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Field Dependence and Student Achievement in Technology-based Learning: A Meta-analysis

by

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Abstract

This investigation was a synthesis of 35 research studies with a total sample size of 3,082 students selected on the basis of Witkin's theory of Field Dependence-Independence. The Hunter-Schmidt approach to meta-analysis was used to determine if a difference in achievement exists between field dependent and field independent students within technology-based learning environments, and whether study, treatment or methodology variables influenced the effect size outcome. The results indicated an achievement difference in favor of field independent learners with a total mean weighted effect size of 0.426 and a pooled standard deviation of 0.311. However, a large proportion of population variance was not accounted for through statistical corrections. A subsequent moderator analysis indicated that the total heterogeneity for each moderator was significant; suggesting the variance among effect sizes was greater than could be expected by sampling error, and unidentified variables and study artifacts likely contributed to the overall effect size.

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This thesis is dedicated to Eric and Ava.

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CHAPTER 1

Background

Traditionally, many psychologists and educators have believed that people's success or failure at learning tasks is attributable to individual differences in abilities. Yet for the past several decades much research has been generated on the processes involved in thinking and learning performance. In the 1950's and 1960's, a movement came into prominence with the idea that cognitive styles could provide a bridge between the study of cognition (i.e., how well we perceive, learn and think) and the study of personality. A small group of psychologists set out to explore individual differences in cognitive styles as an explanation for learning performance (Kagan & Kogan, 1970). Collectively, these efforts emerged into a school of thought in cognitive psychology deemed the "new look", which developed several stylistic constructs, all of which seemed closer to cognition than personality (Sternberg & Zhang, 2001). These early contributions have endured and stimulated scientific inquiry into ideas such as field dependence-independence (Witkin, 1949), impulsivity-reflectivity (Kagan, 1966), leveling-sharpening (Gardner, 1953), and category width (Pettigrew, 1958).

Of the ideas generated, one of the most popular and best researched dimensions of cognitive style is the theory of field dependence and field independence (FDI) first described by Herman Witkin in 1949. His theory conceives of cognitive style in terms of a continuum existing between two polar opposites. To the degree that people score high on field independence they tend to be relatively impersonal, individualistic, interested in abstract subject matter and intrinsically motivated. To the degree that people score low on field independence they tend to be more socially oriented, better able to discern the feelings of others, more dependent on others for reinforcement, and more in need of externally defined objectives (Witkin, 1973). According to the theory, each end of the continuum is considered to be a differentially good fit to different environments, and on average, one style is not to be considered better or worse than another. In this respect, field dependent-independent cognitive styles are distinguished from innate ability.

In light of the specified differences between field dependent and field independent styles, it is no surprise that Witkin's theory has been broadly applied to the field of education. Through the FDI approach, a number of studies have provided insights into such relevant aspects as how students learn social material, the use of mediators in learning, the effects of reinforcement, cue salience, educational-vocational choices and so on (Bertini, 1986). However, contrary to the original conception of the theory as value neutral, studies of cognitive style and its relationship to student achievement began to evolve from investigations intended to predict achievement based upon style (Abousserie, 1992; Luk, 1998). In 1988, Canelos suggested that one major factor influencing effective learning may be that of field dependency. Learners who demonstrate field independence may be better able to abstract information more readily from learning materials and require fewer visual and verbal cues in order to learn effectively. Conversely, the field dependent learner may need a more structured presentation with more visual and verbal cues and more reinforcement. The implication of such research directions is that learners with different styles will not perform equally in response to different forms of instruction.

The hypothesis that learning outcomes will vary as a function of cognitive style has led to the idea that for optimum learning to occur, the nature of instruction should be adapted to the needs of the learner (Jonassen & Grabowski, 1993). Ideally, students can be taught in ways that are sensitive to individual differences -- a difficult practice for the sole educator with a large body of students. However, with the increased use of technology in today's classrooms, adaptation of instruction to individual differences no longer presents with concerns of practicability. Technology potentially provides educators with a new array of tools to help design instruction for individual differences. Consequently, research into the effects of cognitive styles on learning outcomes using educational technology has revitalized interest in styles research.

As with traditional educational research, performance differences between field independent and field dependent learners continue to be hypothesized and investigated in technology-based environments. In a study conducted by Parkinson, Redmond & Walsh (2004), results indicated that field independent learners performed significantly better than field dependent learners in a web based and in a computerized text-based environment. Similarly, Ford and Chen (2000) linked FDI cognitive styles to strategic differences in hypermedia navigation. In contrast, others have suggested that the impact of cognitive style on learning outcomes has proven less important than originally anticipated (Calcaterra, Antonietti & Underwood, 2005).

Statement of the Problem

Although the idea of using technology to accommodate differences in cognitive styles is intuitively appealing, the body of literature which has been generated is inconclusive. Many critics of technology-based styles research find the knowledge accumulated to date to be insufficient and poorly executed (Dillon & Gabbard, 1998). Small sample sizes, condensed treatments, specialized aptitude constructs, and a lack of theoretical linkage between aptitudes and information processing requirements complicate the research findings (Jonassen, 1993). Of particular relevance to this thesis is the conflicting evidence and continued speculation that differences exist between field dependent and independent cognitive styles which differentially impact student achievement (Triantaffillou, 2004; Daniels & Moore, 2000). Through the use of meta-analytic techniques to analyze the inconsistent research that exists concerning FDI, whether or not individual differences exist in learner responses to technology-based environments was examined on a broad scale.

Purpose and Rationale

The intent of this research was to review and analyze studies that have explored the differential effects of FDI on student achievement within technology-based learning environments. The technique of meta-analysis was selected as a method for synthesizing the results of the research as it promotes a scientific approach to the interpretation of quantitative results and provides an alternative to more traditional narrative techniques of research review and integration (Hunter & Schmidt, 2004). Meta-analytic techniques combine the measure of effects from individual studies into an estimate of the overall strength of the effect, and then use the amalgamated outcome to determine significance. It was anticipated that the use of meta-analysis would provide an appropriate statistical technique for determining if contradictory results in the literature are due to real differences in outcomes, or if they are instead due to study artifacts.

Research Questions

The primary question directing this research was: "What is the effect of field dependent and field independent cognitive styles on student achievement in technology-based environments?" In answering the question, the outcome measure evaluated (dependent variable) was either the results of an experimental post-test, or the teacher-assigned course grade.

