991). All other relevant studies are particular to superseded and significantly different versions of the KLSI, and/or focus on internal construct validity and the ipsative (forced-choice) format of the questionnaire, rather than test-retest reliability (Carvajal et al. 2021). A detailed evaluation by Koob and Funk (2002) did conclude that methodological problems, theoretical inconsistencies, and potential ethical concerns plague the KLSI.

Loo (1997) argues that the conventional choice of test-retest statistics mask individual change in learning styles. This masking occurs because conventional test-retest methods focus on group outcomes that introduce an inevitable balancing effect between individual scores. Further, the statistics typically applied measure changes along dimensions (scores) rather than switches between learning style categories. In so doing, they fail to register stability in meaningful terms, such as change from one learning type category to another (Loo 1997). Loo (1997) recommends future studies examine KLSI stability and change relative to the learning style categories, and consider category change above score change. In a more general context, Fan et al. (2019) strongly endorsed the need to consider test-retest stability in more ways than just the use of a balanced population mean. Nevertheless, to date, there have been no test-retest reliability studies of the most commonly used KLSI (version 3.1), and none particular to Australian learners.

A number of studies have used the KLSI instrument to investigate the characteristic learning style preferences of engineers (see for example, Abdulwahed and Nagy 2009; Bernold et al. 2000; Cagiltay 2008; Sharp 2001) and of architects (see for example, Demirbas and Demirkan 2003; Kvan and Yunyan 2005; Tucker 2008). Significantly, learning styles continue to be promoted in the context of engineering and architecture education as an effective categorisation of learners and subsequent guide to effective teaching methods (Ictenbas and Eryilmaz 2011; Jamali and Mohamad 2018; Kowalski and Kowalski 2012; Li et al. 2019; Mansor and Ismail 2012; Tawil et al. 2012; Tulsi et al. 2016). Again, however, there have been no test-retest reliability studies of the KLSI particular to engineering or architecture cohorts.

This study addresses these significant research gaps. A test-retest survey of civil engineering and architecture undergraduate students in Australia is conducted using the KLSI (Version 3.1), over three rounds of data collection at 7-week intervals. In line with previous studies, the data analysis for the test-retest reliability uses a Pearson correlation coefficient. In this study, that approach is extended using a Spearman Rho test. Significantly, and for the first time, the analysis in this study examines the particular dynamics of how the categorisation of individual learning style preferences change over time. A novel geometric representation of the data is developed and presented to clearly illustrate the scale and nature of variability, and thereby the malleability of learning style preferences over a relatively short period of 7 to 14 weeks.

The malleability of the KLSI is of particular interest because it has significance to the utility of the KELM in application. However, given the nature and dynamics of the variability revealed in this study, the malleability of the KLSI also offers important insight into the potential for an emancipation of education more generally.

Method

This study reports on a longitudinal investigation into the variability of KLSI version 3.1, test-retest reliability over a relatively short period. The study analyses the test-retest variation across the distribution of responses and, most particularly, tracks changes in the responses of individual participants in both score and category terms. The longitudinal study is a helpful technique for studying such patterns of change, because the study population is surveyed a number of times (typically 3 times or more), at specific intervals, over an appropriate period, to collect related data sets (Kumar 2019).

Care is required in any longitudinal study, as the circumstances and cognitive states of respondents may also change over time (Ployhart and Vandenberg 2010). There is always the potential in later rounds, as the procedure repeats and becomes more familiar, for the same participants to respond to the same questions with less consideration. Respondents can be in a different state of mind. There may have been influential experiences between test and retest (Kolb 2015). Over time, respondents might further develop their capacity to adapt their learning style preferences to changing environmental demands (Mainemelis et al. 2002). To guard against these issues and minimise environmental change, the study consisted of three rounds of data collection, at relatively short, 7-week intervals. Environmental factors (including the survey administrator, how the survey is introduced, teaching environment, student cohort, etc.) were kept as consistent as possible.

