The Role of Social Context when Learning with Computer Technology: A Series of Meta-Analyses

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ABSTRACT

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This study quantitatively synthesized the literature on the effects of social context (i.e., small group versus individual) when learning with computer technology (CT) on cognitive, process, and affective outcomes. In total, 404 independent findings were extracted from 103 studies involving kindergarten to adult learners. The results indicate that, on average, small group learning had small to moderate positive effects (p<.05) on group task performance ($d_+ = +0.39$), individual achievement ($d_+ = +0.16$), and several other outcomes. No significant social context differences were found on amount of task attempted, academic self-concept, and attitudes toward computers, subject, and teachers. Significant heterogeneity (p<.05), however, was found for several of the outcomes analyzed. Study features analyses were, therefore, performed first univariately and then in multiple weighted least squares regressions to account for the variability in the findings.

In the group task performance outcome, type of tasks, feedback, and presence of others accounted for the significant variability in the findings. When tasks involved factual learning, the effects were consistently positive. When tasks involved more complex problem solving, the superiority of group performance over individual performance was stronger when programs provided no or minimal feedback and when no other peers were working close by.

Different from the results on group task performance, the study features that accounted for the significant variability on individual achievement include group work experience or instruction, group size, subject, type of programs, gender, and relative ability. Small group learning with CT was more effective when: a) students had experience or specific instruction for effective group learning than when no such experience or instruction was reported; b) working in pairs than in 3-5 member groups; c) working with tutorial or drill-and-practice programs than with exploratory or tool programs; d) learning social sciences or computer skills than mathematics, science, reading, and language arts; e) students were female than male; and f) students were of relatively low or high ability rather than medium ability. When all the positive study features were in place, the social context effect was $d_{+} = +0.95$. When none of the positive study features were in place, the social context effect was $d_{+} = -0.22$.

These results and others suggest that social context plays an important role in student learning with CT. However, the role of social context differs between group task performance and individual achievement. While the former is a result of distributed cognition, the latter relies on whether each learner is actively involved in constructing his/her individual knowledge and whether group members assist each other in doing so.

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I. INTRODUCTION

Computer technology (CT) and the tremendous growth of information are transforming the world and the way education is conducted. Electronic data processing, information systems, graphic designs, and computer-mediated communication are making the computer an increasingly indispensable tool in nearly every aspect of work and life. In schools, students are using CT to facilitate their learning in various subjects as well as to acquire knowledge and skills of CT itself to meet the challenges in this rapidly changing technology and information age. For example, in mathematics and science, educators and scientists are beginning to worry that school learning cannot keep pace with the developments in science and suggest using CT to help fill the gap (Molnar, 1997). More efforts are being made by governments and institutions to introduce and integrate computers in schools than ever before. It is estimated that as of the 1992-1993 school year, over 4.4 million computers were installed in more than 17,000 school districts in the U. S. (Sivin-Kachala & Bialo, 1994). In Canada, similar efforts have been made. For example, in 1995, the Ontario Ministry of Education announced a $4 billion plan to put a computer on every student desk (Dare, 1995).

Although CT has great potential for education, past experiences with the integration of older technologies into schools (e.g., radio, television, early computer-assisted instruction) emphasize that merely installing the hardware does not produce the desired outcomes. Successful and effective learning with computers must rely on sound instructional strategies (Albright & Graf, 1991). One of the instructional strategies concerns the social context. Social context here refers to whether students learn with CT individually (i.e., with one computer per student, each working on his/her own task) or in a group (i.e., with two or more students per computer on the same task in a face-to-face setting, or two or more students collaborating on the same task electronically).

Historically, the most common instructional strategy concerning the social context when learning with CT is to have students work individually at a computer. When Skinner (1961) invented his first teaching machine, it was designed to individualize instruction using his principles of operant conditioning through careful sequencing of the instruction and appropriate reinforcement. Later, another influence toward individualized use of computers was from the popular programs such as Individually Prescribed Instruction and Keller's Personalized Systems of Instruction during the 1960s (Kulik, 1983). Because of individual differences such as different prior knowledge, interests, and learning styles, it was believed that learning would be facilitated when instruction could be adapted to the needs of each individual. CT with its flexible sequence, interactivity, and feedback made individualized instruction possible. Therefore, during the 1960s and 1970s, when the computer was first introduced to schools, computer-assisted instruction was usually designed in the form of drill-and-practice and used to individualize student learning. It was hoped that CT would enable each learner to work at his/her own pace, on materials at his/her own difficulty level, and receive immediate feedback for what he/she has done.

The initial expectation that CT would revolutionize education, however, was not realized for many reasons (Means, 1994). First, CT was not adequately advanced and flexible at the time. Second, in terms of the instructional design, the programs were mostly text-based drill-and-practice (Kulik & Kulik, 1986). Third, many teachers feared that they would be replaced by machines. Finally, many teachers and parents feared that learning with computers might produce "social misfits" (Crook, 1994).

Since the 1980s, with the invention of the microcomputer and its ever increasing power, capabilities, and lower prices, there has been a renewed enthusiasm for integrating CT in education. Various types of computer programs have been designed and used in the school. The earlier single type drill-and-practice program has now been expanded into a greater variety: microworlds, intelligent tutorials, simulations and games, interactive hypermedia and multimedia environments, computer-mediated communication, and Web-based courses.

Another difference from the earlier use of computers in schools is that students are more often assigned to work in small groups (Jackson, Fletcher, & Messer, 1986, 1988). Jackson, Fletcher, and Messer cited two reasons for the popular use of small group learning in working with computers. One reason is that having several students work at one computer is a practical solution when there are not enough computers available at school. Another reason is the general change in ideology in public education toward more collaborative or cooperative learning.

Considerable research has been conducted since the mid-1980s investigating the effects of social context when learning with CT. The results, however, are not consistent. Some research found support for group learning. For example, Johnson, Johnson, and Stanne (1986) found that cooperative group learning could overcome the social isolation commonly associated with individual learning with CT and that students learning in small cooperative groups achieved more than students in the individual condition. However, these findings on the effects of group learning were not consistently supported by other research results. In a narrative review of 20 studies comparing small group learning with CT and individual learning with CT, Shlechter (1991) found that the evidence of the effects of small group learning was not yet clear. The research reviewed indicated no consistent effects for either small group or individual learning on students' academic achievement or retention scores.

The apparent inconsistency of the study results on the effects of social context when learning with CT suggests that there might be differential conditions for effective small group or individual learning. Some characteristics in the studies, especially those unique to learning with CT such as learners' experience with computers or design characteristics in the computer program may influence whether small group learning is more effective than individual learning, or vice versa. For example, some learners are experienced computer users; others may be novice users. Inexperience with CT often causes computer anxiety or computer phobia (Jackson, Fletcher, & Messer, 1988). Such anxiety often exaggerates the difficulty level of a computer task. In such cases, collaborating with others may reduce anxiety by providing each other with needed scaffolding and help both emotionally and technically. Similarly, some programs are designed for group collaboration; others are designed for individual practice or exploration. Some programs provide elaborate feedback; others provide minimal or no feedback. Collaborative learning may be more effective when programs are specially designed for group use. On the other hand, programs that provide explanatory feedback or encourage individualized active exploration may give more support for individual learning. Alternatively, the inconsistent findings may be due to the grouping characteristics in the studies such as whether cooperative learning strategies are employed for effective learning.

This unclear nature of the effects of social context when learning with CT and the fact that considerably more research has been conducted on the topic since Shlechter's (1991) review calls for a more systemic and up-to-date research integration of the literature both for theory development and pedagogical guidance.

II. REVIEW OF RELATED LITERATURE

This section reviews areas of the literature that are related to the study on the effects of social context when learning with CT. First, learning and motivational theories that describe why individualized and small group approach support student learning are reviewed to provide a theoretical and conceptual framework. Two areas of empirical research are reviewed next. The research on learning with CT is reviewed to understand how students learn with CT, the general effects of learning with CT, and the instructional design characteristics that impact on student learning. The research on small group learning is reviewed to understand the general effects of small group learning, why small group learning strategies work, and the conditions for effective group work. Finally, the rationale, characteristics, and limitations of meta-analysis for research integration are reviewed.

Learning Theories and Social Context

Support for individualized learning can be found in behavioral and cognitive learning theories. According to behaviorism (e.g, Skinner, 1954), learning occurs through the careful arrangement of the learning environment to induce the correct response and the administration of appropriate reinforcement following the response. For example, in programmed instruction, learning material was divided up into small segments and carefully sequenced so that for every bit of knowledge, the learner would be provided with the opportunity to respond and the correct response would be reinforced. As learners often differ from each other in various ways, the rate of learning also differs from individual to individual (Skinner, 1961; 1987). Therefore, behaviorists believe that learning is most effective when instruction is individualized. Besides programmed instruction, behaviorism has contributed to a number of instructional innovations such as performance objectives, principles of reinforcement, individual learning contracts, and the Personal System of Instruction (Driscoll, 1994). Although many of these innovations (e.g., programmed instruction) are no longer popular today as we recognize the limitations of rote learning, others (e.g., performance objective, principles of reinforcement as a way of motivation) are still widely used with success in many classrooms and in the design of computer programs (Pressley & McCormick, 1995).

Cognitive theories (e.g., Piaget's developmental learning theory, Ausubel's meaningful learning) hold that learning occurs through mental reconstruction of knowledge and that prior knowledge is the most important determinant of what new learning will occur (Driscoll, 1994). According to Piaget (1954), children learn by relating new experiences to their existing knowledge through assimilation or accommodation. Assimilation occurs when a child perceives new objects or events in terms of existing schemas or operations. Accommodation occurs when existing schemas or operations are modified to account for a new experience. Piaget argues that children are at the center of their own development, actively constructing their own understandings of the world. Therefore, cognitivists believe that, for instruction to be effective, it should support the learners' mental reconstruction of knowledge by building on their prior knowledge. Since a learner's existing knowledge may differ across individuals due to different prior experiences or different developmental stages they are at, the best instruction is to adapt to the individual and to encourage active exploration, problem solving, and discovery learning. Although cognitive learning theories differ almost entirely from the behavioral theories of learning, one thing remains common.

That is, both theories regard learning as a solitary endeavor. Therefore, computer programs have been designed and used to support individualized learning under both behavioral and cognitive learning theories until very recently.

With the wide-spread acceptance of Vygotsky's social-cultural theories of learning and cognition, theorists and researchers have begun to see the role of social interaction in facilitating what Piaget called cognitive development (Resnick, 1991). Small group learning can facilitate the process of knowledge construction through peer interaction, elaboration, and cognitive dissonance. Social interaction in small groups may enable learners to see each other's different perspectives, thus promoting disequilibrium of their current state of knowledge and facilitating the accommodation of new knowledge with their existing cognitive structures (Abrami et al., 1995).

The main support for small group learning is found in social-cultural theories of learning (e.g., Vygotsky, 1962, 1978), which regard learning as a social process. Human cognition is believed to be socially grounded, involving the rituals, conventions, technologies, and institutional practices of a culture. Human cognitive development is, therefore, considered as enculturation into the practices of the culture through social interactions. According to Vygotsky, children learn through interacting with adults or more able peers in the zone of their proximal development. Zones of proximal development separate actual development from potential development. When assisted with adult guidance or in collaboration with more capable peers through processes of internalization (Vygotsky, 1978), or appropriation (Newman, Griffin & Cole, 1989), children move beyond their current level of development to achieve the level of their potential development.

The more recent constructivist theories of learning, based on Vygotsky and Piaget, also emphasize the importance of social interaction. According to constructivism, knowledge is constructed by learners as they attempt to make sense of their experiences. Many constructivist theorists adhere to Vygotsky's social negotiation of meaning and believe that social interaction and cognitive elaboration can facilitate individual construction of meaning. Although what the learner already knows provides the framework for constructing new knowledge that may be unique to the individual, group interaction may provide the individual with new perspectives and new information or make the individual aware of gaps and insufficiencies in his/her personal knowledge to aid the process of individual knowledge construction (Perret-Clermont, Perret, & Bell, 1991).

Motivation Theories and Social Context

It is widely believed by both researchers and educators that motivation plays an important role in student educational achievement and task performance (Winne & Marx, 1989). When motivation is high, students tend to exert more effort on their learning tasks. They will work more intensely or persist longer. When motivation is low, less effort will be exerted. They may work less intensely or may give up easily when encountering difficulties.

According to Atkinson's achievement motivation theory, humans have a natural tendency to achieve, to solve problems, and to do well, as well as a tendency to avoid failure (Atkinson, 1966). Motivation in a given task is a balance between the motivation to achieve (which is a function of the motive to achieve, probability of success, and incentive of success) and the motivation to avoid failure (which is a function of the motive to avoid failure, probability of failure, and cost of failure). An important factor in determining a learner's motivational level for learning is, therefore, the difficulty level of the task, especially when learning individually. When the task is too difficult, the individual may have a lower expectancy of success and may give up easily. When the task is too easy, success may not be valued, resulting in low interest and low satisfaction for task completion. Only when tasks are moderately difficult (i.e., challenging but within the ability range of the learner), will the learner be optimally motivated to achieve.

Based on Artkinson's achievement motivation theory, Winne and Marx (1989) proposed a cognitive-processing model of student motivation within classrooms. According to Winne and Marx, student motivation in a given task is both a process and a product of the on-going learning experience. It is recursive and simultaneous. While it determines how actively one is involved in the learning task, it is also 'a state of being' that is constantly updated as one performs the task. Successful progress will activate positive feelings, emotions, and expectations, which will propel one to proceed and exert efforts. If one encounters difficulty (e.g., the intermediate products are not satisfactory), negative emotions and feelings such as frustration would be activated, which, however, may trigger the need for alternative action-related procedures to re-establish control over the task. If the student has alternative procedures, which subsequently lead to progress, more positive emotions such as pride will be activated, which will enhance one's self-concept and increase motivation. If, on the other hand, the student lacks appropriate procedures to re-establish satisfactory progress, then memories of further aversive emotions such as helplessness would be stimulated, resulting in low motivation for further action.

Wiener's (1986, 1992) attribution theory of motivation emphasizes the causal beliefs of students for their success or failure. According to this theory, students' motivations in a given task are often based on whether they attribute their past experiences of success or failure in similar situations to their own efforts, ability, or luck. When past success or failure is attributed to their own efforts and they also believes that their efforts are likely to lead to success in the current task, they will be motivated to try and work hard. On the other hand, when success or failure is attributed to ability or luck, they will be less motivated to exert efforts, which is especially so for low ability students who often attribute their repeated failures to low ability and do not expect success.

Ames (1984) suggests that learning in the individual and small group context may be motivated by different motivational factors. When learning in the individual context, learners may be motivated by competitive motivation or achievement motivation. When evaluation is based on their own performance over time, all students may be motivated to improve, as they are more likely to attribute their success or failure to their own efforts. However, when evaluation is based on some preset criteria or competition with others, low ability students may give up easily as they often have little hope of winning. When learning in small groups, especially when there are group goals, students are often motivated by morality-based motivation, that is, the desire to contribute and help each other to increase the probability of group success. However, when the group fails, lower ability learners are often blamed for their failure to make more contribution, especially when there is inter-group competition. When this happens, the group members may not be motivated to learn together in the future.

When learning in groups, students are also motivated by other motivation factors such as the need for affiliation (Maslow, 1959) and social cohesion (Sharan & Sharan, 1976, 1922). According to Maslow, there are seven basic human needs arranged in hierarchical order: psychological, safety, belonging, esteem, intellectual, aesthetic and self-actualization. Students learning in a group may be especially motivated to exert effort because it may satisfy not only their needs for achievement but also their needs for affiliation and esteem. When a group is cohesive, the members often help each other because they care about the group and the group members.

This section and the previous section reviewed learning and motivation theories that explain how and why individual and group learning works. To better study the role of social context and the conditions for effective small group and individual learning with CT, two areas of research: the research on learning with CT and the research on group learning are reviewed next.

Research on Learning with Computer Technology

CT has been used for learning for about five decades (Monar, 1991). Various types of programs have been developed and used over the time to support student learning: from early mainframe-based or microcomputer-assisted instruction (CAI), to Logo, simulations, hypertext, computer-mediated communication (CMC), and the Internet. Guided by different learning theories, philosophies, or development in technology, each type of program appeared to have its distinct characteristics, purposes, and different ways to facilitate student learning. While research reviews generally showed positive effects for computer-supported learning (e.g., Kulik, Kulik, & Cohen, 1980; Kulik & Kulik, 1991; Niemiec, Samson, Weinstein, & Walberg, 1987), others (e.g., Clark, 1983) argue that the instructional content and the instructional methods embedded in the computer-based instructional treatment are more important than the delivery medium in enabling students to learn. Studies investigating technology design and learner characteristics suggest that different design characteristics have differential effects on student learning and for students of different characteristics.

General Effects of Learning with Computer Technology

Kulik and his colleagues conducted a series of meta-analyses assessing the effectiveness of learning with CT at various educational levels (Kulik, Kulik, & Cohen, 1980; Kulik, Bangert, & Williams, 1983; Kulik, Kulik, & bangert-Drowns, 1985; Bangert-Drowns, Kulik, & Kulik, 1985; Kulik & Kulik, 1986; & Kulik, Kulik, & Schwalb, 1986). Results of these meta-analyses generally indicate small to moderate positive effects. Their latest meta-analysis (Kulik & Kulik, 1991), an update of these earlier meta-analyses, included 254 studies, covering learners of all age levels. Consistent to their earlier findings, they found positive effects of learning with CT for both pre-college students and post-secondary students in all subject areas. Students in the CT condition generally achieved more (ES = +0.30), held more positive attitudes toward computers (ES = +0.34) and instruction (ES = +0.28), and needed less instruction time (average saving time = 30%).

Similar effect sizes were found by other meta-analysts. For example, Niemiec, Samson, Weinstein, and Walberg's (1987) meta-analysis included 48 studies conducted in elementary schools. They found an average moderate effect favoring students learning with CAI (ES = +0.45). These students generally achieved more and held more positive attitudes than those learning in the traditional condition. Samson, Niemiec, Weinstein, and Walberg (1985) reviewed studies at the secondary level. They also found a moderate postive effect size on student achievement (ES = +0.32).

Roblyer, Castine, and King's (1988) meta-analysis included 85 studies on the effects of learning with CT between 1980 and 1987. They found on average small to moderate positive effects on student achievement at the elementary level (ES = +0.32), secondary level (ES = +0.19), and adult level (ES = +0.57). Small positive effects were also found on student attitudes toward self (ES = +0.25) and school/ subject matter (ES = +0.28), but no significant effect was found on student attitudes toward the computer (ES = +0.06).

Characteristics and Effects of Different Types of Programs

Means (1994) classified various types of learning with CT into four main categories according to their distinct purposes, usage, or ways in facilitating student learning: as tutor, as exploratory environment, as tool, and as communication media.

Tutor Programs

Tutor programs are used to directly teach student learning by providing information, demonstration, and practice opportunities. Examples of tutor programs are tutorials or drill-and-practice CAI. The first large-scale computing project, Programmed Logic for Automated Teaching Operation (PLATO), was conducted by Donald Bitzer at the University of Illinois in 1959 (Molnar, 1997). This mainframe-based network system was composed of several thousand terminals at various universities, serving undergraduate education as well as elementary reading through individualized programmed mastery learning. In the 1960's and early 1970's, microcomputer-assisted instruction (CAI) was developed and used widely to assist student learning in mathematics, reading, and other subjects through drill-and-practice and rapid feedback to break away from the whole class lock-step process of instruction (Molnar, 1997; Roblyer, Castine, & King, 1988). In the 1970s, with new developments in artificial intelligence, cognitive science, and advanced technologies, John Seely Brown developed an intelligent CAI program, SOPHIE (a SOPHisticated Instructional Environment), which was able to use intelligently its knowledge base to prompt, stimulate, and tutor students in their learning (Brown, Burton, & Bell, 1974).

Studies on the effects of CAI showed mixed results. While some narrative and box-score reviews (e.g., Jamison, Suppes, & Wells, 1974; Edwards, Norton, Taylor, Weiss, & Van Dusseldorp, 1975; Thomas, 1979; & Orlansky, 1983) found that the majority of studies reported no significant differences between CAI and other methods, other box-score review (Vinsonhaler & Bass, 1972) and meta-analyses (e.g., Burns & Bozeman, 1981; Glass, 1982; Kulik, Kulik, & Bangert-Drowns, 1985; Kulik, Kulik, & Schwab, 1986; Kulik & Kulik, 1991; and Niamiec Samson, Weinstein, & Walberg, 1985) found that, on average, students learning with CAI learned significantly more than students learning under traditional whole class methods at various educational levels. Two meta-analyses focusing on mathematics instruction (Burns & Bozeman, 1981; Glass, 1982) also found that CAI had moderate positive effects on mathematics achievement. Two other reviews of different methods in science instruction, however, showed different results. While Aiello and Wolfle's (1980) meta-analysis found a moderate positive effect of CAI on science achievement, Willett, Yamashita, and Anderson's (1983) meta-analysis found that the mean effect size for CAI was not different from zero.

Exploratory Programs

Exploratory programs are used to encourage student active exploration and discovery learning. Examples of exploratory programs include microworlds (e.g., Logo), simulations, and hypertext-based or hypermedia-based learning environments. Logo was developed by Seymour Papert at MIT in the early 1970's to assist student learning in mathematics through discovery learning (Papert, 1980). Using interesting "microworld" environments such as music and physics, students are encouraged to think as mathematicians while doing Logo programming. Clements and his colleagues conducted a series of studies examining the effects of Logo. Their research indicates that Logo programming increased student performance in both verbal and figural creativity (Clements, 1991), enhanced students' meta-cognitive processing skills (Nastasi, Clements, & Battista, 1990), and increased students' understanding of basic geometry concepts (Clements & Battista, 1990; Yusuf, 1991). Nastasi, Clements, and Battista suggest that the effects of Logo might be due to two of its characteristics: the ability to stimulate students to make their own rules and the open-ended structure that allows students to explore and resolve their cognitive conflicts. Roblyer, Castine, and King's (1988) meta-analysis on the effects of learning with CT between 1980 and 1987 indicates that Logo had moderate positive effects on problem-solving and general thinking skills ($d_+ = +0.39$) and creativity ($d_+ = +0.73$), but the effects on self-concept appeared mixed and not clear.

With increasing power and capabilities in technology in the 1980s, simulations were created and used in science classes to build visual, dynamic, and interactive models of phenomena that would otherwise be impossible, difficult or costly. Research on learning with simulations in science classes (e.g., Woerner, Rivers, & Vockell, 1991) showed that the use of simulations facilitated hypotheses formulating and testing. Research on the use of simulations in teacher training (e.g., Farrell, 1979) found that simulations allowed the pre-service teachers to practice various teaching skills in a low risk environment before facing a classroom of real students. It was found that those working with simulations had greater gains in confidence and problem solving skills.

Hypertext-based or hypermedia-based learning environments were also created in the 1980s. With links between elements of texts as well as other media: graphics, digital sounds, animation, etc., hypermedia-based learning environments aim to enable more learner-controlled active information processing (Jonasson, 1986). The learners can start wherever their interests, prior knowledge, or perspectives lead them, are free to view the interrelationships among chunks of information with enhancement from multiple representations, and to proceed in whatever sequence that makes most sense to them (Driscoll, 1994). For example, Spiro and his colleagues (Spiro, Feltovich, Jacobson, & Coulson, 1991) developed a hypertext-based learning environment, Citizen Kane, for a literature course. The program employs mini-cases for multi-thematic exploration of a film. Hypertext enabled the students to re-edit the film as a function of the thematic content. Spiro and his colleagues' research found that the program facilitated cognitive flexibility in an ill-structured domain. It enabled students to process the information from multi-levels and to construct knowledge through different perspectives and angles.

General Purpose Tool Programs

Tool programs refer to the general-purpose technological tools such as word processing software, spreadsheet software, and data-analysis software, which are used to accomplish tasks such as writing, data storage, data analysis. In writing, mathematics, engineering, and other subject areas, these programs are often used to assist student learning and performance as well as to introduce students to the technologies that are commonly used in the work place.

Dubitsky's (1986) study on the effects of spreadsheet in solving algebra problems indicate that through using the electronic spreadsheet, students learned to understand the functions of the spreadsheet and to devise systematic problem solving strategies that they could transfer from problem to problem. Bangert-Drowns (1993) reviewed studies on the effects of using word processors on students' performance in writing. Their review showed that students writing with word processors produced significantly better writing than did control students. Roblyer, Castine, and King's (1988) meta-analysis on the effects of learning with CT between 1980 and 1987 indicates a small positive effect of using word processors on student achievement ($d_+ = +0.23$).

Computer-Mediated Communication

In the 1990s, computers began to be used as sophisticated communication tools. These tools include e-mail, computer-conferences, computer-supported-collaborative learning (CSCL) systems, and the Internet. They allow groups of teachers and students to communicate and share information electronically, to learn and to collaborate across distance. A wide variety of educative uses of computer-mediated communication (CMC) has been created: distance mentoring, project-based instruction within the classroom or involving community, guest lecturing, retrieval of information from information sources, course management, conferencing, interactive chat, individual and group presentations, peer counseling, practice and experience using emerging technologies, and delivering of instruction (Berge & Collins, 1995). As Berge and Collins described, one of the greatest benefits in using CMC to assist learning is that learning can be extended beyond the classroom walls and that the learners can carry on their learning conversations with their peers and instructors at a time and place convenient to the participants. Another major benefit is that CMC can facilitate participation in authentic projects, collaboration with experts across distance, and writing for a real audience. CMC is being used as both supplemental to conventional classroom instruction and as a medium for distance. For example, in the graduate Educational Technology program at Concordia University, almost all the traditional classroom courses are being supplemented with computer conferences. In the University of Maryland and Duke University, entire Masters degree programs are being offered through the Internet (Molnar, 1997).

