Preparing for the Long Tail of Teaching and Learning Tools

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Abstract: In this paper we apply the concept of "the long tail" (Anderson, 2006) to teaching and learning tools to discuss how the limitations of current Learning Management Systems (LMS) can be overcome to allow instructors to customize the technology they use to support their own classroom practices. Learning tools in the long tail are those that are widely used by a subset of instructors - tools specific to large courses or tools specific to a particular field, and tools that are only used in a few courses or a single course. Using several examples from courses taught on our campus, we show how to put extensibility in the hands of the instructors to create knowledge-age learning technologies that are customizable, interactive and controlled by users.

Introduction

Increasingly, learning management systems (LMS) such as Blackboard or Sakai are seen as one of the most essential Enterprise Services in education. A recent survey of 115 American universities has shown that 89% of students reported that they had taken a course that used a LMS (Smith, Salaway, & Caruso, 2009). In addition, a 2009 survey of US school district administrators estimated that more than a million k-12 students took online courses in the school year 2007-2008 (Picciano & Seaman, 2009). That these systems are basic infrastructure for learning in higher education is already a fact; that they are as common in K-12 education may also soon be true (see Means, Toyama, Murphy, Bakai & Jones, 2009). Yet what do we know about using LMS well for teaching and learning? How can we help teachers to incorporate the promise of Web 2.0 technologies into their classrooms? In this paper, we examine the trends in the evolution of learning management systems and how those systems are currently being used in higher education. We then propose how learning management systems must change by leveraging the "the long tail" (Anderson, 2006) of teaching and learning tools. These suggestions apply to higher education specifically, but also provide guidelines for development and use that may ease the transition as LMS use permeates K-12 education.

Background

Few other campus enterprise systems have the requirements of 24x7 availability, with the ability to scale to support over 10,000 simultaneous users during peak loads. On many campuses, learning management systems must run for months without allowing for an outage to perform major software upgrades. These requirements lead to a very careful and conservative approach to upgrading or changing the LMS software in the middle of a semester. This trend is coupled with increasing penetration of the LMS system as measured by the percentage of students and faculty who are using the LMS (Smith, Salaway, & Caruso, 2009). On our own campus, the annual IT survey shows that 99% of students and 81% of faculty have used our LMS for at least one course in the past year (Lonn & Teasley, 2009).

Because LMS use has become so pervasive in higher education, we have an opportunity to analyze how the average instructor uses these systems across many different subjects. Most analyses of LMS use (Hanson & Robson, 2004; West, Waddoups, & Graham, 2007) point to a distribution that follows the "long tail" typically found in analyses of most online systems (Anderson, 2004). Specifically, the long tail refers to the statistical phenomenon of a power law or Pareto distribution where few items comprise the most use but there is a long tail of many items used with a much lower frequency. This distribution is clearly seen with the use of tools available within LMS, where a few tools are heavily used then usage drops off dramatically after five or six core tools. Overall, document management and broadcast-oriented communication tools (Content Sharing, Assignments, Announcements, Schedule, and Syllabus) comprise 95% of all user actions (Lonn & Teasley, 2009; Hanson & Robson, 2004). By contrast, the tools that are more interactive (Chat, Discussion, and Wiki) are not used as much. While research coming from the Learning Sciences would have much add to the current literature addressing the relative value of teaching with one tool or another, in this paper we leave this to others and focus here on the fact of current LMS use and how to empower instructors improve their own use of these systems.

The two trends of "LMS as critical infrastructure" and "only a few of the tools are heavily used" leads to the inevitable conclusion that LMS development efforts need to focus on improving the core tools which make up the LMS and spend less effort on the long tail of tools. If the trend was extended to infinity, LMS systems of the future might have exactly seven tools which are never changed or upgraded. While this will insure that the core infrastructure is solid, consistent, and reliable, it will have a tremendous negative impact on the ability for instructors and learners to innovate and find new ways to use technology in education. One
possible path forward is that learning management systems will go "underground" - where in order to experiment with innovative ideas, savvy faculty host their own learning management systems under their desks or perhaps run software on their own ISP account. The "Edupunk" movement (e.g., Kuntz, 2008; Young, 2008) expresses this sentiment in a call-to-arms to reject commercial LMS products. This approach does allow instructors to be innovative, but it adds the burden of maintaining a production infrastructure and saps precious energy away from their teaching efforts. Another extreme reaction to the perceived limitations of current LMS is a call to "teach naked" and reject the use of technology in the classroom altogether (Young, 2009). This, however, seems like a “baby with the bathwater” solution that is not likely to be realistic for today’s students who are considered to be the “net generation” and “tech-savvy Millennials” (Junco & Mastrodicasa, 2007).

Rather that going Edupunk or even teaching naked, we believe the solution to this problem is to add features to LMS systems that allow the core functionality to focus on scalability and stability while allowing innovation at the edges by encouraging more use in the long tail. The key to this approach is that we need to add features to LMS systems so that they can be extended without adding a new feature on to the LMS servers or needing to upgrade the LMS to a new version (Severance, Hardin, & Whyte, 2008). The extensibility needs to be placed in the hands of the instructors rather than only in the hands of the LMS system administrators. This DIY (Do It Yourself) attitude reflects the growing capacity of Web 2.0 applications to put users in control of the content and distribution of materials. In popular culture this DIY capability can be seen in zines, self-publishing, and music re-mixes. We believe this approach can be extended to educational tools as well and fulfill Collins & Halverson’s (2009) call for knowledge-age learning technologies to be customizable, interactive and controlled by users. Only then can we meet both the needs of enterprise production and innovative approaches to teaching and have the best of both worlds. The average instructor who only uses 5-6 core tools has access to a scalable and stable toolset, while the instructor with a new idea is allowed to bring that idea into their class in a few days or weeks of effort - all without destabilizing the LMS production system.