The method of data analysis for the test-retest reliability uses a Pearson correlation coefficient test (a statistical measure of the covariance between variables) and a Spearman Rho test (a non-parametric test used to measure the strength of association between two variables). The Pearson correlation test evaluates the linear relationship between two continuous variables. It is the most widely used measure of correlation in general and almost exclusively used in previous test-retest evaluations of the KLSI. However, it is especially suited to a normally distributed dataset that only approximates the data in this and previous such studies. The Spearman Rho test is a more appropriate test for variables that are not normally distributed, or where the relationship is not linear. The results of the KLSI tests can also be analysed visually, by tabulation and charting the results geometrically, plotting variations in responses over time on the same KLSI grid. The tabulation and graphical techniques also reveal key aspects of category change/stability. The tabulation follows recommendations by Loo (1997). Other aspects of the visual mapping used in this study are entirely novel representations of such data, and provide significant new insights into the dynamics of KLSI results not previously or otherwise apparent.

Participants for the study were recruited from a single cohort of 1st/2nd year undergraduate college students enrolled in an Australian university. All students were enrolled in the same compulsory design studio subject, common to the Bachelor of Civil Engineering, Bachelor of Architectural Computing, and Bachelor of Architecture. There were 245 students enrolled in the subject, comprising 21% engineering 28% computing, and 51% architecture students. 48% of students were female and 52% were male. Participation in the study was voluntary, without reward, and conducted outside of normal teaching contact time. All students enrolled in the subject were invited to participate in each round of data collection separately. The same survey administrator explained that the purpose of the study was to assess individual learning style preferences, and provided written instructions on how to complete the survey. Separate informed consent was obtained from each participant for each round of data collection. The study consisted of three rounds of data collection, at 7-week intervals, undertaken at the start, middle and end of a single teaching semester. The learning style preference of each respondent, at each stage, was identified using the procedures described in Kolb and Kolb (2005).

For Round 1 and Round 2, participants were issued with a hard copy of the KLSI (v3.1) (scrambled form) at the end of a normal class teaching period. The first round of data collected 220 responses, and considered 184 of those responses (84%) valid. A response was not valid when found to be incomplete or not answered in accordance with the standard KLSI instructions provided. The second round of data collected 212 responses, and considered 186 responses (88%) valid. For the third round of data, participants received an online copy of the KLSI (v3.1) because by then students in the course were no longer working on campus to complete their final projects. The third round of data collected 99 responses, and considered 96 responses (97%) valid.

As participation for each round was voluntary, it was not possible to require all participants in Round 1 to participate in Round 2 and/or Round 3. Hence, there were changes in the number and constituency of participants across each round. A subset of participants from Round 1 were included in Round 2 (156 in total), and another subset from Round 1 also participated in Round 3 (77 in total). Similarly, a subset of participants from Round 2 were included in Round 3 (76 in total). Thus, from a potential sample size over 3 rounds of 245 + 245 + 245 = 735, there were 220 + 212 + 99 = 531 (72%) responses collected, of which 184 + 186 + 96 = 464 (87%) were valid responses, and from which the test-retest data available is for 156 + 77 + 76 = 309 (67%) useable test-retest data points. Note, all 464 valid responses were used to determine the learning style preferences at particular points in time, with the 309 responses used for test-retest purposes. A smaller subset of respondents again (65 in total) participated in all three rounds of testing and this data is used to further illustrate the change dynamics in individual learning style preferences over sequences of time.

The KLSI (v3.1) comprises twelve partial statements relating to potential learning preferences. For each partial statement, there is a choice of four possible partial endings. For each statement, there is one particular ending to represent each dimension of the KELM. A score for each dimension is totalled across the 12 statements and a spatial location on the KLSI grid is then calculated and plotted. The origin of the categories used to distinguish 'Diverger', 'Assimilator', 'Converger', and 'Accommodator', is offset from the KLSI grid origin (see Figure 1). Kolb and Kolb (2005) recommend the use of an offset determined by the mean score from a dataset of almost seven thousand KLSI results to normalise individual survey results. This shifts the learning style origin to a revised AE-RO balance point located 5.96 units along the Active Experimentation dimension (typically rounded to +6), and AC-CE balance point located 6.83 units along the Abstract Conceptualisation dimension (typically rounded to +7).

Insert Figure 1 Here

Results

The typical representation of learning style preferences for any given KLSI dataset is determined by calculating the overall score on the AC-CE dimension and AE-RO dimension of the KLSI grid for each participant. The average of those scores is then plotted on the KLSI grid, and the learning style category is indicated by the particular quadrant where the value locates. Table 1 presents the average AC-CE and AE-RO dimension scores thus calculated, compared across the three rounds of data collection, and with the reference set values used to determine the KLSI grid origin offset from Kolb and Kolb (2005).

