Attentional Competition in Genuine Classrooms: Analysis of the Classroom Visual Environment

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Abstract

Prior research in laboratory settings suggests highly decorated learning environments reduce attention to instructional tasks hampering learning. However, systematic research examining how the visual environment relates to children's on-task behavior in genuine learning environments is more rare. Thus, it is unknown whether prior laboratory findings can be extended to genuine classrooms and what specific aspects of the visual environment might pose a challenge for children's attention regulation and learning. This study aims to (1) provide a nuanced examination of specific elements of the classroom visual environment (e.g., visual noise, quantity of posters, color darkness, color variability, adherence to general design principles) by analyzing panoramic photographs of 58 classrooms, and (2) investigate whether specific elements of the visual environment are related to rates of on-task behavior. Results indicate on-task behavior *declined* in classrooms containing greater visual noise.

Keywords: Classroom Design; Attention; On-task behavior; Off-task behavior; Visual Distraction

Introduction

In the United States, children spend on average 1,195 hours in a classroom each year (U.S. Department of Education, 2007-2008). Given the substantial amount of time children spend in classrooms, it is important to consider how learning environments can be designed to optimize engagement and learning. Prior research has documented that the physical setting and design of the space may influence attention and learning. Yet, systematic research examining the effect of the classroom *visual environment* on attention and learning has been limited.

Recently, the role of the classroom visual environment on attention and learning has garnered interest from researchers (Barrett, Zhang, Moffat, & Kobbacy, 2013; Barrett, Davies, Zhang, & Barrett, 2015; Fisher, Godwin, Seltman, 2014; Godwin et al., 2016; Hanley et al., 2017; Stern-Ellran, Zilcha-Mano, Sebba, & Binnun, 2016). Elementary school classrooms frequently contain highly decorated visual environments with elaborate themes, bulletin boards, and artwork. These installations are intended to transform classrooms into stimulating learning environments for students (see Figure 1). However, overabundance of sensory stimulation has led some to call the classroom environment a "cacophony of imagery" (Tarr, 2004, p. 1) resulting in "visual bombardment" (Bullard, 2010, p. 110).

Highly decorated visual environments may also inadvertently tax children's developing attention regulation (e.g., Fisher & Kloos, 2016; Ruff & Rothbart, 2001); indeed, we may be placing individuals with the greatest vulnerability to distraction, young children, in the most distracting environments (Fisher et al. 2014). According to the dual model of attention regulation, attention regulation is driven by both exogenous and endogenous factors. Exogenous regulation of attention is considered largely an automatic process, influenced by the characteristics of the stimulus (e.g., brightness, novelty, saliency, motion); conversely, endogenously regulated attention is directed internally and voluntarily based on the individuals' interests and goals (e.g., Jonides, 1981; Miller & Cohen, 2001; Posner, 1980; Pashler, Johnston, & Ruthruff, 2001; Schneider & Shiffrin, 1977). The developmental time course for these two modes of attention regulation differs: Exogenous regulation of attention is present since infancy, whereas endogenous regulation develops gradually into adolescence (Diamond, 2002; Luna, 2009; Posner & Rothbart, 2007). Highly decorated visual environments may result in attentional competition (e.g., between elements of classroom design and instructional activities) that young children may struggle to resolve via endogenous mechanisms of attention regulation.

Figure 1: Example classroom from Google Images

Until recently it was an open question as to whether these design choices influence children's attention allocation and learning outcomes. In the first systematic experimental investigation into this question Fisher, Godwin, and Seltman (2014) brought kindergarten children into a laboratory classroom where they were able to experimentally manipulate (within-subjects) the classroom visual environment by introducing or removing visual displays (e.g., charts, posters, artwork). The authors hypothesized the streamlined version of the classroom would result in greater time on-task and higher learning gains than the highly decorated version of the classroom: As discussed above, attention regulation is still undergoing development when children begin formal schooling (e.g., Fisher & Kloos, 2016; Ruff & Rothbart, 2001) and consequently, a highly decorated classroom may pose a challenge for children's still maturing attention regulation skills. In line with these predictions, Fisher et al. found children spent more time off-task and obtained lower learning outcomes when the learning environment was decorated than when the visual environment was streamlined. Research suggests attentional competition imposed by such decorated learning environments might be heightened for children with special needs, for example children who have Autism (Hanley et al., 2017).