Teaching Tools in the Long Tail
We see learning tools falling into three basic categories: (1) the core 5-10 tools used by nearly every teacher, (2) a set of tools that are widely used by some subset of the teachers - perhaps tools specific to large courses or tools specific to a particular fields like mathematics, and (3) tools that are only used by a few courses or even a tool purpose built for a single course. As we look at the nature of the tools in (1) and compare them to the tools in (3), we are likely to see a transition from tools that "manage" the learning process towards tools that support the learning process. The tools in category (2) are likely a mix of management and learning. This lead to a "long tail" effect where the more learning-oriented tools are in the long-tail. While each individual tool may have a very small "market share" when aggregated together, these long-tail tools may well represent a majority of the overall usage.

The nature of the content-oriented tools (category 1) that are used universally is that their features are likely to be useful to every single instructor, regardless of context or discipline. Hence Category 1 tools comprise the bulk of the distribution of use curve. By contrast, the tools in the second category tend to end up appealing to a smaller but identifiable population of instructors. For example, the CAPA testing system uses LaTeX as its question authoring language and as such naturally appeals fields such as mathematics, chemistry, and physics where most of the instructors with a Ph.D. in those fields learned LaTeX to write and publish papers. Furthermore, CAPA provides a very rich (albeit complex) mechanism for generating many equivalent variations of a problem by altering numeric values randomly. This functionality is very useful for courses where many of the problem sets assigned to students involve numeric calculations. While the CAPA system is very popular for use in first and second year physics, math, and chemistry classes with high-enrollment numbers, it is simply too difficult to learn to ever become widely used for fields like literature or the humanities. This naturally limits the overall number of courses and faculty who will use a CAPA-based system to a small fraction of the market – perhaps less than 2-3% of the overall courses taught. However, for those courses, CAPA is nearly the perfect solution particularly when coupled with the ability to collectively build large question pools across institutions and with some publishers providing CAPA question banks with physics and chemistry textbooks. Since CAPA reflects such a small market share overall, the testing systems provided in mainstream LMS products do not include CAPA-like features and so if you teach a course that needs CAPA – pretty much your only choice is CAPA. For tools in the third category, the potential market share is smaller yet and these tools may have very individualized use that can not necessarily be generalized across disciplines or teaching contexts.

In what follows below, we discuss several examples of category 2 & 3 tools in the long tail and provide detail about the ways in which these tools extend instructors’ use of the standard LMS toolset to meet their unique needs. These examples reflect current teaching practice at the University of Michigan where the enterprise LMS is based on the Sakai open-source LMS.
Student Assessment Management System (SAMS)

In our College of Literature, Science, and Arts (LSA), instructors have access to a CAPA-based system called SAMS (Student Assessment Management System) which is heavily used by the physics, mathematics, and chemistry departments. A requirement unique to SAMS is the need to do extensive data mining across the multiple sections of the same course. Since there are so many sections taught by graduate student instructors in introductory-level courses, SAMS must be able to provide regular reports to course coordinators so that problems encountered by individual student-instructors can be diagnosed and addressed as quickly as possible. In addition, error patterns in problem sets seen across sections provides the main instructor with feedback about which concepts and/or formulas need further elaboration in lecture or additional time in section. For these reasons, SAMS is considered to be a powerful tool in achieving consistently high quality in the teaching of these large-enrollment courses.

Despite its important role in the largest academic unit on campus, SAMS is not in the standard toolset provided by the LMS. Since SAMS is written in PERL and the underlying architecture of the LMS (Sakai) is written in Java and because the requirements for SAMS are so complex (e.g., including rules about to who can see which data and reports), it was never practical to re-write SAMS inside of Sakai. For many years students in classes that used SAMS visited two separate sites for their courses: one course site in the LMS and one course site in SAMS. This was confusing and inconvenient for students and instructors as the SAMS site had its own navigation, login process, and user interface conventions. After an early version of IMS Learning Tools Interoperability was installed in Sakai, we were able to integrate SAMS into Sakai to share identity and roster information with SAMS without any user intervention. We even created a virtual tool in Sakai that made it look like we have built SAMS into Sakai. Instructors can now simply add the SAMS tool to their course site like any built-in Sakai tool. Figure 1 displays the user’s view of SAMS inside of a Sakai course site.

![SAMS Running Within Sakai](image)

**Figure 1.** SAMS Running Within Sakai

Effectively the user experience for both the instructors and students is as if the SAMS tool had been ported into Sakai. There is no need to rewrite any software; we only had to add some integration in SAMS to receive and process the IMS Learning Tools Interoperability launch requests from Sakai. This approach also allows the College of LSA to maintain their strategic access to their data, and to independently upgrade and improve SAMS to meet their needs on their own schedule, unencumbered by the Sakai development or production priorities.

This is an excellent example of how we can develop category 2 tools to meet both the enterprise-wide needs in teaching and learning as well as the school-level needs for teaching and learning. The approach allows reuse of the common capabilities of the enterprise systems while allowing schools or departments to address their own unique needs in focused areas of teaching and learning. An enterprise LMS does not have to be a win-lose proposition across campus.

LectureTools

The LectureTools project provides free tools that support interactivity and enhanced modes of learning during lectures. Like CAPA, LectureTools is most useful for medium to large lecture courses where the teaching staff wants to use support interactions between the instructor and student, and between students as part of the lecture experience. Again we see a situation where the overall population of instructors for whom LectureTools is useful is a fraction of the entire set of courses that are taught at the university. And, here again, the functionality provided by Lecture Tools is not likely to be included into the core functionality of most LMS systems.
Like the SAMS project, we developed a similar virtual tool approach to integrate LectureTools into Sakai. Instructors can add the LectureTools tool to their course site like any other tool built into Sakai. Sakai uses IMS Learning Tools Interoperability to launch and provision course sites in LectureTools, giving students and instructors a seamless user experience from a single course site. Unlike SAMS, the LectureTools service is available to instructors at any university in the US and Canada. These additional schools may or may not use Sakai as their LMS. As IMS Learning Tools Interoperability support is added to all LMS, any school can integrate LectureTools into their campus-wise enterprise LMS systems.

