ABSTRACT

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This work describes an experiment comparing knowledge sharing in two distinct team structures. Given the increasing importance of knowledge in the workplace, especially software engineering, we are interested in paradigms that can assist in knowledge management. To this end, we conducted an experiment to determine how the paired or solo programming model affects knowledge sharing during a software project. We show a pattern of results that suggest pair programming has a positive effect on knowledge sharing. We also find development time is somewhat higher when using paired programming, but product quality is unaffected by programming method though these results are not statistically significant.

An Empirical Study of the Tacit Knowledge Management Potential of Pair Programming

by

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Biography

Dylan G. Wilson received a Bachelor of Science degree in computer science from Winthrop University in 2000. After graduating, he entered the graduate program at North Carolina State University in computer science. In 2000, he also began working for BD Technologies as a software engineer. In this role he develops bioinformatics tools that supports a team of biologists performing complex, high-throughput biological experiments. He continues to work at BD today and will consider pursuing a Ph.D. in computer science in the future. He is especially thankful for the support provided by his friends and family throughout his undergraduate and graduate career.

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Knowledge is experience. Everything else is just information.
-- Albert Einstein

1. Introduction

As knowledge becomes more important in the economy, those firms that leverage knowledge efficiently will be more successful [1]. The study of Knowledge Management (KM) has emerged in response to the heightened importance of knowledge and the need to maximize its usefulness. Much of early KM research was Information Technology (IT) focused, often concerned with building software systems to explicitly record, organize, and disseminate knowledge within an enterprise. The scope of KM research has since broadened and become more multidisciplinary. Specifically, KM researchers are building a more holistic view of the KM problem, including the social and tacit aspects of knowledge. The challenge for future KM strategies is to address these social and tacit aspects of knowledge [2-4].

Our research explores how different styles of work might affect knowledge sharing in small software development teams. In particular, we compare knowledge sharing amongst advanced undergraduate student teams of pair programmers versus teams of solo programmers. Pair programming (PP) [5] is a practice whereby two programmers work together at one computer, collaborating on the same algorithm, code, or test. Further, the term *pair rotation* [5] is used to denote when programmers pair with different team members for varying times throughout a project.

In this thesis, we report the results of a six-week experiment in an advanced undergraduate course at North Carolina State University (NCSU). The students were tasked with developing a web-based application in which anonymous course feedback is provided to instructors as a course progresses. The experiment was designed as an investigation of pair programming with pair rotation as means for managing knowledge. The students were formed into groups of 4-5 students that were designated as pair programming groups or solo groups. The solo groups divided the work items, completed the work alone, and integrated their results. The pair programming groups completed a significant amount of their task with two team members at one computer, dynamically changing the makeup of the pairs.

We hypothesize that when compared with traditional solo group development, software developed by groups using pair programming with pair rotation will be characterized by the following:

1. Higher levels of tacit and explicit knowledge sharing as measured by a post-project assessment/examination of each individual's knowledge of their overall project.
2. Comparable or shorter development time, implying that knowledge sharing occurred essentially without cost.
3. Higher product quality, as measured by a set of functional, black box test cases.

In subsequent sections of this paper, we provide background on the experiment and give detailed analysis of the results. Section 2 gives an overview of pair programming and knowledge sharing. Section 3 describes in detail the experiment carried out at NCSU. Section 4 presents the analysis of our results. Section 5 outlines the conclusions and future work.

2. Background and Related Work

A brief introduction to pair programming research results and knowledge sharing follows.

2.1 Pair Programming

Though pair programming (PP) has been practiced sporadically for decades [5], experimental research into PP is somewhat limited. As early as 1975, Jensen found large improvements in programmer productivity using pair programming on a 30 thousand lines of code (KLOC) Fortran project [6]. Nosek ran an experiment [7] in which 15 full-time programmers were organized into five solo programmers and five groups of pair programmers to write a script that performed a database consistency check. Both solo and pair programmers were given 45 minutes to complete the task. Nosek measured the impact of PP on five independent variables: time, readability, functionality, programmer confidence, and enjoyment. Scores were better for pairs in all measures, but the differences in the time and readability scores were not statistically significant. The combined score of these four variables was about 35% better for pairs than for solo programmers. Nosek notes, but does not elaborate, that the scripts produced by some of the pairs were significantly better than the scripts they bought from expert consultants.

Williams conducted a semester-long experiment using 41 junior/senior-level computer science undergraduates at the University of Utah in 1999 [8]. Students completed four assignments during the experiment; two-thirds of the class (28 students) worked in pairs, and the rest of the students (13 students) worked alone. Williams [8-11] observed that at the end of the project, code written by pairs passed 90% of the acceptance tests while code written by soloists passed only 75%, suggesting a pair-to-soloist defect ratio of 0.6. The results were statistically significant at an alpha level of less than 0.01. The pairs took 15% more person-hours to complete the assignments than solo programmers. However, this time increase was not statistically significant. Detailed economic analysis demonstrated an economic advantage of pair programming over solo programming due to higher quality and minimal time increase [12, 13]. Williams has also reported anecdotal evidence from professional software engineers suggesting pairs in industry do not demonstrate this time increase [5].

Nawrocki et al. engaged 21 senior-level students on four different programming projects ranging in size from 150 to 400 LOC [14]. They divided the students into three groups:

- Extreme Programming (XP) [15] with pair programming (XP-PP),
- XP with solo programming (XP-solo), and
- The Personal Software Process (PSP) [16] with solo programming [16].

The researchers found errors were slightly lower with XP-PP than either of the solo processes. They also concluded that XP-PP was less efficient than suggested by Nosek [7] and Williams [8], and that PSP was less efficient than XP-solo. However, the programs were small enough that the research subjects may not have passed though the inevitable pair-jelling phase [5] in which conditioned solo programmers learn to leverage the power of pair programming. The four programs implemented in this experiment were approximately four times longer than in Nosek's study [7], but were still relatively small.

2.2 Knowledge Management

A complete understanding of KM includes the context in which it has emerged and become important. This context is the shift in the world economy from tangible assets, capitol, and labor to information and knowledge. One of the early heralds of this new information-oriented economy was Thomas Stewart in his 1991 Fortune article entitled "Brainpower." In this article, he pointed to knowledge as an important but undervalued and under-utilized asset to business [17]. In his later book, he argues that the economy is undergoing a revolution: "Growing up […] is a new Information Age economy, whose fundamental sources of wealth are knowledge and communication rather than natural resources and physical labor." [1] As pointed out in the original 1991 article, with the increasing importance of knowledge comes an increasing need to manage it efficiently and effectively. The field of KM is a formal response to this need.

There is no universally accepted definition of knowledge. Therefore, we summarize various views of knowledge and create a definition for the purpose of this work. Davenport and Prusak define knowledge as "… a fluid mix of framed experience, values, contextual information, and expert insight that provides a framework for evaluating and incorporating new experiences and information. It originates and is applied in the mind of knowers." [18]. McDermott emphasizes the social, especially human, aspects of knowledge saying "knowing is a human act" and that "knowledge is the residue of thinking" [19]. Horvath defines knowledge in two distinct ways. From a business view he suggests knowledge is " . . . information with significant human value added" [20]. From a philosophical viewpoint, and in agreement with McDermott, he says knowledge is socially constructed and can therefore, never be cleanly separated from the social interactions under which it was created. For this reason, KM "should focus primarily on increasing the frequency and quality of [social] interactions." [20] Finally, he points out that the differences between knowledge and information are context dependent. Knowledge in one context may be information in another.

For the purposes of this work, we synthesize these views into a working definition of knowledge. We define knowledge as a socially constructed entity, with varying degrees of separability from its creator(s) and the context under which it was created. Knowledge sharing therefore requires a sharing of both the knowledge and significant portions of the context under which it exists.

Knowledge exists in two primary forms, tacit and explicit. Explicit knowledge is easily recorded, and exists primarily in a recorded state and requires little or no context beyond what is actually recorded. Explicit knowledge is not very different from information. Examples of explicit knowledge are business documents and formal business processes. Explicit knowledge is easier to manage as its very nature allows it to be separated and stored apart from its creator.

At the far end of the knowledge-information spectrum is tacit knowledge. Tacit knowledge is very difficult to record and requires significant effort to be converted to explicit knowledge. Examples of tacit knowledge might include the process of choosing a design pattern to solve a complex problem or instructions on how to approach the design of a large software system. Tacit knowledge is built from experience and, as we will explore below, is not easily communicated. It is not amenable to the same management techniques as explicit knowledge [20, 21].

