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Learning Protein Structure with Peers in an AR-Enhanced Learning Environment

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A dissertation

submitted in partial fulfillment of the

requirements for the degree of

Doctor of Philosophy

University of Washington

2013

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Program Authorized to Offer Degree:
College of Education

University of Washington

Abstract

Learning Protein Structure with Peers in an AR-Enhanced Learning Environment

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Augmented reality (AR) is an interactive system that allows users to interact with virtual objects and the real world at the same time. The purpose of this dissertation was to explore how AR, as a new visualization tool, that can demonstrate spatial relationships by representing three dimensional objects and animations, facilitates students to learn chemistry, a discipline requiring students' visual-spatial thinking to comprehend abstract concepts. In addition, this dissertation examined the effect of AR in a collaborative learning environment and the impact of visual-spatial ability and cognitive load on student learning performance.

The Protein Magic Book, developed by Human Interface Technology Laboratory at the University of Washington and the SCRIPPS Research Institute at La Jolla, was the learning material in this study. The Protein Magic Book introduces basic concepts of protein structures with AR representations. Students were randomly assigned into three settings, including studying with texts only (N=26), studying with AR alone (N=26), and studying with AR in dyads (22 pairs). Totally, ninety six students participated in this study. They were required to complete background questionnaire, chemistry self-efficacy scale, and chemistry knowledge test, before

they studied the protein structures. After the learning activity, they took the post-test, cognitive load scales, and visualization rotation test. The results of data screening showed that a nested effect existed within dyads. Therefore, the Hierarchical Linear Modeling (HLM) was employed in data analysis.

The results indicated that students in the AR alone setting gained greater learning performance than those who studied with texts. However, students in the collaborative setting did not perform better than those who studied alone with AR scaffolding. Students with higher visual-spatial ability performed better, and students with higher spatial ability reported less cognitive load, especially AR load. Cognitive load, on the other hand, did not affect student learning performance in this study and students in the collaborative setting did not report higher cognitive load than other groups. Discussion of findings, limitations of this study, and future research directions are presented.

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ACKNOWLEDGEMENTS

I would like to thank my advisor Dr. Robert Abbott for his exceptional support and guidance for my dissertation. He led me to the world of educational statistics, especially HLM modeling. This dissertation could not have been finished without his encouragement, patience, and dedication. I would also like to thank all my committee members, Dr. Brad Portin, Dr. Mark Windschitl, Dr. Deborah McCutchen, and Dr. Tom Furness for their time and guidance to make this dissertation better.

I am also thankful for the support of the Human Interface Technology Laboratory (HIT Lab) for making this study possible. Special thanks to Dr. William Winn, Dr. Tom Furness and Suzanne Weghorst. They opened the door of virtual and augmented reality for me and inspired my thinking and imagination in how to use these advanced technologies in education. In addition, I am grateful to my HIT Lab friends, Eliana Medina, Amlan Mukherjee, and Ruth Fruland. I appreciate the friendship and the time we spent together, which is an important part of my UW memory.

I am grateful to Peggy Wu Cregan, Chiao-Hui Tseng, Pei-Yu Chen, and Lotus Jo-Fu Lin for their friendship and support. I also want to thank Dr. Elizabeth Sanders for her selfless support with my statistical analysis. I also would like to express my gratitude to my parents and my family. Their love and unconditional support gives me the freedom to pursue my dreams. Last, I would love to thank my beloved husband, Harch Ooi, daughter Clare, and the little one who is on the way. This dissertation could not be completed without all of them.

DEDICATION

To Dr. William D. Winn,

a pioneer, a mentor, and a friend, who brought me to this wonderful journey.

CHAPTER 1: INTRODUCTION

1.1. Statement of the problem

Learning chemistry is not easy. In essence, chemistry is a discipline that conveys abstract concepts which cannot be seen in the real world. Hence, it takes a lot of effort to make a connection between a conceptualized chemical world and the real world. In order to help students understand chemistry, a lot of visual representations are involved in chemistry learning. Accordingly, learning chemistry requires visual comprehension (Wu and Shah, 2004). These visual representations, such as chemical structures and molecular models, demonstrate the characteristics of chemical substances and the relationship among molecules. These visual displays require students to think visually and spatially to comprehend the underlining concepts.

However, Wu and Shah (2004) indicated that even though visual representations are commonly used in teaching chemistry, students still have difficulties in understanding and interpreting visual representations. In addition, students are not able to transform the meaning of different chemical representations easily. If using visual representations is inevitable in chemistry learning, what visualization tool can support students' visual-spatial thinking to help them comprehend the visual representations? If there is any, in what ways can it be used to facilitate learning?

1.2. Purpose of the study

The purpose of this study is to explore how a new instructional technology, augmented reality (AR) may use a new kind of visualization to help students learn chemistry. Unlike virtual reality (VR), which separates users from the real world, AR is an interactive interface where people can work in the real world and manipulate three-dimensional (3-D) objects at the same time. That is, virtual objects and real objects coexist in the same place at the same time (Azuma, 1997; Feiner, 2002; Vallino, 2002). An AR system is able to carry multimedia representations including static images, animations, and 3-D objects. More importantly, AR allows users to interact with visual representations with their hands, rather than mouse clicking, which most computer-based simulations do. AR shows great potential to convey visual-spatial concepts and to provide a kinesthetic experience which may facilitate memory encoding (Mathewson, 1999). Therefore, using AR may enhance chemistry learning.

As a new technology, how can AR be integrated into a learning environment? Billinghurst, Kato, and Poupyrev (2001) indicated that AR might enhance collaborative learning in three ways: (1) as a physical object that users must share, (2) as an AR object where users can see virtual objects from their own viewpoint, and (3) as a virtual place where users can interact with AR and manipulate virtual objects. Compared to learning alone, learning with peers provides a "shared place" to elicit social interaction, which encourages students to learn from discussion. This study will examine in what situations AR may be more effective to help students learn. Will students learn more by themselves or with their peers when using AR in learning chemistry?

Another consideration in this study is students' visual-spatial thinking ability. Research has emphasized the importance of visual-spatial thinking in chemistry learning (for example, Mathewson, 1999; Wu and Shah, 2004). Strong correlations between students' spatial abilities and chemistry learning (Carter, LaRussa & Bodner, 1987) have been reported. Since AR is able to convey visual and spatial cues at the same time, which in turn requires users to think about the virtual objects visually and spatially, the students' visual-spatial thinking ability may be an important factor in implementing AR in chemistry learning.

When exposed to a rich visualization-based and collaborative learning environment, will students put more effort into processing what they encounter? In the past, cognitive load theory (Sweller, 1994) generally dealt with designing external representations to reduce learners' external cognitive load. When "the two (visualization and constructive learning environment) meet in the use of external representation" (van Bruggen, Kirschner, & Jochems, 2002), what is the extent of the cognitive load on the learners? Studying cognitive load in a computer supported collaborative learning (CSCL) environment is still new and needs to be explored. In this study, the capacity of cognitive load in an AR-based collaborative learning environment will be investigated (Billinghurst, Kato, & Poupyrev, 2001; van Bruggen, Kirschner, & Jochems, 2002).

1.3. Research questions

The research questions addressed in this study are:

1. Will students benefit from AR in chemistry learning?
2. Will students learn chemistry more effectively in an AR-enhanced peer learning environment?
3. What factors may affect student chemistry learning in an AR-enhanced environment?
4. How much cognitive load will students report in different learning settings?

To examine these research questions, an AR application, the Protein Magic Book , developed at the Human Interface Technology Laboratory (HIT Lab) at the University of Washington and the SCRIPPS Research Institute at La Jolla, will be used as the learning material. The Protein Magic Book is an interactive book which introduces basic concepts about protein structures. The AR technology of the Protein Magic Book requires a webcam to track a specific pattern that uses the computer to render 3-D objects, which are shown on the computer screen. Therefore, in this AR system, users do not have to wear any head-mounted display. This feature allows users to interact with 3-D objects with their hands and manipulate 3-D objects more freely and authentically. More detailed information will be given in the methodology chapter.

1.4. Significance of this study

It is expected that the results of this study will provide deeper understanding of how students learn chemical concepts and inform chemistry educators about what they might consider

in teaching similar topics. Further, since AR is a new technology in education, this study offers a preliminary examination of how AR could be adapted to an educational setting. Last, the results of this study can provide guidance to engineers who design the AR environment in order to improve the interface design.

CHAPTER 2: LITERATURE REVIEW

To elaborate on the research questions, in this section I will discuss theories and research regarding visual-spatial thinking in chemistry learning, cognitive load, collaborative learning, and using augmented reality in education. The theoretical framework of this study will build upon these theories.

2.1. Chemistry learning and Visualization

Chemistry teaching often involves the presentation of a lot of visualization displays that enable students to explore abstract chemical concepts, such as molecular models and chemical structures because molecules or atoms are not visible with our naked eyes (Justi & Gilbert, 2002). In order to assist student learning, chemistry textbooks use many visual representations to introduce rudimentary chemical concepts. Why is understanding structures of different chemical phenomena important? In the textbook of “Lehninger Principles of Biochemistry”, Nelson and Cox (2004) pointed out that when learning about proteins, it is crucial to know their structures because “(it) is essential to the discussion of function in succeeding chapters” (p.159). Wu and Shah (2004) also mentioned that being able to comprehend chemical visualizations will be beneficial for students conducting advanced scientific research. In turn, these chemical visualizations become a common language which facilitates chemists or those who are interested in studying chemistry to communicate with each other (Kozma, Chin, Russell, & Marx, 2000).

Most of these visual representations convey spatial information to show the relationship among molecules or atoms, the comprehension of which requires students' visual-spatial thinking. However, students have difficulties in learning abstract chemical concepts, especially those which involve mental manipulation and spatially-related concepts (Copolo and Hounshell, 1995). Students also report difficulty understanding representations and transforming representations from two dimensional (2D) to three dimensional (3D) representations or vice versa (Wu and Shah, 2004; Wu, Krajcik, & Soloway, 2001). In turn, difficulty comprehending chemical visual representations may impede students' chemistry learning in general.

As new visualization technologies have developed, many scholars built visualization tools for chemistry learning (Kozma and Russell, 1997; Chanlin, 1998; Wu, Krajcik, & Soloway, 2001; Schank and Kozma, 2002). Nevertheless, it is not guaranteed that using visualization technologies will facilitate learning. For example, Chanlin (1998) found that too complex animation did not help learning DNA structures. On the other hand, for simple concepts, there was no difference between 3-D and 2-D displays. Since chemistry education requires visual-spatial thinking to understand visual representations, we need to develop a visualization tool with which students can interact visually and spatially in order to facilitate their learning. In addition, in their study of examining how building virtual environments (VEs) might help students learn, Winn, Hoffman, Hollander, Osberg, Rose, and Char (1999) found that building VEs benefits low-ability students more than high-ability students in their learning performance. In this study, it is predicted that students visual-spatial ability will affect their chemistry learning with AR. Furthermore, students with low visual-spatial ability will benefit more from AR than high visual-

spatial ability students in their learning performance.

2.2. Cognitive load

Cognitive Load Theory (CLT) is an instructional/learning theory which describes the cognitive process in learning (Cooper, 1998; Brunken, Plass, & Leutner, 2003; van Merrienboer & Sweller, 2005). CLT assumes when people learn, the capacity of their working memory is limited (van Merrienboer & Sweller, 2005). Working memory is the primary place to process information from sensory memory. According to Baddeley's model (1986), working memory embodies at least two systems, a visuospatial sketchpad to deal with visuospatial information, and a phonological loop for phonological information. The capacity of these two systems is limited and these two systems act somewhat independent of each other. Therefore, the major task of the instructional designer is to facilitate the use of both kinds of working memory within the limited capacity of each.

Cognitive load refers to "the total amount of mental activity imposed on working memory at an instance in time" (Cooper, 1998). It can be distinguished into three domains: intrinsic load, extraneous load, and germane load (Kirschner, 2002). Intrinsic load is imposed by the nature of the learning material which cannot be altered by instructional design (van Merrienboer & Sweller, 2005). That is, more complex learning tasks impose more intrinsic load. Extraneous load, on the other hand, can be manipulated by instructional intervention. Extraneous load is affected by the manner in which the information is presented. A learning task can be presented in different forms which may result in different amounts of extraneous load. Germane load is what

is required to construct schemata from working memory and place them in long-term memory (Kirschner, 2002). It is the mental effort required for learners to comprehend the material. The capacity of working memory in this theory is the sum of these three loads. Since the intrinsic load cannot be modified, the way to enhance the processing of working memory is to reduce extraneous load and to increase germane load.

Several techniques apply cognitive load theory to instructional design, using what are called "goal-free effect, worked example and problem completion effect, split attention effect, redundancy effect, and modality effect" (Copper, 1998). The design of the Protein Magic Book adapts the design techniques of (1) the worked example effect, which reduces cognitive load by demonstrating all the work to the learners, and (2) the modality effect, which uses separate parts of working memory, including presenting texts, pictorial illustrations, AR visualization, and peer conversation in a collaborative learning setting. First, when students start to use the Protein Magic Book, they are provided a worked example to understand how to interact with the Protein Magic Book, which reduces their uncertainty about the new technology and therefore increases their confidence in interacting with AR. In addition, the Protein Magic Book not only offers students the text part of the content, and some illustrations, but also uses AR to make abstract concepts more concrete, which will “expand working memory” (Cooper, 1998) when learning protein structure. Although auditory information is not presented in the AR technology that underlies Protein Magic Book, the discussion with peers may be another contribution to the modality effect because students may clarify their ideas and acquire more understanding auditorially through peer discussion.

Brunken, Plass, and Leutner (2003) summarized four methods to measure cognitive load. First, indirect, subjective measurement asks learners to report the amount of mental effort that they use in understanding the material after they complete the task. Second, direct, subjective measure requires learners to rate the difficulty of the materials. Third, indirect, objective measurement, which is the most common method to measure cognitive load, makes inferences about load from performance outcomes. The fourth method is direct, objective measurement, which involves the use of neuro-imaging techniques to investigate how the brain works during the task. Similarly, Schultheis and Jameson (2004) described four ways to assess cognitive load: analytic measures, subjective measures, performance measures, and psychophysiological measures. Analytical measures estimate the load by examining the intrinsic difficulty of the material and how much expertise the learner has in order to predict the cognitive load the learner might experience during the task. This is an indirect way to measure cognitive load. Subjective measures ask learners to rate the load they experienced or are experiencing during the task by self reporting. Like indirect measures, objective measures assess the performance of the learner.

In this study, learning performance will be the dependent variable used to determine how much students learn from the Protein Magic Book. Therefore learning performance is not considered to be the measurement of cognitive load. Although psychophysiological measurement appears more direct and objective, Paas, van Merrienboer, and Adam (1994) found subjective ratings more reliable than cardiovascular measures in instructional research. Therefore, this study will use direct, subjective measures as the assessment of cognitive load.