The second question investigated was: "To what extent do these differences vary according to study characteristics, methodology characteristics, and treatment characteristics?" In answering the second question, moderator variables were investigated. Moderator variables are the characteristics of studies that influence the magnitude of the effect sizes. By synthesizing the results of many studies we can have confidence to conclude if there are actual differences between field dependent and independent learners, as well as the influence of different variables on the observed difference (Hunter & Schmidt, 2004). The moderator variables investigated in this meta-analysis included: study characteristics (publication year, publication type, location); methodology characteristics (sample size, research design, pretest equivalence, statistic reported, type of dependent variable, instructional method) and treatment characteristics (duration, academic content, student context, technology used). In this respect, synthesis using meta-analysis was used to integrate and summarize existing research, as well as add new knowledge to our understanding of the variables which might moderate the effects of cognitive style in technology-based learning.

Significance of the Study

The results of this study were intended to synthesize existing research on the impact of field dependence on academic achievement in the context of educational technology. Even a simple verification of the existence of these learner differences can improve the quality of our educational efforts. Knowing how learner characteristics interact with outcomes can clarify if instructional differentiation is appropriate and/or necessary on the basis of cognitive style differences. With the rapidly increasing development and implementation of educational technology systems, the study results can inform the design of instructional systems and advance our knowledge of individual differences in learning behavior.

Delimitations and limitations

In order to create a structure for the study, it was necessary to establish several boundaries. First, as previously indicated, student achievement was determined as scores obtained on post-tests designed by the researchers and given to the participants in the studies, or as final grades as assigned by the instructor in studies where the treatment lasted the length of the course. Second, technology-enhanced learning environments were defined as those which use computers to develop and deliver instructional content to students. Specific technologies selected for inclusion on this basis included computer-assisted instruction, web-based instruction, and e-learning software. Third, the use of different technologies in education changes rapidly. As a result, studies beyond a particular date tend to describe obsolete technology that has since been replaced by newer software. Therefore, only studies published since 1990 were included in this meta-analysis to ensure that the findings are based on relatively recent uses of technology in educational settings. Fourth, to preserve construct validity of the independent variable (cognitive style) selected for this analysis, only those studies which measured FDI using the Group Embedded Figures Test (Witkin, 1971) were included.

Although all studies selected for this meta-analysis were conducted in an educational context, approximately three-quarters of the studies exclusively investigated undergraduate students, and therefore any conclusions are limited to the population presented by the existing research. As well, concerns with reliability arose due to dichotomization (i.e., FI versus FD) of the continuous variable of field dependence-independence as measured by the Group Embedded Figures Test (GEFT). Most research studies in this analysis used statistical means as the rationale for dividing participants into two groups. Nevertheless, forcing a continuous variable into a dichotomous format can create reliability issues (Hunter & Schmidt, 2004), and generalizations of the outcomes should be made with caution. Finally, as with other forms of research, there are limitations related to the techniques of meta-analysis which will be specifically addressed in the literature review section.

Definition of Terms

Many terms used throughout this research are without a standard, accepted meaning, or may be novel to the reader. Therefore, the following definitions are provided to clarify the unique terminology associated with technology-based learning and methods of meta-analysis:

1. Technology-based Learning - the use of computer-mediated instruction as a replacement for, or supplement to, traditional face-to-face instruction to deliver content to students using either: synchronous (real-time, instructor-facilitated) and/or asynchronous (self-directed, self-paced) modes of delivery. Specific technologies used in studies for this meta-analysis included web-based, e-learning, and computer assisted instruction (CAI).
2. E-learning – an educational situation in which the instructor and students are separated by time, location, or both. Education or training courses are delivered to remote locations via synchronous or asynchronous means of instruction deployed via the internet.
3. Computer Assisted Instruction – using computer hardware and software to present instructional content to a student or accept and evaluate student responses. CAI combines the nonlinear and associative features of hypertext and information stored in various types of electronic media (graphics, video, sound, and animation).

4. Web-based instruction - a learning environment that is mediated and supported via the Internet/Intranet and connected to a computer with hyperlinks to resources outside the instructional domain. The instruction is designed so that the computer displays lessons in response to learner/user interactions.
5. Cognitive Style – individual, stable and pervasive differences in how people perceive, organize, store and process information as well as how they think solve problems, learn and relate to others (Witkin, Moore, Goodenough & Cox, 1977)
6. Field Dependence-Independence (FD/FI) – a cognitive style that refers to a person's reliance on external referents and ability to differentiate, and is measured by tests of ability to disembed perceptually (Witkin & Goodneough, 1981).
7. Group Embedded Figures Test – a group administered version of the Embedded Figures Test; used to determine a learner's cognitive style, characterized as field dependent or field independent (Witkin, 1971).
8. Meta-analysis - the process or technique of synthesizing research results by using various statistical methods to retrieve, select, and combine results from previous separate but related studies.(Glass, 1981).
9. Effect Size - is a measure of the strength of the relationship between two variables. Conventionally, an effect size of 0.2 is regarded as being small, 0.5 as medium and 0.8 as large (Cohen, 1977).

Conclusion

According to DeCoster (2004) there are several criteria to consider before selecting a hypothesis for a meta-analysis: 1) there should be a significant available literature on the topic in a quantifiable form; 2) the hypothesis should not require the analysis of an overwhelming number of studies; and 3) there should be some specific knowledge gained from the analysis, such as the resolution of differences in the literature. This meta-analysis meets all three criteria. Of the many studies that have been conducted related to the effects of cognitive style on student achievement within technology-enhanced learning, the findings have been inconsistent, with some claiming to find differences and others claiming none. Considering the nature and quantity of the available research, the literature produced is well-suited to meta-analytic synthesis to address the research questions.

CHAPTER 2

Introduction

Field dependence is an established cognitive style which research has associated with particular capabilities such as success in educational environments. This literature review describes the construct of field dependence, the educational implications for differences in learning characteristics between field types (independent versus dependent), and educational research which investigates the relationship between cognitive styles and achievement. These themes are connected by the overarching question of whether perceptual differences in field dependency impact learning achievement in computing environments. Additionally, key criticisms of field dependence theory and research are reviewed, and the chapter concludes with a discussion of the techniques of meta-analysis which are used to address the research question.