Horvath describes tacit knowledge as opaque, sticky, time-sensitive, and context-dependent [20]. It is opaque because it is difficult to know what you know and sticky because that knowledge is resistant to transfer to others. It is time-sensitive because the valuable knowledge, particularly in a business environment, is constantly changing, requiring continuous refresh and relearning. It is context-dependent because understanding the knowledge requires an ability to understand the context under which the knowledge was created and is applicable.

Tacit knowledge is more difficult to manage, but is more valuable than explicit knowledge [20]. For instance, Nonaka claims that the conversion of tacit knowledge to explicit knowledge is where knowledge creation occurs [22]. Horvath's central premise is that tacit knowledge is more valuable than explicit knowledge in four specific areas: innovation, best practices, imitation, and core competencies [20]. He suggests that innovation is tightly linked to tacit knowledge because tacit knowledge is quickly developed and used during innovation, before it can be formalized and recorded. Best practices are often tacit because they are different from prescribed methods. He relates this to the insurance claims processors studied by Wenger, suggesting that the processors worked together to build a tacit set of best practices to get their job done. Imitation is cited because it is difficult to copy a successful business if the success of the business is due in large part to the successful management of tacit knowledge. Unless a competitor steals the people that hold the knowledge, they will not be able to imitate. With respect to core competencies, Horvath says "By getting a handle on its tacit knowledge assets, a firm can better understand its competitive position and can more effectively select and shape the markets in which in competes." [20] Finally, Lindvall highlights the importance of tacit knowledge in software engineering in particular: "Software development is a human and knowledge intensive activity and most of the knowledge is tacit and will never become explicit. It will remain tacit because there is no time to make it explicit." [23] This sentiment is echoed by Chou, Maurer, and Melnik: " … most of the knowledge in software engineering is tacit." [24]

Early work in Knowledge Management focused on explicit knowledge and was IT-centric, attempting to extend techniques from Information Management [21, 25]. McDermott claims that IT inspired KM but cannot alone bring the KM "vision" to fruition: "The great trap in knowledge management is using information management tools and concepts to design knowledge management systems." [21] Horvath also supports this view by stating that early KM was used primarily to make explicit knowledge more accessible [20]. Others, such as Nonaka, Wenger, and Baker reinforce the idea, directly or indirectly, that the application of technology alone is not sufficient to successfully manage knowledge [22, 25, 26].

Since IT alone will not solve the KM problem, additional techniques have been sought. Given the definition of knowledge above, the social and human aspects must be addressed if knowledge is to be managed. McDermott captures the idea: "Leveraging knowledge involves a unique combination of human and information systems." [21] One technique that may help with the human aspect of managing knowledge, particularly tacit knowledge, is the Community of Practice (CoP) [27]. A CoP is a group of people who share some common interest or pursuit, be it professional or not. These individuals gather, either formally or informally, and share stories and insights gained through experience. The CoP emerges because individuals cannot know everything and need the community to succeed in a complex world. According to Wenger, CoP are "organic," "spontaneous," and "informal," meaning that a CoP naturally forms in a grassroots or bottom-up fashion, often by necessity and without a formal structure [27]. Lave and Wenger have formalized the CoP and have highlighted their importance in a knowledge-intensive environment. CoP are a "… privileged locus for the *acquisition* of knowledge" and a "privileged locus for the *creation* of knowledge." [26]

Unfortunately, the very nature of the CoP puts it at odds with conventional KM. The explicit management of an emergent, organic, spontaneous, and informal process is not straightforward. Firms can encourage CoP creation and provide for their existence, but managing and measuring their contribution to the business has been done only on a very limited basis [27, 28]. CoPs are useful for transferring and creating knowledge efficiently, but they are difficult to manage. We propose that there exists a class of hybrid approaches whereby the benefits of the CoP are maintained while the difficulties associated with managing and measuring their contribution is lessened. We further suggest that teams of pair programmers are an instance of this proposed CoP-hybrid approach because they provide a CoP-like environment while retaining a level of manageability and accountability not present in the CoP. Wenger is clear that team and CoP are not equivalent: "A community of practice is not just an aggregate of people defined by some characteristic. The term is not a synonym for group, team, or network." [26] While CoPs are not teams, a team is not prohibited from being or functioning similar to a CoP [29]. We leave this as an open question, but point to the results of our experiment as a positive indication that pair programming teams may be CoP-like.

Our research builds from Palmieri's work studying KM and PP [30]. Palmieri attempted to answer three hypotheses related to: (1) whether PP reduced the impact of employee turnover; (2) whether PP reduced the tendency people have to hoard knowledge, and (3) whether PP has a positive influence on KM by driving knowledge dissemination and retention. Using a 29-question survey, Palmieri surveyed almost 100 professional programmers. The survey offered no conclusion regarding hoarding knowledge but did support the impact reduction of employee turnover, although without statistical significance. He found, with statistical significance, that "[p]air programming is an effective means of knowledge dissemination and knowledge retention that has a positive influence on the Knowledge Management practices of a company or organization" [30]. These findings indicate PP may be a useful tool for KM. We attempted to confirm these findings by measuring how PP impacts knowledge sharing when compared to solo programming.

2.3 Knowledge Management and Pair Programming

Recently comparisons between knowledge management in traditional versus agile programming methodologies has appeared in the literature. Specifically, Chau, Maurer, and Melnik compare and contrast the differences between agile, such as XP, and traditional programming methods with respect to KM [24]. The overarching difference presented between traditional and agile methods relates back to the notions of tacit and explicit knowledge. In traditional programming methods, knowledge sharing occurs via explicit mechanisms such as documentation. This requires the tacit knowledge of developers to be converted to explicit knowledge, which can be a time-consuming and high-effort endeavour, both initially and ongoing. Chau et al. [24] contrast the two methods on several points. Of particular interest here are the comparisons of agile to traditional methods with respect to documentation, requirements and training.

Furthermore, agile methods stress frequent and close customer involvement when gathering and updating software requirements. Traditional methods, on the other hand, are generally oriented toward exposing and documenting requirements at the beginning, often by a single individual or individuals who may not actually develop the system. Frequent and close contact allows agile developers to update and refine their internal model of the problem while the customer updates their needs. This contact and the communication is largely tacit in nature [24].

Finally, Chou et al. [24] highlight the differences in training between the two methods. In traditional methodologies, training is highly formalized, easily repeatable, and expensive (takes development time). Agile methods instead use techniques such as PP for training. In these cases training consists of a junior developer pairing with a senior developer. This can create problems though, as pair rotation can lead to conflicting information, and may lead to reduced productivity of the senior developer(s). The researchers suggest a hybrid approach to training based on the strengths of both methods: "It should be possible to put in place a training infrastructure that has the benefits of both approaches."

A recent case study offers anecdotal evidence that XP may provide KM benefits. In the study, Benedicenti [31] describes how XP played a crucial role in mediating the knowledge-related problems created by a high-turnover environment. In this study, XP proved to be a very successful method for transferring knowledge rapidly and efficiently. Further, the use of agile-like methods was adopted throughout the organization, from junior development staff through upper management. "Everyone is immediately productive, signifying that the group was effective in transferring knowledge. This knowledge is not only theoretical … but it is also practical, leading to very fast development times." [31]

3. Experiment

In this section, we describe the details of our knowledge sharing experiment and discuss some if its limitations.

3.1. Experimental Details

We ran a formal empirical study to compare knowledge sharing between PP and solo programming. The experiment was conducted at North Carolina State University (NCSU) in the advanced-undergraduate (junior/senior) software engineering course in the Fall 2002 semester. The 140 students attended two 50-minute lectures weekly. Additionally, they attended one weekly two-hour hands-on lab each week. There were six lab sections of at most 24 students taught by four teaching assistants. The course had five two-week programming assignments in which the students worked in pairs, followed by a six-week team project. Students pair programmed for the five two-week programming assignments and assimilated to the practice of pair programming during these ten weeks. The experiment was run during the six-week team project.

We divided the students into 34 groups of four or five students, each in the same laboratory section. The groups were subdivided into three types of development: solo (SO), co-located pair (CP), and distributed pair (DP). The solo groups were to work "traditionally" in that the work would be subdivided, assigned to each team member, and later integrated. The co-located paired groups were to subdivide the work, assign the items to dynamic pairs (practicing pair rotation), and later integrate paired work. The distributed pair also subdivided the work and assigned work items to pairs, but unlike co-located pairs, a distributed pair did not work in the same physical location. Instead, they used collaborative screen-sharing technologies, such as Microsoft NetMeeting™ to work in pairs over the Internet. Distributed pair programming has been found to be a viable alternative for academic team projects [32-34].