2.3.Collaborative learning

Collaborative learning requires students to learn as a team. It contributes to cognitive learning as shown in the CRESST model of learning* (Baker, 1995, derived from Klein, O'Neil, & Baker, 1998). Many studies have shown that collaborative learning can enhance learning in the classroom because, in a collaborative learning setting, students can verbalize what they think, help each other, and complete a task together (Webb, Nemer, Chizhik, & Sugrue, 1995).

In a computer-supported collaborative learning (CSCL) environment, students share external representations of content. van Bruggen, Kirschner, and Jochems (2002) indicated that in a CSCL environment, external representations are a catalyst to "augment" cognitive activities. With compelling visual representation, it is predicted that AR is able to serve the role of a catalyst in a CSCL environment.

However, sharing external representations with other students might result in high cognitive load because it takes more effort to explain what students see to their peers or to understand their peers (van Bruggen, Kirschner, & Jochems, 2002). The Protein Magic Book only offers text and AR representations without any auditory explanation. Therefore, it is assumed that the collaborative learning setting may cause students higher cognitive load through the process of peer discussion. Moreover, students may develop some learning strategies together which leads to the enhancement of germane load, such as asking each other to explain what the content or pictures mean.

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* CRESST model of learning contains five components, including content understanding, problem solving, metacognition, communication, and collaboration.

The next question is how many students will be in the collaborative learning setting in this project. Roth (2001) found when more than two students work in a group, the physical arrangement and computer interaction will “curtail the mutual orientation of the students.” In a group interaction, gestures help students express their opinion in addition to verbalization. Also, access to the visual representations is an important factor in collaborative learning. Having more than two students may decrease their ability to see and interact with the visualized objects and the power of collaborative learning might be lessened. Therefore, to investigate the effect of collaborative learning in this study, two students will be assigned to be a team to study the material together.

2.4. Augmented reality (AR)

Augmented reality (AR) is an interactive system which integrates virtual objects (computer-generated three-dimensional objects) into the real world. In this system, users can work in the real world and handle 3-D virtual objects at the same time. Virtual objects and real objects coexist in the same place and at the same time (Azuma, 1997; Feiner, 2002; Vallino, 2002).

Being a member of the VR family, AR shares some characteristics of VR but has its distinct features (Chen, 2005).

Combining virtual and real objects in a real environment

Seeing real and virtual objects in a real environment at the same time is a very important feature of AR and this is the most distinct feature compared to other educational technologies. First, in contrast to old technologies, such as texts or TV, which only display fixed, manipulated

images on a single interface, in an AR environment, real and virtual objects can be seen at the same time, which will give users more visual stimulation than a single interface. Second, since virtual and real objects can be shown in a "real" environment, this feature offers a more natural and intuitive setting for human-machine interaction. This is also a distinct feature from VR, in which users are occluded from the real world and only interact with virtual objects.

An interactive environment in real time

In an AR environment, users are not passive receivers of what is presented as with TV or books. On the contrary, users can manipulate the real or virtual objects. They gain a sense of control in an AR environment. In addition, they can receive immediate feedback once they do some commands on the virtual objects. That is, AR offers a real-time interaction, which would satisfy users' curiosity and encourage users to learn.

Creating an immersive environment

Does AR create an immersive environment like VR does? AR builds different levels of immersion depending on the technologies. For example, Milgram, Takemura, Utsumi, & Kishino (1994) called monitor-based AR a non-immersive environment, while other types of AR create immersive environments. But how immersive are they? Can they create an environment as totally immersive as VR? Vallino (2002) argued that AR is an "ultimate immersive system" because users can not be more immersed in the "real world." In other words, while VR can create a totally immersive "synthetic" world, AR provides an immersion in the "real" world to interact with virtual objects. The characteristic of immersion would generate a more authentic and intuitive learning environment and therefore arouse users' sense of presence to be more

engaged in such a learning environment.

In addition, AR allows the first-person experience, which means users can observe and interact with the AR environment directly and receive the immediate feedback. The first-person experience increases the degree of immersion and connects users and AR more tightly. Furness, Winn, & Yu (1997) indicated that the degree of immersion is a very important implication for education.

Multimedia and multisensory display

Like most computers, AR can display different representations, such as diagrams, graphics, videos or animations. It also can be manipulated along with sounds and haptic facilities. Users can touch and manipulate the virtual objects, and use their body to interact with them. Therefore, AR not only allows users to see various representations, but also provides a multisensory interface. With this powerful function of multimedia representation, it has great potential to be a scientific visualization tool (McLellan, 2003).

Portability

In order to process huge amounts of data, VR requires high-speed processing computers, head-mounted display (HMD), and cables to build a VR environment. These equipments are heavy, and not easy to prepare in a general classroom. In contrast, the equipment of AR is lightweight and it is simpler to render AR images. For example, in the project of Protein Magic Book, the virtual images are rendered by a laptop and a webcam only. This equipment is more portable, and cheaper than what VR needs.

User Friendliness

Although AR is an emerging advanced technology, users are allowed to create their own virtual images by using ARToolKit or other AR software. It is easier for users themselves to create the virtual images than with VR. Another distinct feature of AR is that in an AR environment, users might not have the symptom of nausea or motion sickness that they might experience in a VR environment. This is because AR provides a mixed world where users can still see the real world and maintain their proprioception. This feature will allow more varieties of users to experience the AR, such as children or older people, especially for those who have nausea or sickness when using in VR.

As a new technology, AR has its particular features that contribute to learning, which are retaining users' view of the world and body learning. Winn (2002b) argued that in an artificial learning environment, cognition is embodied in our physical action. Body movement helps people remember what they perceive and provides a cue for future recall. Chen (2005) indicated that AR is able to facilitate learning in the following ways:

Drawing attention

Drawing students' attention is an important factor in instruction (Keller, 1987; Gagne, Briggs & Wager, 1992). Once students are attracted by the teacher or instructional materials, their curiosity is aroused and they become interested in what happens next. Attention is the catalyst for learning and teaching. Keller (1987) indicated that novelty, surprise, or uncertain events can arouse students' perception and attention. The package of AR is still new for most people. Seeing the virtual objects or 3-D animations in the real world is quite fascinating. AR

always attracts people's attention the first time they see it. In addition, Greimel, Fuhrmann & Kaufmann (2001) pointed out that animated models really arouse students' curiosity and motivation. Therefore, as an educational medium, AR stimulates students' curiosity leading them to the following learning activities.

Interactivity

AR merges the virtual and real world together. This mixed environment not only allows students to interact with virtual objects, but also to work with the real world at the same time. In an AR environment, students are also allowed to interact with their peers, which provides a "shared space" (Billinghurst, Weghorst, & Furness, 1998), and has potential to facilitate collaborative learning. In their Magic Book project, Billinghurst, Kato and Poupyrev (2001) developed a mixed reality in which users could read the physical book and go through the virtual reality any time. They indicated that the Magic Book might be able to enhance collaborative learning in three aspects: (1) as a physical object because users can read the book together, (2)and as an AR object since users can see animated objects from their own viewpoint, (3) and as a virtual place where users can interact with AR and manipulate the animations. With these interactivities, students can acquire first-hand experience, explore the theme, test their hypotheses, and discuss what they see or what they think with their peers. This unique feature surpasses traditional multimedia programs (McLellan, 2003).

Providing a sense of presence

Presence refers to users' subjective experience of being in a computer-generated environment (Witmer & Singer, 1998). Winn (2002a) indicated that the higher the presence the

students have the more engagement and involvement the students feel when they act in the virtual environment. As a result, the students learn more. The reason for this phenomenon is that when students are more engaged in the virtual environment, they are more motivated to interact with the environment, thus resulting in higher levels of learning (Winn, 2002a). In virtual environments, students are allowed to interact with the environment more intuitively and naturally, which encourages them to see and learn more (Winn, 2002a).

Presence also exists in an AR environment but in a different way. Presence in an AR environment should be measured in both the virtual and the real world, not only in the virtual. In the usability testing of the Protein Magic Book (Chen & Winn, 2005), most subjects reported that the most impressive part in interacting with the Protein Magic Book is that they could control the animation. They also enjoyed the process and were engaged in the activities manipulating the virtual objects. In another study, Chen (2005) found that students did not treat virtual objects as screen images. Instead, they interacted with virtual objects as real world objects. For example, when they tried to count the atom number of one amino acid by using AR markers, they counted the atoms "in the air" in front of them rather than on the screen. This evidence implies that virtual objects become a part of the real world, thus providing seamless presence to the users.

Facilitating conceptual learning

With high computer capacity to process large amounts of data, both VR and AR are powerful in representing scientific visualization (McLellan, 2003). Students who have difficulty in transforming 2-D chemical structures to 3-D structures or vice versa can benefit from learning via scientific visualization software (Wu, Krajcik, & Soloway, 2001). In a similar way, AR

facilitates conceptual learning, which is abstract and not visible in our daily life, especially for science learning (Shelton, 2003; Hedley, 2003). Hedley (2003) found that AR was better than a desktop interface in displaying geographic visualization and students in such an environment tended to develop more detailed mental representations.

AR facilitates conceptual learning in many ways. First, AR reifies the abstract concepts into perceptible representations (Winn, 1993; Winn & Jackson, 1999; Winn, 2002a). With the powerful visualization tool, AR is able to create 3-D objects to represent abstract concepts. For example, people cannot see the structure of amino acids with naked eyes, but it can be shown through the AR system. AR not only generates static 3-D objects, but also dynamic ones which students can observe and explore. In addition, students can interact, touch, and even get haptic feedback from the AR system and manipulate the virtual objects in the real world. These interactivities stimulate students to build their mental models and provide them with strong impressions on the abstract concepts. Furthermore, AR not only creates visual images, but also conveys the spatial cues directly to users (Shelton & Hedley, 2004). By using AR, users can obtain a sense of spatial feeling and visualization as well. In the study of usability testing of the Protein Magic Book (Chen & Winn, 2005), users liked to rotate the AR markers to see different orientations of the protein structures. AR shows potential to be applied to the knowledge domain of spatial concepts. In sum, AR expands students' experiences and provides them with another way to learn.

Retain users' view of the world and proprioception

The primary difference between AR and VR is that AR allows users to retain their own view of the real world and keep their propriocetion to the environment (Shelton & Hedley, 2004). This feature allows students to keep "a sense of self" (Shelton & Hedley, 2004) and reduces students' uncertainty about the learning environment. Therefore, it makes students more comfortable to explore the content. Retaining proprioception also allows them to experience the "space" in a more intuitive way. They can identify the spatial relationships and directions among objects, which helps them get a deeper understanding of the phenomenon. Through this understanding, students are more likely to be active learners in an AR environment.

Sensorimotor feedback and body learning

Another feature of AR which enhances learning is that of allowing users to interact with the system. This is accomplished by the students using their body, especially the hands, and provides "sensorimotor feedback" (Shelton, Hedley, 2004). Winn (2002b) argued that physical action plays a great role in cognition embeddedness. The direct manipulation of AR can supplement the deficiency of mouse-based computer-generated animation because mouse manipulation is an indirect physical manipulation (Shelton & Hedley, 2004). In the Protein Magic Book, students did not have to use the mouse or the keyboard to control the size of images. Instead, they could zoom in or zoom out by their hands only. Students put the marker under the webcam and then moved the marker up approaching the webcam to blow up the image and vice versa. They could also rotate the marker to see different orientations of the virtual objects. By body learning, the AR image becomes a "real thing", not only an image on the

computer screen.

Providing a tool which requires users think carefully

AR is a tool which requires users to interact and think critically. (Schank & Kozma, 2002). Since users have to concentrate on the AR system and focus on the changing images, they may think about what happens next, thus making them think more deliberately. Winn and Jackson (1999) also indicated that manipulating objects in virtual environments helps students to think, and "distribute cognitive activities". The role of virtual environments is not only to provide a setting but also acts as "tools for thought".

Regarding the content of the Protein Magic Book, learning protein structure involves students' visual-spatial thinking in order to identify the relationships among molecule, atoms and the way they form proteins. Therefore, it would be beneficial if visualizations could be provided to help students comprehend abstract concepts that could not be seen in the real world. AR is a medium that is able to convey visual displays (both static images and dynamic animations) and spatial cues at the same time. AR also offers a more intuitive interface allowing users to use their hands to manipulate the visualizations rather than clicking and dragging the mouse. These characteristics of AR show great potential for helping students learn protein structure (Almgren, Carlsson, Erkkonen, Fredriksson, Moller, Rydgard, Osterberg, Botschi, Voegtli, & Fjeld, 2005). Moreover, with the scaffolding of the AR visualization, it is assumed that AR will reduce the extraneous cognitive load by interacting with AR displays and enhance their germane load by helping students create mental images.

Finally, research shows that students' self-efficacy, a belief about their capability to

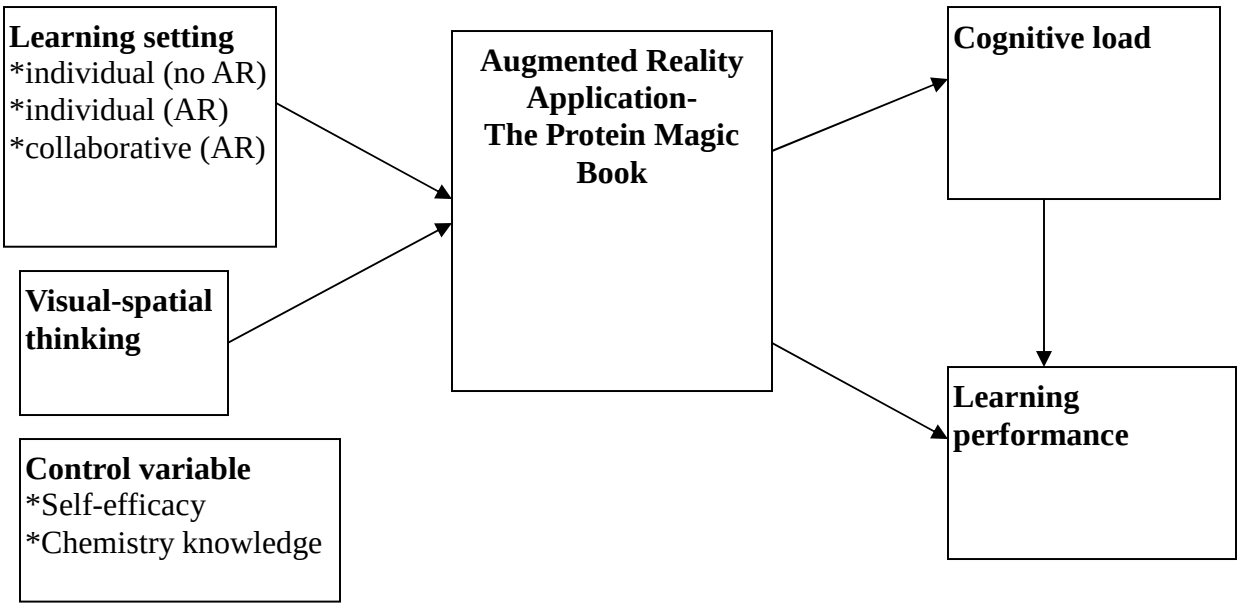
accomplish something, will influence learning performance (Bandura, 1994; Chemers, Hu, & Garcia, 2001). Many studies showed that self-efficacy did predict learning performance in science and mathematics (Lent, Brown, & Larkin, 1986; Meece, Wigfield, & Eccles, 1990; Chemers, Hu, & Garcia, 2001), but little research showed the relationship between self-efficacy and chemistry learning performance (Dalgety, Coll, & Jones, 2003). This study assumes that self-efficacy may influence students' chemistry learning performance, and it will be statistically controlled. In addition, chemistry knowledge will be also statistically controlled in this study.

