ABSTRACT

STAMEY, JOHN W., JR. A Comparison of the Performance of Undergraduate Statistics Students Using Intelligent Learning Objects Versus Those Receiving Traditional Classroom Instruction. (Under the direction of V. William DeLuca, Ed.D.).

This study analyzed undergraduate students' achievement and perception when using Intelligent Learning Objects. Learning objects are digital or non-digital entities that are used for learning, education, or training. Intelligent Learning Objects are an advancement over traditional static Learning Objects, in which student performance is used to determine the actual curriculum materials to be delivered. Intelligent Learning Objects were used in this study to measure student achievement in the delivery of instruction on elementary statistics. Different levels of the Revised Bloom's Taxonomy were used to organize the curriculum material and evaluation questions. At the completion of the study, student perceptions regarding Intelligent Learning Objects were also measured. Undergraduates from a university in the southeast, taking Statistics 201 Lab Introduction to Statistical Analysis, represented the sample for this study. The data for this study were collected in Spring 2006. Undergraduate statistics students from a university in the southeast were also involved in the pilot study in Fall 2005. It was found that Intelligent Learning Objects did provide a statistically significant different in the achievement of the Experimental Group versus the Control Group.

A COMPARISON OF THE PERFORMANCE OF UNDERGRADUATE STATISTICS STUDENTS USING INTELLIGENT LEARNING OBJECTS VERSUS THOSE RECEIVING TRADITIONAL CLASSROOM INSTRUCTION

by
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DEDICATION

This dissertation is dedicated to the memory of the author's parents, Mr. and Mrs. John W. Stamey, Sr.

BIOGRAPHY

John Stamey, Jr. was born in Morganton, NC on November 7, 1955. He is the son of Mr. and Mrs. John W. Stamey of Morganton. He graduated as valedictorian of the 1974 class of Freedom High School in Morganton, NC. He was a member of the National Honor Society, being inducted in 1973.

He received a B.S. in Mathematics and Music, Cum Laude, from Wake Forest University in Winston-Salem, NC in May 1978, and a M.A. in Mathematics from Wake Forest University in May 1980. His thesis, *Stirling Numbers*, was under the direction of Dr. Fred Howard.

After a short career in the actuarial field with Integon Life Insurance Company, John entered graduate school at Clemson University in August 1982. In May 1988, he received an M.S. in Computer Science. His master's paper, entitled *Time Varying Cellular Automata*, was presented at the CA'86 conference at M.I.T. The paper was under the direction of Dr. Dennis Stevenson. John was inducted into the Delta Chi fraternity on May 13, 1989.

After careers in the music industry and screen printing, both in Clemson, SC, he moved to Winston-Salem, NC to pursue a career as a contract computer programmer. In 1998, he returned to the academic world as an instructor in the Department of Computer Science at UNC-Charlotte. In 2000, John became an instructor in the Department of Computer Science at UNC-Pembroke. In 2001, he took the same position at Coastal Carolina University in Conway, SC.

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CHAPTER I: INTRODUCTION

Introduction

This study analyzed undergraduate students' achievement and perception when using Intelligent Learning Objects. Learning objects are digital or non-digital entities that are used for learning, education, or training (IEEE, 2001). Intelligent Learning Objects are an advancement over traditional static Learning Objects, in which student performance is used to determine the actual curriculum materials to be delivered (Stamey, Saunders & Deluca, 2005).

Intelligent Learning Objects were used in this study to measure student achievement in the delivery of instruction on elementary statistics. Different levels of the Revised Bloom's Taxonomy (Bloom, B.S., 1984A, 1956; Anderson, et. al., 2000) were used to organize the curriculum material and evaluation questions. At the completion of the study, student perceptions regarding Intelligent Learning Objects were also measured.

Undergraduates from a university in the southeast, taking Statistics 201 Lab (Stat 201L), Introduction to Statistical Analysis, represented the sample for this study. The data for this study were collected in Spring 2006. Undergraduate statistics students from a university in the southeast were also involved in the pilot study in Fall 2005.

Learning Objects

Learning Objects came about in the early 1990s as a result of work by Wayne Hodgins of Autodesk. In 1992, Hodgins began promotion of his idea for interoperable pieces of learning he called *Learning Objects*, realizing the AUTOCAD industry was in need of a reusable "plug-and-play" learning strategy for training (Hodgins, 2002). Between 1992 and 1995, both the Learning Object Metadata Group (part of NIST, the National Institute of

Science and Technology, http://www.nist.gov) and the Computer Education Management Association (CEdMA, http://www.cedma.org), began defining issues and properties that were important to Learning Objects. These issues included modularity, database centricity and metadata (Jacobson, 2002). In 1994, three groups began working on sets of standards for Learning Objects. The groups were the Institute for Electrical and Electronics Engineers (IEEE), the IMS Global Learning Consortium (IMS), and the European Union's largest provider of digital information, ARIADNE. At about the same time, the Oracle Corporation recognized that Learning Objects would become a critical part of their future training strategy. Oracle's thinking evolved into the Oracle Learning Application (OLA), an authoring environment in which to develop Learning Objects.

In 1997, the US Department of Defense and the White House Office of Science and Technology Policy started the Advanced Distributed Learning initiative (ADL) to help promote the use of the Internet in education. Three years later, ADL released a set of guidelines and specifications for accessibility, interoperability, durability and reuse of learning content on the Internet known as SCORM, the Sharable Content Object Reference Model (Shayo, Gurhrie & Olfman, 2003). The central focus of SCORM was a unit called a Learning Object. SCORM's Learning Objects were based on a similar concept from Object-Oriented Programming (Booch, 1982). The idea was that units of learning could be created, stored, and then reused in a global web-based sharing environment.

In 2002, The Learning Object Metadata (LOM) standard, also known as IEEE Standard 1484.12.1 was finalized. The website containing the LOM standard is http://ltsc.ieee.org/wg12/. LOM defines a model to categorize and describe learning objects. (Skar, Heiberg & Kongsli, 2003)

Wiley (2002) defines Learning Objects as a form of computer-based instruction related to the Object-Oriented paradigm in computer programming. Fundamental to object-orientation is the creation of components (called *objects*) that can be reused. Similar to programmers creating objects, Wiley describes a scheme whereby instructional designers can build small instructional components that may be reused a number of times in different learning contexts. These components are quite small relative to the size of the entire course. Polsani (2004) defines Learning Objects more generally as any form for organizing knowledge and information. The definition is composed of three related elements:

- the Object (the goal and purpose of the knowledge);
- the Process (the method for achieving the goal); and,
- the Ground (conditions and organization that facilitate the process of learning).

Frosch-Wilke (2004) characterizes Learning Objects as having the following four properties. Learning Objects are:

- *self-contained*, so that each one can be used/consumed separately;
- *reusable*, so that one Learning Object can be used in multiple contexts, purposes and locations;
- *may be aggregated*, so that they can be used to build larger instruction units; and,
- *may be labeled with metadata*, so they carry descriptive information and may be searched.

Intelligent Learning Objects

Initially, Learning Objects presented static (non-changing) content and perhaps some questions to evaluate the learner's understanding of the material. Learning Objects are now being developed that exhibit dynamic behavior. Boyle (2003) describes them with adjectives such as *dynamic* and *reusable*. Silveria et. al. (2004) describe an agent-based architecture deployed on the server-side, providing for dynamic content and interaction between Learning Objects. These agent-based structures are called *Intelligent Learning Objects*. Stamey, Saunders and Deluca (2005) describe Intelligent Learning Objects that provide a reinstruction component. Reinstruction is delivered on an as-needed basis and only after an incorrect response to questions presented along with the instructional materials. Pushpageri (2004) describes *Smart Objects* that can evolve and change over time, based on student responses to questions presented along with the instructional materials. Regardless of the approach, Intelligent Learning Objects provide additional dynamic content and evaluation not found in traditional static Learning Objects.

Rationale for the Study

A number of methods have traditionally been used to instruct students in statistics. These include classroom instruction, books/website/textual instruction, recorded lectures (taped, CD-ROM or streaming), programming assignments, alone and/or in combination, and traditional (static) Learning Objects. Repositories such as ARIADNE and MERLOT are being populated with new Learning Objects, almost on a daily basis. While these centralized repositories are providing access to a large number of digital resources, there is a critical need to understand how Learning Objects can successfully be used in pedagogy (Hodgins, H.W., 2002). It is also important to begin measuring the performance of students as they use Learning Objects versus traditional classroom instruction (Stamey, Saunders & Deluca, 2005).

Need for the Study

Currently, very few studies report on effectiveness of Learning Objects, or student perceptions of Learning Objects. The growth in the number of Learning Objects and Learning Object repositories (Vargo, et. al., 2003) as well as the proliferation of dynamically delivered content through Intelligent Learning Objects underscores the need for this study. A secondary need for this study is to determine if, indeed, Learning Objects are perceived as useful by students. Such perceived usefulness will be an important factor in determining the success of integrating Intelligent Learning Objects into a curriculum.

Statement of the Problem

Our previous discussion supports the premise that the development and use of Learning Objects is on the rise. Intelligent Learning Objects are a very recent development, and little research has been documented as to the effectiveness of Learning Objects themselves. This study examined the primary issue of student achievement as a result of using Intelligent Learning Objects; the study also determined students' perception toward Intelligent Learning Objects.

Research Questions

Student performance and perceptions were collected and examined based on measures developed to suit the purposes of this study. The measures were related to the effectiveness of Intelligent Learning Objects as well as perceptions of their use. The primary research question examined in this study was:

> Do students using Intelligent Learning Objects, with curriculum based on the Revised Bloom's Taxonomy along with reinstruction, have a different level of achievement than those using traditional classroom training?

In addition to the primary research question, student opinions about Intelligent Learning Objects were measured. The secondary research question for this study was:

How do students perceive Intelligent Learning Objects?

Limitations of the Study

The following limitations of the study were considered prior to its inception:

1. All students in the research study were students at a university in the southeast. For this reason, the results may be specific to this group of participants.
2. All students used the Intelligent Learning Objects in computer labs that allow for Internet access. As the students were told to "do their best" when using the Intelligent Learning Objects (and while their scores would not be counted as part of their grade in the class), some students may have felt pressure to use Internet resources to enhance their performance when using the Intelligent Learning Objects.

Research Methodology

The research methodology for the Primary Research Question was a pretest-posttest control group design using Nonequivalent Groups. The independent variable was the type of instruction received by the groups. The dependent variables measured the achievement experienced by the students, at different levels of Blooms Taxonomy.

The research methodology used for the Secondary Research Question was a one-shot survey. The methodology used is known as a one-shot case study (Gall, Gall & Borg, 2003).

Outline of Research Methodology

The following steps were used in the course of this study:

1. The text and questions for Intelligent Learning Objects to be used in Statistics 201L in Spring 2006 were developed.
2. A panel of experts reviewed the material to be used in the Intelligent Learning Objects (instructional text, questions and answers) for accuracy (content validation).
3. The faculty of the Statistics Department at a university in the southeast approved the material and the Intelligent Learning Object deployment in their ST 201L classes for Spring 2006.
4. A survey was developed to assess student perception of Intelligent Learning Objects.
5. A panel of experts reviewed the questions on the survey for accuracy (content validation).
6. A pilot test of the delivery system performance and its usability was conducted at a university in the southeast.
7. The statistics text/questions/answers, and questions for the student preference survey were modified insure validity.
8. By random selection, two of the four Statistics 201L classes were selected to receive instruction with Intelligent Learning Objects. The students in these two groups were called the Experimental Group. The students who received traditional classroom lecture instruction were called the Control Group.
9. The pretest was administered to all students participating in the study (both the Experimental Group and the Control Group).

10. The Intelligent Learning Objects were administered to the Experimental Group and traditional lecture was delivered to the Control Group.
11. A posttest was administered to all students participating in the study (both the Experimental Group and the Control Group).
12. Students in the Experimental Group were administered a survey to determine their perception of learning with Intelligent Learning Objects.
13. Data from the posttest were analyzed to determine if there was a significant difference between the performance of the Experimental Group and the Control Group.
14. Data from the survey to determine student preference for Intelligent Learning Objects were analyzed.
15. All quantitative data were interpreted.

Definition of Terms

Learning Objects

Learning Objects are reusable units of instruction that are primarily found in online learning systems. (Learning Object, n.d.) Functionally speaking, Polsani (2003) describes Learning Objects as

- Accessible, through the tagging (labeling) of their content with metadata;
- Convenient, as they can be stored in and referenced from a database;
- Reusable, in order that they may function in different instructional contexts; and,
- Interoperable, so that they are independent of the delivery media and the knowledge management system used for their deployment.

Revised Bloom's Taxonomy

Benjamin Bloom's original taxonomy (Bloom, B.S., 1984A, 1956) has been revised by Anderson, et. al.(2000). The familiar levels have been renamed, and associated with a question that describes the type of achievement that should result at each level.

- Level 1: *Remembering* is evidenced by the student's ability to retrieve relevant information from long-term memory. Restated, we would say "Can the student recall information?"
- Level 2: *Understanding* is evidenced by the student constructing meaning from oral, written and graphic communication. Restated, we would say "Can the student explain the ideas or concepts?"
- Level 3: *Applying* is evidenced by the student being able to carry out a procedure in a given situation. Restated, we would say, "Can the student use the new knowledge in another familiar situation?"
- Level 4 – *Analyzing* is evidenced by the student being able to break material down into parts, determine how the parts are related, and then act upon them. Restated, we would say, "Can the student differentiate between constituent parts of a problem (and then use their knowledge to solve the various parts of the problem)?

Object-Oriented Programming

Also known as OOP, Object-Oriented Programming is a computer programming paradigm of using a collection of units, called objects, to communicate with each other in performing required tasks (Booch, 1990).

WWWC (W3C)

The World Wide Web Consortium (W3C) assists in the development of interoperable technologies (specifications, guidelines, software, and tools) to lead the Web to its full potential. W3C is a forum for information, commerce, communication, and collective understanding. W3C may be found online at http://www.w3.org/.

XHTML

Version 1.0 of XHTML is a reformulation of HTML 4 as an XML application. HTML is a standard tag-based language to organize text for publishing information on the World Wide Web. The XHTML specification is found online at http://www.w3.org/MarkUp/.

XML

XML is a format to structure, store and send data. XML is an acronym for eXtensible Markup Language that allows a collection of information to be structured and enclosed in tags that categorize the type and meaning of the data. (W3C, 2005A)

Tag types such as dissertation, title, author and date describe the type of information contained within a tag. An example of a tag is the pair `<title>......</title>`, that describe the text between `<title>` and `</title>` as information about the title of the dissertation. The XML specification is found online at http://www.w3.org/XML/.

Chapter Summary

This chapter discussed the innovation of Learning Objects, their extension into Intelligent Learning Objects, and the need for research in the field. Evidence has been provided for a premise and method for investigating the use of Intelligent Learning Objects through research questions, definitions of terms, assumptions, and study limitations.

CHAPTER II: REVIEW OF LITERATURE

We begin by describing the general class of Intelligent Tutoring Systems, to which Learning Objects are closely related. Next, we examine the fundamental issues in the deployment of Learning Objects, interoperability, metadata, design, pedagogy, content, and delivery. In conclusion, we examine usability of Learning Objects from their view as software systems.

Intelligent Tutoring Systems

The development of *Intelligent Tutoring Systems* can be traced back to the 1926 when Sidney L. Pressey constructed a machine for students featuring multiple-choice questions and answers. The machine delivered the questions, then provided immediate feedback (Thomas, n.d.). Almost fifty years later, John Self (1974) described the tripartite architecture for Intelligent Tutoring Systems, consisting of:

- Domain Knowledge - the "what" to be taught;
- Student Model - the descriptive view of a student was that of information in a data structure (characteristics and problem-solving performance statistics), while the predictive view of a student was the steps used to solve a problem (a trace of the student's activities); and,
- Tutoring Strategy - how the information were presented to the student, as well as the responses solicited from the student.

This view of Intelligent Tutoring Systems has continued to stay with us in some form or another.

Vygotsky's (1978) argument that cognition is developed in conjunction with social interaction (taking place in the *Zone of Proximal Development*, or *ZPD*) lead to the realization that the computer (a.k.a. the Intelligent Tutoring System) should be more of a computational co-learner than a stand-alone system. This argument is further strengthened by Lave's (1988) *Social Development Theory*, arguing that learning as it normally occurs is a function of the activity, context and culture in which it occurs (i.e., it is situated). Supporting and, in a sense, tying the ideas of Vygotsky and Lave together, Self (1999) comments that the computational co-learner does not need a set of powerful or artificially complex learning techniques (as these are not present in human learners).

Anderson, Boyle & Reiser (1985) describe successful Intelligent Tutoring Systems based on pedagogical principles derived from Anderson's (1983) *ACT* theory of cognition*. Four important principles of ACT* include:

- Use of productions were learning a set of rules represents a unit of a skill;
- Goal structure whereby the conditions surrounding the rules includes a specific goal for the learner to achieve (or problem to be solved);
- Acknowledgement of working-memory limitations; and,
- Knowledge compilation through acquiring new rules for retrieval and use from long-term memory.

Production system rules can take two different forms. Backward inference rules begin with a goal, then identify the subgoals needed to achieve the goal, much like Gordon Davis' (1974) top-down analysis in MIS development. Forward inference rules begin with a collection of goals from which a new foal is to be inferred, much like Davis' (1974) bottom-up analysis in MIS development.

Along with the principles of ACT*, Anderson, Boyle & Reiser advocate immediate feedback to make it easier for the student to integrate information about errors into their learning process. Taking note of successful individual (live) tutors, they also introduce the *model tracing* paradigm. Model tracing involves comparing a correct sequence of steps to solve a problem with the steps taken by a student in solving a problem. Identifying incorrect actions leads to a proper scheme of remedial instruction.

Merrill, et. al. (1992) argue that Intelligent Tutoring Systems should provide two important functions of live tutors. *Scaffolding*, also known as guided learning by doing, allows the tutor to provide support when needed, while allowing the student to do as much of the work as possible. They also attribute immediate *corrective feedback* (Lepper, et. al., 1990) as a second, important step, when giving the student a second chance at solving a problem correctly.

Benjamin Bloom's two-sigma problem states that students who receive some form of individual instruction can perform up to two standard deviations higher than those receiving traditional instruction (Bloom, 1984B). Bloom's landmark findings are corroborated by Anderson, Boyle & Reiser (1985) who found that, in general, students with a private tutor has a four-to-one advantage over students who had only classroom instruction.

Web-based Intelligent Tutoring Systems are used to provide the benefits of online, one-on-one instruction, with the bonus of being automatically reusable and cost-effective (Ong & Ramachandran, 2000). Brusilovsky and Nijhavan (2002) describe Intelligent Tutoring Systems as adaptive hypermedia technologies that allow students to have a dynamic (individualized) experience by selecting content most relevant to their needs. Adaptive and dynamic technologies are especially suited to web-based delivery.

Tutoring strategies specify the sequencing of content, the type of feedback given, types of remediation, and method of recording student input. (Murray, 1999) Stamey, Saunders and Deluca (2005) suggest a tutoring strategy using the following type of conditional logic:

```
Frame of information delivered
Question to evaluate comprehension and understanding
IF (ANSWER TO QUESTION is correct)
THEN
          Proceed to next frame
ELSE
          Proceed to reinstruction (based on question missed)
```

Figure 1. An Example of Conditional Logic for Intelligent Learning Objects.

The development of web-based Intelligent Tutoring Systems follows one of three models (Brusilovsky, Ritter & Schwartz, 1997). The *Master-Slave Model* is used when components do not support inter-system communication. An example of this would be a system that is deployed with a scripting language such as PHP or JavaScript, whereby each client (student end-user) requests all system components dynamically (at runtime) based on the individual student's performance. Once the components are downloaded to the client (end-user) computer, all interactions take place on the client without communication with the server.

The *Communicating Peer Model* allows client-to-client sharing of information. In this model, students can share information with each other about the learning experience such as URLs and comments about the material being presented.

The *Centralized Dynamic Server Architecture Model* is by far the most flexible and open model, whereby student and instructor communications are stored for use by current and future users of the system. Both the Communicating Peer Model and the Centralized Dynamic Server Architecture Model provide for data to be stored and analyzed on the server-side.

Interoperability Standards

Wayne Hodgins (Hodgins and Connor, 2000) discusses three reasons why interoperability standards are important to the ultimate success of Learning Objects. Interoperability standards:

- Facilitate the mixing and matching of content from multiple sources;
- Provide availability of interchangeable content that lends itself to rapid assembly, disassembly and reuse; and,
- Promote freedom from proprietary learning technology of commercial vendors.

Interoperability standards also help ensure the investment made in content and delivery of Learning Objects as sound and as risk-free as possible.

Two organizations are working to develop, manage, and maintain standards that are particularly important to the Learning Object community. The IEEE Learning Technology Standards Committee (LTSC) is an umbrella organization for many groups around the world who are creating learning object metadata, student profiles, course sequencing, computer managed instruction, competency definitions, localization, and content packaging. The LTSC website, http://ieeeltsc.org/, contains the following mission statement for its role in standards for computer managed instruction:

> Today Computer Based Training (CBT) is being written by a diverse number of parties using very diverse tools or authoring systems. Many of the CBT lessons being developed can complement and work well with other lessons developed in different locations with different tools by different people. There is a need to allow these complementary lessons to be brought together and used in a single course. However, this cannot be

> done without defining a standard set of CMI (Computer Managed Instruction) functions and a matching set of CBT functions.

The LTSC is working to combine with the International Standards Organization (ISO) standards by establishing ISO Joint Technical Committee 1 Sub Committee 36 (SC36) on Learning Technology. Their website is found at http://www.jtc1.org/.

ADL and SCORM is a joint program of the Department of Defense and the White House Office of Science and Technology. Their website is found at http://www.adlnet.org/. The purpose of SCORM is the development of guidelines for large-scale development and implementation of distributed learning. SCORM promotes six ideals of:

- Accessibility of learning objects from multiple remote locations through the use of meta-data and packaging standards;
- Adaptability of instructions for the specific needs of individuals and organizations;
- Affordability through efficiency and enhanced productivity;
- Durability to allow changes in underlying operating systems without affecting operation;
- Interoperability over multiple tools and platforms; and,
- Reusability for continued growth and development.

With the inevitability of change in Learning Objects, some mechanism needs to be in place to provide information about changes that occur in them (Brooks, et. al., 2003). This is especially important as, at this time, there are no clear-cut definitions as to the granularity of Learning Objects.

Learning Object Metadata Standards

Development of Standards.

The organization and classification of learning objects is accomplished with *metadata*, which is "data about data." Metadata is generally written in HTML, XHTML or XML. Metadata is divided into three categories:

- Descriptive metadata describing the intellectual content of the resource, including location and general content;
- Administrative metadata describing ownership, file formats and long-term archival management; and,
- Structural metadata describing the internal organization of the resource.

Three standards have emerged within the past several years that have been particularly important in the development of learning objects. Each of these will now be discussed.

Dublin Core Metadata Initiative.

Dublin Core Metadata Initiative (DCMI) came out of a brainstorming session in Dublin, OH in 1994 in an effort to provide structure for categorization and retrieval of web-based library services. The website is http://dublincore.org/. DCMI supports the development of metadata registry infrastructure to provide metadata definitions and documentation in the languages of its end users. To date, more than 20 languages are supported.

There are sixteen metadata elements in the Dublin Core Metadata Set (Dublin Core Metadata, 2004). All elements are optional (in the sense that none are actually required), and elements may be repeated. The fifteen elements, listed and described below, provide general information about the Learning Object resource:

1. Title: formal name of the resource;
2. Creator: entity primarily responsible for creation of the resource and its content;
3. Subject: main topic that describes the content of the resource;
4. Description: element(s) describing the content such as an abstract or a table of contents;
5. Publisher: entity responsible for making the resource available;
6. Contributor: entity responsible for making contributions to the content of the Learning Object; here we see a good example of the use of multiple elements based on multiple contributors;
7. Date: creation date of the resource;
8. Type: description of the general category or function of the resource (Dublin Core has a recommendation for a vocabulary for this element, called DCT1 (Dublin Core-DCT1, 2000);
9. Format: resource information such as file media type and size, hardware and software;
10. Identifier: formal identification systems such as a URL or ISBN number;
11. Source: reference to a Source providing the content, in whole or in part; if the material has been derived from more than one contributing source, there will be more than one Source element;
12. Language: native language of the content, in two or three letter, such as EN or ENG for English (RFC3006, 2001);
13. Relation: reference to related resource(s);
14. Coverage: location of resource, and/or dates for which the content is valid; and,

15. Rights: rights held by the creator such as a copyright.

DCMI is normally written in XHTML or XML tags that can be inserted directly into the code of a Learning Object. A number of generators for DCMI may be found online at http://dublincore.org/tools/.