We used a pre-grouping, self-assessment survey to determine appropriate team composition. This survey can be found in Appendix A. Since our sample size consisted of only 34 groups, we were concerned with the potential of any of the three development-type groups being preferred by higher- or lower-performing students. Therefore, with a focus on forming teams of approximate academic equivalence, we developed an algorithm for forming teams. The team-forming algorithm was performed under the following constraints:

- The students were queried to name class members with whom they did not want to work, and we made a reasonable attempt to respect these requests.
- We avoided any groupings in which there would be only one female in a group.
- We asked the students their preference/ranking of each programming style (SO, CP, or DP) and considered their preferences. Because the majority of development time occurs outside of class, the actual use of the programming style could not be monitored. Therefore, we believe the best method of gaining programming style

conformance was to assign students to their preferred programming style when possible based upon the overall team-forming algorithm.

We calculated each developer's Relative Academic Standing (RAS) as a combination of their self-assessment and their grade in the class. For the self-assessment, we asked each developer to rate his or her experience with Java™ and Java™ Server Pages (JSP). We also provided a free response section where they could list any other relevant technologies with which they were familiar. They were asked to rate themselves on a 0-3 scale for both Java and JSP. In addition, their free response was read and converted to a 0-2 scale based on how much relevant experience they had. The final self-assessment score was calculated as shown in Table 1. The weights for each technology (Java, JSP and Other) represent our estimate of importance of each during the project.

Table 1: Self-Assessment Sample Calculation

Java	2	$0.45\left(\frac{Java}{3}\right)+0.40\left(\frac{JSP}{3}\right)+0.15\left(\frac{Other}{2}\right)$
JSP	1	
Other	1	
Overall Score	0.51	

We calculated their RAS as a weighted average of the self-assessment (30%) and their current grade in the class (70%). We sorted these scores and formed quartiles from which to draw when making groups. To form groups of equal ability, we created teams by drawing one member from each of the four quartiles. This was not always strictly possible due to the constraints listed above, and the fact that some groups had more than four members. Taking into account preferences for working style (paired or unpaired), their statement of who they did not want to pair with, and avoiding groups with one female, we formed 15 co-located pairing groups, seven distributed pairing groups, and 12 solo groups. The formed groups had an average RAS range of 56-73 with a standard deviation of 4.52.

Each group implemented a course-feedback web application using JSP and a MySQL relational database. All groups followed the Extreme Programming (XP) [15] software development methodology. Students used an in-house project management tool (Bryce[1]) to record their requirements (in the form of XP user stories) and to report the time they spent on the project.

We measured the resulting project size using a Java source code metric tool from hyperCision called jMetra[2]. This tool was capable of measuring the LOC, number of classes and number methods for both Java files and JSP files. Since most projects only used JSP, this was an important capability. We did not successfully measure every project due to compile and parse errors. We were able to measure 20 projects and we have summarized the results in Table 2. The LOC count must be considered with one important caveat. The LOC count primarily results from counting JSP files. JSP files are a combination of pure Java, HTML, and JSP tags which are converted into Java classes by the JSP compiler. The resulting Java classes, which are what the LOC count reflects, can be much larger than a typical Java class due to the expansion of the JSP tags and the embedded HTML. For this reason, it may be more instructive to consider the number of methods and number classes when trying to understand the size of the product produced through this project.

Table 2: Summary of project size metrics

Metric	Average	Standard Deviation
LOC	4468	2092
Number of methods	97	33
Number of classes	32	11

Project quality was measured by a set of 40 black-box, functional test cases run by the teaching assistants. Early in the project, the student teams were provided with 31 of the test cases because these tests were considered acceptance test cases; the other nine were instructor-chosen, blind test cases. Project knowledge was measured by a series of questions given as a short-answer and multiple-choice post-project quiz, as will be discussed in Section 4. The quiz was unannounced and questions were detailed, focusing on the specifics of their team implementation. The quiz took 20-30

[1] http://bryce.csc.ncsu.edu
[2] http://www.jmetra.com

minutes to complete and was done as an extra credit assignment at the end of the final examination period.

3.2. Experiment Limitations

There were some limitations to this study. First, we allowed our subjects to choose the type of programming methodology they wanted to use, paired or solo. The choice has some consequences regarding the conclusions we can draw from the experiment. We can still compare the two groups and determine who did better or worse, but we cannot completely explain any observed differences solely based on the difference in programming methodology. By allowing the subject to choose their own treatment group we cannot rule out the existence of a third, undetermined factor, which causes individuals to select one programming method over another and leads to the differences we observed in our dependent variables. On the other hand, we feel strongly that subjects will not participate in the study if they are unhappy with the programming method assigned and that they will be highly unlikely to actually use that method. Our results would have been more compelling if subjects could be assigned to programming style randomly.

Other minor limitations include the design of the quiz, as will be discussed in Section 4. Some of the questions were subjective from both the quiz-taker and quiz-grader's perspective, requiring a guided but subjective answer from the developer and an equally subjective "correct" answer to be arrived at by the quiz grader. Also, the project as a whole could have been better designed to elucidate the differences in knowledge sharing. For example, the project could have been designed to encourage islands of knowledge among the team members.

Empirical studies with students often have external validity concerns due to the size and duration of the project. While our study was well structured, the program was limited in size to the point where a developer could know everything related to their project, inhibiting our ability to fully understand the true KM potential of PP via this experiment. We propose a better project in more detail in Section 5. Additionally, we may have also been more successful at measuring implementation time if the tool used to track time had been automated or more user-friendly. Finally, we were probably overly ambitious with regards to including both distributed pairs and co-located pairs and should have focused solely on PP and SO.

4. Quantitative Results and Analysis

The post-project quiz attempted to measure how much each individual knew about the details of the project implementation. Assuming equal participation, each individual should have the same amount of knowledge about the project, although each would likely have a slightly different focus. A solo developer should have thorough knowledge of the items(s) he or she worked on directly, and only peripherally know about the rest of the project. In contrast, paired developers should have broader knowledge whose average depth is greater than the solo developer. As a proxy measure of developer knowledge, the quiz we developed measures both depth and breadth of knowledge. This measurement will be discussed in more detail below. The quiz was composed of a total of 10 questions with a variety of purposes as outlined in Table 3.

Table 3: Post-Project Quiz Overview

Question Identifier	Purpose	Description
1) Graph	Knowledge Sharing	Diagram major web pages in the implementation
2) Time Accuracy	Group Elimination	Estimate the accuracy of their self-reported project time
3) Session Variables	Not used	List items stored as session variables
4) Schema	Knowledge Sharing	Draw an ER-type diagram of the database schema
5) Extend	Knowledge Sharing	Estimate the amount of work necessary to extend the implementation
6) Technology Familiarity	Baseline for 7-8	Rate on a 1-5 scale personal knowledge of a specific technology*
7) Technology Learned	Knowledge Sharing	Describe how a technology was learned during the project (either individually or from a team member)*
8) Technology Use	Knowledge Sharing	Respond as to whether a technology was used by their group*
9) Model	Group Elimination	Provide the programming model the group used
10) Model Participation	Group Elimination	Estimated percentage of time the individual / group followed the above model
11) Communication	Knowledge Sharing	Describe the primary method for intra-group communication
* Question was repeated three times, once for each of three specific technologies germane to the task (JavaBeans, Cookies, and Prepared Statements)		

Before reporting specific results of the quiz, we explain our approach to filtering and preparing the raw data. We will then consider the response(s) relevant to each hypothesis separately.

For our main hypothesis, knowledge sharing, we initially assumed that the most relevant and meaningful results would be drawn from groups that were diligent in working as either solo or paired programmers. To test this assumption, we used question 10. Question 10 asked each individual to estimate how well he or she followed their assigned programming model which we refer to as model participation (MP). The choices for MP were in the form of percentages, signifying how much of the time a developer programmed using the assigned model; the choices were 25%, 50%, 75% or 90%. Our assumption meant MP would be important in filtering out groups failing to follow their assigned programming model closely enough. Contrary to our assumption, we found no correlation between an individual's MP and their composite quiz score (as will be discussed in Section 4.1.5) for either paired programmers ($r_s = -.08$, $p = 0.55$) or solo programmers ($r_s = -.25$, $p = 0.18$). Figure 1 illustrates this using a box and whisker plot of composite quiz score for each of the four possible levels of MP for all individuals. The same plots for each group (pairs and soloists) look very similar. Due to the lack of correlation we rejected our assumption and accepted all individuals regardless of MP.