AR is an advanced and developing technology and it shows great potential to facilitate learning. Therefore, it is necessary to examine the effectiveness of AR when it is applied in educational domains. Meanwhile, it may provide a clearer picture to understand how AR works and what might affect AR-based learning. In sum, this study will investigate the advantages of AR in chemistry learning while taking cognitive load, visual-spatial thinking, and learning setting (pairs or single students) into account while controlling student self-efficacy and chemistry knowledge.

2.5. Conceptual framework and research hypotheses

The literature review illustrates that due to the characteristics of chemistry education, visual-spatial ability may affect student learning. With its unique visual display, we believe AR has great potential to facilitate chemistry learning. This study examines the effect of AR on student chemistry learning performance, and explores the factors which may affect its effectiveness. Three learning settings are designed to investigate whether AR facilitates learning

compared to learning without the scaffolding of AR, and also whether students perform differently when they study with AR alone or study with AR within dyads. In addition, since visual-spatial ability is an important factor influencing student chemistry learning, it is hypothesized that it will affect student chemistry learning, especially with the scaffolding of AR. This study also investigates how these different settings affect cognitive load as well as the factors which may affect cognitive load. In sum, the conceptual framework of this study is shown as Figure 2-1, followed by the hypotheses corresponding to each research questions.



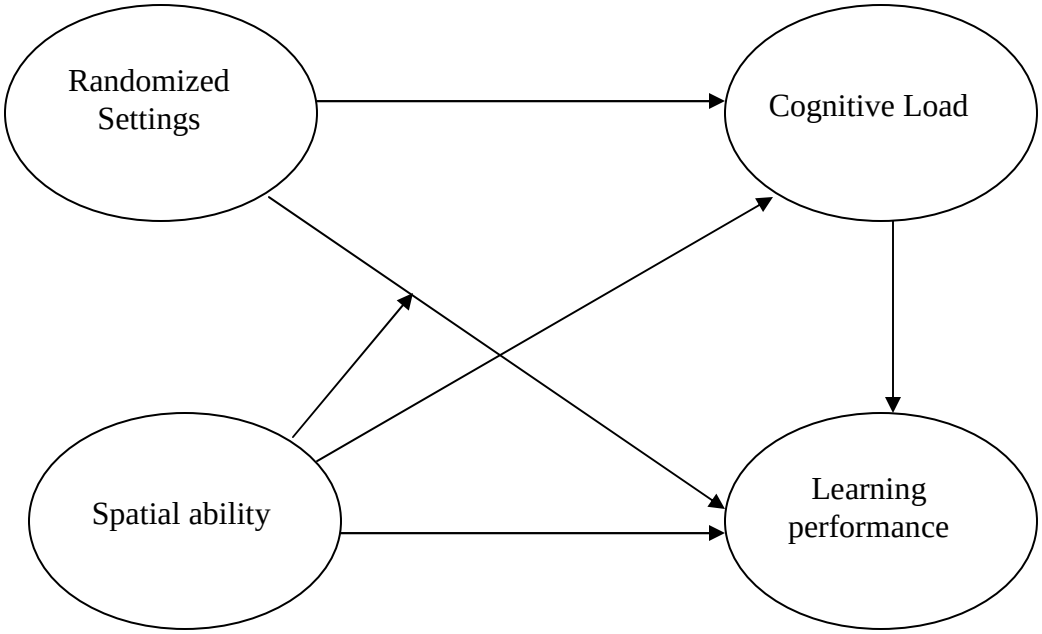


Figure2-1 Conceptual framework of this study

Research hypotheses based on the theoretical framework and research questions are:

Research question 1: Will students benefit from AR in chemistry learning?

H1: Students in the AR alone setting will have greater learning performance than those who study by themselves without AR scaffolding.

Research question 2: Will students learn chemistry more effectively in an AR-enhanced peer learning environment?

H2: With using AR, students in the collaborative setting will learn better than those who study alone.

Research question 3: What factors may affect student chemistry learning in an AR-enhanced environment?

H3: Students perform differently with their level of visual-spatial ability

H4: Students with low visual-spatial ability will benefit more from AR than those with high visual-spatial ability.

H5: Students who experience less cognitive load will have greater learning performance.

Research question 4: How much cognitive load will students report in different learning settings?

H6: Students will not report more cognitive load when they studied alone with AR, compared to those who study without AR scaffolding.

H7: Students in the collaborative setting will report more cognitive load than those who study alone with AR.

H8: Students with higher spatial ability will report less cognitive load.

CHAPTER 3: METHDOLOGY

This study investigated how AR may facilitate chemistry learning in different settings (single v.s. dyad of students) and identified factors that might affect students' learning. This section introduces the instructional material, the Protein Magic Book, describing its components and functionality. In addition, the research setting, characteristics of participants, instruments for data collection, and the research procedures are described.

3.1. Learning material- Protein Magic Book

The Protein Magic Book is an interactive book which introduces basic concepts about protein structures using AR technology. It was developed at the Human Interface Technology Laboratory (HIT Lab) at the University of Washington and the SCRIPPS Research Institute at La Jolla. The Protein Magic Book was built by combining tracking technology, called the ARToolKit, and the images of protein structures displayed by Python Molecule Viewer (PMV) (Sanner, 1999) in order to create an interactive AR environment.

3.1.1. Setting

Unlike other augmented reality applications, which require users to wear goggles or other head- mounted display devices (Feiner, 2002), the Protein Magic Book is used without any devices on the users' body. The Protein Magic Book only requires a laptop and a webcam to

render all virtual images (Figure 2). As we can see in Figure 2, a webcam is fixed on a supporting frame above the laptop. The Protein Magic Book is laid on the laptop keyboard under the camera. The marker (see Figure 3) is a specific picture (a pattern), which the webcam sees and which the software recognizes and uses to select a molecule in a database that is then shown by the PMV software as a 3-D virtual object. All 3-D virtual objects in the Protein Magic Book were created with PMV software and the ARToolKit library. The markers in this book are removable so that users can manipulate the 3-D virtual objects by hand.

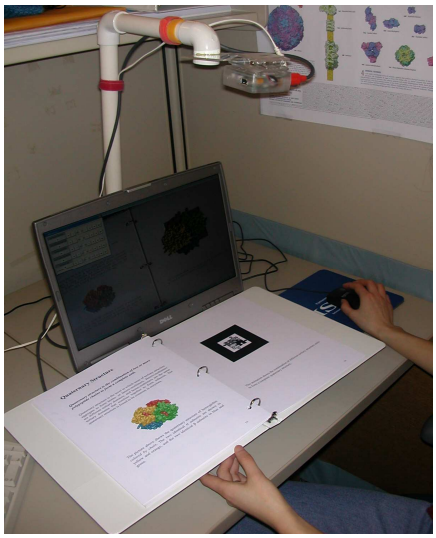


Figure 3-1 Physical setting of Protein Magic Book

3.1.2. Description of Protein Magic Book

The Protein Magic Book is composed of six units. For each unit, there is one page of text description and pictures (text page) and another page dedicated to printed markers, and some instructions (animation page) (Figure 3). Some instructions and questions are listed on the

animation page to help students interact with AR objects and understand the content.

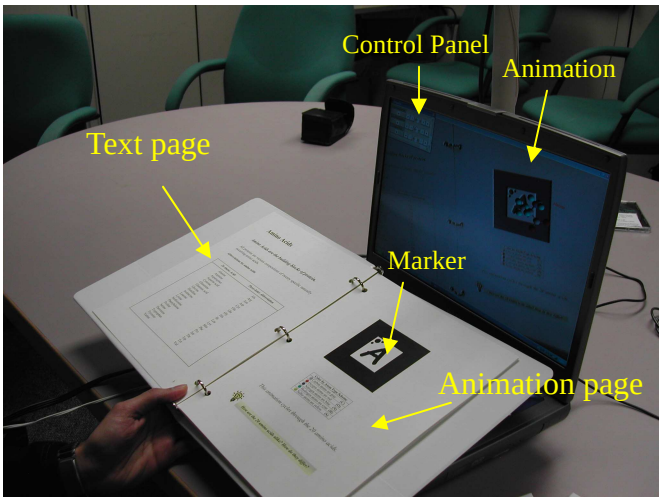


Figure 3-2 Layout of the Protein Magic Book

The content and learning objectives of the six units are as follows:

Unit 1- Introduction to amino acids

- Learning objectives: After reading Unit 1, students will be able to
  - describe what are protein made of and how their components are structured.
  - state the functions of protein in our body.
  - describe the number of amino acids in the human body and their categories.
- The text page describes the function of amino acids in our daily life, the relationship between amino acids and proteins, as well as the names of twenty amino acids. The animation page shows the animated ball-and-stick models of twenty amino acids in alphabetical order.

Unit 2- Peptide bonds

- Learning objectives: After reading Unit 2, students will be able to
  - state the definition of peptide bond.
  - explain the process how the peptide bond is formed.
  - describe the change of the amino acids after they combine with a peptide bond.
- The text page explains how to form a peptide bond with diagrams. The animation page shows two amino acids, and the molecule which represents the composition after those two amino acids combine together.

Unit 3- Primary structure (Figure 4)

- Learning objectives: After reading Unit 3, students will be able to
  - state the definition of primary structure.
  - explain the relationship between peptide bond and the formation of primary structure
- The text page gives the definition of primary structure with a pictorial illustration. On the animation page, there are seven movable markers and a chain diagram. Students can manipulate those markers to make their own primary structure.

Unit 4- Secondary structure

- Learning objectives: After reading the Unit 4, students will be able to
  - state the definition of secondary structure
  - recognize the difference between Alpha helix and Beta strands.

- identify two arrangements of Beta strands.

- The text page describes the definitions of both subunits with pictorial illustration. The animation page shows the process of how to form α helices and β sheets (Figure 5).

Unit 5- Tertiary structure

- Learning objectives: After reading Unit 5, students will be able to
  - state the definition of tertiary structure.
  - describe the difference between secondary structure and tertiary structure.
  - recognize different molecular representations when forming tertiary structure.
- The text page describes the characteristics of tertiary structure. The animation page demonstrates how an α sheet and a β helix form a quaternary structure. Their ribbon model, CPK* (Corey-Pauling-Koltin) model and MSM (Molecular Surface Model) representations are also shown on this page.

Unit 6- Quaternary structure

- Learning objectives: After reading Unit 6, students will be able to
  - state the definition of quaternary structure.
  - describe the process how quaternary structure is formed.
  - explain the representation of quaternary structure.
  - identify the difference between tertiary structure and quaternary structure.
- The text page introduces its components and shows a pictorial illustration of the quaternary structure of hemoglobin. The animation shows the process of forming

* The CPK model depicts each atom as a sphere with a radius equal to its van der Waals radius.

quaternary structure.

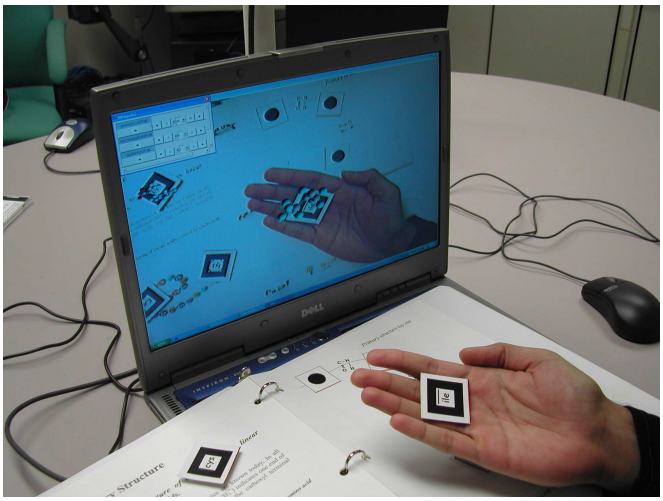


Figure 3-3 Primary structure

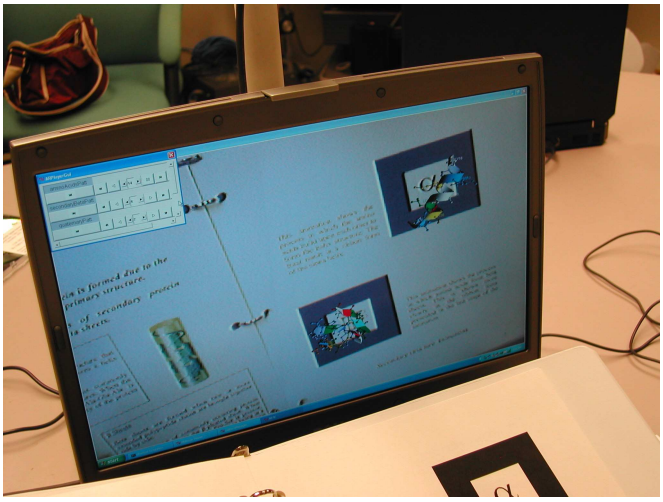


Figure 3-4 Secondary structure

3.2. Setting of the experiment

This study was conducted in the Human Interface Technology Laboratory (HIT Lab) at the University of Washington. The setting included a laptop, webcam, and the Protein Magic Book. A video camera was set behind the participants to record their interaction with the Protein Magic Book and their peers in the collaborative setting. The camera recorded the image on the laptop screen as well.

3.3. Participants

Since this study is about the domain of biochemistry, it is assumed that participants possess basic chemistry knowledge but do not know about the concept of protein structure yet. Their basic knowledge of chemistry will help them get into the research situation easily. Undergraduate students who enrolled in “Organic Chemistry” class (CHEM 237 or CHEM 238) in winter quarter 2006 met those conditions.

One goal of this study was to examine AR use in different learning settings: individual and collaborative learning scenarios. Participants recruited from the “organic chemistry” class were randomly assigned into three groups: AR-single, AR-peer, and control groups. Twenty six subjects were assigned to AR-single condition. Forty four other subjects studied the Protein Magic Book in pairs, resulting in twenty two pairs in the AR-peer condition. The control condition contained twenty six subjects. In sum, Ninety six students took part in this study.