We are currently in the middle of a project integrating LectureTools into Blackboard LMS running at a community college and one commuter campus of the large research university as shown in Figure 2. This project will not only demonstrate the ability of LectureTools to run regardless of which enterprise LMS is in use, but provide a model for allowing cross-campus collaboration in teaching specific courses.

We are using an open-source Blackboard Building Block that supports IMS Learning Tools Interoperability developed by Stephen Vickers of Edinburgh University [www.spvsoftwareproducts.com]. Once the IMS Tools Interoperability integration is completed, the same tool can be used across these three institutions with each set of users experiencing the tool seamlessly integrated into their local LMS user interface. As this pattern is extended, it allows a cross-institutional community to develop where the common thread is the use of the LectureTools platform to augment their lecture experiences. By combining small pools of interest across many campuses, it is possible to end up with a much larger overall demand for a tool or capability. By reducing the integration costs to nearly zero using IMS Learning Tools Interoperability, we increase the likelihood that these cross-institutional communities will form around particular pedagogy or domain specific tools.

In summary, the middle category of tools, Category 2, are those tools that appeal to some subset of the overall teaching space and are very valuable to those teachers and learners. By allowing tools to be scoped at a college or department level or perhaps by bringing a cross-institutional community of interest together, we can match the tool with its level of demand. While the core tools are very focused on the management of learning, the tools in the middle category are generally some combination of "learning management" and content or context specific learning. That is, these more narrow tools will often focus on supporting a particular teaching pedagogy or objective rather than simply moving content around and facilitating students’ access to that content.

**Wisdom of Crowds**

In addition to Category 2 tools that have broad use with a small market segment, there are also tools that only appeal to a very tiny population – perhaps as small as a single instructor (Category 3). The exemplar for this category of tools comes from the book "Wisdom of Crowds" by James Surowiecki (2005). Surowiecki’s book provides examples of how groups of people can have collective intelligence that surpasses the intelligence of any of its individual members. The author uses examples from social science, economics, and game theory to provide a basis to explain the mechanisms that make crowds wise. Often these concepts are explained in the form of a multi-player game where students play a game and then afterwards the class analyzes player behavior to illustrate the point of the exercise.

Often when teachers use the book "Wisdom of Crowds" they play the games with small scraps of paper
and a designated student who "runs" the games. However it is also possible to write computer software that simulates the game and enforces its rules. When computer software is used to run the game, the educational advantage is we can retain the history of player interactions to facilitate a deeper insight into why a player made a move at a particular moment in time. For example, the simplest of the games proposed by Surowiecki has a group guess a numeric value such as the number of jellybeans in a jar. First people independently guess the value and then an average the values is calculated.

This game can be played much more effectively on a computer using student laptops or PDA's rather than averaging numbers on slips of paper. Using technology, students experience first hand how their own guesses may be less accurate that the group mean and the visible display of individual guesses shows more clearly how the collective arrives at the correct answer. To implement the software for the game, we built a simple application that consisted of 118 lines of Python code hosted in the Google Application Engine cloud environment. The tool handled the IMS Basic LTI protocol and implemented the rules of the guessing game. The instructor could reset the game or view the results – the students could simply make a guess. The tool was then integrated into Sakai using IMS LTI and made available in the course site as shown in Figure 3.

![Figure 3. The Number Guessing Application Running in Sakai](image)

The number guessing game was written in about two hours and used in lecture on the same day that it was written. After the game was used for one lecture, there were a few bugs that were found and fixed for use in later lectures. A tech-savvy instructor did the entire process with no impact on, nor involvement of, the enterprise Learning Management System. And since the tool was hosted for free on the Google Application Engine, the instructor did not even have to worry about the infrastructure needed to run the tool.

Another game was written to demonstrate the "Free Rider" problem which occurs when groups are sharing the costs of some shared common good and how people balance the overall group benefit against their own short-term potential for gain. The Free Rider Application had several features that made it very effective for in-class use. First, since the game enforced the rules, it was not necessary to teach anyone how to "run" the game. Also, the game picked five students to play the game automatically. Once the players were selected and the game started, the other students were given a display that updated dynamically as the game was played. So students could learn by playing the game and when they were not playing, they could watch as game masters. The students who were watching could see when players changed strategies and could see the game develop and see which strategies led to the largest payoff.

The games are very simple and easy to write – since they are embedded in a rich LMS, the tools only have to solve the very simple problem related to the lesson at hand. Once these tools are written and put up on Google Application Engine, they could be used by any instructor using the "Wisdom of Crowds" book in their classroom by simply exchanging the IMS Learning Tools Interoperability URL, Key, and Secret.

The number of teachers using "Wisdom of Crowds" in their classroom at any given moment or during any given semester is very small. But at the same time, the effort to develop and the tools is also very small. And the effort involved is small enough that a single teacher might do it simply for his or her own use. Following the example of free applications available in an "apps store" this instructor might also post it on a public site for any other instructor using Surowiecki’s book in their course. This example is toward the far end of the long tail of teaching applications. However, even if it only affects 25 courses across the country in any semester, these tools can be designed to be really helpful for helping students to understand more deeply this material. One could imagine a future where books like "Wisdom of Crowds" might come with already-built games developed and provided by the author or publishers. These games would be ready to plug into the local enterprise LMS using IMS Learning Tools Interoperability.
Required LMS Features to Enable the Long Tail

If we are to address the need to build and use the long tail of learning tools, we must reduce the barriers to plugging new tools into Learning Management Systems. Opening up these systems to outside applications ultimately puts the ability to "add a tool" in the hands of the instructors and allows them to add the new tools in a few clicks and with no intervention on the part of the technical support staff. Sakai is generally designed to give instructors a great deal of control of course content to the instructors. A Basic LTI tool has been developed for Sakai that allows the instructor to easily integrate externally provided tools into Sakai. The primary information needed for to integrate a tool using Basic LTI is a URL, Key, and Secret as shown in Figure 4.