We removed five teams due to incorrect administration of the post-project quiz. Due to miscommunication with the teaching assistant, these teams were allowed to reference their project deliverables to answer the quiz questions. Another three individuals were also removed because they also used project deliverables to complete the quiz. We also completely excluded two more groups after reading their team retrospective. In the retrospective the teams discussed whether they used paired or solo development. We rejected teams whose retrospective clearly suggested they didn't use their assigned model at all. For example, one PP team writes: "…we switched to solo programming….I mainly worked on my parts individually…we did a lot of individual programming." This response eliminated this team despite their claim they spent 75% of their time using CP. Finally, since completing the quiz was voluntary, we had some individuals who did not complete the quiz and therefore could not be analyzed with respect to knowledge sharing.

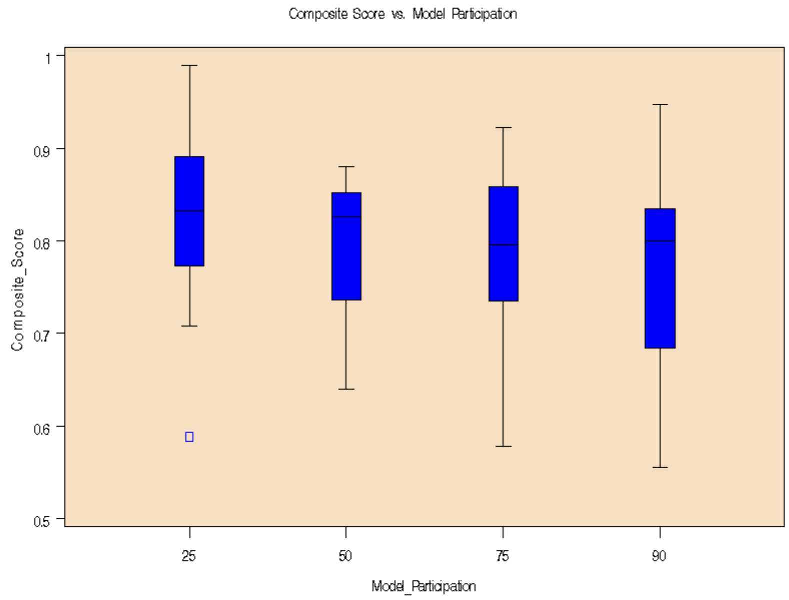

Figure 1: Box plot of composite quiz score by model participation

For the time response, we used question 2, the accuracy of their self-reported time to filter teams who poorly reported their time data via the Bryce tool. We calculated the average time reporting accuracy within each group and only accepted groups whose average accuracy was greater than or equal to 50%, with a group standard deviation of less than 20%.

For implementation quality, the only exclusion of groups was due to lack of data. Quality scores for one lab section were not available. The data were not available because a teaching assistant recorded only the final student scores on the project, not the quality scores computed from the test cases. Table 4 lists the initial and final sample sizes for each major response.

Table 4: Initial and Final Sample Sizes

Grouping	Initial Sample Size	Knowledge Sharing Final Sample Size	Quality Final Sample Size	Time Final Sample Size >=50%, <20%
Co-located Pairs	61 (15 groups)	38 (10 groups)	14 groups	9 groups
Distributed Pairs	29 (7 groups)	19 (6 groups)	5 groups	4 groups
Pairing (Total)	90 (22 groups)	57 (16 groups)	19 groups	13 groups
Solo	50 (12 groups)	32 (9 groups)	10 groups	7 groups
Total	140 (34 groups)	89 (25 groups)	29 groups	20 groups

For all quantitative measures, we analyzed if there is a statistically significant difference between the pair programming and solo programming groups. To accomplish this, we employ a variety of statistical tests as appropriate. For all comparisons, we considered differences statistically significant if $p <= 0.05$. Since we were interested in the difference between paired and solo groups we combined the results from the distributed and co-located pairs into a single group for all results and analyses that follow.

4.1 Knowledge Sharing

In our analysis of knowledge sharing, we examine the following hypotheses:

$H_{0,1}$: The method of programming (solo, paired) and knowledge about project are statistically independent at the 0.05 level.

$H_{1,1}$: The method of programming (solo, paired) and knowledge about project are statistically dependent at the 0.05 level.

We are presenting this section in a bottom up fashion; we analyse each individual question on the quiz first, and finally present a cumulative quiz score. We will relate this to the notion of depth versus breadth of knowledge in the discussion.

4.1.1. Graph

The first question of interest for the knowledge sharing analysis is question 1, "Graph." Students were required to draw a directed graph of the major web pages used in their implementation. To grade this question, we manually examined each group's web application and drew up our own version of the directed graph. When necessary, we also used their source files to make the graph. We compared our correct answer to their answer, making several counts:

- Total number of nodes (N) in our answer, the total number of nodes in their answer (n), and the total number of correct nodes (cn) in their answer; and
- Total number of links (l) they drew and the total number of correct links (cl) they drew.

We deemed a node correct if its name or description were sufficiently close to the actual name or the functionality provided by the node. We deemed a link correct if it connected nodes that were directly connected or indirectly connected where the nodes in-between were not pictured on the graph. We did not attempt to determine the total number of correct links in their entire web application due to the difficulty in accurately and fairly determining every possible link in each implementation.

Using these counts, we produced several ratios; correct nodes to total nodes (cn/N), correct nodes to the number of nodes they drew (cn/n), and correct links to the number of links they drew (cl/l). We took this result and averaged it with the ratio of correct links (cl/l). Table 5 presents a sample calculation. In this example, the overall score of 0.8 is a result of the individual drawing about 50% of the total graph, where everything they drew was 100% was correct.

Table 5: Example Calculation of Graph Score

Total Possible Nodes (N)	29	$0.5\left(\frac{cl}{l}\right)+0.25\left(\frac{cn}{N}\right)+0.25\left(\frac{cn}{n}\right)$
Nodes drawn (n)	13	
Correct nodes (cn)	13	
Links drawn (l)	12	
Correct links (cl)	12	
Overall Score	.80	

For question 1, Graph, descriptive statistics are presented in Table 6 and a box plot is shown in Figure 2. The Shapiro-Wilk[3] test for normality suggested the data were not normal for either pairs (W = 0.88, p < .0001) or soloists (W = 0.63, p < .0001). For this reason, we performed the Wilcoxon rank sums test, the nonparametric version of the t-test. Performance was almost equal, soloists performed slightly better (Mdn. = 0.83) than pairing teams (Mdn. = .82). The difference was not significant, z = 0.15, p = 0.88.

Table 6: Descriptive statistics for Graph

Style	N	Mean	Median	Std. Dev.
PP	57	0.77	0.82	0.14
SO	32	0.75	0.83	0.22

[3] As implemented in R version 1.8.1 for Windows

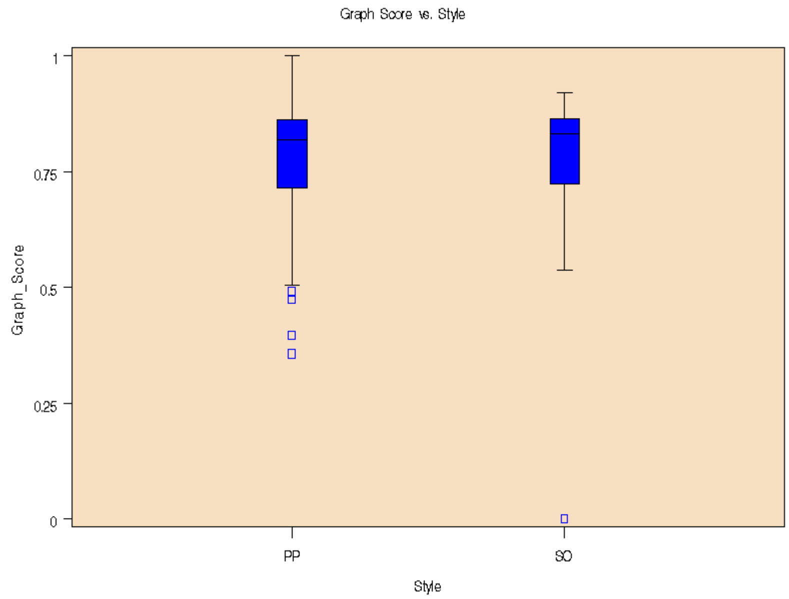

Figure 2: Box plot for Graph

4.1.2 Schema

The dynamic content of each team's web application utilized a relational database (MySQL). For question 2, Schema, we had the developer diagram the database tables and fields. To find the correct answer, we exported each team's database tables and used Microsoft Access to produce a diagram of the actual database schema. We compared the Access-generated diagram to developer's response on the quiz. We made several counts:

- The number of tables and fields they drew (t and f respectively) on the quiz
- The number of <u>correct</u> tables (ct) and <u>correct</u> fields (cf) on the quiz; and
- The number of tables and fields in their actual schemas (T and F respectively)

We took similar ratios as before with both tables and fields (ct/t, ct/T, cf/f, cf/F) and computed a weighted average of these ratios, as shown in

Table 7. We took this approach so we could discriminate and penalize wrong answers more severely than incomplete answers. A sample calculation is presented in

Table 7.