Research on the effects of CMC indicated various positive effects. In a study on using CMC in two courses, Ellsworth (1995) found that flexibility and asynchronous communication enhanced both the teaching and the learning process. It helped to meet various learning and personality needs, promote brainstorming and active thinking, facilitate group interaction, timely and individualized feedback, and access to faculty and resources. Shell et al.'s (1996) study indicate that the use of a variety of CMC tools facilitated more constructivist, knowledge-building oriented learning, which appeared to enhance student collaboration and higher achievement for high school students.

Molnar (1997) described some global networks in science education that encouraged project-oriented inquiry-based learning and student collaboration across distance. One example is the National Geographics KidsNet developed by Robert and his staff at TERC. In 1991, the KidsNet was used by more than 6,000 classrooms in 72 countries. Students collected data and analyzed trends on such topics as acid rains and water quality that were of current scientific, social, and geographic interests. They also communicated with each other and with scientists using e-mail. Most teachers using the network reported that it significantly increased students' interest in science.

Factors Influencing the Effects of Learning with Computer Technology

In reviewing general media comparison studies, Clark (1983) argued that the media alone would not do the teaching. Through a re-analysis of a sample of the studies meta-analyzed by Kulik and Kulik and their colleagues during the early 1980s, Clark (1985) concluded that the instructional content and the instructional methods embedded in the computer-based instructional treatment were more important than the delivery medium in enabling students to learn more. Since Clark's caution about the media comparison studies, an increasing number of studies have been conducted investing different design and learner characteristics that may influence the effects of learning with CT. Factors that were found to influence the effects of learning with CT are reviewed in this section.

Technology Design Characteristics

Several meta-analyses have indicated different results for different types of programs. Niemiec, Samson, Weinstein, and Walberg's (1987) meta-analysis on the effects of learning with CT at the elementary level found that the effects appeared higher for drill and practice programs (ES = +0.47) and tutorials (ES = +0.34) than for problem solving (ES = +0.12).

Similar results were found by Kulik nd Kulik's (1991) meta-analysis of studies at pre-college levels but not at post-secondary levels. They found that at pre-college levels, CAI (ES = +0.36) appeared more effective than CEI (i.e., computer-enriched instruction, which is similar to exploratory and tool programs defined by Means, 1994). The mean effect size for the latter was not significantly different from zero. But at the post-secondary levels, the mean effect sizes for CAI and CEI were both significantly positive and not different from each other (ES = +0.27, & +0.34, respectively).

Roblyer, Castine, and King's (1988) meta-analysis of studies published between 1980 and 1987 found no significant difference between drill-and-practice, tutorial, and other applications in mathematics instruction or in reading. The mean effect sizes for each type of programs were small to moderate. However, the authors found that the effects for Logo (ES = +0.39) were significantly more positive than those for CAI (ES = +0.20).

Sivin-Kachala and Bialo (1994) reviewed research on learning with technology in schools during 1990-1994. They found five major instructional design characteristics in software that significantly affected student learning. These five characteristics are types of programs, instructional control, type of feedback, embedding of cognitive strategies, and inclusion of animated graphics. The study that compared the effects of tutorial and tool programs in mathematics for high school students indicate differential achievement gains. While those using the tutorial program demonstrated higher achievement in computational skills, those using the tool program achieved higher in conceptual understanding. Studies on instructional control showed that students learning under mainly learner-control conditions outperformed those learning under mainly system-control conditions. Studies on feedback showed that students working with programs that provided feedback performed better than those working with programs that provided no feedback and that those receiving adaptive feedback performed better than those receiving static feedback. Other studies on cognitive strategies found that embedding cognitive strategies such as repetition, rehearsal, paraphrasing, outlining, cognitive mapping, drawing analogies and inferences in computer programs facilitated student learning. Studies with animated graphics in reading and physics found that using animated graphics in the programs resulted in significantly higher achievement or less time.

Azevedo and Bernard (1995) conducted a meta-analysis of 22 studies on the effects of different types of feedback. They found large positive effects of feedback on student learning when measured by immediate achievement tests (ES = +0.80) and moderate positive effects when measured by delayed posttests (ES = +0.35). They also found that students receiving feedback that not only verified the correctness of the learner's answer but also the underlying causes of error achieved significantly higher than students receiving evaluative feedback only.

Davie and Inskip (1992) studied the effects of designing fantasy role-plays, providing pre-structured databases, and involving guest visits in a computer-mediated distance learning course in literature. Their qualitative research results suggest that these instructional design strategies promoted the success of their CMC course. The authors, therefore, argue that the success of CMC courses depends on creative instructional design to support active learning and participation.

Lundgren-Cayrol (1996) studied the effects of different levels of facilitator intervention in computer conferences that supported an undergraduate distance learning course in educational technology. She found that different levels of facilitator intervention had differential effects on student learning. Those who learned under the higher level of intervention achieved significantly higher than those who learned under the lower level of intervention. Her research suggests that the effectiveness of CMC on student learning may depend on adequate instructional design and intervention.

Learner Characteristics

Jackson, Fletcher, and Messer (1988) studied the effects of experience on microcomputer use in primary schools. The results of their study showed that learners' experience with CT was an important factor. They found that inexperience with computers often caused computer anxiety or computer phobia, which tend to exaggerate the difficulty level of a computer task.

Similar findings were observed by other researchers. When studying the effects of networked computers on class discussion, Bump (1990) noticed that, at the beginning stage, not knowing enough functionality of the computer system added stress to the students. The author found that the students felt frustrated and that it usually took time for students to gain ease in the use of the system. Bridwell, Sirc, and Brooke (1985) also found that experience with computer programs influenced the effects of using word processors for writing.

Niemiec, Samson, Weinstein, and Walberg's (1987) meta-analysis on the studies conducted in elementary schools indicates that CAI (especially drill-and-practice programs) was most effective for lower ability students and for students at lower primary grades, especially when tasks were simple, involving paired association such as vocabulary acquisition and mathematics computation.

Different from the above findings. Roblyer. Castine. and King's (1988) meta-analysis found that the mean effect size for low-achieving students (ES = +0.45). although somewhat higher. was not significantly different from that for regular students (ES = +0.32).

Some researchers have studied gender differences when working with computers. While common hypotheses often suggest that male students learn more from computers, Roblyer, Castine, and King's (1988) review of about 10 studies that provided separate results for males and females indicate no significant difference between males and females in their achievement. Their results on student attitudes toward computers indicate a somewhat higher mean effect size for male students (ES = +0.29) than female students (ES = +0.05). However, the difference was not statistically significant.

This section reviewed the research on learning with CT: the overall effects, the characteristics of different types of programs, and the factors that appear to influence the effects of learning with CT. The research reviewed indicates that, on average, learning with CT generally has more positive effects on various student cognitive and affective outcomes. However, effective learning appeared to depend on some design characteristics in the computer programs such as type of programs, feedback, learner control, and design orientation and some learner characteristics such as learners' computer experience, and ability levels.

Research on Small Group Learning

Ruth Stang (1958) defined small group learning as a small group of students engaged in "planned, shared experiences which foster desirable changes in individual members and in the group as a whole." The concept of students working in small groups was not a modern idea. It was widely used by rabbinic scholars in ancient Israel (Sharon & Sharon, 1990). Small group learning was also advocated by Dewy in the 1930s. Over the years, different types of group work have been used in education. They include peer tutoring, reciprocal peer tutoring, multiple ability groups, and various cooperative learning methods. Most research, however, was conducted since 1970 when cooperative learning methods began to gain their popularity in public schools (Henderson, 1992).

General Effects of Small Group Learning

Johnson and Johnson (1989) reviewed 475 studies comparing classrooms using cooperative learning approaches versus those using competitive or individualistic approaches in a meta-analysis. Their results indicate that students in the cooperative condition learned significantly more than those in either the competitive condition (ES = +0.67) or the individualistic condition (ES = +0.64). Cooperative learning strategies also produced medium to large positive effects on student attitudes toward the subject matter and learning, liking of other students, feelings of social support, and self-concept.

Slavin (1989) did a meta-analysis on cooperative learning studies using his "best evidence" approach. His review showed a small positive effect of cooperative learning on student achievement (ES = +0.21). He also found that students learned significantly more in groups where both positive interdependence and individual accountability strategies were used than when either one was used alone.

Abrami et al. (1995) summarized a number of explanations about why and how cooperative small group learning increases student learning and motivation. Explanations from the motivational point of view include cooperative incentives (Slavin, 1983), social interdependence (Johnson & Johnson, 1989, 1992a, 1992b), morality-based motivation of cooperation (Ames, 1984), and social cohesion (Cohen, 1994a; Sharan & Sharan, 1976, 1992). These explanations focus on the positive interdependence that often exists in cooperative groups. When a group of students are working for a common goal, or perceive that they are positively interdependent, or try to conform to the group norm, or when the group is cohesive, they are encouraged to help each other and to exert their efforts. Learning explanations suggest that students learn more in cooperative groups because of cognitive elaboration (Dansereau, 1985; Webb, 1989), promotive interactions and student thinking (Johnson & Johnson, 1989, 1992a, 1992b), cognitive development (Damon, 1984, 1991), group practice (Rosenshine & Stevens, 1986), or time on task (Fisher & Berliner, 1985). Webb's research on peer help-giving and receiving indicated that giving and receiving correct answers only was not enough in increasing student learning when problem solving and that only elaborate explanation was positively related to student achievement in such situations. According to Johnson and Johnson (1992a), cooperative learning promotes cognitive and meta-cognitive activity through higher instructional expectations, oral rehearsal of materials, heterogeneous groups, perspective-taking, peer monitoring, peer feedback, and controversy among group members. Cognitive developmental views (e.g., Damon, 1984), growing out of those of Piaget and Vygotsky, suggest that children interaction in groups help students master social and cognitive processes, generate ideas, and think creatively. By giving each other feedback and by debating, children are encouraged to abandon misconceptions and search for better solutions.

More recently, Lou et al. (1996) conducted a meta-analysis on within-class grouping comparing small group learning (including both cooperatively structured groups and non-structured groups) versus whole class instruction. Their results showed that, on average, there is a small positive effect of small group learning over whole class instruction on student cognitive achievement (ES = +0.17). However, their results showed that there was significant heterogeneity in the effect sizes analyzed. Through study features analyses, they identified a number of factors that significantly influenced the effects of small group learning on student achievement. These factors and others that influence small group learning are reviewed in the next section.

Factors Influencing the Effects of Small Group Learning

Studies and reviews investigating the variability in the effects of small group learning have identified a number of factors that significantly influenced the effects of small group learning. These factors include grouping characteristics, task characteristics, and learner characteristics.

Grouping Characteristics

A variety of group learning strategies are often employed when students learn in small groups. Members may cooperate on one goal, compete against each other, or have individual goals. In some studies, specific cooperative learning strategies may be used to ensure positive interdependence and individual accountability; in other studies, students may be generally encouraged to work together; in still other studies, there may be no specific strategies employed at all. Slavin's (1989) meta-analysis of cooperative learning studies suggest that strategies that foster both individual accountability and group interdependence are more effective than either alone in ensuring the success of cooperative learning.

Lou et al. (1996) found that students learned more under cooperative outcome interdependence than when no such structure was in place. They also found that the effects of small group learning varied depending on different group sizes, grouping basis, amount of teacher training in the cooperative learning methods, and adaptation of instructional material and methods to small group learning. Their results indicate that small teams of three to four members were more effective than larger groups, that group learning was most effective when grouping was based on mixed criteria than ability alone, and that teacher training in and experience with small group instructional strategies and adaptation of instruction methods and materials helped maximize student learning in small groups.

Task Characteristics

When working in groups, students may work on a variety of tasks. Some tasks may be ill-structured or open; others may be highly-structured or closed. Cohen's (1994b) review on small group learning found that groups were not productive when tasks were closed and there was only one fixed answer to the question; groups were more productive when tasks were open for multiple perspectives and solutions. Cohen argues that in the former case, extended group discussions may not be necessary; whereas in the latter case, open exchange and elaborated discussion are necessary to facilitate conceptual learning through cognitive dissonance and elaboration.

Learner Characteristics

Lou et al. (1996) also found that small group learning had differential effects for students at different relative ability levels. Although the mean effect sizes were positive for all ability levels, group learning was more effective for lower ability learners than for medium ability learners. In addition, they found that different group ability composition had differential effects for students at different ability levels. Lower ability students learned more in heterogeneous groups, whereas medium ability students learned more in homogeneous ability groups. For high ability students, there was no significant difference whether they learned in heterogeneous or homogeneous groups. Lou et al. suggest that low ability students may gain most when they have more able peers provide them with timely and elaborated assistance and guidance; high ability may benefit from providing those elaborated explanations. Medium ability students, however, may not benefit from heterogeneous groups when they neither give nor receive explanations. Homogeneous ability grouping may be better for medium ability students because they may share in giving and receiving explanations among themselves. In addition, Lou et al. suggest that homogeneous grouping may benefit from group cohesiveness since students may share similar expectations about group goals. Medium and high ability students may especially benefit from homogeneous grouping without compromising their aspirations or pace of learning to accommodate the lower ability students.

This section reviewed research on small group learning in general. The research reviewed indicates that, in general, small group learning has positive effects on student learning and other outcomes. Group learning is effective when students learn under cooperative learning strategies such as positive interdependence and individual accountability, when tasks are more open or ill-structured, when group sizes are small, and when teachers have experience with or training in small group instructional strategies and adapt instruction methods and materials for small group learning. Group composition may have differential effects for students at different ability levels. While low ability students generally benefit more in heterogeneous groups, medium ability students benefit more in homogeneous groups.

Meta-Analysis

The goal of educational research is to describe, explain, and predict the processes that improve the quality and efficiency of learning (Wilson, 1972). An individual study, however, is often limited by the scope, sample characteristics, and measurement criteria, etc. used in the study. Thus, it generally has very low generalizability beyond the characteristics of the study. Another constraint that limits the strength of a claim in social research is the way the research hypothesis is tested (Meehl, 1967). Statistical tests can support but never prove a theory or research hypothesis by rejecting its null hypothesis (Campbell & Stanley, 1966). Therefore, to study a phenomenon or some treatment effect more fully, many studies are often conducted on the same phenomenon for different samples and in different settings to test its generalizability as well as to improve internal validity.

The purpose of research integration is to summarize the findings from various studies conducted in one area by various authors in similar or different settings, with similar or different populations, or using similar or different instruments. Through synthesis, the research integration aims to achieve better explanations by accumulating evidence of an effect or by painting a more holistic picture. The research integration tries to examine if a treatment effect is generalizable across settings or populations, or whether the relationship is dependent on some conditions. Cook et al. (1992) listed six criteria for useful research integration:

- It makes the study topic very clear.
- It includes only substantively relevant studies.
- The studies included represent a wide range of populations of persons, settings, and times.
- They represent a heterogeneous collection of exemplars of both the treatment and the effect.
- They represent a broad range of potential explanatory variables.
- Possible biases in individual studies are not more in one direction than the other.

Difference between Narrative Reviews and Meta-Analysis

There are two main approaches for conducting research integration: the traditional narrative review and the quantitative meta-analytic synthesis. The traditional narrative review, by its definition, reviews studies conducted in an area by narrative description. The strength of narrative reviews is that the descriptions of the studies are often detailed. Depending on the perspectives and understanding of the author(s), some insights can be drawn from such reviews. However, narrative reviews often fail to meet all the six criteria described above (Cook et al., 1992). They are often limited in scope. With the hundreds of studies now accumulated in an area, it is often difficult or impossible for a narrative reviewer to describe all the studies in detail any more. Thus, the selection of studies to be reviewed and the interpretation of the results are often dependent upon the reviewer's own perspective or purpose. Consequently, several different narrative reviews can reach contradictory results. For example, the early narrative reviews on cooperative learning produced very contradictory results, which may be due to the fact that each reviewer either explored a different question, or differed in scope, or used individual or group outcome measure, or was selective in research cited (Abrami et al., 1995).

In accumulating results across a group of relevant studies on an issue, a narrative reviewer often determines the treatment effect by vote counting the number of significant positive findings against the number of the significant negative findings. If more votes are positive, then the treatment is judged to have a positive effect; if more votes are negative, then the treatment is judged to have a negative effect; if positive and negative votes are about equal or more votes are not significant, then the treatment is judged to have a mixed or no effect. The judgement via vote counting can be misleading sometimes since a consistent significant effect is not necessarily a large finding (Abrami, Cohen, & d'Apollonia, 1988). For example, with a large sample size, a very small effect can reach statistical significance. On the other hand, a study with a large effect but a small sample size may have a power too low to reject the null hypothesis.

Meta-analysis is a set of quantitative review techniques that has the promise to overcome many of the limitations of the traditional narrative review (Cook et al., 1992). It was first introduced to the social science research by Glass (1976). Meta-analysis usually employs effect sizes (i.e., standardized mean difference between experimental and control groups) as a common metric to integrate the findings from a group of primary studies on the same or similar issue, and aggregate the results across the studies quantitatively to arrive at an estimated mean effect size. In the case where the findings from different studies appear inconsistent, the variability is explored through study features analysis to determine if the treatment effect is moderated by some study characteristics.

Main Approaches of Meta-Analysis

There are three main approaches in conducting a meta-analysis: the Glassian approach (Glass, McGaw, & Smith, 1981), the homogeneity approach (Hedges & Olkin, 1985), and the variance partitioning approach (Hunter, Schmidt, & Jackson, 1982). The main differences among the three approaches are the unit of analysis and the treatment of error variance (d'Apollonia, 1997). The Glassian meta-analysis uses the study as the unit of analysis for each outcome and unweighted regression as the method of exploring variability in the effect sizes. The strength of using the study as the unit of analysis is that the effect sizes are independent. However, it runs the risk of mixing different constructs, creating the so-called "apple-and-orange" problem. Using unweighted regression enables many straightforward inferential statistics to be employed. But the problem of unweighted regression analysis in meta-analysis is that the homogeneity assumption of many of the straight-forward inferential statistical procedures may be violated due to the fact that when the sample sizes in the studies vary greatly, the nonsystematic variances also vary (Hedges & Olkin, 1985).

The homogeneity approach (Hedges & Olkin, 1985) uses the pooled-subject as the unit of analysis and attempts to control for the nonsystematic variance of the effect sizes by weighting on the inverse of the sampling variance. This approach rests on the assumption that the nonsystematic variance of effect sizes is inversely proportional to the sample size of the finding on which the estimate is based. Thus, more weight is given to studies or findings that have larger sample sizes. In addition, the homogeneity approach uses this sampling variance to test whether all findings share a common effect size through a chi-square statistic (Q_T), whether the effect sizes differ across classes of a study feature (Q_B), and whether there is homogeneity within classes (Q_W, or goodness-of-fit). Thus, this approach appeared to improve on the Glassian approach described above through its ability to control for sampling variance by weighting on sample sizes and its ability to test the homogeneity of the effect sizes.

The variance partitioning approach (Hunter, Schmidt, & Jackson, 1982; Hunter & Schmidt, 1990; Hunter & Schmidt, 1994) also used the pooled-subject as the unit of analysis and attempts to control for the nonsystematic error variance. In addition to weighting on sample sizes as in the homogeneity approach, this approach also attempts to correct for study imperfection or artifacts such as random errors of measurements in dependent variables, artificial dichotomization of continuous independent variables, range restriction in dependent variables, or imperfect construct validity. The argument for these corrections is that errors stemming from study imperfections are artifactual in character due to imperfections in research methods, and thus, unnecessarily distort results. The rationale is that perfect studies that are free from measurement errors and are perfectly construct-valid should provide more accurate evaluation of scientific theories.

However, in reality, corrections for these artifacts are not easy since information regarding these artifacts is not always present in all studies. Moreover, it is often difficult to make appropriate corrections for artifacts affecting the independent variable in true experiments (Hunter & Schmidt, 1994).

Strengths of Meta-Analysis

Compared with the traditional narrative review, meta-analysis has several advantages. First, it has a much *greater capacity* than the narrative review to handle the large number of studies that have been conducted in an area (Glass, 1976). While a narrative review can usually handle no more than a dozen studies, a meta-analysis can review several hundred studies.

Secondly, meta-analysis is *more objective* in its review procedures. It usually employs comprehensive electronic searches as well as branching to recover all the relevant literature. It uses predetermined inclusion and exclusion criteria to determine study inclusion for the review. Study features are usually coded and effect sizes extracted by multiple coders and checked for coding reliability. Then statistical methods are used to analyze the results and explore the variability. By employing these objective procedures, meta-analysis can often reduce researcher biases in research integration.

Thirdly, meta-analysis can increase *precision and reliability* in its results (Cooper & Hedges, 1994). By employing effect size as a common scale to integrate findings across studies, it can not only demonstrate whether the treatment has an overall positive or negative effect and whether the difference is significant, but also the magnitude of the treatment effect, and the confidence interval. Through more sophisticated processes of integrating and contrasting primary study results, meta-analysis can separate description of parts of a literature distinguished by both methodological and theoretical criteria and empirically test for the influence of research quality on study outcomes. It can provide a more precise estimate of the association between the treatment and study outcomes than a single study due to increased sample sizes (Matt & Cook, 1994).

Fourthly, meta-analysis can test *generalization* and *moderating influences* of a treatment effect. It can test the generalizability of a finding across settings, time, subjects, and researchers, which is usually not possible by most primary studies and a nuisance for traditional narrative reviewers. The heterogeneity of studies entering a meta-analytic research synthesis provides researchers with opportunities to explore whether any target categories are confounded with substantive irrelevancy and to describe patterns across conditions. Therefore, meta-analysis promotes greater confidence in generalizations than a single study (Cooper & Hedges, 1994; Eagly & Wood, 1994).

Finally, the results of meta-analytic reviews can *indicate weaknesses as well as strengths* of the existing research and direct future primary research in those directions that would most effectively improve the quality of empirical evidence and examine plausibility of theories (Cooper & Hedges, 1994; Eagly & Wood, 1994). For example, when there is a large and diverse body of research studies (i.e., representing a wide range of conditions such as different laboratories, different subject populations, and different measuring instruments) on a particular instructional strategy and the results of the meta-analysis indicate that the effects are quite consistent, we can conclude that there is a strong evidence for the effects of that instructional strategy and no further primary studies are needed on the issue (Eagly & Wood, 1994). When the overall results are heterogeneous but the variance can be explained by a few study characteristics, they provide useful working hypothesis to be tested in future experimental studies. When heterogeneity could not be explained by the study features identified, they can inspire thoughtful analyses and the development of new theories to explain the phenomenon. For successful integration of the research results and the moderator variables analyses, meta-analyses would require adequate information be provided on the statistical results of the studies and on the substantive and methodological features in the study. Results of the meta-analyses can indicate where such information is lacking in the reported studies in the field and encourage primary researchers to provide such information in their future research.

Criticisms and Limitations of Meta-Analysis

Meta-analysis, however, is not without problems or limitations. Most of them concern the way meta-analysis is implemented. For example, one of the criticisms meta-analysis often receives is that the results of a meta-analysis are often sensitive to the inclusion and exclusion criteria used for study inclusion. A different criterion can produce very different effect sizes. Therefore, to do a good meta-analysis, it is important that a meta-analyst be very careful about inclusion and exclusion criteria. The criteria should clearly reflect the right boundaries for the question being investigated in the meta-analysis.

Another criticism meta-analyses sometimes receive is the so-called "apples and oranges" problem, that is, the mixing of different constructs in the effort of integration. However, as Matt and Cook (1994) point out, it is often necessary to mix apples and oranges in order for them to generalize to fruit. A finding that is true across different samples, different settings, etc. has higher generalizability. However, mixing different categories of outcomes such as cognitive and affective outcomes may be confusing. Thus, in this meta-analysis, different categories of outcomes were analyzed separately.

Many meta-analysts extract multiple findings per study, which may cause problems of non-independence of observation. Since statistical tests normally assume independence of data, this may cause inflated error rate in an unpredictable way. However, it may not be so much of a problem when the findings are analyzed separately for different outcomes. Similarly, separate effect sizes provided by different subjects (e.g., males and females) from a study may not be especially problematic when all the effect sizes are weighted by sample sizes since the overall weight provided by separate findings based on separate samples will be the same as one finding based on the total sample (Lou et al. 1996). The problem of non-independence becomes serious when multiple findings are extracted for the same subjects on the same category of outcomes. Fortunately, several ways are now available to deal with this problem: the multivariate solution (Hedges & Olkin, 1985; Raudenbush, Becker, & Kalaian, 1988), the composite solution (Rothenthal & Rubin, 1986), and the univariate solution. Both the multivariate solution and the composite solution usually require estimates of the covariance or correlation metrics among the correlated effect sizes. In the univariate approach, only one of the set of the possibly correlated effect sizes (e.g., the mean or median, a randomly selected effect estimate, or the most theoretically relevant estimate) is used in the analysis (Matt & Cook, 1994).

