

# CLUSTERING OF DESIGN DECISIONS IN CLASSROOM VISUAL DISPLAYS

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## ABSTRACT

In this paper, we investigate the patterns of design choices made by classroom teachers for decorating their classroom walls, using cluster analysis to see which design decisions go together. Classroom visual design has been previously studied, but not in terms of the systematic patterns adopted by teachers in selecting what materials to place on classroom walls, or in terms of the actual semantic content of what is placed on walls. This is potentially important, as classroom walls are continuously seen by students, and form a continual off-task behavior option, available to students at all times. Using the k-means clustering algorithm, we find four types of visual classroom environments (one of them an outlier within our data set), representing teachers' strategies in classroom decoration. Our results indicate that the degree to which teachers place content-related decorations on the walls, is a feature of particular importance for distinguishing which approach teachers are using. Similarly, the type of school (e.g. whether private or charter) appeared to be another significant factor in determining teachers' design choices for classroom walls. The present findings begin the groundwork to better understand the impact of teacher decisions and choices in classroom design that lead to better outcomes in terms of engagement and learning, and finally towards developing classroom designs that are more effective and engaging for learners.

## Categories and Subject Descriptors

I.5.8 [Pattern Recognition]: Clustering—algorithm

## General Terms

Algorithms, Design.

## Keywords

Clustering, teacher, design decisions, classroom decorations

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LAK '14, March 24 - 28 2014, Indianapolis, IN, USA  
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<http://dx.doi.org/10.1145/2567574.2567605>

## 1. INTRODUCTION

Throughout the history of education, there has been interest in designing classrooms for children that best support effective pedagogy. The goal has been to select spatial designs for children's classrooms that likely influence both pedagogy and experience in meaningful fashions [21]. Much of the literature in this area has considered the layout of desks and students, such as whether desks point to the teacher, or students sit in circles facing each other [13]. Another theme has been the visual design of the classroom. Colorfully decorated walls have become a staple of modern classrooms [8]. There has been steady interest in the impacts of differences in the design and utilization of classroom walls [9], which students look towards for hours a day [26]. Differences in classroom design can have substantial impacts on student engagement and learning. In specific, Weinstein [28] found that extensive shelving and clearer display of materials reduced off-task behavior and increased the frequency in which students used manipulative materials and games. By contrast, it has been hypothesized that colorful room designs may increase distractibility and off-task behavior, at least for younger learners [16, 26]. Additionally, Barret et al. [3] reported that several classroom design parameters were significantly associated with learning outcomes in elementary school students. Importantly, the authors initially hypothesized that the features "color" and "complexity" would be positively related to student learning, but instead found that these features were negatively related to students' learning outcomes.

However, much of this work has considered visual design attributes in isolation, identifying positive and negative correlates to learning [25] of specific visual design choices. By contrast, there is relatively little literature that considers that specific visual elements may form a systematic design chosen by teachers. In addition, much of prior work has solely considered the visual aspects of what teachers place on walls, as opposed to the semantic content of what is placed on walls.

Better understanding teachers' systematic design choices for walls may be useful towards understanding which designs are more pedagogically useful, and whether some designs are distracting. For example, using walls as a posting place for instructional materials may be distracting to students, causing off-task behavior [6], carelessness [7], or other forms of disengagement. Considerable research has suggested that disengaged behaviors of this nature may reduce learning and achievement [22]. While teachers play a dominant role in influencing students' attention,

the amount of time in which students actively attend to instructional activities is limited; this makes students more susceptible to distractions within their immediate surroundings [23]. Identifying the sources of these disengaged behaviors can help teachers understand what interventions can improve students' patterns of motivation and engagement [10]. Within the classroom setting, walls have also been used to regulate student behaviors and attention [cf. 27], displaying classroom rules and charts about which students are following classroom rules [24].

By considering teachers' design choices for walls more systematically, we may be able to see which overall choices have positive impacts, and eventually may be able to create wall design patterns that best promote engagement and learning. Over the years, educational design patterns have been integrated into several domains of learning technology, including the development of computer science courses [4], web-based instruction [15] and e-learning [11]. These design patterns can in turn be used in discovery with models analyses [18] to discover which design patterns are associated with better learning outcomes and less disengagement. A list of positive design features is likely to be less useful than a set of design patterns, since there are several ways to combine the individual components teachers use in classroom wall design.