Table 7: Example Calculation of Schema Score

Total Actual Tables (T)	8	$$0.25\left(\frac{ct}{T}\right)+0.25\left(\frac{ct}{t}\right)+0.25\left(\frac{cf}{F}\right)+0.25\left(\frac{cf}{f}\right)$$
Total Actual Fields (F)	58	
Total tables they drew (t)	9	
Total fields they drew (f)	37	
Correct Tables (ct)	7	
Correct Fields (cf)	19	
Overall Score:	.62	

Descriptive statistics for Schema are presented in Table 8 and a box plot is shown in Figure 3. The responses were non-normal in the paired group (W = 0.91, p = 0.0004) and across both groups (W = 0.94, p = .0007) but were more normal in the solo group (W = 0.95, p = .17). Due to overall non-normality, we again used the Wilcoxon rank sums test. Pairs performed slightly better (Mdn. = 0.74) than soloists (Mdn. = 0.72). The difference was not significant, z = 0.12, p = 0.90.

Table 8: Descriptive statistics for Schema

Style	N	Mean	Median	Std. Dev.
PP	57	0.67	0.74	0.23
SO	32	0.70	0.72	0.18

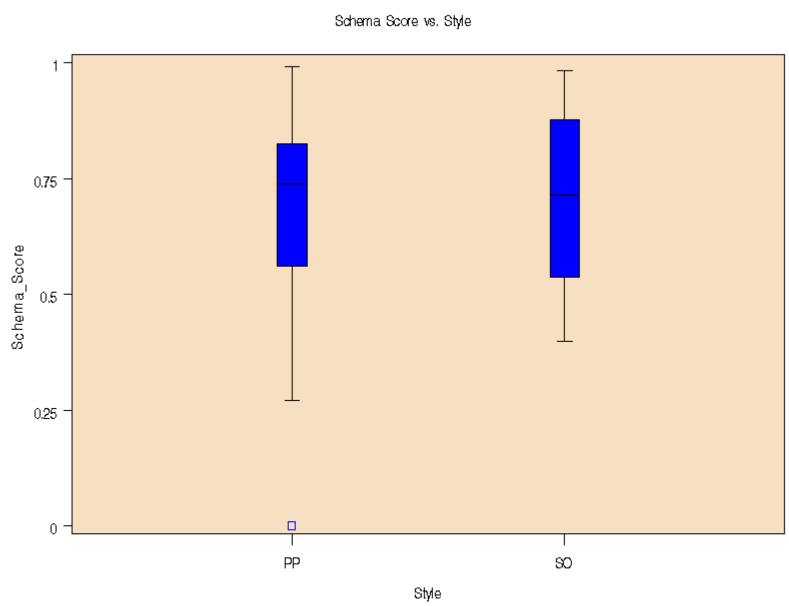

Figure 3: Box plot for Schema

4.1.3 Extend

"Extend," question 5, asked the student to rate on a 1-5 scale how difficult they thought it would be for their implementation to be extended slightly to implement a new requirement. The answers formed a 1-5 Likert scale of difficulty where each answer gave a generic description ranging from "no changes" to "very difficult." To increase understanding of each answer and to make the answer more concrete, we included with each answer a description of what that level of difficulty might entail. To score this question, we studied each group's implementation and produced what we considered the right answer. We then compared our answer to the developer's and found the absolute difference between the two. The resulting data are ordinal, suggesting the Wilcoxon Rank Sums test. Soloists (Mdn = 1.0) did not perform significantly different from paired teams (Mdn = 1.0) on Extend, $z = -.76$, $p = 0.45$. Descriptive statistics for Extend are found in Table 9.

Table 9: Descriptive statistics for Extend

Style	N	Mean	Median	Std. Dev.
PP	57	0.82	1.0	0.68
SO	32	0.75	1.0	0.84

4.1.4 Technology Use

We asked a related set of three questions intended to measure knowledge sharing directly and knowledge of the implementation. We picked three specific technologies or techniques that were likely to be used by some of the groups. These technologies, JavaBeans, cookies, and prepared statements, were specific and germane to what the teams were trying to accomplish with their implementation. We asked (1) how much they knew about the technology; (2) where they learned about the technology; and (3) whether their group used the technology in the project. We asked each question three times, once for each of the three technologies.

The questions regarding how a technology was learned will be considered later, as these are not directly testing knowledge of the project. With respect to knowledge, we now consider the question: "Did your group use technology T_n?" where T_n was one of the three technologies of interest. We refer to this question as "Technology Use." We determined the correct answer by searching through each team's implementations for keywords that must exist if they used a particular technology. We added up the total number wrong for each individual (max = 3) and compared the two groups. These data are ordinal since getting none wrong is better than getting one wrong and so on. The data are not ratio because we cannot reasonably state that someone who got one wrong knows twice as much as one who gets two wrong. Again, since the data are ordinal we used the Wilcoxon Rank Sums test. Pair programmers did slightly better (M = 0.19, SD = 0.40) than soloists (M = 0.44, SD = 0.72) but without statistical significance, z = 1.51, p = 0.13. Table 10 presents relevant descriptive statistics for Technology Use.

Table 10: Descriptive statistics for Technology Use

Style	N	Mean	Median	Std. Dev.
PP	57	0.19	0.0	0.40
SO	32	0.44	0.0	0.72

4.1.5 Composite Quiz Score

As mentioned earlier, we are presenting the knowledge sharing results in a bottom up fashion. We now consider a composite quiz score that combines the previous four questions into a single number. This number represents the average project knowledge of each individual. To compute this average, we first converted Extend and Technology Use to a 0-1 scale. This was accomplished by subtracting the raw response from the maximum possible value for that response (4 for Extend, 3 for Technology Use) and then dividing the result by the maximum value for the response. The terms involving Extend and Technology Use in Table 11 should clarify this calculation. To calculate the composite knowledge score, we averaged the transformed scores for Extend and Technology with the scores from Graph and Schema . The formula and an example calculation are in Table 11.

Table 11: Sample calculation of composite score

Graph	0.91	$0.25(Graph) + 0.25(Schema) + 0.25\left(\frac{(4 - Extend)}{4}\right) + 0.25\left(\frac{(3 - TechUse)}{3}\right)$
Schema	0.92	
Extend	1	

Technology Use	2	
Composite Score	0.73	

Before analyzing these data, we found a strong positive correlation between an individual's RAS (the pre-grouping score, as outlined in Section 3) and the individual's composite score. After dropping two outliers whose RAS was less than 20, we found a strong correlation across groups ($r = 0.48$, $p < .0001$) and within each group for pairs ($r = 0.55$, $p < .0001$) and soloists ($r = 0.39$, $p = 0.033$). Since we were looking for an effect of programming style on composite score, we needed to adjust the response by the covariate (RAS) before comparing composite scores between groups. The appropriate analysis is the Analysis of Covariance (ANCOVA) where RAS is the covariate. Using this analysis we found that RAS was significantly related to the composite score, $F(1, 84) = 27.96$, $p < .0001$, suggesting that higher RAS scores lead to higher composite scores. Figure 4 illustrates the positive association between RAS and composite score for both PP and SO programming models. After controlling for the covariate RAS, the main effect of programming style on composite score was weakly significant, $F(1, 84) = 1.18$, $p = .068$. Furthermore, the difference indicated the composite score for paired programmers was slightly higher ($M_{adj} = 0.80$, $SE_{adj} = 0.011$) than solo programmers ($M_{adj} = 0.76$, $SE_{adj} = 0.015$).

