A Meta-Analysis of Variables Affecting Learning from Dynamic versus Static Visualizations: Implications for Cognitive Load Theory

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Outline

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Meta-Analyses of Dynamic versus Statics

Instructional animation versus static pictures: A meta-analysis

Tim N. Höffler, Detlev Leutner

Abstract

A meta-analysis of 26 primary studies, yielding 76 pair-wise comparisons of dynamic and static visualizations, reveals a medium-sized overall advantage of instructional animations over static pictures. The mean weighted effect size on learning outcome is $d = 0.371$ (95% CI 0.250–0.491). Moderator analyses indicate even more substantial effect sizes when the animation is representational rather than decorative ($d = 0.401$, 95% CI 0.269–0.533), when the animation is highly realistic, e.g., video-based ($d = 0.764$, 95% CI 0.391–1.133), and/or when procedural motor knowledge is to be acquired ($d = 1.064$, 95% CI 0.723–1.405). The results are in line with contemporary theories of cognitive load and multimedia learning, and they have practical implications for instructional design.

$\text{k} = 76, \text{d} = 0.37^{1}$

$\text{k} = 140, \text{g}+ = 0.23^{2}$


Comparing apples and oranges? A critical look at research on learning from statics versus animations

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ABSTRACT

Many of the studies that have compared the instructional effectiveness of static with dynamic images have not controlled all the moderating variables involved. This problem is present not only in instructional pictures concerning the curricular topics (e.g., science, technology, engineering and mathematics: STEM), but also in those depicting extracurricular tasks (e.g., human movement tasks). When factors such as appeal, media, realism, size, and interaction are not tightly controlled between statics and animations, researchers may often be comparing apples with oranges. In this review, we provide a categorization of these confounding variables and offer some possible solutions to generate more tightly controlled studies. Future research could consider these biases and solutions, in order to design more equivalent visualizations. As a result, more conclusive evidence could be obtained identifying the boundary conditions for when static or dynamic images are more suitable for educational purposes, across both curricular and extracurricular tasks.

Seven Biases in Visualization Comparisons

Secondary versus Primary Knowledge

# Predicting Visualization Instructional Effects

<table>
<thead>
<tr>
<th>Theoretical perspective</th>
<th>Rationale</th>
<th>Easier visualization</th>
</tr>
</thead>
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<tr>
<td>Secondary knowledge (STEM)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mental animation&lt;sup&gt;1&lt;/sup&gt;</td>
<td>Hard to infer movements from statics</td>
<td>Dynamic</td>
</tr>
<tr>
<td>Overwhelming processing&lt;sup&gt;2&lt;/sup&gt;</td>
<td>Hard to cope with the pace of dynamic</td>
<td>Statics</td>
</tr>
<tr>
<td>Transient information effect&lt;sup&gt;3&lt;/sup&gt;</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Primary knowledge (Manipulative–procedural)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unnaturalness</td>
<td>Hard to cope with static (paused) or irregular motion</td>
<td>Dynamic</td>
</tr>
</tbody>
</table>

Gender Imbalance in Instructional Dynamic Versus Static Visualizations: a Meta-analysis

Juan C. Castro-Alonso, Mona Wong, Olusola O. Adesope, Paul Ayres, Fred Paas

Abstract

Studies comparing the instructional effectiveness of dynamic versus static visualizations have produced mixed results. In this work, we investigated whether gender imbalance in the participant samples of these studies may have contributed to the mixed results. We conducted a meta-analysis of randomized experiments in which groups of students learning through dynamic visualizations were compared to groups receiving static visualizations. Our sample focused on tasks that could be categorized as either biologically secondary tasks (science, technology, engineering, and mathematics: STEM) or biologically primary tasks (manipulative-procedural). The meta-analysis of 46 studies (82 effect sizes and 5474 participants) revealed an overall small-sized effect ($g^+ = 0.23$) showing that dynamic visualizations were more effective than static visualizations. Regarding potential moderators, we observed that gender was influential: the dynamic visualizations were more effective on samples with less females and more males ($g^+ = 0.36$). We also observed that educational level, learning domain, media compared, and reporting reliability measures moderated the results. We concluded that because many visualization studies have used samples with a gender imbalance, this may be a significant factor in explaining why instructional dynamic and static visualizations seem to vary in their effectiveness. Our findings also support considering the gender variable in research about cognitive load theory and instructional visualizations.