![Figure 4: Setting the URL, Key, and Secret in the Sakai Basic LTI Tool](image)

Since the IMS Basic LTI tool will send roster information to the externally provided tool, it is important to make sure that the instructor is aware that this is happening and approves the release of any identifying information using the configuration options shown in Figure 5.

![Figure 5: Privacy Controls in the Sakai Basic LTI Tool](image)

The IMS Basic LTI specification makes any data that contains identifying information optional. The default in Sakai is not to send any identifying information so the teacher must explicitly agree to send the identifying information to the external tool.

The developers of each LMS will make their own choices about which aspects of LTI are placed in the hands of instructors and which aspects of configuration are only available to system administrators or technical support staff. The Sakai tool allows local customization of the configuration process for LTI, giving system administrators fine-grained access control over which features and capabilities are made available to the Instructors. This allows each institution to progress toward the model of many tools in the long tail at the pace that is comfortable and sustainable for their organization.

Conclusion

We present the case for adding more flexibility to Learning Management Systems and putting that flexibility in the hands of instructors. By making it possible to easily integrate more narrow and learning-centered tools into the LMS without requiring a change in production software or server reboot, we make it far more practical for teachers and students to experiment with new tools and to find the right set of tools for their particular course, supporting a move from accidental to intentional pedagogy (McGee, Carmean & Jafari, 2005). Once the barriers are removed from within the LMS, a market for these externally hosted tools can develop—particularly
in the "middle tail" category where tools have broad applications within a narrow segment of the population. We would hope that many commercial and free tools would be developed and made easily available – resulting in many innovative experiments that can lead to a greatly improved learning experience for students of any age.

Once the barriers for implementation are reduced even further, we envision that tools will be written by teachers or students to solve very focused learning needs. As LMS evolve and interoperability standards improve, many of these tools will be very simple to develop and use because they will be placed in the rich context of a mainstream LMS.

Perhaps the most exciting aspect of enabling teachers to build, exchange, and use thousands or even hundreds of thousands of new tools is how we enable the exploring of an increasingly wide range of new ways to teach. In addition, by opening the enterprise LMSs to virtually unlimited expansion, we have a place to explore emerging approaches such as social learning and the increased use and remixing of content from Open Educational Resources in new and novel ways. In a sense, while we can see an immediate exciting future that this approach enables, the truly exciting innovations are those that we can't even imagine because we are locked into the content-delivery patterns of the current crop of enterprise LMS. Finally, by opening up these opportunities to instructors we simultaneously open them up for students to build, organize, and use tools for their own collaboration and learning purposes.

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Students’ Use of Multiple Strategies for Spatial Problem Solving

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Abstract: In scientific problem solving, spatial thinking is critical for reasoning about spatial relationships in three-dimensions and representing spatial information in diagrams. Despite the importance of spatial thinking, little is known about the underlying cognitive components of spatial thinking and the strategies that students employ to solve spatial problems. Namely, it is unclear whether students employ imagistic reasoning strategies while engaged in spatial thinking. In the present study, we investigate which strategies students use to solve spatial chemistry problems and the relationships between strategy choice, achievement, spatial ability and sex. The results indicate that students employ multiple strategies that include the use of diagrams and heuristics rather than merely relying on imagistic reasoning. Moreover we observed women to employ strategies differently than men after extended instruction in the domain.

Objectives & Theoretical Framework
A recent report from the National Research Council (2006) identifies spatial thinking as a critical component of scientific problem solving and reasoning and advocates for training spatial thinking in the science classroom. Such a call is consistent with the content of science instruction, which often requires students to reason about the three-dimensional relationships of objects and phenomena that are of interest to scientists. For example, chemistry students must learn about the three-dimensional structure of molecules, physics students must learn about the trajectory of projectiles and geology students must learn how geological structures transform over time. Given the prevalence of spatial thinking across the sciences, several researchers have suggested that student aptitude for spatial thinking, as measured by spatial ability psychometrics, predicts their success in science classrooms (Pallrand & Seeber, 1984; Wu & Shah, 2004) and careers (Shea, Lubinski, & Benbow, 2001). Indeed, a host of studies have shown positive correlations between visuo-spatial ability and achievement in several science domains (Carter, LaRussa, & Bodner, 1987; Hegarty & Sims, 1994; Kehnert, Lippa, Montello, Tendick, & Hegarty, 2006). Consequently, these findings have led to claims that sex differences in spatial ability are responsible for sex differences in science achievement (cf. Fogg, 2005).

Despite the importance of visuo-spatial ability, questions remain about the cognitive components of spatial thinking. Typically, spatial thinking in science has referred to imagistic reasoning that includes mental imagery, mental rotation, spatial perspective taking and spatial visualization (Bodner & Guay, 1997). However, practicing scientists and novice students alike successfully solve spatial tasks through the use of external diagrams, models, and computer simulations that may or may not recruit these cognitive processes (Stieff, 2007; Stieff & Raje, 2010; Trafton, Trickett, & Mintz, 2005). Also, a variety of domain-specific analytic algorithms and heuristics have been reported that lead to solutions with little to no use of spatial information given in a spatial problem (Schwartz & Black, 1996; Stieff, 2007). The availability and utility of these alternative strategies raises several questions about the components of spatial thinking and their role in scientific problem solving at all levels.