Table 12 provides descriptive statistics for composite, including both unadjusted and adjusted means.

Table 12: Descriptive statistics for Composite

Style	N	Mean	Std. Dev.	Adjusted Mean	Adjusted Std. Err.
PP	57	0.79	.0939	0.80	.011
SO	30	0.77	.09435	0.76	.015

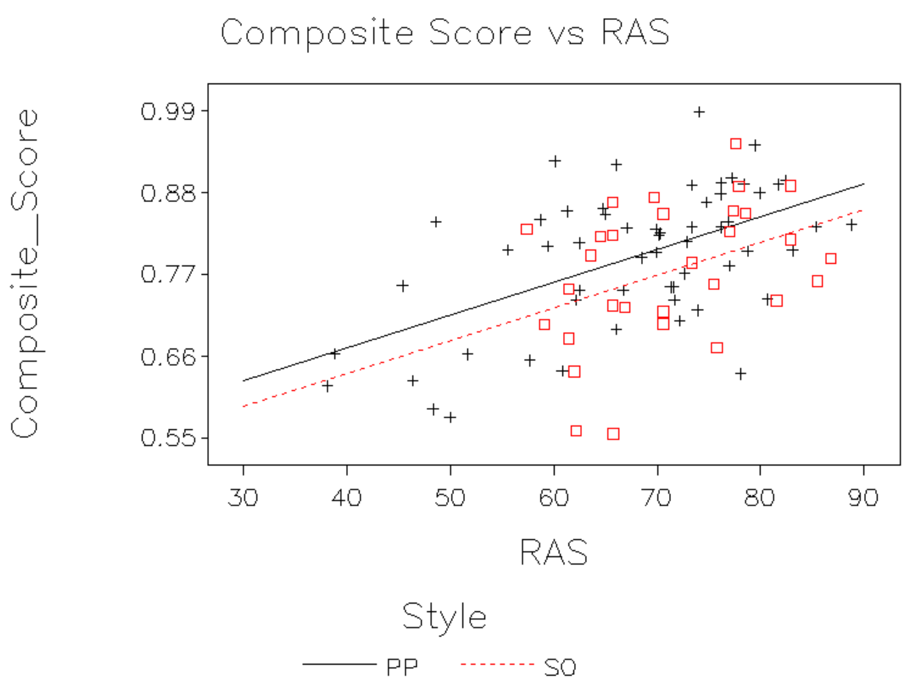

Figure 4: RAS vs. Composite score

To conclude, we return to our original hypothesis regarding knowledge sharing (Hypothesis 1), stating that paired programmers would exhibit a higher level of knowledge sharing than solo programmers. Using our post-project quiz, we have shown no statistical difference in groups when considering each question individually. However, when the results are combined into a composite score, representing the average knowledge level of the developer, we have shown weakly significant evidence suggesting pairs may have a higher level of post-project knowledge than soloists ($p < .068$). Statistically, we must fail to reject the null hypothesis:

$H_{0,1}$: The method of programming (solo, paired) and knowledge about project are statistically independent at the 0.05 level.

4.1.6 Methods of Learning

The previous questions have attempted to indirectly measure knowledge sharing by directly measuring post-project knowledge each individual possessed regarding their team's project. We also measured knowledge sharing directly on the quiz. We asked each developer how he or she came to know about each of the three target technologies mentioned earlier (JavaBeans, prepared statements, and cookies). We were interested in instances where individuals learned about a technology from a team member versus when they learned the technology on their own. Since the data were somewhat sparse, we recoded the responses. We recoded them such that the results were converted from *how many* technologies (Max. = 3) did you learn (on your own / from a teammate) to: did you learn *any* of the three technologies (on your own / from a teammate). The results are presented in Table 13 and Table 14. Each row represents a programming style and each column provides a count of the number of individuals falling into the category defined by the column heading. For example, in Table 13, 38 of 57 pair programmers did not learn any technologies on their own while 19 of 57 did, representing 67% and 33% of pair programmers respectively. A chi-square test of independence was performed to examine the relation between programming model and how new technologies were learned. The relationship between programming model and learning a technology on your own was not significant X^2 (89) = 0.34, p = 0.56. Likewise the relationship between programming model and learning technologies from a team member was also not significant X^2 (89) = 0.0, p = 1.0. In contrast to the questions that produced the composite quiz score above; these two results directly measure knowledge sharing. These results do no allow us to reject the null hypothesis:

$H_{0,1}$: The method of programming (solo, paired) and knowledge about project are statistically independent at the 0.05 level.

Table 13: Learned on Own Contingency Table

	Did Not Learn on Own	Learned on Own	Totals
PP	38 66.67%	19 33.33%	57
SO	24 75.00%	8 25.00%	32
Totals	62	27	89

Table 14: Learned from Team Contingency Table

	Did Not Learn from Team	Learned from Team	Totals
PP	33 57.89%	24 42.11%	57
SO	19 59.38%	13 40.63%	32
Totals	52	37	89

4.2: Implementation Time

Turning our attention to hypothesis 2, we now examine whether programming style had an effect the time necessary to complete the project. Specifically, we state our hypothesis as:

$H_{0,2}$: The method of programming (solo, paired) and implementation time are statistically independent at the 0.05 level.

$H_{1,2}$: The method of programming (solo, paired) and implementation time are statistically dependent at the 0.05 level.

During the project, each developer recorded and reported his or her development time via the Bryce tool. Unfortunately, developers were less than cooperative using the self-reporting mechanism. As mentioned above, we used question 2 on the post-project quiz to drop the least accurate groups with respect to time reporting. We accepted groups with a time reporting accuracy within 50% of actual and where group's standard deviation of accuracy was less than or equal to 20%. Twenty groups out of the original 34 remained and were analyzed for implementation time. Table 15 provides a summary of the time reporting accuracy reported by all individuals on the quiz.

Table 15: Reported Time accuracy

Programming Style	Average Time Accuracy	Std. Deviation of Accuracy
PP	66.86 %	11.66
SO	62.11 %	15.50

We normalized each group's total effort by the number individuals in the group. According to the Shapiro-Wilk test the data were non-normal, ($W = 0.88$, $p = .016$), and we performed the Wilcoxon rank sums test. Pairs took more time per person (Mdn. = 19.48) compared to soloists

(Mdn. = 11.56) and the difference was weakly significant, z = -1.66, p = 0.063. Since we found earlier that RAS was strongly positively correlated with composite score, as reported in section 4.1.5, we explored whether implementation time may be related to average RAS, but we could find no such correlation. Table 16 provides descriptive statistics for implementation time while Figure 5 shows a box plot of effort per person vs. programming style. Although these results offer weak statistical evidence suggesting there may be a difference in implementation time, formally we must fail to reject the null hypothesis:

$H_{0,2}$,: The method of programming (solo, paired) and implementation time are statistically independent at the 0.05 level.

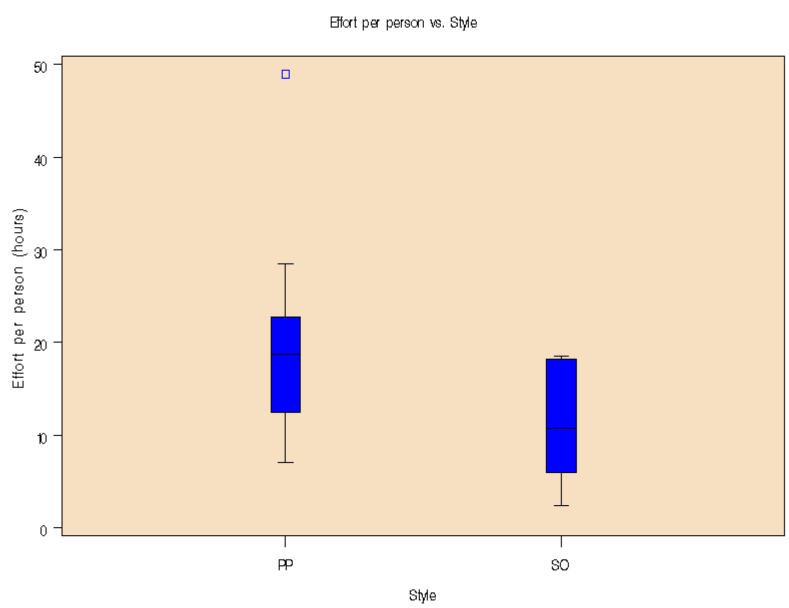

Figure 5: Box plot for Implementation Time

Table 16: Descriptive statistics for Implementation Time

Style	N	Median	Mean	Std. Dev.
PP	13	18.75	19.48	11.10
SO	7	10.75	11.56	6.46

4.3: Implementation Quality

Finally, we address hypothesis 3, that pair programmers would produce a higher quality product than solo programmers. Specifically we test the following:

$H_{0,3}$: The method of programming (solo, paired) and implementation quality are statistically independent at the 0.05 level.