Keywords Dynamic and static visualization · Gender and spatial ability · STEM and manipulative-procedural tasks · Cognitive load theory · Meta-analysis

Outreach for the Meta-Analysis

Gender and visuospatial processing in multimedia STEM learning

Multimedia learning research comparing effectiveness of static and dynamic visualizations in STEM disciplines has revealed mixed results, because it has ignored gender differences among its participants. Although research is suggestive for gender differences in visuospatial processing, the future to report gender compositions in every study makes it impossible to draw conclusions on the moderating effects of these differences on learning. Dr. Juan Cristóbal Castro-Alonso, an educational psychology researcher with focus on multimedia at Universidad de Chile, has led a meta-analysis to establish whether gender imbalance exists in research on learning through visualization and how it might be affecting study outcomes.

COGNITIVE RESOURCES ARE LIMITED
Dr. Castro-Alonso and his collaborators in Australia and the Netherlands have previously noted that different types of instructional materials might be better at supporting the learning of different types of tasks. They have argued that these differences are related to the functioning of specific neural systems that underpin the acquisition of particular skills, and are also mediated by the amount of mental resources required to process the specific multimedia materials.

For example, with dynamic materials like videos or animations, the learner must often process more information due to the transient nature of dynamic presentations. Despite this concern, dynamic materials appear to be better at supporting manipulative tasks, i.e., tasks that require physical action (like selecting objects on a screen). In contrast, static images seem more effective at supporting learning for non-manipulative tasks, i.e., tasks that are more cognitive than physical (like solving abstract symbol problems).

This difference can be explained by cognitive load theory, which proposes that a learner has a limited amount of cognitive resources (working memory) and any loss of this capacity to tasks that do not demand support learning or require more processing is detrimental to the overall learning effectiveness. If more cognitive resources are spent on processing teaching materials, there is often not enough left over to efficiently complete the task at hand.

MIRROR NEURONS TO THE RESCUE
While an evolutionary approach to cognitive load theory, it has been suggested that dynamic images might be able to help support learning tasks that require movement because manipulative tasks utilized as a primary skill in humans and are therefore likely processed by a separate system (for example, motor neurons). This specialized circuit allows learning of manipulative skills from transient images without exerting extra effort. In contrast, learning a new manipulative skill from a moving image requires effort to relate the information before attempting the task. As such, by the time the student attempts the task, processing learning materials has already diminished their cognitive resources. In this case, the use of dynamic multimedia may hinder rather than support student performance.

BUT NOT SO FAST
A plausible theoretical framework for understanding, Dr. Castro-Alonso points out that the data on learning from visuals is complex and difficult to interpret with any degree of certainty. First, it remains unclear whether differences between learning efficacy from static versus dynamic images in fact exist. Studies that report these differences often neglect to control for many potentially moderating variables that relate to the materials themselves. Some of these factors are, gender, socio-economic status, age, and interaction. Second, participants’ variables—gender, visuospatial abilities, and attractiveness of learning materials—were not considered when studies were pooled together. They also looked to identify the factors that affect any existing differences.