A major purpose of meta-analysis is to explain variability in the findings through study characteristics. What and how many study features to code is often a critical choice to make. On one hand, when not coding enough study features, the richness of the primary studies is lost and the factors that may have influenced the treatment effects are missed, thus, leading to misspecification in the results. On the other hand, coding too many items may increase coding time and the probability of capitalizing on chance in statistical analyses (Stock, 1994). One solution recommended by some meta-analysts (e.g., Glass, McGaw, & Smith, 1981; Hunter & Schmidt, 1990; Stock, 1994) is to use theoretical or domain knowledge to guide the selection process so that only those substantive and methodologically relevant items are coded. Stock (1994) listed four evaluation criteria: 1) goals of the synthesis; 2) adequacy of information in study reports; 3) whether or not coders can reliably code this information; and 4) costs of coding. Abrami, Cohen, and d'Apollonia (1988) developed a nomological coding procedure that may be used to deal with the second criterion in the above list as well as to avoid possible researcher bias when selecting variables to code. In this procedure, the coder(s) reads all or a sample of the studies to be reviewed and identifies which characteristics have been studied in each study and then counts the frequency of each studied characteristics. Those with enough frequencies can then be included for study features coding.

There are many cases where significant heterogeneity remains after some variability has been accounted for by a few of the study features analyzed. Heterogeneity may threaten statistical conclusion validity, reducing the certainty about the relationship between the identified study features and the treatment. Such a meta-analysis result suggests that the phenomenon is poorly understood and that some unknown factors may explain the variability in the findings. However, publication of these heterogeneous results can serve to inspire future thoughtful analyses, new theories, and novel predictors that can explain discrepant outcomes (Eagly & Wood, 1994).

Care should be exercised in interpreting the results of a meta-analysis even when heterogeneity can be resolved. When all the studies integrated are of experimental nature, causal inferences may be made on the overall effect of the experimental treatment when the confidence interval does not contain zero (Miller & Pollock, 1994). However, for the results concerning study features analyses, meta-analyses can only provide evidence that are correlational in nature because categories of a study feature are between-study factors that no meta-analysts can assign randomly to different studies.

Finally, there is the problem of sampling bias. The meta-analyst is more often confronted with published studies than unpublished studies; therefore, the results are often biased toward usually significantly positive findings than significantly negative and null findings. However, the effect or existence of this bias can be tested in the meta-analysis empirically. As to whether the result from the collected studies represents the true population parameter, this is not a question unique for the meta-analysis but true for the whole paradigm of the quantitative research. If one's purpose is to make inference and generalize from samples to the large population, one can never know absolutely about the real population unless the whole population is tested.

Meta-analysis has extended scientific methodology--including objectivity, precision, and repeatability--to the review of empirical research. With all its limitations, it remains the most advanced technique for research synthesis today. Thousands of meta-analyses have been published in almost all fields in social sciences. In U.S. health care and medical research, it was recommended that health care policies be based on systematic synthesis of research evidence (Cooper & Hedges, 1994).

This section described the goals of research integration, differences between narrative reviews and meta-analyses, main approaches of conducting a meta-analysis, and the strengths and weaknesses of meta-analysis.

Rationale and Purposes of the Study

Learning is a complex phenomenon (Ertmer & Newby, 1993). While some learning and motivation theories emphasize the importance of individual differences, others emphasize the role of social interaction in facilitating cognitive development and motivation. However, the two sets of theories may not be viewed as in an either-or kind of relationship. As is well said by Driscoll (1994), "Theories are shades of truth." Many theories may each provide insight into some aspects of learning and development. The research on learning with CT indicates that several technology and learner characteristics can significantly influence whether and how learning with CT can be effective. The research on small group learning indicates that several grouping, task, and learner characteristics can significantly influence student learning. These findings have important implications for the present study on the effects of small group learning with CT. It is possible that both sets of factors may influence whether small group or individual learning may be more effective when learning with CT.

Viewed from a systems perspective, any learning situation consists of a number of factors that are related to each other, influence each other, and impact on whether or how much learning takes place. In developing a prescriptive distance education learning theory, Boyd (1993) described eight dimensions of these interrelated variables based on theories of organization and effective instruction. These eight dimensions are: psychostructure of the participant, agreed learning goals, subject matter, design of instructional materials, media, social structure, setting, and control (i.e., rules, feedback, and consequences). Boyd argues that all these eight sets of variables should be specified for any viable and effective distance education learning system. An important implication from this theory is that the effects of social context may interact with other factors in the learning system to influence student learning. For example, whether the technology is well designed may influence whether the learner may be motivated enough to work individually. Similarly, whether the learner has sufficient knowledge for a given learning task may influence whether he/she can accomplish the learning goal individually or require some help from others.

Other instructional design theorists (e.g., Bruner, 1961; Reigeluth, 1983; Gagné, 1985) have suggested that instructional strategies should vary depending on different goals of learning, different levels of the task demand, and different learner characteristics. Gagné (1985) categorizes learning into five different types of learning outcomes: verbal information, intellectual skills, cognitive strategies, attitudes, and motor skills. Due to the different nature of learning for each learning outcome, a different set of conditions is required for optimizing learning, retention, and transferability. Different levels of the learner's task knowledge and the level of cognitive processing required by the task may call for different instructional strategies (Gagné, Briggs, & Wager, 1988).

Keller (1983) suggests that instruction should not only be systemically designed on the basis of cognitive considerations but also on motivational considerations.

According to his model of motivational design of instruction, there are four basic conditions for student motivation: interest, relevance, expectancy, and satisfaction. When the learner is interested in a learning task, perceives it to be personally relevant, expects a high likelihood of success, and values the consequences of the success, he/she will be motivated to learn.

Literature on situated cognition suggests that contexts play an important role in human cognition (Brown, Collins, & Duguid, 1989). Knowledge is often context-dependent. What one does in one situation may not be the same in another situation. What is learned in one context may not transfer to a different context. Students learning in the individual or group context may use different strategies for learning and require different skills. For example, Trowbridge and Durnin (1984) found that while students working in small groups were more likely to seek each other's assistance, those working individually were more likely to review earlier parts of the instructional material to arrive at correct answers. Research on problem solving also indicates that problem solving skills used in groups do not necessarily transfer to individual problem solving skills (Bender, 1986).

Meta-analysis, with its ability to integrate a large number of studies, to test for generalizability across conditions, and to identify factors that may account for the variability in the studies, is a useful means to summarize this literature. It can not only estimate the magnitude of small group learning effects, but also test for consistency of the findings across different conditions, and to identify factors that may influence the effects of small group learning with CT.

The purpose of this study is, therefore, to conduct an extensive meta-analysis of the literature to provide a better understanding of the role of social context when students learn with CT and to provide empirical guidance for effective pedagogical practice. The study, thus, attempts to: a) integrate all the primary studies done to date that compared the effects of small group learning with CT versus individual learning with CT on student achievement and other outcomes such as task performance, learning processes, and attitudes; b) resolve inconsistencies in the results from different studies; c) identify conditions for effective small group learning with CT as well as conditions when individual learning might be better; and (d) to build a parsimonious model for effective small group learning with CT. Specifically, the research questions are:

(1) Does small group learning with CT compared to individual learning with CT enhance student achievement and other outcomes? If so, to what extent?

(2) What study features moderate the effects of social context when learning with CT? Is the moderating influence of study features similar across different outcomes?

(3) What are some optimal conditions for effective small group learning with CT? For example, when and what type of small group learning facilitates better learning with CT?

(4) Are there any conditions where individual learning with CT may be more effective? For example, what design characteristics in the computer programs that may facilitate better individual learning?

III. METHOD

The meta-analytic procedures for conducting this review consisted of the following five major steps: operational definitions and inclusion/exclusion criteria, identification of studies, outcomes and study features coding, calculation of effect sizes, and data analyses. Each of these steps is described below.

Operational Definitions and Inclusion / Exclusion Criteria

This meta-analysis quantitatively integrates the findings from primary research on the effects of social context when students learn with CT. The operational definitions of the research question and inclusion / exclusion criteria are:

Focus

- This meta-analysis is concerned with *learning with CT* only. Therefore, all studies must involve situations where students learn with computers (i.e., students are directly involved in using computers for learning, whether learning CT skills or using CT to learn other subjects).

Independent Variable

- The *independent variable* of this meta-analysis is *social context:* learning with computers *in small groups* (i.e., with two or more students per computer on the same task in a face-to-face setting, or two or more students collaborating on the same task electronically) versus learning with computers *individually* (i.e., with one computer per student, each working on his/her own task). Therefore, all studies must have an experimental design comparing small group learning with CT versus individual learning with CT. Case studies without control groups are excluded.

- The minimum group size is 2 and the maximum group size is 10 (10 was used as an inclusion criteria when coding the studies but in reality the largest group size found in any of the studies was 5).

Outcomes

- All cognitive outcomes, process measures, and affective outcomes reported in the primary studies were initially included. Different types of outcomes were coded and analyzed separately (see the Section "Outcomes and Study Features Coding" for the types of outcomes coded and analyzed. Some outcomes were dropped due to small sample sizes).
- For effect size calculation, all studies had to report measured outcomes for both experimental and control groups. Studies with insufficient data for effect size calculations (e.g., with means but no standard deviations or inferential statistics) were excluded.

Study Features

- All levels of learners (from kindergarten to adults, whether school learning or professional training) were included. The purpose of including all levels of learners is to see whether the effects of small group learning with computers are generalizable across different types of students and different types of learning.
- All quantitative studies with sufficient data for both the experimental and control groups were included. Study quality (e.g., student equivalence across conditions) was coded and analyzed.
- Studies that differed along other substantive study features (e.g., technology design characteristics, task characteristics, grouping characteristics, and learner

characteristics) were included, coded, and analyzed to determine if the relationships between the independent variable and the outcomes were moderated by any substantive characteristics in the studies (see the Section "Outcomes and Study Features Coding" for the study features coded and analyzed in this meta-analysis).

Identification of Studies

Studies included in this meta-analytic review were first located through a comprehensive search of the literature and then selected by applying the above inclusion and exclusion criteria. Three main sources were used in the literature search. Electronic searches were performed on the ERIC (1966 - 1996), PsycLit (1974 - 1996), and Dissertation Abstracts (1965 - 1994) databases. Manual searches were performed on the Educational Technology Index and Dissertation Abstracts International (1994-1996). Although the search strategy varied depending on the database, search terms included: *computer* and any terms related to small group learning such as cooperative or collaborative learn*, or small group*, or team**. Finally, through branching from primary studies and review articles, other citations were found and included.

Using the inclusion and exclusion criteria described in the previous section, abstracts from electronic and manual searches, and references from primary studies and review articles were examined to identify potential studies to include. If there was doubt, the study was collected. Next, the collected studies were read independently by two researchers for possible inclusion. Any study that was considered for exclusion by one researcher was cross-checked by the other. One hundred and three studies met all the inclusion criteria. The earliest study was published in 1964 and the latest in 1996, with the majority of the studies published since 1990.

Outcomes and Study Features Coding

The purpose of coding outcomes and study features was to identify those methodological and substantive characteristics that may be responsible for significant variations in the findings. Three steps were followed in coding the studies. First, based on the review of the related literature, a broad coding scheme was developed outlining four categories of substantive study features that might interact with the effects of social context when learning with CT. These four categories are technology characteristics (including type of programs, design orientation, feedback, instructional control, and setting of collaboration), task characteristics (including subject, type of tasks, task structure, and task difficulty level), grouping characteristics (including group composition, group learning strategy, group size, number of sessions, and session intensity), and learner characteristics (including grade level, relative ability level, gender, computer experience, personality, and motivation). In addition, outcome features (such as type of outcome, whose outcome, and outcome measure time) and methodological features (such as student equivalence and publication status) were also outlined in the coding scheme.

Next, using the broad scheme as a framework, a random sample of 25% of the primary studies were nomologically coded to identify salient study features in the literature as well as salient categories within each study feature so as to avoid researcher bias (Abrami, *et al.*, 1988; Abrami, d'Apollonia, & Cohen, 1990). As a result of the nomological coding, the original coding scheme was revised and developed into a codebook (see Appendix 1). Outcomes and features with more than three occurrences in the sample were included in the codebook. Table 1 describes the 16 outcomes included in this review. Table 2 describes the 23 study features analyzed for some of the heterogeneous outcomes in this meta-analysis. Unfortunately, some study features with almost no variability (i.e., over 90% of the findings are of the same category) or too few cases (i.e., less than 5) to be included in the analyses were subsequently dropped.

Finally, each study was coded for its study features and outcomes using the codebook. The coding was performed by two coders independently. Their initial coding agreement was 80.55%. Disagreements between the two coders were resolved through discussion and further review of the disputed studies.

Table 1. *Outcomes included in this meta-analysis*

Outcomes	Description
Cognitive outcomes	
*Group task performance** (G)	Performance scores during tasks (e.g., number of words correct, grades on group assignments). For those learning in groups, group outcome was used.
*Individual achievement** (I)	Achievement scores measured individually by immediate or delayed posttests.
Success rate (I)	Percent of learners who succeeded, involving both group tasks and individual tasks.
Process measures	
Peer interactions (I)	Including cognitive interaction (e.g., help giving and receiving) and positive social interaction (e.g., praise and encouragement).
Interactivity with programs (G)	Amount of time or frequency interacting with computer programs (e.g., time using keyboard, number of reviews, frequency of checking options, elaborate feedback, concepts, doing practice items or quizzes, etc.)
Task completion time (G)	The total amount of time spent in completing the task, including both on-task and off-task time.
Amount of task attempted (G)	Amount of task attempted included number of words attempted, number of responses produced, etc.
Use of strategies (I)	Including use of self-regulating strategies or appropriate strategies for the task.
Perseverance (I)	Task perseverance, e.g., stayed longer on task; had less number of incomplete tasks.
Affective outcomes	
Attitude toward computers (I)	Attitude toward computers in general, including computer anxiety reduction.
Attitude toward subject (I)	Attitude toward the subject being learned.
Attitude toward learning with computers (I)	Attitude toward instruction or learning the subject matter with computers.
Attitude toward group work (I)	Attitude toward learning in small groups.
Attitude toward classmates (I)	Attitude toward classmates, including academic or social recognition.
Attitude toward teachers (I)	Perception of teacher academic support.
Academic self-concept (I)	Self-perception of learning ability.

Note. * Achievement was recoded into *individual achievement* and *group task performance* based on the results of preliminary analyses that the effect sizes for group outcomes were significantly higher than those for individual outcomes. G = group measure for those learning in groups; I = individual measure, that is, all students were assessed individually.

Table 2. *Study features coded*

Study features	Description
Outcome features	
Outcome type	What type of outcome was measured? (In the case of achievement, whether the skills measured were of higher-order or lower-order?)
Outcome measure time	Was the outcome measured during the treatment, immediately after the treatment, or by delayed posttests?
*Group or individual outcome**	Was the outcome group result or individually assessed?
Methodological features	
Student equivalence	What attempts were made to achieve the equivalence of students in the experimental and control conditions?
Publication status	Was the study published or unpublished?
Substantive features	
<u>*Technology characteristics*</u>	
Type of programs	What type of computer programs was used? Was it a tutorial, drill-and-practice, exploratory environment (e.g., simulations, microworlds, Logo), tool for other tasks (e.g., word processor for writing, e-mail or computer-conference for course assignments), or programming languages?
Design orientation	Was the program designed for individual or for group use?
Feedback	Did the program provide no, minimal, or elaborate feedback?
Instructional control	Was the instruction more learner-controlled or more system-controlled?
<u>*Task characteristics*</u>	
Subject	What was the subject area studied by the students?
Type of tasks	Did the task involve problem solving or factual learning?
Task structure	Was the task open or closed?
Task familiarity	Were the students familiar with the task?
<u>*Grouping characteristics*</u>	
Group composition	On what bases were student assigned to groups?
Presence of others	Were other peers working close by?
Group learning strategy	Was there a specific cooperative strategy used in the experimental condition?
Group work exp./ instruction	Did students have previous group work experience or were they provided with training/instructions for effective group work?
Group size	What was the average number of students in a group?
Number of sessions	What was the length of the experimental treatment?

Table 2 (Continued)

Study features	Description
Session duration	What was the intensity of the experimental treatment (e.g., minutes per session)?
<u>*Learner characteristics*</u>	
Grade level	What was the students' grade level? If post-secondary, were the students in college, military, or professional training?
Relative ability level	What was the relative ability level of the students in the class?
Gender	What was the gender of the students?
Computer experience	Did the students have previous computer experience?

Note. The following study features were also coded but dropped from analyses due to 70% missing data or almost no variability: *outcome measure source, teacher support, setting of collaboration, task difficulty level, and amount of task-related peer interaction.*
[a] *Group or individual outcome* was used in the preliminary analyses, whose results led to the subsequent recoding and specification of these characteristics for each outcome described in Table 1.

Effect Size Calculations

The basic index for the effect size calculation is the mean of the experimental group minus the mean of the control group divided by the pooled standard deviation (PSD). The main reason for using the PSD is that the assumption of homogeneity of variance in the population is often reasonable; in which case, the PSD is more stable and provides a better estimate of the population variance than the control group SD alone (Hedges & Olkin, 1985; Hunter & Schmidt, 1990; Rosenthal, 1991). Another reason for the choice of the PSD is that estimated effect sizes based on incomplete results (e.g., t values, F values, ANOVA tables, or p levels) are more readily comparable to calculated effect sizes.

In studies that report posttest data only, we used the posttest mean difference in the numerator and the posttest PSD in the denominator. In studies that provided gain scores or both pretest and posttest data, we used the gain score difference in the numerator to control for pretest differences, but the posttest PSD was used in the denominator rather than the gain score PSD since the gain score PSD is usually smaller than the posttest PSD (Glass, McGaw, & Smith, 1981), thereby more conservative. When the posttest SDs were not provided in the study, we tried to estimate the posttest PSD whenever possible. Such estimation requires *r*, which is, unfortunately, not usually reported in studies. In several cases, we had to estimate a "typical" reliability for that class of measures based upon our knowledge of the literature. Specifically, we estimated $r = .85$ for standardized tests and $r = .75$ for unstandardized tests.

Effect sizes from data in the form of *t* value, *F* value, *p* level, frequencies, *r* value, etc. were computed via formulas provided by Glass, McGaw, and Smith (1981) and Hedges, Shymansky, and Wordworth (1989). For studies that reported only a significance level, effect sizes were estimated. When the direction of the effect was not available, the estimated effect size was zero. When the direction was reported, a "midpoint" approach was taken to estimate a representative *t* value (i.e., midpoint between 0 and the critical *t* value for the sample size to be significant) (Lou et al., 1996; Sedlmeier & Gigerenzer, 1989).

Formulas for calculating effect sizes were entered into the EXCEL (Microsoft, 1993) computer program. Raw data for each finding were extracted by two researchers separately and then checked for reliability. The initial agreement between the two researchers was 93%. Disagreements were subsequently resolved through discussion and further review of the disputed study finding.

Number of Findings Extracted

There are generally two major approaches regarding the number of findings to be extracted from each study: a single finding per study or multiple findings per study. The advantage of extracting only one finding per study is that the assumptions of independence are met for statistical tests. However, a major problem with this approach is that the differences within a study between different categories of subjects (e.g., males and females), or between different treatments under investigation (e.g., groups using specific cooperative learning strategies versus groups that were only generally encouraged to work together), or between different outcome measures (e.g., achievement and task performance) are lost. In addition, among outcomes of different constructs (e.g., achievement and attitude), it is difficult to combine the results or decide which one to extract.

Multiple effect sizes extracted from a single study, on the other hand, can be problematic because methods of research integration normally assume that effect sizes are independent. Non-independence can increase Type I and Type II error rate (Glass, McGaw, & Smith, 1981). This problem of dependence was resolved in the following three ways in the present meta-analyses. First, findings for each outcome were analyzed separately. Only one finding per outcome was extracted from each study unless they represented different subjects. This approach enables one to examine different outcomes while ensuring independence among the findings for each outcome (Gleser & Olkin, 1994). Secondly, multiple effect sizes provided by the same subjects for the same category of outcome (e.g., achievement measured by the posttest and by the delayed posttest) were dealt with by taking a single, random sample from among the set of correlated effect sizes per feature for each affected study. This method eliminates the problem of dependency while ensuring that all levels of a study feature were represented (Lou et al., 1996). For example, for the analysis of outcome measure time, the selection of within-group findings was made randomly from among outcomes measured by immediate posttests and delayed posttests. This method was applied after all the study findings had been extracted and coded. Thirdly, when findings within the same category of outcomes in a study were not distinguishable by any of the study features coded, the effect sizes were averaged.

The study findings were extracted by two coders separately. The initial coding agreement on the number of findings to extract per study was 87.16%. Disagreements between the coders were resolved through subsequent discussion and further review of the disputed findings. Overall, there were 571 findings extracted prior to random sampling within studies. Random sampling procedure was applied to 281 correlated findings, of which 114 independent findings were selected. Analysis on the selected and non-selected findings found no difference between the two sets. Thus, after random sampling, 404 independent findings were selected for analysis.

Data Analyses

The unit of analysis was the independent study finding as is described in the above section. Each outcome was analyzed separately. For each outcome, four steps were generally followed in the data analysis: 1) data screening and outlier analysis, 2) estimation of the mean effect size and homogeneity analysis, 3) if the data were significantly heterogeneous, study features were analyzed univariately to identify what factors significantly accounted for variability across the findings, and 4) based on the univariate analyses, multiple regression models were tested.

Data Screening and Outlier Analyses

Data screening was performed using the SPSS (1994) frequency and descriptive procedures. Several study features with almost no variability (e.g., *measure source, setting of collaboration*) or with over 70% missing data (e.g., *teacher support and task difficulty*) were dropped from further analysis. Categories within some variables (e.g., *group size, subject areas*, and *type of learners*) were combined based on frequency distributions, conceptual meaning, and the preliminary results from the homogeneity analyses.

Outlier analyses were performed using standardized residual procedures (Hedges & Olkin, 1985). A few outliers with standardized residuals larger than ±2.00 were identified. These data were then carefully examined to see if there were any computational errors in the studies or if there was any feature in these studies that made them different from other studies. Two computational errors were found in one study and their values were corrected based on other information available in the study. For other outliers, no computational or other serious errors were found. In addition, no obvious difference was found between these data and others in terms of their study features. Consequently, it was decided that these data should be included in the data analyses, especially in the study features analyses since excluding them might lead to biased results in the study features analyses. However, in order to avoid their over-influence due to their extreme values, these effect sizes were modified (i.e., their absolute values reduced) to bring their residuals just below or equal to ±2.00 (Tabachnick & Fidell, 1996). When there was more than one outlier within an analysis, the differences between these outliers were kept by scaling (i.e., their values were reduced by a common denominator).

Estimation of Mean Effect Sizes and Homogeneity Analyses

Effect sizes extracted from studies were aggregated and tested for consistency via the homogeneity approach developed by Hedges and Olkin (1985). Each effect size was first corrected for bias and weighted by the inverse of its sampling variance. Thus, more weight is given to findings that are more reliably estimated or are based on larger sample sizes. The weighted effect sizes were, then, aggregated to form an overall weighted mean estimate of the small group learning effects (d_+). The significance of d_+ is judged by its 95% confidence interval. If the confidence interval does not contain zero, d_+ is considered significantly positive or negative depending on the sign of the mean value. To determine whether the findings shared a common effect size, the set of effect sizes was tested for homogeneity by the homogeneity statistics (Q_T). When all findings share the same population effect size, Q_T has an approximate chi-square distribution with k-1 degrees of freedom, where k is the number of effect sizes. If the obtained Q_T value is larger than the critical value, the findings are determined to be significantly heterogeneous, meaning that there is more variability in the effect sizes than chance fluctuation would allow. For each heterogeneous outcome, variability in the findings was explored through study features analyses first univariately and then with multiple regression models, which are described in the following sections.

Univariate Analyses of Study Features for Heterogeneous Outcomes

In the univariate analyses, each study feature is tested through two homogeneity statistics, between-class homogeneity (Q_B) and within-class homogeneity (Q_W). Q_B tests for homogeneity of effect sizes across classes. It has an approximate chi-square distribution with p-1 degrees of freedom, where p is the number of classes. If Q_B is greater than the critical value, it indicates significant difference between the classes of effect sizes. When a study feature has more than two classes, Scheffé post-hoc comparisons were performed to control for Type I error rate. Q_W indicates whether the effect sizes within each class are homogeneous. It has an approximate chi-square distribution with m-1 degrees of freedom, where m is the number of effect sizes in each class. If Q_W is greater than the critical value, it indicates that the effect sizes within the class are not homogeneous. Univariate study features analyses were conducted using a meta-analysis software DSTAT (Johnson, 1989) for its relative convenience in analyzing a large number of variables.

Multiple Regression Model Testing for Heterogeneous Outcomes

Multiple regression models were tested using SPSS for Windows 6.1 (SPSS, 1994). Based on the results from the univariate analyses, two weighted least squares regression analyses were performed for each of the heterogeneous outcomes. Analysis 1 aims to identify study features that accounted for significant unique variances in the findings. All the significant predictors identified from the univariate analyses were entered as one block in a simple weighted least squares regression. Significance of each regression coefficient was determined by z-test, where the standard error (SE B) in the output of SPSS was adjusted by a factor of the square root of the Mean Square error (MS_E) for the regression model according to Hedges and Olkin (1985), because the output in the SPSS was based on a slightly different model than the fixed model used here.