One method for understanding systematic choices, that is, which smaller-scale choices fit together, is to use clustering [20]. A cluster algorithm can give insight into which individual elements frequently co-occur, as part of overall patterns. Recent work in educational data mining has attempted to achieve similar goals toward the discovery of meaningful patterns in educational data. Amershi and Conati [1] applied an unsupervised clustering algorithm to determine which student interaction patterns distinguished high or low learning; they were able to move from relatively low-level student actions to understandable and usable patterns. Similarly, Fouts and Myers [14] made use of clustering to analyze various types of classroom environments during science instruction. In specific, classrooms with high levels of student involvement, teacher support, group affiliation, order and organization, and teacher innovation were associated with better attitudes toward science [14]. These studies highlight the value of using an exploratory approach to study the combination of distinct features within different learning environments.

In this study, we use clustering analysis to investigate features of classroom wall design. This analysis adds to the existing literature on classroom visual and physical design, by studying which wall design elements go together, and whether there are clusters where the same type of wall element can be part of very different wall use strategies.

Within this paper, we research this question using data from 30 elementary school classrooms in the Northeastern United States. Classrooms were photographed after school, systematically coded by designers, and analyzed using k-means clustering. Through this method, we will study the groupings in classroom wall design.

## 2. METHODOLOGY

### 2.1 Data Collection

30 classrooms from local charter, private, and religious schools in the Northeastern United States were recruited for the present study. The following was the distribution of the different schools: 14 charter classrooms, 13 private classrooms, and 3 religious classrooms. Within these schools, the sample included 7 kindergarten classrooms, 7 first-grade classrooms, 7 second-grade

classrooms, 3 third-grade classrooms, and 6 fourth-grade classrooms. Photographs of classroom walls were taken during the fall semester (October-December 2012).

### 2.2 Coding Scheme

To understand the types of flat materials placed on the classroom walls, we coded for content, using a coding system developed for this purpose, the Classroom Wall Coding System, CWaCS 1.0. For each classroom wall photographed, units of analysis were identified with a box in the qualitative analysis software program Hyper-RESEARCH v3.5.2 [19]. All units in the walls were then coded in terms of three categories: *academic*, *non-academic*, and *behavior*. *Academic* items are relevant for student learning and were sub-classified into two sub-categories: *academic organizational* and *academic topics*. *Academic organizational* items regard the organization of class activities and were sub-classified into eight sub-categories: *goals for the day*, *group assignments*, *job charts*, *labels*, *schedule day/week*, *yearly schedule*, *skills*, and *homework*. *Academic topics* pertain to specific content learning materials and were further classified into five sub-categories: *content specific*, *procedures*, *resources*, *calendars/clocks*, and *other*. *Non-academic* items provide general information such as school policy, teacher information, and decorative items. *Non-academic* items were sub-classified into five categories: *motivational slogans*, *decorations*, *decorative frames*, *student art*, and *other non-academic*. *Behavior* materials aim to influence student behavior (e.g., good behavior charts, book challenge points). *Behavior* was subdivided into four sub-categories: *behavior management*, *progress charts*, *rules*, and *other behavior*. Two trained coders coded approximately half of the 30 classrooms each. Both trained coders then coded the same four classrooms (13%); interrater agreement was very good (Cohen's kappa = .91). Approximately half of the wall displays (51%) were related to academic content; the other 49% involved other categories.

### 2.3 Analytical Method

Given the hierarchical coding scheme, and its application to the data, we computed the frequency of each type of visual design feature observed within the four walls of each classroom. We focused on the upper level of aggregation, given the relative sparsity of the sub-categories across the relatively small sample of classes.

We then applied clustering to the resultant data set. Clustering is defined as the process of grouping a set of objects, such that those belonging to the same cluster share similarities in their feature vectors [29].

K-means, the most straightforward and popular clustering algorithm, was used in the present paper because of its fast and easy implementation and interpretation. The k-means method produces k clusters. It first involves the formation of k initial clusters, typically (and in this case) placed randomly. Given this initial clustering, member points are allocated according to the nearest centroids. Once points are allocated, cluster centroids are reassigned. This process of recalculating and updating the centroids is repeated until the convergence criteria are met [29].