3.4. Instruments

3.4.1. Predictor measurements

Students completed several questionnaires or tests before and after the experiment.

1. Personal background questionnaire: This questionnaire included student demographic information, experiences of learning chemistry, and computer experiences (see Appendix I).
2. Chemistry self-efficacy scale: To assess chemistry self-efficacy of students, the part of self-efficacy measurement of the Chemistry Attitude and Experiences Questionnaire (CAEQ) was adopted (Dalgety, Coll, & Jones, 2003). This self-efficacy questionnaire was developed recently and it showed high reliability (Cronbach's α=0.96). There are 17 items in this questionnaire. Students responded on Likert scales ranging from 1 (not confident) to 7 (totally confident). Students were asked to answer how confident they felt when they undertook different chemistry-related tasks. The scale score had high internal consistency in this study (Cronbach's α=0.89).
3. General chemistry knowledge test: In order to assess students' prior knowledge about general chemistry, participants answered questions on a general chemistry knowledge test. Fifty five questions are derived from the About.com website (http://about.com/) covering acid base (10 items), everyday chemistry (10 items), atoms (10 items), periodical table (5 items), phases (10 items) and chemical change (10 items). Two experienced chemistry teachers examined the questions and selected twenty questions that required students to demonstrate prior knowledge of general chemistry. The Cronbach's α of this test was 0.6.

4. Spatial ability: After the instruction finished, students completed the Purdue Visualization of Rotations Test (Bodner and Guay, 1997) to measure their spatial ability. The Purdue visualization of rotations test is a tool commonly used to measure spatial ability in chemistry education (Wu & Shah, 2004). The Purdue Visualization of Rotations Test consists 20 items with which students are required to demonstrate their ability to visualize the rotation of three-dimensional objects. Students had 10 minutes to finish the test.

3.4.2. Outcome measures

1. Cognitive load measurement: Four types of methods to measure cognitive load (Brunken, Plass, & Leutner, 2003) include (1) indirect, subjective measures, (2) direct, subject measures, (3) indirect, objective measures, and (4) direct, object measures. This study made use of “direct, subjective measures” to measure cognitive load. A direct, subjective measure is a self report of how difficult people feel the materials are. In this study, students were asked to evaluate the cognitive load of the texts and the AR visualization separately. The response scale was a 7-point Likert scale (1= not hard at all, 7 =very hard).
2. Post-test: Once students finished the learning activity, they answered questions related to the content in 10 minutes. The questions were short-answer and consisted of pictures for the students to explain. Two content experts rated the responses and the inter-rater reliability of the ratings was 0.87.

3.5. Procedures

This study went through five steps. First, before students started the learning activity, they were asked about their personal background by questionnaire and prior knowledge by a test of general chemistry knowledge. They also completed a self-efficacy scale before starting the learning activity. Second, they were shown an example of how to use the AR interface by manipulating three amino acids. In this process, they also practiced “think-aloud”. I explained how to do the think-aloud and they practiced it when they worked with those three amino acids.

Following the exercise, students in the AR conditions studied the Protein Magic Book individually (AR-single) or in pairs (AR-peer) for twenty minutes. During the learning activity, they were asked to think aloud to vocalize what they were doing and what they were thinking. If the students did not speak aloud, I asked them some questions. For example, I might ask “Why do you rotate the marker that way?” or “why do you want to show this to your partner?” In addition to speaking aloud, they were asked to answer the questions on the animation page. As for students in the peer group, they were told to read the book, manipulate the AR markers, discuss the content, and answer the questions listed on the animation page with their peer together before they started the learning activity.

After the learning activity, all of the students took the post-test and cognitive load scales to assess their learning performance. The cognitive load scale made it easier to know how hard they thought about the content of each unit and the AR visual displays. It takes ten minutes to complete the Purdue Visualization of Rotation Test; therefore, students took this test at the end of

the experiment. As for the control group, they went through the same process, except that they individually read the material without AR.

3.6. Data Screening and analysis method

Prior to any analysis, descriptive statistics were utilized for each variable. Because this study involved group factors, it was necessary to evaluate the data in order to determine the appropriate methods to analyze (Bauer, Sterba, and Hallfors, 2008).

3.6.1. Analysis of pre-treatment measures

In order to examine the group differences associated with the treatment condition, hierarchical linear modeling (HLM) analysis was conducted. First, the intraclass correlation was estimated for each pre-treatment measure, including spatial ability, chemistry knowledge, and self-efficacy scores. The examination of the intraclass correlation indicates the extent to which the pre-treatment measures are influenced by the grouping level (Tabachnick & Fidell, 2007).

The group-level nesting effects on the chemistry test, rotation test, and self-efficacy scale were examined. The intraclass correlation coefficient ρ for the above variables were 0.03, 0.00, and 0.06, respectively (shown in Table 3-1). The results showed for the pre-treatment measures of chemistry knowledge, spatial ability, and self-efficacy, the variation between groups was not significantly different from zero so that these variables could be analyzed at the individual level.

Table 3-1 Final estimation of variance component of the variables for chemistry knowledge, spatial ability, and self-efficacy

	Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
Chemistry knowledge	INTRCPT1, U0	0.48	0.23	23	22.38	>.50
	Level 1, R	2.63	6.92			
	Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
Spatial ability	INTRCPT1, U0	0.08	0.01	23	23.93	0.41
	Level 1, R	3.39	11.50			
	Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
Self efficacy	INTRCPT1, U0	0.17	0.03	23	24.54	0.37
	Level 1, R	0.71	0.50			

The measures of the covariates of chemistry knowledge and self-efficacy were transformed to z scores within each treatment condition.

3.6.2. Analysis of outcome measures

The post-test score and the measure of cognitive load were two outcome measures after

students participated in the treatments. Table 3-2 shows the means and standard deviations for each outcome measure. The result of ANOVA indicates that students performed differently in their post-test ($F(2,114)=4.15$, $p<.05$, MSE=77.70), but not in their cognitive load. To gain deeper understanding about student cognitive load, the cognitive load was measured from three parts: text load, picture load, and AR load. Although no group differences were found for these three loads, students in the AR-peer treatment seemed to have higher ratings in these three loads.

Table 3-2 Mean and standard deviation of outcome measures for three treatments

	AR-single N=26		AR-peer N=44		Control N=26		F value
	Mean	SD	Mean	SD	Mean	SD	
Post-test	30.75	2.3	26.89	5.37	28.46	3.79	6.56*
Cognitive load	2.06	0.91	2.27	0.89	2.02	0.73	0.86
Text load	2.26	1.08	2.39	1.11	2.00	0.70	1.25
Picture load	1.94	0.91	2.23	0.97	2.03	0.81	0.92
AR load	1.99	0.93	2.18	1.08	-	-	0.53

*$p<.05$

When dealing with dyads' learning performance, one approach is to take dyad mean as the outcome measure for the dyad. The analysis that calculated the dyad mean on the outcome in the AR-peer condition and the individual scores in the AR-single and control condition ANOVA shows that an overall significant differences exist among the three treatments ($F(2, 71)=4.70$, $p<.05$, MSE=81.18). The follow-up comparisons indicate that students learning protein structure with AR alone (Mean=30.75, SD=2.30) performed significantly better than those in the AR-peer learning condition (Mean=27.14, SD=5.91) before the covariates were entered. Even after the

two covariates (self-efficacy and chemistry knowledge) were entered into the analysis, the treatment conditions still predicted the student learning outcomes ($F(2, 69)=4.82$, $p<.05$, MSE=74.95).

Table 3-3 shows that the intraclass correlation coefficient of the post-test (learning performance) ρ was 0.53, which implied a grouping effect existed in this study. That is, the learning performance in the AR-peer condition differed among groups in the condition. The hierarchical linear modeling method was used to assess the treatment effects, taking the nesting of students in the dyad into account.

Table 3-3 Final estimation of variance components of the variables for post-test score and cognitive load

	Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
Post-test	INTRCPT1, U0	3.70	13.67	23	104.27	.01*
	Level 1, R	3.46	11.98			
	Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
Cognitive load	INTRCPT1, U0	0.03	0.01	23	27.91	0.22
	Level 1, R	0.85	0.73			

3.6.3. Hierarchical Linear Modeling (HLM) Models

The main purpose of this study was to explore whether students performed differently in

three treatments. The Hierarchical Linear Modeling (HLM) models were used to examine the research hypotheses taking into account the nested effect within dyads. In this model, Posttest was treated as the dependent variable. Chemistry knowledge and self-efficacy at Level 1 served as control and fixed effect variables. In Level 2, we used contrast coding and treated Control group as the reference. Contrast 1 modeled the effect of AR-single plus AR-peer compared to control, while Contrast 2 was the contrast between AR-single and AR-peer. To detect the effect of each covariate, the order of entry was: self-efficacy, chemistry knowledge, spatial ability, and cognitive load respectively.

In this model, we also considered the allowance of heterogeneous variance within the treatment dyads. Given that, the heterogeneous variance modeling was also taken into account with the HLM analysis.

The general equation used for the two-level conditional model is represented as:

MODEL 1

Level 1

$\text{Posttest} = \beta_0 + \beta_1 * (\text{Efficacy\_z}) + \beta_2 * (\text{Chem\_z}) + r$

where $\text{Var}(rij) = \sigma^2_{ij}$ and $\log(\sigma^2_{ij}) = \alpha_0 + \alpha_1 * (\text{Contrast2}_{ij})$

Level 2

$\beta_0 = \gamma_{00} + \gamma_{01} * (\text{Contrast 1}) + \gamma_{02} * (\text{Contrast 2}) + \mu_0$

$\beta_1 = \gamma_{10}$

$\beta_{2=}\gamma_{20}$

Bauer, Sterba and Hallfors (2008) proposed another HLM model to evaluate group-based treatment while control participants are not grouped. This analysis explicitly represents the nested effect of grouped participants and also takes the individual effect into consideration. The model of multiple treatments is shown as follows with dummy coding:

MODEL 2

Level 1

$\text{Posttest} = \beta_0 + \beta_1 * (\text{Treatment1}) + \beta_2 * (\text{Treatment2}) + r$

Level 2

$\beta_0 = \gamma_{00}$

$\beta_1 = \gamma_{10} + \mu_1$

$\beta_2 = \gamma_{20}$

These two models were tested with all nested variables in this study and the results show no differences between these two models. Therefore, in Chapter 4, the results were interpreted from Model 1 while the results from Model 2 were only presented without explanation next to Model 1.

CHAPTER 4: RESULTS

This chapter describes the results of this study. First, I describe the personal characteristics and prior computer experiences of the subjects. Next, due to the effect of intraclass correlation, hierarchical linear modeling (HLM) is employed to investigate the research questions. Followed by HLM analysis, the effect of AR on student learning is presented with ANCOVA analysis. Last, the analysis of the effect in dyad learning group treatment is presented.

4.1. Subjects

4.1.1. Personal characteristics

One hundred and seventeen students took part in the study. The average age was 19.63 year-olds (SD=2.55). Thirty eight were male and fifty eight were female. The sample was randomly assigned to three treatments and gender was not associated with the treatment groups (shown in Table 4-1, χ^2=0.97, p>.05).

Table 4-1 Gender in the three treatment conditions

		Treatment			
		AR-single	AR-peer	Control	**Total**
Gender	Male	10	18	10	38
	Female	16	26	16	58
Total		26	44	26	96

χ^2=0.97, p>0.05

The means and standard deviations of pre-treatment measures are shown in Table 4-2 divided by three groups. Group differences were not found for scores on chemistry knowledge and spatial ability but were found on self-efficacy ($F(2, 93)=3.20$, $p<.05$).

Table 4-2 Students measures by chemistry test, self-efficacy scale, and rotation test

	AR-single N=26		AR-peer N=44		Control N=26		F value
	Mean	SD	Mean	SD	Mean	SD	
Chemistry knowledge	15.35	2.28	14.75	2.67	13.92	3.11	1.99
Self-efficacy	5.18	0.65	5.08	0.68	4.71	0.83	3.20*
Spatial ability	14.77	2.97	14.30	3.23	14.15	4.10	0.24

*$p<.05$

4.1.2. Computer experiences

Seventy five students (78.1%) reported that computers were used as part of their courses. The Chi-square test showed that there are no differences across three groups ($\chi^2=4.24$, $p>.05$). Regarding the use of media in the chemistry classroom, eighty nine students (92.7%) had the experience that the chemistry teacher used media in the classroom in addition to textbooks. These media included models, graphs, computer simulations, videos, and other media (shown in Table 4-3). The Chi-square test shows no group differences among the three treatment conditions (($\chi^2=3.13$, $p>.05$) with the use of media in the classroom.

Table 4-3 The use of media in the classroom

	N	Percentage
No	7	6.3%
Yes	89	92.7%
Graphs	69	71.9%
Model	78	81.3%
Computer simulation	58	60.4%
Video	47	49.0%
Others	12	12.5%
Missing data	1	0.9%

Because the experience of video games might be a factor that influenced student ability when interacting with AR, student video game experiences were investigated. Table 4-4 shows that sixty eight students (70.8%) had the experiences of playing video games. No group differences were found in the video game experiences ((χ^2=1.05, p>.05). Further, students' self rated skill in playing video games is shown in Table 4-5.

Table 4-4 Student experiences on video games

	N	Percentage
No	28	29.2%
Yes	68	70.8%
Frequency of playing video game		
A lot	7	7.3%
Often	14	14.6%
Sometimes	24	25.0%
Seldom	23	24.0%

Table 4-5 Skill in playing video games (frequency)

Question	1 (not at all)	2	3	4	5	6	7 (very skillful)	Mean	SD
Skill in playing video games	15 (15.6%)	15 (15.6%)	22 (22.9%)	10 (10.4%)	15 (15.6%)	15 (15.6%)	4 (4.2%)	3.58	1.81

The survey also showed 33.3% of the students spent 2-3 hours on the computer every day (see Table 4-6). Only 13.5% of the students spent more than 5 hours on the computer. The major four reasons for the students to use the computer were: checking e-mail, online shopping, online surfing, and chatting with friends (see Table 4-7).

Table 4-6 Time spending on the computer per day

	N	**Percentage**
Less than one hour	2	2.1%
1~2 hours	18	18.8%
2-3 hours	32	33.3%
3~4 hours	21	21.9%
4~5 hours	13	13.5%
More than 5 hours	10	10.4%

Table 4-7 The purpose of using computers

	N	**Percentage**
Checking e-mail	94	97.9%
Word processing	89	92.7%
Online surfing	81	84.4%
Chatting with friends	60	62.5%
Online shopping	31	32.3%
Playing video games	28	29.2%
Playing online games	28	29.2%
Others	18	18.8%
Computer program designing	9	9.4%

4.1.3. Collaboration

Students in the AR-peer Treatment were asked about their collaboration with the other member on a seven-point scale. Table 4-8 shows the means and standard deviations of the values on their efforts to collaborate with peers. Students considered that peer collaboration was helpful and also thought the collaboration made it easier to understand the content.