In Analysis 2, hierarchical weighted least squares regressions (Hedges & Olkin, 1985) were performed to develop a parsimonious model. Student equivalence between experimental and control groups was entered at Step 1 to control for the methodological quality of the studies. Variables identified from Analysis 1 that explained significant unique variance were entered stepwise at Step 2. Other variables that were significant in the univariate analyses but did not explain significant unique variances in Analysis 1 were entered next stepwise. Then, variables that were marginally significant in the univariate analyses were entered to account for additional variance. Finally, other non-significant variables were entered to see if any additional variance might be explained by other variables. At each block, only variables that explained significant additional variability were retained in the model. In the weighted least squares regression, the sums of squares for regression (Q_R) (which is similar to Q_B in the univariate categorical model analysis) has an approximate chi-square distribution with p-1 degrees of freedom, where p is the number of variables entered. Additional variance explained by each variable is the difference between Q_R at the step and at previous step (i.e., Q_R *increment*), which is tested as a chi-square with 1 degree of freedom when the variable is dichotomous. Model specification is tested by goodness-of-fit statistics Q_E (which is similar to Q_W in the univariate categorical model analysis) with k-p degrees of freedom.

The multiple regression analyses have two advantages over the univariate analyses. First, in the univariate analyses, the Type I error rate may be inflated due to the number of tests that are performed. In the multiple regression analyses, the error rate is controlled. The second advantage of multiple regression analyses is that it can control for shared variance among the study features to develop a parsimonious model.

All variables were dummy coded into dichotomous variables for the multiple regression analyses. A few variables with more than two levels were combined into dichotomous variables based on the post-hoc analyses results of each of these study features. The higher value(s) was coded into 1, the lower value(s) was coded into 0, and the missing data was coded into either 1 or 0 depending on whether its mean effect size was similiar to the higher value or the lower value. The reason for choosing dichotomous variables over creating numerous dummy variables was the concern over low power if numerous dummy variables were to be created (Abrami, Lou, & Spence, under review). The recoding was done globally for all the five heterogeneous outcomes with first considerations given to cognitive outcomes and the pattern that appeared to exist across the outcomes. The main reason for the global coding was to make the coding consistent across the outcomes so that the influence of a study feature on cognitive, process, and affective outcomes may be compared. The specific codings for each variable are presented in the Appendix 2.

Testing the Interactions between Study Features and Outcomes

For study features that explained significant variability but exhibited a different pattern across group task performance and individual achievement outcomes, a multivariate interaction test was performed to test whether the study feature had two separate slopes for the two outcomes according to Raudenbush, *et al.* (1988). First, correlations between the two outcomes from the same study were estimated from the original study whenever possible. For those studies that did not provide such information, estimation was made by averaging the known correlations. Next, covariance for each pair of the correlated outcomes within the same study was calculated and substituted into a variance-covariance matrix. For studies that contributed only one outcome, covariance was zero. Weighted least squares regression was then run to test the interaction effect by testing a series of models in increasing complexity. The first model tested whether there was a common effect by entering only a constant as the predictor. The second model tested whether there was a separate effect size for different outcomes by entering only the two outcomes as predictors. The third model tested whether there were separate intercepts and a common slope by entering the two outcomes and a study feature that showed possible interaction effect. The final model tested whether there were separate regressions for different outcomes. Significant interaction was identified if the increment regression sums of squares for the final model was significant. Multivariate interaction tests were performed using SPSS for Windows 6.1.

IV. RESULTS

A brief description of the studies reviewed in this meta-analysis is provided first, followed by the presentation of the results in cognitive outcomes, process measures, and non-cognitive outcomes.

Description of the Studies

In total, 404 independent effect sizes were extracted from 103 studies involving 18,319 learners comparing the effects of small group learning with CT versus individual learning with CT. The majority of the studies included cognitive outcomes (19 on group task performance, 80 studies on individual achievement, and 4 on success rate). Fewer studies included process measures (31 studies on task completion time, 11 on amount of task attempted, 8 on interactivity with computers, 4 on peer interaction, and 2 on perseverance) or affective outcomes (19 studies on attitude toward subject, 16 on attitude toward computers, 11 on attitude toward group work, 6 on attitude toward classmates, 3 on attitude toward learning subject with computers, 3 on academic self-concept, and 1 on attitude toward teachers).

Most of the outcomes, especially cognitive outcomes, were measured by locally developed or teacher-made instruments or criteria specific to what had been learned on the computer tasks. The majority of the studies were well controlled, employing either random assignment of students to experimental and control conditions or using statistical control for quasi-experimental studies. About half of the studies were published journal articles and half were unpublished reports or doctoral dissertations. Only two studies involved group collaboration via computer-mediated communication; all the other studies involved group collaboration in face-to-face settings. The majority of the computer programs were designed for individual use or had no description of special design for group use. Group size in the studies varied from 2 to 5. Most of the studies involved learners from elementary to university level schools; only a few involved adult professional training.

Cognitive Outcomes

Three cognitive outcomes were analyzed in this meta-analysis: group task performance, individual achievement, and success rate. *Group task performance* compared how well groups as opposed to individuals performed during the computer learning task(s). It included measures such as number of words correct, number of problems solved successfully, or degrees of success. *Individual achievement* refers to individual achievement scores measured individually on immediate or delayed posttests. Most of these measures were locally developed or teacher-made, measuring either higher-order (i.e., problem solving) or lower-order skills (i.e., factual recall) specific to what had been learned on the computer tasks. *Success rate* refers to the percentage of learners who succeeded in either group tasks or individual tasks. Results of the overall effects are presented first, followed with study features analyses of heterogeneous outcomes.

Overall Effects

Results of the overall homogeneity analyses for each of the three cognitive outcomes are presented in Table 3. On average, there was a small to medium positive effect size for small group learning on student cognitive outcomes: group task performance ($d_+ = +0.39$), individual achievement ($d_+ = +0.16$), and success rate ($d_+ =$

+0.28), as compared to individual learning. The 95% confidence intervals indicate that all the three weighted mean effect sizes were significantly positive. On average, students working together in small groups not only produced significantly better results than students working individually during the computer learning tasks, but those who learned in groups also achieved more in the individually measured posttests, and more learners working in groups succeeded than did those working individually.

Table 3. *Weighted mean effect sizes on cognitive outcomes*

		before outlier procedures			after outlier procedures		
Outcomes	*k*	d_+	95% CI	Q_T	d_+	95% CI	Q_T
Group task performance	34 (19)	+0.40	+0.27/+0.53	77.92*	+0.39	+0.27/+0.52	68.78*
Individual achievement	146 (80)	+0.16	+0.12/+0.21	253.40*	+0.16	+0.11/+0.20	204.08*
Success rate	6 (4)	+0.28	+0.03/+0.53	4.28			

Note. *k* is the total number of independent findings integrated. The values in parentheses are the numbers of studies from which the findings were extracted. d_+ is the weighted mean effect size. 95% CI is the 95% confidence interval for d_+, Q_T is the homogeneity statistics, where * = p<.05, indicating that the effect sizes integrated are heterogeneous.

However, homogeneity statistics indicate that the findings in both group task performance (Q_T = 68.78, df = 33) and individual achievement (Q_T = 204.08, df = 145) were significantly heterogeneous. These results indicate that the superiority of group learning over individual learning with computers was not uniform on either group task performance or individual achievement. Therefore, study features analyses were conducted on each of the two datasets.

Study Features Analyses on Group Task Performance Findings

In the group task performance data, the effect sizes ranged from -0.86 to +2.53, with 28 effect sizes above zero favoring group task performance and 6 effect sizes below zero favoring individual task performance. The learning sessions in most studies lasted 10-60 minutes. Only one study reported that the students had no computer experience and thirteen reported that the students had computer experience. Only one study reported separate results for students of different relative ability levels. No study provided any information about program design orientation and student group work experience or instruction. As a result, these study features were not analyzed for this dataset.

Univariate Analyses

Table 4 presents the results of the univariate analyses on group task performance findings. Of the nineteen study features analyzed, five were found to explain significant variability in the findings, which are described in the following subsections.

Methodology characteristics. Student equivalence was significantly related to the variability in the group task performance findings (Q_B = 16.30, df = 1). The mean effect size for findings reported in well-controlled studies (d_+ = +0.46) was significantly more positive than for those reported in studies where student ability equivalence was not controlled or unknown (d_+ = +0.10). However, within-class homogeneity statistics indicate that the subset of findings from well-controlled studies (Q_W = 59.93, df = 28) were not homogeneous, indicating considerable variability within the subset. Publication status was not significantly related to the group task performance findings.

Table 4. *Results of univariate study features analyses: Group task performance findings*

Study features	Q_B	k	d_+	95% CI	Q_W
	Outcome and methodology features				
Student equivalence	4.43*	34			
well-controlled		29	+0.46	+0.32 / +0.60	59.93*
non equivalent/unknown		5	+0.10	-0.20 / +0.40	4.43
Publication status	0.07	34			
	Technology characteristics				
Type of programs	2.49	34			
Feedback	17.72*	25			
no		17	+0.46	+0.25 / +0.67	26.03
minimal		6	+0.52	+0.22 / +0.82	9.06
elaborate		2	-0.84	-1.43 / -0.25	0.01
Instructional control	0.87	33			
	Task characteristics				
Subject	1.74	32			
Type of tasks	12.67*	34			
problem solving		25	+0.30	+0.16 / +0.44	46.57*
factual learning		9	+0.96	+0.62 / +1.30	9.55
Task structure	2.04	33			
Task familiarity	1.35	23			
	Grouping characteristics				
Group composition	16.43*	21			
homo. ability		6	+0.19	-0.12 / +0.50	24.33*
hetero. gender		3	+0.51	-0.12 / +1.14	0.20
homo. gender		8	+0.48	+0.25 / +0.71	12.45
friendship		1	+0.04	-0.61 / +0.69	0.00
more than one criteria		2	+1.21	+0.69 / +1.73	3.01
Presence of others	3.75	34			
Group learning strategy	3.50	34			
Group size	2.04	34			
Number of sessions	1.01	32			
	Learner characteristics				
Grade level	6.76*	33			
pre-secondary		20	+0.37	+0.20 / +0.53	35.99*
secondary		5	+0.86	+0.43 / +1.29	11.86*
college/university		8	+0.20	-0.03 / +0.44	3.74
Gender	0.13	14			

$p < .05$

Note. Q_B is the between-class homogeneity statistics. k is the number of findings. d_+ is the weighted mean effect size. 95% CI is the 95% confidence interval for d_+. Q_W is the within-class goodness-of-fit statistics.

Technology characteristics. Feedback type had a significant influence on the effect of social context on group task performance (Q_B = 17.72, df = 2). Whether there was no feedback, or whether feedback was minimal, students performed better on the task in groups than individually (d_+ = +0.46, d_+ = +0.52, respectively). However, when elaborate feedback was available in the computer programs, individuals performed significantly better than groups (d_+ = -0.84). Within-class homogeneity statistics indicate that each of the three subsets of findings were homogeneous, suggesting consistent findings within each subset. Type of programs and instructional control were not significantly related to the variability in the group task performance findings.

Task characteristics. Type of tasks was significantly related to the effect magnitude of social context on group task performance (Q_B = 12.67, df = 1). Although group performance appeared significantly better than individual performance for both problem-solving tasks (d_+ = +0.30) and factual-learning tasks (d_+ = +0.96), the latter mean effect size is significantly larger than the former. Within-class homogeneity statistics indicate that the subset of findings involving factual learning tasks (Q_W = 46.57, df = 24) were not homogeneous, indicating considerable variability within the subset. Subject, task structure, and task familiarity were not significantly related to the variability in the group task performance findings.

Grouping characteristics. Effect sizes varied significantly for different group compositions (Q_B = 16.43, df = 5). The largest superiority of group performance over individual performance was produced by the groups that were formed on more than one criteria (d_+ = +1.21). The mean effect size for homogeneous gender grouping was also significantly positive. However, there was no significant mean difference between homogenous gender grouping and heterogeneous gender grouping (d_+ = +0.51 and +0.48, respectively). In the homogeneous grouping, no significant mean difference was found between all male groups and all female groups. No significant mean difference was found in the group task performance between groups of other compositions and individuals. However, as the number of findings extracted for each type of group composition was small, the results may be limited to the characteristics in the studies.

Presence of others was marginally significant ($p<.10$). The influence of social context was greater when no other peers were around (d_+ = +0.54) than when there were other peers working close by (d_+ = +0.28). Group learning strategy, group size, and number of sessions were not significantly related to the variability in the group task performance findings.

Learner characteristics. Social context had a differential influence on group task performance for students at different grade levels (Q_B = 6.67, df = 2). At both pre-secondary (d_+ = +0.39) and secondary levels (d_+ = +0.86), students performed significantly better on the task in groups than individually. However, at college or university levels, group task performance was not significantly superior to individual task performance. Within-class homogeneity statistics indicate that the subsets of findings involving pre-secondary (Q_W = 35.99, df = 19) and secondary students (Q_W = 11.86, df = 4) were not homogeneous, indicating considerable variability within each subset. Gender was not significantly related to the variability in the group task performance findings.

Multiple Regression Model Development

In order to understand and control for shared variances among the study features, two multiple regression analyses were performed. Analysis 1 tests whether each of the univariately significant predictors independently accounted for significant variance in the findings. Analysis 2 attempts to develop a parsimonious model.

Analysis 1. Testing unique variances. Unique variances accounted for by each variable were tested in a weighted least squares regression with all 5 significant study features identified from the univariate analyses entered as one block. Results of the analyses are presented in Table 5. Three variables independently accounted for significant unique variances in the findings, with student equivalence accounting for 5%, feedback 13%, and types of tasks 12% of the total variance. Two other variables (group composition and grade level) did not explain significant unique variances due to their collinearity with the other variables.

Table 5. *Testing unique variances explained by significant study features: Group task performance findings*

Study features	*B*	*SE B*	*part* r^2	Q_R	Q_E
				33.41*	39.46
Student equivalence	.36*	.18	.05		
Feedback	1.29*	.41	.13		
Type of tasks	.57*	.19	.12		
Group composition	.03	.28	.00		
Grade level	-.06	.15	.00		
(constant)	-1.17	.46			

*$p < .05$

Note. *B* is the unstandardized regression coefficient. *SE B* is the Standard Error of the *B*. *part* r^2 is the part correlation squared. Q_R is the Sum of Squares associated with all the predictors in the regression model. Q_E is the Goodness-of-fit statistics.

Analysis 2. Model development. In Analysis 2, a hierarchical weighted least squares multiple regression was run with student equivalence entered at Step 1 and all other variables entered in blocks based on the results of Analysis 1 and univariate analyses. Block 1 included type of tasks and type of feedback, which were identified in Analysis 1 to account for significant unique variances in the findings. Block 2 included group composition and grade level that were significant in the univariate analysis but did not explain significant unique variance in Analysis 1. Block 3 included presence of others that was marginally significant in the univariate analyses. Finally, all other variables were entered to account for any additional variability. Within each block, variables were entered stepwise.

After controlling for student equivalence, three variables accounted for the significant variability in the group task performance findings (see Table 6). Feedback and type of tasks that were significant in Analysis 1 remained significant in Analysis 2. Group composition and grade level, which were significant in the univariate analyses, did not explain significant additional variance due to their collinearity with the three variables already in the model. However, after variance due to the three variables had been accounted for, presence of others, which was only marginally significant in the univariate analysis, accounted for a significant amount of additional variance in the findings. Together, the four variables accounted for 52% of the total variability in the findings. Goodness-of-fit statistics (Q_E = 34.93, df = 29) indicate that the model fits the data and that the remaining variability was due to chance fluctuations.

Table 6. *Multiple regression model of study features: Group task performance findings*

Predictors	*Step #*	*B*	Q_R	Q_R *Increment*	Q_E	*% exp.*
Student equivalence: controlled	1	.37	4.67	4.67*	68.20*	6%
Feedback: no/minimal	2	1.38	24.53	19.86*	68.35*	34%
Type of tasks: factual learning	3	.56	33.18	8.65*	39.70	46%
Presence of others: no/unknown	4	.32	37.94	4.76*	34.93	52%
Intercept for the model		-1.35				

*$p < .05$

Note. *B* is the unstandardized regression coefficient upon entry. Q_R is the Sum of Squares associated with all the predictors in the regression model. $Q_{R\,Increment}$ is the additional Sums of Squares associated with the new predictor. Q_E is the goodness-of-fit statistics for the model. *%exp.* is the percent of variance explained by the model.

Thus, the model indicates that in studies where student ability was well controlled across experimental conditions, students performed significantly better on the task in groups than individually when computer programs provided no or minimal feedback, when tasks involved factual learning, and especially when no other peers were working close by. Under all these conditions, group performance were 1.13 standard deviations better than individual performance (95% confidence interval is +0.72 to +1.54). When all these conditions were absent (i.e., in not so well controlled studies, when elaborate feedback was available from the computer program, when tasks involved problem solving, and when there were other peers working close by), students working individually performed significantly better than those working in groups ($d_+ = -1.35$, 95% interval is –2.15 to –0.55).

Study Features Analyses on Individual Achievement Findings

In the individual achievement data, the effect sizes ranged from -1.14 to +3.37, with 88 effect sizes above zero favoring group learning, 11 effect sizes equal to zero, and 47 effect sizes below zero favoring individual learning. Both univariate and multivariate study features analyses were performed in order to account for the variability across the findings. Results of the univariate study features analyses are presented first, followed with results from the multiple regression analyses.

Univariate Analyses

Twenty-three study features were analyzed univariately on the individual achievement findings. Results of the analyses are presented in Table 7. Of the twenty-three study features analyzed, six were found that significantly influenced the relationship between social context and individual achievement, which are described in the following subsections.

Outcome and methodology characteristics. None of the four outcome and methodological features significantly moderated the effect of social context on individual achievement. Group learning was superior to individual learning on both lower-order and higher-order skills, measured by either immediate or delayed posttests, in published or unpublished studies. In the majority of the studies, student equivalence across conditions was well controlled. The mean effect size was more positive in well-controlled studies (d_+ = +0.17) than in studies where group equivalence was unknown or unequal (d_+ = +0.04), but the difference was only marginally significant ($p<.10$).

Technology characteristics. Type of programs significantly influenced the effect of social context on student individual achievement (Q_B= 6.81, df = 2). Six types of programs were initially identified and coded, which were then combined into three categories based on both conceptual similarity and empirical results. Results of the analyses indicate that social context had a significantly greater influence on individual

Table 7. *Results of the univariate study features analyses: Individual achievement finding*

Study features	Q_B	*k*	d_+	*95% CI*	Q_W
Outcome and methodology features					
Outcome type	2.02	133			
Outcome measure time	2.93	146			
Student equivalence	3.52	146			
Publication status	1.56	146			
Technology characteristics					
Type of programs	6.81*	145			
tutorial/drill-practice		94	+0.19	+0.13 / +0.25	154.72*
exploratory/tool		38	+0.06	-0.03 / +0.15	20.34
programming language		13	+0.24	+0.10 / +0.38	21.88*
Design orientation	.10	146			
Feedback	1.44	71			
Instructional control	.88	109			
Task characteristics					
Subject	11.69*	144			
math/science		62	+0.12	+0.05 / +0.19	4.38*
reading/writing		6	+0.13	-0.08 / +0.34	1.57
social science		41	+0.22	+0.11 / +0.33	55.15
computer skills		27	+0.25	+0.15 / +0.36	40.98*
professional skills		8	-0.07	-0.25 / +0.11	5.10
Type of tasks	5.20*	139			
problem solving		86	+0.13	+0.07 / +0.18	87.06
factual learning		53	+0.25	+0.16 / +0.34	103.60*
Task structure	1.95	121			
Task familiarity	3.69	55			
Grouping characteristics					
Group composition	11.95	99			
Presence of others	.10	146			
Group learning strategy	7.22*	146			
specific cooperative		91	+0.20	+0.14 / +0.26	134.54*
general encouragement		21	+0.03	-0.09 / +0.14	26.67
no specific/individualistic		34	+0.12	+0.01 / +0.23	35.65
Group work exp./instruction	1.29*	146			
yes		37	+0.31	+0.21 / +0.41	59.13*
unknown		109	+0.11	+0.06 / +0.17	133.66
Group size	2.99	146			
Number of sessions	.16	129			
Session intensity	0.00	100			
Learner characteristics					
Grade level	2.71	141			
Relative ability level	3.98	57			
Gender	9.17*	21			
female		10	+0.50	+0.25 / +0.74	19.98*
male		11	+0.02	-0.16 / +0.20	20.32*
Computer experience	1.72	43			

* $p < .05$

Note. Q_B is the between-class homogeneity statistics. *k* is the number of findings. d_+ is the weighted mean effect size. 95% CI is the 95% confidence interval for d_+. Q_W is the within-class goodness-of-fit statistics.

achievement when students were using tutorial or drill-and-practice programs (d_+ = +0.19)[1] or learning programming languages (d_+ = +0.24) than when using exploratory or tool programs (d_+ = +0.06). The latter mean effect size was not significantly different from zero. Within-class homogeneity statistics indicate that the subsets of findings for tutorial or drill-and-practice (Q_W = 154.72, df = 93) and programming languages (Q_W = 21.88, df = 12) were, however, not homogeneous, indicating considerable variability within each subset. Other technology characteristics analyzed such as design orientation, feedback, and instructional control were not significantly related to the variability in the individual achievement findings.

Task characteristics. Subject (Q_B = 11.69, df = 4) and type of tasks (Q_B = 5.20, df = 1) were significantly related to the variability on individual achievement. Larger mean effect sizes were found in learning social sciences (d_+ = +0.22) and computer skills (d_+ = +0.25) than in mathematics (d_+ = +0.12), reading or writing (d_+ = +0.13), and professional skills (d_+ = -0.07). The latter two means were not significantly different from zero. Similarly, larger effect sizes were found when tasks involved factual learning (d_+ = +0.25) than problem solving (d_+ = +0.13), although both means were significantly positive. Within-class homogeneity statistics indicate that the subsets of findings for math or science (Q_W = 84.38, df = 61), computer skills (Q_W = 40.98, df = 26), and factual learning (Q_W = 103.60, df = 52) were significantly heterogeneous, indicating considerable variability within each subset. Task structure and task familiarity were not significantly related to the variability in the individual achievement findings.

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[1] In all cases when $d > 0$, it indicates that the results favour students learning in groups.

Grouping characteristics. Group learning strategy (Q_B = 7.22, df = 2) and group work experience or instruction (Q_B = 11.29, df = 2) were significantly related to the variability on individual achievement. Group learning was more effective when specific cooperative learning strategies were employed (d_+ = +0.20) than when only general encouragement was given to the students (d_+ = +0.03) or when no specific or individualistic group learning strategy was used (d_+ = +0.12). Similarly, the mean effect size was more positive when students had group work experience or instruction (d_+ = +0.31) than when no such information was reported (d_+ = +0.11). However, within-class homogeneity statistics indicate that the subsets of findings where specific cooperative learning strategies were used (Q_W = 134.54, df = 90) and where students had group work experience or instruction (Q_W = 59.13, df = 36) were not homogeneous, indicating considerable variability within each subset.

Effect sizes also varied for different group compositions (Q_B = 11.95, df = 6). However, the difference was only marginally significant (p<.10). The mean effect sizes were significantly positive for heterogeneous ability groups (d_+ = +0.24), homogenous ability groups (d_+ = +0.19), and grouping based on more than one criteria (d_+ = +0.17). Same gender and friendship groups had the lowest mean effect sizes (d_+ = -0.04, -0.07, respectively). No study provided separate results for males and females. Therefore, it was not clear whether the effect sizes were similar or different for all male groups and all female groups. One study where all subjects were female, however, had a positive mean effect size. The goodness-of-fit statistics indicate that while the other subsets of findings were homogeneous, the subset of findings for heterogeneous ability groups was significantly heterogeneous (Q_W = 86.45, df = 50). Further analyses indicate that when heterogeneously grouped, both low and high ability students benefited significantly more than when working individually (d_+ = +0.64, +0.44, respectively); for medium ability students, the effect of learning in heterogeneous ability groups was not significantly different from learning individually.

Group size was also marginally significant ($p<.10$). The mean effect size was more positive when students worked in pairs (d_+ = +0.18) than when they worked in three-to-five member groups (d_+ = +0.09). Presence of others, number of sessions, and session intensity were not significantly related to the variability in the individual achievement findings.

Learner characteristics. A few studies reported individual achievement findings separately for males and females. Of the few findings analyzed, social context showed a differential effect for male and female students (Q_B = 9.17, df = 1). The effect is significantly greater for female students (d_+ = +0.50) than for male students (d_+ = +0.02). However, within-class homogeneity statistics indicate that both subsets were significantly heterogeneous, indicating considerable variability within each subset (Q_W = 19.98, df = 9 for females; and Q_W = 20.32, df = 10 for males).

The effect of social context appeared most positive for low ability learners (d_+ = +0.33). For high ability learners, the mean effect size was smaller but also significantly positive (d_+ = +0.22). For medium ability learners, the effect was not significantly different from zero (d_+ = +0.10). However, the difference between the three groups was not statistically significant in the univariate analysis. Grade level and computer experience were not significantly related to the variability in the achievement findings.