Insert Table 1 Here

Figure 2 shows the spatial placement of the mean balance point for each dataset, relative to the offset learning style quadrants using the standard 'zoomed-in' view around the offset KLSI origin. Figure 2 indicates that (on average) the learning style relevant to the group in Round 1 was Assimilator; in Round 2 was Diverger; and in Round 3 was borderline Diverger. A period of 7 to 14 weeks should not change learning style preferences so significantly.

The use of a mean balance point score to represent the learning style preference for a group of participants is entirely common in the literature. However, there are numerous examples for which the description by a mean is clearly misleading (Limpert and Stahel 2011). A small number of studies do present the data graphically, but studies that report the full scatter and distribution of individual results are rare (see D'Amore et al. 2012, for one of these rare exceptions). Figure 3 presents the distribution of individual learning style preference score results for each participant in this study, particular to Round 1 of the data capture. Larger dots denote overlapping individuals.

Insert Figure 3 Here

Whenever the KLSI results for a group are presented in the form of a scatter diagram, from this or any other study, the dispersion always mirrors that shown in Figure 3. Equivalent representations for Rounds 2 and 3 show an identical level of dispersion. In other words, whilst it may seem reasonable to assign a particular learning style to a group of learners based on the mean of the distribution, what evidence there is points clearly to the fact that every group of learners is likely to contain a wide diversity of individual KLSI results. Individual results range extensively across all learning style quadrants, and assigning a single learning style characterisation to any such group is misleading at best. Indeed, over the three rounds, the use of a mean value to represent each group wrongly categorised 77.47% of participants. This would strongly indicate that the use of a mean balance point to categorise the learning style preference of a group is a significant misrepresentation of the individual KLSI learning style preferences.

In keeping with previous protocols, this study examines variation in the mean KLSI scores between Rounds 1-2 (7 weeks), Rounds 2-3 (7 weeks), and Rounds 1-3 (14 weeks). Table 2 lists the test-retest reliability results using both the Pearson correlation test and Spearman Rho test. In either test, a result between 0.5 and 1 demonstrates a strong, positive correlation; and a result between -0.5 and -1 demonstrates a strong but negative correlation. Positive or negative results between 0.3 and 0.5 represent moderate correlations. Results between -0.3 and +0.3 are recognised as weak correlations.

Insert Table 2 Here

Whilst some values (highlighted in bold) are slightly within the strong correlation (highest value 0.587) and some values (highlighted in italics) are slightly within the weak correlation ranges (lowest value 0.277), overall these results are consistent with previous studies in that they indicate a moderate, positive test-retest correlation. All values are statistically significant.

Notwithstanding the moderate statistical test-retest correlation, however, a key question remains whether the variation has significant impact on the categories of learning style preferences indicated by the KLSI scores. To address this question the study has developed a novel graphical technique. Further to plotting the individual KLSI balance point scores graphically in Figure 3, the movement in scores for each individual between tests has also been represented. Figure 4 shows the location of each participant at Round 1 as a small dot. The location of the same participant at a Round 2 as a larger dot. The distance travelled between the two is shown as a thin connecting line. For the first time in any study of KLSI data presentation and test-retest analysis, Figure 4 reveals the key dynamics of the population. Equivalent representations of the movements from Rounds 2 to 3 and Rounds 1 to 3 show identical dynamics. Across all three test-retest rounds, as indicated by the length and direction of the thin connecting lines, individual KLSI balance point scores are shown to change materially in terms of direction, distance, across learning style categorisation boundaries, and across balance points on both the AC-CE and AE-RO dimensions.

Insert Figure 4 Here

A measure of the extent of this variation can be calculated by averaging the absolute movement on each dimension (AC-CE and AE-RO) of the KLSI grid (absolute movement avoids having movements in opposite directions cancelling each other out). Combining the movements on both the AC-CE dimension and the AE-RO dimension (a simple summation of the two grid distances in each dimension is used as the travel distance, rather than calculating point-to-point, direct geometric distance), a total travel distance can be calculated for each individual:

The results of these calculations are presented in Table 3. AC-CE and AE-RO distribution values are presented separately to demonstrate that the travel direction is not biased to a particular dimension. The average overall travel distance across a single time period is between 13.80 and 14.99 on the KLSI grid. This distance is hugely significant when set in the context of the maximum travel distance required to move the single point mean value for any round of testing back to the off-set learning style origin – and potentially thereby changing the identified learning style preference for the group to any of the alternative learning style quadrants. From Table 1, the maximum travel distance required to return any mean balance point to the KLSI grid offset origin (and thereby switch to any of the other learning styles) is only (7.40-6.83) + (5.96-2.24) = 4.29. The average overall travel distance across a single time period from Table 3 is between 13.80 and 14.99 on the KLSI grid, which is 3 times the maximum travel distance required.