Table 4-8 Collaboration in the AR-Peer Treatment

Question	N	Mean	SD
How much did you collaborate? possible rating: 0: not at all, 7: a lot	44	4.70	1.21
Was the peer collaboration helpful? possible rating: 0: not at all, 7: very helpful	44	5.34	1.36
Did the collaboration make it easier to understand the content? possible rating: 0: not at all, 7: much easier	44	5.30	1.32

In order to assess student perceptions about collaborative learning across treatment conditions, students were asked two hypothetical questions. One was "Did you work harder to understand the material by working with your partner than if you had studied this material on your own for students in the AR-single treatment" (shown in Table 4-9). Compared to the control treatment, students in the AR-single treatment reported that they would work harder in a collaborative learning setting. The result of ANOVA indicates that group differences exist among these three treatment conditions ($F(2, 93)=43.23$, $p<.01$, $MSE=111.90$). The post hoc comparison with Tukey HSD method (AR-peer>AR-single, mean difference=2.79; AR-peer>Control, mean difference=3.29) shows students in the AR-peer condition would work harder with a peer than in the other treatments.

Table 4-9 Comparison among the three groups regarding how hard to study alone or work with peers (1=not at all, 7=very hard)

Question	N	Mean	SD
AR-single Treatment			
Did you work harder to understand the material by working with your partner than if you had studied this material on your own?	26	2.73	1.73
AR-peer Treatment*			
Did you work harder to understand the material on your own than if you had studied this material by working with a partner?	44	5.52*	1.68
Control Treatment			
Did you work harder to understand the material by working with your partner than if you had studied this material on your own?	26	2.23	1.33

*the score was reversed to represent students' efforts on working with a partner

Another question asked students whether they would put more effort if they had studied the material by working with a partner or by themselves. Student responses (Table 4-10) show that students studied with AR alone tended to put more efforts to work with a partner compared to the control group. The result of ANOVA shows that students rated their efforts differently from groups to groups ($F(2, 71)=5.01$, $p<.01$, $MSE=16.64$). The Tukey HSD post hoc comparison demonstrates that students in the AR-single treatment and AR-peer treatment would exert more efforts to work with a partner than control treatment (AR-single>Control, mean difference=1.43; AR-peer>control, mean difference=1.52).

Table 4-10 Comparison* among the three groups regarding how much efforts they spend to study alone or work with peers (1=not at all, 7=very hard)

Question	N	Mean	SD
AR-single Treatment			
Did you put more efforts to understand the material by working with your partner than if you had studied this material on your own?	19	4.00	1.76
AR-peer Treatment			
Did you put more efforts to understand the material on your own than if you had studied this material by working with a partner?	34	4.09**	1.91
Control Treatment			
Did you put more efforts understand the material by working with your partner than if you had studied this material on your own?	21	2.57	1.71

*Missing data: 22 cases

**the score was reversed to represent students' efforts on working with a partner

4.2. Performance differences among treatments

Treatments only

Table 4-11 shows that student learning performance differed between the treatment of AR-single and AR-peer (t=-4.14, $p<.05$). The value of the coefficient indicates that students learning with AR alone got higher scores than those in the dyads. The final estimate of variance components was not significant ($\chi^2=30.04$, $p>.05$), indicating that the remaining variance for the Level 1 intercept was random since the model with heterogeneous variances fit significantly better ($\chi^2(1)=11.36$, $p<.01$), only the results for this model are shown in the results section.

Table 4-11 Treatment only model with heterogeneous variance modeling (Model 1)
Dependent variable: post-test

Fixed Effect	**Coefficient**	**Standard error**	**T ratio**	**df**	**P value**
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	28.70	0.39	74.03	21	0.01
Contrast 1, γ_{01}	0.12	0.28	0.43	21	0.67
Contrast 2, γ_{02}	-1.93	0.47	-4.14	21	0.01

Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	0.04	0.01	21	30.04	0.09

Model	Number of parameters	Deviance
1.Homogeneous sigma_squared	5	541.54
2.Heterogeneous sigma_squared	6	530.17

Model Comparison	Chi-Square	df	P-value
Model 1vs Model 2	11.36	1	0.01

Table 4-12 Treatment only (Model 2)
Dependent variable: post-test

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	28.46	0.68	42.03	93	0.01
Peer v.s. Control, γ_{01}	-1.57	1.18	-1.33	23	0.20
AR-single v.s. Control, γ_{02}	2.29	0.96	2.39	93	0.02

Random effect	Standard deviation	Variance component	df	Chi-square	P value
INTRCPT1, μ_0	3.85	14.84	21	73.29	0.01
Level 1, R	3.45	11.92			

Treatments + Self-efficacy

Next, one covariate self-efficacy was entered. The result (shown in Table 4-13) indicates that the treatment significantly predicted student learning performance (t=-4.20, $p<.05$ for Contrast 2) but self-efficacy did not (t=0.96, $p>.05$).

Table 4-13 Treatment + self-efficacy model with heterogeneous variance modeling (Model 1)
Dependent variable: post-test

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	28.70	0.39	74.44	21	0.01
Contrast 1, γ_{01}	0.11	0.28	0.41	21	0.69
Contrast 2, γ_{02}	-1.95	0.46	-4.20	21	0.01
For Efficacy slope, β_1					
INTRCPT2, γ_{10}	0.34	0.35	0.96	92	0.34

Random effect	Standard deviation	Variance component	df	Chi-square	P value
INTRCPT1, μ_0	0.04	0.01	21	29.54	0.10

Model	Number of parameters	Deviance
1.Homogeneous sigma_squared	6	541.03
2.Heterogeneous sigma_squared	8	529.26

Model Comparison	Chi-Square	df	P-value
Model 1vs Model 2	11.76	1	0.01

Table 4-14 Treatment + self-efficacy model (Model 2)
Dependent variable: post-test

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	28.47	0.68	41.72	92	0.01
Peer v.s. Control, γ_{01}	-1.60	1.18	-1.36	23	0.19
AR-single v.s. Control, γ_{02}	2.29	0.96	2.37	92	0.02
For Efficacy slope, β_1					
INTRCPT2, γ_{10}	0.25	0.40	0.64	92	0.53

Random effect	Standard deviation	Variance component	df	Chi-square	P value
INTRCPT1, μ_0	3.78	14.29	21	73.34	0.01
Level 1, R	3.48	12.10			

Treatments + Self-efficacy + Chemistry knowledge

When the other covariate (chemistry knowledge) was added into the model, it was a significant predictor (t=2.70, $p<.05$) (shown in Table 4-15) in addition to the treatments (t=-4.31, $p<.05$). But self-efficacy was not a significant predictor (t=0.58, $p>.05$).

Table 4-15 Treatment + self-efficacy + chemistry test model with heterogeneous variance modeling (Model 1)
Dependent variable: post-test

Fixed Effect	**Coefficient**	**Standard error**	**T ratio**	**df**	**P value**
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	28.67	0.37	77.34	21	0.01
Contrast 1, γ_{01}	0.11	0.27	0.39	21	0.70
Contrast 2, γ_{02}	-1.91	0.44	-4.31	21	0.01
For Efficacy slope, β_1					
INTRCPT2, γ_{10}	0.95	0.35	0.58	91	0.56
For Chemistry slope, β_2					
INTRCPT2, γ_{20}	0.21	0.35	2.70	91	0.01

Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	0.04	0.01	21	29.08	0.11

Model	Number of parameters	Deviance
1.Homogeneous sigma_squared	7	533.24
2.Heterogeneous sigma_squared	8	522.39

Model Comparison	Chi-Square	df	P-value
Model 1vs Model 2	10.85	1	0.01

Table 4-16 Treatment + self-efficacy + chemistry test model (Model 2)
Dependent variable: post-test

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	28.46	0.67	42.60	91	0.01
Peer v.s. Control, γ_{01}	-1.58	1.12	-1.42	23	0.17
AR-single v.s. Control, γ_{02}	2.22	0.94	2.35	91	0.02
For Efficacy slope, β_1					
INTRCPT2, γ_{10}	0.09	0.39	0.24	91	0.81
For Chemistry slope, β_2					
INTRCPT2, γ_{20}	1.05	0.38	2.73	91	0.01

Random effect	Standard deviation	Variance component	df	Chi-square	P value
INTRCPT1, μ_0	3.43	11.76	21	63.12	0.01
Level 1, R	3.40	11.59			

Treatments +Self-efficacy + Chemistry knowledge + Spatial ability

The spatial ability effect was found in Table 4-17 to predict student learning outcomes (t=2.55, $p<.05$). Students with higher spatial ability had better learning performance. Also the effect of experimental treatments was predictive (t=-4.25 for Contrast 2). The test of the residual variance of the Rotation slopes yields $\chi^2=29.64$ with df=21, $p>.05$, suggesting that after controlling for spatial ability, there is no systematic variation on post test.

Table 4-17 Treatment + self-efficacy + chemistry test + spatial ability model with heterogeneous variance modeling (Model 1)
Dependent variable: post-test

Fixed Effect	**Coefficient**	**Standard error**	**T ratio**	**df**	**P value**
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	24.76	1.58	15.70	21	0.01
Contrast 1, γ_{01}	0.07	0.26	0.28	21	0.78
Contrast 2, γ_{02}	-1.86	0.43	-4.35	21	0.01
For Efficacy slope, β_1					
INTRCPT2, γ_{10}	0.31	0.35	0.91	90	0.37
For Chemistry slope, β_2					
INTRCPT2, γ_{20}	0.65	0.36	1.79	90	0.08
For Spatial slope, β_3					
INTRCPT2, γ_{30}	0.27	0.11	2.55	90	0.01

Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	0.04	0.01	21	29.64	0.10

Model	Number of parameters	Deviance
1.Homogeneous sigma_squared	8	525.91
2.Heterogeneous sigma_squared	9	516.16

Model Comparison	Chi-Square	df	P-value
Model 1vs Model 2	9.76	1	0.01

Table 4-18 Treatment + self-efficacy + chemistry test + spatial ability model (Model 2)
Dependent variable: post-test

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	24.10	1.76	13.72	90	0.01
Peer v.s. Control, γ_{01}	-.164	1.08	-1.52	23	0.14
AR-single v.s. Control, γ_{02}	2.05	0.92	2.23	90	0.23
For Efficacy slope, β_1					
INTRCPT2, γ_{10}	0.20	0.38	0.52	90	0.61
For Chemistry slope, β_2					
INTRCPT2, γ_{20}	0.72	0.39	1.84	90	0.07
For Spatial slope, β_3					
INTRCPT2, γ_{30}	0.31	0.12	2.67	90	0.01

Random effect	Standard deviation	Variance component	df	Chi-square	P value
INTRCPT1, μ_0	3.28	10.77	21	61.67	0.01
Level 1, R	3.30	10.91			

Because spatial ability was significantly predictive of post test, the relationship between the AR effect and spatial ability on student learning performance was examined. The results (in Table 4-21) show that spatial ability was still significantly predictive (t=3.12, p<.01), but not the AR effect, nor the interaction effect of AR and spatial ability (t=-0.38, p>.05). Figure 4-1 demonstrated that those two lines did not cross over each other, indicating that there was no significant interaction between AR and spatial ability.

Table 4-19 Contrast 1 + spatial ability+ spatial ability*AR
Dependent variable: post-test

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	22.48	2.12	10.60	22	0.01
AR v.s. Control, γ_{01}	-0.07	1.63	-0.04	22	0.97
For Spatial slope, β_1					
INTRCPT2, γ_{10}	0.36	0.11	3.12	92	0.01
AR v.s. Control, γ_{11}	-0.03	0.07	-0.38	92	0.70

Random effect	Standard deviation	Variance component	df	Chi-square	P value
INTRCPT1, μ_0	3.59	12.88	22	99.06	0.01
Level 1, R	3.31	10.95			

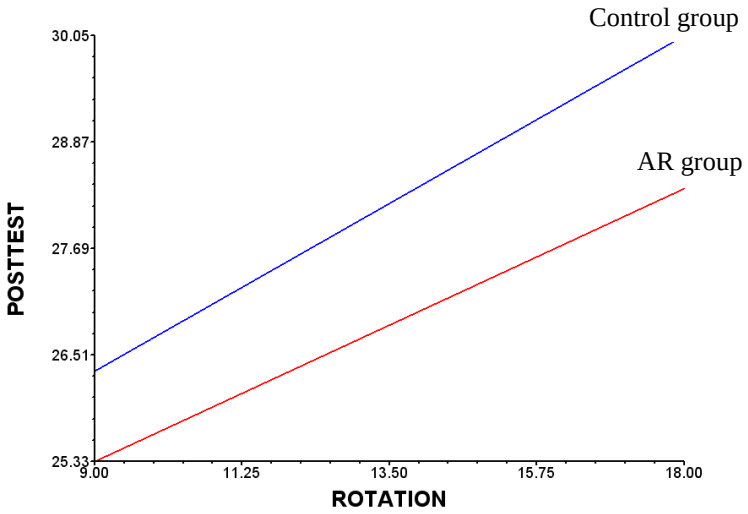


Figure 4-1 Interaction between AR and spatial ability on student learning performance

Treatments + Self-efficacy + Chemistry knowledge + Cognitive load

The results indicate (shown in Table 4-19) that cognitive load did not significantly add to the prediction of post test learning outcomes (t=0.15, $p<.05$) after the other covariates were taken into account. Chemistry knowledge and AR-single effect were significantly predictive in this model.

Table 4-20 Treatment + self-efficacy + chemistry test + cognitive load model with heterogeneous variance modeling (Model 1)
Dependent variable: post-test

Fixed Effect	**Coefficient**	**Standard error**	**T ratio**	**df**	**P value**
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	28.54	0.93	30.82	21	0.01
Contrast 1, γ_{01}	0.10	0.27	0.38	21	0.71
Contrast 2, γ_{02}	-1.92	0.45	-4.30	21	0.01
For Efficacy slope, β_1					
INTRCPT2, γ_{10}	0.21	0.35	0.60	90	0.55
For Chemistry slope, β_2					
INTRCPT2, γ_{20}	0.95	0.35	2.69	90	0.01
For Load slope, β_3					
INTRCPT2, γ_{30}	0.06	0.40	0.15	90	0.88

Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	0.04	0.01	21	29.06	0.11

Model	Number of parameters	Deviance
1.Homogeneous sigma_squared	8	533.23
2.Heterogeneous sigma_squared	9	522.37

Model Comparison	Chi-Square	df	P-value
Model 1vs Model 2	10.86	1	0.01

Table 4-21 Treatment + self-efficacy + chemistry test + cognitive load model (Model 2)
Dependent variable: post-test

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	28.55	1.15	24.85	90	0.01
Peer v.s. Control, γ_{01}	-1.57	1.23	-1.39	23	0.18
AR-single v.s. Control, γ_{02}	2.22	0.95	2.34	90	0.02
For Efficacy slope, β_1					
INTRCPT2, γ_{10}	0.09	0.40	0.23	90	0.82
For Chemistry slope, β_2					
INTRCPT2, γ_{20}	1.05	0.39	2.72	90	0.01
For Load slope, β_3					
INTRCPT2, γ_{30}	-0.05	0.46	-0.10	90	0.92

Random effect	Standard deviation	Variance component	df	Chi-square	P value
INTRCPT1, μ_0	3.43	11.78	21	62.33	0.01
Level 1, R	3.43	11.74			

Treatments + Self-efficacy + Chemistry knowledge + Spatial ability + Cognitive load

Last, all covariates were put into analysis (shown in Table 4-22), including treatments, two covariates (self-efficacy and chemistry knowledge), spatial ability, and cognitive load. In this full model, the AR effect and spatial ability were found to be predictive (t=-4.37 for Contrast 2=-4.37, t=2.57, $p<.05$). Chemistry knowledge was marginally significant predictive ($p<.08$) for student learning performance.