Multiple Regression Model Development

In order to understand and control for shared variances among the study features, two multiple regression analyses were performed. Analysis 1 tests whether each of the univariately significant predictors independently accounted for significant variance in the findings. Analysis 2 attempts to develop a parsimonious model.

Analysis 1: Testing unique variances. The six significant predictors ($p<.05$) identified from the univariate study features analyses were tested for their unique variances in a multiple weighted least squares regression. All were entered as one block. The results are presented in Table 8. Of the six variables entered, four accounted for significant unique variances in the findings, with group work experience/instruction independently accounting for 3%, gender 3%, and subject 2 % of the total variance. The other three variables (group learning strategy, type of tasks, and type of programs) did not explain significant unique variances due to their collinearity with the other variables.

Table 8. *Testing unique variances explained by significant study features: Individual achievement findings*

Study features	*B*	*SE B*	part r^2	Q_R	Q_E
				31.24*	174.18*
Group work exp./instruction	.17*	.07	.03		
Group learning strategy	.06	.06	.00		
Gender	.30*	.13	.03		
Type of tasks	.04	.06	.00		
Type of programs	.10	.06	.01		
Subject	.11	.05	.02		
(constant)	-.05	.05			

*$p<.05$

Note. *B* is the unstandardized regression coefficient, *SE B* is the Standard Error of the *B*. *part* r^2 is the part correlation squared. Q_R is the Sum of Squares associated with all the predictors in the regression model. Q_E is the Goodness-of-fit statistics.

Analysis 2: Model development. In Analysis 2, a hierarchical multiple regression was run with student equivalence entered first to control for study quality. Other substantive variables were entered in Blocks based on the results from the univariate analyses and the unique variance analysis. Block 1 included group work experience/ instruction, gender, and subject that explained significant unique variance in Analysis 1. Block 2 included group learning strategy, type of tasks, and type of computer programs that did not explain significant unique variance in Analysis 1 but were significant in the univariate analyses. Block 3 included outcome measure time, group composition, and group size that were marginally significant in the univariate analyses ($p<.10$). Finally, all other variables were entered as Block 4 to account for any additional variability. Within each block, the method of entry was stepwise.

Results of this analysis are presented in Table 9. After controlling for student equivalence, six variables were retained in the model. Group work experience/instruction, subject, and gender that were significant in Analysis 1 remained significant in Analysis 2. Among the three variables that were significant in the univariate analyses but not significant in Analysis 1, only type of programs explained a significant amount of additional variance after variance due to the four variables already in the model had been accounted for. Group learning strategy and type of tasks did not explain significant additional variance due to their high correlation with group work experience/instruction and type of programs, respectively. After variance due to the five variables had been removed, group size and relative ability level, which were either marginally significant or non-significant, explained significant additional variance. Together, the seven variables accounted for 21% of the total variability in the findings. Goodness-of-fit statistics (Q_E = 162.27, df = 138) indicates that the model fits the data and that the remaining variance was due to sampling errors.

Table 9. *Multiple regression model of study features: Individual achievement findings*

Predictors	*Step #*	*B*	Q_R	Q_R *Increment*	Q_E	*% exp.*
Student equivalence: controlled	1	.13	3.53	3.53	201.90*	2%
Group work exp./instruct.: yes	2	.19	14.14	10.61*	191.29*	7%
Subject: social sci./comp. skills	3	.16	23.36	9.22*	182.07*	11%
Gender: female	4	.30	28.82	5.46*	176.61*	14%
Programs: non-exploratory/tool	5	.11	33.38	4.56*	172.05*	16%
Group size: pairs	6	.13	38.76	5.38*	166.66*	19%
Relative ability level: low & high	7	.17	43.15	4.39*	162.27*	21%
Intercept for the model		-.22				

*$p < .05$

Note. *B* is the unstandardized regression coefficient upon entry. Q_R is the Sum of Squares associated with all the predictors in the regression model. $Q_{R\ Increment}$ is the additional Sums of Squares associated with the new predictor. Q_E is the goodness-of-fit statistics for the model. *%exp.* is the percent of variance explained by the model.

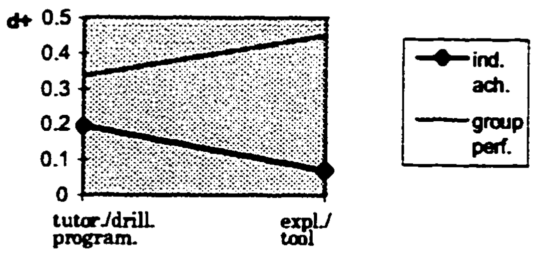
Thus, the model indicates that in studies where student equivalence was well controlled across conditions, the most important predictor of the effect of social context on student individual achievement when learning with CT is whether students had small group work experience or instruction for effective cooperative learning. Group learning was more effective when students had group work experience or instruction, when they worked in pairs, on tutorial or drill-and-practice programs, especially in learning social sciences or computer skills, for female students and relatively low or high ability students but not medium ability students. When all these positive conditions are present, students learning in small groups may achieve 0.95 standard deviation more than those learning individually (95% confidence interval is +0.61 to +1.28). When all these positive conditions are absent, individual learning may be significantly more effective ($d_+ = -0.22$, 95% confidence interval is –0.40 to –0.03).

Comparing Group Task Performance and Individual Achievement

For six study features that explained significant variability but appeared to exhibit a different pattern across individual achievement and group task performance outcomes, a multivariate approach (Raudenbush, *et al.*, 1988) was used to test whether there was any significant interaction between the study features and the two outcomes concerned. Each of the predictors was tested by a series of four models in increasing. The first model tested whether there was a common effect by entering only a constant as the predictor. The second model tested whether there was a separate effect size for different outcomes by adding the two outcomes as predictors. The difference between Q_R for the second and the first models was 12.82 with df = 1, suggesting that there was a significant main effect for type of the outcomes. The effect sizes for group task performance were significantly larger than the effect sizes for individual achievement. The third model tested whether there were separate intercepts and a common slope by adding the study feature that showed possible interaction effect. The final model tested whether there were separate regressions for the study feature on the two outcomes. Significantly separate slopes were found for four study features: type of programs ($Q_{R\ interaction} = 4.73$), type of feedback ($Q_{R\ interaction} = 20.05$), subject ($Q_{R\ interaction} = 6.55$), and type of tasks ($Q_{R\ interaction} = 8.57$). Patterns of the relationship between each of the study features and the two outcomes are presented in Figures 1-4 and are described below.

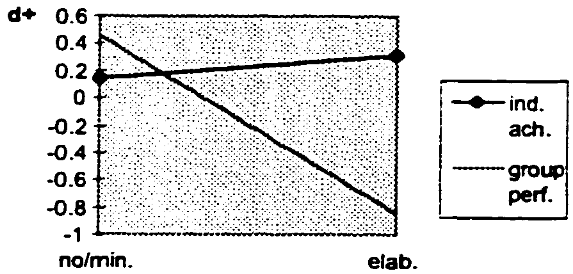
Type of programs. Figure 1 presents the mean effect sizes on group task performance and individual achievement when learning with different types of programs. When working on tutorial or drill-and-practice programs or learning computer programming, small positive effect sizes were found on both group task performance and individual achievement. However, when working on exploratory programs or using computer programs as tools for other tasks, although there was a medium positive effect on group task performance, the effect on individual achievement was not significantly different from zero.

Figure 1. Interaction effect of type of programs and type of outcomes

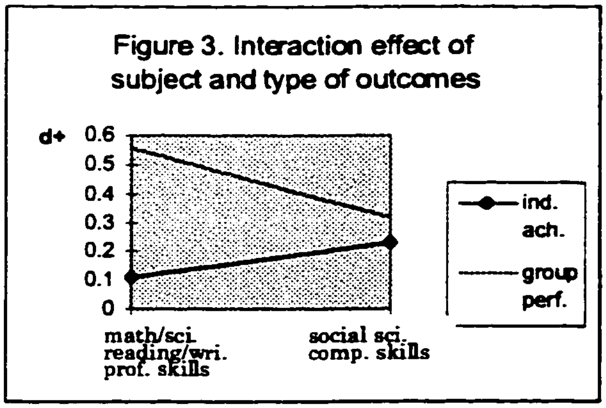


Feedback. Figure 2 presents the mean effect sizes on group task performance and individual achievement when different types of feedback were available from the programs. When programs provided no or minimal feedback, positive effects were found on both group task performance and individual achievement. However, when programs provided elaborate feedback, the mean effect size on individual achievement was positive, favoring students working in small groups, but significantly negative on group task performance, thus favoring students working individually.

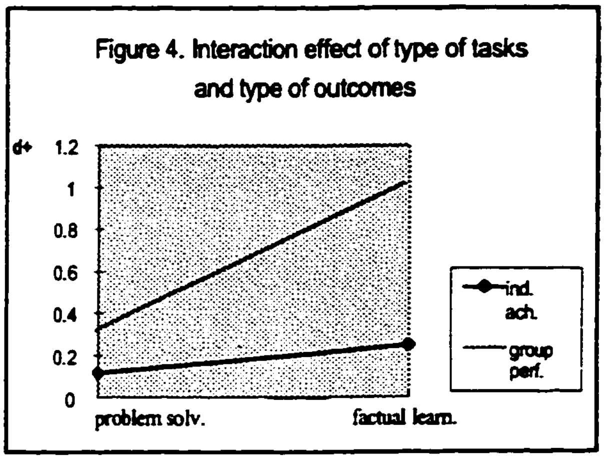
Figure 2. Interaction effect of type of feedback and type of outcomes



Subject. Figure 3 presents the mean effect sizes for group task performance and individual achievement when different types of subject matter were involved. When learning social sciences or computer skills, small positive effects were found on both group task performance and individual achievement. However, when learning mathematics, science, reading, writing, or professional skills, although there was a medium positive effect on group task performance, there was no significant effect on individual achievement.



Type of tasks. Figure 4 presents the mean effect sizes for group task performance and individual achievement when working on different types of tasks. When working on problem solving tasks, there were small positive effects on both group task performance and individual achievement. When working on factual learning tasks, there was a large positive effect on group task performance but only a small positive effect on individual achievement.



Process Measures

Six process measures were identified and analyzed in this meta-analysis: peer interaction, interactivity with programs, task completion time, amount of task attempted, use of strategies, and perseverance. *Peer interaction* included both cognitive interaction (e.g., help giving and receiving) and positive social interaction (e.g., praise and encouragement). The two types of interaction was combined due to 1) only a small number of findings were available for each type of interaction and 2) preliminary analyses indicate that there was no significant difference in the effect sizes for cognitive interaction and positive social interaction. *Interactivity with programs* measured the frequencies or amount of time interacting with the programs (e.g., using keyboard, accessing reviews, checking options, elaborate feedback, concepts, or doing practice items or quizzes). *Task completion time* refers to the total amount of time the group or individuals spent in completing their task(s). *Amount of task attempted* included number of words attempted, number of responses produced, and etc. *Use of strategies* included use of self-regulating strategies or appropriate task strategies. *Perseverance* measured student perseverance on task (e.g., stayed longer on task or had a less number of incomplete tasks). Results of the overall effects of social context on these process measures are presented first, followed with study features analyses of the heterogeneous outcomes.

Overall Effects

Table 10 presents the results of the overall homogeneity analyses for each of the process measures. Social context significantly influenced student task behaviors and learning processes. On average, students learning in groups had a significantly higher frequency of peer interaction (d_+ = +0.33), a higher frequency of using appropriate strategies (d_+ = +0.66), and are more perseverant on tasks (d_+ = +0.48) than those learning individually. However, students working individually generally had a significantly higher frequency of interactivity with the computer program (d_+ = -0.18,) and needed significantly less task completion time (d_+ = -0.21) than those working in small groups. No mean difference was found between groups and individuals in the amount of tasks attempted (d_+ = +0.03). Homogeneity statistics indicate that the findings on interactivity with programs (Q_T = 13.44, df = 14), use of strategies (Q_T = 10.72, df = 6), and perseverance (Q_T = 2.60, df = 3) were homogeneous, suggesting that the effect sizes integrated were quite consistent. However, the results on the latter two outcomes were based on only a few findings. Their generalizability may be limited to the characteristics in the studies.

Table 10. *Weighted mean effect sizes on process measures*

		before outlier procedures			after outlier procedures		
Outcomes	*k*	d_+	95% CI	Q_T	d_+	95% CI	Q_T
Peer interactions	6 (4)	+0.33	+0.05/+0.61	50.72*			
Interactivity with programs	15 (8)	-0.27	-0.46/ -0.09	13.44			
Task completion time	56 (31)	-0.25	-0.34/ -0.16	179.47*	-0.21	-0.31/ -0.12	142.94*
Amount of task attempted	25 (11)	+0.01	-0.14/+0.16	65.63*	+0.03	-0.12/+0.17	54.12*
Use of strategies	7 (4)	+0.66	+0.40/+0.92	10.72			
Perseverance	4 (2)	+0.48	+0.17/+0.78	2.60			

Note. *k* is the total number of independent findings integrated. The values in parentheses are the numbers of studies from which the findings were extracted. d_+ is the weighted mean effect size. 95% CI is the 95% confidence interval for d_+. Q_T is the homogeneity statistics, where * = p<.05, indicating that the effect sizes integrated are heterogeneous.

The set of effect sizes on peer interaction ($Q_T = 50.72$, df = 6) were significantly heterogeneous. The effect sizes ranged from –0.90 to +1.60, with 4 positive effect sizes indicating that students working in groups had higher frequencies of peer interaction, 1 zero effect indicting no difference between groups and individuals, and 1 negative effect size indicating that individuals had higher frequencies of peer interaction. Further examination indicates that, although all were measured individually, the one negative effect size was based on a very different type of measure. While the other five findings were based on peer interaction within group and across groups, the one negative effect size was measuring the frequency of requesting help across groups only, which was, therefore, biased toward those working individually. Due to the small number of findings in this dataset and also due to the fact that the variability in the findings could essentially be explained by the one anomaly described above, no study features analysis was performed for this dataset.

The sets of findings on task completion time ($Q_T = 142.95$, df = 55) and amount of task attempted ($Q_T = 54.12$, df = 24) were also significantly heterogeneous. Study features analyses were, therefore, performed to explore the variability.

Study Features Analyses on Task Completion Time Findings

Fifty-six independent findings compared the time groups or individuals took in completing their tasks. Effect sizes ranged from +1.39 to –2.15, with 23 effect sizes above zero showing that groups worked faster than individuals and 31 effect sizes below zero showing that individuals worked faster than groups. Results of the univariate and multivariate study features analyses are presented and described below. As only three findings involved special design for group use, this study feature was not analyzed.

Univariate Analyses

Twenty-one study features were analyzed univariately on the task completion time findings. Results of the analyses are presented in Table 11. Eight features were identified that significantly influenced the effects of social context on task completion time, which are described in the following subsections.

Methodology characteristics. Student equivalence ($Q_B = 8.05$, df = 1) and publication status ($Q_B = 22.22$, df = 1) were significantly related to the variability in the task completion time findings. The effect sizes were significantly more positive in poorly controlled studies ($d_+ = +0.17$) than in well-controlled studies ($d_+ = -0.26$), in published studies ($d_+ = +0.07$) than in unpublished studies ($d_+ = -0.40$). However, within-class homogeneity statistics show that none of the subsets was homogeneous, indicating considerable variability within each subset of the data.

Task characteristics. Three task characteristics, subject ($Q_B = 8.74$, df = 3), type of tasks ($Q_B = 20.96$, df = 1), and task familiarity ($Q_B = 6.55$, df = 2) were significantly related to the variability on task completion time. On average, groups took longer time in completing their tasks than individuals in all subject areas, but more so when learning social sciences ($d_+ = -0.70$) and computer skills ($d_+ = -0.27$) than in learning mathematics or science ($d_+ = -0.14$) and reading, writing, or language arts ($d_+ = -0.12$). Similarly, groups took longer time when working on factual learning tasks ($d_+ = -0.55$) than problem solving tasks ($d_+ = -0.18$). However, when tasks were new and not provided

Table 11. *Results of univariate study features analyses: Task completion time findings*

Study features	Q_B	k	d_+	95% CI	Q_W
	Outcome and methodology features				
Student equivalence	8.05*	56			
well-controlled		50	-0.26	-0.36 / -0.16	120.99*
non-equivalent/unknown		6	+0.17	-0.11 / +0.45	13.90*
Publication status	22.22*	56			
published		25	+0.07	-0.08 / +0.22	65.36*
unpublished		31	-0.40	-0.52 / -0.28	55.36*
	Technology characteristics				
Type of programs	0.08	56			
Feedback	2.87	26			
Instructional control	1.08	41			
	Task characteristics				
Subject	8.74*	56			
math/science		37	-0.14	-0.25 / -0.02	109.80*
reading/writing/lang.		2	-0.12	-0.54 / +0.29	0.29
education/business/social sci.		10	-0.70	-1.01 / -0.38	18.32*
computer application/prog.		7	-0.27	-0.51 / -0.04	3.14
Type of tasks	20.96*	50			
problem solving		32	-0.07	-0.19 / +0.06	49.26*
factual learning		18	-0.55	-0.72 / -0.38	43.60*
Task structure	1.24	47			
Task familiarity	6.55*	30			
familiar		11	+0.05	-0.28 / +0.38	7.47
new with training		9	-0.15	-0.35 / +0.05	2.98
new without training		10	+0.26	+0.02 / +0.49	15.34*
	Grouping characteristics				
Group composition	3.35	39			
Presence of others	0.47	56			
Group learning strategy	9.17*	56			
specific cooperative		35	-0.31	-0.42 / -0.19	103.08*
general encourage.		4	+0.16	-0.12 / +0.45	10.32*
no specific/individualistic		17	-0.09	-0.31 / +0.12	19.04
Group work exp./instruction	4.64*	56			
yes		12	-0.36	-0.52 / -0.19	62.06*
unknown		44	-0.14	-0.26 / -0.02	76.24*
Group size	0.07	56			
Number of sessions	1.59	52			
Session intensity	0.59	40			
	Learner characteristics				
Grade level	19.83*	54			
pre-secondary		19	-0.07	-0.22 / +0.09	47.31*
secondary		8	-0.43	-0.65 / -0.21	10.92
college/university		24	-0.20	-0.52 / -0.21	39.97*
adult		5	-0.34	-0.01 / +0.68	24.90*
Relative ability level	3.51	12			
Gender	0.01	9			
Computer experience	3.08	22			

*$p < .05$

Note. Q_B is the between-class homogeneity statistics. k is the number of findings. d_+ is the weighted mean effect size. 95% CI is the 95% confidence interval for d_+. Q_w is the within-class goodness-of-fit statistics.

with any demonstration or training, groups worked faster than individuals (d_+ = +0.26). No significant difference was observed in the task completion time between groups and individuals when tasks were familiar or when tasks were new but were provided with demonstration or training. Within-class homogeneity statistics, however, indicate that the subsets of findings for math /science, social sciences, problem solving, factual learning, and new task without training were significantly heterogeneous, suggesting considerable variability within each of the subsets. Task structure was not found to be significantly related to the variability in the task completion time findings.

Grouping characteristics. Both group learning strategy (Q_B = 9.17, df = 2) and group work experience or instruction (Q_B = 4.64, df = 1) were significantly related to the variability on task completion time. Groups took significantly longer time than individuals when they used specific cooperative learning strategies such as turn taking or agreeing on answers (d_+ = -0.28) and when they had group work experience or were provided with specific instructions for group work (d_+ = -0.36). When only general encouragement or no specific instruction or individualistic strategy was given, no significant difference was found between groups and individuals in their task completion time. Within-class homogeneity statistics, however, indicate that only the subset of findings involving no specific or individualistic group learning strategy was homogeneous (Q_W = 19.07, df = 16). Group composition, presence of others, group size, number of sessions, and session intensity were not significantly related to the variability in the task completion time findings.

Learner characteristics. Grade level was significantly related to the variability on task completion time (Q_B = 18.54, df = 3). At secondary school (d_+ = -0.43) and college or university (d_+ = -0.20) levels, groups took longer time than individuals. At pre-secondary school and adult levels, no significant difference was found in task completion time between groups and individuals. Within-class homogeneity statistics, however, indicate that only the subset of findings involving secondary levels was homogenous (Q_W = 10.92, df = 7). A few studies reported results for different ability levels and gender or provided information on student computer experience, no significant moderating effect was found based on these findings

Multiple Regression Model Development

In order to understand and control for shared variances among the study features, two multiple regression analyses were performed. Analysis 1 tests whether each of the univariately significant predictors independently accounted for significant variance in the findings. Analysis 2 attempts to develop a parsimonious model.

Analysis 1. Testing unique variances. Unique variances accounted for by each variable were tested in a weighted least squares regression with all the eight significant predictors entered as one block. Results of the analysis are presented in Table 12. Four study features accounted for significant unique variances in the findings: publication status 7%, type of tasks 6%, task familiarity 3%, and group learning strategy 3%. Subject, group learning strategy, group work experience/instruction, and grade level did not explain significant unique variances due to their collinearity with other variables.

Table 12. *Testing unique variances explained by significant study features: Task completion time findings*

Study features	B	$SE\ B$	$part\ r^2$	Q_R	Q_E
				56.18*	7.97*
Student equivalence	-.20	.17	.00		
Publication status	.41*	.13	.07		
Subject	-.20	.12	.02		
Type of tasks	-.42*	.14	.06		
Task familiarity	.37*	.17	.03		
Group learning strategy	-.24*	.12	.03		
Group work exp./instruction	.00	.00	.01		
Grade level	-.21	.15	.01		
(constant)	.28	.23			

*$p < .05$

Note. B is the unstandardized regression coefficient; $SE\ B$ is the Standard Error of the B; $part\ r^2$ is the part correlation squared, Q_R is the Sum of Squares associated with all the predictors in the regression model, Q_E is the Goodness-of-fit statistics.

Analysis 2. Model development. In Analysis 2, a hierarchical multiple regression was run with student equivalence entered at Step 1 and all other variables entered in blocks based on the results from Analysis 1 and the univariate analyses. Block 1 included publication status, type of tasks, task familiarity, and group learning strategy that were significant in Analysis 1. Block 2 included subject, group work experience/instruction, and grade levels that were significant in the univariate analyses but not significant in Analysis 1. Block 3 included computer experience that were marginally significant in the univariate analysis. Block 4 included all other variables to account for any additional variance. Within each block, method of entry was stepwise.

Results of Analysis 2 are presented in Table 13. After controlling for student equivalence, four study features accounted for the significant variability in the task completion time findings. Task familiarity, publication status, and type of tasks that were significant in Analysis 1 remained significant after controlling for student equivalence.

Group learning strategy, although significant in both the univariate analysis and the multiple regression Analysis 1, did not explain significant additional variance after variance due to student equivalence, task familiarity, publication status, and type of tasks had been accounted for. Other univariately significant variables (i.e., subject, group work experience/instruction, and grade level) that were not significant in Analysis 1 did not explain significant additional variance, either. However, after variance due to student equivalence, task familiarity, publication status, and type of tasks were removed, type of programs that was not significant when analyzed individually accounted for significant additional variance in the findings.

Table 13. *Multiple regression model of study features: Task completion time findings*

Predictors	*Step #*	*B*	Q_R	Q_R *Increment*	Q_E	*% exp.*
Student equivalence: controlled	1	-.43	8.06	8.06*	136.08*	6%
Task familiarity: new & no train.	2	.63	30.62	22.56*	113.53*	21%
Publication status: published	3	.33	40.67	10.05*	103.47*	28%
Type of tasks: factual learning	4	-.31	47.92	7.25*	96.22*	33%
Type of programs: toolexpl.	5	-.31	53.81	5.89*	90.33*	37%
(Intercept for the model)		.20				

*$p < .05$

Note. *B* is the unstandardized regression coefficient upon entry; Q_R is the Sum of Squares associated with all the predictors in the regression model; Q_R *Increment* is the additional Sums of Squares associated with the new predictor; Q_E is the goodness-of-fit statistics for the model; *%exp.* is the percent of variance explained by the model.

These results suggest that while findings from published studies generally showed no significant difference in the tasks completion time between students working in groups and individually, findings from unpublished dissertations or reports showed that students working in groups needed significantly more time in completing their tasks than those working individually. When tasks were familiar, involving factual learning, and when programs were exploratory in nature or were used as tools for other tasks, individuals generally needed significantly less time than groups in completing their tasks on computers. On the other hand, when tasks involved problem solving and were new to the students and no training was provided, and when the programs were tutorial, drill-and-practice, or learning programming languages, groups took less time than individuals in completing their tasks. Together, the five significant predictors accounted for 37% of the total variability in the findings (Q_R = 53.81, df = 4). However, goodness-of-fit statistics (Q_E = 90.33, df = 50) indicate that the model does not fit the data and that significant variability remains to be explained.

Study Features Analyses on Amount of Task Attempted Findings

In the amount of task attempted data, the effect sizes ranged from −1.98 to +1.33, with 9 effect sizes below zero favoring students learning individually and 16 effect sizes above zero favoring students learning in groups. All the 25 findings were based on group performance versus individual performance during the learning task. Twenty-four findings were extracted from studies where student ability equivalence across conditions was well controlled. Only one finding was from a study where student equivalence was unknown; but the effect size was not significantly different from the other findings. Only one effect size was based on group size of three. All the others involved pairs. The majority of the findings did not provide information on student group work experience or instruction for effective group work. Due to the small number of findings in the dataset, only study features with sufficient variability were analyzed.