IMS/IEEE LOM Metadata Initiative.

The IMS/IEEE LOM Metadata Initiative (IMS Metadata, 2002) provides a more comprehensive framework of eighty-six elements from which digital resources may be described. The IMS project began in 1997 from the EDUCOM consortium (now EDUCAUSE), a group of higher education institutions in the US who were working to develop open (as in open-source) specifications for content sharing and metadata. IMS assimilated the NIST (National Institute of Standards and Technologies) metadata effort, and developed a strategic partnership with ARIADNE, the European Learning Object repository. In 1998, IMS and ARIADNE submitted a joint proposal to the Institute of Electrical and Electronic Engineers (IEEE), which became the basis for the IMS/IEEE LOM (Learning Object Metadata) project. The website may be found at http://ltsc.ieee.org/wg12/.

While the IMS/IEEE LOM project provides a large and encompassing range of metadata information, the IMS today prefers to view the eighty-six IMS/IEEE LOM metadata elements in two sets. The first set consists of nineteen IMS Core elements, describing fundamental properties of Learning Object resources. The second set consists of sixty-seven elements that, together, form the Standard Extension Library, or SEL (IMS Metadata, 2002).

IMS/IEEE LOM is a metadata model that has nine different categories, which include the following descriptions of the Learning Object resource. Six of the categories provide both

IMS Core information and information from the SEL, while the other three provide only information from the SEL.

- General: specifying the title, language and description;
- Lifecycle: specifying the version and contributors;
- Metametadata: specifying the metadata scheme and language used;
- Technical: specifying the format and location;
- Educational: containing all SEL descriptors such as level of interactivity and age range;
- Rights: specifying the cost and copyright restrictions;
- Relation: containing all SEL descriptors, describing related Learning Object resources;
- Annotation: containing all SEL descriptors, and providing anecdotal comments about the Learning Object resource; and,
- Classification: containing a description and keywords describing the resource.

IMS/IEEE LOM metadata is stored as XML, with each object represented in a tree structure. The tree is a hierarchical structure that contains (Mathematics Metadata Task Force, 2000):

- A *root* node representing the object being described;
- A set of *categories* that describe things such as property rights and creation;
- Categories have *elements* that name specific properties for each category (such as date and contributors for category creation); and,
- Categories have *leaves* that provide the actual data found in the elements (such as July 4, 1776 as an actual creation date).

A total of eighty-six distinct metadata elements make IMS/IEEE LOM metadata an unpopular choice for vendors developing interoperable Learning Object products (Freisen, 2004). A conversion of Dublin Core metadata into IMS/IEEE LOM (Nilsson, 2005) is underway.

CanCore Metadata Project.

The CanCore metadata project, found at http://www.CanCore.ca/, is an attempt at distilling best practices from IMS/IEEE LOM into a smaller set of forty-eight (48), more manageable set of metadata tags. The categories and number of elements chosen by CanCore include (Freisen, Fisher & Roberts, 2002):

- General (7)
- LifeCycle (4)
- Metametadata (6)
- Technical (7)
- Educational (5)
- Rights (3)
- Relation (2)
- Annotation (omitted)
- Classification (14)

Other Metadata Issues.

The Resource Description Framework (RDF) is a framework for providing a more powerful descriptive component to plain XML. The RDF specifications are part of the W3C's initiative toward the Semantic Web, and may be found at http://www.w3.org/RDF/. While XML allows almost complete freedom to describe information with its hierarchical (nested) tag architecture, problems arise when things are scaled to larger levels, such as the World Wide Web. XML does not provide an ordering of elements, to suggest relationships such as larger/largest. XML also does not provide any help in determining different types of data. For example, the meaning of "48 degrees" (as a temperature or a degree of longitude) cannot be determined simply from the tags enclosing that piece of data (Bray, 1998). These are two reasons that the addition of metadata through RDF can potentially add important meaning in the task of providing data for Learning Objects.

Learning Object Repositories

Repositories support the availability and interchange of Learning Objects. Three repositories recognized throughout the worldwide Learning Object community are known by the acronyms ARIADNE, MERLOT, and NSDL/ SMETE.

ARIADNE was developed through efforts of the European Union and the Swiss Government, ARIADNE is an acronym that stands for The Alliance of Remote Instructional Authoring. Its mission is the development of a truly European knowledge pool for distributed education. The website is found at http://www.ARIADNE-eu.org/. The Knowledge Pool System, or KPS, was developed to promote sharing and reuse of Learning Objects. Query tools are available for KPS that allow users to find objects of their choosing in the Local Knowledge Pool. ARIADNE has adopted the IMS/IEEE LOM XML Standard ("Transformations of ARIADNE XML into instances of LOM," n.d.). The exact implementation of the transformation mapping may be found in an article entitled "Mapping ARIADNE to LOM." (n.d.)

MERLOT is an acronym that stands for Multimedia Educational Resource for Online Learning and Teaching. The website may be found at http://www.merlot.org/. MERLOT is the major Learning Object repository in the United that primarily searches its own archives. Other repositories searched by MERLOT include EdNA Online and SMETE, through a federated search of all available databases.

NSDL and SMETE work together to promote K-12 learning in science, Math, Engineering and Technology (hence the acronym). They many be found, respectively at http://www.nsdl.org/ and http://www.smete.org/. The aim of NSDL is to build seamless services from users with different platforms. Three levels of interoperability supported include:

- Federation: a set of standards to which member libraries can agree;
- Harvesting: use of a simple wrapper in conjunction with Dublin Core metadata for those institutions that do not agree to federation; and,
- Gathering: using web-crawler techniques to collect information from organizations not part of NIST.

Learning Object Design

Pitkanen and Silander (2004) define three context areas that must be considered in developing Learning Objects. These context areas include content, pedagogy and delivery technology. Each of these context areas are further examined in terms of the development criteria of independence, multi-usability and adaptability.

Qin & Hernandez (2004) present a slightly different analysis of constructing Learning Objects. They view Learning Objects as a combination of three areas: discipline knowledge, learning theory and enabling technology. Each of these areas is then analyzed in terms of content, presentation and application. The similarity of these two approaches underscores the importance of content, curriculum and delivery technology in the design of Learning Objects.

One issue that has been important to the Learning Object community, since the beginning, is dynamic assembly of Learning Objects. Dynamic assembly occurs when one informational query responds with integrated content from potentially many different content providers. For this to be accomplished, Learning Objects should exhibit the following behaviors:

- Modularization and encapsulation;
- Acting as customizable building blocks; and,
- Empowering learners so they can, ultimately, create their own learning modules.

IBM's Dynamic Search Engine was developed (Farrell, Liburd & Thomas, 2004) to all three issues listed above.

Curriculum Considerations

Redeker (2003) suggests a curriculum model that can be useful for both producers (faculty) and consumers (students) of Learning Objects. From largest granularity to the smallest, Redeker suggests course, partial course, Learning Unit, and Knowledge Unit. The *Knowledge Units* are composed of three types of Learning Objects:

- Receptive Learning Objects that are used by a learner; with these, they can maintain a high level of interest with no interactivity;
- Interactive Learning Objects that engage the user, much like computer-based training (CBT) for up to five minutes; and,
- Cooperative Learning Objects that provide for brainstorming, debating, or problem-solving sessions with other learners in a group setting.

Learning Units are defined as containers for collections of thematically related Knowledge Units.

Cisco Systems defines *Knowledge Objects*, similar to Learning Objects, as units of instruction based on one objective and composed of either static or dynamic (interactive) content. Cisco applies a rule that Knowledge Objects can have no more than 7+/-2 topics, referred to as knowledge objects. The number 7 +/- 2 is recognized from George Miller's work on the capacity of short term memory (Miller, 1956). Cisco also has a well-defined procedure for creating Knowledge Objects from topics that are relative to their discipline found in training materials and existing professional development courses. (Griffeths, et. al., 2004)

Learning Objects in the Classroom

A study by Chalk, Bradley & Pickard (2003) at London Metropolitan University showed that 400 first-semester Computer Science students demonstrated a much improved performance with the use of Learning Objects. No further details of the research were given in their report. However, Chalk, et. al. did infer that while Learning Objects by themselves may not have caused the performance improvement, there was a high correlation between the use of Learning Objects and students considered high achievers.

Farrell, Luburd & Thomas (2004) reported results of a usability study based on use of IBM's Custom Course System, featuring dynamic assembly of Learning Objects. The results of the usability study were quite positive, and are reported in Table 1. One major result of the system test is that IBM found users spent less time searching for information, and more time studying information.

In the summer of 2002, a first semester Computer Science course was taught at Carnegie-Mellon University which was supplemented with Learning Objects using the Adaptive Book technology (Adanchik & Gunaeardena, 2003). In spite of the challenging nature of this intense summer course taught in five weeks, students were reaching advanced topics such as data structures in the middle of the second week. Instructors had previously found that extended office hours and providing lecture notes in advance did not materially help students in this situation. They had also found that only 10% of students would participate in online discussions using a content management system.

Stamey, Saunders and Deluca (2005) underscore the importance of immediate feedback from the instructor, as well as the importance of tracking learner actions. Student use of Learning Objects for test preparation can be monitored to determine topics that need additional reinforcement. In their study, Learning Objects were used over a span of three classes in a first semester Computer Science course. The material in the Learning Objects provided information and exercises on the construction of *WHILE* loops, *FOR* loops, and *type casting* in the Java programming language. Results of a survey of student perceptions about Learning Objects were positive, with the students requesting more Learning Objects in the course. The students felt that Learning Objects would provide useful reference throughout the course. Students also found the immediate feedback quite helpful.

Other research has reported some interesting uses of Learning Objects in teaching. The use of multimedia, in particular, video, has been successfully integrated into a distance learning course on American Sign Language (Conceicao & Lehman, 2002). Kassanke, El-Saddik & Steincker (2001) report of development of Learning Objects at the Technical University of Darmstadt and the University of Paderborn, both in the area of Operations Research and Management Science. No descriptive statistics were given in the report.

Table 1

IBM's Usability Study of Dynamic Learning Object Assembly

Measure	Results
Time Learning Object system was available to users	1 month
Number of users with access to the system	114
Number of users spending more than one hour on the system	84
Number of users filling out evaluation forms at the end	73
Overall satisfaction rating (4 or 5 on a Likert Scale)	81%
Percent believing LO system would enhance knowledge/skills	81%
Percent preferring LO learning method to others	52%
Percent finding navigation of custom courses easy	90%
Number of positive (hand-written) comments	12
Number of negative (hand-written) comments	2

Learning Objects as Software Systems

Learning Objects may be thought of as both software systems and learning systems. McConnell (2002) defines three components that are necessary for the creation of the form of software systems: design requirements, system architecture, and implementation (system construction). Once created, software solutions must be *extensible* so that additional operational capabilities can be easily added. Finally, they must be *scalable* with the flexibility to support additional users. These attributes all work together in development of software systems with the highly desirable property of reusability.

The *design requirements* of Learning Objects describe the set of behaviors that the project owners wish to have implemented in the final product. Nugent, et. al. (2004) specify a Learning Object for an introductory Computer Science class that includes a brief tutorial explaining a concept, a set of real-world examples to illustrate the concepts, a set of practice exercises, and a set of graded problems. Implicit in the design of Learning Objects is the need for a student login and tracking system, as well as (at least) some minimal security for the results.

The *architecture* of Learning Objects is a set of specifications providing technical specifications such as the internal organization and implementation, the handling of input and output, data management, and security. Greer (2004) specifies a Learning Object system through the type of middleware, the database platform, a specific metadata standard, and ability to export in XML for data sharing.

The *implementation* of Learning Objects includes issues such as development methodology, human interaction features such as searching and help systems, communication protocols for interoperability, and quality of service (up-time). These issues are discussed in the eduSource implementation (Hatala, et. al., 2004). Services provided to the end-user include the ability to search repositories, receive alerts upon changes in metadata relative to each account holder, and object delivery using SOAP (Simple Object Access Protocol).

Once created, the extensibility of Learning Objects may be described relative to the terms adaptability, scalability and reusability. *Adaptability* is the ability of a system to be used with content for which it was not originally intended. Scalability refers to the ability of a system to gracefully expand to accommodate more users or more content. *Reusability* is the extent and ease to which parts of a software system can be used in other software systems (McConnell, 2005).

Longzhuang et. al. (2003) describe a Learning Object architecture that is adaptable on both the client and server sides. At the client interface, the Learning Object adapts the presentation to the student's learning pace. On the server side, a trace of the student's learning activities is captured to build up a data store of learner modeling information.

Design Patterns (Gamma, Helm, Johnson & Vlissides, 1995) have been used to provide solutions to programming problems that become large (or, have the need to be scalable). Three design patterns have been specifically identified as providing programming solutions to Learning Object development in solutions where scalability is a factor. These patterns include the abstract factory, the proxy, and the serializer (Pahl & Barrett, 2004).

The *abstract factory design pattern* is used to create as many instances of an object as needed (when a programming system executes), without needing prior knowledge of the number or type that will be needed. This pattern provides extensibility by facilitating the creation of many users of different types. The *proxy pattern* is used to provide a seamless, uniform interface to different client/student objects. The *serializer pattern* is used to provide a uniform interface for storing different types of student objects.

Bloom's Taxonomy

Bloom's Taxonomy: Original and Revised

Bloom's Taxonomy of educational objectives was developed by Benjamin Bloom and a group of associates in the early/mid 1950s (Bloom, et. al, 1958) to provide a basis for measuring qualitative differences in types of thinking. Bloom's Taxonomy has become one of the most widely adopted guides for curriculum planning. The intent was in developing a method to classify behaviors important in the learning process. The original framework described learning in three domains:

- Cognitive Domain: knowledge-based with a hierarchy of six levels;
- Affective Domain: attitude-based with a hierarchy of five levels; and,
- Psychomotor Domain: skill-based with a hierarchy of six levels.

The cognitive domain category was composed of a six-level hierarchy that provides a useful structure through which levels of understanding may be categorized. Organized by increasing amounts of learning, Bloom's Taxonomy is summarized as follows:

1. Knowledge: the ability to observe and recall information, as well as exhibiting knowledge of dates, events, places and ideas;
2. Comprehension: the ability to understand information by grasping its meaning, interpret facts, compare and contrast concepts and ideas;
3. Application: the ability to use information, methods, concepts, theories in new situations ;
4. Analysis: the ability to see patterns and the organization of parts, as well as the ability to determine the type of method to be used to solve a problem;
5. Synthesis: the ability to use known ideas to create new ideas, generalize, and relate knowledge from several different areas; and,
6. Evaluation: the ability to determine the value of theories and ideas, as well as to make choices based on argument and/or facts.

The widespread acceptance of Bloom's original Taxonomy lead two of his former students, Lorin Anderson and David Krathwol to think about updating the Taxonomy after nearly forty years since its publication. Three related groups were brought together, including cognitive psychologists, curriculum theorists and instructional researchers, and testing and assessment specialists.

The result, published in 2001, is known as the Revised Bloom's Taxonomy (Anderson, et. al, 2001). It included a new set of terminology for the category names, described as verbs rather than nouns:

- Knowledge became REMEMBERING
- Comprehension became UNDERSTANDING
- Application became APPLYING
- Analysis became ANALYZING
- Synthesis became EVALUATING
- Evaluation became CREATING

Descriptions of the six levels of the hierarchy were described in a crisper and cleaner manner:

- REMEMBERING: retrieving relevant knowledge from long-term memory;
- UNDERSTANDING: constructing meaning from oral, written or graphic messages;
- APPLYING: carrying out a procedure in a particular situation;
- ANALYZING: breaking a problem into its constituent parts, then determining their relationship and solution;
- EVALUATING: making judgments based on known criteria; and,
- CREATING: using elements together to form a new pattern or structure.

Use of Bloom's Taxonomy

O'Leary. et. al. (2006) describe the undergraduate curriculum in Computer Science currently found at nine key universities in China. This curriculum incorporates major elements of the ACM 2004 Computer Science curriculum with Bloom's Taxonomy.

- Year one emphasizes foundational programming and problem solving, with a strong focus at Level One of Bloom's Taxonomy (Knowledge), and some emphasis on Level Two (Comprehension).
- Year two focuses on whole-system development, thus introducing modularization and object-oriented programming. Here, there is a strong focus at Level Two of Bloom's Taxonomy (Comprehension), with some emphasis on Level Three (Application).
- Year three is aimed at giving students the ability to develop a reasonably large industrial/commercial application. There is a strong focus at Level Three of Bloom's Taxonomy (Application), with some emphasis on Level Four (Application).
- Year four focuses on preparing students for a transition into industry, usually including both an internship as well as academic thesis research. There is a strong focus at Level Four of Bloom's Taxonomy (Analysis), with some emphasis on Levels Five (Synthesis) and Six (Evaluation).

Bloom's Taxonomy is found to be useful in ordering course content when teaching programming concepts to business majors (Roussev & Rousseva, 2004). As programming is considered an act of synthesis (Bloom's Taxonomy, Level Five), the development of a solid background in lower-order skills would prove to be successful in a JavaScript class. Basic programming constructs and ideas were first modeled with the construction of statecharts, activities at Levels Two and Three of Bloom's Taxonomy. An experimental study of two similar groups of students showed a significant difference in the performance of the treatment group (who spent additional time being trained in lower-order skills).

Some researchers have even gone so far as to segregate students into groups, requiring evidence of different cognitive accomplishment for different grades. Lister and Leaney (2003) report weaker introductory computer science students being required to demonstrate knowledge and comprehension through the ability to read and understand programs, traditional tasks at Level One and Level Two of Bloom's Taxonomy. "Middling" students attempt traditional programming tasks, while the strongest students are given free reign to attempt projects at the higher levels of synthesis and evaluation levels of Bloom's Taxonomy.

Reeves (1990) reports teaching of business ethics with tasks at the six different levels of Bloom's Taxonomy. The successful progression of students to the higher levels of cognitive tasks was found to correlate with students' increasing interest, motivation and commitment to business ethics.

Not only is Bloom's Taxonomy useful for ordering and sequencing curriculum materials, but it is also useful in developing questions to test for understanding. These questions can involve students in cognitive tasks, from simple to complex (Vidakovic, Bevis & Alexander, 2004). Morris, Porter and Griffiths (2004) agree that assessment tools can be successfully designed in alignment with desired and observable outcomes.

Learning Theory and Learning Objects

Sequencing

Van Patten, Chao and Reigeluth (1986) surveyed general sequencing of instruction with digital media. They first define the differing scope of *macro strategies* and *micro strategies* differ in their scope. Macro strategies are used to organize a set of related topics and skills into lessons; they deal with the overall management of the presentation of multiple content ideas (topics). Micro strategies describe the organization of facts, concepts, principles and procedures within a lesson; they deal with the presentation of a single topic.

Sequencing is the process of breaking content into small elements. Determining the order of presentation of multiple topics is the sequencing challenge at the macro level. Sequencing also plays an important role at the micro-level, as it addresses the presentation of the actual examples and practice exercises for one particular topic. It is important to note that different sequences of the same micro-instructional events can result in different instructional outcomes.

Two general approaches to sequencing, which may be implemented at either the macro- or the micro-level, include logical sequences and scrambled sequences. Logical sequences of instruction, generally, present a new concept after others have been presented upon which the new concept depends. A dependency graph can be created where the nodes are the topics to be presented and the arcs identify the order of presentation.

Scrambled sequences of instruction date from Skinner's idea of stimulus-response sequences. (Skinner, 1953) In scrambled sequences of instruction, topics are presented in an unordered or random manner; successive passes through the same instructional material will generally not have the same sequence of events.

Important strategies for macro-level sequences include:

- Jerome Bruner's spiral approach is based on the idea of revisiting basic ideas, repeatedly, building upon them until the learner has grasped the full concept. This simple-to-complex sequence is an active process. New ideas or concepts are constructed by the learner based upon current and/or past knowledge. (Bruner, 1960)

- Ausubel's general-to-detailed sequence based on "progressive differentiation," whereby the learner gains greater meaning as new relationships (links) to a topic are acquired. (Ausubel, 1963)
- Gagne's hierarchical sequence for intellectual skills suggests that a skill cannot be acquired unless the learner possesses certain prerequisite skills. (Gagne, 1962)
- Mager's Criterion Referenced Instruction gives the learner freedom to create their own learning sequence. This sequence is based on their mastery of pre-requisite lessons (Mager & Pipe, 1984).
- Merrill's Component Display Theory allows the learner select their learning sequence based upon the instructional components provided. (Merrill, 1983)

Two main strategies are used in micro-level sequences (Berlanga & Garcia, 2003):

- Rule-Example versus Example-Rule: Two different ways of presenting a rule (or a theory) and an example are rule-example (presenting the rule first) versus example-rule (presenting a motivating example first).
- Order of instances describes the order in which examples (or practice examples) are presented - usually from simplest to the most complex.

Berlanga & Garcia also identify two additional kinds of adaptive strategies for intelligent tutoring systems.

- Interactions between learners and the learning environment may be either synchronous or asynchronous interactions. Asynchronous activities allow learners to participate when time allows, within a general time frame. Synchronous activities occur when learners (usually in conjunction with other learners and perhaps an instructor) participate in real-time.

- Feedback adaptation is based on General Systems Theory, originally developed by biologist Ludwig von Bertalanffy in the 1940's. General Systems Theory takes the view that every system is a feedback system. Such a view allows for immediate behavioral changes when feedback is given (Bertalanffy, 1950).

A more recent look at Curriculum Sequencing and Tutoring Strategies in Intelligent Tutoring Systems was done by Murray (1999). Curriculum Sequencing operates at a larger level of granularity, organizing materials into a hierarchy of courses, modules, lessons and presentations which are related by prerequisite, part, and other relationships. In order to provide an intelligent sequence of topics (at this highest level of granularity), content is stored as canned text and graphics.

Sequencing of the content is determined dynamically (at run-time), based on student performance. Tutoring Strategies are defined at a smaller level of granularity. Like Curriculum Sequencing, content for Tutoring Strategies is stored as canned text and graphics. However, decisions for the sequencing of curriculum materials can be handled at the individual question level (the smallest level of granularity). Trausan-Matu, et. al. (2002) discuss an intelligent tutoring system through which students learn about finance. From a glossary of terms, the system provides a list of relevant websites based on the term selected.

The term "reinstruction" is introduced into the Intelligent Learning Object literature by Stamey, Deluca and Sanders (2005) as the primary mechanism through which their Intelligent Learning Objects differ from traditional static Learning Objects. For each frame of instruction, there is a question the student must answer to test their comprehension of the material in the frame. If the student correctly answers the question, they move to the next frame. If they do not answer the question correctly, they are provided with an additional frame of reinstruction accompanied by a question testing comprehension. Reinstruction is similar to the ideas of Curriculum Sequencing and Tutoring Strategies in Intelligent Tutoring Systems found in Murray (1999).

Types of Knowledge

The extent and variety of knowledge brought to a learning situation by a student influences all aspects of how the information is processed. Tacit knowledge and content knowledge are two important ways in which we act upon new information.

Tacit knowledge is implicit, operating at the level of conscious awareness. Sociocultural behaviors such as helping a person in need would be an example of tacit knowledge. (Gredler, 2001, p. 181). Content knowledge can be either knowledge organized around a particular content area or more general discipline knowledge organized around fundamental principles that define a field (such as the study of computer algorithms by time/space complexity).

Tacit and content knowledge allow us to make inferences about new information. Bors and McLeod (1996) found that prior knowledge is a good predictor of rate of learning and retention of facts. This observation leads us to examine the Revised Bloom's Taxonomy as a structure for building knowledge. Bloom (in Anderson, et. al. 2001) describes categories of cognitive process that build upon one another. One must be able to first remember (retrieve relevant knowledge) before one can understand (construct meaning from messages). Once one can understand, one can apply (carry out or use procedures in a given situation).