The present paper aims to identify the underlying cognitive components that comprise spatial thinking in science. We address this aim with four questions: What strategies do problem solvers use to solve tasks that involve spatial thinking? Does strategy choice predict success on a variety of spatial tasks? Do spatial ability and sex predict strategy choice? How does instruction affect strategy choice? We address each of these questions by examining student problem solving in the domain of organic chemistry. Historically, this domain has privileged the role of visuo-spatial ability due to the content of organic chemistry which includes the analysis of three-dimensional relationships within and between molecular structures (Mathewson, 1999; Wu, Kračič, & Soloway, 2001; Wu & Shah, 2004); yet, little is known about what strategies students employ when considering these relationships. Previously, Stieff and Raje (2010) have shown that expert chemists engage in spatial thinking using a variety of domain-specific diagrammatic and analytic strategies as opposed to mental imagery; however, strategy use among chemistry students remains unknown. Here, we build on the work of Stieff and Raje, by examining college students’ choice of problem solving strategies for solving spatial organic chemistry problems to determine the extent to which chemistry students employ multiple strategies and how strategy choice changes with increasing domain knowledge.
Study 1
In Study 1, we designed a strategy choice questionnaire that first asked students to solve 10 canonical organic chemistry assessment tasks. On each task, students were asked to indicate how they solved the problem using a list of known strategies applicable to the task. Previously, Stieff and Raje (2010) documented experts’ use of specific imagistic and non-imagistic strategies for solving organic chemistry problems; the findings of that study were used to populate the list in the present work. The goal of Study 1 was to identify patterns of strategy use among students and any associations between strategy choice, achievement and sex.

Method
Thirty-nine college students (20 males, 19 females) who had completed 6 months of instruction in organic chemistry were asked to complete a chemistry strategy choice questionnaire. The strategy questionnaire consisted of 10 organic chemistry problems that asked participants (1) to identify spatial relationships between molecules or substituents within a molecule and (2) to consider spatial transformations of molecular diagrams. All chemistry problems were scored for correctness using a binary rubric (1 = correct, 0 = incorrect). Participants were also asked to report the strategy they used to solve each chemistry problem by selecting from a list of possible strategies applicable to each problem. Participants were allowed to choose more than one strategy and to write in their own strategy if they believed that none of the choices matched their strategy. Each list of strategies for individual problems was developed in an earlier protocol study conducted by Stieff and Raje (2010); each strategy was coded according to a priori categories of strategy type listed in Table 1. Briefly, categories included those strategies that relied more extensively on reasoning via mental imagery (Spatial-Imagistic), diagrams (Spatial-Diagrammatic), rules and heuristics that operated on spatial information (Spatial-Analytic) and rules and heuristics that operated on non-spatial information (Algorithmic). Participants could also indicate if they knew the answer to a problem (Recall) or if they randomly guessed (Guessing). We note that the three categories that include the spatial prefix involve the direct consideration of spatial information while the algorithmic category does not. In cases where participants wrote in their own strategies, two researchers independently coded the free responses according to the four categories in Table 1. Comparison of the two raters’ codes indicated an inter-rater reliability score above 85%.

Table 1: Strategy Categories.

<table>
<thead>
<tr>
<th>Strategy Type</th>
<th>Example Fixed-Choice Strategy Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spatial-Imagistic</td>
<td>I tend to imagine the molecule in 3D and rotate it &quot;in my head&quot;.</td>
</tr>
<tr>
<td></td>
<td>I tend to imagine myself moving into the paper or around the molecule.</td>
</tr>
<tr>
<td>Spatial-Diagrammatic</td>
<td>I tend to first draw a basic skeletal structure and then make changes as I go.</td>
</tr>
<tr>
<td></td>
<td>I tend to redraw the molecule using a different chemical representation to help me think about it.</td>
</tr>
<tr>
<td>Spatial-Analytic</td>
<td>I tend to assign R/S labels to each molecule.</td>
</tr>
<tr>
<td>Algorithmic</td>
<td>I just know that in stable molecules particular groups must be in a specific relationship.</td>
</tr>
<tr>
<td></td>
<td>I tend to use a specific formula to calculate the number of stereoisomers.</td>
</tr>
</tbody>
</table>

Results & Discussion
Figure 1 summarizes the frequency of each strategy choice across the 10 tasks. Among the 418 strategies reported, participants selected Spatial-Analytic strategies most frequently (36%) followed by Spatial-Diagrammatic strategies (26%), Spatial-Imagistic strategies (22%) and finally Algorithmic strategies (16%). Figure 2 shows a detail of strategy frequencies by task. The distribution of strategies differed dramatically among the ten tasks, which suggests that students freely switched between the different types of strategies depending on each task. For example, the majority of reported strategies applied to Tasks 1, 5, 6, and 8 were Spatial-Analytic strategies, but Spatial-Imagistic strategies were reported more often on Tasks 9 and 10. The dataset was further analyzed to determine whether participants used primarily one strategy for each task or applied multiple strategies. In total, we were able to identify the strategy used by participants in 326 (83.5%) of the 390 cases of problem solving. The remaining 64 cases either lacked strategy choice information or were solved via Guessing or Recall. As Table 2 illustrates, 240 tasks (73.6%) were solved with only one type of
strategy, 80 tasks (24.5%) were solved with two types of strategies, and 6 tasks (1.8%) were solved with three or more types of strategies. In cases where participants used only one strategy, Spatial-Analytic strategies were reported most frequently. Interestingly, in cases where participants selected two types of strategies, the majority of reported strategies involved the use of a Spatial-Diagrammatic strategy and one other type of strategy. Notably, we observed a negative correlation between the number of participants who successfully completed a problem and the number of participants who used two or more strategies, \( r(10) = -0.654, p = 0.040 \), which suggests that students tend to apply multiple types of strategies as questions become more difficult.