Univariate Analyses

Table 14 presents the results of the univariate study features analyses on the amount of task attempted findings. About half of the findings were from published studies and half from unpublished dissertations or reports. There was no significant difference between the published and unpublished findings. Ten substantive study features explained significant variability in the findings, which are described in the following subsections.

Technology characteristics. Three technology characteristics, type of programs (Q_B = 7.87, df = 2), feedback (Q_B = 8.64, df = 2), and instructional control (Q_B = 10.64, df = 1) were significantly related to the variability on amount of task attempted. Groups attempted a significantly larger amount of the task than did individuals when working on exploratory or tool programs (d_+ = +0.27); no significant difference was found between groups and individuals when working on tutorial or drill-and-practice programs or learning programming languages. Similarly, groups attempted a significantly larger amount of the task than did individuals when no feedback was available from the programs (d_+ = +0.35); no significant difference was found between groups and individuals when either minimal or elaborate feedback was available from the programs. When instruction was mostly learner-controlled, groups made more attempts than did individuals (d_+ = +0.27); however, when instruction was mostly system-controlled, individuals made more attempts than did groups (d_+ = -0.23). Within-class homogeneity statistics, however, indicate that the subset of effect sizes involving tutorial or drill-and-practice programs (Q_W = 45.88, df = 12), minimal feedback (Q_W = 33.79, df = 6), and

Table 14. *Results of univariate study features analyses: Amount of task attempted findings*

Study features	Q_B	k	d_+	95% CI	Q_W
		outcome and methodology features			
Publication status	2.57	25			
		Technology characteristics			
Type of programs	7.87*	25			
tutorial/drill-practice		13	-0.15	-0.34 / +0.04	45.88*
exploratory/tool		10	+0.27	+0.01 / +0.53	6.46
programming		2	+0.37	-0.27 / +1.00	1.30
Design orientation	1.80	25			
Feedback	8.64*	19			
no		10	+0.35	+0.07 / +0.63	6.62
minimal		7	-0.22	-0.48 / +0.04	33.79*
elaborate		2	+0.13	-0.48 / +0.75	0.16
Instructional control	10.64*	25			
mostly learner		17	+0.27	+0.05 / +0.48	16.47
mostly system		8	-0.23	-0.44 / -0.02	34.40*
		Task characteristics			
Subject	4.13	24			
Type of tasks	1.53	25			
Task structure	7.29*	25			
open		14	+0.24	+0.02 / +0.47	1 2.50
closed		11	-0.17	-0.37 / +0.03	41.72*
Task familiarity	0.12	17			
		Grouping characteristics			
Group composition	30.76*	21			
hetero. ability		6	+0.20	-0.09 / +0.49	7.68
homo. ability		8	+0.13	-0.15 / +0.41	11.53
hetero. gender		1	-0.40	-1.54 / +0.75	0.00
homo. gender		2	+0.95	+0.10 / +1.79	0.15
friendships		3	-0.18	-0.49 / +0.12	4.99
more than 1 criteria		1	-1.72	-2.44 / -0.99	0.00
Group learning strategy	9.06*	25			
specific cooperative		9	+0.08	-0.15 / +0.32	12.96
general encourage.		6	-0.28	-0.54 / -0.03	25.75*
no specific/individualistic		10	+0.29	+0.00 / +0.57	13.75
Number of sessions	7.67*	25			
one		15	+0.25	+0.03 / +0.48	15.06
more than one		10	-0.17	-0.37 / +0.03	38.79*
Session intensity	3.03	23			
		Learner characteristics			
Grade level	7.79*	24			
pre-secondary		11	-0.17	-0.37 / +0.03	41.72*
secondary		10	+0.20	-0.06 / +0.46	7.10
college/university		4	+0.38	-0.06 / +0.81	4.90
Relative ability level	8.39*	13			
low		4	+0.32	+0.01 / +0.64	3.82
medium		5	-0.34	-0.66 / -0.03	2.25
high		4	+0.00	-0.34 / +0.34	9.78*
Gender	3.53	7			

Table 14. (continued)

Study features	Q_B	k	d_+	95% CI	Q_W
Computer experience	8.02*	9			
yes		6	+0.36	-0.03 / +0.76	4.70
no		3	-0.53	-1.01 / -0.06	19.30*

*$p<.05$

Note. Q_B is the between-class homogeneity statistics. k is the number of findings. d_+ is the weighted effect size. 95% CI is the 95% confidence interval for d_+. Q_W is the within-class goodness-of-fit statistics.

system control (Q_W = 34.40, df = 7) were not homogeneous, indicating considerable variability within each dataset. Design orientation was not significantly related to the variability on amount of task attempted.

Task characteristics. Task structure significantly moderated the effect of social context on amount of task attempted (Q_B = 7.29, df = 1). Groups attempted significantly more of the task than did individuals when working on open tasks (d_+ = +0.24). No significant difference was found between groups and individuals when working on closed tasks. Homogeneity statistics, however, indicate that the subset of effect sizes involving closed tasks was not homogenous (Q_W = 41.72, df = 10). Subject, type of tasks, task familiarity were not significantly related to the variability in the findings.

Grouping characteristics. Group compositions (Q_B = 30.76, df = 5), group learning strategy (Q_B = 9.06, df = 2), and number of sessions (Q_B = 7.67, df = 1) were significantly related to the variability on amount of task attempted. Only homogeneous gender groups attempted a significantly larger amount than did individuals; however, as the number of findings for each type of group composition was small, the results may not be highly generalizable. Groups attempted a larger amount of the task than did individuals when either no specific learning strategies were used or individualistic learning strategies were used (d_+ = +0.29); when groups were encouraged to work together, individuals attempted a larger amount of the task than did groups (d_+ = -0.28); however, when groups used cooperative learning strategies, there was no significant difference in the amount of the task attempted. In studies in which instruction spanned one session, groups attempted a larger amount of the task than did individuals (d_+ = +0.25); in studies in which instruction spanned more than one session, no significant difference was found between groups and individuals. Within-class homogeneity statistics indicate that the subsets of effect sizes involving general encouragement to work together (Q_W = 25.75, df = 5), studies that lasts more than one session (Q_W = 38.79, df = 9) were not homogenous, indicating considerable variability within each subset. Session intensity was not significantly related to the variability in the findings.

Learner characteristics. Three learner characteristics, grade level (Q_B = 7.79, df = 2), relative ability (Q_B = 8.39, df = 2), and computer experience (Q_B = 8.02, df = 1) were significantly related to the variability on amount of task attempted. The mean effect size appeared more positive for college or university students than for secondary or pre-secondary students, but none was significantly different from zero. Low ability students attempted a higher amount of the task when working in small groups than when working individually (d_+ = +0.32); medium ability students completed more when working individually than in small groups (d_+ = -0.34); for high ability students, there was no significant difference whether working individually or in small groups (d_+ = +0.00). When students had computer experience, there was no significant difference between groups and individuals in the amount of the task attempted; when students had no computer experience, individuals attempted a larger amount of the task than did groups. Within-class homogeneity statistics indicate that the subsets of effect sizes involving pre-secondary grades ($Q_w = 41.72$, df = 10), high ability students ($Q_w = 9.78$, df = 3), and no computer experience ($Q_w = 19.30$, df = 2) were not homogenous, indicating considerable variability within each subset.

Gender was marginally significant ($p<.10$). Female students learning in groups attempted a significantly larger amount of the task than did female students learning individually ($d_+ = +0.78$). There was no significant difference between male students learning in groups and individually in the amount of task attempted. However, there was considerable variability in the findings for male students ($Q_w = 12.75$, df = 4).

Multiple Regression Model Development

Analysis 1: Testing unique variances. The nine significant predictors ($p<.05$) identified from the univariate study features analyses were tested for their unique variances in a multiple weighted least squares regression. All were entered as one block. The results are presented in Table 15. Of the nine variables entered, only relative ability significantly accounted for unique variance in the findings. Grade level did not enter due to its collinearity with task structure and group composition.

Analysis 2. In Analysis 2, a hierarchical weighted least squares multiple regression was run based on the results from the univariate analyses and Analysis. Block 1 included relative ability level that explained significant unique variance in Analysis 1. Block 2 included all other univariately significant predictors. Block 3 included session intensity and gender that were marginally significant in the univariate analyses. Block 4 included all other variables to account for any additional variance. Within each block, the method of entry is stepwise.

Table 15. ***Testing unique variances explained by significant study features: Amount of task attempted findings***

Study features	*B*	*SE B*	*part* r^2	Q_R	Q_E
				26.09*	29.74*
Instructional control	-1.00	.93	.03		
Type of feedback	-.49	.61	.01		
Type of programs	.05	.35	.00		
Task structure	.08	.65	.00		
Number of sessions	-.37	.44	.01		
Group learning strategy	.14	.19	.00		
Group composition	.11	.21	.00		
Relative ability level	.70*	.20	.21		
Computer experience	.44	.47	.02		
(constant)	.36	.32			

*$p < .05$

Note. *B* is the unstandardized regression coefficient, *SE B* is the Standard Error of the *B*. *part* r^2 is the part correlation squared. Q_R is the Sum of Squares associated with all the predictors in the regression model. Q_E is the Goodness-of-fit statistics.

Results of this analysis are presented in Table 16. Three variables entered the model. They are relative ability level, instructional control, and design orientation, each explaining a significant amount of additional variability in the findings after variance had been accounted for by variables already entered in the previous steps. Adding more variables did not explain significant additional variability. Overall, the model accounted for 52% of the total variance (Q_R = 29.18, df = 2). Goodness-of-fit statistics indicate the model fits the data (Q_E = 26.65, df = 21).

Thus, the model indicates that groups attempted a significantly larger amount of the task when the instruction was mostly learner-controlled and when programs had no special design for group use, especially for low ability learners. Under these conditions, the amount of the task attempted by groups was 1.80 standard deviation greater than that attempted by individuals. On the other hand, when tasks were system-controlled and when the programs had special design for group use (e.g., dual key), medium ability or high ability learners accomplished significantly more working individually ($d_+ = -1.31$).

Table 16. *Multiple regression model of study features: Amount of task attempted findings*

Predictors	*Step #*	*B*	Q_R	Q_R *Increment*	Q_E	*% exp.*
Relative ability level: low	1	1.38	4.23	4.23*	51.61*	8%
Instructional control: learner	2	.70	22.34	18.11*	33.49*	40%
Design orientation: individual	3	.98	29.18	6.84*	26.65	52%
(Intercept for the model)		-1.31				

*$p < .05$

Note. *B* is the unstandardized regression coefficient upon entry; Q_R is the Sum of Squares associated with all the predictors in the regression model; Q_R *Increment* is the additional Sums of Squares associated with the new predictor; Q_E is the goodness-of-fit statistics for the model; *%exp.* is the percent of variance explained by the model.

Affective Outcomes

Seven different attitudes and one self-concept outcome were identified and analyzed. All measures were taken individually after the treatment. Results of the overall effects are presented first, followed by study features analyses of heterogeneous outcomes.

Overall Effects

The weighted mean effect sizes, 95% confidence intervals, and the homogeneity statistics for each outcome are presented in Table 17. The average effect size of all the affective outcomes was +0.17, which is significantly positive favoring students learning in small groups. Significantly positive effect sizes were found on student attitude toward learning with computers ($d_+ = +0.41$), attitude toward group work ($d_+ = +0.43$), and attitude toward classmates ($d_+ = +0.23$). No significant difference was found between students learning in small groups or individually on their attitudes toward computer, subject, teacher, or academic self-concept. Homogeneity statistics indicate that except for attitude toward group work, all the other datasets were homogeneous, indicating that the findings on these outcome measures were consistent. For the dataset on attitude toward group work, the findings were significantly heterogeneous ($Q_T = 94.80$, df = 16). Study features analyses were, therefore, performed on this outcome to identify the factors that influenced student attitude toward group work.

Table 17. *Weighted mean effect sizes on affective outcomes*

Outcomes	k	before outlier procedures d_+	95% CI	Q_T	after outlier procedures d_+	95% CI	Q_T
Attitude twd. computer	21(16)	+0.02	-0.10/+0.14	18.90			
Attitude twd. subject	28(19)	+0.06	-0.04/+0.16	31.90			
Attitude twd. learning with computers	7(3)	+0.41	+0.11/+0.72	11.89			
Attitude twd. group work	17(11)	+0.45	+0.32/+0.57	116.21*	+0.43	+0.31/+0.55	94.80*
Attitude twd. classmates	16(6)	+0.23	+0.06/+0.40	18.63			
Attitude twd. teacher	8(1)	+0.21	-0.08/+0.50	3.93			
Academic self-concept	8(3)	+0.03	-0.20/+0.26	1.57			

Note. *k* is the total number of independent findings integrated. The values in parentheses are the numbers of studies from which the findings were extracted. d_+ is the weighted mean effect size. 95% CI is the 95% confidence interval for d_+. Q_T is the homogeneity statistics, where * = p<.05, indicating that the effect sizes integrated are heterogeneous.

Study Features Analyses on Attitude toward Group Work Findings

The effect sizes in the attitude toward group work data ranged from -0.39 to +3.40, with 14 positive, 1 zero, and 2 negative. The majority of the findings were from well-controlled but unpublished reports or dissertation, involving pre-secondary school students, learning mathematics or science, working in heterogeneous ability groups, in the presence of other peers. Due to the small number of findings in the dataset, only study features with sufficient variability were analyzed.

Univariate Analysis

Table 18 presents the results of the univariate study features analyses on the attitude toward group work findings. Six study features explained significant variability in the findings, which are described in the following subsections.

Table 18. *Results of univariate study features analyses: Attitude toward group work findings*

Study features	Q_B	k	d_+	95% CI	Q_W
		Outcome and methodology			
Student equivalence	7.19*				
well-controlled		15	+0.50	+0.37 / +0.63	83.08*
non-equivalent/unknown		2	+0.02	-0.30 / +0.35	4.53
Publication status	12.34*	17			
published		2	+0.83	+0.57 / +1.08	5.26
unpublished		15	+0.31	+0.17 / +0.45	77.20*
		Technology characteristics			
Type of programs	35.78*	17			
tutorial/drill-practice		13	+0.57	+0.42 / +0.72	25.61*
exploratory/tool		3	-0.13	-0.36 / +0.11	6.41
programming language		1	+1.28	+0.78 / +1.77	0.00
Instructional control	3.39	9			
		Task characteristics			
Type of tasks	0.11	16			
Task structure	1.61	10			
		Grouping characteristics			
Group learning strategy	3.34	17			
Group work exp./instruction	0.76	17			
Group size	43.46*	15			
two		11	+0.99	+0.81 / +1.12	21.57*
three to five		4	0.00	-0.17 / +0.35	9.77
Number of sessions	13.36*	16			
one		5	+1.13	+0.78 / +1.49	29.12*
more than one		11	+0.29	+0.15 / +0.42	52.27*
		Learner characteristics			
Grade level	13.35*	17			
pre-secondary		10	+0.67	+0.49 / +0.85	48.06*
secondary		3	+0.15	-0.11 / +0.42	7.18
college/university		4	+0.27	+0.08 / +0.48	26.21*
Relative ability level	0.04	8			

* $p < .05$

Note. Q_B is the between-class homogeneity statistics. k is the number of findings. d_+ is the weighted effect size. 95% CI is the 95% confidence interval for d_+. Q_W is the within-class goodness-of-fit statistics.

Methodology characteristics. Student equivalence (Q_B = 7.19, df =) and publication status (Q_B = 12.31, df = 1) were significantly related to the variability on attitude toward group work. Well-controlled studies (d_+ = +0.50) reported higher effect sizes than studies where student equivalence was not well-controlled or unknown (d_+ = +0.21). The latter was not significantly different from zero. Published journal articles (d_+

= +0.83) reported higher effect sizes on attitude toward group work than unpublished dissertations or reports (d_+ = +0.31).

Technology characteristics. Effect sizes varied for different types of computer programs (Q_B = 35.78, df = 2). The influence of social context had a greater effect on attitude toward group work when students worked with tutorial or drill-and-practice programs (d_+ = +0.57) or programming languages (d_+ = +1.28) than when they worked with exploratory programs or tool programs (d_+ = +0.13), which is not significantly different from zero.

Grouping characteristics. Group size (Q_B = 43.48, df = 1) and number of sessions (Q_B = 13.36, df = 1) were significantly related to the variability in the findings. The influence of social context had a greater effect on attitude toward group work when students worked in pairs (d_+ = +0.99) than when students worked in three-to-five-member groups (d_+ = 0.00). Close examination of the findings revealed a negative linear relationship between group size and student attitude toward group work: the larger the group size, the less positive the attitude toward group work when learning with computers (d_+ = +0.99 for pairs, +0.15 for triads, and –0.33 for large four-to-five-member groups). The influence of social context on attitude toward group work was greater in studies employing one session (d_+ = +0.97) than in studies that lasted more than one session (d_+ = +0.29), although both means were significantly positive.

Learner characteristics. The influence of social context on attitude toward group work was greater in studies that involved pre-secondary school students (d_+ = +0.67) than college or university students ($d_+ = +0.27$) and secondary school students ($d_+ = +0.15$). The last mean effect size was not significantly different from zero.

Multiple Regression Model Development

Analysis 1: Testing unique variances. The six significant predictors ($p<.05$) identified from the univariate study features analyses were tested for their unique variances in a multiple weighted least squares regression. All were entered as one block. The results are presented in Table 19. Of the six variables entered, two accounted for significant unique variances in the findings, with group size and number of sessions independently accounting for 35% and 7% of the total variance, respectively. The other four variables (student equivalence, publication status, grade level, and type of programs) did not explain significant unique variances.

Table 19. *Testing unique variances explained by significant study features: Attitude toward group work findings*

Study features	B	$SE\ B$	part r^2	Q_R	Q_E
				77.54*	17.61*
Group size	1.03*	.18	.35		
Number of sessions	.52*	.20	.07		
Publication status	-.20	.20	.01		
Grade level	.13	.15	.00		
Type of programs	-.22	.24	.00		
Student equivalence	-.33	.24	.02		
(constant)	.25	.29			

*$p< .05$

Note. B is the unstandardized regression coefficient, $SE\ B$ is the Standard Error of the B. part r^2 is the part correlation squared. Q_R is the Sum of Squares associated with all the predictors in the regression model. Q_E is the Goodness-of-fit statistics.

Analysis 2: Model development. In Analysis 2, a hierarchical multiple regression was run with student equivalence entered at Step 1 and other variables entered in blocks based on the results of Analysis 1 and the univariate analyses. Block 1 included group size and number of sessions that were significant in Analysis 1. Block 2 included all the other univariately significant variables. Finally, all the other non significant variables were entered to account for any additional variability. Within each block, the method of entry was stepwise.

Results of this analysis are presented in Table 20. After variance due to student equivalence was removed, only the two variables that explained significant unique variances in Analysis 1 entered the hierarchical regression model. Adding more variables did not explain significant additional variability. Together, the three variables accounted 78% of the total variability in the findings. Goodness-of-fit statistics ($Q_E = 21.30$, df = 13) indicates that the model fits the data and that the remaining variance was due to chance fluctuations. Thus, the model indicates that the most important predictor of student attitude toward group work was group size. Optimal attitude toward group work tended to be found when students learned in pairs and in short one-session studies.

Table 20. *Multiple regression model of study features: Attitude toward group work findings*

Predictors	*Step #*	*B*	Q_R	Q_R *Increment*	Q_E	*% exp.*
Student equivalence	1	.48	7.21	7.21*	87.93*	8%
Group size: pairs	2	.99	63.69	56.48*	31.46*	67%
Number of sessions: one	3	.60	73.85	10.16*	21.30	78%
Intercept for the model		.02				

*$p < .05$

Note. *B* is the unstandardized regression coefficient upon entry. Q_R is the Sum of Squares associated with all the predictors in the regression model. Q_R *Increment* is the additional Sums of Squares associated with the new predictor. Q_E is the goodness-of-fit statistics for the model. *%exp.* is the percent of variance explained by the model.

Summary

The purpose of this study was to quantitatively synthesize the research on the effects of social context when learning with CT, to explain the variability across studies, and to identify optimal conditions for effective small group and individual learning with computers. Through a comprehensive literature search, 103 studies were identified that examined the effects of small group learning with CT versus individual learning with CT on various cognitive, process, and affective outcomes for kindergarten to adult learners. The earliest study included was published in 1964 and the latest in 1996, with the majority of the studies published since 1990. From these studies, a total of 404 independent effect sizes were extracted and each was coded for its outcome, methodology, and substantive study features in order to integrate the findings and to account for any significant variability found in the effect sizes. The data in each outcome was analyzed using Hedges and Olkin's (1985) homogeneity approach. Each effect size was corrected for bias and weighted by the inverse of its variance to ensure that more weight is given to findings that are more reliably estimated or are based on larger sample sizes. For outcomes where effect sizes were found to be significantly heterogeneous, study features were first analyzed univariately to identify significant predictors. Based on the results of the univariate analyses, two weighted least squares multiple regression analyses were then performed. Analysis 1 tests for unique variance explained by each significant predictor. Analysis 2 attempts to account for shared variance among the predictors and develop a parsimonious model.

Table 21 summarizes the results of the overall effects of social context on cognitive, process, and affective outcomes. On average, small group learning with CT, as

Table 21. *Summary of the overall effects*

Outcomes	*k*	d_+	Q_T
Cognitive	186	+0.19*	289.45*
♦Group task performance	34 (19)	+0.39*	68.78*
♦Individual achievement	146 (80)	+0.16*	204.08*
Success rate	6 (4)	+0.28*	4.28
Process	113	+0.12*	368.68*
Peer interactions	6 (4)	+0.33*	50.72*
Interactivity with programs	15 (8)	-0.27*	13.44
♦Task completion time	56 (31)	-0.21*	142.94*
♦Amount of task attempted	25 (11)	+0.03	54.12*
Use of strategies	7 (4)	+0.66*	10.72
Perseverance	4 (2)	+0.48*	2.60
Affective	105	+0.16	214.65*
Attitude toward computer	21 (16)	+0.02	18.90
Attitude toward subject	28 (19)	+0.06	31.90
Att. twd. learning with CT	7 (3)	+0.41*	11.89
♦Attitude toward group work	17 (11)	+0.43*	94.80*
Attitude toward classmates	16 (6)	+0.23*	18.63
Attitude toward teacher	8 (1)	+0.21	3.93
Academic self-concept	8 (3)	+0.03	1.57

*$p<.05$

Note. *k* is the total number of independent findings integrated. The values in parentheses are the numbers of studies from which the findings were extracted. d_+ is the weighted mean effect size, where* indicates that the effect size is significantly. Q_T is the homogeneity statistics, where * indicates that the effect sizes integrated are heterogeneous. ♦indicates results with outliers modified.

compared with individual learning CT, had more favorable effects on student cognitive, process, and affective outcomes. Moderate positive effects of small group learning were found on group task performance (d_+ = +0.39), peer interaction (d_+ = +0.33), use of strategies (d_+ = +0.66), task perseverance (d_+ = +0.48), attitude toward learning with computers (d_+ = +0.41), and attitude toward group work (d_+ = +0.43). Small positive effects were found on individual achievement (d_+ = +0.16), success rate (d_+ = +0.28), and attitude toward classmates (d_+ = +0.23). However, groups learning together with only one machine generally had a small negative effect on student interactivity with programs (d_+ = -0.27) and task completion time (d_+ = -0.21). No significant difference was found between students learning in small groups and individually in the amount of task attempted, attitude toward computers, subject, teacher and academic self-concept.

Significant heterogeneity, however, was found for five of the outcomes analyzed: group task performance (Q_T = 68.78, df = 33), individual achievement (Q_T = 204.08, df = 145), task completion time (Q_T = 142.94, df = 55), amount of task attempted (Q_T = 54.12, df = 24), and attitude toward group work (Q_T = 94.80, df = 16). Study features analyses were, therefore, conducted first univariately and then multivariately for each of the five heterogeneous outcomes to identify factors that are related to the variability in the findings.

Student equivalence across conditions was significantly related to the variability in three of the five heterogeneous outcomes: group task performance, task completion time, and attitude toward group work. In the individual achievement findings, the relationship between the effect sizes and student equivalence was found marginally significant. In all the four cases, larger mean effect sizes were found for findings that were extracted from well-controlled studies than from studies where group equivalence was not controlled or unknown. Due to this significant difference between well-controlled studies and poorly controlled studies, student equivalence was used as a kind of covariant (i.e., entered at Step 1) in the multiple regression analyses to control for study quality in the model development for each of these four datasets.

Three study features (type of tasks, type of feedback, and presence of others) accounted for the significant variability on group task performance after controlling for student equivalence. The advantage of group performance over individual performance was significantly greater when tasks involved factual learning than problem solving, when no or minimal feedback than elaborate feedback was available from the programs, and when there were no other peers working close by than when there were other peers working close by. When all the positive study features were in place, $d_+ = +1.13$ favoring group performance. When none of the positive study features were in place, $d_+ = -1.35$ favoring individual performance. Together the four variables accounted for 52% of the total variance in the group task performance findings. The goodness-of-fit statistics indicate that the model fits the data.