Reinstruction and Intelligent Tutoring Systems

Wood and Wood (1996) describe patterns of individual instruction as being marked by two principles: give more help when the learner needs assistance; and, give less help when the learner gains in proficiency. These two principles are called Contingent Instruction. While these two rules seem quite simple and straightforward at the abstract level, they turn out to be quite difficult to sustain in reality. Wood and Wood report that the flexibility of contingent instruction can be difficult to achieve without the reliability of computer-based tutoring systems.

Wood and Wood (1996) report four principles (attributed to an unnamed paper by J.A. Anderson in 1988) that Intelligent Tutoring Systems can follow to provide Contingent Instruction. These include:

- Providing instruction in the problem-solving context when needed;
- Providing immediate response to learner errors;
- Avoiding assistance while the learner is successful; and,
- Providing reminders of the learning goal (perhaps through a trace of what the learner has achieved so far.

The algorithmic flavor of Contingent instruction is associated with Anderson's general theory of learning, drawn from information processing. The terms used are based upon (and implemented) much the same as the architecture of a computer. The performance of cognitive tasks is based on the idea of memory structures, a sequence of instructions (mental operations), and the product (information) (Anderson, 1990).

The Intelligent Learning Objects of Stamey, Deluca and Saunders (2005) follow Anderson's Four Principles:

- When the student does not successfully answer a question about curriculum material, additional instruction (reinstruction) is provided.
- The student's answer is immediately marked as either correct or incorrect.
- If the student does not miss a question about material in a frame, no additional instruction (reinstruction) is provided.
- A running score of correct and incorrect answers is provided as the grade is returned with each answer.

The notion of testing is important in the Intelligent Learning Objects. Gredler (2001, p. 184) acknowledges tests (and testing) is not a neutral event. Testing requires information be retrieved from long term memory and then be interacted upon by the learner. The repeated interaction through tests is found to increase student scores in tasks such as learning word lists. This underscores the importance of testing as a fundamental mechanism of Intelligent Learning Objects.

Usability of Intelligent Learning Objects

Usability, in the e-learning world, is defined by the ability of an object to support or enable a very particular concrete goal (Feldstein, 2002). As usability is typically studied prior to the actual deployment of a Learning Object, outcomes can be potential indicators of a learner's success (Sicilia & García, 2003). For this reason, usability studies are important to the deployment of Learning Objects on the World Wide Web.

Neilsen (2003) defines computer system usability as a measure of quality that assesses the ease-of-use found in using an interface. He identifies five components that, together, provide a measure of quality and usability on the World Wide Web:

- Learnability: How easy is it for users to accomplish basic tasks the first time they encounter the design?
- Efficiency: Once users have learned the design, how quickly can they perform tasks?
- Memorability: When users return to the design after a period of not using it, how easily can they reestablish proficiency?
- Errors: How many errors do users make, how severe are these errors, and how easily can they recover from the errors?
- Satisfaction: How pleasant is it to use the design?

As of much the content of Learning Objects is composed of text, a *scannable* layout which features concise text and lists (either bullet-points or numbered) speeds and facilitates reading of webpages (Neilsen, 2000, pp. 100-103). The file size of graphical images must be kept at a minimum as users find the most satisfaction in websites that download fully and quickly (Neilsen, 2000).

Neilsen and Landauer (1993) find that 80% of all major usability errors are found with as few as five participants in a study, and almost 100% are found with twelve participants in a study. The advantage of this finding is that ten participants can reasonably (and economically) participate in two different usability studies, one following the other, theoretically finding 96% of all major usability problems.

Tullis and Stetson (2004) compared four known instruments for assessing website usability. Of the four, the System Usability Scale (SUS) developed at Digital Equipment Corporation was found to be the best predictor of user satisfaction / usability. The SUS was found to reach near 100% accuracy when taken by twelve participants in the study.

Chapter Summary

Chapter Two began with a discussion of Intelligent Tutoring Systems, within which Learning objects are classified. Issues of interoperability and metadata were discussed, in a discussion of extensibility of Learning Objects. Next, the review discussed availability of Learning Objects in repositories, the curriculum design of Learning Object curriculum design, and experience with the use of Learning Objects in the classroom. The review concluded with a look at the software implementation issues of Learning Objects, the relation of Learning Objects to learning theory, and usability issues.

CHAPTER III: RESEARCH METHODOLOGY

Introduction

This chapter describes the quantitative research designs used to determine both the effectiveness of Intelligent Learning Objects, as well as students' perceptions of this new technological learning environment. We describe the research design, the research questions, the independent and dependent variables, the target and sample population, the instrument development, the data collection procedures, the statistical data analysis and the pilot study that measured both the effectiveness of Intelligent Learning Objects and students' perceptions of Intelligent Learning Objects.

Research Questions

Intelligent Learning Objects are a recent technology to be applied to a student's learning experience. Furthermore, Intelligent Learning Objects allow for instruction to be designed to assist the student if problems in performance are noted. To this end, the primary research question was:

> Do students, using Intelligent Learning Objects with curriculum based on the Revised Bloom's Taxonomy along with reinstruction, have a different level of achievement than those using traditional classroom training?

The following Null Hypotheses were analyzed to answer this question:

> H_{01}: There is no significant difference in the level of achievement, at Level 1 and 2 (recognizing and understanding) of the Revised Bloom's Taxonomy, between students using Intelligent Learning Objects (with curriculum featuring reinstruction) and those receiving traditional classroom training.

H_{02}: There is no significant difference in the level of achievement, at Level 3 (applying) of the Revised Bloom's Taxonomy, between students using Intelligent Learning Objects (with curriculum featuring reinstruction) and those receiving traditional classroom training.

H_{03}: There is no significant difference in the level of achievement, at Level 4 (analyzing) of the Revised Bloom's Taxonomy, between students using Intelligent Learning Objects (with curriculum featuring reinstruction) and those receiving traditional classroom training.

The secondary research question, for subjects who received instruction with Intelligent Learning Objects was:

How to students perceive Intelligent Learning Objects?

Research Design

The research design to study the primary research hypothesis was pretest-posttest control group design with Nonequivalent Groups Design (hereafter NEGD). Such a study is structured like a traditional pretest-posttest randomized experiment, except that the groups are not selected by random assignment. NEGD generally uses intact groups we have reason to believe are similar, such as comparable classes (Trochim, 2000A). Traditional notation for this type of design, is seen in Figure 2, written in notation developed by Campbell & Stanley (1963).

Experimental Group	N	O	X	O
Control Group	N	O		O

Figure 2. Nonequivalent Group Design.

Each row represents a subset of the sample population involved in the experiment. In this research design, the N preceding each row indicates that the groups were selected under NEGD. The first O in both rows indicates a pretest was given. The second O in each row indicates a posttest was given. The X in the top row indicates this group received an experimental treatment; in this study, the experimental treatment was instruction with Intelligent Learning Objects. The *Control Group* is defined as those participants who received instruction with traditional classroom lecture. The *Experimental Group* is defined as those participants who received instruction with Intelligent Learning Objects.

Four steps were involved in using the pretest-posttest control group design of research design (Gall, Gall & Borg, 2003, p. 392):

1. Intact classes were selected and assigned as the Experimental and Control groups.
2. Both groups received a pretest.
3. A treatment, using Intelligent Learning Objects for delivery of selected portions of the course material, was given to the Experimental group.
4. A posttest was administered to both groups.

The *Student Perception Survey* was tested with a pencil-and-paper survey of the group receiving the experimental treatment (using the Intelligent Learning Objects). The survey was administered following the posttest. The survey sought to determine whether the students perceived the Intelligent Learning Objects as an effective tool in delivering unit content. This type of research design used to study the secondary research hypothesis was a one-shot case study.

Independent and Dependent Variables

In the quantitative research design chosen for the primary research question, the phenomenon under consideration was the cause-and-effect relationship between two types of variables. Independent variables are the presumed cause, and dependent variables are the presumed effect. In our study, we hypothesized that the use of Intelligent Learning Objects would produce a difference in student achievement. In this hypothesis, the use of the Intelligent Learning Objects was the independent variable. The dependent variables were the levels of student achievement on the posttest at Levels 1 and 2, Level 3 and Level 4 of the Revised Bloom's Taxonomy.

Target and Sample Populations

The target population for the primary research question, defined as all subjects of interest, was all college students. The sample population was a set of four intact Statistics 201 Lab (ST 201L) Sections at a university in the southeast. The ST 201L classes were held in Spring 2006. As the five ST 201L classes began and ended within thirty minutes of each other, and as the classes were held on weekdays Monday through Thursday. The schedule of lab classes and the number of students in each was as follows:

- Section 1 – 1:30PM to 4:00 PM, Monday – 24 students
- Section 2 – 1:00PM to 3:30 PM, Tuesday – 24 students
- Section 3 – 1:30PM to 4:00 PM, Wednesday – 23 students
- Section 4 – 1:30PM to 4:00 PM, Wednesday – 22 students
- Section 5 – 1:00PM to 3:30 PM, Thursday – 23 students

The target population for the Student Preference Survey was all undergraduate college students. The sample population consisted of the three intact classes who used the Intelligent Learning Objects during the course of this study.

Internal Validity

The key question about the internal validity of any study is whether observed changes may be attributed to the treatment, and not attributed to other possible causes. We examined the internal validity of the study examining the primary research question.

The major threat to internal validity of a multiple group study is that any factor other than the treatment leads to a difference in the posttests of the groups. This type of threat is called a Selection Threat. Six primary causes of a Selection Threat, and their application to this study, are discussed below (Trochim, 2000B).

The Selection-History threat is an event, other than the experimental treatment, that either group might experience. As students in both the Control Group and the Experimental Group attend the same university, there is a possibility that students in one group would learn of the different treatment given the other group. Furthermore, students in the Experimental Group might have permitted students in the Control Group to have access to the Intelligent Learning Objects system. Selection-History was considered a major threat to the internal validity of this study.

The Selection-Maturation threat is a result of normal development and maturity between the time of the pretest and the time of the posttest. As the time between the pretest and the posttest was less than six weeks, Selection-Maturation was not considered to be a major threat to the internal validity of this study.

The Selection-Testing threat occurs when students experience some incremental learning from the pretest, and their scores on the posttest are affected, accordingly. As it was assumed the majority of the students had not seen this material before, it was assumed they would have little memory of the pretest by the time the posttest is given. For that reason, Selection-Testing was not considered to be a major threat to the internal validity of this study.

The Selection-Instrumentation threat occurs when there is any change in the test given to one group, for whatever reason. The materials for the Intelligent Learning Objects and the posttest were intended to be the same for both groups. However, it is possible that the lab instructors who taught the material in the traditional manner could do a much better than average job during their instruction, giving subjects in the Control Group an advantage. For this reason, Selecting-Instrumentation was considered to be a minor threat to the internal validity of this study.

The Selection-Mortality threat occurs when there is a dropout of one or more subjects in either group. If this were to occur, the postests would not have the same difference as if all of the students (who originally started) were present. As the dates for the administration of this experiment are prior to the last day to drop the course with a grade of "W" in the Spring Semester (March 24), Selection-Mortality was considered to be a very minor threat to internal validity of this study.

The Selection-Regression Threat occurs when one group has more extremes on the pretest than the other. Should one group have more extreme pretest scores, at either the high or low end, those students would tend to regress more toward the mean (later in the study). Selection-Regression threat was tested for both during the pretest. Prior to this examination, the size of both groups (approximately fifty each) indicated that the Central Limit Theorem would apply, and both groups should be approximately equal at the beginning of the study. For this reason, Selection-Regression Threat was considered to be a minor threat to the internal validity of this study.

Data Collection Procedures

A list of five ST 201L sections was obtained before the beginning of the Spring 2006 semester. Three of the sections, the Experimental Group, were selected at random to receive instruction by Intelligent Learning Objects (the *treatment*) on four topics appropriate to ST 201L. The other two sections, the Control Group, were to receive a short lecture on these topics, delivered from a written script to eliminate bias. The Control Group also received a short set of homework exercises with which they were to practice skills introduced in the lecture. The labs met once a week. The study took place during March-April 2006. The posttest was administered in the last week of April, 2006.

To investigate the primary research question, a pretest was administered to all ST 201L students participating in the study at the beginning of the first lab in which the study began. A posttest was administered to all ST 201L students at the beginning of the second lab period held in March 2006. The posttest was also understood, by the students, to be a part of their final grade.

To investigate the secondary research question, a Student Preference Survey was administered to all subjects who received instruction from the Intelligent Learning Objects. The purpose of this survey was to examine students' interest in Intelligent Learning Objects, in order to determine the feasibility of Intelligent Learning Objects as a tool for delivering information in both traditional and distance learning classes. The Student Preference Survey was delivered to the lab sections receiving experimental treatment the week after the subjects took the posttest. The week-long delay in administering the survey was an attempt to eliminate bias that might occur if the subjects did not do well on the posttest, which was assumed to count as part of their final grade.

Letters authorizing this study were obtained from the Institutional Review Boards of North Carolina State University and a university in the southeast. Copies of these two letters may be found in Appendix A.

Development of the Intelligent Learning Object System

The Intelligent Learning Objects system was developed by the author between October 2005 and January 2006. It is written in ColdFusion and runs on a Windows 2003 server. The Intelligent Learning Objects system allows learners to view a collection of browser screens of information on a particular topic and questions for comprehension, called *frames*. If the learner is not successful in answering the question on the material presented in the frame, a second screen containing reinstruction and an additional question for comprehension is presented.

Users of the system had password-protected personal accounts so that the information collected from use of the system could be stored in an Access database for further analysis. Types of data that were collected included:

- Number of questions answered correctly (both original instruction and reinstruction); and,
- The time needed to answer each question.

Curriculum Development

Four Intelligent Learning Objects, each devoted to one topic, were presented to the students in the Experimental Group. Students in the Control Group received a lecture based on the same content found in the Intelligent Learning Objects. The topics for the Intelligent Learning Objects were:

- The Poisson Distribution
- Populations and Samples
- ReExpression
- Sampling Techniques

The curriculum and materials for the Intelligent Learning Objects may be found in Appendix B. The materials were used in the study as part of the undergraduate course lab in statistics, ST 201L, taught at a university in South Carolina.

Each Intelligent Learning Object consisted of questions at different levels of Bloom's Taxonomy. The curriculum materials developed for the Intelligent Learning Objects began with introductory questions at Revised Bloom's Levels One and Two, associated with skills of remembering and understanding. Next, there were questions at Level Three, associated with applying concepts from lower levels; these questions generally consisted of computations performed by the students. Finally, there were questions at Level Four, measuring the student's ability to determine when to apply a topic, as well as how to apply the topic.

Content Validation of ILO Curriculum Materials

This questionnaire is to validate the teaching material (text and questions) for the Intelligent Learning Objects that are to be used in ST 201 Lab in Spring 2006. (*Note that a set of four questions will be asked for each question in every ILO*)

For each item, please circle your opinion. Opinions are to be measured as follows:

5= Strongly Agree content represents the topic properly
4= Agree content represents the topic properly
3= No opinion either way content represents the topic properly
2= Disagree content represents the topic properly
1= Strongly Disagree content represents the topic properly

Also, please help determine the level of skill and learning found in each question. The levels are:
Level 1 – Remembering: Can the student RECALL the information?
Level 2 – Understanding: Can the student EXPLAIN the ideas or concepts?
Level 3 – Applying: Can the student USE the new knowledge in another familiar situation?
Level 4 – Analyzing: Can the student DIFFERENTIATE between constituent parts?

Instruction i - Please circle your answer. If it is a 2 or 1,
Please write in comments that would help in making changes.
5=Strongly Agree 4=Agree 3=No Opinion 2=Disagree 1=Strongly Disagree

Question i - Please circle your answer. If it is a 2 or 1,
Please write in comments that would help in making changes.
5=Strongly Agree 4=Agree 3=No Opinion 2=Disagree 1=Strongly Disagree

Level of Skill – Please circle the level that best describes this instruction and question
Recall Explain Use Differentiate

Reinstruction i - Please circle your answer. If it is a 2 or 1,
Please write in comments that would help in making changes.
5=Strongly Agree 4=Agree 3=No Opinion 2=Disagree 1=Strongly Disagree

Reinstruction Question i - Please circle your answer. If it is a 2 or 1,
Please write in comments that would help in making changes.
5=Strongly Agree 4=Agree 3=No Opinion 2=Disagree 1=Strongly Disagree

Level of Skill – Please circle the level that best describes this reinstruction and question
Recall Explain Use Differentiate

Figure 3. Content Validation of ILO Curriculum Materials.

The curriculum materials were reviewed by a panel of three statistics content experts including:

- Dr. Eric Howington, Assistant Professor of Statistics Coastal Carolina University and Director of the ST 201 / ST 201 Lab classes (Ph.D. in Applied Statistics, University of Alabama)
- Dr. Prashant Sansgeri, Professor and Chair of the Department of Mathematics and Statistics at Coastal Carolina University (Ph.D. in Statistics, University of Wyoming)
- Dr. Keshav Jagannathan, Assistant Professor of Statistics at Coastal Carolina University (Ph.D. in Statistics, Bowling Green University)

All Intelligent Learning Object content and evaluation questions were examined for content validity, which is an inspection of the test items to determine if they did cover content relevant to the STAT 201L course (Gall, Gall and Borg, 1999). The form used for content validation is seen in Figure 3.

Instrument Development

Validity

Validity, in social research, answers the question "Are we measuring what we intend to measure?" Two important types of translation validity are face validity and content validity. Face validity is a surface-level view of an instrument to determine if "at face value" the instrument is a good translation of the construct (information) of which it is being used to judge. Face validity is no more than a quick judgment, and is not necessarily made by experts in the field. "The theory behind content validity, as opposed to face validity, is that experts are aware of nuances in the construct that may be rare or elusive of which the layperson may not be aware" (Rymarchk, 2000).

Content validity is an organized examination by experts in the field of an instrument to determine if it is a good translation of the constructs (information) for which it is being used to judge (Trochim, 2000C). Being judged by experts, content validity is a much stronger judge of validity. Content validity was used to determine the validity of the instruments used in this study. Content validation for this study will be examined in two subsequent sections.

Reliability

The reliability of an instrument is a measure of its internal consistency. The term reliability means "repeatability" or "consistency" (Trochim, 2004D). An instrument is considered reliable if it would give us the same result again and again. Two types of tests for reliability are generally used in social research: split-half reliability, and Cronbach’s Alpha (and related measures).

The split-half reliability procedure randomly divides the questions into two sets and the correlation between the scores on each of the sets would be compared. A stronger measure of reliability is Cronbach's Alpha which computes an average of all combinations of split-halves. Cronbach's Alpha is appropriate for tests that are not scored dichotomously (correct or incorrect). In the case of a dichotomous test, Kuder-Richardson Formula 20 is appropriate for use (Gall, Gall and Borg, 2003, p. 198; Sheel, 1981). Cronbach’s Alpha is a general form of Kuder-Richardson Formula 20. It may be noted that Kuder-Richardson Formula 20 will usually yield a lower reliability coefficient than Cronbach’s Alpha.

As the pretest and posttest were almost identical, Kuder-Richardson Formula 20 was used to compute the reliability of the individual items on the pretest. There were 16 questions on the pretest, and a total of 67 subjects took the pretest. The reliability coefficient of the pretest, computed with Kuder-Richardson Formula 20 was .8732.

Pretest Content Validation Survey

This questionnaire is to validate the Pretest for the Intelligent Learning Objects that are to be used in ST 201 Lab in Spring 2006.

For each question on the pretest, please circle your opinion. Opinions are to be measured as follows:

5= Strongly Agree content represents the topic properly
4= Agree content represents the topic properly
3= No opinion either way content represents the topic properly
2= Disagree content represents the topic properly
1= Strongly Disagree content represents the topic properly

Also, please help determine the level of skill and learning found in each question. The levels are:
Level 1 – Remembering: Can the student RECALL the information?
Level 2 – Understanding: Can the student EXPLAIN the ideas or concepts?
Level 3 – Applying: Can the student USE the new knowledge in another familiar situation?
Level 4 – Analyzing: Can the student DIFFERENTIATE between constituent parts?

Question i - Please circle your answer. If it is a 2 or 1,
Please write in comments that would help in making changes.
5=Strongly Agree 4=Agree 3=No Opinion 2=Disagree 1=Strongly Disagree

Level of Skill – Please circle the level that best describes this instruction and question
Recall Explain Use Differentiate

Figure 4. Pretest Content Validation Survey.

Pretest and Posttest Development

The pretest, found in Appendix C, was developed to measure students' current knowledge of the following four areas in statistics: the Poisson Distribution; ReExpressing data, Populations –versus- Samples, and Types of Sampling. There were four questions from each topic on the pretest. Two questions per topic measured Recognition and Understanding (the Revised Bloom's Taxonomy, Levels 1 and 2). One question measured Application (the Revised Bloom's Taxonomy, Level 3). One question measured Analysis (the Revised Bloom' Taxonomy, Level 4). Figure 4 shows the type of instrument that was used to measure content validity of the pretest.

Posttest Content Validation Survey

This questionnaire is to validate the Posttest for the Intelligent Learning Objects that are to be used in ST 201 Lab in Spring 2006.

For each question on the pretest, please circle your opinion. Opinions are to be measured as follows:

5= Strongly Agree content represents the topic properly
4= Agree content represents the topic properly
3= No opinion either way content represents the topic properly
2= Disagree content represents the topic properly
1= Strongly Disagree content represents the topic properly

Also, please help determine the level of skill and learning found in each question. The levels are:
Level 1 – Remembering: Can the student RECALL the information?
Level 2 – Understanding: Can the student EXPLAIN the ideas or concepts?
Level 3 – Applying: Can the student USE the new knowledge in another familiar situation?
Level 4 – Analyzing: Can the student DIFFERENTIATE between constituent parts?

Question i - Please circle your answer. If it is a 2 or 1,
Please write in comments that would help in making changes.
5=Strongly Agree 4=Agree 3=No Opinion 2=Disagree 1=Strongly Disagree

Level of Skill – Please circle the level that best describes this instruction and question
Recall Explain Use Differentiate

Figure 5. Posttest Content Validation Survey.

The posttest, found in Appendix D, was developed to measure students' achievement in the same four areas as the pretest in Statistics. There were questions from each topic at different levels corresponding to the Revised Bloom's Taxonomy on the posttest at the first four levels of the Revised Bloom's Taxonomy. Figure 5 shows the type of instrument that was used to measure content validity of the posttest. One question on the Posttest Content Validation Survey was posed for each question on the posttest.

Student Perception Survey Instrument Development

A survey, found in Appendix E, was created to collect subjects' opinions and perceptions about using the Intelligent Learning Objects. The survey was created based on a survey by Burgess (2003) studying students' perceptions of WebCT. In creating a survey, the content validity of the instrument is of primary importance (Gall, Gall & Borg, p. 223). Content validity is "typically determined by content experts, who define in precise terms the domain of specific content that the test (or survey) is to represent" (Gall, Gall & Borg, pp. 191-192). The survey was reviewed by a panel of three statisticians:

- Dr. Eric Howington, Assistant Professor of Statistics Coastal Carolina University and Director of the ST 201 / ST 201 Lab classes (Ph.D. in Applied Statistics, University of Alabama)
- Dr. Prashant Sansgeri, Professor and Chair of the Department of Mathematics and Statistics at Coastal Carolina University (Ph.D. in Statistics, University of Wyoming)
- Dr. Keshav Jagannathan, Assistant Professor of Statistics at Coastal Carolina University (Ph.D. in Statistics, Bowling Green University)

Figure 6 shows the type of instrument that was used to measure content validity of the Student Perception Survey. The reliability of an instrument is the amount of measurement error present in the scores yielded by the questionnaire. Reliability is a property of the test's score, and not of the test itself (Gall, Gall & Borg, 2003, p.196).

Student Preference Survey Content Validation

This questionnaire is to validate the Pretest for the Intelligent Learning Objects that are to be used in ST 201 Lab in Spring 2006.