Whether the detrimental effects of decorated learning environments on children's attention allocation extend beyond the laboratory and into genuine classrooms is unknown; however, there is some evidence to suggest specific features of the classroom visual environment are associated with student *learning outcomes* in real classrooms. Barrett and colleagues (2013) found that visual complexity and color were negatively related to student achievement measures – an unexpected finding given the author's original hypothesis that greater stimulation would be more advantageous for learning. Currently, it is unknown what the optimal amount of visual stimulation is in learning environments and whether this level of stimulation changes as a function of development. It is possible that some moderate amount of color and visual complexity in the visual environment is optimal -- providing inviting spaces for learning without inducing competition for attention. There is preliminary evidence to support this idea as Barrett et al. (2015) found evidence of a curvilinear relationship between color and visual complexity and student achievement. However, since attention was not a focal component of Barrett's work it is unknown whether the mechanism by which design influences learning is by shaping how children allocate their attention.

Systematic research is needed to better understand the relationship between classroom design and attention in order to create more optimal learning environments. The present work aims to (1) extend prior laboratory work to real classrooms to examine whether children's patterns of attention allocation are related to variability in the visual environments of real classrooms, and (2) provide a more nuanced examination of specific aspects of the visual environment and basic design principles that may influence children's on-task behavior in elementary classrooms.

Method

Participants

Fifty-eight elementary school classrooms participated including: 12 Kindergarten, 13 first-grade, 13 second-grade, 5 third-grade, 13 fourth-grade classrooms, as well as 2 mixed grade classrooms (children 6-9 years of age). Inclusion of primary as well as upper elementary grade levels extends prior work by assessing whether prior laboratory findings can be generalized across grade-levels.

At each observation session, all children present in the participating classroom were observed. The average number of children observed within a single observation session was 18.34 children (SD = 3.14) and on average 51% were female and 49% were male. Participating classrooms were from schools in and around a medium sized city in the northeastern Unites States and included public charter and private schools. Due to the nature of the Institutional Review Board (IRB), no student demographic information could be collected. However, in an effort to provide context for the sample, basic descriptive statistics for the communities and schools the sample was drawn from are provided below: Median household income[1] ranged from \$7,890 to \$72,500 (M = \$43,400, SD = \$20,229). Data regarding student eligibility for free and reduced lunch[2] was available for 5 of 14 participating schools. Mean percentage of eligible students was 74% (SD = 12%, range: 63%-89%). School enrollment data by race/ethnicity[2] was available for 13 of 14 participating schools. Mean enrollment data by race/ethnicity was as follows: American Indian/Alaska Native <1% (range: 0%-0.52%), Asian or Asian/Pacific Islander 2.39% (range: 0%-10.51%), Hispanic 1.63% (range: 0%-5.49%), Black 31.66% (range: 0.36%-96.14%), White 57.54% (range: 2.15%-99.27%), Hawaiian Nat./Pacific Isl. <1% (range: 0%-0.63%), Two or more races 6.62% (range: 0%-15.91%). The data reported here are novel and not reported elsewhere; a subset of these classrooms were part of a larger parent study examining children's patterns of attention allocation in genuine learning settings – those data are reported elsewhere (Godwin et al., 2016; Godwin et al., under review).

[1] Data obtained from https://www.niche.com
[2] Data obtained from https://nces.ed.gov/ccd/elsi/

Design and Procedure

Coding Behavior Each classroom was observed twice in the fall. Two observations were undertaken to gain a more reliable estimate of children's on and off-task behavior. Due to scheduling constraints one of the 58 classrooms had only a single observation session. The average delay between observation sessions was 3.6 days (Range: 1-10). Each observation session lasted for approximately 1 hour.