Table 2: Numbers and types of strategy used for each task.

<table>
<thead>
<tr>
<th>No. reported strategies used</th>
<th>Strategy type</th>
<th>Frequency</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Spatial-Imagistic</td>
<td>49</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Spatial-Diagrammatic</td>
<td>47</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Spatial-Analytic</td>
<td>107</td>
<td>240 (73.6%)</td>
</tr>
<tr>
<td></td>
<td>Algorithmic</td>
<td>37</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>SI+SD</td>
<td>16</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SI+SA</td>
<td>15</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SD+SA</td>
<td>21</td>
<td>80 (24.5%)</td>
</tr>
<tr>
<td></td>
<td>SD+AL</td>
<td>21</td>
<td></td>
</tr>
<tr>
<td>3 or more</td>
<td>-</td>
<td>-</td>
<td>6 (1.8%)</td>
</tr>
<tr>
<td>Total</td>
<td>-</td>
<td>-</td>
<td>324</td>
</tr>
</tbody>
</table>

Note. Dashes indicate no further analysis was conducted. SI=spatial-imagistic, SD=spatial-diagrammatic, SA=spatial-analytic, AL=algorithmic. 64 tasks coded as recall/guessing/unknown are not included.

The relationship between correctness and type of strategy used was tested using a Pearson’s \( \chi^2 \) test for 2 (use of each strategy) x 2 (correctness) contingency table. Using an alpha level of 0.05, no association between success and strategy use was found, indicating that strategy choice does not have an impact on whether a participant answer a task correctly. Sex differences in problem-solving success and strategy choice were tested using an independent two-sample \( t \)-test. The mean total correctness score of male participants (\( M = 4.25, SD = 1.45 \)) was not found to differ from the mean total correctness score of female participants (\( M = 4.15, SD = 1.12 \)), \( t(37) = 0.22, p = 0.41 \). Likewise, strategy choice did not differ significantly between female and male participants, as illustrated in Figure 3. Men and women displayed similar patterns of strategy choice: in order of reported strategy use, both groups employed Spatial-Analytic, Spatial-Diagrammatic, Spatial-Imagistic and Algorithmic strategies. In order to examine the relationship between sex and strategy choice, strategy scores of participants were calculated by counting the numbers of each strategy used across the ten survey items. \( t \)-tests to
compare Spatial-Imagistic, Spatial-Diagrammatic, Spatial-Analytic and Algorithmic strategy scores between male and female were not found to be statistically significant at an alpha level of 0.05.

Figure 3. Overall frequency of strategy choice by males and females.

Study 2
In Study 2, we adapted the strategy choice questionnaire for group administration via a remote personal response system (i.e., “clickers”) in an organic chemistry classroom during instruction. Although Study 1 established that students primarily made use of spatial-analytic strategies for solving organic chemistry tasks, the participants in that study had completed several months of instruction in the domain. Thus, Study 1 yielded no information about how student strategy choice changes with instruction. Therefore, we conducted Study 2 to determine whether students employed spatial-analytic strategies in the context of an organic chemistry course and whether students employed the same strategies uniformly over the course of instruction.

Method
103 undergraduate students enrolled (sex was reported for 90 students: 33 males and 57 females) in a 6-week intensive organic chemistry course were assigned unique personal response devices to respond to adapted strategy choice questions administered during the course. Over the duration of the course, students were asked 10 unique organic chemistry questions and related strategy choices. Questions were administered approximately once each week of instruction. During the final meeting of the course, students were asked 8 organic chemistry questions and related strategy choices that included 6 of the 10 questions administered during earlier sessions of the course. All questions were presented on large LCD televisions at the front of the classroom and students answered questions by clicking a multiple-choice answer on their assigned device. The scoring rubric and strategy categories from Study 1 were used to analyze student responses. Notably, the adapted questions in Study 2 did not contain algorithmic strategies as the course instructor deemed that the strategy survey questions that included algorithms were beyond the scope of her course. In addition, unlike the strategy survey questionnaire, students were not able to choose more than one strategy per problem because the classroom clicker system could not capture multiple answers per student for a given question. Students were able to report their own strategies after each class if they employed a strategy not presented in the provided options.

Among the 103 students, 91 students volunteered to complete a spatial ability battery that included the Vandenberg Mental Rotation Test (Vandenberg & Kuse, 1978) and Guay’s Visualization of Views (McDaniel & Guay, 1976). Descriptive statistics of strategy choice were generated for each task and strategy use on both administrations of the 6 questions was compared. Unlike Study 1, group administration of the questions permitted students to interact and discuss their responses prior to inputting an answer on their clicker devices and the course instructor assigned these questions for course credit; therefore, the independence of student answers to chemistry problems could not be guaranteed and reports of student achievement were not considered valid for analysis. In contrast, because students did not receive credit for strategy responses and the instructor emphasized that there was no correct answer to these questions, we considered student responses to these questions valid for analysis.
Results & Discussion

The distribution of strategy choices at each administration time point in the classroom is presented in Table 3. As indicated, the students reported that they employed Spatial-Imagistic strategies more than any other strategies both during and after instruction. Excluding recall, guess, and unreported strategies, Spatial-Imagistic strategies were most frequently reported by students (947 times, 64.95%), followed by Spatial-Diagrammatic strategies (397 times, 27.23%) and Spatial-Analytic strategies (114 times, 7.82%). Although Spatial-Imagistic strategies dominated both during and after organic chemistry instruction, comparison between the two occasions suggests that fewer Spatial-Imagistic strategies were employed after instruction while Spatial-Diagrammatic and Spatial-Analytic strategies were reported more frequently.