Insert Table 3 Here

The maximum travel distance across a single time period achieved by any individual participant in this study is, AC-CE = 37 and AE-RO = 40. That is almost equal to the maximum travel distance possible (AC-CE = 36 + 6.83 = 42.83, and AE-RO = 36 + 5.96 = 41.96). Thus, even if an individual KLSI score starts close to the maximum possible distance away from the offset origin, participants in this study demonstrate that they are capable of sufficient change in preferences over the course of just a few weeks, to still cross over any threshold into a different learning style quadrant/category.

Loo (1997) argues that an analysis of learning style categorisation and both stability and changes from one category to another over time would yield a more accurate picture of learning styles, and be of particular interest to educators. Following the principal recommendation of Loo (1997), the learning style categorisation is presented in a tabular form in Table 4, comparable to the presentation of Loo (1997, Tables III to V). Frequency counts for each learning style category is in parentheses in Table 4, following the percentage value.

Insert Table 4 Here

Table 4 presents the changes in learning style categorisation for time periods (Rounds) 1 to 2 2 to 3, and 1 to 3. The low level of stability in the categorisation between rounds is evident. Full stability would be indicated by a 100% value in each of the greyed cells of Table 4, signifying all those categorised as Assimilator in time period 1 remained as an Assimilator in time period 2, and so on. In fact, overall, the individual categorisation remained stable for an average of only 48.54% of cases. Conversely, 51.46% of participants crossed between at least one category boundary of the offset learning styles grid (that is, changed learning styles) within a 7 or 14 week period. That result aligns with the results provided by Ruble and Stout (1991), which show 46.64% of participants changed categories (based on the data given in Ruble and Stout 1991, p. 487, Table. 3), and Loo (1997), which found a 48.03% equivalent variation (based on the data given in Loo 1991, p. 99, Table. III). The evidence indicates that a significant proportion of participants over all three studies (49.02%) materially changed their learning style preferences over a period of just a few weeks.

Figure 5 shows the final output of this graphical test-retest analysis. Further to plotting the individual movement in balance point scores for each participant across a single test-retest period in Figure 4, Figure 5 shows the movement of those individuals (65 in total) who participated in all three rounds of test-retest datasets. The location of each individual at Round 1 is shown as a small dot, the location of the same individual at Round 2 is shown as a medium dot, the location of the same individual at Round 3 is shown as a larger dot, and the distance travelled between as a thin connecting line.

Insert Figure 5 Here

The representation in Figure 5 illustrates the dynamic of individual learning style preferences as indicated by the KLSI balance point calculations for individuals across two consecutive 7-week periods. Table 3 includes the results of calculated travel distance for the same dataset. The average overall travel distance reflects the average distances for each period and amounts to 28.67 overall on the KLSI grid. These results confirm the lack of stability, the scale of movement, and the lack of consistent direction of travel over time. There is movement in all individual scores over even a short period of time. The travel distance is materially significant, as far as it moves many participants across learning style category borders. The direction of movement is inconsistent, and appears random.

Discussion

This longitudinal study has examined the test-retest reliability of one of the most popular learning style preference categorisation instruments, the KLSI, in the specific setting of engineering and architecture higher education in Australia. Plotting the distribution of individual results graphically (Figure 3) demonstrates key flaws in the typical use of the mean value to represent the distribution of any KLSI study. Assigning a single learning style category to a group of learners based on the mean balance score is inappropriate, as it significantly misrepresents (wrongly categorises) the majority (77.47%) of participants. The skewed nature of the distributions also questions the relevance of those majority of previous KLSI test-retest variability studies, almost exclusively based only on the Pearson correlation applied to the group as a whole. The use of a Spearman Rho test is more appropriate, although the results in this study were equivalent between the two tests.