In this paper, since the number of clusters was not prescribed in advance, different possibilities were randomly applied beginning with a given minimum of k=1. The results are discussed below.

The next step was to determine what distinguishes classrooms in terms of visual design features, by studying which variables characterize each cluster's differences from the other clusters. In

order to study this, the means plus and minus one standard deviation were computed for all attributes within each cluster. Calculations from both these equations were then compared against the corresponding overall averages of each type of visual feature. Significant differences between these values revealed which visual features each of the resultant clusters were particularly extreme on.

Clusters were then analyzed based on the distribution of the different schools (e.g. charter, private, and religious). In particular, we used the Monte Carlo method to investigate whether patterns of teachers’ design decisions were associated with a particular kind of school.

### 3. RESULTS

As previously mentioned, we systematically tried different numbers of clusters within the k-means algorithm. After 4 clusters, new clusters primarily represented outliers. We found that k=4 clustering had one singleton (outlier) cluster (already seen with 2 clusters); the k=5 clustering was identical, except there was an additional cluster with two outlier data points; further addition of clusters provided more outlier clusters. Since outlier clusters do not provide information on cross-class trends, we selected the clustering analysis for k=4 for further analysis. The resultant clusters varied somewhat in size: cluster 1 (n=6), cluster 2 (n=15), cluster 3 (n=8), and cluster 4 (n=1).

In order to identify visual features that distinguished between the clusters, the means and standard deviations of clusters were compared against the overall averages of each visual feature. Table 1 summarizes a list of distinct visual features for each cluster. Plus and minus signs correspond to high and low values.

**Table 1: Distinguishing visual features for k=4**

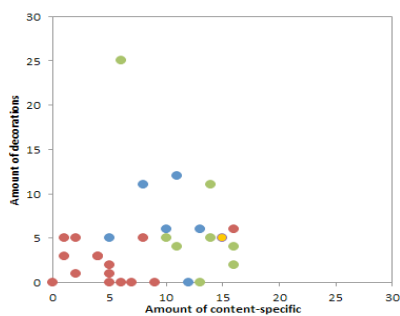
Feature	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Content specific		-	+	+
Decorations	+	-	+	
Labels	+	-		
Other nonacademic	+			+
Procedures				+
Student art			+	

There were observable differences between the feature averages in different clusters. Classrooms grouped in cluster 1 had walls with considerable numbers of labels and non-academic content, particularly in the form of decorations. This cluster represented classroom walls covered with organizational and decorative content. Cluster 1 was the only group that had average levels of content-related decorations, whereas the rest of the clusters were significantly above or below the mean for this feature. As shown in the high cluster averages and standard deviations, classrooms included in Cluster 3 were particularly high in terms of academic, content, decorations, and student art. Cluster 3 reflected walls that were covered in content-specific and decorative materials. Conversely, classrooms belonging to Cluster 2 had walls that were relatively low in academic content, labels, and decorations. Cluster 2 was also extreme on the content-specific feature, but in the opposite direction, having classroom walls with relatively little content-specific content. Classroom walls in cluster 2 classrooms were also low on academic and decorative content. The singleton Cluster 4 had walls with substantial amounts of other nonacademic, procedural, and content-specific materials.

Relative to other groups, this cluster represented classroom walls that were considerably distinct on other nonacademic wall material, content-specific content, and procedures. Interestingly, every cluster had at least some wall displays related to classroom behavior; there was no cluster where this design choice was rare.

In summary, the amount of content-specific and decorative materials distinguished most of the classrooms. Figure 1 illustrates the differences among clusters in terms of these features. From this scatterplot, we can see that the classrooms in Cluster 2 showed relatively low amounts of content-specific and decorative displays compared to the rest of the other clusters. Cluster 1 generally had more decorations and content-specific displays. Cluster 3 had relatively more content-specific content and less decorations than other classrooms (except for one outlier within this cluster). Cluster 4 (outlier) was relatively similar to Cluster 3 in terms of these variables (but differed strongly in terms of other non-academic content).

**Figure 1: Feature comparisons among clusters**



#### 3.1 Clusters and Type of School

One additional research question that was asked of this data is whether the clusters were related to the type of school. In other words, are some design decisions driven by the fact that the school is a charter school, a private school, or a religious school?