Reports of strategy use on the six questions appearing both during and after instruction were examined further to clarify changes in strategy use after instruction. As indicated in Table 4, after instruction the average number of Spatial-Imagistic strategies across all tasks reported decreased ($t(102) = -3.98, p < .001$), and the average number of Alternative strategies increased ($t(102) = 4.95, p < .001$). Figure 4 illustrates the frequency of reported strategies for each of the six questions at each presentation. Examination of these items indicates that students do indeed employ Spatial-Imagistic strategies less frequently after instruction. Interestingly, distributions of strategy choice after instruction varied across the six question items. For questions 1 and 6, reports of using Spatial-Analytic strategies rose dramatically, while reports of using Spatial-Diagrammatic strategies rose relatively higher on questions 2 and 4. In contrast, no noticeable difference in the relative use of each strategy type was seen on questions 3 and 5. Examination of these six items revealed that students not only adopted strategies alternative to Spatial-Imagistic Strategies after instruction, but the choice of strategy after instruction was related to the task itself.

Table 3: Frequency of strategy use.

<table>
<thead>
<tr>
<th>Types of strategy</th>
<th>During instruction</th>
<th>After instruction</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spatial-Imagistic</td>
<td>596 (73.22%)</td>
<td>351 (54.50%)</td>
<td>947 (64.95%)</td>
</tr>
<tr>
<td>Spatial-Diagrammatic</td>
<td>172 (21.13%)</td>
<td>225 (34.94%)</td>
<td>397 (27.23%)</td>
</tr>
<tr>
<td>Spatial-Analytic</td>
<td>46 (5.65%)</td>
<td>68 (10.56%)</td>
<td>114 (7.82%)</td>
</tr>
<tr>
<td>Total</td>
<td>814 (100%)</td>
<td>644 (100%)</td>
<td>1458 (100%)</td>
</tr>
</tbody>
</table>

*10 question items were administered during instruction and 8 items were administered after instruction.

Table 4: Mean number of Spatial-Imagistic and Alternative strategies reported during and after instruction.

<table>
<thead>
<tr>
<th>Types of strategy</th>
<th>During the instruction</th>
<th>After the instruction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$M$        $SD$</td>
<td>$M$        $SD$</td>
</tr>
<tr>
<td>Spatial-Imagistic</td>
<td>3.56       1.48</td>
<td>2.63       1.91**</td>
</tr>
<tr>
<td>Alternative strategies</td>
<td>0.99       1.09</td>
<td>1.83       1.79**</td>
</tr>
</tbody>
</table>

*Note. Scores for each category range from 0-6 excluding recall and guessing strategies.** $p < 0.001$
Associations between spatial ability and strategy choices were analyzed via ANOVA. The 91 students who completed the spatial ability psychometrics were categorized into three groups based on their performance on the Mental Rotation Test (MRT) and Visualization of Views Test (VoV): High ($N=31$, $M=51.94$, $SD=13.02$ for MRT and $M=17.74$, $SD=4.56$ for VoV), Medium ($N=30$, $M=34.20$, $SD=10.39$ for MRT and $M=8.71$, $SD=4.44$ for VoV), and Low ($N=30$, $M=15.40$, $SD=12.08$ for MRT and $M=4.21$, $SD=3.58$ for VoV). Table 5 illustrates the results from the ANOVA. On the first presentation of each strategy question, the use of Alternative strategies did not vary with spatial ability ($F(2, 88)=0.96$, ns) at an alpha level of 0.05. After instruction, however, we observed a trend in the data that indicated students in the lower ability group employed Alternative strategies more frequently than higher spatial ability students ($F(2, 88)=3.10$, $p=0.05$). Associations between each student’s strategy choice and spatial ability were analyzed via a Multivariate Analysis of Variance (MANOVA) test of Alternative strategy scores with within-subjects effect of administration time (i.e., during and after the instruction) and between-subjects effect of spatial ability group. The analysis failed to show a significant interaction between student strategy choice after instruction and spatial ability, Wilk’s $\lambda=0.968$, $F(2, 88)=1.43$, ns. Thus, spatial ability was not found to predict the use of any particular strategy after instruction.

Table 5: Comparison of Alternative scores during and after the instruction in three spatial ability groups

<table>
<thead>
<tr>
<th>Occasions of the task</th>
<th>High</th>
<th>Medium</th>
<th>Low</th>
<th>$F(2,88)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>During the instruction</td>
<td>0.90</td>
<td>1.07</td>
<td>1.30</td>
<td>1.06</td>
</tr>
<tr>
<td>After the instruction</td>
<td>1.35</td>
<td>1.56</td>
<td>2.43</td>
<td>2.17</td>
</tr>
</tbody>
</table>

Finally, relationships among sex, spatial ability and strategy choice were investigated. Using an alpha level of 0.05, males were found to outperform females on the Mental Rotation Test ($M=45.63$, $SD=16.07$ for male, $M=27.62$, $SD=17.63$ for female, $t(83)<0.001$) and on the Visualization of Views ($M=13.42$, $SD=8.27$ for male, $M=8.66$, $SD=5.94$ for female, $t(83)=0.003$). During instruction, males and females did not differ in use of Spatial-Imagistic strategies ($M=3.81$, $SD=1.36$ for male, $M=3.32$, $SD=1.40$ for female, ns) or the use of Alternative strategies ($M=1.00$, $SD=0.87$ for male, $M=1.07$, $SD=1.10$ for female, ns). After instruction, however, females were observed to use Alternative strategies more frequently than males ($M=1.24$, $SD=1.56$ for male, $M=2.47$, $SD=1.79$ for female, $t(88)=0.002$); however, the difference between male and female use of Spatial-Imagistic strategies was marginal ($M=3.21$, $SD=1.92$ for male, $M=2.53$, $SD=1.83$ for female, $t(88)=0.096$). Repeated measures analysis of Alternative strategy scores involving within-subjects effect of administration time (i.e., during and after instruction) and between-subjects effect of sex resulted in significant interaction between sex and occasion of the tasks (MANOVA, Wilk’s $\lambda=0.892$, $F(1, 88)=21.31$, $p=0.002$).