Field Dependence Theory and Educational Implications

FDI Theory & Measurement

Cognitive styles have been of interest to researchers and practitioners for several decades. With more than 4000 references in the literature, field dependence-independence (FDI) has received the most attention by researchers of all the cognitive styles (Chinien & Boutin, 1992). FDI research originally began in laboratory studies during World War II because Herman Witkin and his associates tried to understand individual differences in 'perceptions of the upright' (Witkin & Goodenough, 1981). At that time, FDI research was understood as individual differences in perceiving the vertical direction of space using either environmental referents or bodily cues. After performing hundreds of experiments, an important realization came when Witkin found himself accurately predicting the degree of field dependence participants would display on the basis of brief conversations with them. Ideas of the importance of personality became associated with the manner of perceiving the upright in space (Goodenough, 1986).

Among the many personality correlates of field dependence subsequently investigated and reported in the literature, those that involved social-interpersonal behavior played the largest role in re-development of Witkin's theory. As evidence amassed on the nature of individual differences in perception of the upright and the greater interpersonal autonomy of field independent individuals, the idea of psychological differentiation became important to explaining the field dependence dimension. Persons capable of functioning without being affected by the ever-changing visual world were also less affected by the ever-changing social world (Goodenough, 1978). With this insight, Witkin redefined field independence as a dimension of autonomy, or self-nonself differentiation as expressed in upright perception and in social functioning (Witkin & Goodenough, 1981). Field dependent people were viewed as more socially orientated, with a preference for physical closeness and a tendency toward greater emotional openness in communications with others. In contrast, field independent people were identified as more abstract, not very interested in others, and functioned with greater individual autonomy in social-interpersonal behavior (Witkin & Goodenough, 1977).

A second discovery that broadened Witkin's original theory was the finding that field independence in upright perception is related to success in locating camouflaged or embedded figures (Witkin, Lewis, Hertzman, Machover, Meissner, & Wapner, 1954). Correlations between field dependence and the Embedded-Figures Test (EFT) became understood in terms of a common requirement for perceptual analysis. Just as Witkin had used an earlier rod and frame test to determine an individual's level of field dependency, the EFT produced similar results with a simpler test which required observers to disembed a plain figure (e.g., rod) from a complex pattern (e.g., frame). The disembedding interpretation was a major conceptual extension in Witkin's attempt to understand individual differences in perceptual functioning, and provided a new and more convenient assessment method (Witkin & Goodenough, 1981).

Today, adaptations of the EFT are regularly used to assess the FDI construct in research settings. The Children's Embedded Figure Test (CEFT) is a 25 item test for children in the five to ten year age range. This version has not been available since 2002 likely because the test is designed to be individually administered and is less attractive to researchers who wish to test large numbers of children within a limited amount of time. The more widely used Group Embedded Figures Test (GEFT) has reportedly been used in the literature since 1970 (DeTure, 2004) and is the most commonly used instrument to measure FDI (Chen & Macredie, 2004). The GEFT is a group administered version of the EFT. It is a timed paper-and-pencil performance test for persons over wide age range (including children). The test presents examinees with 8 simple figures and 25 complex figures. One of the 8 simple figures is embedded within each of the 25 complex figures. The test-takers' task is to locate and trace, within the context of the complex figures, as many of the simple figures as possible within three timed sections. The score on the GEFT is the number of items correctly traced. The higher one's score, the more field independent one is; the lower, the more field dependent. The total possible score on the GEFT is 18. Psychometric data in the test manual reports a reliability coefficient for the GEFT of .82 based on correlating parallel forms of the two scored and equally timed parts of the test (Witkin, Oltman, Raskin & Karp, 1971).

In reviewing the literature on the adequacy of the Group Embedded Figures Test, a concern commonly reported is that it measures only one end of the field dependence-independence continuum. Use of the GEFT has relegated the measure of field dependence to the absence of field independence (Linn & Kyllonen, 1981), or what Moran (1985) calls "a measure of inaccuracy rather than a stylistic preference". A second difficulty is that different researchers have assigned different levels to similar scores on the GEFT because the test manual does not provide guidelines. Despite these issues, research which investigates FDI is likely to include levels of field dependence as determined by the EFT or the GEFT. No other test is as well represented in the literature (Hall, 2000).

Characteristics of Field Types

Early on, the practical value of measures of field dependence-independence for education were evident to Witkin and he began to view the potential of FDI as widely applicable to educational settings (Witkin, Moore, Goodenough, & Cox, 1977). Decades of subsequent research using the GEFT to investigate perceptual and problem solving tasks has suggested that individuals are different in the ways they process information. These findings have revealed characteristic differences between field dependent (FD) and field independent (FI) learners and how they perceive and interact with the learning environment. For example, Jonassen and Grabowski (1993) state that FD learners are more likely to be affected by the learning environment and more easily accept structure or idea of instructions presented. They tend to perceive information in a holistic manner, and have a difficult time attending to relevant cues, especially if given nonsalient attributes (Davis & Cochran, 1990). They are sociable, like to work in groups, and tend to have better learning achievement in subjects which require interpersonal or socially-based skills (Witkin & Goodenough, 1981). Conversely, field independent learners are more likely to construct their own knowledge by selecting information from the learning environment. Some research has supported that they require less structuring aids and impose structure on a field when it lacks a clear or inherent one (Witkin & Goodenough, 1981). They are not easily influenced by social cues, and they like to have distance in social relations. In addition, they are more abstract oriented and would like to express concepts via analysis (Riddle, 1992). Higher scores on the GEFT have also been correlated with achievement in abstract areas like math, science, and computer-related subjects (Witkin & Goodenough 1981). In a review of the research on field dependent and independent learners, Garger and Guild (1987) used an educational perspective to summarize the characteristic differences between types as shown in Table 1.

Table 1

Characteristics of Field Dependent-Independent Learners

	Field Dependent	Field Independent
1	Perceives globally	Perceives analytically
2	Experiences in a global fashion, adheres to structures as given	Experiences in an articulate fashion, imposes structures or restrictions
3	Makes broad general distinctions among concepts, sees relationships	Makes specific concept distinctions, little overlap
4	Social orientation	Impersonal orientation
5	Learns material with social content best	Learns social material only as an intentional task
6	Requires externally defined goals and reinforcements	Has self-defined goals and reinforcements
7	Needs organization provided	Can self-structure situations
8	Uses spectator approach for concept attainment	Uses hypothesis-testing approach to attain concepts

Garger and Guild's comparison suggests that field dependent and independent individuals may differ in their respective approaches to learning. The idea that both field dependent and field independent learners have unique strengths in acquiring knowledge has tended to dominate educational perspectives in cognitive styles research (see also Thompson & Thompson, 1987; Witkin, Moore, Goodenough, & Cox, 1977).