Table 4-22 Treatment + self-efficacy + chemistry test + spatial ability model with heterogeneous variance modeling (Model 1)
Dependent variable: post-test

Fixed Effect	**Coefficient**	**Standard error**	**T ratio**	**df**	**P value**
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	24.41	1.85	13.22	21	0.01
Contrast 1, γ_{01}	0.06	0.26	0.25	21	0.81
Contrast 2, γ_{02}	-1.87	0.43	-4.37	21	0.01
For Efficacy slope, β_1					
INTRCPT2, γ_{10}	0.33	0.35	0.94	89	0.35
For Chemistry slope, β_2					
INTRCPT2, γ_{20}	0.65	0.36	1.77	89	0.08
For Spatial slope, β_3					
INTRCPT2, γ_{30}	0.28	0.11	2.57	89	0.01
For Load slope, β_4					
INTRCPT2, γ_{40}	0.14	0.39	0.37	89	0.72

Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	0.04	0.01	21	29.53	0.10

Model	Number of parameters	Deviance
1.Homogeneous sigma_squared	9	525.90
2.Heterogeneous sigma_squared	10	516.02

Model Comparison	Chi-Square	df	P-value
Model 1vs Model 2	9.88	1	0.01

Table 4-23 Treatment + self-efficacy + chemistry test + spatial ability model (Model 2)
Dependent variable: post-test

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	24.01	2.04	11.77	89	0.01
Peer v.s. Control, γ_{01}	-1.65	1.09	-1.52	23	0.14
AR-single v.s. Control, γ_{02}	2.05	0.92	2.21	89	0.03
For Efficacy slope, β_1					
INTRCPT2, γ_{10}	0.20	0.39	0.52	89	0.60
For Chemistry slope, β_2					
INTRCPT2, γ_{20}	0.72	0.40	1.82	89	0.07
For Spatial slope, β_3					
INTRCPT2, γ_{30}	0.31	0.12	2.65	89	0.01
For Load slope, β_4					
INTRCPT2, γ_{40}	0.04	0.45	0.08	89	0.94

Random effect	Standard deviation	Variance component	df	Chi-square	P value
INTRCPT1, μ_0	3.28	10.75	21	60.76	0.01
Level 1, R	3.32	11.05			

Cognitive load as outcome measure

One major concern in this study was whether students learning together with AR will lead to more cognitive load than those who study alone. Due to the nested effect among AR-peer groups, HLM was used to examine the hypothesis. The result shown in Table 4-24 demonstrates that cognitive load was not significantly different between AR-peer groups and AR-single treatment (t=-0.89, p>.05).

Table 4-24 Treatment + self-efficacy + chemistry test with heterogeneous variance modeling (Model 1)
Dependent variable: cognitive load

Fixed Effect	**Coefficient**	**Standard error**	**T ratio**	**df**	**P value**
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	2.27	0.13	17.11	21	0.01
AR single v.s. peer, γ_{01}	-0.20	0.22	-0.89	21	0.38
For Efficacy slope, β_1					
INTRCPT2, γ_{10}	0.03	0.11	0.22	66	0.83
For Chemistry slope, β_2					
INTRCPT2, γ_{20}	-0.08	0.11	-0.71	66	0.48

Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	0.02	0.01	21	24.71	0.26

Model	Number of parameters	Deviance
1.Homogeneous sigma_squared	6	180.81
2.Heterogeneous sigma_squared	7	180.78

Model Comparison	Chi-Square	df	P-value
Model 1vs Model 2	0.03	1	>0.50

Table 4-25 Treatment + self-efficacy + chemistry test (Model 2)
Dependent variable: cognitive load

Fixed Effect	**Coefficient**	**Standard error**	**T ratio**	**df**	**P value**
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	2.27	0.13	17.06	66	0.01
AR single v.s. peer, γ_{01}	-0.20	0.22	-0.90	22	0.38
For Efficacy slope, β_1					
INTRCPT2, γ_{10}	0.02	0.11	0.22	66	0.48
For Chemistry slope, β_2					
INTRCPT2, γ_{20}	-0.08	0.11	-0.71	66	0.83

Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	0.01	0.01	0	0.01	>0.50
Level 1, R	0.88	0.77			

Cognitive load was divided into three parts: text-load, picture-load, and AR-load. Spatial ability might play a role to influence cognitive loading among these three parts. Therefore, in order to gain a deeper understanding, HLM was employed to detect the effect of spatial ability on different cognitive loads in AR-peer and AR-single groups. As shown in Table 4-26, spatial ability did significantly influence the AR-load (t=-2.97, p<.01), indicating students with higher spatial ability report less AR-load when studying Protein Magic Book. Nevertheless, spatial ability was not significantly predictive for picture-load (t=-0.139, p>.05) and text-load (t=-1.01, p>.05).

Table 4-26 Treatment + self-efficacy + chemistry test + spatial ability model with heterogeneous variance modeling (Model 1)
Dependent variable: AR-load

Fixed Effect	**Coefficient**	**Standard error**	**T ratio**	**df**	**P value**
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	3.85	0.58	6.62	21	0.01
AR single v.s. peer, γ_{01}	-0.13	0.25	-0.52	21	0.61
For Efficacy slope, β_1					
INTRCPT2, γ_{10}	0.02	0.12	0.13	65	0.90
For Chemistry slope, β_2					
INTRCPT2, γ_{20}	0.04	0.13	0.35	65	0.72
For Spatial slope, β_3					
INTRCPT2, γ_{30}	-0.12	0.04	-2.97	65	0.01

Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	0.02	0.01	21	21.81	0.41

Model	Number of parameters	Deviance
1.Homogeneous sigma_squared	7	191.15
2.Heterogeneous sigma_squared	8	190.94

Model Comparison	Chi-Square	df	P value
Model 1vs Model 2	0.21	1	0.01

Table 4-27 Treatment + self-efficacy + chemistry test + spatial ability model (Model 2)
Dependent variable: AR-load

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	3.86	0.58	6.65	65	0.01
AR single v.s. peer, γ_{01}	-0.13	0.23	-0.56	22	0.58
For Efficacy slope, β_1					
INTRCPT2, γ_{10}	0.01	0.12	0.12	65	0.71
For Chemistry slope, β_2					
INTRCPT2, γ_{20}	0.05	0.13	0.37	65	0.91
For Spatial slope, β_3					
INTRCPT2, γ_{30}	-0.12	0.04	-2.99	65	0.01

Random effect	Standard deviation	Variance component	df	Chi-square	P value
INTRCPT1, μ_0	0.01	0.01	0	0.01	>0.50
Level 1, R	0.95	0.90			

Furthermore, we were also interested in the differences of these three cognitive loads among students. That is whether these three cognitive loads differ within the students. Because AR-load did not appear in the control treatment, the analysis was done with text-load and picture-load among three treatments first, and then the three types of loads were examined only in AR groups (AR-peer and AR-single) with repeated measures models.

First, the treatment effect among the three groups was not predictive (Wilk's Lamda=2.56, $p>.05$), but there was a significant difference between text-load and picture-load (Wilk's Lamda=6.50, $p<.05$), withstudents' text-load (Mean=2.22) was significantly higher than picture-load (Mean=2.07). Second, in AR groups, the treatment effect was not significant either (Wilk's Lamda=.678, $p>.05$), while the within subjects effect exists (Wilk's Lamda=5.09, $p<.01$). Students rated the text-load (Mean=2.33) significantly higher than the picture-load (Mean=2.08).

4.3. Comparison of the AR-single with control on outcome measures

One of the research questions asked in this study was whether AR would facilitate student learning. Although students in the peer group also used AR to learn the concept of protein structure, their learning performance was nested within the group, resulting in some contaminations on their learning outcomes, rather than by AR alone. Therefore, in order to detect the effect of AR without the peer effect on student learning performance, only students in the AR-single treatment condition were included in this analysis. ANCOVA was employed in the following analysis and the variables of self-efficacy and chemistry knowledge were treated as covariates.

4.3.1. Learning performance

Compared to control students, Table 4-28 shows AR students did perform differently ($F(1, 48)=6.77$, $p<.05$). Students with the scaffolding of AR performed better than those who only read the texts.

Table 4-28 ANCOVA analysis for the AR learning performance
Dependent variable: post-test

Source	SS	df	MS	F	P value
Intercept	45317.21	1	45317.21	4711.34	0.02
Self-efficacy	0.37	1	0.37	0.04	0.85
Chemistry	28.50	1	28.50	2.96	0.09
AR	65.11	1	65.11	6.77	0.01
Error	461.70	48	9.62		

4.3.2. Interaction between Spatial ability and AR

However, with the control of student spatial ability (shown in Table 4-29), the effect of AR disappears ($F(1, 28)=0.07$, $p>.05$). The result illustrates that student spatial ability shows a statistical significance on the learning performance ($F(1, 12)=2.20$, $p<.05$). Additionally when the interaction factor between AR and spatial ability was put into analysis (Table 4-30), no interaction effect between AR and spatial ability was found.

Table 4-29 ANCOVA analysis for the AR learning performance and spatial ability
Dependent variable: post-test

Source	SS	df	MS	F	P value
Intercept	347.65	1	347.65	47.21	0.01
Self-efficacy	7.82	1	7.82	1.06	0.31
Chemistry	0.38	1	0.38	0.05	0.82
AR	3.32	1	3.32	0.45	0.51
Spatial	194.01	12	16.17	2.20	0.03
Error	265.07	36			

Table 4-30 ANCOVA analysis for the AR-spatial ability interaction
Dependent variable: post-test

Source	SS	df	MS	F	P value
Intercept	182.09	1	182.09	27.57	0.01
Self-efficacy	6.85	1	6.85	1.04	0.32
Chemistry	7.29	1	7.29	1.10	0.30
AR	0.49	1	0.49	0.07	0.79
Spatial	160.18	12	13.35	2.02	0.06
Spatial*AR	80.11	8	10.01	1.52	0.20
Error	184.96	28	6.61		

4.3.3. Cognitive load

Regarding the effect of AR on student cognitive load, Table 4-31 shows AR was not significantly predictive after controlling self-efficacy and chemistry knowledge.

Table 4-31 ANCOVA analysis for cognitive load
Dependent variable: cognitive load

Source	SS	df	MS	F	P value
Intercept	4.64	1	4.64	7.09	0.01
Self-efficacy	1.71	1	1.71	2.61	0.11
Chemistry	1.01	1	1.01	1.54	0.22
AR	0.09	1	0.09	0.14	0.71
Error	31.44	48	0.66		

In addition, the effect of spatial ability did not predict the amount of cognitive load. The result as shown in Table 4-32, did not support the hypothesis that students with higher spatial ability will have less cognitive load ($F(12, 37)=0.24$, $p>0.05$).

Table 4-32 ANCOVA analysis for cognitive load and spatial ability
Dependent variable: cognitive load

Source	SS	df	MS	F	P value
Intercept	4.78	1	4.78	6.05	0.02
Self-efficacy	1.37	1	1.37	1.74	0.20
Chemistry	0.12	1	0.12	0.15	0.70
Spatial	2.27	12	0.19	0.24	1.00
Error	29.26	37	0.79		

4.4. Analysis of effects in the AR-peer learning treatment

In addition to investigating the overall effect of treatments on student learning performance, examination of how students would learn in the AR-peer treatment condition was another concern in this study. First, the intercorrelations of pre-treatment and outcome measures were examined at the individual level (shown in Table 4-33).

Table 4-33 AR-peer treatment intercorrelations at individual level (N=44)

Measures	1	2	3	4	5	6	7	8
1.Post-test	-							
2.Self-efficacy	0.14	-						
3.Chmistry	0.33**	0.22*	-					
4.Spatial	0.34**	0.03	0.32**	-				
5.Load	-0.33	-0.07	0.06	-0.12	-			
6.Collabration	-0.16	-0.03	-0.02	0.10	-0.09	-		
7.Helpfulness	-0.24	-0.06	-0.17	-0.14	0.02	0.29	-	
8.Understand	-0.25	-0.22	-0.20	-0.17	-0.03	0.33*	0.86**	-

*p<0.05, **p<0.01

As we can see in Table 4-33, the post-test had a moderate relationship with chemistry knowledge and spatial ability (r=0.33, p<.01 for chemistry knowledge, and r=0.34, p<.01 for spatial ability). Self-efficacy was related to chemistry knowledge with a low relationship (r=0.22, p<.05), while chemistry knowledge was associated with spatial ability with r=0.32, p<.01. Student self-rated collaboration score had a moderate relationship with student perception of the helpfulness of AR with r=0.33, p<.05. The perception of the helpfulness of AR was highly

correlated with the perception regarding whether the collaboration made it easier to understand the content (r=0.86, p<.01).

The intercorrlations at the dyad level was shown in Table 4-34 by taking the mean of each dyad measures into analysis. The post-test scores were significantly associated with chemistry knowledge and spatial ability (r=0.57, p<.01and r=0.43, p<.05, respectively). At the dyad level, spatial ability was related to cognitive load (r=-0.43, p<.05). In addition, student perception of the helpfulness of AR had a high relationship with the perception about the collaboration to make it easier to understand the content (r=0.83, p<.01). However, compared to the individual level, the relationship between self-efficacy and chemistry knowledge, chemistry knowledge and spatial ability, as well as student self-rated collaboration score and the perception about the helpfulness of AR, these were not significant correlated.