Of particular significance, the results presented in this study demonstrate that there is movement in all individual KLSI scores over time, even relatively short periods of several weeks. This is significant procedurally, because there has been no previous mapping or measurement of individual movement of KLSI scores in travel distance terms over time. When analysed, the travel distance between tests is materially significant, as it is more than capable of moving individuals across and between KLSI learning style quadrants and categories. More than 50% of participants change learning style categories over a period of just 7 or 14 weeks. There is no consistent direction or scale of movement apparent within any given group or any given individual over any of the 7-14 week periods. Thus, the results of this study question fundamentally the utility of any single point in time, snapshot of learning style preferences based on the KLSI.

This challenge to the validity of a learning style snapshot has wide-ranging implications. The dynamics challenge the basic claim that KLSI learning style preferences remain stable over time (Kolb and Kolb 2018). Learning style preferences appear to vary significantly over a period of just a few weeks. The scale of this dynamic is also significant because it disconnects the use of learning style snapshots from subsequent outcomes. For example, Rogowsky et al. (2015, 2020) demonstrate that providing instruction based on a one-time, snapshot of learning style preferences does not appear to improve learning outcomes. This lack of outcome may in part be accounted for because the snapshot does not represent the changing learning style preferences over the full period of instruction. Notwithstanding, of course, that the entire concept of learning styles may also be a neuromyth (Kirschner 2017).

If there is some validity to the underlying KELM learning modes (Carvajal et al. 2021), then the dynamics of the learning style preferences measured by the KLSI over time, revealed in this study, could mean either of two things: the KLSI is not a reliable measure of stable learning style preferences; or, the KLSI is a reliable measure of highly dynamic learning style preferences. If the KLSI is an unreliable measure, then so also are the many applications of the KELM that depend on the use of KLSI.

If, on the other hand, the KLSI does reliably capture a very dynamic, apparently randomised, learning style preference, this would in turn also invalidate much of the current utility of the KLSI. For example, if learners are already by nature so dynamic and fluid in their learning style preferences, then perceived weaknesses in learning style preferences (as 'revealed' by a KLSI snapshot, for example) are only transient and therefore immaterial. Ultimately, with such dispersal of individuals across all learning style categories, there is little purpose in using the KLSI to assess or distinguish between categories of learning style preferences. If learning style preferences are in a constant state of flux, then categorising individuals in order to better match them with the demands of learning tasks, to increase learning effectiveness (Passarelli and Kolb 2020), is pointless. If there is no consistency in travel direction around the KLSI grid, then there is no basis for teaching strategies that seek to map or promote the so-called Cycle of Learning (Kolb 1974). And so on…

The dispersal and inconsistency of the individual learning style preferences revealed in this study would indicate, at best, that individuals already roam freely, rapidly, and extensively through and across learning style categories. This dynamic endorses views such as Zhang and Sternberg (2005) and Fan et al. (2019), that learning styles are not permanent traits of genetic inheritance or particular environmental factors, but (if controllable to any degree) are malleable states. However, the findings of this study would go further and warrant broader questions into the nature of the dynamic. Are all fields and stages of education equally dynamic? Is the dynamic peculiar to the open-ended, more creative structure of the design studio teaching and/or affordances of the learning environment (Young et al. 2020) particular in this study? Is the fluidity of movement from one category to another helpful or in some way important to learners, and worthy of active encouragement? Are there alternative teaching strategies to current practice, better able to accommodate and acknowledge, or indeed leverage, such dynamic changes in learning style preferences? If student learning preferences are constantly changing, and are so malleable, is it more reasonable for teachers to stick with the belief that students will learn better the way that they themselves were taught (Espinosa et al. 2020), and to stop even trying to accommodate a range of competing styles?

The malleability of the learning style categorisation also endorses the argument by Marton and Booth (1997), and many others, that the more fundamental 'constitutional' issues of experiencing and understanding should take priority concern and focus over (evidently) superficial and transient issues such as learning preferences. Rather than seeking to describe categorisation schemes for different learning styles that simply do not obtain from one moment to the next, more attention should be given to the important commonalities that attend across time and across student groups (Willingham et al. 2015).