Educational Applications and Student Achievement

In view of the differences described in Table 1, one question emerges as critical to understanding the relationship between cognitive style and learning: are field-dependent and field-independent students equally well adapted for academic success? A considerable amount of relevant data has been collected in the course of studies which have tested the relationship between cognitive style and academic achievement. Much of the research would indicate that FDI theory is not value-free because field independent students are consistently associated with better academic performance (Zhang & Sternberg, 2006). For example, Moore and Dwyer (1994) examined the effect that coding (black and white or color) and testing mode (visual or verbal) would have on the achievement of undergraduate students in an anatomy lesson. Their results indicated that field-independent students consistently scored higher than field-dependent students across all criterion tests. Similarly, Bernardi (2003) investigated the moderating effects associated with field dependence-independence on students' performance in financial accounting. The data indicated that performance depended upon whether the student was classified as a field-independent or field-dependent learner.

In addition, Leo-Rhynie (1985) investigated whether there is a significant difference in performance between students who select science options and those who choose arts courses, and whether field independent students perform significantly better or worse than field dependent students in science and art courses. Results indicated that field independence was found to be important for the A-level success of students regardless of whether they chose arts or science courses.

Taken as a whole, studies dedicated to specific academic subjects as well as those dealing with global achievement indicate that field dependent students have a consistently lower academic achievement than their field independent colleagues (Tijanero & Paramo, 1998).

Other studies, however, would suggest that the field dependence construct is more value-differentiated. Varma and Thakur (1992) investigated whether students with field-dependent and field-independent cognitive styles differed in their achievement in different subjects. Field independent learners showed higher achievement in mathematics and physical sciences while field dependent learners showed higher achievement in social science and literature. As well, when investigating relationships between field dependent-independent styles and students' achievement in psychology, Feij (1976) found that art-trained students showed a positive relationship between field independence and achievement while the math-trained students displayed a negative relationship. Studies such as these suggest that FDI styles may have an adaptive value, with one or the other more functional depending on the academic discipline.

Differentiation between articulation types can also reveal itself when students are instructed with different teaching materials. A study by Satterly and Telfer (1979) examined the relationship between FDI and advance organizers in learning and retention. A significant interaction between instructional treatments and cognitive style was observed which indicated that in the complex task of processing material, field dependent students required more help in being made aware of the structure of the materials (imposed organization) so as to facilitate their knowledge acquisition.

Other researchers have published similar findings on the equalizing effects of teaching materials. Kiewra and Frank (1986) found field dependent learners recalled more text when provided with structure during acquisition and recall; Chobot (1985) determined that providing questions before a passage facilitated field dependents' short-term retention of knowledge; and Reardon and Moore (1988) found that providing structure and separating complex information into a more manageable format improved field dependent learners' performance.

The evidence reviewed thus far on the differences between field dependent and field independent learners would support the opinion of Tinajero and Paramo (1998) that the academic progress of a considerable part of the student population can be hindered by the way in which they deal with information. However, a number of researchers have not found any difference in learning achievement between field dependent and field independent learners. Macniel (1980) determined that there was no statistical significance in students' learning achievement in a lesson on behavioral modification regardless of different instructional treatments, cognitive styles, or the interaction between them. Similarly, Chandran (1985) investigated the role that FDI may play on achievement in chemistry as measured by tests of laboratory application, chemical calculations, and content knowledge. Correlational analysis, multiple regression analysis and path analysis were performed on the data and all produced similar results: FDI played no significant role in chemistry achievement.

Conclusion

The contradictory findings from the educational literature raise questions related to the academic implications of FDI. For instance, are there characteristic differences between field dependent and field independent learners, do these differences impact learning achievement, and can varied instructional approaches balance out potential differences? These questions remain unresolved in the literature, and have resulted in the ubiquitous call for yet more studies to better understand these relationships (Angelie & Valanides, 2004; Davis, 1991).

Field Dependence Theory and Technology-Based Learning

In response to questions raised in traditional educational research many investigators have anticipated that technology-based learning can bridge the gap between individual differences and instruction (Gagnon, Neuman, McKnight, & Fryling, 1986). The use of educational technology is believed to accommodate different learning styles and different entry levels of skill because of its flexibility and its potentially high level of learner control (Ayersman & Minden, 1995). By bridging the gap between instruction, computers, and cognitive styles, it may be possible to present materials in a way that encompasses individual differences.

For purposes of this study, three different types of technology-based research were used to examine the impact of cognitive styles on student achievement: distance learning (eLearning), web-based learning (hypertext/hypermedia) and computer-assisted instruction (CAI). These forms of instruction were selected as they are commonly employed in educational settings and have amassed a considerable body of recent research. Further descriptions of these learning environments and a review of the research findings represented by each category follows in the next three sections.

Distance Learning

For some time now, colleges, universities and other learning institutions have provided students with the option of enrolling in classes off campus (Roberts, 1999). In distance education, learner and teacher are not in a face-to-face relationship on a continuing basis. The face-to-face relationship is replaced with some form of mechanical or electronic communication: print, tutorial, telephone, teleconference, audio, video, broadcasting, computer. The transmission of instruction to students at a distance defines the nature of distance education programs as 'teacher-independent' (Keegan,1990). Hence, students are required to direct their study themselves.

According to Luk (1998), the requirement for distance learners to structure their own learning may explain findings in the literature that point to differences in achievement between field dependent and field independent students. The impersonal nature of distance education places a heavy emphasis on specific analytic skills and provides little opportunity for interaction, which is a disadvantage to field dependent students. This may also explain why Thompson (1988) indicated that field dependent students who register for distance education have lower academic achievement and are more likely to “drop out” of distance education programs.

To investigate the impact of individual differences in distance education environments, eight of the 37 studies included in this meta-analysis looked to differences in field dependence as a explanation for possible discrepancies in achievement. Of these, five studies reported that there were no statistically significant differences. For example, Buck (2004) studied how field dependent and field independent learners differ and how dominant mediation or cognitive abilities differ in academic performance, completion rates, and navigation styles in a secondary distance learning environment. A total of 149 students were measured over a 4 week period. The study revealed that there were no differences in the group means for module quizzes or scores, nor in completion rates or navigations skills.