For each question on the pretest, please circle your opinion. Opinions are to be measured as follows:

5= Strongly Agree content represents the topic properly
4= Agree content represents the topic properly
3= No opinion either way content represents the topic properly
2= Disagree content represents the topic properly
1= Strongly Disagree content represents the topic properly

Question i - Please circle your answer. If it is a 2 or 1,
Please write in comments that would help in making changes.
5=StronglyAgree 4=Agree 3=NoOpinion 2=Disagree 1=StronglyDisagree

Figure 6. Student Preference Survey Content Validation.

Survey Administration

The students in the Experimental Group were surveyed using a pen and paper instrument after the posttest was given to both groups (the Control Group and Experimental Group). The first section of the instrument incorporated questions about the use of Intelligent Learning Objects. The second section of the instrument collected demographic information. The approach is similar to Burgess (2003).

Statistical Data Analysis

Pretest and posttest data were used to determine the difference in learning based on traditional lecture versus the use of ILOs. A t-test was used to determine if there was a statistically significant difference, at α=05, between the achievement of the Control Group and achievement of the Experimental Group on the posttest.

As the standard deviation of the population was not known, a t-test (using the Student's t-distribution) comparing the difference of the means of the two groups was used. This inferential statistic is appropriate for use in this study, based on examples found in Agresti & Finlay (1997).

Frequency data were collected based on responses from participants who used ILOs. Descriptive statistics were used to assess the responses on the survey from subjects who had used ILOs. The following information was reported for each question on the survey:

- the average of the responses (given on a five-point Likert scale);
- the mean; and,
- the standard deviation.

Pilot Study

The pilot study for this investigation was given to one section of ST 201L in November 2005. There were twenty students in this lab section. The primary goal of the pilot study was:

- to verify the Intelligent Learning Object system worked properly and could deliver study materials and questions to a group of students in real-time;
- to determine the usability of the Intelligent Learning Object system from the standpoint of the subjects; and,
- to collect and validate data from the Intelligent Learning Object system when used by an intact class/lab.

To determine the general quality of the Intelligent Learning Object system, a usability test was developed using the following five quality components. (Neilsen, 2003):

- Learnability: How easy is it for users to accomplish basic tasks the first time they encounter the design?
- Efficiency: Once users have learned the design, how quickly can they perform tasks?
- Memorability: When users return to the design after a period of not using it, how easily can they reestablish proficiency?
- Errors: How many errors do users make, how severe are these errors, and how easily can they recover from the errors?
- Satisfaction: How pleasant is it to use the design?

The usability test was given at the conclusion of the pilot study. A copy of the usability test may be found in Figure 7. A summary of the results, found in Table 2, show a high degree of usability acceptance from the subjects in the pilot study. Data collected for the usability study is found in Appendix F.

Usability Study Survey

1. I was quickly able to determine how to log in and begin using the system to answer questions.

   Strongly Agree   Agree   Neutral   Disagree   Strongly Disagree

2. The system was set up so that the questions were easily found and submitting the answers was straightforward.

   Strongly Agree   Agree   Neutral   Disagree   Strongly Disagree

3. The system was primarily error-free in it operation.

   Strongly Agree   Agree   Neutral   Disagree   Strongly Disagree

4. If I used the system in about a week, I would not have any problems understanding how to log in, view questions, and submit answers.

   Strongly Agree   Agree   Neutral   Disagree   Strongly Disagree

5. The design of the system (web-based, pull-down menus to select responses) made it easy to use the system.

   Strongly Agree   Agree   Neutral   Disagree   Strongly Disagree

6. Any other comments, questions or ideas.

Figure 7. Usability Study Survey.

Chapter Summary

The methodology for investigating the use and student perceptions of Intelligent Learning Objects was presented in this chapter. The research strategy was presented in two parts. The first part involved a pretest-posttest control group design with nonequivalent groups determine if there was, indeed, a difference in performance between the Control Group and the Experimental Group. The second part involved a survey of student preferences to examine students' interest in Intelligent Learning Objects to determine the feasibility of Intelligent Learning Objects as a tool for delivering information in both traditional and

Table 2

Usability Survey Questions and Response Measures

Survey Question	Average Response
I was quickly able to determine how to log in and begin using the system to answer questions.	4.4167
The system was set up so that the questions were easily found and submitting the answers was straightforward.	4.6667
The system was primarily error-free in it operation.	4.4167
If I used the system in about a week, I would not have any problems understanding how to log in, view questions, and submit answers.	4.6250
The design of the system (web-based, pull-down menus to select responses) made it easy to use the system.	4.6250

distance learning classes. Appropriate statistical methods were proposed for the analysis of the data for each part of the research strategy. A pilot study enhanced the research methodology.

CHAPTER IV: FINDINGS

Findings

This study had two purposes. The primary research question was used to determine if student performance is improved using Intelligent Learning Objects, as opposed to receiving traditional classroom instruction. The secondary research question was used to determine students' opinions about Intelligent Learning Objects. A pretest-posttest experiment with a Control Group and an Experimental Group provided the framework for investigating the primary research question. A Student Preference Survey of subjects who used the Intelligent Learning Objects, the Experimental Group, provided the framework for investigating the secondary research question.

The first section of this chapter describes the results of the investigation into the primary research question. The first subsection describes the subjects in this study. Included in this section are descriptions of the subjects, how they were split into the Control Group and the Experimental Group, and statistics describing the stratification of the two groups by class (freshman, sophomore, junior and senior).

The second subsection describes how the sample data was collected. It discusses the procedure for collecting the data for the pretest and posttest, as well as adjustments that were made based on subject attendance and inconsistency.

The third subsection describes the data that was collected from the Intelligent Learning Objects. Descriptive statistics summarize the correct responses to instruction and reinstruction.

The fourth subsection presents the findings associated with a quantitative analysis of the difference between the Control Group and the Experimental Group. This analysis is based on the difference of means between the pretest and posttest scores of the two groups.

The second section presents the findings associated with a quantitative analysis of the Student Preference Survey, taken by subjects in the Experimental Group who used the Intelligent Learning Objects. This analysis is based on the descriptive statistics that summarize a pencil-and-paper survey.

Primary Research Question Findings

Description of Subjects

The primary research question in this investigation was:

> Do students, using Intelligent Learning Objects with curriculum based on Revised Bloom's Taxonomy along with reinstruction, have a different level of achievement than those using traditional classroom training?

The sample used to test the primary research hypothesis was all undergraduate students taking ST 201L at a university in the southeast during the Spring 2006 semester. Table 3 gives a breakdown of students by section, along with their academic year.

Five sections of intact classes participated in the study. Three sections were chosen at random to receive the experimental treatment of instruction with Intelligent Learning Objects. The remaining two sections served as the Control Group. A total of 116 students were enrolled in all five sections of ST 201 Lab. Forty-seven (47) subjects were enrolled in the Control Group sections, and sixty-nine (69) subjects were enrolled in the Experimental Group sections.

Table 3

Demographics of Subjects in Control and Experimental Group

Section	Group	FR	SO	JR	SR	Total
Monday – 1:30 PM	Control	3	8	8	6	24
Tuesday 1:00 PM	Experimental	3	7	8	6	24
Wednesday – 1:30 PM	Experimental	0	7	10	6	23
Thursday – 1:00 PM	Experimental	2	8	9	3	22
Thursday – 3:00 PM	Control	1	8	11	3	23
	TOTAL	8	36	46	24	116

Data Collection

While attendance was an implicit requirement for subjects in ST 201 Lab, not all subjects attended all sessions. Absences during the class periods of the Control Group yielded a total of 29 subjects (61.07%) who completed both the pretest and the posttest. Absences also accounted for a total of 38 subjects (55.07%) who completed both the pretest and the posttest in the Experimental Group. Of the 38 subjects who took both the pretest and the posttest in the Experimental Group, four were removed as they did not complete the posttest and two tests were removed due to inconsistency. For this reason, the Experimental Group consisted of 32 subjects. A summary of students who took only the pretest, only the posttest, neither the pretest nor the posttest and both the pretest and posttest is found in Table 4.

Table 4

Subjects by Participation in Pretest and Posttest

Section	Both	Pretest	Posttest	No Test	Total
Control Group					
Monday – 1:30 PM	14	3	1	6	24
Thursday – 3:00 PM	15	5	1	2	23
Subtotal	29	8	2	8	47
Experimental Group					
Tuesday 1:00 PM	16	5	2	1	24
Wednesday – 1:30 PM	10	5	6	2	23
Thursday – 1:00 PM	12	7	2	1	22
Subtotal	38	17	10	4	69
Total – Both Groups	67	25	12	12	116

Intelligent Learning Object Data Collected

Subjects in the Experimental Group received instruction from Intelligent Learning Objects. One Intelligent Learning Object was used for instruction during each week. Each Intelligent Learning Object had three frames of instruction and a question to measure understanding of the material. If the question was answered incorrectly, an additional frame of instruction (called Reinstruction) was delivered. The Reinstruction also included a question to measure understanding of the material. Tables 5 through 8 show the performance of subjects who used the Intelligent Learning Objects.

Table 5

Descriptive Statistics of Intelligent Learning Object Instruction

ILO	Subjects	Questions Attempted	Mean Questions Correct	SD	Percent Correct
1	57	3	1.3728	0.7165	45.76%
2	41	3	1.5000	1.0555	50.00%
3	42	3	1.7381	0.8570	57.94%
4	16	3	1.3888	0.9785	46.29%

Table 5 contains descriptive statistics on the number of subjects who used each of the Intelligent Learning Objects, the number of questions they answered correctly (the mean), and the standard deviation. Each Intelligent Learning Object was composed of three frames of information. The mean number of questions answered correctly for each Intelligent Learning Object, along with the standard deviation for each Intelligent Learning Object, is reported in this table. Intelligent Learning Object 1 (The Poisson Distribution) had the fewest questions answered correctly, while Intelligent Learning Object 3 (ReExpression) had the most questions answered correctly.

Table 6 contains descriptive statistics on the number of Reinstruction questions that were delivered, as well as the subjects' success in answering questions of comprehension. Intelligent Learning Object 1 (Poisson Distribution) and Intelligent Learning Object 4 (Sampling Techniques) had the most reinstruction delivered, averaging 1.6272 and 1.6112 questions respectively. The least amount of reinstruction was associated with Intelligent

Table 6

Descriptive Statistics of Intelligent Learning Object Reinstruction

ILO	Subjects	Reinstruction Questions Attempted	Mean Questions Correct	SD	Percent Correct
1	57	1.6272	0.3893	0.5257	23.92%
2	41	1.5000	0.8611	0.8669	57.41%
3	42	1.2619	0.7142	0.7741	56.59%
4	16	1.6112	0.6111	0.8498	37.93%

Learning Object 3 (ReExpression). Intelligent Learning Object 2 (Populations and Samples) and Intelligent Learning Object 3 (ReExpression) had the largest percent of questions answered correctly, averaging 57.41% and 56.59% respectively.

Table 7 contains descriptive statistics on the average time needed by subjects to complete the Intelligent Learning Objects. The standard deviation describes the spread of the data. When the means are different, as they are in Table 7, one way to compare them is through the coefficient of variation (CV). The CV provides a consistent measure for comparing the relative spread of data from different samples when the sample means and sample standard deviations are different. (Agresti & Finlay, 2001) It is computed as CV = SD/Mean. In Table 7, we see the CVs of the completion times for Intelligent Learning Objects 2, 3 and 4 are quite close, ranging between 73.62% and 79.89%. Intelligent Learning Object 1 had a CV of 49.32%, indicating that subjects completed this topic quicker, relative to the total time spent on the other Intelligent Learning Object.

Table 7

Descriptive Statistics of Intelligent Learning Object Completion Time (In Seconds)

ILO	Subjects	Mean	SD	CV
1	57	367.5789	181.7991	49.32%
2	41	109.9756	81.9306	74.31%
3	42	163.0698	120.7722	73.62%
4	16	75.6250	60.4107	79.84%

The pretest and posttest were similar, and tested for comprehension in the four statistical topics covered by both Intelligent Learning Objects and the traditional lectures. The pretest and posttest each had a total of sixteen questions, with four questions on each of four topics. In general, two of the questions tested comprehension at Level 1 and 2 of the Revised Bloom's Taxonomy, one question tested comprehension at Level 3 of the Revised Bloom's Taxonomy, and one question tested comprehension at Level 4 of the Revised Bloom's Taxonomy.

Questions testing at Levels 1 and 2 of the Revised Bloom's Taxonomy required true/false answers. Questions testing comprehension at Levels 3 and 4 of the Revised Bloom's Taxonomy required computation; partial credit was given for work done toward answering these questions.

Findings From Inferential Statistics

The data from the pretests and the posttests was first analyzed using descriptive statistics. This data, found in Table 8, contains the number of subjects who took both the

Table 8

Descriptive Statistical Summary of Pretest and Posttest

	N	Pretest Mean	Posttest Mean	Difference Mean	SD of Difference
Level 1 and 2					
Control Group	29	5.3571	5.0714	-0.29	1.80
Experimental Group	38	5.2500	5.4375	0.19	1.78
Level 3					
Control Group	29	1.5536	2.1607	0.607	0.95
Experimental Group	38	2.1250	1.0577	0.55	1.06
Level 4					
Control Group	29	1.4286	1.0714	-0.345	0.91
Experimental Group	38	1.1250	1.5625	0.39	1.05
All Subjects					
Control Group	29	8.3393	8.3035	-0.01	1.34
Experimental Group	38	8.5000	8.5781	0.39	1.34

pretest and posttest, the mean of the difference between the scores of the pretest and the posttest scores, and the variance.

For Levels 1 and 2 of the Revised Bloom's Taxonomy, the difference of means of the Control Group subjects between the pretest and the posttest (for questions answered correctly) was -0.29. The Control Group answered an average of 0.29 fewer questions correctly on the posttest than they did on the pretest. The difference of means of the Experimental Group (for questions answered correctly) between the posttest and the pretest was +0.19. The Experimental Group answered an average of 0.19 more questions correctly on the posttest than they did on the pretest. For Levels 1 and 2 of the Revised Bloom's Taxonomy, the Experimental Group showed greater achievement than the Control Group.

For Level 3 of the Revised Bloom's Taxonomy, the difference of means of the Control Group (for questions answered correctly) between the posttest and the pretest was +0.607. The Control Group answered an average of 0.607 more questions correctly on the posttest than they did on the pretest. The difference of means of the Experimental Group subjects between the pretest and the posttest (for questions answered correctly) was +0.55. The Experimental Group answered an average of 0.55 more questions correctly on the posttest than they did on the pretest. For Level 3 of the Revised Bloom's Taxonomy, the Control Group showed greater achievement than the Experimental Group.

For Level 4 of the Revised Bloom's Taxonomy, the difference of means for all Control Group subjects between the pretest and the posttest (for questions answered correctly) was -0.345. The Control Group answered an average of 0.345 fewer questions correctly on the posttest than they did on the pretest. The difference of means of the Experimental Group (for questions answered correctly) between the posttest and the pretest was +0.39. The Experimental Group answered an average of 0.39 more questions correctly on the posttest than they did on the pretest. For Level 4 of the Revised Bloom's Taxonomy, the Experimental Group showed greater achievement than the Control Group.

To extend the analysis of the data, all three strata were combined. For Levels 1 through 4 of the Revised Bloom's Taxonomy, the difference of means for all Control Group subjects between the pretest and the posttest (for questions answered correctly) was -0.01. The Control Group answered an average of 0.01 fewer questions correctly on all questions on the posttest than they did for all questions on the pretest. The difference of means of the Experimental Group (for questions answered correctly) between the posttest and the pretest was +0.39. The Experimental Group answered an average of 0.39 more questions correctly for all questions on the posttest than they did for all questions on the pretest. For Levels 1 through 4 of the Revised Bloom's Taxonomy, the Experimental Group showed greater achievement than the Control Group.

The data for the Control Group and the Experimental Group was next analyzed using a hypothesis test of the difference in means between the two groups. The assumptions for this test were:

- The standard deviations for each of the groups were known; and,
- The samples were independent.

All hypotheses were tested in the form H_0:$\mu 1$-$\mu 2$=0 versus H_1: $\mu 1$-$\mu 2$>0, where μ_1 is the mean of the Experimental Group and μ_2 is the mean of the Control Group.

H_{01} states: There is no significant difference in the level of achievement, at Level 1 and 2 (recognizing and understanding) of Revised Bloom's Taxonomy, between students using Intelligent Learning Objects and students receiving traditional classroom training. Subjects receiving traditional classroom lecture and examined at Levels 1 and 2 of Revised Bloom's Taxonomy, as predicted, (M=-0.29, SD=1.80) reported no difference in performance than those subjects who received instruction with Intelligent Learning Objects (M=0.19, SD=1.78), t(57)=1.02, p-value=0.156 (one-tailed). The null hypothesis was not rejected at α=.05, concluding there was no significant difference in performance of the subjects who received instruction with Intelligent Learning Objects at Revised Bloom's Taxonomy Levels 1 and 2.

H_{02} states: There is no significant difference in the level of achievement, at Level 3 (applying and analyzing) of Revised Bloom's Taxonomy, between students using Intelligent Learning Objects and students receiving traditional classroom training. Subjects receiving traditional classroom lecture and examined at Level 3 of Revised Bloom's Taxonomy, as predicted, (M=0.607, SD=0.95) reported no difference in performance than those subjects who received instruction with Intelligent Learning Objects (M=0.55, SD=1.06), t(57)=.23, p-value=0.592 (one-tailed). The null hypothesis was not rejected at α=.05, concluding there was no significant difference in performance of the subjects who received instruction with Intelligent Learning Objects at Revised Bloom's Taxonomy Level 3.

H_{03} states: There is no significant difference in the level of achievement, at Level 4 (applying and analyzing) of Revised Bloom's Taxonomy, between students using Intelligent Learning Objects and students using traditional classroom training. Subjects receiving instruction with Intelligent Learning Objects and examined at Level 4 of Revised Bloom's Taxonomy, (M=0.39, SD=1.05) reported a significant difference in performance over those subjects who received traditional classroom instruction (M=-0.345, SD=0.91), t(57)=3.15, p-value=.001 (one-tailed). The null hypothesis was rejected at α=.05, concluding there was a significant difference in performance of the subjects who received instruction with Intelligent Learning Objects at Revised Bloom's Taxonomy Level 4.

To extend the analysis of the data, all three strata were combined. For subjects using Intelligent Learning Objects at all levels of Revised Bloom's Taxonomy, (M=0.39, SD=1.34) reported a significant difference in performance than those subjects who received traditional classroom lecture (M= -0.01, SD=1.34), t(175)=2.01, p-value=.023. The null hypothesis was rejected at α=.05, concluding there was a significant overall difference in performance of the subjects who received instruction with Intelligent Learning Objects at Revised Bloom's Taxonomy Levels 1 through 4.

Additional Findings

Table 9 shows the correlation between the final course grades of the subjects and their scores on the pretests and the posttests. For both the pretest and the posttest, the correlation the Experimental Group and both tests were higher than for the Control Group, showing a moderate to low degree of correlation.

Table 9

Correlation Between Course Grades and Tests

Group	Pretest	Posttest
Control Group Course Grades	+0.2169	-0.1457
Experimental Group Course Grades	+0.4005	+0.2806

Secondary Research Question Findings

Survey Data Collected and Related Information

The three sections (intact classes) of the Experimental Group participated in the Student Preference Survey. After the posttest was administered to these subjects, a pencil-and-paper survey was administered. Of the 69 subjects were enrolled in the sections constituting the experimental group, 48 of these subjects completed the Student Preference Survey. A breakdown of these subjects by class and major is found in Table 10.

Description of Subjects

The secondary research question, for subjects who received instruction with Intelligent Learning Objects was:

How to students perceive Intelligent Learning Objects?

The sample used to measure data for the secondary research hypothesis was the subjects in the Experimental Group.

Survey Findings, Frequency Counts and Descriptive Statistics

The results of the Student Preference Survey are found in Table 11. For the majority (95.8%) of subjects, this study was the first time they had used an Intelligent Tutoring System. Approximately 70% of the subjects appeared to have no problem using the system, not requiring additional instruction or help from the instructor during the face-to-face class meetings. Slightly more than half of the subjects felt that Intelligent Tutoring Systems were useful in communicating the ideas presented, and were useful for learning the ideas presented. A large majority of the subjects (85.41%) felt that reinstruction was a useful technique when a question was missed. Three-fourths of the subjects felt that Intelligent Tutoring Systems should not be the only contact with the instructor in a course.

Chapter Summary

This chapter presented the findings associated with this investigation. The data from the pretest-posttest study was analyzed with a two-sample t-test to investigate the primary research question. Subject performance, based on levels of Revised Bloom's Taxonomy was compared. Data collection, a description of the subjects, the data collection, and the results of descriptive and inferential statistics was presented. For the three research hypotheses, H_{01} and H_{02} were not found to be significant at $\alpha = .05$. H_{03} was found to be significant at $\alpha = .05$. A combination of all hypothesis was also found to be significant at $\alpha = .05$. Data from a one-shot pencil-and-paper survey was analyzed using frequency counts and descriptive statistics.

Table 10

Subject Participants By Major

Section	FR	SO	JR	SR	Total
Biology	1	4	2	1	8
Chemistry	--	--	--	1	1
Communication	--	--	--	1	1
Computer Science	--	--	1	2	3
Education	--	1	1	--	2
Health	--	5	5	1	11
Interdisciplinary Studies	--	--	--	1	1
Marine Science	1	5	7	4	17
Mathematics	1	2	--	--	3
Physical Education	1	--	--	--	1
TOTAL	4	17	16	11	48

Subject preference was analyzed. Data collection, a description of the subjects, the data collection, and the results of descriptive statistics was presented. A majority of the students felt the Intelligent Learning Objects they had used were useful in both communicating ideas, as well as for learning. They also felt that reinstruction was a key component for learning.

Table 11

Responses from Student Preference Survey

Question	Frequency Yes	Percent Yes	Frequency No	Percent No
Is this the first time you have used an intelligent tutoring system?	46	95.833%	2	4.166%
Did you need additional instruction in using the intelligent tutoring system?	14	29.167%	34	70.834%
Was the intelligent tutoring system useful for communicating the ideas presented?	26	54.167%	22	45.833%
Was the intelligent tutoring system useful for learning the ideas presented?	25	52.083%	23	45.817%
Was the reinstruction helpful (when you first missed a question) ?	41	85.417%	7	14.583%
Would you enroll in a distance learning course with Intelligent objects as your only contact with the instructor?	12	25.000%	36	75.000%

CHAPTER V: SUMMARY, CONCLUSIONS, IMPLICATIONS, AND RECOMMENDATIONS

This chapter begins with a discussion of the background and motivation for the investigation presented herein. A summary of the research questions and hypotheses that were tested, the subjects and setting, and the instruments developed for this investigation are reviewed. The findings are presented, followed by conclusions and implications of the work, as well as recommendations for further research.

Background of the Study

Learning Objects came about in the early 1990s as a result of work by Wayne Hodgins of Autodesk. "Learning Objects" was the name used for interoperable pieces of learning that could provide a reusable "plug-and-play" learning strategy for training (Hodgins, 2002). Intelligent Learning Objects (Stamey, Deluca & Saunders, 2005) extend the concept of Learning Objects, providing immediate feedback for students, as well as offering Reinstruction on topics where students did not successfully answer questions.

In this study, Intelligent Learning Objects were used to measure student achievement in the delivery of instruction on elementary statistics. Different levels of the Revised Bloom's Taxonomy (Anderson, et. al., 2000) were used to organize the curriculum material and evaluation questions. Intelligent Learning Objects provided both instruction as well as Reinstruction in the event that students were not successful in the evaluation questions.

A literature review prior to this investigation described Learning Objects, and research as to their effectiveness in the classroom. Intelligent Learning Objects were described as an extension of Learning Objects. No previous studies were found describing

Intelligent Learning Objects with Reinstruction, nor the use or effectiveness of Intelligent Learning Objects in the classroom.

Research Questions and Hypotheses Tested

Student performance and perceptions were collected and examined, based on measures developed for this study. The primary research question examined in this study was:

> Do students, using Intelligent Learning Objects with curriculum based on Bloom's Taxonomy along with Reinstruction, have a different level of achievement than those using traditional classroom training?