Research assistants were trained using the Baker-Rodrigo Observation Method Protocol (BROMP; Ocumpaugh, Baker, & Rodrigo, 2015) which is employed in field settings to code observational data. Research assistants completed extensive training, which included practice sessions coding videotapes as well as live observations. Inter-rater reliability was established prior to beginning the study. Kappa values ranged from 0.79 to 0.84, which exceeds the .75 level noted as an "excellent" level of agreement for observations in field settings (Fleiss, 1981).

Research assistants collected the observational data using the HART app for Android handheld computers (Baker et al., 2012). Research assistants used a round-robin coding strategy in which each child is observed individually. The order in which children are observed is determined at the beginning of each observation session. The round-robin coding strategy prevents research assistants from focusing only on salient behaviors. Each child is observed until the first clearly identifiable behavior is observed or until 20s elapses (whichever occurs first). Once the first unambiguous behavior is coded, the research assistant proceeds to code the next child in the rotation and a new 20s observation period begins. This process was repeated for the entire observation so that each child is observed multiple times throughout the session (M=16.2 observations per child, per session) resulting in 34,289 total observations. No student identifying information was collected; thus, it was not possible to link observations across sessions. Consequently, students within each session were treated as unique. Note that treating the children within each session as a different set of students artificially inflates statistical power. There is no known way to correct for an unknown number of participants being tested more than once. In a related study (Godwin et al., 2016) that used a similar design and thus faced a similar issue (although to a greater extent since they had 6 observations per classroom), to correct for this problem the conventionally accepted alpha-level (.05) was divided by the number of observations. In the present study, we follow a similar strategy and report the outcomes of the analyses with regards to both the conventional criterion of significance (alpha = .05) and a more conservative alpha-level (.05 divided by 2 observations, corrected alpha-level of .025).

Observers first classified children's behavior as either on or off-task. Direction of gaze was used as the primary determinant of whether a behavior was on or off-task but research assistants also utilized contextual information (e.g., teacher instructions). Children were considered on-task if they were looking at the teacher (or aid), the instructional activity, or instructional materials. Off-task behavior was noted if the child was looking anywhere else and the source of the distraction was recorded. Six sources of off-task behavior were coded: (1) *self-distraction*, (2) *peer distraction*, (3) *environmental distractions* (e.g., looking at classroom displays not part of the instructional activity), (4) inappropriate use of *school supplies*, (5) *walking* around the classroom when not instructed to do so, and (6) *other distractions* (off-task behaviors that did not fit into the aforementioned categories as well as behaviors that were clearly off-task but the source of the distraction could not be clearly identified). Note observers were trained to reposition themselves within the classroom to disambiguate behaviors whenever possible; however, observers were also instructed to be unobtrusive. Consequently, relocating was not always possible due to the position of a specific child or due to concerns that relocating would disrupt ongoing instruction. The category *unknown* was also employed if the child was not in the room (e.g., they had gone to the restroom) or if the observer could not determine if the behavior was on-task or off-task. These categories were mutually exclusive.

In order to be as non-intrusive as possible, researchers observed children using peripheral vision and side-glances. This approach has been used successfully in prior research with elementary (Godwin et al. 2016), middle, and high school students (Baker, 2007; Baker, D'Mello, Rodrigo, & Grasser, 2010; Ocumpaugh et al. 2015).

The type of instructional format was also recorded as prior research has documented that instructional format is related to elementary students' patterns of attention allocation (Godwin et al., 2016). Four types of instructional format were coded: individual work (i.e., work that students are completing independently such as completing a worksheet), small group work (i.e., work that occurs with partners, small groups, or in centers in which groups are working independently of other groups), whole group while working at desks (i.e., when the class is seated at their desks and the teacher is providing instruction to the entire class), and whole group while working on the carpet (when the class is seated on the carpet or floor and the teacher is providing instruction to the entire class).

Coding classroom photographs High-resolution panoramic photographs were taken of each classroom to document the visual surfaces of the classroom environment. Photographs were taken with a Canon EOS Rebel T2i digital camera mounted on a Gigapan– a commercially available robotic platform used to capture high-resolution panoramic images. Photographs were taken within 2 months of the date in which the classroom observation occurred (1.8 months before to 1.6 months after).