The extent of the malleability revealed in this study also plays into the more radical reconsideration of education proposed by Lewis (2013), Murphy (2020a), and others. Driven, as education appears to have become, by measurement and notions of continuous improvement, Lewis (2018) and Murphy (2020b) argue that the likes of standardised testing, transactional teaching, and active lifelong learning increasingly miss-frames and constrains education, effectively rendering it inoperable. The advent of learning style theories, leading up to the current focus of KLSI so clearly on standardised measurement and tailored 'self-making' (Passarelli and Kolb 2020), would fit naturally as one of the measurements and continuous improvement drivers of the current educational practice malaise, as characterised by Lewis (2018) and Murphy (2020b). By revealing the full malleability and dynamics of individual learning style preferences, this study lends further evidence to the proposition that the act of learning is fluid with the potentiality that talent, aspiration and opportunity seek to realise (Sellar

2015). The failure of KLSI to establish a meaningful and stable learning style preference for college-level engineering and architecture students means they are not locked into a particular learning approach, and conveys greater agency to the learner. In so doing, it offers empirical evidence to support the growing calls for an emancipation of education and helps drive the 'global dialogue' called for by Zhao et al. (2020).

Ultimately, when projecting the findings from a limited sample size of relatively homogenous participants, from a specific field of specialisation, in a single cultural context, at a particular point in an educational program, generic findings should always be qualified. The sample size for this study is limited, but entirely consistent with much of the research in the field. Nevertheless, even given this limited data sample, the findings on dynamics and reliability are already apparent. Further studies are to be encouraged where a similar protocol is followed using the graphical and analytical techniques developed for this study to investigate the underlying dynamics.

Conclusion

This study seeks to shed new light on one of the most influential learning style models, the KELM, and to determine the extent to which the KLSI is a reliable test-retest measure of learning style preferences. If the KLSI is unable to establish a meaningful learning style preference, then many aspects of the KELM currently embedded in teaching and learning practice require urgent reconsideration.

Over three rounds of testing, the use of the mean value of each group wrongly categorised the learning style preferences for 77.47% of participants. We conclude that the use of a mean balance point to represent the learning preference of any group is a significant misrepresentation of that group distribution.

Over 50% of participants changed their learning style preference categorisation materially over a period of just a few weeks. Almost 15% of participants changed their learning styles across both dimensions of the KLSI grid. There is significant movement in individual scores over time. The direction of movement is inconsistent, it changes over time periods, and appears random. We conclude that learning style preferences are both unstable and unpredictable.

The full dynamics of individual movement, and the variability of learning style preferences revealed in this study indicate one of two potential situations: either, the KLSI does not reliably capture relatively stable learning style preferences; or, the KLSI does reliably capture a very dynamic, apparently randomised, learning style preference. If the KLSI does not reliably capture relatively stable learning style preferences, then it is an unreliable measure and needs to be abandoned or substantially revised.

If the KLSI does reliably capture a highly malleable learning style preference, then the scale and inconsistency of those changes over time (as revealed in this study) indicates that individuals already roam freely, rapidly, and extensively through and across the KLSI learning style categories. Seeking to establish a snapshot of learning style preferences at any particular point in time is no indication that the learning style preference identified is characteristic of an individual or group beyond that singular moment in time. The use of a single point in time, snapshot use of the KLSI is misleading. Thus, under either of the two potential situations, we conclude that the KLSI measurement of individual learning style preferences lacks effective purpose or utility.

The focus of this study is specific to the KLSI applied to a limited sample of undergraduate civil engineering and architecture college students in Australia. Nevertheless, the findings do have broader relevance to the study and utility of learning style models and instruments more generally, across levels, disciplines, and national borders. The KLSI categorisation seeks to highlight differences in learning preferences, but these demonstrably fail to obtain from one moment in time to the next. The possibility then is that such dynamics signal the act of learning, as an act of agency, is malleable and fluid with potentiality and choice. This would be a very positive signal. We conclude that whether or not the KELM is a neuromyth, and whether or not the KLSI does or does not accurately capture learning style preferences, in all contexts, the more meaningful focus for teaching and learning practice would be to focus on the commonalities across students and student groups. In any event, the KLSI appears to have little, if any, meaningful purpose per se.

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Table 1. A comparison of the average AC-CE and AE-RO dimension scores.