The Primary Research Question was investigated with pretest-posttest Control Group design using Nonequivalent Groups (intact classes). Based on the principle research question, the following three research hypotheses were investigated:

> H_{01}: There is no significant difference in the level of achievement, at Level 1 and 2 (recognizing and understanding) of Revised Bloom's Taxonomy, between students using Intelligent Learning Objects (with curriculum at along with Reinstruction) and those using traditional classroom training.
>
> H_{02}: There is no significant difference in the level of achievement, at Level 3 (applying and analyzing) of Revised Bloom's Taxonomy, between students using Intelligent Learning Objects (with curriculum at along with Reinstruction) and those using traditional classroom training.
>
> H_{03}: There is no significant difference in the level of achievement, at Level 4 (applying and analyzing) of Revised Bloom's Taxonomy, between students using

Intelligent Learning Objects (with curriculum at along with Reinstruction) and those using traditional classroom training.

The treatment was administered through the use of an online Intelligent Learning Object system and curriculum developed and written by the investigator. The curriculum materials were validated by experts in the field of statistics.

The independent variable was the type of instruction received by each group. The dependent variable measured the achievement experienced by the students at different levels of the Revised Bloom's Taxonomy.

In addition to the primary research question, student opinions about Intelligent Learning Objects were measured. The secondary research question for this study was:

How to students perceive Intelligent Learning Objects?

The secondary research question was investigated with a one-shot survey, taken of the subjects in the Experimental Group. Statistical data was collected with a pencil-and-paper survey. The survey was developed by the researcher, after a model developed and used successfully by Burgess (2003). Frequency data was compiled with responses from subjects in the Experimental Group.

Subjects and Setting

Undergraduates from a university in the southeast taking an Introduction to Statistics Lab represented the sample for this study. The Experimental Group consisted of students from three sections of Introduction to Statistics Lab, and the Control Group consisted of students from two sections of Introduction to Statistics Lab. All students received instruction in the same laboratory classroom on the campus, and at approximately the same time during the day.

The Control Group received instruction with a traditional lecture and an accompanying PowerPoint presentation. The Experimental Group received instruction with Intelligent Learning Objects. The Intelligent Learning Object curriculum was designed so that there were two frames of instruction at the Revised Bloom's Taxonomy Level 1 and 2, followed by one frame of instruction at the Revised Bloom's Taxonomy Level 3.

The data for this study was collected in Spring 2006. Undergraduate statistics students from the same university were also involved in the pilot study in Fall 2005.

Instrumentation

Data to investigate the primary research question was collected using a pretest and posttest developed by this investigator for this study. The pretest and posttest were similar, each having four sections corresponding to each of the four topics covered in the curriculum: Poisson Distribution; Populations and Samples; ReExpression; and, Sampling Techniques. Topics tested student achievement at different levels of the Revised Bloom's Taxonomy. Achievement for each of the four topics was tested with four questions. In general, two true-false questions were used to test student achievement at Revised Bloom's Levels 1 and 2. One computational question tested student achievement at each of Revised Bloom's Level 3 and Level 4.

Data to investigate the secondary research question was collected using a pencil-and-paper survey. Students in the Experimental Group were asked questions similar to those used by Burgess (2003) in determining student opinions about WebCT. The first section of the instrument incorporated questions about the use of Intelligent Learning Objects. The second section of the instrument collected demographic information.

Summary of Findings

Primary Research Question

The primary research question was based on a measure of the difference in the learning between students who used Intelligent Learning Objects and students who received traditional classroom instruction. Three research hypotheses were used to measure the difference between the two types of instruction. Each hypothesis examined the difference in learning at different levels of Revised Bloom's Taxonomy. One additional hypothesis was constructed from the three research hypotheses to measure the effect across Levels 1 through 4 of the Revised Bloom's Taxonomy.

H_{01} stated: There is no significant difference in the level of achievement, at Level 1 and 2 (recognizing and understanding) of the Revised Bloom's Taxonomy, between students using Intelligent Learning Objects (with curriculum at along with Reinstruction) and those using traditional classroom training. This investigation failed to support this research hypothesis. The Experimental Group had a .19 increase in the mean number of questions answered correctly (from the pretest to the posttest), while the Control Group experienced a decrease of .29 questions in the mean number of questions answered correctly (from the pretest to the posttest). The Experimental Group averaged answering four-tenths (.40) more questions correctly than did the Control Group. The null hypothesis was rejected at α=.05, concluding there was a significant difference in performance of the subjects who received instruction with Intelligent Learning Objects at the Revised Bloom's Taxonomy Levels 1 and 2.

H_{02} stated: There is no significant difference in the level of achievement, at Level 3 (applying and analyzing) of the Revised Bloom's Taxonomy, between students using

Intelligent Learning Objects (with curriculum at along with Reinstruction) and those using traditional classroom training. This investigation supported this research hypothesis. We note that the Experimental Group had an increase of .55 in the mean number of questions answered correctly (from the pretest to the posttest), while the Control Group experienced an increase of .607 questions in the mean number of questions answered correctly (from the pretest to the posttest). For all practical purposes, there was no difference in the performance of the two groups. The null hypothesis failed to be rejected at α=.05, concluding there is no significant difference in performance of the subjects who received instruction with Intelligent Learning Objects at the Revised Bloom's Taxonomy Level 3.

H_{03} stated: There is no significant difference in the level of achievement, at Level 4 (applying and analyzing) of the Revised Bloom's Taxonomy, between students using Intelligent Learning Objects (with curriculum at along with Reinstruction) and those using traditional classroom training. This investigation failed to support this research hypothesis. It is important to note that the Experimental Group had a .39 increase in the mean number of questions answered correctly (from the pretest to the posttest), while the Control Group experienced a decrease of .345 questions in the mean number of questions answered correctly (from the pretest to the posttest). The Experimental Group averaged answering three-fourths of a question (.74) more than did the Control Group. This finding was quite statistically significant at α=.05, with a t-statistic of 3.15 and a p-value of .001. The null hypothesis was rejected at α=.05, concluding there was a significant difference in performance of the subjects who received instruction with Intelligent Learning Objects at the Revised Bloom's Taxonomy Level 4.

A null hypothesis to combine $H_{01,}$ H_{02} and H_{03} stated: There no significant difference in the level of achievement, at Levels 1 through 4 of the Revised Bloom's Taxonomy, between students using Intelligent Learning Objects (with curriculum at along with Reinstruction) and those using traditional classroom training. This investigation failed to support this combined null hypothesis. It is important to note that the Experimental Group had a .39 increase in the mean number of questions answered correctly (from the pretest to the posttest), while the Control Group experienced a decrease of .01 questions in the mean number of questions answered correctly (from the pretest to the posttest). This finding was statistically significant at α=.05, with a t-statistic of 2.01 and a p-value of 0.023. The null hypothesis was rejected at α=.05, concluding there was a significant difference in performance of the subjects who received instruction with Intelligent Learning Objects at Levels 1 through 4 of the Revised Bloom's Taxonomy.

Secondary Research Question

The secondary research question was used to examine student perceptions of Intelligent Learning Objects. Students in the Experimental Group provided answers to a set of questions on this topic using a pencil-and-paper survey. An important question asked was based on the implementation of the "intelligence" in the System, termed Reinstruction. Reinstruction was implemented as follows: if a subject did not correctly answer a question based on the text presented, additional instruction and a question to measure comprehension were also presented.

A large majority of the subjects (85.41%) felt that Reinstruction was a useful technique when a question was missed. Three-fourths of the subjects felt that Intelligent Tutoring Systems should not be the only contact with the instructor in a course. A small majority of students felt that intelligent tutoring systems, and in particular Intelligent Learning Objects:

- were useful in communicating the ideas presented (M=54.167%); and,
- were useful in learning the ideas presented (M=52.083%).

Conclusions

The primary research question under investigation was supported by the data collected from the sample. Significant relationships were found between the use of student achievement and the use of Intelligent Learning Objects as opposed to traditional classroom instruction in the investigation of two of the three research hypothesis. A significant relationship was also found in the investigation of a null hypothesis representing a combination of the three research hypotheses.

The secondary research question under investigation was supported from the data collected. A large majority of the students who used Intelligent Learning Objects had a positive view of the reinstruction component.

This research concluded that Intelligent Learning Objects can provide instruction at the same level or better than traditional classroom instruction. Furthermore, students have a positive view of Intelligent Learning Objects.

Implications

What the investigation was undertaken to examine the effect of Intelligent Learning Objects on student achievement. A number of considerations may be considered as they apply to future use and research in the field.

This study is one of the larger studies, in terms of participants, in the field of Learning Objects and Intelligent Tutoring Systems. The study provides a statistically significant result about the use of Intelligent Learning Objects as a substitute for traditional classroom instruction, and also provides a model from which other studies may be replicated.

Results of the study show that Intelligent Learning Objects have a number of implications. First and foremost, Intelligent Learning Objects have potential to improve student achievement when learning small, focused topics of instruction.

Intelligent Learning Objects have the potential of immediate time savings for students. The average length of time necessary for in-class instruction for the Control Group was 15 minutes. Data from Table 7 shows that the average length of time spent by students with the Intelligent Learning Objects was 2:58, just under three minutes.

The time involved in creating the curriculum for the Intelligent Learning Objects was not large, averaging three to four hours per topic. However, Intelligent Learning Objects can be used as often as needed by an unlimited number of students. This reuse of the curriculum material provides instructors with an excellent return on their time investment. Over and above Intelligent Learning Objects custom-created for a particular class, the increasing availability of Learning Objects in repositories provides a wealth of learning experience to students with no time or monetary cost to the instructor except for time spent selecting appropriate Learning Objects for their students' use.

Finally, Intelligent Learning Objects are viewed positively by students who used them. The availability of generally low-cost or no-cost intelligent tutoring systems accepted by students will lead to their increased use by students.

Recommendations for Future Research

This investigation used online instruction based on a curriculum fashioned around the Revised Bloom's Taxonomy and with Reinstruction. The experience gained from this study has suggested a number of recommendations for further study in the area of Learning Objects and Intelligent Tutoring Systems. The following recommendations are made for further study.

Additional research is needed replicate the results of the study, to determine whether or not the result achieved was based on random chance, or if indeed, Intelligent Learning Objects do out perform traditional classroom instruction.

A change needs to be made in the manner in which the Intelligent Learning Objects are perceived by the students. In this study, a potential problem was that the posttest was given under the assumption that it would not affect the grade of the subjects. The pretest was given under the assumption that it would somehow be factored into the grade of the subjects.

The Intelligent Learning Objects used in this study were text-based. An immediate enhancement would be the addition of graphical images. This would ultimately lead to the potential of interactive graphical components for the Intelligent Learning Objects. To enhance the co-learning experience (Self, 1999; Vygotsky 1978), it would advisable to collect student comments during future deployments of Intelligent Learning Objects. These comments can be edited and combined to provide helpful assistance along the way for students.

The addition of other features such as a dashboard to give students access to current and previous scores would increase the user-friendliness of the Intelligent Learning Object system, while providing additional access to feedback.

The statistical methods used in this study were based on a priori hypotheses tested by the researcher. Another method of data analysis is based on a posteriori examination of the data to identify interesting subsets of the observations. Such analysis falls into the discipline of data mining (LaRose, 2005, pp. 41-42). When the data collected from the pretest-posttest study was examined for trends, it was found that subjects who had an initial score of 50% or less on the pretest (meaning 8 or less questions were answered correctly) had an increase from the pretest to the posttest. Descriptive statistics found in Table 12 shows the average increase between subjects in the Control Group and the Experimental Group was 500% higher for those subjects who used the Intelligent Learning Objects, as opposed to those who received traditional classroom instruction.

Intelligent Learning Objects can certainly be extended to fields other than statistics. Appropriate quantitative fields for their application include technology education, computer science, mathematics and business administration. Additional investigation also needs to be done to determine suitable use of Learning Objects and Intelligent Learning Objects as part of a larger curriculum. Such investigations would determine the usefulness of Learning Objects and Intelligent Learning Objects:

- when used as the sole instructional tool for a topic;
- when used in conjunction with classroom instruction, either introducing subtopics or providing reinforcement of topics presented in class; and,
- When used as part of an online/distance learning curriculum.

Table 12

Performance of Subjects Scoring Less than 50% on the Pretest

Test	Control Group	Experimental Group	N
Average Pretest Score	7.041	6.633	14
Average Posttest Score	7.291	8.133	14
Average Increase	0.250	1.500	14

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APPENDIX A: IRB Exemption Letter

North Carolina State University is a land-grant university and a constituent institution of The University of North Carolina

Office of Research and Graduate Studies

NC STATE UNIVERSITY

Sponsored Programs and
Regulatory Compliance
Campus Box 7514
1 Leazar Hall
Raleigh, NC 27695-7514
919.515.7200
919.515.7721 (fax)

From: Debra A. Paxton, Regulatory Compliance Administrator
North Carolina State University
Institutional Review Board

Date: May 2, 2006

Project Title: None.

IRB#: 143-06-4

Dear Mr. Stamey:

The research proposal named above has received administrative review and has been approved as exempt from the policy as outlined in the Code of Federal Regulations (Exemption: 46.101.b.1). Provided that the only participation of the subjects is as described in the proposal narrative, this project is exempt from further review.

NOTE:

1. This committee complies with requirements found in Title 45 part 46 of The Code of Federal Regulations.
   For NCSU projects, the Assurance Number is: M1263; the IRB Number is: 01XM.

2. Review de novo of this proposal is necessary if any significant alterations/additions are made.

Please provide your faculty sponsor with a copy of this letter. Thank you.

Sincerely,

Debra Paxton
NCSU IRB

APPENDIX B: Intelligent Learning Object Curriculum for the Experimental Group

Intelligent Learning Object 1 – The Poisson Distribution

The Poisson Distribution - Frame 1 – Instruction

Some events are rather rare, they don't happen that often. For instance, car accidents are the exception rather than the rule. Still, over a period of time, we can say something about the nature of rare events. An example is the improvement of traffic safety, where the government wants to know if wearing seat belts reduce the number of death in car accidents. Here, the Poisson distribution can be a useful tool to answer question about benefits of seat belt use. Other phenomena that often follow a Poisson distribution are death of infants, the number of misprints in a book, the number of customers arriving, and the number of activations of a Geiger counter. The Poisson distribution was derived by the French mathematician Poisson in 1837, and the first application was the description of the number of death by horse kicking in the Prussian army (Bortkiewicz, 1898).

The Poisson distribution resembles the binomial distribution in that is models counts of events. For example, a Poisson distribution could be used to model the number of accidents at an intersection in a week. However, if we want to use the binomial distribution we have to know both the number of people who make enter the intersection, and the number of people who have an accident at the intersection, whereas the number of accidents is sufficient for applying the Poisson distribution. Thus, the Poisson distribution is cheaper to use because the number of accidents is usually recorded by the police department, whereas the total number of drivers is not.

FROM http://www.math.sfu.ca/~cschwarz/Stat-301/Handouts/node64.html Copyright 1998: Carl J. Schwarz cschwarz@cs.sfu.ca, Retrieved January 10, 2006.

The Poisson Distribution - Frame 1 – Question

We know that during the year, 4,317,000 cars went through the intersection of Main and First Avenue last year. There were 123 accidents recorded at this intersection. To determine the probability that two accidents happened in one day with the Poisson distribution, we use the quantity (or quantities)

a. total cars
b. number of accidents
c. total cars / number of accidents
d. number of accidents / total cars

The Poisson Distribution - Frame 1 – Reinstruction

We remember that the Poisson distribution can be used to model the number of accidents at an intersection in a week. For this, all we need is the weekly accident rate.

The binomial distribution can tell us the same thing. However, if we want to use the binomial distribution we have to know both the number of people who make enter the intersection, and the probability of people having an accident at the intersection. If we have both the number of cars and the number of accidents, we can then use EITHER the binomial distribution or the Poisson distribution.

The Poisson Distribution - Frame 1 – Reinstruction Question

We know that during the year, 4,317,000 total cars went through the intersection of Main and First Avenue last year. There were 123 accidents recorded at this intersection. To determine the probability that two accidents happened in one day with the Poisson distribution, we use the quantity (or quantities)

a. total cars

b. number of accidents

c. total cars / number of accidents

d. number of accidents / total cars

The Poisson Distribution - Frame 2 – Instruction

In order to use the Poisson Distribution, three important conditions must hold. First, counts of events in which we are interested is relatively small, relative to the number of overall events, which is large. Consider the number of people who get Leukemia in New York City. With approximately 8 million people living in the Big Apple, and the percentage of people who get having Leukemia 0.011%, these numbers represent a large population and a sufficiently small occurrence of the event in question.

Second, all events are independent. Going back to Bernoulli Trials, we remember that an event has one of two possible outcomes. As an example, it is generally accepted that there is a 16% chance that projects may be finished on-time and within budget. If the chance of one project being completed on-time and within-budget does not, at all, affect the chance of a different project being completed on-time and within-budget, then the projects meet the requirement for independence.

Third, the average rate does not change over the period of interest. Examples of experiments where a Poisson distribution holds include:

- Counting number of birth defects in a hospital in a year (we have a fixed period of time)
- Counting the number of defects on a car (we have a fixed region of space)
- Counting the number of typographical errors on a page (again, we have a fixed region of space)

The Poisson Distribution - Frame 2 – Question

Which event is not a rare enough event to contemplate using the Poisson Distribution?

a. the number of bulk orders for bicycles over $100,000

b. the number of people over 110 years of age

c. the number UFO sightings in Greenland in January

d. the number of males in families of size 4

Populations and Samples - Frame 2 – Reinstruction

The advantage of the Poisson Distribution is that it keeps us from having to compute some almost impossible computations of C(n, k), where n is too large for a computer to compute (n-k)!. Also, it is very difficult to compute (a very small p)$^{\text{(a very large number)}}$ such as $(.00011)^{35000}$. Even though we could use normal probabilities to help approximate these numbers, the accuracy of normal probabilities when p$^{\text{(a very large number)}}$ is less than ten is not good at all.

Populations and Samples - Frame 2 – Reinstruction Question

For a town of 100,000 families, there are 2500 people who live in apartments. Here, p=.25 and n=100,000. Problems using this scenario are potentially excellent uses for the Poisson Distribution.

a. TRUE

b. FALSE

The Poisson Distribution - Frame 3 – Instruction

Computing Poisson probabilities: Assume that you have the rate of occurrences in a large sample. We can compute the probability of a certain number of these occurrences happening.

Parameters:

λ = rate of occurrence for this sample

λ = (number of individuals) x (rate of occurrence)

λ can range from 0 upwards and does NOT have to be an integer.

X must be an integer = 0, 1, 2, 3, ...

The Poisson formula is:

P(observing X occurrences when the rate is λ) =$(e^{-\lambda}\lambda^{x})/X!$

For example, let λ be the rate of occurrence, such as 1.5 (maybe the number of dead fish found in a large aquarium every month). We want to know the probability that 5 fish (X=5) will die in a month. As the monthly rate of dead fish is 2000 x .075%, λ = 2000 x .075% = 1.5. With X = 5, we determine there is a 0.0141, or 1.41% chance of five fish dying in a month.

The Poisson Distribution - Frame 3 – Question

Assume that due to a new additive you use in the water of a large aquarium, the death rate has become .075% over the year when there were 2000 fish. What was the chance that NO fish will die in one month? [i.e., P(X=0)]

The Poisson Distribution - Question 3 - Reinstruction

Remember that to compute λ, you must multiply the number of trials (usually the large number) by the probability of a success (the small number, p). So, the formula is λ = n

* p. The number X, representing the value for which we want to calculate the probability is found in the left column of each table.

The Poisson Distribution - Question 3 - Reinstruction Question

Assume that due to a new additive you use in the water of a large aquarium, the death rate has become .070% over the year when there were 2000 fish. What was the chance that NO fish will die in one month?

Intelligent Learning Object 2 – Populations and Samples

Populations and Samples - Frame 1 – Instruction

In general, we work with a random SAMPLE to create statistics that estimate characteristics of the entire group from which the sample was taken. The entire group of subjects in which we are interested is called a POPULATION. Examples of populations include

- All College Freshmen
- All Professional Athletes
- All Members of a Club in Your Local Town.

Characteristics we wish to represent include central tendency (the MEAN), and the spread (the STANDARD DEVIATION). If these characteristics are computed using every member of a population, they are called PARAMETERS. If these characteristics are computed using a random sample taken from the population, they are called STATISTICS. Statistics are used to estimate the value of population parameters.

Populations and Samples - Frame 1 – Question

Both statistics and parameters require a random sample to be properly computed.

a. TRUE

b. FALSE

Populations and Samples - Frame 1 – Reinstruction

Statistics require a random sample from the population of interest to be interpreted correctly. Parameters are computed using every member of a population of interest. If you have the data for every member of your population of interest then random sampling is not necessary. If you have a group of all 15 stockholders of a small corporation in one room and compute their average number of shares, then this average is a parameter.

Populations and Samples - Frame 1 – Reinstruction Question

Given a population of interest, parameters require fewer sample items to be calculated than do statistics.

a. TRUE

b. FALSE

Populations and Samples - Frame 2 – Instruction

The POPULATION MEAN is nothing more than the average of one attribute of every person in the sample. The average is computed as (Sum of all attributes) / N where N is the number of subjects in the population. Suppose we want the average age of all young people who play softball in the county recreation system. Each one of these students had to fill out a form prior to playing, with their age filled in. Assuming there are 150 players, we sum all of the ages and then divide by 150. We have a completely accurate average of the ages of the players in this league. The SAMPLE MEAN is computed with the same technique, except that the individuals whose ages are used to calculate the statistic are selected at random. Assuming there are n individuals selected, then the sample mean is (Sum of attributes from selected subjects) / n.

Populations and Samples - Frame 2 – Question

If we take a random sample from the 150 players and compute the average of this sample, this statistic (the sample mean) will always be the same as the population mean parameter.

a. TRUE

b. FALSE

Populations and Samples - Frame 2 – Reinstruction

By the luck of the draw, it is possible that the sample mean and the population mean will be the same for our 150 players in the county. However, there are no guarantees. If the sample mean and the population mean are NOT the same, then the sample mean will likely be very close to the population mean.

Populations and Samples - Frame 2 – Reinstruction Question

If we take a random sample from the 150 players and compute the average of this sample, this statistic (the sample mean) will never be the same as the population mean parameter.

a. TRUE

b. FALSE

Populations and Samples - Frame 3 – Instruction

Suppose that you are in some course and have just received your grade on an exam. It is natural to ask how the rest of the class did on the exam so that you can put your grade in some context. Knowing the mean or median tells you the "center" or "middle" of the grades, but it would also be helpful to know some measure of the spread or variation in the grades. Let's look at a small example. Suppose three classes of 5 students each take the same exam and the grades are:

Class 1	Class 2	Class 3
82	82	67
78	82	66
70	82	66
58	42	66
42	42	65

Each of these classes has a mean, $\bar{x}$, of 66 and yet there is great difference in the variation of the grades in each class. One measure of the variation is the range, which is the difference between the highest and lowest grades. In this example the range for the first two classes is 82 - 42 = 40 while the range for the third class is 67 - 65 = 2. The range is not a very good measure of variation here as classes 1 and 2 have the same range yet their variation seems to be quite different. One way to see this variation is to notice that in class 3 all the grades are very close to the mean, in class 1 some of the grades are close to the mean and some are far away and in class 2 all of the grades are a long way from the mean. It is this concept that leads to the definition of the standard deviation.

Let's look at class 1. For each student calculate the difference between the students grade and the mean.

Class 1	$x_i - \bar{x}$
82	16
78	12
70	4
58	-8
42	-24

The average of these differences could now be calculated as a measure of the variation, but this is zero. What is really needed is the distance from each grade to the mean not the difference. You could take the absolute value of each difference and then calculate the mean. This is called the mean deviation, i.e. mean deviation = $\frac{\sum |X_i - \bar{X}|}{n}$, where n is the number of students in the class. For class 1 this is 64/5 = 12.8. Another way to deal with the negative differences is to square each difference before adding.

Class 1	$X_i - \bar{X}$	$(X_i - \bar{X})^2$
82	16	256
78	12	144
70	4	16
58	-8	64
42	-24	576

The sum of this column is 1056. To find what is called the standard deviation, s, divide this sum by n-1 and then, since the sum is in square units, take the square root. For class 1 this gives $s = \sqrt{\frac{\sum (X_i - \bar{X})^2}{n-1}} = \sqrt{\frac{1056}{4}} = 16.2$.