Table 4-34 AR-peer treatment intercorrelations at dyad level (N=22)

Measures	1	2	3	4	5	6	7	8
1.Post-test	-							
2.Self-efficacy	0.35	-						
3.Chmistry	0.57**	0.32	-					
4.Spatial	0.43*	0.37	0.39	-				
5.Load	-0.01	-0.13	-0.09	-0.43*	-			
6.Collabration	-0.11	0.03	-0.01	0.11	-0.05	-		
7.Helpfulness	-0.16	-0.05	-0.25	0.01	-0.02	0.39	-	
8.Understand	-0.26	-0.17	-0.40	-0.19	-0.03	0.40	0.83**	-

*p<0.05, **p<0.01

Next, we examined the nested effect among dyads with the examination of intraclass correlation again. Table 4-35 showed a high intraclass correlation coefficient ρ=0.43, indicating a nested effect existed among those dyads. Therefore, the hierarchical linear model method again was used to test hypotheses. Individual measures such as self-efficacy, chemistry knowledge, spatial ability, cognitive load, collaboration efforts, perception about the helpfulness of collaboration, and the perception regarding whether the collaboration made it easier to understand the content were put in the Level 1. In Level 2, the group means of each covariate were included. In addition to the above factors, the effect of gender was also examined. Except for the gender factor, all individual factors were treated as group mean-centered when entering the model, while all level 2 factors were transformed as grand mean-centered.

Table 4-35 Final estimation of variance component of the variables for post-test in groups

	Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
Post-test (Peer only)	INTRCPT1, U0	3.53	12.47	21	52.41	0.01
	Level 1, R	4.08	16.67			

4.4.1. Homogenous gender versus mixed gender groups

Gender might be an issue in the peer learning group because of the composition. One composition is a homogeneous combination, for example, male with male or female with female. The other combination is heterogeneous, such as one male with a female or vise vesa. This analysis explored whether the gender composition would affect peer learning. Twelve groups

were heterogeneous with their gender composition while ten groups were homogeneous (seven female pairs and three male pairs). In the hierarchical linear model, gender was put in the Level 1 as a predictor while the characteristic of the gender composition (heterogeneous or homogeneous) was put in the Level 2. These two predictors were entered separately. The equations are represented as:

Model 1

Level 1

$\text{Load} = \beta_0 + \beta_1 * (\text{Male}) + r$

Level 2

$\beta_0 = \gamma_{00} + \mu_0$

$\beta_1 = \gamma_{10}$

Model 2

Level 1

$\text{Load} = \beta_0 + r$

Level 2

$\beta_0 = \gamma_{00} + \gamma_{01} * (\text{Heterogeneous}) + \mu_0$

Table 4-36 illustrates that the gender of the subjects did not predict the learning outcomes ($t=0.97$, $p>.05$). Likewise, the heterogeneous/homogeneous composition did not have an effect on student learning performance (shown in Table 4-37).

Table 4-36 Gender model (individual level)
Dependent variable: post-test

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	26.33	1.15	22.96	21	0.01
For Male slope, β_1					
INTRCPT2, γ_{10}	1.35	1.40	0.97	42	0.34
Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	3.56	12.66	21	52.36	0.01
Level 1, *r*	4.08	16.64			

Table 4-37 Gender model (dyad level)
Dependent variable: post-test

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	27.55	1.58	17.46	20	0.01
Heterogeneous, γ_{01}	-1.22	1.93	-0.63	20	0.54
Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	3.62	13.10	20	51.44	0.01
Level 1, *r*	4.08	16.67			

4.4.2. Self-efficacy test

The examination of the effect of self-efficacy on student learning performance in the dyads shows (Table 4-38) that there were no effects of self-efficacy on the post-test among students(t=-0.24, *p*>.05). Further, the impact of the dyad mean self-efficacy on student learning performance was not significant either (t=1.76, *p*>.05)(Table 4-39).

Table 4-38 Self-efficacy model (individual level)
Dependent variable: post-test

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	26.89	0.95	28.30	21	0.01
For Efficacy slope, β_1					
INTRCPT2, γ_{10}	-0.19	0.81	-0.24	42	0.82

Random effect	Standard deviation	Variance component	df	Chi-square	P value
INTRCPT1, μ_0	3.56	12.66	21	52.36	0.01
Level 1, *r*	4.08	16.64			

Table 4-39 Self-efficacy model (dyad level)
Dependent variable: post-test

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	26.89	0.89	30.24	20	0.01
EfficacyGroup, γ_{01}	3.38	1.92	1.76	20	0.09

Random effect	Standard deviation	Variance component	df	Chi-square	P value
INTRCPT1, μ_0	3.29	10.80	20	45.92	0.01
Level 1, *r*	4.08	16.67			

4.4.3. Chemistry knowledge

Student prior knowledge might play a role to affect their learning performance (shown in Table 4-40 and Table 4-41). The effect of student individual chemistry knowledge on student learning performance was not significant (t=0.38, $p>.05$). However, at the dyad level, the effect of dyad group mean of student prior knowledge on post-test was significantly predictive (t=3.16, $p<.05$), indicating that the dyads that had higher group scores on chemistry knowledge tended to

obtain higher learning performance.

Table 4-40 Chemistry knowledge model (individual level)
Dependent variable: post-test

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	26.89	0.95	28.3	21	0.01
For Chemistry slope, β_1					
INTRCPT2, γ_{10}	0.38	0.24	1.54	42	0.13
Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	3.55	12.59	21	53.14	0.01
Level 1, *r*	4.05	16.44			

Table 4-41 Chemistry knowledge model (dyad level)
Dependent variable: post-test

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	26.89	0.78	34.38	20	0.01
Chemistry Group, γ_{01}	1.47	0.47	3.16	20	0.01
Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	2.54	6.47	20	35.52	0.02
Level 1, *r*	4.08	16.67			

4.4.4. Spatial ability

Table 4-42 shows that there was no spatial ability effect on student learning performance (t=0.99, $p>.05$). But for the dyad level, the average of student spatial ability of the dyads was significantly related to dyad mean post-test performance (t=2.74, $p<.05$, shown in Table 4-43).

Table 4-42 Spatial ability model (individual level)
Dependent variable: post-test

Fixed Effect	**Coefficient**	**Standard error**	**T ratio**	**df**	**P value**
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	26.89	0.95	28.3	21	0.01
For Spatial slope, β_1					
INTRCPT2, γ_{10}	0.38	0.24	1.57	42	0.12
Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	3.56	12.59	21	53.84	0.01
Level 1, *r*	4.03	16.23			

Table 4-43 Spatial ability model (dyad level)
Dependent variable: post-test

Fixed Effect	**Coefficient**	**Standard error**	**T ratio**	**df**	**P value**
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	26.89	0.86	31.33	20	0.01
Spatial Group, γ_{01}	0.77	0.28	2.74	20	0.01
Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	3.08	9.49	20	42.76	0.01
Level 1, *r*	4.08	16.67			

4.4.5. Cognitive load

The results in Table 4-44 and Table 4-45 indicate that no statistical significant effects were found for cognitive load on the dyad learning performance from either the individual level or dyad average level.

Table 4-44 Cognitive load model (individual level)
Dependent variable: post-test

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	26.89	0.95	28.3	21	0.01
For Load slope, β_1					
INTRCPT2, γ_{10}	-0.63	0.78	-0.81	42	0.42
Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	3.50	12.22	21	50.86	0.01
Level 1, *r*	4.14	17.18			

Table 4-45 Cognitive load model (dyad level)
Dependent variable: post-test

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	26.89	0.95	28.30	20	0.01
Load Group, γ_{01}	-0.02	1.49	-0.02	20	0.99
Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	3.68	13.51	20	52.41	0.01
Level 1, *r*	4.08	16.67			

4.4.6. Collaboration effort

Students in the AR-peer treatment condition were asked about their perceptions regarding their collaboration. The first question asked the amount of effort they put in the collaboration. Table 4-46 and Table 4-47 show that their collaboration effort and the dyad mean collaborative effort did not predict their learning performance.

Table 4-46 Collaboration effort model (individual level)
Dependent variable: post-test

Fixed Effect	**Coefficient**	**Standard error**	**T ratio**	**df**	**P value**
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	26.89	0.95	28.30	21	0.01
For Collab slope, β_1					0.15
INTRCPT2, γ_{10}	-1.84	1.27	-1.45	42	
Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	3.62	13.08	21	56.56	0.01
Level 1, *r*	3.93	15.45			

Table 4-47 Collaboration effort model (dyad level)
Dependent variable: post-test

Fixed Effect	**Coefficient**	**Standard error**	**T ratio**	**df**	**P value**
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	26.89	0.94	28.47	20	0.01
Collab Group, γ_{01}	-0.45	0.87	-0.52	20	0.61
Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	3.64	13.25	20	51.78	0.01
Level 1, *r*	4.08	16.67			

4.4.7. Helpfulness of collaboration

It was found in Table 4-48 that student perception about the helpfulness of the collaboration was not significantly predictive (t=-1.55, *p*>.05), indicating that students' rating of peer collaboration was not related to performance. In addition, no effect was found at the dyad level to predict student learning performance (t=-0.99, *p*>.05, shown in Table 4-49).

Table 4-48 Helpfulness model (individual level)
Dependent variable: post-test

Fixed Effect	**Coefficient**	**Standard error**	**T ratio**	**df**	**P value**
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	26.89	0.95	28.30	21	0.01
For Helpfulness slope, β_1					
INTRCPT2, γ_{10}	-1.01	0.65	-1.55	42	0.13
Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	3.64	13.27	21	57.94	0.01
Level 1, *r*	3.88	15.08			

Table 4-49 Helpfulness model (dyad level)
Dependent variable: post-test

Fixed Effect	**Coefficient**	**Standard error**	**T ratio**	**df**	**P value**
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	26.89	0.94	28.63	20	0.01
Helpfulness Group, γ_{01}	-0.81	0.82	-0.99	20	0.34
Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	3.61	13.01	20	51.22	0.01
Level 1, *r*	4.08	16.67			

4.4.8. Easy to understand with AR

Last, students' perceptions about whether the collaboration would make it easier to understand the content was not related to their performance either at the individual level or dyad level (shown in Table 4-50 and Table 4-51).

Table 4-50 Understanding model (individual level)
Dependent variable: post-test

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	26.89	0.95	28.30	21	0.01
For Understand slope, β_1					
INTRCPT2, γ_{10}	-0.76	0.71	-1.08	42	0.29
Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	3.57	12.76	21	54.30	0.01
Level 1, *r*	4.01	16.09			

Table 4-51 Understanding (dyad level)
Dependent variable: post-test

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	26.89	0.92	29.30	20	0.01
Understand Group, γ_{01}	-1.51	1.13	-1.33	20	0.20
Random effect	**Standard deviation**	**Variance component**	**df**	**Chi-square**	**P value**
INTRCPT1, μ_0	3.47	12.04	20	48.89	0.01
Level 1, *r*	4.08	16.67			

4.4.9. Spatial ability as a predictor of cognitive load

Based on their correlations, spatial ability was related to cognitive load in the dyad level but not in the individual level. To gain further understanding, their relationships were analyzed both in dyad level and individual level with HLM. As we can see in Table 4-52 and Table 4-53, both in individual and dyad level, spatial ability was significantly predictive (t=-2.75, p<.01 at individual level, and t=-3.17, p<.01, at dyad level), indicating in an AR-peer learning environment, students with higher spatial ability indicated they had less cognitive load. When we divided cognitive load into AR-load, text-load, and picture-load, as shown in Table 4-54 and Table 4-55, AR-load was affected by spatial ability both in individual and dyad level (t=-.3.52, p<.01; t=-4.31, p<.01, respectively). Nevertheless, spatial ability did not predict the change of text-load and picture-load either in individual or dyad level (For text-load, individual level, t=-0.97, p>.05, dyad level, t=-1.52 p>.05; for picture-load, individual level, t=-1.70, p>.05, dyad level, t=-2.03, p>.05).

Table 4-52 Spatial ability model (individual level)
Dependent variable: cognitive load

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	3.51	0.48	7.25	21	0.01
For Spatial slope, β_1					
INTRCPT2, γ_{10}	-0.09	0.03	-2.75	42	0.01

Random effect	Standard deviation	Variance component	df	Chi-square	P value
INTRCPT1, μ_0	0.21	0.04	21	23.09	0.34
Level 1, *r*	0.83	0.69			

Table 4-53 Spatial ability model (dyad level)
Dependent variable: cognitive load

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	3.88	0.51	7.66	20	0.01
Spatial Group, γ_{01}	-0.11	0.04	-3.17	20	0.01

Random effect	Standard deviation	Variance component	df	Chi-square	P value
INTRCPT1, μ_0	0.22	0.05	20	22.90	0.29
Level 1, *r*	0.83	0.68			

Table 4-54 Spatial ability model (individual level)
Dependent variable: AR load

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	4.48	0.70	6.40	21	0.01
For Spatial slope, β_1					
INTRCPT2, γ_{10}	-0.16	0.05	-3.52	42	0.01

Random effect	Standard deviation	Variance component	df	Chi-square	P value
INTRCPT1, μ_0	0.08	0.01	21	20.82	>.05
Level 1, *r*	0.95	0.90			

Table 4-55 Spatial ability model (dyad level)
Dependent variable: AR load

Fixed Effect	Coefficient	Standard error	T ratio	df	P value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	4.64	0.58	7.95	20	0.01
Spatial Group, γ_{01}	-0.17	0.04	-4.31	20	0.01

Random effect	Standard deviation	Variance component	df	Chi-square	P value
INTRCPT1, μ_0	0.05	0.01	20	18.89	>.05
Level 1, *r*	0.10	0.99			

CHAPTER 5: DISCUSSION AND CONCLUSION

This dissertation explored the effect of augmented reality on student chemistry learning, especially the peer learning in an AR-based environment, as well as the factors that may influence student learning, such as cognitive load and visual-spatial ability. This chapter presents the findings of this study based upon each research question and related research hypotheses, and then discusses the questions raised from the findings. Last, conclusions are considered at the end of this dissertation.

5.1. Findings and Discussion

Research question 1: Will students benefit from AR in chemistry learning?

Finding 1: Students in the AR-alone setting had greater learning performance than those who studied by themselves without AR scaffolding.

In the ANCOVA analysis by simply comparing those who studied only with texts and those with AR scaffolding, the result showed students with AR scaffolding did perform better. This finding corresponds to several researchers' claim (Shelton, 2003; Hedley, 2003; Chen, 2005; Chen & Winn, 2005) that AR has great potential to facilitate learning. Chemistry is a subject which conveys more abstract concepts and requires students to put more efforts into building up conceptual mental models. In addition, in order to describe or explain those abstract concepts, it is not uncommon to use visual-spatial displays in chemistry education. Being a powerful

multimedia display tool (McLellan, 2003), especially enabling the presentation of 3-D images and animations, in this study, AR did help students to learn the concepts of protein structure, which requires understanding of spatial relationships in structures. Shelton and Hedley (2004) mentioned that AR can convey the spatial cutes directly to users and students were more likely to develop more detailed mental representations (Hedley, 2003), which in turn, helped them understand and learn the concepts more.

Research question 2: Will students learn chemistry more effectively in an AR-enhanced peer learning environment?

Finding 2: With using AR, students in the collaborative setting did not learn better than those who studied alone with AR.