Six study features (group work experience or instruction, group size, subject, type of programs, gender and relative ability) accounted for the significant variability on individual achievement after controlling for student equivalence. Small group learning with CT was more effective when students had group work experience or instruction for cooperative group work than when no such experience or instruction was reported, when working in pairs than in 3-5 member groups, when working with tutorial or drill-and-practice programs than with exploratory or tool programs, when learning social sciences or computer skills than mathematics, science, reading, and language arts, for female than male students, and for relatively low and high ability rather than medium ability students. When all the positive study features were in place, $d_+ = +0.95$ favoring students learning in groups. When none of the positive study features were in place, $d_+ = -0.22$ favoring students learning individually. Together, the seven variables in the model accounted for

21% of the variance in the individual achievement findings. The goodness-of-fit statistics indicate that the remaining variance was due to sampling errors.

Three study features (publication status, type of tasks, and task familiarity) were significantly related to the variability on task completion time after controlling for student equivalence. While findings from published journals showed no significant difference in the task completion time between students learning in groups and individually, findings from unpublished dissertations or reports showed that students working in groups needed significantly more time in completing their tasks than those working individually. Groups took significantly more time than individuals when tasks were familiar and involving factual learning. Together the five variables explained 37% of the total variance. However, the goodness-of-fit statistics indicate that the model does not fit the data and that significant variability remained to be explained.

Three study features (relative ability, instructional control, and design orientation) accounted for the significant variability on amount of task attempted. While low ability students attempted a significantly higher amount of the task when working in small groups than when working individually, medium ability students attempted significantly less working in small groups than individually. For high ability students, there was no difference whether working in small groups or working individually. Groups attempted a higher amount of task than did individuals when instruction was mostly learner-controlled and the program design was individually oriented; but when instruction was mostly system-controlled and the programs had special design for group use, individuals attempted a higher amount of task. Together, the three variables accounted for 52% of the total variance. The goodness-of-fit statistics indicate that the model fits the data.

Two study features (group size and number of sessions) accounted for the significant variability on attitude toward group work after controlling for student equivalence. Moderate to large positive effect sizes were observed when students worked in pairs. Small to moderate positive effect sizes were observed when students worked in triads. However, when students worked in four-to-five-member groups, negative effect sizes were observed. One-session studies reported more positive effect sizes than did studies that lasted more than one session. Together, the three variables accounted for 78% of the total variance. The goodness-of-fit statistics indicate that the model fits the data.

V. DISCUSSION

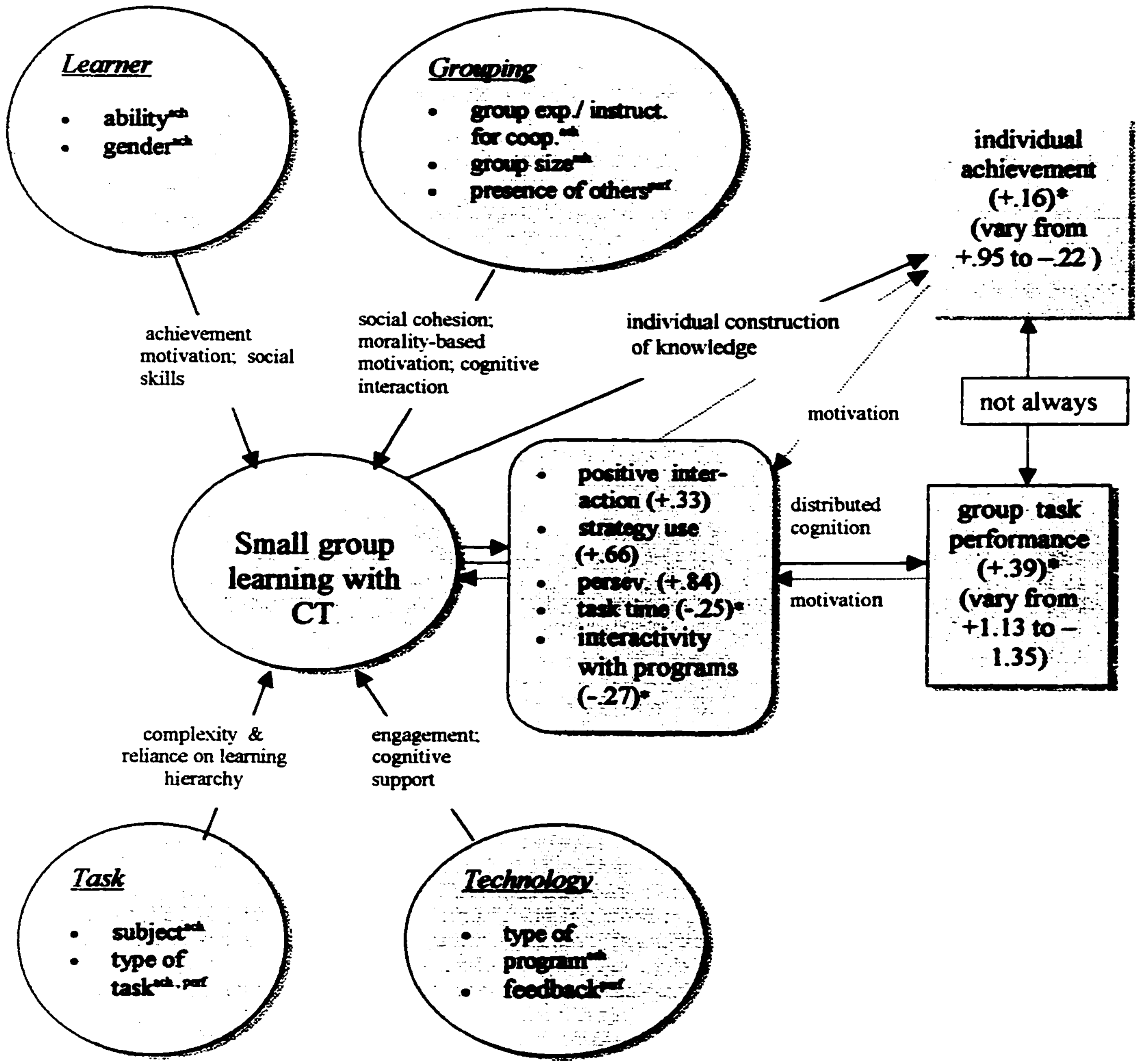
This study quantitatively synthesized the literature on the effects of social context when learning with CT on cognitive, process, and affective outcomes based on 404 independent findings from 103 studies involving 18,319 kindergarten to adult learners. Results of the study will be discussed in the following sections: 1) difference between group task performance and individual achievement; 2) factors influencing group task performance; 3) factors influencing individual achievement; 4) learning processes and affective outcomes; 5) strengths, limitations, and future directions; and 6) conclusion and recommendations.

Difference between GroupTask Performance and Individual Achievement

Two major types of cognitive outcomes were identified in the studies that compared small group learning with CT versus individual learning with CT. They are group task performance and individual achievement. The former compares group performance versus individual performance during the task. The latter compares the achievement scores of those who learned in small groups versus those who learned individually on individually administered immediate or delayed posttests. Results of this review indicate that, on average, there was a moderate positive effect of small group learning on group task performance and a small positive effect on individual achievement when learning with CT. The former is significantly larger than the latter.

Figure 5 presents an explanatory model of the factors and processes that influence the effects of social context on student task performance and learning based on the results from this study and theories of motivation and learning. The differential magnitude of

Figure 5. An Explanatory Model of Small Group Learning with CT: Factors and Processes that Influence the Effects of Social Context on Group Task Performance and Individual Achievement



Note. Positive numbers indicate effect sizes favoring small group learning; negative numbers indicate effect sizes favoring individual learning; *indicates that the effect sizes analyzed were significantly heterogeneous; ^{ach} = significant predictor on achievement; ^{perf} = significant predictor on task performance.

——— analyzed
——— hypothetical

effect sizes on group task performance and individual achievement may be explained by the difference between distributed cognition and the construction of individual knowledge. According to Hutchins (1991), when a group of individuals work together on a task, it forms a distributed cognition and has cognitive properties beyond any individuals. Due to differences in perception, experience, or prior knowledge, the interpretation each member may form of a given problem is often different from others. Thus, when working together, the group is capable of doing more than any of its members can by comparing alternative interpretations and solutions, correcting each other's misconceptions, forming a more holistic picture of the problem if the task is complex, or simply by pooling resources.

The smaller positive effect on individual achievement may be explained by different conditions involved in the individual construction of knowledge. Although group interaction may provide a context for members to learn from each other, learning may depend on whether each member is motivated to be actively involved in constructing knowledge. According to Piaget (1954), a learner must actively construct meaning for learning to occur. Simply being exposed to more answers during group work is not enough to facilitate one's knowledge construction. Webb's (1882a, 1982b, 1984) research on help giving indicates that only elaborate explanations facilitate student learning. Therefore, while the collective wisdom may all be reflected in the task performance of the group, how much one is able to learn from each other and is subsequently demonstrated on an individual achievement test may depend on how motivated the members are to ask for and provide explanations. Furthermore, group task performance may not depend on the efforts and contributions of all members. Instead, in many cases, when there is no specific strategy to ensure equal participation, superior group result may reflect the contribution of the high ability members rather than the learning of all members.

Significant heterogeneity was found in both the group task performance and individual achievement findings, indicating that group performance was not always superior to individual performance and that students did not always learn more from working in small groups. Further more, different factors appeared to influence the effect of social context on group task performance and individual achievement. These results are discussed in the next two sections.

Factors Influencing Group Task Performance

Three study features accounted for the significant heterogeneity in the findings on group task performance: type of tasks, feedback, and presence of others after controlling for student equivalence across conditions. The superiority of group task performance over individual task performance was greater: a) when tasks involved factual learning than problem solving; b) when programs provided no or minimal feedback than elaborate feedback; and c) when no other peers were working close by than when there were peers working close by. When tasks involved factual learning, there was a consistent large superiority of group task performance over individual task performance. When tasks involved more complex problem solving, group performance, on average, was also superior to individual performance, but there was considerable variability in the findings. Group performance had largest advantage over individual performance when program provided no or minimal feedback and when no peers were working close by. However, when elaborate feedback was available from the programs and when there were other peers working close by. individuals appeared to outperform groups.

Hill's (1982) review on group task performance versus individual task performance in general learning environment also found that group performance was generally superior to individual performance. In quantitative tasks, he found that groups usually benefited from the pooling of resources, opportunities for correcting each other's errors, and the statistical cancellation of errors in the computation of average performance. In complex problem solving tasks, group performance, in general, was also better than individual performance but group members made less effort when they preferred to work individually and when their abilities were low.

The difference between the present review and Hill's (1982) may be due to the unique learning context when learning with CT. According to Webb (1982a, 1982b, 1984), learning in small groups depends on giving and receiving elaborate feedback. When students learn with CT, the computer may serve as a special group member. When it provides no feedback or gives correct answers only, students learning alone may not get the feedback they need. Similarly, when no other peers are working close by, students working alone may have little chance of giving or receiving necessary help. Under these conditions, working in small groups may be especially advantageous since group members may be the only sources that provide the needed performance support.

When the computer program provides elaborate feedback and when there are other peers working close by, individuals may outperform groups. Under these conditions, those working individually may get specific performance support from either the computer program or other individuals working on the same tasks, especially when tasks are difficult. Some research suggests that when the elaborate feedback is well designed, the computer program may provide more effective feedback than group members can. For example, Roussey, Fariolo, and Piolat's (1992) research suggests that when working in groups, collaborative talk often does not focus on important task features (e.g., the meta-linguistic features of a text, the mental functioning of writing). With appropriate and effective feedback from programs, students working individually may be able to get their work done correctly and quickly without help (or disturbance) from their group members. Similarly, when working individually but with other peers working close by, students may benefit from concentration on their own work, free exploration as well as cognitive and positive social interaction with peers when needed.

However, the results of the interaction analysis between type of feedback and type of outcomes indicate that although social context appeared to have a negative effect on group task performance when elaborate feedback was available from the programs, results on individual achievement indicate a different finding. These findings show that students who learned in small groups generally achieved higher than those who learned individually when measured on individual achievement posttests. Further examination indicates that only one study found a negative effect of social context on individual achievement under the elaborate feedback condition.

The apparently differential influence of elaborate feedback on task performance and achievement may be due to several reasons. First, as the number of findings with elaborate feedback on group task performance and individual achievement was small and was extracted from different studies, the elaborate feedback involved may be of different nature and quality. It is possible that the feedback available in the studies that measured task performance might be more effective, easier to understand, and more motivating than those in the studies that measured achievement. Second, according to theories and research on group learning (e.g., Brown, Collin, & Duguid, 1989; Forman & Cazden, 1985; Webb, 1982a, 1982b), articulation of ideas is an important aspect that facilitates student learning in small groups. It is possible that the articulation of ideas and cognitive dissonance between peers may create deeper processing of ideas and, therefore, better construction of one's own knowledge. Third, the differential effects may be due to the characteristics of the tasks involved in the studies and the characteristics of the learners. In the studies where individuals performed or learned better, the tasks were complex and difficult and the learners were generally not well equipped with the ability to help each other on the important aspects of the task. In the studies where students learned or performed better in small groups, the tasks appeared to encourage more sharing of each other's knowledge and perspectives. However, as the number of findings involving elaborate feedback on both group performance and individual achievement were small and they were not extracted from the same studies, these results should be interpreted with caution. More research is needed for further verification.

In summary, the significant factors on group task performance suggest that task performance, as a result of distributed cognition, may benefit not only from the resources that are available among the group members, but also from the support by other peers working close by, or from the explanatory feedback provided by the programs. However, the differential influence of feedback on the effects of social context on group task performance and individual achievement suggests that higher task performance does not necessarily mean similar learning gains on individual achievement.

Factors Influencing Individual Achievement

Six study features (group work experience or instruction, group size, relative ability of students, gender, subject, and type of programs) were found that accounted for the significant variability on individual achievement after controlling for student equivalence across conditions. These factors influenced whether small group learning had a large positive effect (+.95 SD) or a small negative effect (-.22 SD) on student individual achievement (see Figure 5). Each of these significant predictors are discussed below under group learning characteristics, learner characteristics, and task and technology characteristics. Whenever possible, related results on other process or affective outcomes will also be discussed to provide a better understanding.

Group Learning Characteristics

Group work experience or instruction and group size significantly influenced the effects of small group learning on individual achievement. Significantly higher individual achievement gains were found in studies where students had group work experience or were provided with specific instructions for effective cooperative group work than in studies where no such description was provided. Effects of small group learning was significantly more positive when students worked in pairs than when they worked in groups that contained three to five members. Positive attitudes and positive learning processes when students have group work experience or instruction and when they work in pairs may be plausible explanations for the significant learning gains. Results from affective and process measures show that under these conditions students generally had a more positive attitude toward group work. They also spent more time on task and attempted a larger amount of the task than those learning individually.

Motivation theories on group work (e.g., Sharon & Sharon, 1976, 1992; Shepperd, 1993) suggest that not all groups function well. For example, a group may not function well when some members do not exert efforts or exert minimal efforts. When a group is cohesive, learners may help each other because they care about their group members and their group. Experience in group work may enable members to use strategies for effective group work. Specific instruction for cooperative learning ensures that students learning in a group will have positive interdependence as well as individual accountability. Positive interdependence may motivate students to contribute and help each other to achieve their group goal through morality-based motivation (Ames, 1984). Individual accountability can help minimize social loafing (Shepperd, 1993) and ensure that each member will make an effort to learn. Research on cooperative learning (e.g., Slavin, 1983, 1992; Johnson & Johnson, 1989, 1992a) suggests that these cooperative learning strategies can significantly increase student learning. When students are working for a common goal, or perceive that they are positively interdependent, or try to conform to the group norm, or when the group is cohesive, they are encouraged to help each other and to exert their efforts.

Similar findings were found in Lou et. al.'s (1996) meta-analyses on within-class grouping versus whole class learning in general. Lou et al. found that students learned more in cooperative groups than in other groups, in smaller groups than in larger groups. However, the finding concerning group size appeared somewhat different from what was found in Lou et al., where the optimal group size was found to be 3-4 members. The difference may be due to the physical requirement when students learn with computers. Group size may have to be small enough for all group members to sit comfortably around the computer in face-to-face collaborations, as was the case in most of the studies included in this meta-analysis. Another possible explanation may be that when learning with computers, the computer itself seems to function as a prominent group member or tutor. Other members have to coordinate well in order to work coherently and at similar pace with this special group member. For example, when working with computers, the variety of perspectives due to a larger group size may make it difficult to choose the instructional sequences and the content. Thus, a group of smaller size is usually easier than a group of larger size to coordinate and to motivate students to contribute equally and help each other.

Learner Characteristics

Two learner characteristics (relative ability level of students and gender) significantly moderated the effects of group learning on individual achievement. On average, there was a medium positive effect size of small group learning for low ability students, a small positive effect size for high ability students, but no effect for medium ability students. Examination of group composition showed that the significant heterogeneity lied mainly in the heterogeneous ability groups. When the groups were homogeneous in ability, there was a consistent small positive effect of group learning for all students. However, when the group was heterogeneous in ability, there was a moderate positive effect for both low and high ability students, but zero effect for medium ability students.

The consistent positive effects of homogeneous ability grouping over individual learning may be explained by pooling of resources (Hill, 1982), cognitive elaboration (Dansereau, 1985), giving and receiving explanations (Webb, 1982a, 1982b, 1984), and group cohesiveness when working with computers. Results on process measures and affective outcomes analyzed in this study indicate that when learning in small groups, students generally used more learning or appropriate task strategies, had more cognitive and positive social interaction, and had more positive attitude toward group work and toward peers than those working alone.

The positive effects of homogeneous ability grouping for low ability students appeared different from Hill's (1982) finding and theory on group versus individual performance in general learning situations. Hill suggests that only high ability learners benefit from pooling of resources in homogeneous high ability groups and that low ability learners do not benefit because of lack of resources in homogeneous low ability groups. Results of this meta-analysis suggest that the latter finding concerning low ability students was not true when learning with computers. This may be due to the possibility that the content and pace of learning in computer programs, especially in tutorials and drill-and-practice programs, can often be adjusted to meet the different needs of students at different ability levels. With appropriate learning materials and tasks made possible with computers, low ability students in homogeneous low ability groups are also able to benefit from the pooling of resources, cognitive elaboration, and cohesive pace of learning. When learning with CT, the computer may also serve as an able member in the group. It may provide the low ability learners with needed guidance, effective feedback, and structure. Alternatively, it may stimulate and challenge them with appropriate questions and tasks.

The finding of differential effects of heterogeneous ability grouping for students of different relative ability is similar to that found in Lou et al.'s (1996) meta-analysis on within-class grouping. In their meta-analysis, they found that low ability students benefit most in heterogeneous ability groups and that high ability students also benefit from heterogeneous ability groups. Lou et al. explained that in heterogeneous ability groups, low and high ability students benefit from receiving and giving explanations. Receiving explanation helps low ability students correct misconceptions and acquire appropriate learning strategies. Giving explanations helps high ability students clarify and organize their own learning. In this meta-analysis, results on student attitude toward group work also showed that in heterogeneous ability cooperative pair groups, both high and low ability students have positive attitude toward group work, which may be a result of group cohesion and mutual satisfaction from giving and receiving help. Positive attitude would, in turn, lead to more effective group work and, therefore, more effective learning. Lou et al. suggest that medium ability students may not benefit when learning in heterogeneous ability groups because in these groups they may neither give nor receive explanations.

Findings on the amount of task attempted analyzed in this study may provide another explanation for the differential effects of social context on student individual achievement for students of different relative ability. The results indicate that while low ability students generally attempted a larger amount of task working in small groups compared to working individually, medium ability students generally attempted a larger amount of task when working individually than in small groups. For high ability students, there was no difference whether they worked in groups or individually. These results show a similar pattern as those found on individual achievement.

The results on gender indicate that social context had a significantly differential effect for male and female students. While there was a medium positive effect of small group learning on individual achievement for female students, there was no difference in the individual achievement results for male students whether they learned in a group or individually.

The differential effects of social context for male and female students may be explained by a process measure analyzed in this study. In the amount of task attempted data, it was found that while female students tend to attempt a larger amount of the task when working in small groups than individually, male students tend to attempt a similar amount of the task whether working in small groups or individually.

Another possible explanation may be found in Gunterman and Tovar's (1987) qualitative data on the task behaviors of male and female students. Gunterman and Tovar found that while working in homogeneous gender groups, male students exhibited much more off-task and antagonist verbalizations than female groups or mixed gender groups, where more cooperative and task related behaviors were often observed. In their observations of male groups, it was found that there was little asking of suggestions, opinions, or information related to the task at hand. When suggestions and opinions were given, they were usually given spontaneously in a manner indicative of an attempt to deflate the partner' status. These results suggest that the higher learning gains for female students may be due to their social or interpersonal skills.

Task and Technology Characteristics

Subject, type of tasks, and type of programs were significantly related to the variability in the individual achievement findings. On average, small group learning had positive effects on individual achievement in all subjects, on both problem solving tasks (i.e., applying different knowledge and skills or involving higher reasoning skills) and factual learning tasks (i.e., acquiring facts, concept, and principles). However, the effect sizes generally appeared larger in learning social sciences or computer skills than mathematics, science, reading, language arts or professional skills. Similarly, the effect sizes were generally larger with factual learning tasks than with problem solving tasks. Effects of small group learning were also positive when students worked on tutorial, drill-and-practice programs, or when learning programming languages. However, when working on exploratory programs (e.g., simulations or hypertext databases) or using programs as tools for other tasks (e.g., word processor for writing), there was no significant mean difference in the posttest achievement between those learning in small groups and individually, in spite of a significant superiority of groups on group task performance.

These findings, especially the ones concerning type of tasks and type of programs, appeared quite different from what was predicted by Ertmer and Newby's (1993) and Lauzon and Moore (1989). Ertmer and Newby argued that group discussion and collaboration are more effective when tasks require higher levels of cognitive processing such as problem solving. Similarly, Lauzon and Moore argued that individualized instruction and CAI are the most effective and efficient means of learning basic facts;

when students move toward more advanced learning, peer collaboration and discussion are more effective. A different moderating effect of types of tasks is found in this review.

There are several plausible explanations for these findings. First, problem solving usually involves high level reasoning skills or applying several different kinds of knowledge or skills, which in a large part often depend on one's prior knowledge. They are not as easily improved through group interaction as in acquiring factual information, where contribution and correction from others may be more easily assimilated and retained. Thus, when working on complex problem solving tasks, especially when programs are exploratory in nature or used as tools, even though group performance may be significantly better than individual performance due to pooling of knowledge, skills, and efforts of all members, each member may only learn as much as his/her prior cognitive schema is able to assimilate or accommodate. It should be noted, however, that the effects of social context was on average positive for both problem solving tasks and factual learning tasks.

Second, complex problems usually require high levels of mental processing. When working in groups, especially when programs are exploratory in nature, the collaborators usually focus on actions and results rather than taking the time to articulate their mental processes or provide explanations for their actions (Daiute, 1989). Conscious regulatory means are often not elicited in collaborative talk (Roussey, Farioli, & Piolat, 1992). Thus, how one member successfully solved a problem or part of a problem may not be easily learned by the observers. Therefore, although group performance may be better than individual performance because of distributed cognition of all members by having more insights, interpretations, and perspectives, each learner may or may not be able to learn more from each other depending on how active he/she is in constructing his/her own understanding and whether members help each other in doing so. Whereas when learning individually, each student is free to explore his/her own ways of solving the problem, especially when the tasks are challenging but within the ability level of the learner and when the programs are stimulating and engaging. Under these conditions, students learning individually may be free to make their own plans, explore according to their own perspectives, and proceed at their own pace. Experience in solving one's own problem and testing one's own hypotheses may enable students working individually learn as much or more than those working in groups, especially when effective group learning strategies are not in place.

Third, motivation may be another important explanation for the differential effects of social context when students used different types of programs. Results on attitude toward group work analyzed in this study indicate that the mean effect sizes were more positive when students were using tutorial or drill-and-practice programs than when they were using exploratory or tool programs. This may be because tutorial and drill-and-practice programs may not be as engaging as exploratory or tool programs. Therefore, learning with peers when using tutorials or drill-and-practice programs might be much more enjoyable and motivating than working alone.

Fourth, it is possible that commonly-used outcome measures such as multiple-choice questions are usually more sensitive to the discrete factual knowledge usually learned from tutorials, drill-and-practice programs or programming languages than to the complex problem solving strategies that might be acquired when working with exploratory or tool programs.

Kulik and Kulik's (1991) meta-analysis on the effects of learning with CT suggest differential effects of exploratory or tool type programs for students at different grade levels. In this meta-analysis on the effects of social context when learning with CT, no significant interaction effect was found for type of programs and grade levels. The effects of social context were more positive with drill-and-practice or tutorial programs than with exploratory or tool programs for both pre-secondary and post-elementary students.

Niemiec, Samson, Weinstein, and Walberg's (1987) meta-analysis on the effects of learning with CT at the elementary level suggest different effects for drill-and-practice and tutorial programs. No significant difference was found in this meta-analysis in the effects of social context for the two types of programs.