A similar calculation gives a standard deviation of 21.9 for class 2 and 0.7 for class 3. So for class 3, where the grades are all close to the mean, the standard deviation is quite small, for class 1, where the grades are spread out between 42 and 82, the standard deviation is considerably larger and for class 2, where all the grades are far from the mean, the standard deviation is larger still. The standard deviation is the quantity most commonly used by statisticians to measure the variation in a data set.

The reason that the denominator in the calculation of s is n-1 deserves a comment. To look at this lets change the example. Suppose that I am interested in the number of hours per day that high school students in North America spend doing their mathematics homework. The "population" of interest is all high school students in North America, a very large number of people. Let’s call this number N. My real interest is the mean and standard deviation of this population. When talking about population statisticians usually uses Greek letters to designate these quantities, so the mean of the population is written $\mu = \frac{\sum X_i}{N}$, (μ is the Greek letter mu). Likewise the standard deviation is $\sigma = \sqrt{\frac{\sum (X_i - \mu)^2}{N}}$, ($\sigma$ is the Greek letter sigma). Notice that here the denominator in the calculation is N.

Rather than trying to deal with this large population a statistician would usually select a "sample" of students, say n of them, and perform calculations on this smaller data set to estimate mu and sigma. Here n might be 25 or 30 or 100 or maybe even 1000, but certainly much smaller than N. To estimate mu it seems natural to use , the mean of the sample. Likewise to estimate sigma it seems reasonable to use $\sqrt{\frac{\sum (X_i - \bar{X})^2}{n}}$, but this quantity tends to underestimate sigma, particularly for small n. For this and other technical reasons the quantity $\sqrt{\frac{\sum (X_i - \bar{X})^2}{n}}$ is a usually preferred as the estimator to use for sigma.

If you have a calculator that computes the standard deviation it is a good exercise to see if it divides by n or n-1. Take the three number data set -1, 0, 1, calculate the standard deviation both ways by hand and then use your calculator to see which method it uses.

Populations and Samples - Frame 3 - Question

Assume the sum of the squares of a population of size 15 is 1000. The POPULATION VARIANCE is:

a. 8.15

b. 8.45

c. 8.75

d. None of the above.

Populations and Samples – Frame 3 - Reinstruction

Assume the sum of the squares of a population of size 5 is 500. Then the POPULATION VARIANCE is SQRT (100) = 10. Assume the sum of the squares of a sample of size 5 is 500. Then, the SAMPLE VARIANCE is SQRT (125) = 11.18. As you can see, the numbers are definitely different.

Populations and Samples - Frame 3 - Reinstruction Question

Assume the sum of the squares of a population of size 15 is 1000. The POPULATION VARIANCE is

A. 8.15

B. 8.45

C. 8.75

D. None of the above.

Intelligent Learning Object 2 – ReExperession

ReExpression - Frame 1 – Instruction

Frequently, we will want to reExpress data that shows a curved relationship so that we can apply the powerful tools we learned with regression. Given two columns of data, the relationship between them still exists if all numbers in one column have the same operation applied to them. One frequently-used technique of re-expressing data occurs when we raise all of the numbers in one column to a particular power. Some standard powers that we can raise data to include 2, 1/2 and -1.

ReExpression - Frame 1 – Question

Here is some data. What will the result be if we raise each of these numbers: {2, 4, 6, 8, 10} to the power -1?

Please select an answer:

a. {-2, -4, -6, -8, -10}
b. {1/2, 1/4, 1/6, 1/8, 1/10}
c. {-1/2, -1/4, -1/6, -1/8, -1/10}
d. {22, 44, 66, 88, 1010}

ReExpression - Frame 1 – Reinstruction

Raising a number x to the -1 power simply places that number x as the denominator. As an example, 10-1 is 1/10 (or .10).

ReExpression - Frame 1 – Reinstruction Question

Raising the number 4 to the power -1 will give

a. -4
b. 1/4
c. -1/4
d. 44

ReExpression - Frame 2 – Instruction

Logarithms are another way to convert data. First, we need to review the concept of Base 10 Logarithms, or common logs. Here is an example that should make things clear:

- $31.623 = 10^{1.5}$

This leads us to the following rule for logarithms:

- $\log_{10}X = Y$ really means that $10^Y = X$.

Thus, A LOGARITHM IS REALLY AN EXPONENT. For Base 10 Logarithms, the logarithm of any number Y is the power to which you must raise 10 to equal Y. That power is X. We then have the following set of relationships:

- For Y between 1 - 10 (10^0 - 10^1), the base 10 logarithm X is between 0 and 1
- For Y between 10 - 100 (10^1 - 10^2), the base 10 logarithm X is between 1 and 2
- For Y between 100 -1000 (10^2 - 10^3), the base 10 logarithm X is between 2 and 3
- etc.

ReExpression - Frame 2 – Question

You can tell the range of a number based upon its logarithm.

Please select an answer:

a. TRUE
b. FALSE

ReExpression - Frame 2 – Reinstruction

Numbers in base 10 are mapped into a system where they are represented by 10 to a power. Thus, 10 raised to any power can be thought of as being between two powers of ten. We know 10^2 is 100. We know 10^3 is 1000. Then, any number between 2 and 3, such as 2.5 (represented as $10^{2.5}$) is between 100 and 1000.

ReExpression - Frame 2 – Reinstruction Question

The number $10^{3.5}$ represents a number that is between

a. 0 - 10

b. 10-100

c. 100-1000

d. None of the above

ReExpression - Frame 3 – Instruction

Our goal is to find some type of way to transform a curved scatter plot into a more straightened representation of the data so that we can use powerful tools such as linear regression. One way to do this is to raise numbers to a power, such as to square them or to take their square root. Many times, a curved relationship in data can be removed with the use of the common log. By applying the common log, you can reduce the effect of large jumps in scale that occur in your data. Many times, these jumps become larger and larger. You are almost guaranteed to straighten out extreme upward or downward sloping data by taking the logarithm of that data. Given the following two numbers, 357 and 3570, we would convert them into the common log as follows: We know that for some number x, $10^x = 357$. Using Excel, the formula $=LOG_{10}357$ gives the answer 2.552668. So, $10^{2.552668} = 357$. The formula $=LOG_{10}$ 3570 gives the answer 3.552668. So, $10^{3.552668} = 3570$.

ReExpression - Frame 3 – Question

Given the following data:

1	3	5
100	300	500

Re-Expressing the lower row with the common log gives:

a. 10, 30, 50

b. 100, 300, 500

c. 1000, 3000, 5000

d. None of the above

Re-expression - Frame 3 – Reinstruction

In using Excel Formulas, you will find that $10^2 = 100$ and that $10^3 = 1000$. These are formulas you will recall from basic algebra. If you wanted to compute them with Excel, you would use the following formulas:

- Since $10^2 = 100$, then 10^2=100
- Since $10^3 = 1000$, then 10^3=1000

ReExpression - Frame 3 – Reinstruction Question

Does $500 = 10^{2.5}$?

a. TRUE

b. FALSE

Intelligent Learning Object 4 – Sampling Techniques

Sampling Techniques - Frame 1 – Instruction

In statistics, a simple random sample from a population is a sample chosen randomly, so that each possible sample has the same probability of being chosen. One consequence is that each member of the population has the same probability of being chosen as any other. In small populations such sampling is typically done "without replacement", i.e., one deliberately avoids choosing any member of the population more than once. Although simple random sampling can be conducted with replacement instead, this is less common and would normally be described more fully as simple random sampling with replacement. Conceptually, simple random sampling is the simplest of the probability sampling techniques. It requires a complete sampling frame (a list of all members of the population), which may not be available or feasible to construct for large populations. Even if a complete frame is available, more efficient approaches may be possible if other useful information is available about the units in the population. Systematic sampling is the selection of every nth element from a sampling frame, where n, the sampling interval, is calculated as:

n = Number in population / Number in sample

Using this procedure each element in the population has a known probability of selection. This makes systematic sampling functionally similar to simple random sampling. It is however, much more efficient and much less expensive to do. The researcher must ensure that the chosen sampling interval does not hide a pattern. Any pattern would threaten randomness. A random starting point must also be selected.

Simple Random Sampling (n.d.) Retrieved January 1, 2006 from http://en.wikipedia.org/wiki/Simple_random_sampling

Systematic Sampling (n.d.) Retrieved January 1, 2006 from

http://en.wikipedia.org/wiki/Systematic_sampling

Sampling Techniques - Frame 1 – Question

Using the 1st 4th 9th 16th 25th 36th … elements is the best way to implement a simple random sample.

a. TRUE

b. FALSE

Sampling Techniques - Frame 1 – Reinstruction

Random samples are frequently specified for certain experiments. Along with a random number table, the idea of selecting subjects that are evenly spaced apart in a list (sampling frame) is a straightforward way to create a sample that enjoys all of the properties of being a random sample. Assume we want a sample of size 50 from a group (population) of 500. Here, k=500/50 = 10. We will pick one subject in the first ten. Assume you select the 7th subject. You then select subjects 17, 27, 37, etc., creating your sample size of 50

Sampling Techniques - Frame 1 – Reinstruction Question

A simple random sample does not require a sampling frame (a list of all members of a population).:

a. TRUE

b. FALSE

Sampling Techniques - Frame 2 – Instruction

Subjects are selected from the population at a regular interval (e.g., once an hour, every other lot, etc.) For example, we denote the sample size as n and the population size as N. Let k = N/n, the population size divided by the desired sample size. A systematic random sample selects a subject at random from the first k names in the sampling frame, and then selects every kth subject listed after that one. The number k is called the skip number.

Agresti, A. & Finlay, B. (1997) Statistical Methods for the Social Sciences, 3rd Edition. New York: Prentice Hall.

Sampling Techniques - Frame 2 – Question

Assuming a population size of 400 and a skip number of 20, how many subjects will be selected for a stratified sample?

Sampling Techniques - Frame 2 – Instruction

Subjects are selected from the population at a regular interval (e.g., once an hour, every other lot, etc.) For example, we denote the sample size as n and the population size as N. Let k = N/n, the population size divided by the desired sample size. A systematic random sample selects a subject at random from the first k names in the sampling frame, and then selects every kth subject listed after that one. The number k is called the skip number.

Agresti, A. & Finlay, B. (1997) Statistical Methods for the Social Sciences, 3rd Edition. New York: Prentice Hall.

Sampling Techniques - Frame 2 – Question

Assuming a population size of 400 and a skip number of 20, how many subjects will be selected for a stratified sample?

Sampling Techniques – Frame 3 - Instruction

Stratified sampling is a method of sampling from a population in statistics. When sub-populations vary considerably, it is advantageous to sample each subpopulation (stratum) independently. Stratification is the process of grouping members of the population into relatively homogeneous subgroups before sampling. The strata should be mutually exclusive: every element in the population must be assigned to only one stratum. The strata should also be collectively exhaustive: no population element can be excluded. Then random sampling is applied within each stratum. This often improves the representative ness of the sample by reducing sampling error. It can produce a mean that has less variability than the mean from a simple random sample of the population. Examples of a stratified random sample would include:

- Strata by gender (male, female)
- Strata by citizenship (USA, Mexico, Canada)
- Strata by political affiliation (Democrat, Republican, Independent, Libertarian, Other)

Proportional allocation uses a sampling fraction in each of the strata that is proportional to that of the total population. If the population consists of 60% in the male stratum and 40% in the female stratum, then the relative size of the two samples (one males, one females) should reflect this proportion

Sampling Techniques - Frame 3 – Question

In the strata by political affiliation, {Democrat, Republican, Libertarian} does not precisely fit the definition of a stratified sample.

Please select an answer:

a. TRUE

b. FALSE

Sampling Techniques - Frame 3 – Reinstruction

The definition of a stratified sample has two important points. The strata should be mutually exclusive - every element in the population must be assigned to only one stratum. The strata should also be collectively exhaustive: no population element can be excluded. All members of the population should be represented in exactly one stratum (no more and no less). As an example in the question above, no mention was made of individuals who were not affiliated with a party.

Sampling Techniques - Frame 3 – Reinstruction

Question In a stratified sample, an important rule is to sample the same number of people from each subgroup.

a. TRUE

b. FALSE

APPENDIX C: Pretest

Pretest: This is a test on some topics that we will be covering. We want to see if you have any knowledge of them before we cover them. This quiz in no way will be counted as a grade. It is purely for informational purposes.

Name ___________________________________ Grade **NONE TO BE RECORDED**

1. Which probability would be most likely used with the Poisson distribution when approximating rare events?

   a. 0%   b. .0275%   c. 50%   d. 100%

2. The Poisson Distribution can be used to estimate the probability of no cars arriving at a tollbooth in a particular minute, if we know that (on the average) 1.5 cars arrive per hour.

   TRUE   FALSE

3. If, on the average, 1.5 cars arrive at a tollbooth per minute, compute the probability that five cars will arrive in one minute.

4. Knowing that the standard deviation of the Poisson Distribution is .01, and knowing we are computing P(X=1), what is the unknown quantity in the formula for P(X=1)?

   a. *e*   b. λ c. X   d. None of the above

5. A population and a sample are the same thing.

   TRUE   FALSE

6. A statistic is always more accurate than a parameter when estimating a population.

   TRUE   FALSE

7. Given class scores of {82, 78, 70, 58, 42}, compute the mean and the standard deviation.

8. Given 5000 test scores, assume X is the SQRT of the sum of the square of each score less the average. What is the most appropriate number to put in the denominator of the calculation of the standard deviation?

a. 4999 b. SQRT 4999 c. 5000 d. SQRT 5000

9. The most common way of ReExpressing data is to use powers such as 1/2, 1/3, 1/4 and 1/5. TRUE FALSE

10. One cannot ReExpress data by raising a number to the power of -1.

TRUE FALSE

11. 5,678 falls into the logarithm range of 2-3.

TRUE FALSE

12. When row two of this data is converted using the common log, it will have a linear pattern. TRUE FALSE

1	2	3	4	5
10000	1000	100	10	1

13. A simple random sample requires a sampling frame.

TRUE FALSE

14. You can take the first 50 elements of a population of 5000 for a simple random sample.

TRUE FALSE

15. If there are 5000 people in your sampling frame and you sample every 50th one, how many people will be in your simple random sample?

16. If you are going to create a stratified sample of students in a school, each stratum must exactly have the same number of students in order to be valid.

TRUE FALSE

APPENDIX D: Posttest

Evaluation of Additional Topics – Statistics 201 L – Spring 2006

Name ____ Score __________

1. Which probability would be most likely used with the Poisson Distribution when approximating rare events?

    a. Zero

    b. Very Small

    c. Close to one

    d. Actually, all probabilities can be used to approximate rare events.

2. The Poisson distribution can be used to estimate the probability of one car arriving at a tollbooth in a particular minute, if we know, on the average, how many cars arrive per minute.

    TRUE

    FALSE

3. If, on the average, two cars arrive at a tollbooth per minute, compute the probability that no cars will arrive in one minute.

4. Knowing that the standard deviation of the Poisson Distribution is .025, what is the unknown quantity in the formula for P(X=1)?

    a. e

    b. λ

    c. X

    d. None of the above

5. A population and a sample are generally different sets.

TRUE

FALSE

6. Select the most accurate:

a. A Statistic

b. A Sample

c. A Parameter

d. A Population

7. Given class scores of {72, 88, 50, 68, 72}, compute the mean and the standard deviation.

8. For a sample of size 5, discuss why using n in the computation for the standard deviation is not as appropriate as using n-1.

9. The most common way of ReExpressing data is to use powers such as -.50, -1.00 and -2.00.

TRUE

FALSE

10. One cannot ReExpress data by raising a number to the power of +1.

TRUE

FALSE

11. 5,678 falls into the logarithm range of 1-2.

TRUE

FALSE

12. When row two of this data is converted using the common log, it will have a linear pattern:

TRUE

FALSE

1	2	3	4	5
50000	5000	500	50	5

13. A simple random sample does not require a sampling frame.

TRUE

FALSE

14. You can take the first 100 elements of a population larger than 100 for a simple random sample.

TRUE

FALSE

15. If there are 5000 people in your sampling frame and you sample every 100th one, how many people will be in your simple random sample?

16. If you are going to create a stratified sample of students in a school, each strata may not have exactly have the same number of students in order to be valid.

TRUE

FALSE

APPENDIX E: Student Preference Survey

Student Preference Survey on Intelligent Learning Objects

Year in School: Freshman Sophomore Junior Senior Other

Major Field of Study:

Is this the first time using an Intelligent Tutoring System?

Did you need additional instruction in using the Intelligent Learning Objects?

YES NO

Were the Intelligent Learning Objects useful for communicating with the ideas presented?

YES NO

Were the Intelligent Learning Objects useful for learning the ideas presented?

YES NO

Did you have any technical problems with the Intelligent Learning Objects (please select all that apply)?

Logging on

Selecting Lessons

Posting/responding to questions

Other

Did not have any problems

Which one item would you like to see Intelligent Learning Objects used for?

Used in conjunction with classroom instruction

Used as the only means to present instruction

Quizzes / tests

Communication with the instructor

Other

Was the reinstruction helpful (when you first missed a question)?

YES NO

Would you enroll in a distance education course with Intelligent Learning Objects as your only contact with the instructor?

YES NO

APPENDIX F: Usability Test Results

Table F1

Usability Test Results

	Question 1	Question 2	Question 3	Question 4	Question 5
Respondent 1	4	5	2	5	5
Respondent 2	5	5	5	5	5
Respondent 3	5	5	5	5	5
Respondent 4	4	5	4	5	4
Respondent 5	5	4	5	5	5
Respondent 6	4	5	4	5	5
Respondent 7	5	4	5	5	5
Respondent 8	4	5	4	5	5
Respondent 9	4	5	4	5	5
Respondent 10	5	5	5	5	5
Respondent 11	2	4	4	4	4
Respondent 12	4	4	4	4	4
Respondent 13	5	5	5	5	5
Respondent 14	4	4	4	3	4
Respondent 15	4	5	4	4	4
Respondent 16	5	5	5	5	5
Respondent 17	4	4	4	4	4
Respondent 18	5	5	5	5	5
Respondent 19	5	5	5	4	4

Respondent 20	4	4	4	4	4
Respondent 21	5	5	5	5	5
Respondent 22	4	4	4	4	4
Respondent 23	5	5	5	5	5
Respondent 24	5	5	5	5	5
AVERAGES	4.4164	4.6667	4.4167	4.6250	4.6250

Student Comments

1.) If you get the answer wrong you can simply back up to the page where your answer was submitted and change your answer to be correct.

2.) Edit spelling

3.) Some instructions could be added to the login screen

APPENDIX G: Homework Problems for Control Group

STAT 201L - Homework Problems for the Poisson Distribution

1. We know that during the year, 4,317,000 cars went through the intersection of Main and First Avenue last year. There were 123 accidents recorded at this intersection. To determine the probability that two accidents happened in one day, we could use

A. the Binomial Distribution

B. the Poisson Distribution

C. Both Binomial and Poisson

D. Neither Binomial and Poisson

2. Which event is not a rare enough event to contemplate using the Poisson Distribution?

A. the number of bulk orders for bicycles over $100,000

B. the number of people over 110 years of age

C. the number UFO sightings in Greenland in January

D. the number of males in families of size 4

3 Assume that due to a new additive you use in the water of a large aquarium, the death rate has become .055% over the year when there were 2000 fish. What was the chance that NO fish will die in one month?

4. If there are 2000 trials and if the probability of success is .0004, then the Expected Value of X with a Poisson Distribution and the Variance of X have the same number.

A.TRUE

B. FALSE

STAT 201L - Homework Problems for Populations and Samples

1. Both statistics and parameters require a random sample to be properly computed.

   A. TRUE

   B. FALSE

2. If we take a random sample from the 150 players and compute the average of this sample, this statistic (the sample mean) will always be the same as the population mean parameter.

   A. TRUE

   B. FALSE

3. Assume the sum of the squares of a population of size 15 is 1000. The POPULATION VARIANCE is

   A. 8.15

   B. 8.45

   C. 8.75

   D. None of the above

STAT 201L - Homework Problems for ReExpression

1. Here is some data: {2, 4, 6, 8, 10} What will the result be if we raise each of these numbers: to the power -1?

   A. {-2, -4, -6, -8, -10}

   B. {1/2, 1/4, 1/6, 1/8, 1/10}

   C. (-1/2, -1/4, -1/6, -1/8, -1/10}

   D. {22, 44, 66, 88, 1010}

2. You can tell the range of a number based upon its logarithm.

   A. TRUE

   B. FALSE

3. Given the following data:

1	2	3	4	5
5	50	500	5000	50000

Re-Expressing the lower row with the common log gives:

STAT 201L – Homework Problems for Sampling Frames

1. Using the 1^{st} 4^{th} 9^{th} 16^{th} 25^{th} 36^{th} … elements is the best way to implement a simple random sample.

A. TRUE

B. FALSE

2. Assuming a population size of 400 and a skip number of 20, how many subjects will be selected for a stratified sample?

3. In the Strata by political affiliation, {Democrat, Republican, Libertarian} does not precisely fit the definition of a stratified sample.