Conclusions & Implications

The above results offer some tentative answers to the questions we posed initially. First, the findings clearly illustrate that students employ a variety of strategies to solve tasks that involve spatial thinking. In Study 1, we
observed students to rely more consistently on Spatial-Analytic and Spatial-Diagrammatic strategies as opposed to Spatial-Imagistic strategies, as typically believed. Likewise, in Study 2, we observed students to employ Spatial-Imagistic strategies preferentially during instruction, yet adopt more alternative strategies by the end of the course. Moreover, we also observed students to fluidly switch between different types of strategies between tasks. The findings of the present work suggest that students choose task-dependent strategies in a manner similar to expert chemists and apply multiple strategies on problems of increased difficulty. These results indicate that students are aware of the availability of diverse strategies and are willing to employ alternative strategies. In other words, students are not limited to reasoning about spatial information in molecular structures via imagistic reasoning, but can reason about spatial information with a variety of strategies.

The results also indicate that strategy choice does not predict success on spatial tasks in chemistry. The findings in Study 1 suggest that students reach equivalent levels of achievement regardless of whether they employ strategies that involve reasoning via mental imagery or alternative strategies. Equally important, we did not observe significant differences in achievement between men and women on chemistry tasks. Despite these findings, we did observe that multiple strategies were applied on tasks that the majority of students failed to solve. This finding is consistent with the literature on flexible strategy choice that reports individuals employ multiple strategies on tasks of increased difficulty (cf. Siegler, 1996). The use of multiple strategies, however, did not lead to increased success on such tasks. Thus, it did not appear that the application of one or more strategy types (e.g., Spatial-Imagistic, Spatial-Analytic, Spatial-Diagrammatic, Algorithmic) predicts achievement. That is, each strategy is equally likely to result in success or failure on a given task.

Study 2 permitted us to examine the relationship between strategy choice and instruction in the context of an organic chemistry classroom. The results of that study clearly illustrate that instruction has a direct effect on strategy choice. In the beginning of the course, we observed students rely primarily on Spatial-Imagistic strategies to solve spatial tasks; by the end of the course, we observed a sharp increase in the use of strategies alternative to Spatial-Imagistic strategies. Interestingly, the participants in Study 2 reported greater use of Spatial-Imagistic strategies at the end of instruction while the participants in Study 1 reported greater use of Spatial-Analytic strategies. We believe the reason for this discrepancy is due to two important differences between the participants in each study. First, the students received instruction over different time periods. The students in Study 1 completed ~20 weeks of instruction during course of an academic year; however, the students in Study 2 learned less material in a 6 week summer course. It is possible that the longer duration of study in Study 1 resulted in better apprehension of and preference for alternative strategies. Similarly, the instructors for each course reported notable differences in their own emphasis on strategy use. The instructor in Study 1 reported she was ‘bad at visualization’ and emphasized diagrammatic and algorithmic heuristics, but the instructor in Study 2 reported she attempted to teach as many strategies as possible for the benefit of the students. Thus, instructional differences may have resulted in the observed differences in strategy preference. Nevertheless, although students in Study 2 reported using Spatial-Imagistic strategies as their primary strategy, the increased use of domain-specific alternative strategies suggests that as expertise develops, students may rely less on imagistic reasoning and more on heuristics to solve spatial tasks.

Study 2 also permitted us to examine the relationship between spatial ability, sex and strategy choice in the classroom. Although the results of that study do not indicate a direct relationship between spatial ability, sex and strategy choice, they do suggest a potential interaction may exist. First, our findings clearly show that over the course of instruction women reported a significant increase in the use of alternative strategies compared to men. Second, our findings tentatively suggest that low spatial students may preferentially switch from Spatial-Imagistic strategies to alternative strategies after instruction; high spatial students do appear to rely on Spatial-Imagistic strategies throughout instruction. Thus, the data suggests that low-spatial females preferentially switch to alternative strategies. Two major limitations of the Study limit the validity of these findings. First, our analysis relies solely on students’ strategy reports on 6 questions. The results of Study 1 indicate that several strategies are task-specific and our reliance on so few tasks casts doubt on the interpretation of these findings. Second, students were asked to respond to the clicker questions in Study 2 under classroom time constraints and they were also permitted to collaborate on their responses. Thus, there was an increased risk in Study 2 of failing to detect changes in strategy choice and individual differences in spatial ability. Nevertheless, we believe the trends in the data suggest a potential interaction between spatial ability, sex and strategy choice does exist and warrants further investigation.

Taken together, the results of the present studies indicate that spatial thinking in advanced scientific problem solving, specifically organic chemistry, involves a range of strategies that vary significantly in the extent to which they rely on imagistic reasoning. Of particulate note, our findings suggest that students approach the study of organic chemistry using mental rotation and other spatial-imagistic strategies to reason about molecular structures, but quickly adopt a variety of algorithms and heuristics after instruction. This behavior leads us to question the utility of instructional methods that emphasize the exclusive focus on training students to use imagistic strategies (e.g., by improving students’ visuo-spatial ability, Ferki, Vrtacnik, Blejč, & Gril, 2003). Rather, we suggest instead that students may benefit most from instruction that teaches the applicability

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of multiple strategies, as in Study 2. Moreover, the present study did not identify significant correlations between sex and chemistry problem solving success. This result contradicts previous claims that men outperform women in science due to their aptitude for spatial reasoning (Fogg, 2005). Rather, our findings suggest that female students apply the same strategies as male students with equal levels of success in chemistry and that they are likely to switch to alternative strategies when necessary in a course.

References


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