A meta-analysis is a type of study that compiles all studies that aim to answer a specific question. Studies are selected on pre-specified inclusion and exclusion criteria, and then combined to identify a common effect. Dr. Castro-Alonso and colleagues aimed to examine whether differences in learning efficacy between static visuospatial images and dynamic visuospatial images were comparable. A group learning from static images and a group learning from dynamic visualizations. Studies were included if they reported measurable outcomes that could be used in statistical analysis and where they included tasks that could
Method

Selection Criteria

1. Published 1990–2017
2. Written in English
3. Peer-reviewed journal article
4. Compared, in a between-subjects design, the learning effects of at least one dynamic visualization with at least one static visualization
5. Depicted STEM or manipulative–procedural task
6. Experiments where participants were randomly assigned to groups
7. Only school or university samples
8. Reported measurable outcomes of performance (e.g., retention and transfer tests)
9. Included data to calculate effect sizes
10. Reported the gender ratio for the total sample
Method

Flow Diagram
Results

Overall $g^+ = 0.23$

Dynamic over statics

Results

No differences between STEM and manipulative-procedural tasks
STEM (secondary) tasks: *mental animation* perspective
Manipulative–procedural (primary) tasks: *unnaturalness* perspective

Significant heterogeneity between the effect sizes
Participants characteristics
Intervention characteristics

Results

Participant Characteristics: Gender

Median split

<60% females  \( N = 2,932, k = 35 \)  \( g^+ = 0.36 \)

\( \geq 60\% \) females  \( N = 2,542, k = 47 \)  \( g^+ = 0.07 \)

With fewer females (and more males), more advantage of dynamic over statics

Males may benefit more from dynamic visualizations than females
Results

Participant Characteristics: Spatial Ability (Visuospatial Processing)

Only 23% \((k = 19)\) of the effects measured a spatial variable (caution).

Mostly mental folding (spatial visualization). Also mental rotation.

Usually, the ability helped learning from both dynamic and static visualizations.

Results

Participant Characteristics: Educational Level

Elementary school   \( N = 199, k = 7 \) \( g^+ = 0.53 \)

Middle school      \( N = 423, k = 8 \) \( g^+ = 0.44 \)

University          \( N = 4,650, k = 63 \) \( g^+ = 0.19 \)

Decline in the effectiveness of dynamic over static visualizations as the students develop
Unpublished Results

Participant Characteristics: University Discipline

<table>
<thead>
<tr>
<th>Discipline</th>
<th>k</th>
<th>$g^+$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education</td>
<td>5</td>
<td>0.32</td>
</tr>
<tr>
<td>Mixed</td>
<td>4</td>
<td>0.26</td>
</tr>
<tr>
<td>Psychology</td>
<td>11</td>
<td>-0.09</td>
</tr>
</tbody>
</table>
## Results

### Intervention Characteristics: Learning Domain

**STEM**

<table>
<thead>
<tr>
<th>Area</th>
<th>N</th>
<th>k</th>
<th>g+</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geology and other sciences</td>
<td>565</td>
<td>11</td>
<td>0.38</td>
</tr>
<tr>
<td>Biology and medicine</td>
<td>1,866</td>
<td>11</td>
<td>0.27</td>
</tr>
<tr>
<td>Technology, engineering, and mathematics</td>
<td>932</td>
<td>15</td>
<td>0.15</td>
</tr>
</tbody>
</table>

**Manipulative–Procedural**

<table>
<thead>
<tr>
<th>Area</th>
<th>N</th>
<th>k</th>
<th>g+</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nonsyllabi</td>
<td>571</td>
<td>14</td>
<td>0.34</td>
</tr>
<tr>
<td>Syllabi</td>
<td>523</td>
<td>8</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Unpublished Results

Intervention Characteristics: Duration of Experimental Sessions

< 60 minutes  \( k = 20 \)  \( g^+ = 0.43 \)

≥ 60 minutes  \( k = 25 \)  \( g^+ = 0.22 \)
Conclusions and Implications

Dynamic visualizations less effective for:
Technology, engineering, and mathematics secondary tasks
Syllabi primary tasks

Dynamic visualizations more effective for:
Younger students
Males

Acknowledge the gender variable
Report gender composition (total and per group)
Include equal gender composition per groups
Employ the same number of women and men

Coming Soon!

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