A. TRUE

B. FALSE

4. If we know that 45% of the certified project managers are males,

then there are exactly 500 x 20% x 45% = 45 of them. Suppose a company has the following staff:

male, full time 90

male, part time 18

female, full time 9

female, part time 63

Total 180

and we are asked to take a sample of 40 staff, stratified according to the above categories. The number of female part-time subjects in the stratified sample would be

A. 50

B. 10

C. 5

D. 35

APPENDIX H: Control Group PowerPoint Lectures

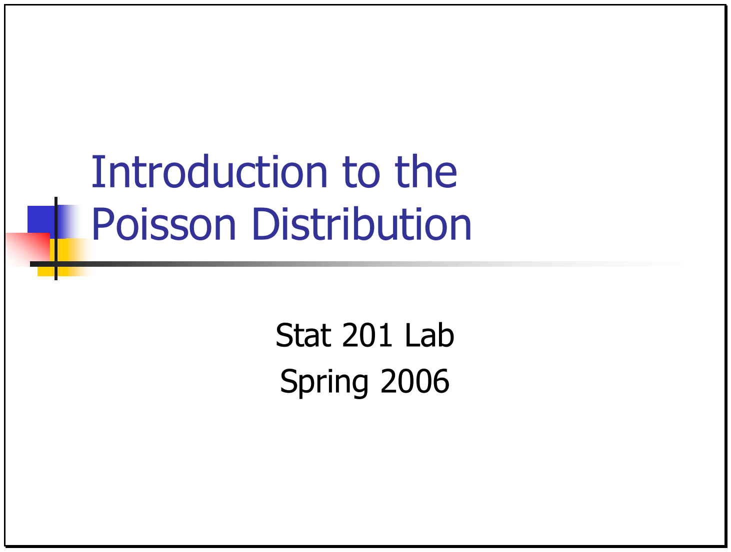

Figure H1. **Poisson Distribution PowerPoint: Introduction**

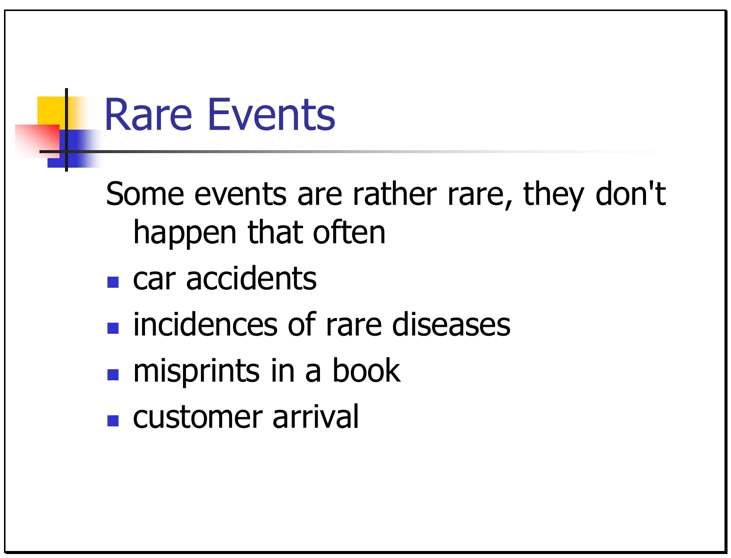

Figure H2. **Poisson Distribution PowerPoint: Rare Events**

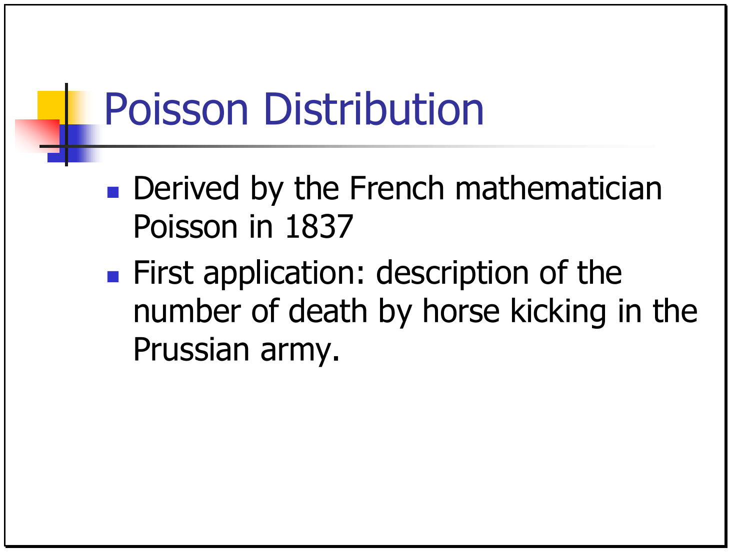

Figure H3. **Poisson Distribution PowerPoint: Poisson Distribution**

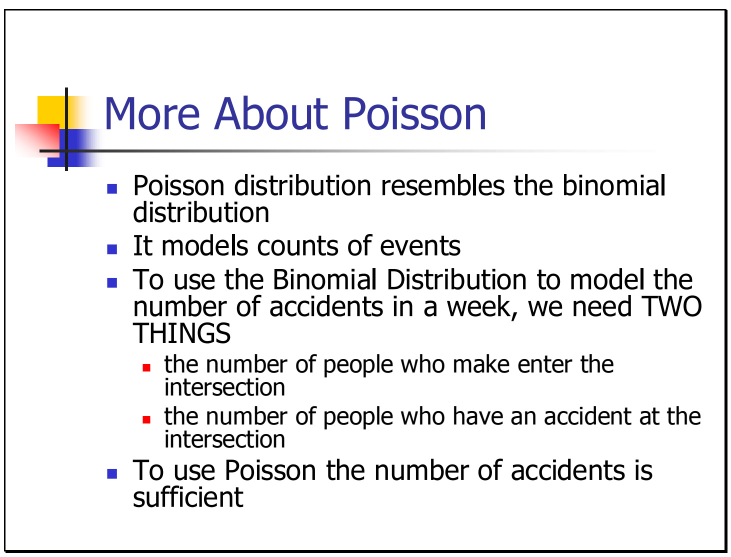

Figure H4. **Poisson Distribution PowerPoint: More About Poisson**

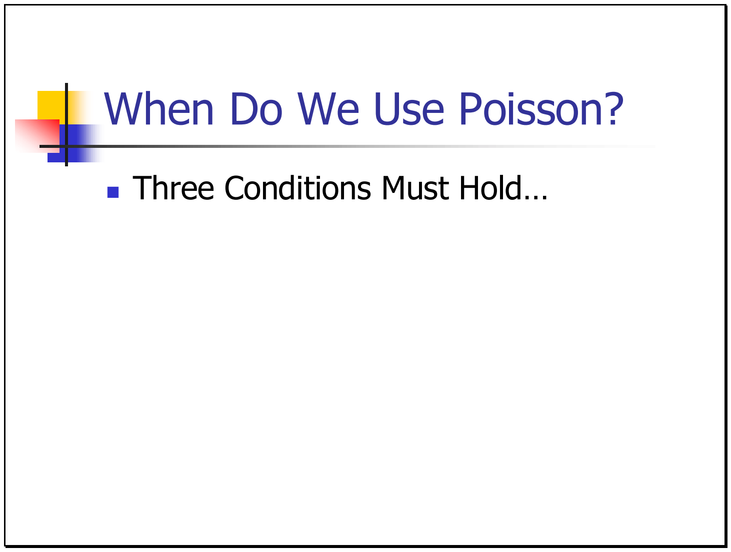

Figure H5. **Poisson Distribution PowerPoint: When do we use Poisson?**

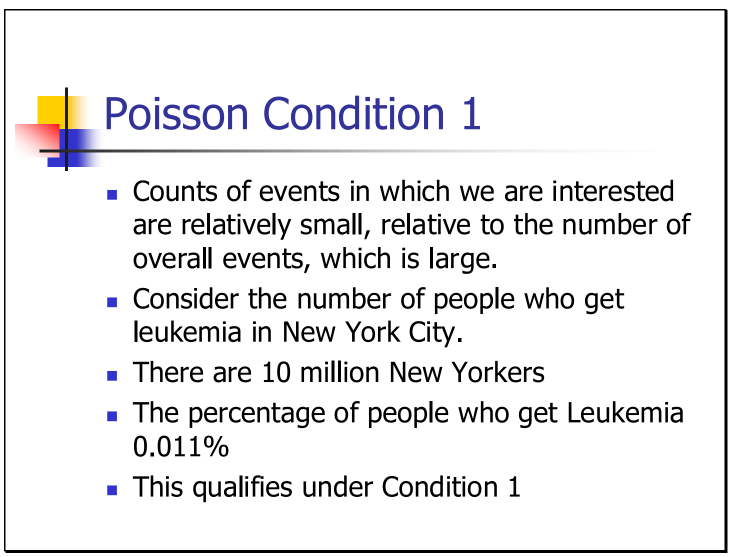

Figure H6. **Poisson Distribution PowerPoint: Poisson Condition 1**

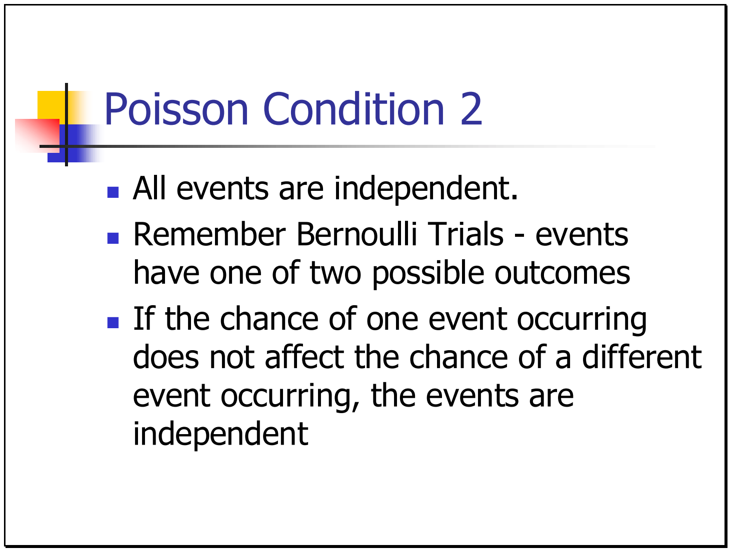

Figure H7. **Poisson Distribution PowerPoint: Poisson Condition 2**

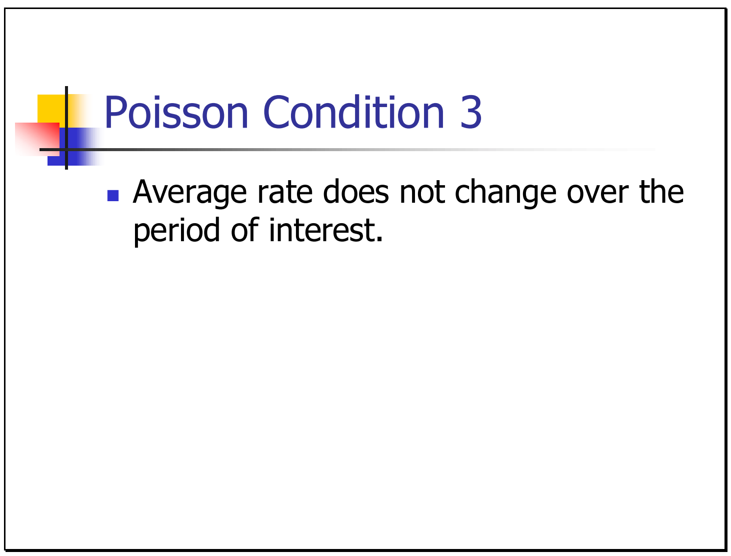

Figure H8. **Poisson Distribution PowerPoint: Poisson Condition 3**

Computing Poisson Probabilities

- Assumptions: We have the rate of occurrences in a large sample.
- Parameters:
  - λ = rate of occurrence for this sample
  - λ = (number of individuals) x (rate of occurrence)
  - λ can range from 0 upwards and does NOT have to be an integer.
  - X must be an integer = 0, 1, 2, 3, ...

Figure H9. **Poisson Distribution PowerPoint: Computing Poisson Probabilities**

Using The Poisson Formula

P(observing X occurrences when the rate is λ)
= $(e^{-\lambda}\lambda^{x})$ / x!

- EX: λ is the number of occurrences, such as 1.5 (the number of dead fish found in a large aquarium every month).
- We want to know the probability that 5 fish (X=5) will die in a month.
- The monthly rate of dead fish is 2000 x .075%
- So, λ = 2000 x .075% = 1.5
- From the formula, there is a 0.0141, or 1.41% chance of five fish dying in a month.

Figure H10. **Poisson Distribution PowerPoint: Using the Poisson Formula**

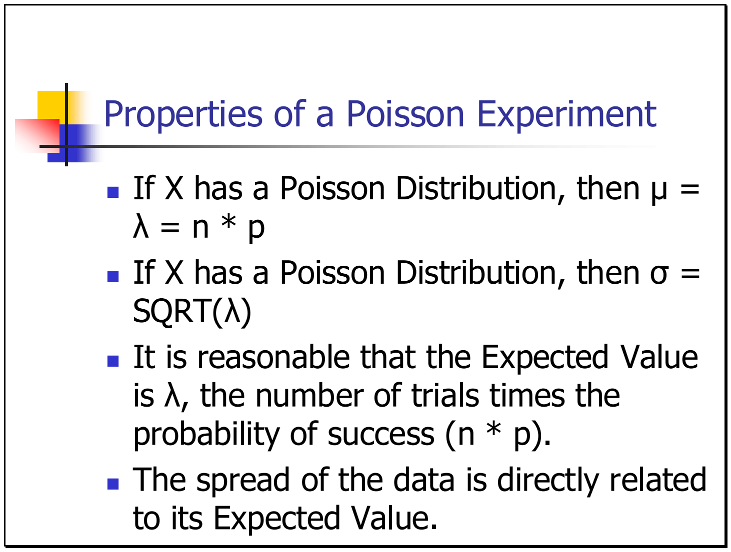

Figure H11. **Poisson Distribution PowerPoint: Poisson Properties of an Experiment**

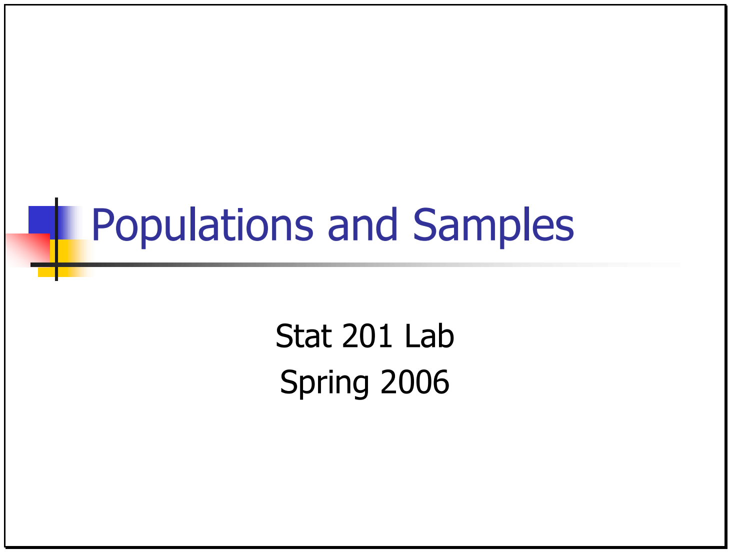

Figure H12. **Populations and Samples PowerPoint: Introduction**

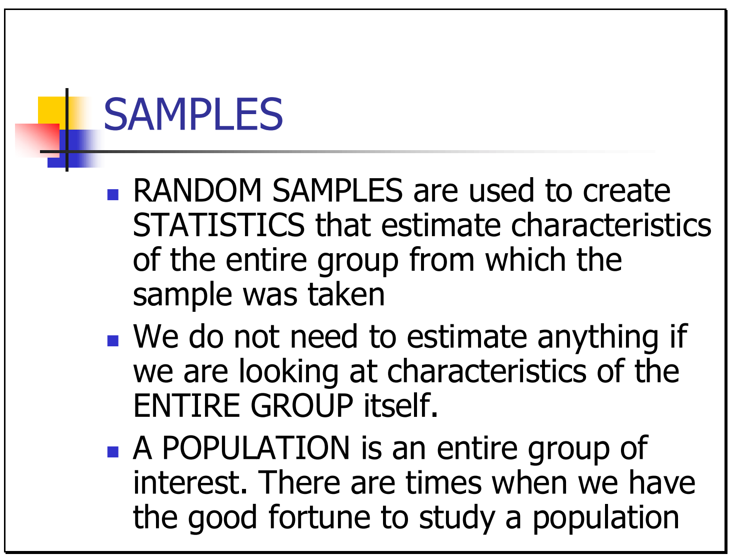

Figure H13. **Populations and Samples PowerPoint: Samples**

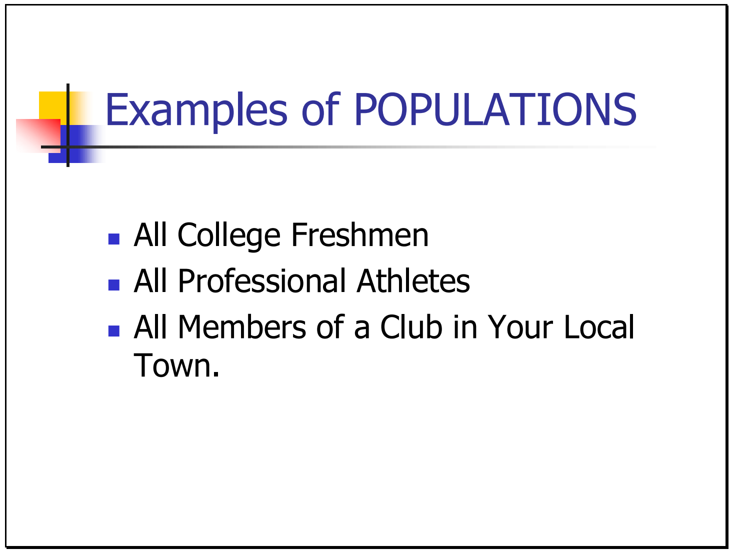

Figure H14. **Populations and Samples PowerPoint: Examples of Populations**

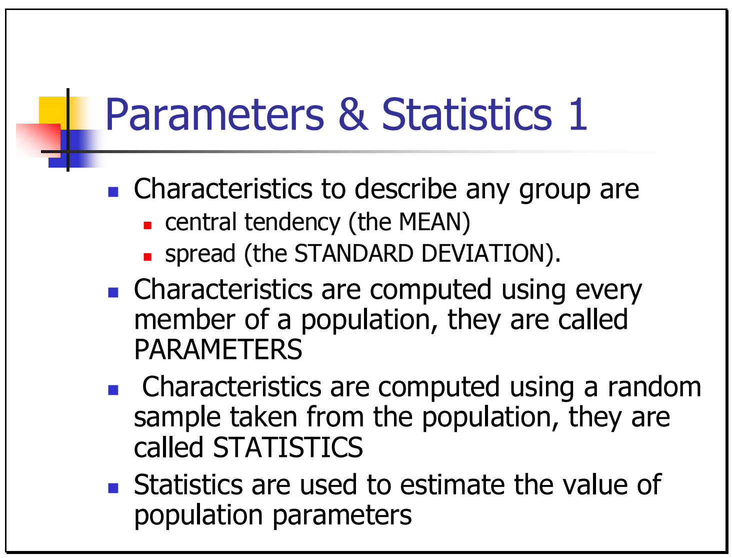

Figure H15. **Populations and Samples PowerPoint: Parameters & Statistics 1**

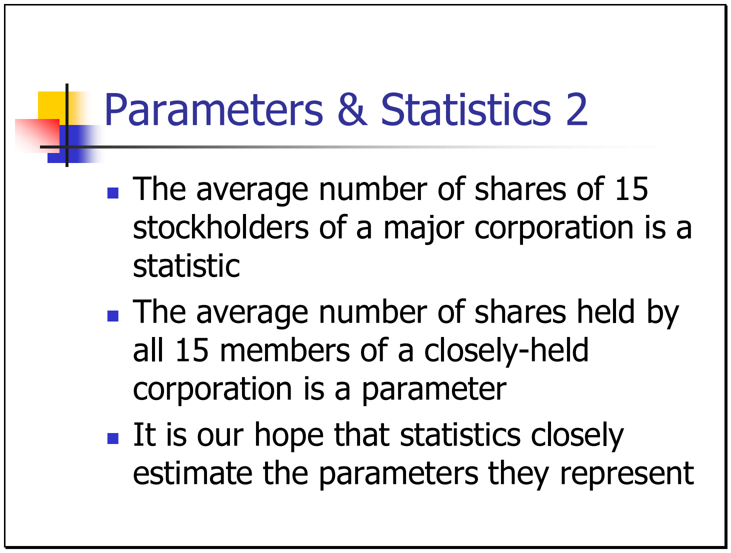

Figure H16. **Populations and Samples PowerPoint: Parameters & Statistics 2**

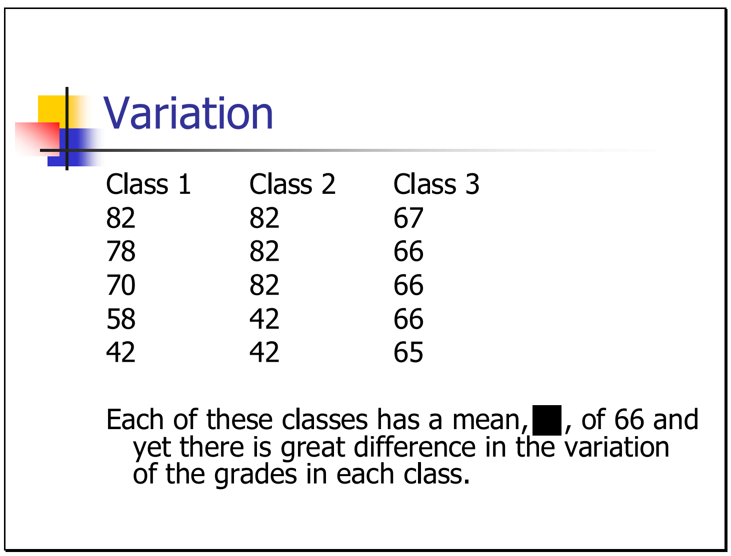

Figure H17. **Populations and Samples PowerPoint: Variation**

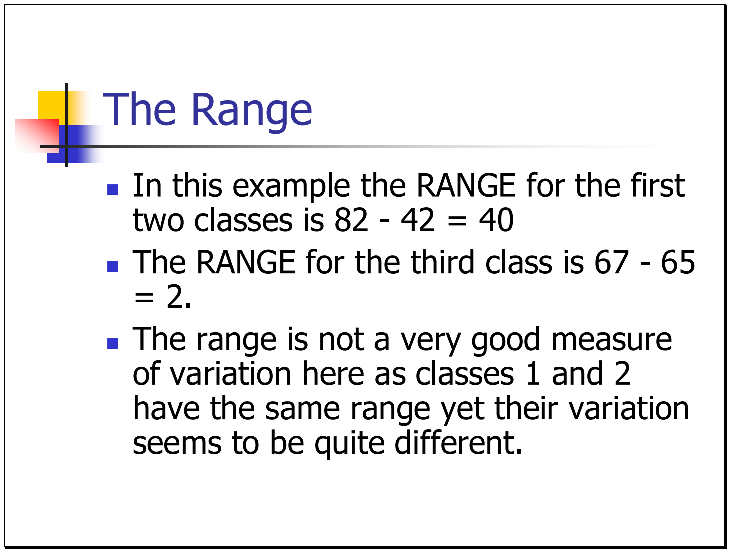

Figure H18. **Populations and Samples PowerPoint: The Range**

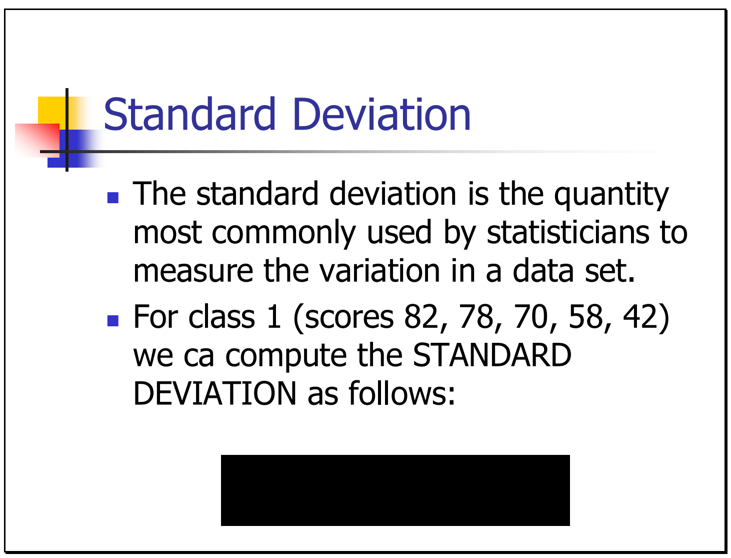

Figure H19. **Populations and Samples PowerPoint: Standard Deviation**

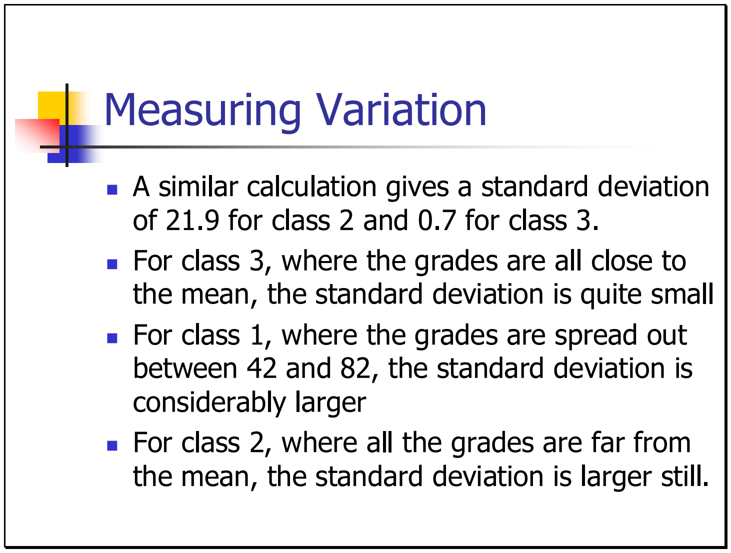

Figure H20. **Populations and Samples PowerPoint: Measuring Variation**

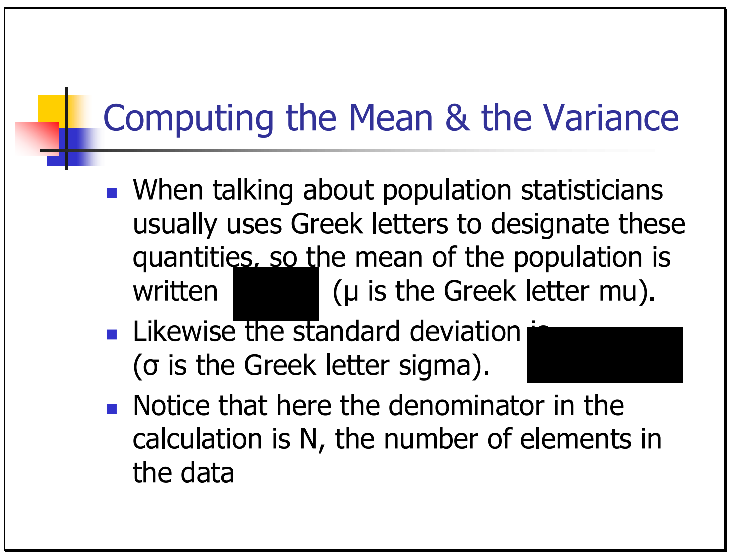

Figure H21. **Populations and Samples PowerPoint: Computing the Mean & the Variance**