Similarly, Shih and Gamon (2002) analyzed the relationships among student achievement, learning strategies, learning patterns, learning styles (as measured by the GEFT) and student characteristics. Their study involved 74 students taking web-based university courses in Zoology and Biology. Results showed that field dependent students scored almost the same on the post test as field independent students, and no significant differences were found by a t-test. They concluded that students with different cognitive styles learned equally well, and did not differ in their use of learning strategies and patterns of learning. Additionally, findings published by Musgrove (2002), and Roberts (1999) both concurred that cognitive style was not an effective factor in influencing student achievement in remote learning.

Alternatively, three studies did note significant differences in achievement between field dependent and field independent students. Luk (1998) conducted two separate investigations of the relationship between field dependence and academic learning in the context of distance education. Both studies involved Bachelor of Health nursing students in Hong Kong. The first study involved 51 students and the second included 113 students. In both studies, results indicated that field independent nurses performed significantly better than field dependent ones. The researchers suggested that the impersonal learning environment of distance education may have contributed to the learning difficulties of field dependent students.

Additional support for achievement differences can be found in Parcells (2008) who examined the effects of matching or mismatching the design of asynchronous distance education to the field dependent and the field independent learner. The study included 18 graduate students enrolled in a teaching methods course. An analysis of the post test scores showed a significant effect for module design, but no significant effect for either cognitive style or the interaction of cognitive style and module design. However, the author attributed the lack of difference between field dependent and field independent post test scores to the benefits of matching instruction to the cognitive style of the learner. Parcells concluded that the use of an instructional design that matched the needs of the field dependent learner had a positive impact on the achievement results as measured by pre-and post test scores. A summary of the distance education literature reviewed for this meta-analysis is provided in Table 2.

Table 2

Literature review of field articulation (FDI) in distance education

Author(s)	N	Task	Duration	Outcome Variable	Result
Buck, 2004	110	Lesson Module in High School Advanced Placement English	< One Month	Post Test	NS
Musgrove, 2002	108	Undergraduate Nursing Course	Course Term	Class Grade	NS
Roberts, 1999	16	Undergraduate Agricultural Communications Writing Course	Course Term	Class Grade	NS
Shih & Gamon, 2002	74	Undergraduate Zoology and Biology Courses	Course Term	Class Grade	NS
Luk, 1998a	51	Undergraduate Nursing Course	< One Month	Class Grade	S
Luk, 1998b	113	Undergraduate Nursing Course	< One Month	Class Grade	S
Parcels, 2008	18	Teaching Methods Lesson	< One Day	Post Test	S

Web-based Instruction

Web-based learning, also known as eLearning, is a type of education where the medium of instruction is computer technology. As the application of hypermedia-based systems and internet use continues to increase at all levels of education, students are faced with an educational environment that may pose both challenges and opportunities (Archer, 2003). Because hypermedia systems are based on link and node structures, they differ from the more traditional linear instruction. According to Triantafillou (2004) in an ideal web site, the structure is evident to the user and the information is organized coherently and meaningfully. Navigational tools are essential in order to assist learners to organize the structure of the web site as well as the connections of the various components. A coherent resource collection will allow the user to construct an accurate mental model of the topic.

Some research has suggested that field dependent learners are less likely to impose a meaningful organization on a field that lacks structure and are less able to learn conceptual material when cues are not available (Witkin, Moore, Goodenough, & Cox, 1977). Jonassen and Wang (1993) have argued that field independent learners generally prefer to impose their own structure on information rather than accommodate the structure that is implicit in the learning materials. Additionally, research by Ford and Chen (2000) has shown that learners with a high degree of field dependence take a more global approach to problem solving and thrive when structure is provided. Because learners vary in their degree of field dependence, the type of instructional design can impact learning achievement.

While some studies have documented that field dependent and field independent learners utilize a hypermedia learning program in different ways, these different patterns of use have not consistently resulted in different learning outcomes. Of the 11 web-based studies included in this meta-analysis, four did not determine any significant differences in achievement between field dependent and field independent learners. For instance, in a study designed to investigate the effects of cognitive style (FDI) and internet search efficiency for 48 undergraduate college students, Palmquist and Kim (2000) found no differences in performance between field types. In a further lack of support, Tarantafillou (2004) studied 74 fourth-year undergraduate students to determine whether adaptive hypermedia can accommodate cognitive styles and improve learning outcomes. Students in an experimental group studied through an adaptive educational system, while students in a control group studied through a traditional hypermedia-based environment. The results did not show a significant main effect for cognitive style for learner achievement; however, all participants performed better in the adaptive hypermedia condition. Similarly, researchers Day (1995) and Lee (2006) concluded from their respective studies that cognitive style was not significant and looked to other factors such as instructional design and prior subject knowledge as more beneficial to learning outcomes.

Conversely, seven web-based studies included in this analysis did determine that field dependence has a significant influence on performance in hypermedia environments. Archer (2003) examined the relationship between instructional aids (concept maps and outlines) and level of field dependence and achievement in web-based instructional systems (n=63). Results indicated that there was no interaction between level of field dependence and the instructional aid treatment; however, field dependent participants generally had lower mean scores on the assessment which were statistically significant for cognitive style. Additionally, Cameron and Dwyer (2005) found that field independent students outperformed field dependent students on all criterion measures, and suggested that differences may be due to less efficient information processing on the part of the field dependent learner.

In other studies which have demonstrated significant differences, research has shown that field independent learners typically outperform field dependent learners on measures of achievement. For example, Hsu and Dwyer (2004) investigated the effects of cueing questions in hypermedia programs on the performance of field independent and field dependent students on criterion tests measuring understanding. One hundred and thirty two college students were assigned to one of three hypermedia programs: no cueing questions; factual questions and comprehension questions. Post test results indicated that FI students achieved better overall, FD students performed better in the comprehension treatment than the factual treatment, and FD students in the factual treatment performed better than those who received no questions. Hsu and Dwyer concluded that FI learners improved when they received higher order questions, and FD learners improved in proportion to the depth of the processing instigated by the adjunct questions.

Similar achievement differences in favor of independent learners were also found in studies by Chou and Lin (1998) in an investigation of navigation map types and cognitive styles; Hsu, Frederick, and Chung (1994) who examined the effect of metacognitive skill tools on field dependence; Fullerton (2000) who studied the interaction between cognitive style and internet document manipulation style on student achievement; and Ku (2000) in an investigation of pre-set learning goals and learner cognitive styles. A summary of the web-based instruction literature reviewed for this meta-analysis is provided in Table 3.