In investigating this, we determined that 5 out of the 6 charter schools were in Cluster 1, and that 10 out of the 15 private schools were in Cluster 2. However, it was not clear whether these proportions were due to chance, and there is not a straightforward statistical test for answering this question. An alternative approach is to run a Monte Carlo analysis [17] where we assume chance distribution of classrooms to clusters (based solely on the clusters’ size), and see how often these proportions are obtained. Hence, in our Monte Carlo analysis, we assumed that classrooms were randomly assigned to clusters in the following proportions: Cluster 1 (6/30), Cluster 2 (15/30), Cluster 3 (8/30), and Cluster 4 (1/30), regardless of private, charter or religious status.

We assigned clusters in this fashion 10,000 times. Based on the Monte Carlo analysis, we found that the probability that 5 out of 6 charter schools would be grouped in Cluster 1 based solely on their proportion in the data set was 0.0405 (i.e. p=0.0405). The probability that 10 out of 15 private schools would be grouped in Cluster 2 based solely on their proportion in the data set was 0.0131 (i.e. p=0.0131). In both cases, then, random chance would result in the effect seen less than 5% of the time. This result indicates that charter schools were disproportionately represented in Cluster 1 and private schools were disproportionately represented in Cluster 2. As such, something in the school culture and practices of charter schools in this region results in significantly greater amounts of wall decorations than other types

of schools. By contrast, some aspect of the school culture or practices of private schools in this region results in low numbers of wall displays.

#### 4. DISCUSSION AND CONCLUSIONS

The present study forms a first step in investigating visual classroom design using a clustering algorithm. While it is common practice for teachers to consider and discuss what to place on the walls of their classrooms, this is rarely an emphasis in educational research [12]. As such, the implications of this study provide a first empirical look at how teachers systematically design the visual classroom environment.

Our findings indicate that one big difference between classrooms was whether teachers chose to focus their walls on content-specific topics, which combined with other design decisions in interesting ways. For instance, as mentioned earlier, walls in the singleton Cluster 4 were predominantly covered with content-specific, procedural, and non-academic materials. The teacher from this cluster likely made use of visual displays for guiding student learning, focusing on academic topics and procedures. He or she also utilized the wall space for posting general information and teacher-related content. This combination of features may represent a type of teacher who seems to view visual displays as a means of recalling or referring to information that is particularly intended for students or educators.

Similar to this, Cluster 3 was also particularly high on content-specific wall displays. In addition to exhibiting content-specific topics, a significantly high amount of decorations was observed within this set of classrooms; this was the only group that had substantial amounts of student artwork displays. In a national survey of instructional strategies, Burton [5] found that some teachers post artworks to engage and motivate their students. Similarly, teachers from this cluster may regard decorative materials as motivational tools for learning. However, walls rich in class work and academic displays do not necessarily indicate better use of wall space. Considerable amounts of wall displays can potentially appear cluttered and disorganized, making it more difficult for students to recognize and find pertinent information [2]. In addition, content-specific material may not be useful in many situations, such as mathematics content during a language arts lesson.

The integration of high academic and decorative material seen in these clusters is a stark contrast to the classrooms belonging to Cluster 2. This group of classrooms had the opposite pattern from Cluster 3, with low amounts of both academic and nonacademic wall displays. This reflects a set of teachers – many of them private school teachers – who rarely use academic displays, labels, or decorations in designing a classroom. Teachers who refrain from displaying various types of decorative materials may consider wall decorations to be distractors from learning. It has also been hypothesized that teacher effectiveness may be higher when teachers don't need to compete with visually stimulating wall displays for student attention [2, 26]. Consistent with these hypotheses, Godwin and Fisher [16] found significantly higher proportions of student off-task behavior in learning settings furnished with high amounts of visual materials, as compared to learning settings with few sources of visual distraction. Further studies need to be conducted to understand the link between specific types of classroom decorations and attention, as well as the motivations behind the infrequent use of specific visual features by these teachers.

The last cluster, Cluster 1, includes classrooms where walls were covered with organizational and nonacademic information, rather than content-specific. Given the substantial amount of labels, decorations, and teacher-related content, classrooms in this cluster represent print-rich environments. Since labels were used to describe materials and areas in the classroom, this set of teachers, primarily charter school teachers, likely made use of print displays to help students navigate their way around the classroom.