Classroom photographs were coded by trained research assistants to assess the quality of the visual environment including: *Visual Noise*, "*Flats*" or the quantity of visual displays, "*Design Composition"* or adherence to basic design principles, *Color Darkness*, and *Color Variety*. Details regarding each variable are provided below.

Visual Noise is an index of the overall degree of visual distractions present in the classroom based on the amount of decorations and level of general clutter. Each classroom photograph was rated on a 5-point likert scale for the presence of decorations/displays (e.g., charts, posters, maps, art work, ceiling displays, etc.) and the degree of clutter (e.g., general organization, storage on top of furniture, open storage, window sills containing clutter or utilized as storage, clutter on the floor) with 1 indicating low levels of decoration/clutter and 5 indicating high levels of decoration/clutter present in the classroom. The decoration and clutter scores were averaged together to create a *Visual Noise* score, to capture the degree of overall visual clutter. A hypothesis-blind coder was trained to code the photographs by the first author. Training consisted of verbal instructions, reviewing worked examples, and completing a training set of 40 photographs to establish inter-rater agreement. The training set was coded by the first author of this paper and a hypothesis blind researcher. Cohen's kappa was calculated for each subscale and for each subscale a substantial level of agreement was obtained (Landis & Koch, 1977); Weighted Cohen's Kappa: decorations/displays=.69, $p<.0001$; degree of clutter=.65, $p<.0001$). Data from the hypothesis blind coder was used for the analysis.

Flats provide a more nuanced and objective measure of visual noise by indexing the quantity of wall space covered by displays or "flats". As discussed previously, prior laboratory research (Fisher et al., 2014) indicates learning environments that are highly decorated with charts, posters, and art work (i.e., flats) can reduce children's on-task behavior and diminish learning compared to learning environments that are visually streamlined. However, it is currently unknown whether these effects scale to real classrooms. Thus, we are interested in examining whether the quantity of wall space covered by displays in real classrooms was related to children's patterns of attention allocation. The measure of *Flats* was obtained by tracing the decorated items in Google Sketch Up v8.0.14345 on a layer. The surface area was calculated for the flat items traced and for the whole wall. The two numbers were used to calculate a percentage of the wall covered. We measured the height and length of the wall in centimeters with a Bosch DLR 130 laser distance measurer. We calculated the measure for the wall in square centimeters and multiplied it by the ratio of flats to estimate the surface in square centimeters for flats.

We hypothesized that the quantity of materials displayed in real classrooms would be an important factor in determining children's patterns of attention allocation, but it is also possible the manner in which these materials are displayed is consequential. For example, classrooms that contain large quantities of flats displayed in accordance with general design guidelines may be less distracting than displays that violate basic design principles, thus posing a heavier burden on children's attention. *Design Composition* is a composite variable that assessed the degree to which aspects of the classroom environment align with general design guidelines namely principles of orientation, alignment, and grouping (e.g., Lidwell, Butler, & Holden, 2003; Müller-Brockmann, 1981; Weinschenk, 2011). Coding of the classroom photographs for alignment with the design guidelines was completed by a research assistant trained in design. Details regarding each design guideline are provided below.

Orientation was scored as a binary variable in which a score of 1 indicates the orientation of the displays are uniform (i.e., all displays are in the same direction) and 0 indicates the displays were oriented differently from one another. Each wall was scored separately and the average of the walls was used as the index for the classroom. Alignment was scored as a binary variable in which a score of 1 indicates the displays were aligned in a grid pattern and 0 indicates the alignment of the displays was haphazard. Each wall was individually coded for alignment and the average of the walls was calculated and used as the index of alignment for the classroom. Grouping was also scored as a binary variable in which a score of 1 indicates that similar displays and furniture are placed together, and a score of 0 reflects that groupings contain dissimilar items; for example, a bulletin board with many disparate posters (e.g., math, spelling, rules of conduct). The design variables were standardized using Z-scores and averaged together to create the composite variable *Design Composition.*