Table 3

Literature review of field articulation (FDI) in web-based instruction

Author(s)	N	Task	Duration	Outcome Variable	Result
Day, 1996	54	Technical Writing Agricommunications	Course Term	Course Grade	NS
Lee, 2006	52	Educational Technology Lesson	< One Day	Post Test	NS
Palmquist & Kim, 2000	48	On-Line Database Search Performance	< One Day	Post Test	NS
Triantafillou et al., 2004	66	Multi-media Technology Systems Lesson	< One Day	Post Test	NS
Archer, 2003	63	Election of 1912 Lesson	< One Day	Post Test	S
Cameron & Dwyer, 2005	300	Anatomy of a Heart Attack Interactive	< One Day	Post Test	S
Chou & Lin, 1998	121	Computer Network Module	< One Day	Post Test	S
Fullerton, 2000	62	Tutorial in Human Anatomy	< One Day	Post Test	S
Hsu & Dwyer, 2004	132	Anatomy Science Module	< One Day	Post Test	S
Hsu et al., 1994	40	Pearl Harbour Lesson	< One Day	Post Test	S
Ku, 2000	180	Lyme Disease Lesson	< One Day	Post Test	S

Computer-Assisted Instruction

A great deal of attention has been given in recent years to the use of computer assisted instruction (CAI) in education. Courses or parts of courses provided by CAI generally require students to work at their own pace through a structured set of learning experiences. Learners are responsible for scheduling their learning time and completing the coursework exercises (Grabinger & Jonassen, 1988). It has been assumed that such courses will lead to learners completing their instruction more efficiently and with greater satisfaction because they are in control of their own progress. CAI materials are able to present text and graphic materials to learners in a coordinated manner and the use of exercises and questioning techniques means that the learners are active during the learning process (Abousserie, 1992).

Some research has indicated that CAI has the potential as an instructional medium to individualize the learning process (Rasmussen & Davidson, 1996). Canelos (1988) has suggested that one major factor influencing effective learning may be that of field dependence (FDI). They suggest that learners who demonstrate field independence may be better able to abstract information more readily from learning materials and require fewer visual and verbal cues in order to learn effectively. Conversely, the field dependent learner may need a more structured presentation with more visual and verbal cues and more reinforcement. Alternatively, Ross (1997) found that CAI may not be suitable for all learning styles. It may be more beneficial to some learners than others. For example, graphics and visually active instruction primarily assists field dependent learners (Fitzgerald & Semrau, 1998).

The question of whether or not cognitive style has a differential effect on achievement in computer-assisted learning was investigated in the remaining 19 studies included in this meta-analysis. Of this body of research, 10 found no differences between field dependent and independent learners in CAI environments. For example, Abousserie (1992) investigated cognitive style, gender, attitude toward using computer-assisted learning (CAL) and academic achievement among 143 university students. An analysis of variance revealed there was no difference in achievement between field dependent and field independent groups. As well, Daniels and Moore (2000) investigated whether field dependents, due to perceptual and cognitive restructuring characteristics, would benefit from having a choice of single or multiple channel message presentation modes. This hypothesis was rejected as no score differences were found between experimental and control groups for dependent learners. A separate analysis of the post test scores also revealed no significant differences in mean scores between cognitive types.

In further support, Katz (1999) found that use of a CAI program could be employed as a lab substitute with no adverse effect on academic achievement, regardless of level of field dependency; Stegall (1998) indicated that differences in cognitive style in a self-paced CAI laboratory had no effect on achievement; and Yoon (1993) discovered no main effect for cognitive style on the achievement of 166 students who completed nine different lessons in multiplication facts.

In other studies which support the null hypothesis, researchers have found differences in performance between FI and FD learners but not in achievement. For example, Fitzgerald and Semrau (1998) determined that FI users were more efficient in utilizing information gained through a CAI program in the problem-solving activities; however, in spite of different usage patterns, outcomes were similar for the FD and FI students.

On the other hand, there are nine studies included in this review which have published significant differences in achievement between levels of field dependence in CAI. Summerville (1997) examined whether matching or mismatching participants with their tendency toward field dependence or independence had any effect on achievement in a hypermedia CAI environment. Summerville found that field independent students significantly outperformed field dependent students regardless of the treatment type. Similarly, Cao (2006), Chuang (1999), Hall (2000), Khine (1996), Leader and Kline (1996), Umar (1999), Weller (1995) and Weymer (2002) each found that field independent students outperformed field dependent learners in post test measures of achievement across multiple conditions. A summary of the computer-assisted instruction literature reviewed for this meta-analysis is provided in Table 4.

Table 4

Literature review of field articulation (FDI) in computer-assisted instruction

Author(s)	N	Task	Duration	Outcome Variable	Result
Abouserie, 1992	76	Nine Physiology Tutorial Packages	Course Term	Post Test	NS
Daniels & Moore, 2000	80	Presidential Primary Election Process Lesson	< One Day	Post Test	NS
Fitzgerald & Semrau, 1998	23	Behavioral Disorders Case Studies (4)	Course Term	Post Test	NS
Katz, 1999a	56	Horticulture Laboratories	Course Term	Post Test	NS
Katz, 1999b	63	Horticulture Laboratories	Course Term	Post Test	NS
Stegall, 1998a	26	Agricultural Laboratories	Course Term	Course Grade	NS
Stegall, 1999b	23	Agricultural Laboratories	Course Term	Course Grade	NS
Yoon, 1993b	79	Arithmetic Skills Lessons	< One Week	Post Test	NS
Cao, 2006	156	Human Anatomy Lessons	< One Day	Post Test	S

Author(s)	N	Task	Duration	Outcome Variable	Result
Chuang, 1999	175	Physics – Forces Lesson	< One Day	Post Test	S
Hall, 2000	102	Geography Puzzle Lessons	< One Day	Post Test	S
Khine, 1996	75	Dinosaurs Lesson	< One Day	Post Test	S
Leader & Klein, 1996	75	EarthQuest Science Lesson	< One Day	Post Test	S
Summerville, 1997	177	Hypercard Tutorials	< One Day	Post Test	S
Umar, 1999	75	Information Technology Lesson	< One Day	Post Test	S
Weller, 1995	22	Computer Ethics Tutorials	< One Day	Post Test	S
Weymer, 2002	90	Technology Tutorials	< One Day	Post Test	S

Conclusion

Overall, the research on achievement differences between field dependent and independent learners in technology-based learning is ambiguous. It has also contributed more issues to those already found in traditional learning environments. The studies which report consistently higher achievement for field independent learners have raised the question of innate differences in ability between field articulation types. On the other hand, research which reports no differences in achievement profiles is often mitigated by measured differences in performance profiles. The literature also continues to leave open both the question of whether individual learning styles can lead to greater academic achievement and whether style can be used a diagnostic variable in determining the needs of individual learners in technology learning programs. Finally, it remains unclear as to whether potential achievement differences apply generally to technology, or are specific to a particular design and use of technology applications.