Data Groups	Size		CE	RO	AC	AE	AC-CE	AE-RO
Reference set	6977	Mean	25.39	28.19	32.22	34.14	6.83	5.96
		Stnd.Dev.	6.43	7.07	7.29	6.68	11.69	11.63
Round 1 dataset	184	Mean	24.25	31.03	31.65	33.27	7.40	2.24
		Stnd.Dev.	7.01	6.46	6.43	6.92	11.19	10.99
Round 2 dataset	186	Mean	25.33	29.69	31.35	33.72	6.02	4.03
		Stnd.Dev.	6.25	6.08	6.46	6.79	10.62	10.83
Round 3 dataset	96	Mean	24.61	29.38	31.35	34.66	6.74	5.28
		Stnd.Dev.	6.62	6.92	6.77	7.12	11.60	12.34

Table 2. Test-retest reliability results using Pearson Correlation and Spearman Rho.

Rounds	Size	Test	CE	RO	AC	AE	AC-CE	AE-RO
1-2	156	Pearson Corr.	0.473	0.395	**0.587**	**0.514**	0.497	0.410
		Spearman Rho	**0.500**	0.351	**0.583**	**0.541**	**0.535**	0.409
2-3	76	Pearson Corr.	0.344	0.436	0.363	**0.519**	0.307	0.485
		Spearman Rho	0.455	0.445	0.411	**0.514**	0.407	0.463
1-3	77	Pearson Corr.	0.331	*0.278*	*0.277*	**0.549**	*0.295*	0.469
		Spearman Rho	0.369	*0.297*	0.346	**0.514**	0.365	0.466

Note: Values underlined are significant at the 0.05 level. All other values are significant at the 0.01 level.

Table 3. Travel distance between each test-retest period.

Rounds	Size	Test	AC-CE	AE-RO	Travel
1-2	156	Mean	7.97	9.42	13.80
		Stnd.Dev.	7.91	7.65	9.11
		Median	6.00	7.00	11.36
2-3	76	Mean	9.38	9.67	14.99
		Stnd.Dev.	9.02	8.07	10.32
		Median	7.00	8.00	12.81
1-3	77	Mean	9.04	9.82	14.88
		Stnd.Dev.	8.96	7.47	9.63
		Median	7.00	8.00	12.81
1-2-3	65	Mean	17.48	18.55	28.67
		Stnd.Dev.	15.66	12.52	16.73
		Median	13.00	16.00	25.56

Table 4. Stability and change in learning style categorisations.

Time 1	Time 2			
	Assimilator 26.28% (41)	Accommodator 25.00% (39)	Converger 19.23% (30)	Diverger 29.49% (46)
Assimilator 33.33% (52)	48.08% (25)	11.54% (6)	19.23% (10)	21.15% (11)
Accommodator 23.72% (37)	10.81% (4)	45.95% (17)	13.51% (5)	29.73% (11)
Converger 19.87% (31)	19.35% (6)	16.13% (5)	45.16% (14)	19.35% (6)
Diverger 23.08% (36)	16.67% (6)	30.56% (11)	2.78% (1)	50.00% (18)

Time 2	Time 3			
	Assimilator 25.97% (20)	Accommodator 22.08% (17)	Converger 23.38% (18)	Diverger 28.57% (22)
Assimilator 31.17% (24)	45.83% (11)	29.17% (7)	4.17% (1)	20.83% (5)
Accommodator 20.78% (16)	18.75% (3)	37.50% (6)	25.00% (4)	18.75% (3)
Converger 24.68% (19)	15.79% (3)	5.26% (1)	57.89% (11)	21.05% (4)
Diverger 23.38% (18)	16.67% (3)	16.67% (3)	11.11% (2)	55.56% (10)

Time 1	Time 3			
	Assimilator 21.05% (16)	Accommodator 23.68% (18)	Converger 30.26% (23)	Diverger 25.00% (19)
Assimilator 25.00% (19)	47.37% (9)	10.53% (2)	31.58% (6)	10.53% (2)
Accommodator 25.00% (19)	10.53% (2)	52.63% (10)	15.79 % (3)	21.05% (4)
Converger 19.74% (15)	6.67% (1)	13.33% (2)	60.00% (9)	20.00% (3)
Diverger 30.26% (23)	17.39% (4)	17.39% (4)	21.74% (5)	43.48% (10)

Figure 1. The learning style origin offset, typical zoomed-in area, and maximum dimensions of the KLSI grid.

Figure 2: The balance points (R1, R2, R3) for each round of KLSI data presented using the ‘zoomed-in’ region.

Figure 3: Individual KLSI balance points for Round 1.

Figure 4: Changes in individual KLSI balance points between Rounds 1 and 2.

Figure 5: Changes in individual KLSI balance points between Rounds 1 2 and 3.