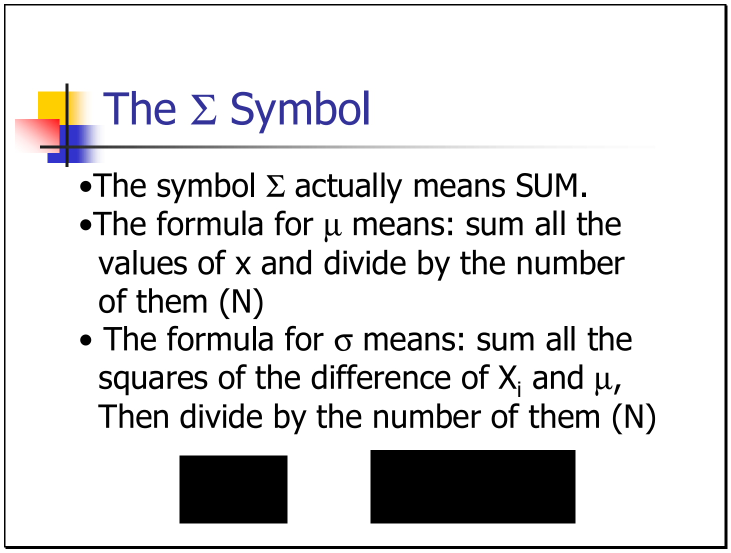

Figure H22. **Populations and Samples PowerPoint: The Σ Symbol**

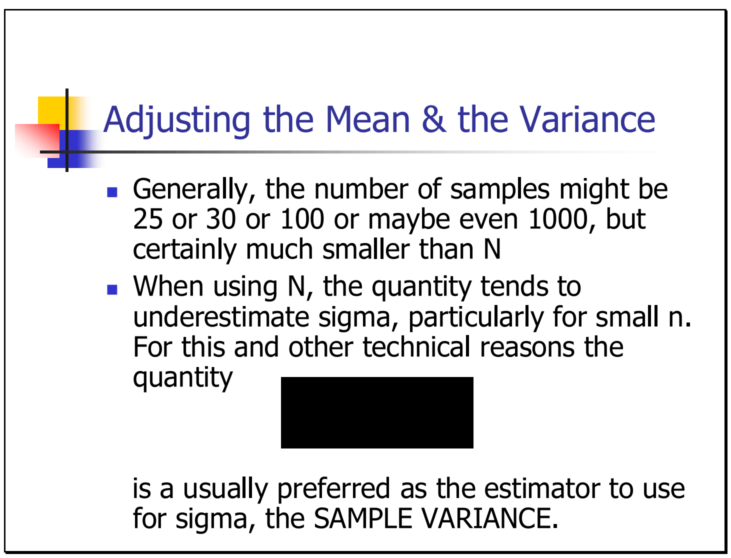

Figure H23. **Populations and Samples PowerPoint: Adjusting the Mean & the Variance**

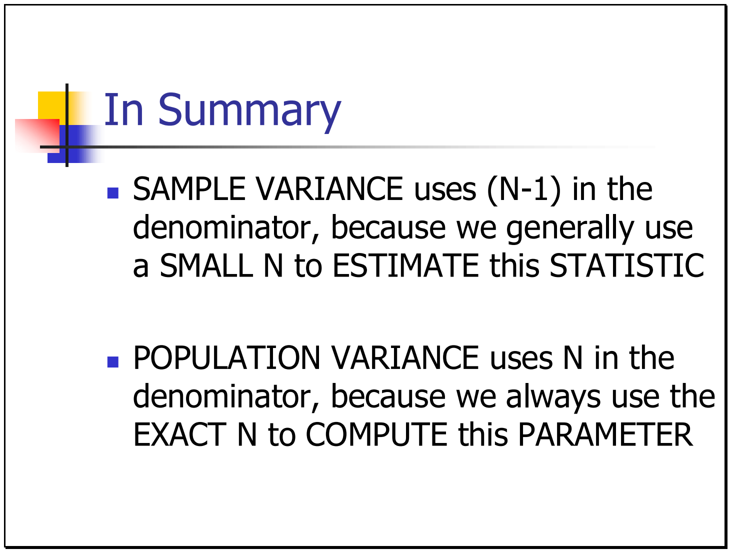

Figure H24. **Populations and Samples PowerPoint: In Summary**

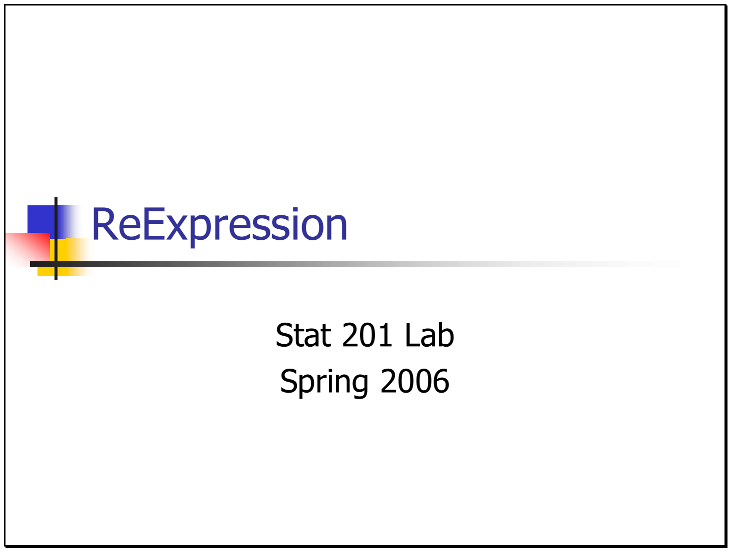

Figure H25. **ReExpression PowerPoint: Introduction**

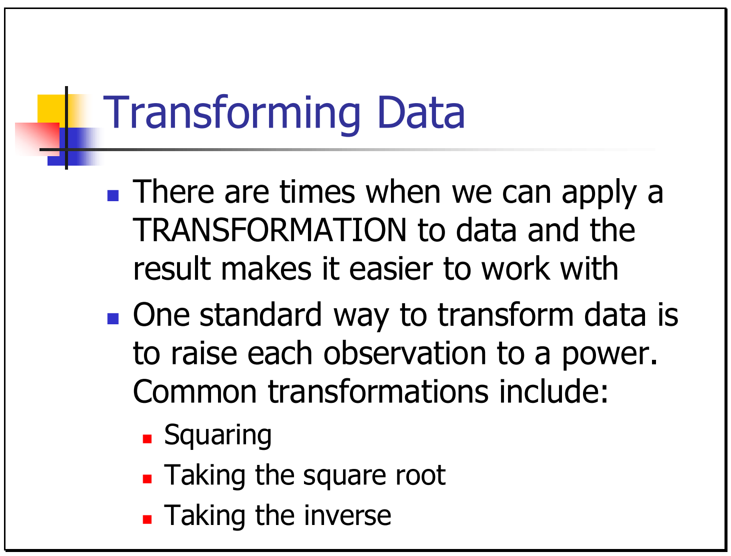

Figure H26. **ReExpression PowerPoint: Transforming Data**

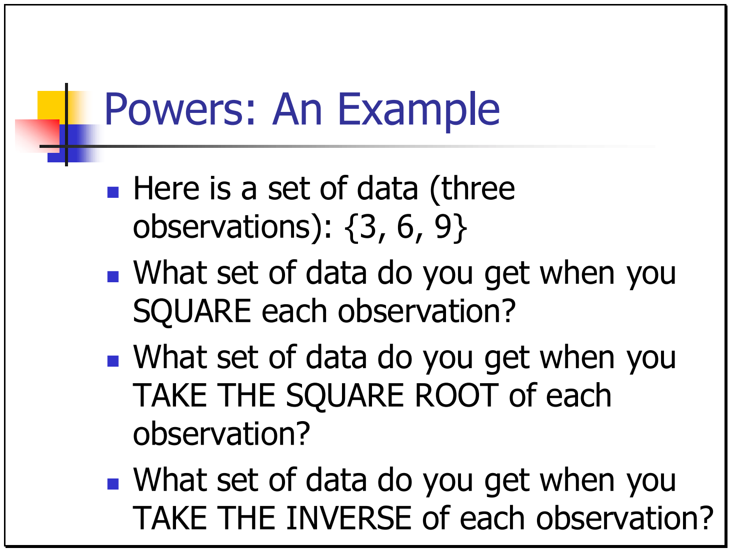

Figure H27. **ReExpression PowerPoint: Powers: An Example**

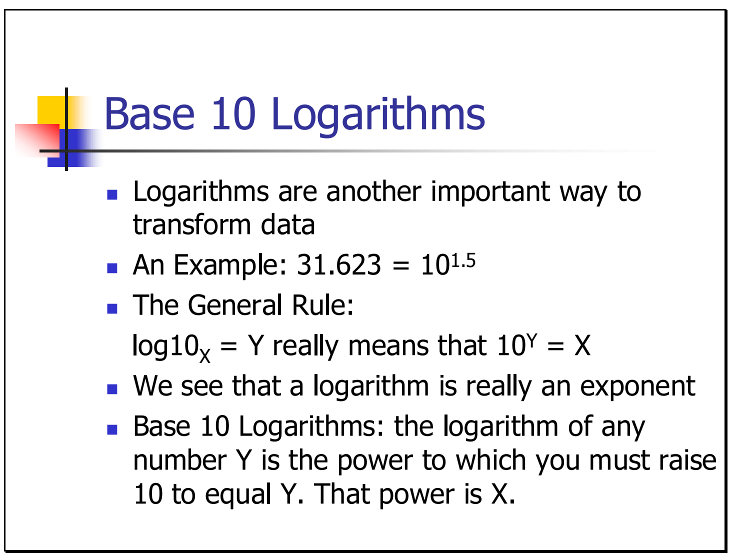

Figure H28. **ReExpression PowerPoint: Base 10 Logarithms**

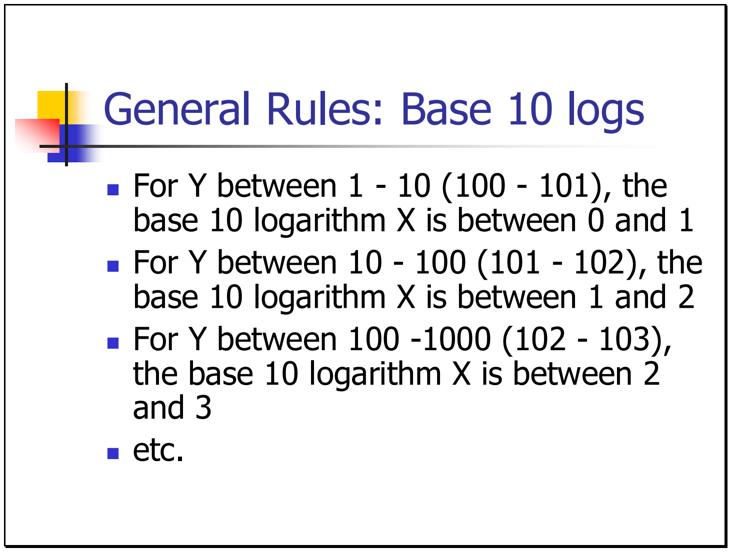

Figure H29. **ReExpression PowerPoint: General Rules: Base 10 logs**

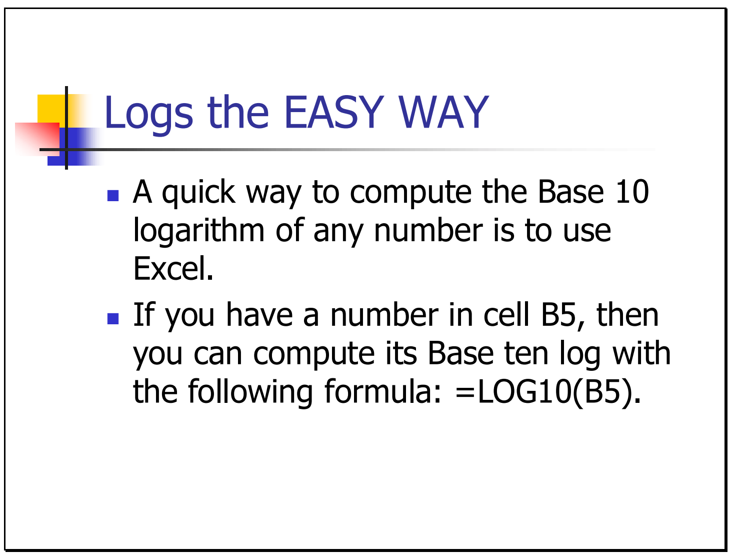

Figure H30. **ReExpression PowerPoint: Logs the EASY WAY**

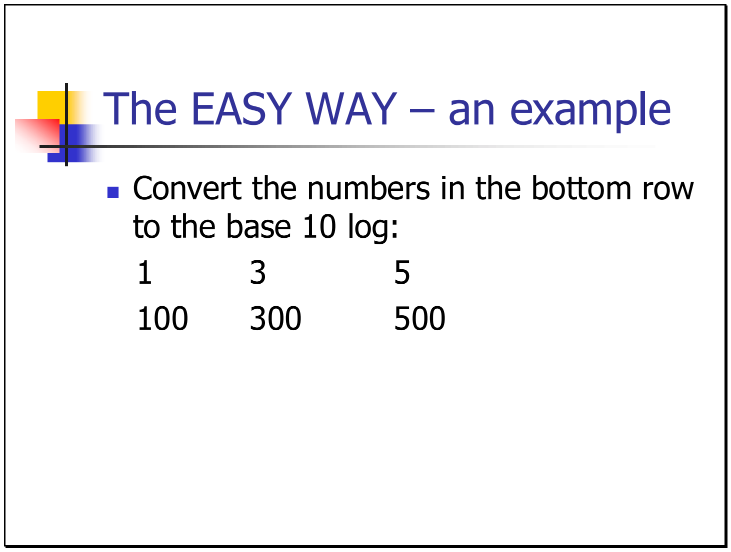

Figure H31. **ReExpression PowerPoint: The EASY WAY – an example**

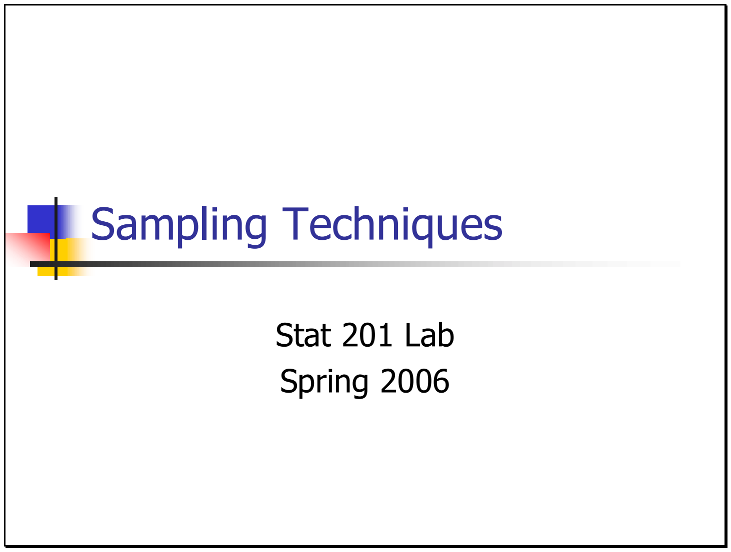

Figure H32. **Sampling Techniques PowerPoint: Introduction**

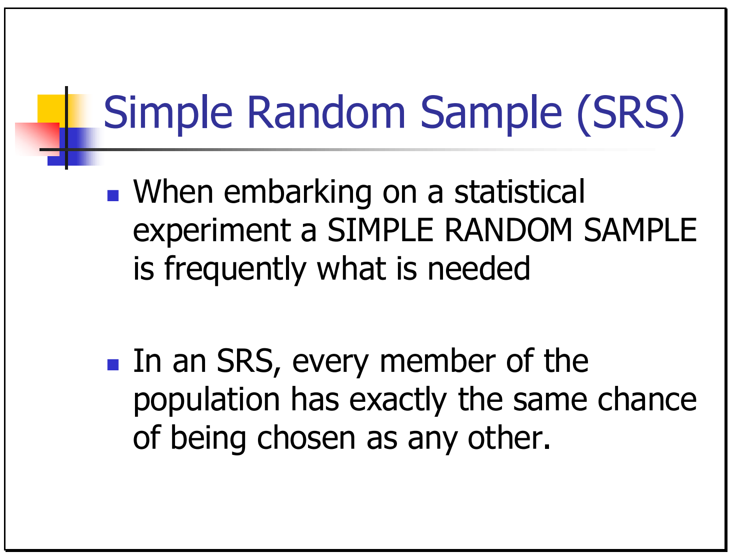

Figure H33. **Sampling Techniques PowerPoint: Simple Random Sample (SRS)**

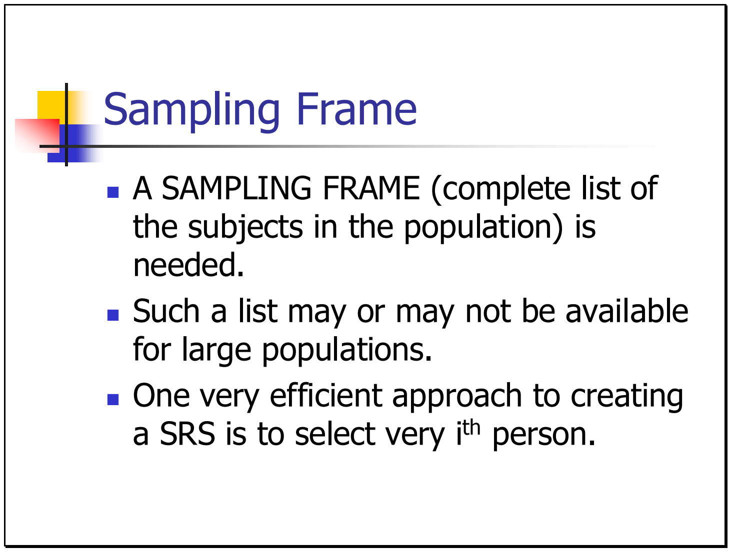

Figure H34. **Sampling Techniques PowerPoint: Sampling Frame**

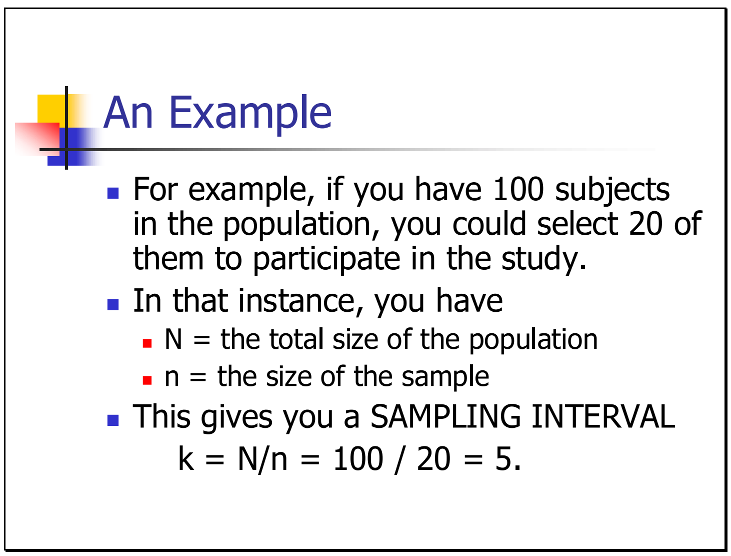

Figure H35. **Sampling Techniques PowerPoint: An Example**

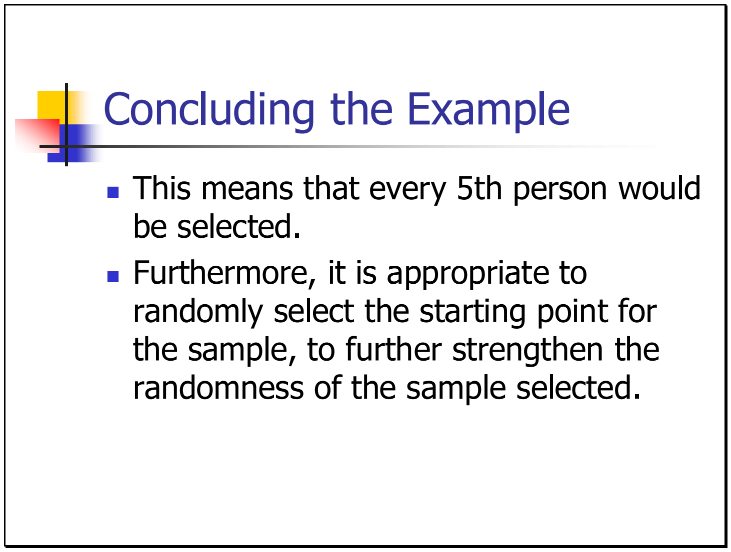

Figure H36. **Sampling Techniques PowerPoint: Concluding The Example**

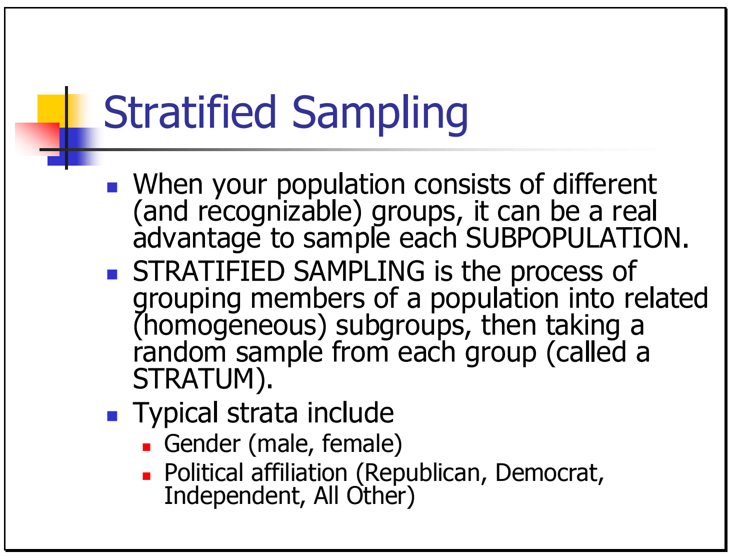

Figure H37. **Sampling Techniques PowerPoint: Stratified Sampling**

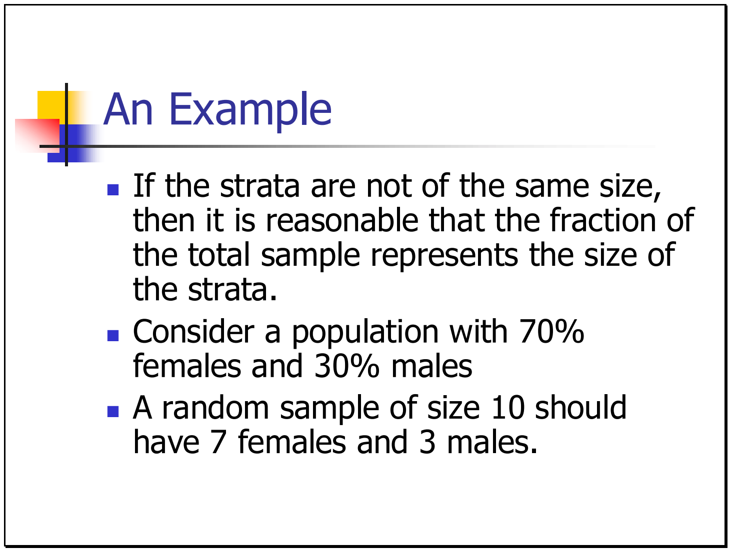

Figure H38. **Sampling Techniques PowerPoint: An Example**