Key Criticisms

The research presented herein provides no clear answers to the question of achievement differences between style types. Other investigators have come across similar findings which have formed the basis of a number of critical analyses (e.g., Dillon & Gabbard, 1988; Curry, 1990). Studies of cognitive styles, particularly FDI, in technology-mediated environments have received much criticism due to variations in methods used to establish FD/FI sample groups, differences in lengths of treatment, and forms of intervention.

Criticisms FDI Research

First, reliability evidence of the GEFT is not supportive. While all the studies reported herein used the Group Embedded Figures Test (GEFT) (Witkin, Oltman, Rashkin, & Karp, 1971) as a basis for determining field dependence-independence, methods for assigning subjects to groups varied in terms of using established norms for the instrument, re-norming within the sample group, or regressing the scores from low to high. Researchers such as Clark and Feldon (2005) as well as Curry (1990) claim that the instrument developers (Witkin, et al., 1971) have not provided enough information for their style classification decisions. For example, a number of researchers used GEFT and identified their participants as two groups (field dependent / field independent) (e.g., Shih & Gamon, 2002; Musgrove, 2002) or three groups (field dependent, field neutral, and field independent) (e.g., Hall, 2000; Lee, 2006). Based on Witkin's original research, FDI exists with a continuous range. Participants can only show their tendencies toward either end of the continuum (Riddle, 1992). In addition, the identifying point for FD or FI groups is varied. A number of researchers identified participants by using the participants' median (Palmquist & Kim, 2000), mean with standard deviation score (Daniels & Moore, 2000), the median of the instrument (Musgrove, 2002), or even the national mean (Shih & Gamon, 2001). Because of this, it is not easy to tell whether the significant difference was due to the real difference between the groups or the way they identified the groups.

Second, there was no evidence of long term studies in the literature which have traced whether a learners' cognitive style is malleable. Curry (1990) has argued that there is not enough empirical evidence to show whether cognitive style is temporally stable or will change over a longer period of time. Even though Claxton and Ralston (1978) reported that cognitive styles were stable in their three year longitudinal study of 40 students, Pinto, Geiger, and Boyle (1994) reported opposite findings in the same period of study for students at two universities.

Finally, relevant factors in learning and instructional settings remain uncertain. In addition to field dependence/independence, studies have examined relationships between other learner characteristics, such as prior experience with computers, prior knowledge in the domain area, and class rank in hypermedia-based instruction. For example Lee (2006) examined differences in achievement for passive versus active learners with a hypermedia program with and without instructional cues and found that students were not equally successful in exploring for information. As well, Ausburn and Ausburn (1978) argued that cognitive style mismatches with instruction can be only one of several reasons why learners fail in learning. Researchers who try to match instruction to cognitive style can only solve one source of failure. This approach also confounds the interpretation of outcomes because if the instruction fails to produce the expected outcomes, it is difficult to determine whether the failure is due to faulty instruction or to other factors (e.g., Lee, 2006; Summerville, 1997).

In response to these issues, several theorists have urged that investigators try to establish and realize the validity and reliability of the concepts in this discipline, determine the relevant factors in the teaching and learning situation, and measure FDI and outcomes with prudence and consistency. Otherwise, research will only realize a part but not the whole picture of the field (Cassidy, 2004; Curry, 1990).

Criticisms of FDI Theory

In addition to issues related to technology-based research, there have been criticisms raised with respect to measurement of FDI using the GEFT. For example, a number of researchers have argued that this approach generalizes performance on perceptual tasks to personality and social behavior and that this is an 'over-dilation' of the theory (Griffiths & Sheen, 1992). Another common argument is that the approach and the test are designed to measure learners' intelligence or psychological capabilities other than cognitive styles (Riding & Rayner, 1998). FI learners often perform better, and this cognitive style is easy to connect to intelligence.

On the contrary, a number of researchers have argued that the relationships between cognitive style and intelligence or other psychological capabilities are extremely negligible and lack empirical evidence (Ausburn & Ausburn, 1978). Messick (1984) argued that cognitive styles measure more dimensions than intellectual abilities, and cognitive styles are typically bipolar but abilities are normally unipolar. In order to prevent confusion with intelligence ability, researchers suggest controlling the intelligence variable for conducting the experiments between cognitive styles and other factors (Ausburn & Ausburn, 1978). Sternberg (1997) also stated that these arguments cannot diminish the value of field dependence theory. FDI has value not only in visually complex areas, but also in measuring psychological ability like spatial competence.

Meta-Analysis as a Research Method

It would appear that criticisms of FDI literature and theory are as divisive as the body of research they represent. Hence, the "conflicts in the literature have become conflicts in the reviews" (Hunter & Schmidt, 2004, p-18). Historically, researchers have produced a 'literary method' type of review from numerous bodies of research. While one reviewer can find a set of studies that supports her viewpoint, another can find just as many studies that contrast those findings. A point to consider is that conflicting study results may be entirely artifactual. All studies contain measurement error, lack perfect construct validity, and have sampling error. Therefore no single study or small selected subgroup of studies can provide a basis for conclusions about collective knowledge (Rosenthal & Rosnow, 2008). According to Hunter and Schmidt, the reliance on significance testing in social science research leads to errors in traditional review studies. The small sample studies typical of psychological research produce contradictory results, and reliance on significance tests causes study results to appear even more conflicting. For example, the 5% error rate used in the tests of significance for this meta-analysis is guaranteed only if the null hypothesis is true. If the null hypothesis is false, then the error rate can go as high as 95%.

As an alternative to the use of significance testing, Hunter and Schmidt (2004) recommend the use of meta-analysis at the level of review. Meta-analysis integrates the findings across several studies to reveal the simpler patterns of relationships that underlie research literatures, and provides a basis for theory development. It can also "…correct for the distorting effects of sampling error, measurement error, and other artifacts that produce the illusion of conflicting results" (p.17). From this perspective, the conflicting results and over reliance on statistical significance as presented in this literature review are ideally suited to meta-analytic procedures. The statistical process of cleaning up and making sense of the field dependence research can clarify the knowledge that exists, and potentially provide clearer directions about what the remaining research needs are.