In summary, the results on individual achievement suggest that group learning skills, interpersonal skills, and small group size are important in facilitating student learning in small groups. Effective cooperative learning strategies such as turn-taking and agreeing on answers that emphasize both positive interdependence and individual accountability can help ensure that each member is actively involved not only in contributing to the joint task performance but also in assisting each other in the construction of individual knowledge. Students learning in groups must coordinate well to learn together. A group of smaller size is generally easier to coordinate than a group of larger size when learning with CT, especially in the face-to-face collaboration. Better interpersonal skills that many female students enjoy may enable them to be better group learners.

Task and program characteristics are also important in influencing the effect of social context on student learning. Group learning is especially effective when programs are used to directly teach students new content or are used as practice exercises, which are usually less motivating for students to work alone, than when programs are used as exploratory environments or tools for other tasks.

Learning Processes and Affective Outcomes

Results of this review indicate that small group learning with CT has a small to moderate positive effect on positive peer interaction, use of strategies, task perseverance, attitude toward learning subject with computers, attitude toward group work, and attitude toward classmates. However, students learning in small groups generally have less interactivity with programs and need more time for task completion. Whether learning in small groups or individually, students have similar amount of task attempted, similar attitudes toward computers, subject, teachers, and similar academic self-concepts.

These results suggest that students learning in the group or individual context often benefit from different learning processes. While those learning in small groups may benefit from peer interaction, students learning individually may benefit from more opportunities to interact with programs and from better focus on task.

According to Vygotsky's (1978) social learning theory, cognitive interaction between group members can enable the learners to achieve what they cannot achieve alone by creating a zone of proximal development, especially when there are knowledge gaps between the members. Piaget's (1954) cognitive learning theory also suggests that learning occurs through a process of assimilation or accommodation. Cognitive interaction among the peers may facilitate both of these knowledge construction processes through helping each other or through peer discussion. Peer interaction may also enable learners to identify knowledge gaps that motivate students to learn more.

Motivation theories of learning suggest that a learner' level of motivation affects learning (Atkinson, 1966; Weiner, 1992). Positive social interaction such as praise and encouragement helps to boost learners' confidence, reduce their perception of task difficulty, and motivate them to exert efforts and to persist on their tasks. Successful efforts can enable the learners to attribute their success to efforts rather than to ability, which may be especially important for low ability learners. According to Wiener (1992), only when success or failure is attributed to efforts will the learners be motivated to persist and to work hard. Evidence of positive effects of group learning on low ability student's motivation is found in this review. When working in small groups, low ability students working in a group attempted a significantly larger amount of the task than those working individually. This higher motivation and efforts may help explain why group learning is especially effective for low ability learners.

Positive social and cognitive interaction also helps to improve students' attitude toward peers, group work, and toward learning with CT. These positive attitudes help to create a cohesive group learning environment. When a group is cohesive and when members are willing and able to help each other, students working in small groups, especially in pairs, may find learning with CT more enjoyable than those working individually. They may perceive the task as being more interesting, more personally relevant, and easier to succeed. These positive perceptions, therefore, may lead to higher motivation, more efforts, and, consequently, more learning.

Significant heterogeneity in student attitude toward group work, however, indicates that not all students learning with CT in small groups had positive attitude toward group work. Results of the study features analyses indicate that student attitude toward group learning with CT varied depending on group size and number of sessions in the study. More positive attitudes were expressed by students who worked in pairs (d_+ = +0.99) than in triads (d_+ = +0.15) or 4-5 member groups (d_+ = -0.33). The positive effects for pair work with CT may be explained by group cohesiveness and positive learning support that learners may find in each other. The negative effects for 4-5 member groups may be explained by the difficult task in coordinating a large group if students are highly interdependent upon each other, such as having to agree on answers, be all present for work outside class, or leave time for group processing when learners would rather spend time working on their interesting programs. Although these cooperative learning strategies may enable students to help each other, but when a group is large in size, it might be too difficult and time-consuming to coordinate among all the members.

While motivation in group learning may depend more on group cohesiveness and efforts required for coordination, motivation in the individual learning context may depend mainly on the characteristics of the task and the characteristics of the programs. Results of this review indicate that when students learned individually, they generally interacted more with computer programs and needed less time for task completion. However, there was significant heterogeneity in the task completion time. Study features analyses indicate that there appear to be differential conditions for efficient individual or group work. Individuals needed less time when tasks were familiar and when they were learning factual knowledge and using exploratory or tool programs. But when tasks were unfamiliar, when problem solving, or using tutorial or drill-and-practice programs, students learning in small groups were more efficient in completing their tasks. According to Atkinson's (1966) achievement motivation theory, when tasks are moderately difficult, learners will be optimally motivated to achieve as they offer the most challenge and, therefore, most value for success. Thus, when working with exploratory or tool programs, students may be more motivated than when working with tutorial or drill-and-practice programs. When tasks are familiar, students may have less need for group support. When tasks are unfamiliar and when problem solving, students may benefit more from working with others. When using tutorial or drill-and-practice programs, learning together with others may be more interesting.

In summary, opportunities for knowledge construction and motivation are two important factors that facilitate student learning. Superior group performance does not necessarily imply more learning for each member. Effective learning in small groups depends on cognitive elaboration, positive social interaction, group cohesion, group learning strategy, and student motivation. Effective individual learning depends more on the characteristics of the program in challenging and motivating the learner and in providing opportunities for active and meaningful knowledge construction.

Strengths, Limitations and Future Directions

This meta-analysis employed comprehensive literature searches, theory-guided as well as nomological coding of salient outcomes and study features in the literature, and rigorous data analyses via Hedges and Olkin's (1985) homogeneity approach. Variability in five significantly heterogeneous outcomes were explored both univariately and multivariately. The results extend the knowledge on the role of social context when learning with CT on various cognitive, process, and affective outcomes. It has answered the question of whether and to what extent small group learning with CT is more effective than individual learning with CT and on what type of outcomes. It has identified a number of study features that moderated the effects of social context when learning with CT. It has developed parsimonious models that explained variability in four of the heterogeneous outcomes. It has also developed an explanatory model for group task performance and individual achievement. However, the results of this meta-analysis, like others, are somewhat limited by the data that is available in the primary studies.

First, as results concerning explanatory features are correlational in nature, strong causal inferences are not warranted. Some of the study features, especially those that do not explain significant unique variances in the multiple regression analyses, often co-vary with other study features, which makes unambiguous interpretation impossible. Results are especially tentative when the heterogeneity within the dataset is not resolved, as is the case with the task completion time findings. It is possible that factors not identified by this researcher or the primary researchers may explain some of the variability in the study findings.

Second, as meta-analysts do not have experimental control over data, some of the analyzed study features had small sample sizes or unequal sample sizes, which reduces the sensitivity of the analyses. For example, the analyses of the moderating effects of gender are based on about a dozen findings for each gender on individual achievement, fewer on process measures, and none on affective outcomes. Therefore, the results concerning this study feature may not be as well understood and generalizable as those that had larger sample sizes. More primary studies are needed to verify the generalizability of the differential effects of social contexts for male and female students and to better understand the reasons for the difference.

Similarly, the number of findings involving elaborate feedback was relatively small on individual achievement outcome as well as on other outcomes. More research is needed to verify the negative effects of small group learning on group task performance and the positive effects on individual achievement when elaborate feedback is available from the programs. Research is needed to determine if there is a relationship between these two different results or if they were the results of the different quality of the feedback in the programs.

Third, results of this meta-analysis may be limited by the design quality of the programs used in the primary studies. For example, the majority of the programs were designed with individual orientation or with no special design for group work. A few programs that provided special design for group use such as dual keyboards or computer allocation of turn-taking had not been as successful as expected in ensuring effective group learning. For example, Light , Foot, Colbourn, and McClelland (1987; Foot, 1986) used dual keyboard to ensure simultaneous participation and collaboration of the group members in solving "Towers of Hanoi" problems. Those learning in groups showed better individual performance only in the tasks that were identical to the ones that were used during learning and not in generalization tasks, which suggests that the learning was superficial and had not generalized into a solution strategy. The authors also noted that there was little verbal discussion between the partners. In later experiments (Foot, 1986), students were asked to give justifications for their answers. The results appeared mixed. In one experiment comparing groups with justification versus individual learning, those learning in groups performed better than individuals in the immediate individual posttest but individuals performed better in the delayed individual posttest. In another experiment comparing groups with justification versus individuals with justification, groups performed better in the delayed individual test. These results indicate that more effective designs for use by groups are needed to ensure more successful group learning with computers.

Fourth, results of this meta-analytic research may be limited by the way group and individual learning was implemented in the studies. In most of the studies, groups collaborated in the face-to-face setting around a computer on the same task. Those working in the individual condition were often forbidden to talk to each other. It is possible that a combination of the two may ensure more effective learning. For example, two group members may each work at his/her own computer on the same task or different parts of the same task but are responsible for helping each other when needed. Such combination ensures both individual accountability or learning and positive interdependence, which can help ensure active individual construction of knowledge and benefit from distributed cognition. It may also satisfy both the achievement motivation when tasks are challenging but within the ability level of the learners and the social or academic needs when tasks are difficult or not very interesting. This may be accomplished in either the face-to-face collaboration setting or the distance learning setting. In the former context, the two members may sit side by side to ensure easy interaction as well as individual control of one's own task. In the latter context, two members or more can interact via electronic means such as e-mail, computer conferences, or other CSCL systems.

Only two studies (Savard, Mitchell, Abrami, & Corso, 1995) included in this meta-analysis employed distance collaboration, where group members collaborated on assignments via e-mail. However, the results were not as effective as expected, probably due to several causes as explained by the authors. Firstly, the "distance education" environment was simulated rather than real. In the first study, group collaboration on-line was ad-hoc. Students were attending a face-to-face course in business strategies. For this research, they were assigned a case study homework to be completed within a week with a partner or alone via e-mail. In order to simulate distance education environment, students were told not to talk to their partners face-to-face for this assignment. In the second study, students completed two case studies on-line with a partner or alone during class time in a computer lab. To simulate the distance learning environment, all communication between group members and the instructor was via e-mail. Because of the simulation nature, electronic group collaboration might not have filled a real social or academic need on the part of the students. Instead, it might have created frustration for having to write to each other rather than talking face-to-face, particularly when students were not very familiar with the electronic tool. Secondly, although there was a group grade allocated, no structure was in place to ensure individual accountability, which may lead to social loafing. Research on task performance and productivity suggests that social loafing may occur if members perceive an inequality of efforts, personal responsibility, and involvement or if some members do not value the task (Shepperd, 1993). Thirdly, e-mail might not be an effective means for the group task concerned. More effective groupware now available such as computer conferences, chat, or CSCL systems may be more user-friendly and effective for group collaboration. More research is needed to determine if the benefits of face-to-face collaboration when learning with computers may generalize to group collaboration across distance in computer-mediated learning and to determine if the factors that influenced the effects of social context identified in this meta-analysis may generalize to computer-mediated distance learning.

Finally, results from this research suggest some relationships between the various outcomes analyzed (see Figure 5). However, as these relationships were not directly examined, they are only hypothetical relationships that await verifications in future research.

Conclusions and Recommendations

The results of the series of meta-analyses conducted in this study indicate that social context plays an important role when students learn with CT. On average, small group learning had more positive effects than individual learning on cognitive, process, and affective outcomes. When used appropriately, students learning in small groups may achieve +.95 standard deviation higher than those learning in small groups. However, results on many outcomes were significantly heterogeneous and were influenced by technological, task, grouping, and learner characteristics. Specific conclusions and recommendations drawn from this review are offered below as a guide for teachers in considering social context when helping students to learn with CT.

Cognitive outcomes

1. More students tend to succeed when working in small groups than individually (d_+ = +0.28).

2. When students learn with CT in small groups, there is, on average, a moderate superiority of group task performance over individual task performance ($d_+ = +0.39$) and a small positive effect on individual achievement ($d_+ = +0.16$). The former is significantly larger than the latter.
3. Group task performance, as a result of distributed cognition, may be influenced by three major factors: type of tasks, feedback, and presence of others. A consistently larger positive effect may be expected when students work on factual learning tasks ($d_+ = +0.96$). When tasks involve more complex problem solving, there is in general a moderate positive effect on group task performance ($d_+ = +0.30$). However, effects may vary significantly depending on whether the programs provide no or minimal feedback or elaborate feedback and whether there are other peers working close by. Larger effects may be expected when programs provide no or minimal feedback and when no other peers are working close by. Under these conditions, working in groups may be especially advantageous as group members may be the only sources that provide needed performance support. When programs provide elaborate feedback, individuals may outperform groups when tasks are difficult. However, superior task performance does not necessarily mean superior individual achievement.
4. Six major factors (Group work experience or instruction, group size, subject, type of programs, gender, and relative ability) may influence the effects of social context on student individual achievement. Effects are significantly more positive when: a) students have group work experience or are provided with specific instruction for cooperative group work ($d_+ = +0.31$) than they do not ($d_+ = +0.11$); b) working in pairs ($d_+ = +0.18$) than in larger 3-5 member groups ($d_+ = +0.9$); c) learning social

sciences or computer skills (d_+ = +0.23) than mathematics, science, reading, and language arts (d_+ = +0.11); d) work with drill-and-practice or tutorial programs (d_+ = +0.19) than with programs that are exploratory in nature (e.g., simulations and microworld) or as tools for other tasks (e.g., graphic program for design or word processor for writing) (d_+ = +0.06); e) especially for female (d_+ = +0.50) than male students (d_+ = +0.02); and f) for low (d_+ = +0.33) or high ability (d_+ = +0.22) than medium ability students (d_+ = +0.10, $p<.05$). When all the positive study features were in place, students learning in small groups may achieve 0.95 standard deviation higher than those learning individually. When none of the positive study features were in place, students learning individually may achieve 0.22 standard deviation higher than those learning in groups.

<u>Learning Processes</u>

5. Students working in small groups or individually tend to exhibit different task behaviors. When learning in small groups, students engage significantly more in cognitive interaction or positive social interaction between peers (d_+ = +0.33), use more learning strategies or appropriate task strategies (d_+ = +0.66), and are more perseverant on task (d_+ = +0.48). When learning individually, students engage significantly more in the computer programs (d_+ = -0.27) and need less time in completing their tasks (d_+ = -0.25), especially when tasks are familiar, involving factual learning, and when programs are exploratory in nature or used as tools for other tasks.
6. On average, students tend to attempt a similar amount of the task whether learning in small groups or individually. However, characteristics of learner and technology can

significantly influence whether students may attempt a larger amount of the task working individually or in small groups. Low ability students (d_+ = +0.32) tend to attempt a larger amount of the task when working in small groups than individually, but medium ability students (d_+ = -.34) tend to attempt a smaller amount of the task working in groups than individually; for high ability students (d_+ = 0.00), they tend to attempt a similar amount of the task whether working in small groups or individually. Students learning in small groups tend to attempt a larger amount of task than individuals when instruction is mostly learner-controlled (d_+ = +0.27); but when instruction is mostly system-controlled, those learning individually often attempt a larger amount of the task (d_+ = -0.23). Students learning in small groups tend to attempt a larger amount of the task than those working individually when the program design is individually oriented (d_+ = +0.11); but when the programs have special design for group use, individuals may attempt a larger amount of the task (d_+ = -0.09).

Affective Outcomes

7. Through learning together, students generally have more positive attitude toward learning with computers (d_+ = +0.41), more positive attitude toward classmates (d_+ = +0.23), and more positive attitude toward group work (d_+ = +0.28), especially when students work in pairs and for one-session only. Whether working in small groups or individually, students tend to have similar attitudes toward computers, toward the subject concerned, toward teachers, and similar self-concept.

Learning with CT is becoming increasingly important and popular in this technology and information age. Various computer programs and web-sites have been developed to facilitate student learning in various subjects as well as computer skills. Results of the series of meta-analyses conducted in this study suggest that social context can play an important role when students learn with CT. When small group learning is used appropriately, it can have a significantly positive effect on group task performance, individual achievement, and other processes and attitude outcomes.

However, group task performance, as a result of distributed cognition, is significantly different from individual achievement, which relies more on whether each learner is actively involved in constructing his/her own knowledge and in helping each other to do so. To ensure active learning in small groups, teachers need to consider whether students have group work experience. If students do not have such experience, it is important to provide students with specific instructions on effective cooperative learning strategies. Group learning skills, interpersonal skills, and small group size are important in facilitating student learning in small groups. Effective cooperative learning strategies such as turn-taking and agreeing on answers that emphasize both positive interdependence and individual accountability can help ensure that each member is actively involved not only in contributing to the joint task performance but also in assisting each other in the construction of individual knowledge. Students learning in groups must coordinate well to learn together. A group of smaller size is generally easier to coordinate than a group of larger size when learning with CT, especially in the face-to-face collaboration. Better interpersonal skills that many female students enjoy may enable them to be better group learners. Therefore, for male students to work effectively together, it may be especially important that effective group learning strategies are encouraged.

Task and program characteristics are important factors that may influence whether students are more motivated to learn in small groups or individually and whether they will learn more in small groups or individually. Group learning is especially effective when programs are used to directly teach students new content or are used as practice exercises, which are usually less motivating for students to work alone. When programs are challenging and interesting, when tasks involve high levels of mental processing, active exploration and discovery learning, and when learners are motivated to learn, individual learning with CT may be as effective or more effective to ensure that each learner will be actively involved in constructing his or her knowledge and, therefore, learn more. However, when learning individually, students should be encouraged to help each other when needed.

Small group learning and individual learning should not be mutually exclusive. Literature on self-regulated learning suggests that efficient and effective learners are those who can use different learning strategies according to different conditions (Brown, 1987; Zimmerman, 1990). Similarly, good instructional design and good instructors are those who employ different instructional strategies depending on different technology, task, and learner characteristics. When used appropriately, small group as well as individual work can make learning with CT more effective, efficient, and enjoyable.

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APPENDIX I. Codebook

Please note that all the study features codings are at the finding level.(i.e., all individual findings in a study are to be coded separately).

IDENTIFICATION

Study #
Finding # (i.e., each effect size that can be extracted from a study and fits into one of the four types of contrast described in #5 below).
Author Name
Year of publication

OUTCOME FEATURES

Outcome type (add a column next to this for notes on the type)

cognitive outcomes

11) achievement - lower order skills (i.e., more simple tasks such as recall of facts, rules, etc.)
12) achievement - higher order skills (i.e., more complex tasks or tasks that involve synthesis or inference)
13) task performance
14) success rate (e.g., percent of people succeeded)
19) achievement - missing or other (specify)

process measures

21) cognitive interaction
22) positive social interaction
23) interactivity with programs
24) task completion time
25) off-task behaviors
26) amount of task attempted (e.g., # of problems completed, # of words attempted, # of ideas generated, productivity)
27) use of strategies
28) perseverance
29) other (specify)

attitudes

31) toward computers
32) toward subject (including anxiety with subject, but with the sign reversed)
33) toward learning with computers
34) toward group work

35) toward classmates
36) toward teachers
39) other (specify)

self-concept
41) academic self-concept (i.e., related to self-perception of learning ability)
42) general self-concept (e.g., self-esteem; not specific to learning ability)

Whose outcome
1) group product
2) individual assessment
999) missing

Time of outcome measure
1) during the task (e.g., score of the task product, or intermediate score, or task performance, or behavior during the task)
2) immediate posttest (including end of unit test)
3) delayed posttest (i.e., tests taken more than 3 days after the treatment)

Outcome measure source
1) standardized tests
2) researcher-made tests
3) teacher-made tests
999) missing

Estimate (i.e., whether the effect size is being estimated from significance or non-significance level)
1) estimated
0) not estimated

DESIGN FEATURES AND PUBLICATION STATUS

Experimental design
1) post-test only control group design (i.e., only posttest scores are used)
2) pre-post control group design (i.e., comparing gain scores of the two treatment groups, or using pretest as a covariant)
3) repeated measure design (i.e., same subjects are used in the two treatments)
999) missing

Student equivalence between treatments
1) random assignment into treatments
2) random assignment into treatment after matching
3) non-equivalent (i.e., intact classes and there was no measurement showing that the groups were equivalent)

4) statistics control (i.e., intact classes or groups but some pretest measures show that the groups were not different)
5) same students
999) missing

Type of publication
1) journal
2) book chapters
3) report (including conference papers)
4) dissertation

TECHNOLOGY AND APPLICATION CHARACTERISTICS

Types of computer programs
1) tutorial (i.e., primary instruction)
2) drill-and-practice (i.e., secondary, or practice and reinforcement)
3) exploratory (e.g., simulation, micro world, adventure games)
4) tool (e.g., word processor, spreadsheets)
5) programming language
6) communication (i.e., CMC)
999) other or missing

Design orientation
1) for individual (default, i.e., if no specific design for group use was described)
2) for group

Type of feedback
1) no feedback
2) minimal (i.e., informing whether the responses were correct or incorrect)
3) elaborate (i.e., providing explanations for correct answer or incorrect answers)
999) missing

Instructional control (infer if possible)
1) mostly learner-control
2) mostly system-control
999) missing

Technical/functional support (i.e., whether lab facilitator, instructor, or others were present to provide demonstration or help relating to the functional use of the programs)
1) yes
2) no
999) missing

Content support (i.e., whether the instructor or others were present to answer content-related questions during the task)

1) training or demonstration about the task or its content material
2) task as part of the regular class
3) no
999) missing

Settings for group work

1) face-to-face
2) electronic only (i.e., distance education)
3) adjunct (i.e., face-to-face class plus electronic communication or assignments, etc.)

TASK CHARACTERISTICS

Subject

1) mathematics
2) reading or language arts
3) writing
4) science
5) geography
6) computer programming
7) computer application programs
8) physical education
9) research methods
10) medicine
11) military training
12) other (specify)

Types of knowledge to be learned

1) problem solving (i.e., more toward applying different knowledge and skills; or involving higher reasoning skills)
2) factual learning (e.g., acquiring facts, concepts, and principles, i.e., more toward rote learning)
999) missing

Task structure (including solution path)

1) open or ill-structured
2) closed (i.e., with only one fixed answer or path)
999) missing

Task familiarity

1) familiar
2) new with training

3) new without training
999) missing

Task difficulty (try to infer from the description in the study)
1) not difficult
2) moderately difficult
3) difficult or complex
999) missing

GROUPING CHARACTERISTICS

Group composition
1) random assignment
2) homogeneous on ability
3) heterogeneous on ability
4) homogeneous on gender
5) heterogeneous on gender
6) friendship or student choice
7) other (specify)
999) missing

Presence of others (i.e., whether there are other peers working close by)
1) yes
2) no
999) missing

Group learning strategy (Note down in the column next to it the specific group strategies used in the study)
1) specific cooperative group strategies used (e.g., role assignment, team scores, agree on answers)
2) encouraged to work together (general directions only)
3) other or no strategies specified
999) missing

Group work exp./instruction
1) provided with training within the study
2) provided with written material
3) had previous experience with group work
4) no group experience
999) missing

Group size (continuous)

Number of sessions (continuous)
999) missing

Session Intensity (minutes per session)
999) missing

Amount of task-related peer interaction (try to infer from the description of the study)
1) no or hardly any
2) moderate or frequent
999) missing

LEARNER CHARACTERISTICS

Grade level
1-12) grades (specify)
13) college or university
20) military
30) industry/business

Relative ability level (i.e., relative to those in the class/group)
1) low
2) medium
3) high
999) missing or mixed

Gender
1) male (more than 70%)
2) female (more than 70%)
999) missing or mixed

Computer experience
1) no experience
2) with experience
999) missing

APPENDIX II. Dummy Coding for the Multivariate Analyses

All variables were dummy coded into dichotomous variables for the multivariate analyses. A few variables with more than two levels were combined into dichotomous variables based on the post-hoc analyses results of each of these study features. The higher value(s) was coded into 1, the lower value(s) was coded into 0, and the missing data was coded into either 1 or 0 depending on whether its mean effect size was similar to the higher value or the lower value. The reason for choosing dichotomous variables over creating numerous dummy variables was the concern over low power if numerous dummy variables were to be created (Abrami, Lou, & Spence, in preparation). The recoding was done globally for all the five heterogeneous outcomes with first considerations given to cognitive outcomes and the pattern that appeared to exist across the outcomes. The main reason for the global coding was to make the coding consistent across the outcomes so that the influence of a study feature on cognitive, process, and affective outcomes may be compared.

Student equivalence

1	well-controlled
0	non-equivalent/unknown

Publication status

1	published
0	unpublished

Type of programs

1	tutor/programming/unknown
0	exploratory/tool

Design orientation

1	individual/unknown
0	group

Feedback

1	no/minimal/unknown
0	elaborate

Instructional control

1	mostly learner
0	mostly system/unknown

Subject

1	social sciences/computer skills
0	math/science/reading/writing/language arts

Type of tasks

1 factual learning
0 problem solving/unknown

Task structure

1 closed
0 open/unknown

Task familiarity

1 new without training/unknown
0 familiar/new with training

Group composition

1 heterogeneous ability
0 other/unknown

Group work exp./instruction

1 yes
0 unknown

Group learning strategy

1 specific cooperative
0 general encouragement/no specific/individualistic

Group size

1 2
0 3 - 5

Presence of others

1 no/unknown
0 yes

Number of sessions

1 one session
0 more than one sessions/unknown

Session intensity

1 more than 60 min.
0 10 - 60 minutes/unknown

Grade level

1 pre-secondary
0 secondary, college/university, adult/unknown

Relative ability level

1	low/high
0	medium/unknown/mixed

Gender

1	female
0	male/unknown/mixed

Computer experience

1	yes
0	no/unknown