Color Darkness and Variability were included in the present study as prior research found a negative association between color and achievement (Barrett et al., 2013); however, subsequent work suggested the relationship between color and achievement may be curvilinear (Barrett et al., 2015). *Color Darkness* was assessed following Barrett Zhang, Davies, and Barrett's (2015) color brightness guidelines. Coders used a 5-point likert scale, which ranged from 1 to 5 indicating lightest to darkest (see scoring from Barrett et al., 2015 for additional details). Similarly, *Color Variability* was assessed on a 5-point scale in which a score of 1 indicates no variation and 5 indicates great variation in color. The following seven classroom elements were scored for both color darkness and variability: floor, walls, desks, chairs, other furniture, wall displays, and ceiling displays. The scores for each classroom element were averaged together to create the variables *Color Darkness and Color Variability.* A hypothesis-blind coder was trained to code the photographs for *Color Variability and Color Darkness* following Barrett and colleagues coding scheme to the best of our ability. Training consisted of verbal instructions, reviewing worked examples, and completing the training set of 40 photographs to establish inter-rater agreement. The training set was coded by the first author of this paper and the hypothesis blind researcher. Results regarding *Color Variability* and *Color Darkness* are forthcoming.

Results

On-Task Behavior and Common Off-Task Behaviors

In the present study children were largely on-task; 72.7% of all coded behaviors were categorized as on-task, which is in line with prior research (e.g., Godwin et al. 2016; Karweit &

Slavin, 1981). Although children were largely on-task, off-task behaviors did occur (27.3%) with *Peer Distractions* (46.4%) comprising the most common source of off-task behavior. *Environmental Distractions* (12.9%), *Self Distractions* (11.3%), *Supplies* (12.5%) and *Other* off-task (13.2%) behaviors occurred regularly, although less frequently than *Peer Distractions*. *Walking* occurred infrequently (3.6%). For the analyses examining the relationship between classroom design and patterns of attention allocation, we elected to focus on models predicting rates of *on-task* behavior to ensure sufficient power given that on-task behavior is more frequent than any specific type of off-task behavior.

Classroom Photograph Analysis Preliminary Results

A series of generalized linear models fit by pseudo likelihood method were conducted to assess whether specific components of the visual environment tended to be associated with rates of on-task behavior controlling for student gender, grade-level (Kindergarten, First-grade, Second-grade, Third-grade, Fourth-grade, and Mixed grade classrooms), as well as instructional format (individual, small group, whole carpet, whole desk). Proc GLIMMIX and the Kenward-Roger correction for degrees of freedom were employed in SAS (9.4). All models include a random intercept at both the student level and session level. Preliminary results for models in which *Visual Noise*, *Flats*, and *Design Composition* are predictors of on-task behavior are presented below.

Model 1: Visual Noise as a Predictor of On-task Behavior Recall that *Visual Noise* reflects both the quantity of decorations as well as the general amount of clutter present within the classroom. On average, classrooms tended to contain relatively high amounts of *Visual Noise* (M = 3.73, SD = .98, range: 1.5 to 5.0). In Model 1 fraction of on-task behavior was entered as the dependent variable and four variables were entered as predictors: visual noise, gender, grade-level, and instructional format. Random intercepts were included at the student and session level (X^2 = 286.58, p < .0001). In this model, *Visual Noise* was found to be a significant predictor of students' on-task behavior controlling for gender, grade-level, and instructional format at the conventional alpha-level (.05) and a marginally significant predictor at the more conservative alpha-level (.025); B = -.11, t(109.8) = -2.08, p = .04 (see Table 1). For every 1 SD increase in *Visual Noise* the odds of being on-task decrease by 10.4% (100*(1-exp(-0.11))).

In order to ascertain whether specific qualities of the visual environment or design features are predictive of students' patterns of attention allocation, we examine whether the quantity of flats and design composition were predictive of students' on-task behavior. Note that models for color variability and color darkness are forthcoming.

Table 1. Estimates and associated p-values for generalized linear models predicting fraction of on-task behavior controlling for gender, grade-level and instructional format. Random intercepts included at the student and session level.