Features from the behavior category were also not found to be significant in distinguishing between clusters. Behavior-specific features were common across all clusters and types of schools.

Considering these clustering findings, the importance of the content-specific feature suggests that educators have different approaches in displaying academic content with other decorative materials. The clusters found also indicate that the display features can interact in different ways. As shown in Clusters 1 and 2, the preference for posting decorations and labels seems to be associated with each other.

The degree to which teachers post organizational and decorative content is possibly related to a certain type of school. This may relate more broadly to some of the goals adopted at these schools, as well as more general school culture and practices. For example, at the Charter schools studied, considerable emphasis is placed on literacy development; students have 2.5 hours of reading and writing each day. This may explain why these schools are more likely to encourage print-rich environments, where students are immersed in colorful decorations and functional text. This could also explain why considerable amounts of decorations and labels were observed in this cluster that was substantially comprised of charter schools. In contrast, the relatively visually sparse classrooms represented in Cluster 2 predominantly came from private schools. This suggests that private school teachers in this region may consider visual displays distracting. However, these hypotheses are clearly speculative at this point, and further research is necessary to explore these possibilities. In particular, it may be valuable to interview teachers about their classroom display choices in order to understand these choices better. Nevertheless, the type of school appears to be another relevant factor in determining specific patterns in teachers' design decisions.

Overall, the reported findings suggest that there is systematicity in how teachers from varying schools choose to decorate their classroom walls. While a number of previous studies note the importance of classroom design on learning, much of this prior research discusses design factors as individual components. To the best of our knowledge, our paper is the first to report clustering outcomes on the systematic patterns teachers use to design classroom walls. In a classroom setting where environmental features are all interrelated [3], understanding a set of design patterns is more pedagogically useful than investigating features in isolation.

Given that the sample studied here was drawn from a single region, future broader-scale research is necessary to be able to generalize these results to a wider population of schools and educators. Beyond this, it may be worthwhile to further examine why private and charter schoolteachers differ in choices of wall design, perhaps integrating interviews to better understand these choices. Another interesting area for future work might be to explore clustering from the wall level and determine if there are any significant differences in the content between the main (e.g. whiteboard and blackboard) and supporting walls. Prior work has indicated that wall organization strategies, wherein main and

supporting walls are clearly defined, show considerably higher percentages of skill acquisition in academic tasks [10].

Perhaps, the most important area of future work is to study the impact of visual design choices on other variables of interest. Different schools in the region studied make distinct choices about how to use classroom walls; what are the effects of these choices? There are significant differences in between classrooms and across classes studied - nearly half of the wall displays is unrelated to academic topics. It may be valuable to examine how the visual content and organization of classroom walls influence student performance. Studying how classroom design choices influence children's engagement and learning outcomes will help us to understand the impacts of these design choices, and to move towards an era when classroom visual design is engineered based on data rather than intuition.

## 5. ACKNOWLEDGEMENTS

We thank Nigel Acorn, Kevin Kan, and Mimi Weber for their help collecting data. We also thank the children, parents, and teachers who made this project possible. The work reported here was supported by the Institute of Education Sciences, U.S. Department of Education, through Grant #R305A110444. The opinions expressed are those of the authors and do not represent views of the Institute or the U.S. Department of Education.