$H_{1,3}$: The method of programming (solo, paired) and implementation quality are statistically dependent at the 0.05 level.

To measure implementation quality, we applied a set of test cases to the final project. These tests were a set of 40 black-box tests, of which students were given access to 31 of the 40 tests. Providing 31 of 40 black-box tests may partially explain this lack of significant difference between the two groups. We attempted to get a breakdown of results by the 31 known to nine unknown tests to examine whether the results might be different for the nine blind tests. Unfortunately, the teaching assistants collected only overall scores so these data were not available.

Soloists had slightly higher quality scores (Mdn. = 0.96) than pair programmers (Mdn. = 0.95). According to the Wilcoxon rank sums test the difference was not significant, $z = -.07$, $p = 0.94$. Summary statistics may be found in Table 17 and a box plot is available in Figure 6. These results offer no statistical evidence that PP had an effect on product quality; we therefore fail to reject the null hypothesis:

$H_{0,3}$: The method of programming (solo, paired) and implementation quality are statistically independent at the 0.05 level

Table 17: Summary statistics for Quality

Style	N	Mean	Median	Std. Dev.
PP	19	0.94	0.95	0.071
SO	10	0.94	0.96	0.069

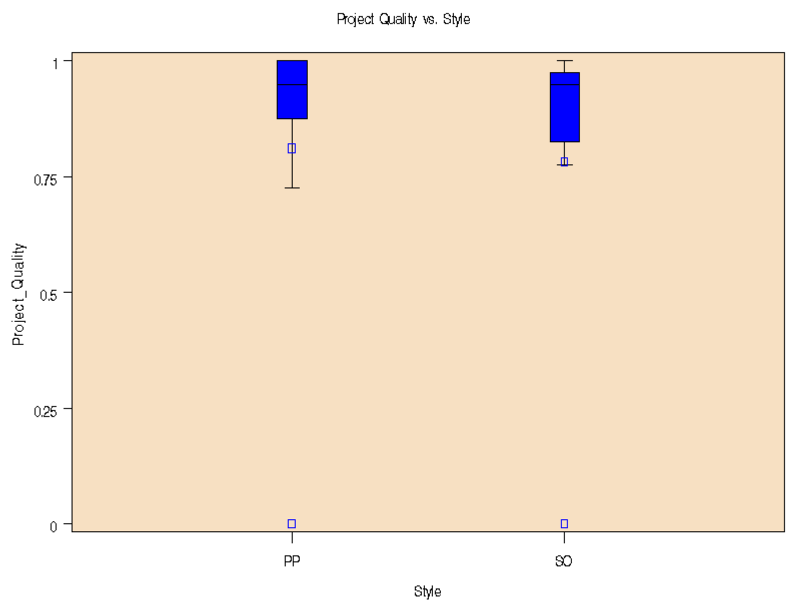

Figure 6: Box plot for Quality

Table 18 provides a summary of all results presented in this section. It presents the results for each response as measured for both groups. The last column presents the result of the appropriate statistical test for each response, and the corresponding p-value.

Table 18: Quantitative Results Summary

Examination	Model Participation	Mean / Median	Standard Deviation	Statistical Result
Knowledge Sharing				
Graph	Pairs	0.77 / 0.82	0.14	z = 0.15, p = 0.88
	Soloists	0.75 / 0.83	0.22	
Schema	Pairs	0.67 / 0.74	0.23	z = 0.12, p = 0.90
	Soloists	0.70 / 0.72	0.18	
Extend	Pairs	0.82 / 1.0	0.68	z = -.76, p = 0.45
	Soloists	0.75 / 1.0	0.84	
Technology Use	Pairs	0.19 / 0.0	0.40	z = 1.51, p = 0.13
	Soloists	0.44 / 0.0	0.72	
Composite Score	Pairs	0.80[4]	0.011[5]	F (1,84) = 1.18, p = 0.068
	Soloists	0.76[4]	0.015[5]	
Learned on Own				X^2 (89) = 0.34, p = 0.56
Learned from Team				X^2 (89) = 0.0, p = 1.0
Time and Quality				
Time	Medium	19.48 / 18.75	11.10	

[4] Mean adjusted for RAS
[5] Standard Error for adjusted mean

	High	11.56 / 10.75	6.46	z = -1.66, p = 0.063
Quality	Medium	0.95 / 0.95	0.071	z = -.07, p = 0.94
	High	0.94 / 0.96	0.069	

4.4: Discussion

Returning our attention to the knowledge-sharing hypothesis, we would like to explore the results of the quiz in more depth. We will discuss in depth the different questions asked on the quiz and how they relate to our definition of knowledge. As mentioned earlier, we recognize two types of knowledge, explicit and tacit. Explicit knowledge is knowledge that can easily be recorded and therefore easily shared. Tacit knowledge, in contrast, is both difficult to record and difficult to share. We have attempted to compare how two very different software development methodologies effect knowledge sharing. Since knowledge is divided into these two predominant forms we point our discussion in the direction of understanding in terms of these two types.

Questions Graph and Schema were measures of explicit knowledge. The information necessary to answer these questions could be gathered from the product deliverable without any contextual information or tacit knowledge. With respect to these two questions, we observed a pattern in the answers to Graph not present or possible with Schema. We found that developers with superficial knowledge of the problem and their team's implementation could get an inflated score without necessarily demonstrating knowledge of their actual system. That is, if the project had a user requirement such as "take survey," and a student knew his or her team had all the major links on a main menu page, he or she could correctly guess and draw a link between a "main menu" node and a "take survey" node. Therefore, a high score on graph did not necessarily mean an individual actually had a working knowledge of the system. For this reason, and the fact that Graph was more subjective, we consider Schema to be a slightly better measure of explicit knowledge.

While Schema and Graph measure explicit knowledge, Extend and Errors attempt to measure developer's tacit knowledge. A correct answer for Extend required knowledge about how the entire system was put together, the overriding principles the group used, and the experience of putting it together. Extend presents an interesting situation. It asks the developer to estimate how hard it would be to extend their implementation given a specific new feature outlined in the question. The strength of the question is that it requires both broad and deep knowledge about the implementation, where most of the knowledge is tacit. Its major drawback is that the answer is subjective, both on the part of the developer and the part of the evaluator. We had to study the implementations carefully and make our subjective estimate of the difficulty and then compare that to the developers' subjective estimate of the difficulty.

We also claim that Technology Use, which requires knowledge of the specific technologies used, is somewhat tacit in nature, because groups did not explicitly record which technologies they used; it was implicit in their implementation. Arguably, those teams that shared more experience and more tacit knowledge about the problem and their solution would have an easier time recalling which technologies the team used, even if the individual had no part in the actual technology. The results of these questions suggest that pairs were slightly better equipped to answer questions requiring tacit knowledge than soloists. Overall, these results were not statistically significant, but the pattern of success for pairs with respect to tacit knowledge argues that there may be some advantage to pairing as it applies to tacit knowledge. As mentioned earlier, we consider PP to be a CoP-like environment that acts as an efficient mechanism of tacit knowledge transport between individuals.

5. Summary and Future Work

In this study we were interested in how programming style, either paired or solo affected three things: knowledge sharing, implementation time, and implementation quality. Summary results for each hypothesis is presented in Table 19. Of these three, we were most interested in knowledge sharing. To assess the difference in knowledge sharing, we made up a post-project quiz asking pointed questions about the product their team delivered. These questions required knowledge of the project, and we claim the level of knowledge exhibited on the quiz is related to how much knowledge was shared across the team throughout the project. From this quiz, we studied the differences in knowledge between groups for each individual question and for the quiz as a whole. We did not find any significant difference between soloists and paired teams for any individual question. We did find weak statistical evidence suggesting paired developers had slightly higher composite quiz scores. This finding only emerged after we controlled for each individual's RAS, or pre-grouping score. The RAS was a combination of current grade in the course and a score based on their experience with technologies that would be important during the course of the project. RAS was positively and significantly correlated with the composite score on the quiz.