Billinghurst, Weghorst, & Furness (1998) stated that AR could provide a “shared space”, allowing people to work and interact with peers, thus facilitating collaborative learning. However, the finding of this study did not support it. On the contrary, students studied with AR alone performed better than those who studied with peers. In addition, this study did not confirm Phelps & Damon’s (1989) result that peer collaboration is an effective way to help students learn reasoning tasks, either. This finding may be influenced by some conditions. Much collaborative learning research were conducted in a natural classroom setting (e.g. Phelps & Damon, 1989; Summers, 2006), while this study was employed in an experimental environment which contains some restrictions which may not be beneficial for collaborative learning.

Time limitation. Unlike other studies which may take one semester or even longer period of time to conduct a collaborative learning setting, this study only allowed twenty minutes for all three groups to complete the reading task while collaborative learning is a socioconstructive dynamic process which requires much input of time (Summers, 2006). With group interaction, discussion, and complete the main task, twenty minutes may seem too limited, resulting in students might not be able to study or digest the material thoroughly, especially they had to deal with AR manipulation and peer conversation at the same time.

Peer acquaintance. Since students were randomly assigned to one of the three treatments, most of the students in the peer group did not know each other until they arrived the lab. They were only introduced to each other with names and started to do all the tasks. As I observed, they usually needed some time to warm up. Some groups even just read the material by themselves and manipulated AR tools alternately without much discussion. Therefore, peer acquaintance may be a factor to influence the result of their performance.

Novice vs. expert. The role play might affect group dynamics in this study. In some groups, one of the students knew the concept of protein structure or was more knowledgeable about biochemistry. Therefore, he/she was more likely to dominate the discussion, and on the other hand, the other student might just listen to what his/her peer talked. This unbalanced discussion might cause different learning performance, too.

Technology access. The other factor which might influence student learning is the access to AR. For example, some students like to play or manipulate AR markers more than other students and, as a result, the other student might not enough time to experience the movement of AR animation and body learning. In addition, not all the markers are moveable in the Protein Magic Book. Some of animations required users to rotate the whole book and the fixed markers were designed on the right hand side of the book. In other words, the student who sat on the right side tended to have more opportunity to interact with the book and AR.

Collaborative learning strategy. Although the students in the peer group were informed that they had to work together to complete the learning activity, they still had the freedom to decide how they would like to collaborate together. As I observed, some groups might talk about their division of labor and how they work together before they started to read the book, while some groups might just read the content individually with few interactions. As a result, the collaborative learning effect in this study would not be so significant due to unstructured collaborative learning guidance and interactions. For future studies, it is suggested to offer structured collaborative learning instructions/guidance, or learning strategies, such as jigsaw technique, to amplify the effect of collaborative learning. In addition, some questions or hints required students to think or solve together could be added into the content design as a catalyst to encourage peer interactions.

Gender pairing might be another factor to affect student interaction. However, based upon the findings in peer group analysis, gender composition did not impact their learning performance in this study. In sum, the collaborative learning setting contains complex group

dynamics and which in turn may cause the nested effect among peer groups in this study.

Despite failing to support the research hypotheses, the questionnaire results revealed that students perceived peer collaboration was helpful and made it easier to understand the content. It seems that students appreciated the function of peer collaboration to help them learn the concept of protein structure. Therefore, future research on collaborative learning in an AR-enhanced environment should consider the above issues and create a well-designed collaborative learning environment in order to detect the value of AR to facilitate learning with peers.

Research question 3: What factors may affect student chemistry learning in an AR-enhanced environment?

Finding 3: Students performed differently with their level of visual-spatial ability.

Finding 4: Students with low visual-spatial ability did not benefit more from AR than those with high visual-spatial ability.

Finding 5: Students who experienced less cognitive load did not have greater learning performance.

In this study, visual-spatial ability and cognitive load were considered to impact student learning performance. The findings revealed that after controlling self-efficacy and chemistry knowledge, visual-spatial ability affected student learning performance while cognitive load did not. The finding showed that students who possess higher visual-spatial ability achieved greater learning. This finding again demonstrates the importance of visual-spatial ability both in chemistry learning (Wu and Shah, 2004; Copolo and Hounshell, 2005) and interaction with 3-D

images/animations of AR (Mathewson, 1999). However, students with low visual-spatial ability did not benefit more from AR in this study. The possible explanation might be the fact that some complicated 3-D representations in this study require students process more mental rotations and understanding (Chanlin, 1998), and may not offer enough support to overcome barriers faced by those students with low visual-spatial ability.

As for the second factor, cognitive load, the finding did not support the hypothesis that cognitive load could predict the learning performance. Although the design of Protein Magic Book was followed the techniques to reduce the extraneous load, the 3-D representations of protein structure and the manipulation of AR markers might be too new for most of students so that they need more mental process to comprehend the material, especially to see the relationships among texts, pictures and AR animations. In turn, in the limited of time, the work load was bigger than usual and did not result in better learning performance.

Research question 4: How much cognitive load will students report in different learning settings?

Finding 6: Students did not report more cognitive load when they studied alone with AR, compared to those who studied without AR scaffolding

Finding 7: Students in the collaborative learning setting did not report more cognitive load than those who studied alone with AR.

Finding 8: Students with higher visual-spatial ability reported less cognitive load.

Finding 9: Students with higher visual-spatial ability reported less AR-load.

The findings regarding cognitive load did not support prior findings that students in a peer learning setting may gain more cognitive load. As discussed earlier, with the limited time of twenty minutes to complete the reading task, students might not have much time to discuss the details or advanced conversation about protein structure, thus the amount of their cognitive load was not significantly different from other groups. However, the questionnaire results showed that students in the peer learning condition reported that they would work harder with peers than students in the other treatments. Also, they indicated that they would put in more efforts to work with partners compared to students who studied alone with texts only. In other words, the collaborative environment motivated them to put more efforts to understand the material, but we did not see the similar results from cognitive load analysis. Additional research is needed to investigate the gain of cognitive load in an AR-enhanced peer learning environment.

It was found in this study that visual-spatial ability reduced the overall cognitive load, especially the AR-load. Again, these findings support the claim that visual-spatial ability is important in chemistry learning. Furthermore, it revealed that studying with AR scaffolding requires the input of visual-spatial ability to comprehend the spatial relationships in 3-D representations (Shelton & Hedley, 2004). Therefore, it suggests that developing students' visual-spatial ability is essential in both chemistry learning and spatial-relationship based 3-D representations.

5.2. Conclusions

This study was an exploration to examine the effect of AR alone with the collaborative learning setting on chemistry learning. The results shown above imply that learning with the scaffolding of AR may facilitate student chemistry learning. With more and more visualization tools involved in chemistry education, it is suggested to utilize AR to help students learn. Although students in the peer group did not perform better than the other groups, they considered collaboration with peers as being very helpful and this made it easier to understand the content. Therefore, a well-designed collaborative learning environment with AR scaffolding is needed for future research. In addition, the study revealed that visual-spatial ability is an important factor to influence on chemistry learning, as well as the overall cognitive load and the load on AR. This finding indicates that developing student visual-spatial ability should be considered when preparing AR learning materials in chemistry learning. Nevertheless, this study did not support the cognitive load theory that students in a peer learning setting would report more cognitive load. Due to the experimental setting and limited time, which might impede the social interaction among peers, additional research is needed to investigate this relationship in collaborative learning groups using AR.

Several limitations of this study suggest the need for further research. First, the study might be replicated with a larger sample size over a longer period of time. Second, this study examined the AR application in chemistry learning. Generalizing the results to other domains should be done cautiously because the characteristics of 3-D representations of AR support the essence of chemistry learning which requires student visual-spatial ability. Not all disciplines are suitable to

utilize AR to help students learn. Third, the lab setting is different from normal classroom settings. The design of how to use AR in a classroom setting should be reconsidered to fit the classroom setting and group dynamics in the class. Fourth, in the procedure of this study, the measure of visual-spatial ability was collected after students interacted with AR, which may impact the interpretation of visualization test and the score as well due to the pre-mental spatial training with AR 3-D presentations before the test. Therefore, it is suggested to collect the data on the visualization test before the main reading task.

This study mainly focused on quantitative analysis to examine the effect of peer learning in an AR-enhanced environment. For future research, it is suggested to also include qualitative data into analysis. Combining quantitative and qualitative data together may offer a different perspective and a deeper understanding about how students think about learning with AR and with peers. In addition, it is suggested to conduct the study in a classroom setting with collaborative learning and AR scaffolding in order to obtain more long-term social interaction among peers. Following it, a discourse analysis might be interesting to explore the relationships among peers, technology, and the learning materials itself. By doing so, a deeper understanding of how students perceive peer interaction and AR as a learning tool could be gained. Third, when forming the peer group, it is suggested to eliminate the nested effect in the future research, which may bring more covariates and complexity into the research. Last, with more and more 3-D visualization tools developed in chemistry education, it would be helpful and beneficial to discover the relationship between AR and chemistry instructors' pedagogical perspective of utilizing AR in the classroom, including their perceptions of AR, teaching strategies, and student

classroom preparation for implementing AR. When science instructors are better prepared to use AR well, students can benefit most from this powerful visualization tool.

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Appendix I

Personal background questionnaire

About you

1. Gender : ☐male; ☐female
2. Age:
3. Major:

Your experience in chemistry class

4. Have you taken any chemistry courses in high school and the UW? ☐Yes; ☐No
   ☐If so, which courses, and where did you take them?
   _____
   _____

5. Have you taken any biochemistry courses in high school and the UW? ☐Yes; ☐No
   ☐If so, which courses, and where did you take them?
   _____
   _____
6. What chemistry course are you taking this quarter?
   _____
   _____

7. Have you ever used a computer to learn something as part of the course (any course)?
   If so, what was it?

_____

8. Based on your chemistry learning experience, did your chemistry teacher use any media in the classroom to help you learn in addition to the textbook?

   ☐Yes, If he/she did, what kind of media he/she used? ☐graphs; ☐model;
   ☐computer simulation; ☐video; ☐others
   ☐No

Your computer experience

9. Do you play video games?

☐No

☐Yes, I play video games ☐a lot; ☐often; ☐sometimes; ☐seldom,

*since the year of

*The name of my favorite video game is

10. Please evaluate your skill in playing video games

Very skillful				not skillful at all
5	4	3	2	1
☐	☐	☐	☐	☐

11. In what year did you start to use computer? The year of

And the Internet? The year of

12. How long on average do you spend on the computer per day?

☐less than one hour ☐1~2 hours ☐2~3 hours ☐3~4 hours ☐4~5 hours

☐ more than 5 hours

13. What do you use a computer for? (check your **top four** choices)

☐word processing ☐online shopping ☐chatting with friends

☐playing video games ☐playing online games ☐checking e-mail ☐online surfing

☐computer program designing ☐others

~end~

Appendix II
Cognitive Load Scale

Please rate how hard did you have to work in order to understand the material when you were interacting with it. Circle the number that best describes you feel.

About the texts

	not hard at all						very hard
Unit 1- Introduction	1	2	3	4	5	6	7
Unit 2- Peptide bonds	1	2	3	4	5	6	7
Unit 3- Primary structure	1	2	3	4	5	6	7
Unit 4- Secondary structure	1	2	3	4	5	6	7
Unit 5- Tertiary structure	1	2	3	4	5	6	7
Unit 6- Quaternary structure	1	2	3	4	5	6	7

About the pictures

	not hard at all						very hard
Unit 1- Introduction	1	2	3	4	5	6	7
Unit 2- Peptide bonds	1	2	3	4	5	6	7
Unit 3- Primary structure	1	2	3	4	5	6	7
Unit 4- Secondary structure	1	2	3	4	5	6	7
Unit 5- Tertiary structure	1	2	3	4	5	6	7
Unit 6- Quaternary structure	1	2	3	4	5	6	7

About the AR visualization

	not hard at all						very hard
Unit 1- Introduction	1	2	3	4	5	6	7
Unit 2- Peptide bonds	1	2	3	4	5	6	7
Unit 3- Primary structure	1	2	3	4	5	6	7
Unit 4- Secondary structure	1	2	3	4	5	6	7
Unit 5- Tertiary structure	1	2	3	4	5	6	7
Unit 6- Quaternary structure	1	2	3	4	5	6	7

Appendix III

Protein Structure Test

1. Give a definition of protein by answering the following questions

   What are proteins made of?

   How are their components structured?

   name two functions of protein

2. What is a peptide bond?

3. What molecule results when the peptide bond is formed?

4. What are the two major kinds of secondary structure?

5. If eight amino acids form a primary structure, how many peptide bonds will you have?

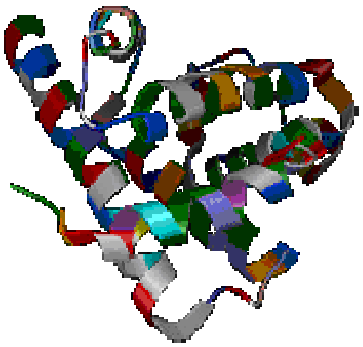
6. What is meant by tertiary structure?

7. How is tertiary structure different from secondary structure?

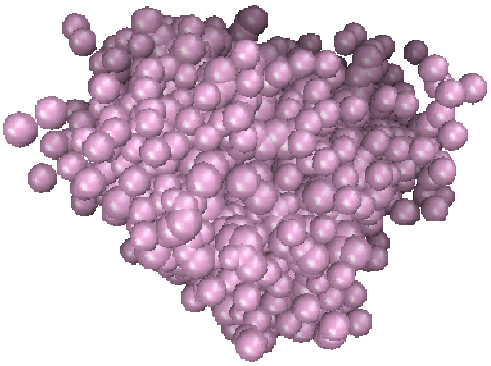
8. Answer the following questions about Picture 1.
   circle where α helices and β strands are.
   find antiparallel and parallel strands if there is any and indicate them.

Picture 1

9. Picture 2 and 3 show one type of myoglobin in different representations.



Picture 2



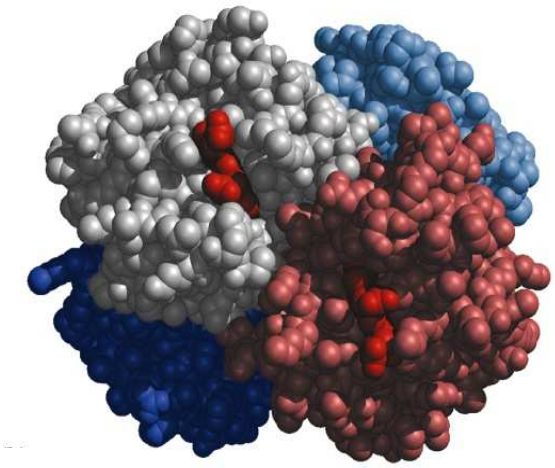
Picture 3

9.1. What are these two representations called respectively?

9.2. What type of protein structure of each one represent?

9.3. What are the differences and similarities of these two types of representations shown as Picture 2 and Picture 3?

10. Answer the following questions about Picture 4



Picture 4

10.1. In Picture 4, each color shows different subunits. What level of protein structure is represented in Picture 4?

10.2. What is the main difference between Picture 4 and Picture 3?