## 6. REFERENCES

- [1] Amershi, S., and Conati, C. 2009. Combining unsupervised and supervised classification to build user models for exploratory learning environments. *Journal of Educational Data Mining*, 2, 1, 18-71.
- [2] Apps, L., and MacDonald, M. 2012. Classroom aesthetics in early childhood education. *Journal of Education and Learning*, 1, 1, 49-59.
- [3] Barret, P., Zhang, Y., Moffat, J., and Kobbacy, K. 2013. A holistic, multi-level analysis identifying the impact of classroom design on pupils' learning. *Building and Environment*, 59, 678-689.
- [4] Bergin, J. 2000. Fourteen pedagogical patterns. In *Proc of the 5<sup>th</sup> European Conference on Pattern Languages of Programs*.
- [5] Burton, D. 2004. Exhibiting student Art. *Art Education*, 57, 6, 41-46.
- [6] Caldwell, J.H., Huitt, W.G., and Graeber, A.O. 1982. Time spent in learning: Implications from research. *The Elementary School Journal*, 82, 470-480.
- [7] Clements, M.A. 1982. Analyzing children's errors on written mathematical tasks. *Educational Stud in Math*, 11, 1, 1-21.
- [8] Collingford, C. 1978. Wall Displays- children's reactions. *Education* 6, 2, 3-13.
- [9] Creekmore, S. 1987. Effective use of classroom walls. *Intervention and School Clinic*, 22, 341-348.
- [10] Dawson, S., McWilliam, E., and Tan, J. 2008. Teaching Smarter: How mining ICT data can inform and improve learning and teaching practice. Hello! Where are you in the landscape of educational technology? In *Proc of ascilite Melbourne*.
- [11] Derntl, M., and Pitrik, R. M. 2005. The role of structure, patterns and people in blended learning. *Internet and Higher Education*, 8, 111-130.
- [12] Diller, D. (2008). *Spaces & Places: Designing Classrooms for Literacy*. Stenhouse Publishers, Portland, ME.
- [13] Fernandez, A., Huang, J., and Rinaldo, V. 2011. Does where a student sits really matter? – The impact of seating locations on student classroom learning. *International Journal of Applied Educational Studies*, 10,1, 66-77.
- [14] Fouts, J. T., and Myers, R. E. 1992. Classroom environments and middle school students' view of science. *Journal of Educational Research*, 85, 6, 356-361.
- [15] Frizell, S. S., and Hübscher, R. 2002. Supporting the application of design patterns in web-course design. In *Proc of World Conference on Educational Multimedia, Hypermedia and Telecommunications, Denver, Colorado*, 544-549.
- [16] Godwin, K.E., and Fisher, A. V. 2011. Allocation of attention classroom environments: Consequences for learning. In *Proc of the XXXIII Annual Conference of the Cognitive Science Society*.
- [17] Halton, J. 1970. A retrospective and prospective survey of the Monte Carlo method. *Siam Review*, 21, 1, 1-63.
- [18] Hershkovitz, A., Baker, R., Gobert, J., Wixon, M., and Sao Pedro, M. 2013. Discovery with Models: A Case Study on Carelessness in Computer-based Science Inquiry. *American Behavioral Scientist*, 57,10, 1479-1498.
- [19] HyperResearch. n.d. Retrieved on January 28, 2014 from <http://www.researchware.com/products/hyperresearch.html>
- [20] Jain, A.K., Murty, M.N., and Flynn, P. J. 1999. Data clustering: A review, *ACM Computing Surveys*, 31, 264-323.
- [21] Lim, F., O'Halloran, K., and Podlasov, A. 2012. Spatial pedagogy: Mapping meaning in the use of classroom space. *Cambridge Journal of Education*, 42, 2, 235-251.
- [22] Pardos, Z. A., Baker, R. S., San Pedro, M. O., Gowda, S. M., and Supreeth, S. M. 2013. Affective states and state tests: Investigating how affect throughout the school year predicts end of year learning outcomes. In *Proc of the 3rd Int'l Conference of Learning Analytics and Knowledge*.
- [23] Raca, M., and Dillenbourg, P. 2013. System for assessing classroom attention. In *Proc of the 3<sup>rd</sup> International Conference on Learning Analytics and Knowledge*.
- [24] Rademacher, J. A., Callahan, K., and Pederson-Selye, V.A. 1998. How do your classroom rules measure up? Guidelines for developing an effective rule management routine. *Intervention in School and Clinic*, 33, 5, 284-289.
- [25] Simonsen, B., Fairbanks, S., Briesch, A., Myers, D., and Sugai, G. 2008. Evidence-based practices in classroom management: considerations for research to practice. *Education & Treatment*, 31, 3, 351-380.
- [26] Tarr, P. 2004. Consider the walls. *Young Children*, 59, 3, 88-92.
- [27] Walker, H. M., Horner, R. H., Sugai, G., Bullis, M., Sprague, J., Bricker, D., and Kaufman, M. 1996. *Journal of Emotional and Behavioral Disorders*, 4,4, 194-209.
- [28] Weinstein, C. 1977. Modifying student behavior in an open classroom through changes in the physical design. *American Educational Research Journal*, 14, 249-262.
- [29] Witten, I. H., and Frank, E. 2005. *Data Mining: Practical machine learning tools and techniques*. Morgan Kaufman, San Francisco, CA.