Table 19: Summary of findings by hypothesis

Hypothesis	Findings
H1: Pairs will exhibit more knowledge sharing	No evidence on individual questions. Weakly significant evidence found supporting hypothesis for the composite quiz score.
H2: Pairs will have comparable or shorter development time	Weakly significant results suggesting pairs took longer than soloists.
H3: Pairs will produce a higher quality product	No significant evidence suggesting a difference in product quality

We then considered whether programming style affected a difference the time necessary to implement the web application. This comparison resulted in an unexpected finding. There was weak statistical evidence suggesting pairs took almost twice as long to develop the product. This refutes earlier findings, both anecdotal and statistical, such as those in [5, 7, 8][9][13]. One possible explanation is that by combining distributed and co-located pairs we introduced distributed pairing overhead not seen before in co-located pairing. This does not seem to be the case as the results from the distributed groups were quite similar to the results from co-located groups. Another explanation may stem from significant differences in time reporting accuracy between the two groups. We looked for these differences in the reporting accuracies and reporting accuracy standard deviations within paired and solo groups and could find nothing significant. The best explanation may stem from the perceived and actual difficulty in using the Bryce tool to record time spent. For instance, in their retrospective one individual said of the time tracking tool: "The Bryce system discouraged us from entering input because it was confusing, difficult to use and bug-laden." It may be that pairs, due to positive pair pressure were more likely to overcome difficulties with the tool and record their time.

Finally, we also compared the quality of the final product created using the two programming methods. The comparison was made using 40 black box acceptance tests executed by the teaching assistants assigned to the various lab sections. The majority of the tests (31) were shared with the students before the end of the project. We found almost no difference in quality between the two methods.

Knowledge management, particularly tacit knowledge management, is both highly important and thus far, quite difficult to manage when compared to explicit knowledge. One technique that shows promise for the management of tacit knowledge is the CoP. CoP, by their very nature, do not lend themselves to management in a formal business environment. We have proposed the existence of CoP-like hybrid approaches that are imbued with the benefits of the CoP, but are more manageable than the classic CoP. Furthermore, we have suggested that pair programming is an instance of the CoP-hybrid approach. This suggestion is supported, somewhat inconclusively, by this study of student-software engineers. We found that individuals working as pair programmers exhibited slightly higher levels of knowledge of their project than solo programmers. These results were weakly statistically significant, suggesting that a difference between methods may exist.

We consider this work to be a moderately successful exploratory study which suggests PP may have a positive and significant effect on knowledge sharing and knowledge management within software development teams when compared to solo programming methodologies. It would be instructive to carry out a similar experiment that incorporates the lessons we have learned in our study, particularly with respect to the project to be completed and the post-project quiz. Specifically, we recommend a larger Java–only project, designed with obvious points of separation that would encourage silos of knowledge to develop within a team. The quiz would ask specific questions probing into each of the various knowledge silos. Further, in contrast to the quiz developed for this work, the quiz developed in this scenario should have one right answer for as many questions as possible. This will reduce the time necessary to evaluate the quiz and more importantly reduce measurement error due to subjectivity. Ultimately, given the value of knowledge, particularly tacit knowledge, substantiating the findings made here and doing so more conclusively should be of some value to both the software engineering field and the knowledge management field.

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6. Appendices

6.1. Team Project Preference Form

Name ____

Lab Section _______________________________________

What is your experience level with Java Server Page programming

__________ Very Good _____________ Good ___________ Some ________None

What is your experience level with Java programming

__________ Very Good _____________ Good ___________ Some ________None

List any experience you have with web development tools (such as Dreamweaver or Front Page), HTML, ASP, database, etc.

____

____

For your work outside of structured lab times, rank your preference for the following working arrangements (1=most preferable, 3 = least preferable):

________________ **Co-located pair programming.** You meet somewhere in person to work with team members as you do in the class lab periods.

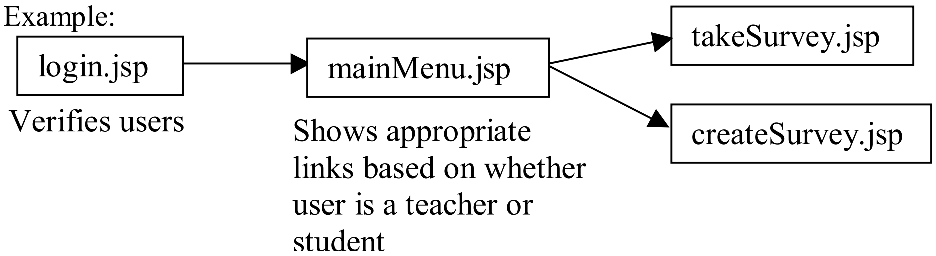
________________ **Distributed pair programming.** You pair program with team members, but you collaborate over the Internet, say from your apartment or dorm room. We'll give you guidance on how to do this. You must have high speed Internet access to choose this option.

_________________ **Solo program.** The program is divided into parts. Each of you choose a part and integrate periodically with your team mates.

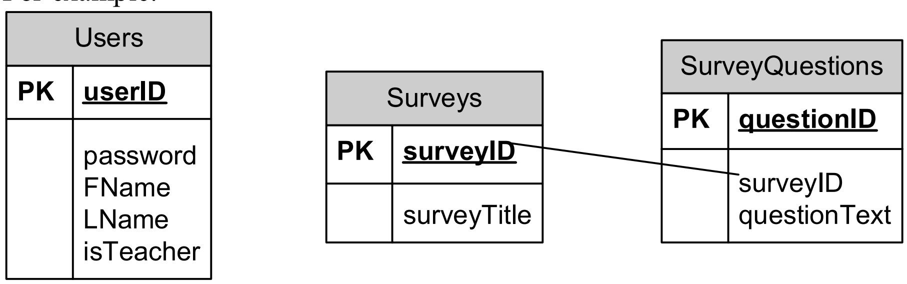
Please list the names of people in your lab section that you DO NOT want to pair with.

6.2. Post Project Quiz

1. Diagram the major JSP files in your system. Draw and label boxes for each major page and draw arrows showing flow between pages. Give a **brief** description for each page. For Example:



2. Diagram the database tables used in your schema and draw connecting lines between primary and foreign-keys. List as many fields as possible and give a short description of each table. For example:



3. List as many of the types of information your implementation stores as session variables or in cookies (example: userId). If you wrote a class like “User” which included several variables please box those variables together and label them with the class name.

4. How accurate are your Bryce time records?
   a. Very accurate (reported time is < 10% off from reality)
   b. Fairly accurate (< 25% off)
   c. Not very accurate (< 50% off)
   d. Not accurate (> 50% off)

5. Suppose the customer made it a requirement to allow for any number of questions in the survey. How hard would it be for your implementation to handle this?
   a. No changes – Our group implemented this ability
   b. Very Easy – We would have to work out the UI for entering an unknown number of questions, but otherwise we have loops that can handle any number of questions when displaying surveys, storing results and calculating results.
   c. Somewhat easy – We have some loops but we also copied and pasted code sections.
   d. Somewhat difficult – We mostly have code that looks the same ten times where only the question number changes.
   e. Very difficult – We didn’t consider that at all, we would have a lot of work to do.

Note: We repeated the next three questions (6-8) three times with three different technologies: JavaBeans, Cookies, and Prepared Statements

6. Rate your knowledge/experience with ***Technology*** on a 1-5 scale where 1 is low and 5 is high

   1 2 3 4 5

7. How did you learn about ***Technology***?
   a. I don't know much about ***Technology***
   b. I knew about them before this project
   c. I learned about them from a team member
   d. I learned about ***Technology*** on my own during this project

8. Did your group use ***Technology***? Yes No
   If yes, did you suggest the group use ***Technology***? Yes No

9. Which programming model did your group use?
   a. Collocated Pair Programming
   b. Distributed Pair Programming
   c. Solo Programming

10. What percentage of time did your group follow the programming model?
    a. > 90%
    b. > 75%
    c. > 50%
    d. < 50%

11. What was the primary method of group communication
    a. Wolfware forum
    b. Majordomo ListServ
    c. Yahoo Groups
    d. AIM/ICQ/MSN Messenger
    e. Other (please specify)____________________________