		Estimates	***p***
Models Predicting On-task Behavior	Visual Noise	-.11	.04
	Flats	-.08	.09
	Design Comp.	-.03	.64

Model 2: Flats as a Predictor of On-task Behavior In Model 2, we examined whether the quantity of flats, displays present within a classroom, is predictive of students on-task behavior. On average, participating classrooms tended to cover almost one quarter of a given wall with flats (M = 23.26, SD = 7.02); however, there was considerable variability with some classrooms only utilizing 5% of the space on a given wall and other classrooms covering nearly 40% of the space on a given wall with displays and posters (Flats range: 5.19 to 39.35). In this model, flats, gender, grade-level, and instructional format were entered as predictors of the fraction of students' on-task behavior. For the analysis, the variable flats was transformed into a z-score. Random intercepts were also included at the student and session level (X^2 = 286.53, p < .0001). Controlling for gender, grade-level, and instructional format, flats was found to be a marginally significant predictor of students' on-task behavior at the conventional alpha-level (.05) but not at a more conservative alpha-level (.025); B = -0.08, t(106.7) = -1.71, p = .09 (see Table 1). For every 1 SD increase in flats the odds of being on-task decrease by 7.7% (100*(1-exp(-0.08))).

Model 3: Design Composition as a Predictor of On-task Behavior *Design Composition* assessed the extent to which the classroom environment is consistent with general design guidelines including the principles of orientation, alignment, and grouping. In general, classrooms tended to adhere to the principles of orientation (M = .82, SD = .22) and grouping (M = .90, SD = .17); however, adherence to the design principle of alignment was not quite as common (M = .61, SD = .29). For the present analysis these variables were converted into z-scores and averaged together to create a composite variable, design composition. Design composition, gender, grade-level, and instructional format were entered as predictors of the fraction of students' on-task behavior. Random intercepts were also included at the student level and session level (X^2 = 286.60, p < .0001). Controlling for gender, grade-level, and instructional format, design composition was not a significant predictor of students' on-task behavior at both the more conservative alpha-level (.025) and the conventional alpha-level (.05); B = -.03, t(108.5) = -.47, p = .64.

Discussion

The results from the present study extend our prior understanding of how the design of the classroom visual environment can influence students' attention allocation. The present work speaks to the generalizability of prior laboratory work and suggests that in genuine classrooms, greater amounts of visual decorations and clutter are negatively related to overall rates of on-task behavior. In a sample of fifty-eight elementary school classrooms we found that children exhibit *less* on task-behavior in classrooms containing more visual noise. A similar trend was observed for classrooms that had greater amounts of displays (flats), although this predictor became non-significant at the more conservative alpha-level. Thus, children's patterns of attention allocation were related to variability in the features of the visual environment of *real* classrooms.

These findings corroborate prior laboratory work (Fisher et al., 2014; Hanley et al., 2017; Stern-Ellran et al., 2016) and indicate that in genuine classrooms decorated visual environments are associated with reductions in on-task behavior. As visual noise and quantity of flats increased, the tendency for children to maintain attention to the instructional activity decreased.

The present study included a wider age range of students than found in prior laboratory studies which focused predominately on the effects of the visual environment on young children[3] (e.g., Stern-Ellran et al., 2016; Fisher et al., 2014). In the present study, children from five grade levels (K-4) were recruited. Even when controlling for grade-level, the visual environment was predictive of students' rates of on-task behavior pointing to the visual environment as a potential source of distraction not only among young children, but also across elementary school.

One possibility put forth in the prior literature is that both low and high levels of stimulation from the visual environment *may* be suboptimal. Indeed, prior research found evidence of a curvilinear relationship between color variability and *academic achievement* (Barrett et al., 2015). Future analyses will assess the possibility that the relationship between color variability and *attention* may be curvilinear as well.

Future research is needed to examine how best to provide stimulation without overwhelming student's attentional capacity across different points in development. The present work makes an important contribution to the field and begins to provide a foundation for creating research based design principles educators and designers can utilize to create more optimal learning environments.

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[3]Hanley et al. (2017) included a wider age range of participants, but the focus of their work was on the potential impact of the visual environment on atypical populations.

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