Meta-analytic reviews typically describe a) the magnitude of the effects, b) their variability, c) their level of statistical significance, and d) the nature of the moderator variables from which one can predict the relative magnitude of observed effects. More specifically, meta-analysis is a set of procedures designed to accumulate experimental and correlational results across independent studies that address a related set of research questions. There are a variety of different statistical procedures for conducting meta-analysis involving the accumulation of outcome data, such as the computation of correlations r, standardized differences between mean scores d, F statistics, t statistics, X^2 statistics, p values or *z-scores* (Glass, 1976). The goal of meta-analysis is to combine results across studies to yield an overall estimate of effect between independent and dependent variables, as well as to compare effects between studies to identify any moderating factors (Hunter & Schmidt, 2004). A key assumption is that each study provides a different estimate of the underlying relationship with the population. By accumulating results across studies, one can gain a more accurate representation of the population relationship that is provided by individual studies (Rosenthal, Rosnow & Rubin, 2000).

While there are a variety of meta-analysis techniques that have evolved from Glass' original work in 1971 (see Table 5 for a comparison of three major statistical approaches), this thesis will focus on the methods developed by Hunter and Schmidt (Hunter, Schmidt & Jackson, 1982, Hunter & Schmidt, 1990).

Table 5

Three Meta-Analytic Approaches and Questions of Central Tendency, Variability and Prediction (Johnston, Mullen & Salas, 1995).

	Meta-analytic approach		
General analytic question	Hedges & Olkin (1985)	Rosenthal (1991); Rosenthal & Rubin (1978)	Hunter & Schmidt (1990); Hunter, Schmidt, & Jackson (1982)
Central tendency	Mean weighted effect size; confidence intervals (significance levels)	Mean weighted effect size; combined probability (significance levels)	Mean weighted effect size; confidence intervals (significance levels)
Variability	Homogeneity statistic	Diffuse comparison of effect sizes	Test of no variance across effects
Prediction	Continuous models categorical models; contrasts between mean weighted effect sizes	Correlations, blocking, focused comparisons of effect sizes	Correlations; blocking

The Hunter-Schmidt approach is inferential in nature and deals with variation in study effect sizes due to sampling error and other artifacts. This variation in effect sizes is referred to as a 'random effects model'. The distinction between a 'fixed' and 'random' effects model is that fixed effect models assume *a priori* that one population parameter underlies all studies in the meta-analysis, while a random-effects model allows for population parameters to vary from study to study. A major purpose of random-effects models is to estimate this variation. The basic model is subtractive – the estimate of population variance is the variance that is left after variance due to sampling error and other artifacts is subtracted out. If the variation is still large after corrections, the influence of moderator variables is then investigated. Moderator analysis is performed by breaking down the data into at least two subsets with respect to a theoretically relevant variable through the use of blocking variables (such as type of technology or subject matter). For these subsets separate meta-analyses are computed. In order to classify as a moderator, the following requirements have to be met: 1) the population effect size varies from subset to subset, and 2) the residual variance averages lower in the subsets than for the data as a whole (Hunter & Schmidt, 2004).

Another distinction in the Hunter and Schmidt method is that it uses a different calculation of the effect size. Rather than following the Glassian method of using the control group standard deviation, this model uses the pooled within-group standard deviation by using d rather than d_G. According to the example provided (p-283), the control group standard deviation (d_G) has much more sampling error than the within-group standard deviation (d). A second advantage is that most studies have a value for t or F and, hence, permit the computation of d. Many reports do not present standard deviations, and so d_G cannot be computed (Hunter & Schmidt, 2004).

Benefits and Limitations

The Hunter and Schmidt approach produces a number of outcomes of analysis including average effect size, study variation, variation attributable to sampling error, and a list of moderators accounting for remaining variation (Hunter, Schmidt, & Jackson, 1982). However, as with any research method meta-analysis has both limitations and benefits.

Limitations

Sampling bias and the file drawer problem. This criticism suggests that there is a bias because studies retrieved do not reflect the population of studies conducted. Since the probability of publication is increased by the statistical significance of the results, the studies are not representative of all studies conducted. To address this concern, a procedure that addresses the concern that researchers file away their statistically nonsignificant studies will be used in this meta-analysis which estimates the number of studies it would take to place an obtained overall p level down to a barely significant level (Rosenthal & Rosnow, 2008).

Loss of information. This criticism suggests that summarizing a research domain by a single value (such as d) loses valuable information. However, it should be noted that comparing a body of studies in a meta-analysis is as much about understanding the differences in results as it is about summarizing the overall results of the set. Rosenthal and Rosnow (2008) note that "even within a single study, experimenters have historically found it quite helpful to compute the means of two groups, even though computing a mean always involves a 'loss of information'" (p.666).

Heterogeneity of primary studies. This criticism is equated to "taking apples and oranges and averaging such measures as their weights, sizes, flavors, and shelf lives" (Rosenthal & Rosnow, 2008, p. 68). However, in all research synthesis (literary and quantitative), individual studies are rarely the same in terms of the samples, operationalization of independent and dependent variables and measurement methods. Variability in research studies is common and applies to other methods of synthesis as well, such as narrative review (Olkin, 1996).

Insufficient data reported. A criticism leveled at meta-analysis which is difficult to refute concerns the exclusion of studies due to insufficient data reporting. It is true that many studies that may have been included in this thesis were rejected due to insufficient data reporting. To eliminate this problem, Cooper and Hedges (1994a) recommend that journal editorial boards should make the sufficient reporting of data a requirement for publication. This would included sufficient descriptive statistics so that the effect reported can be used for future meta-analyses.

Benefits

Focus on Effect Sizes. Most quantitative research largely relies on the null hypothesis. Through a variety of statistical tests (e.g., t-test, ANOVA, etc) the null hypothesis is tested. The data is converted to a probability value (p value). The rule is that if the *p*-value is less than .05, we reject the null hypothesis, meaning that the difference between the two groups is not zero. The null hypothesis asks a 'yes/no' question and we either reject or fail to reject the hypothesis. Although the p value does not equal effect size, some researchers indicate that a *p*-value of .0001 is a 'big' effect. As discussed previously, the focus in meta-analysis is on effect sizes, not significance testing. The determination of whether the differences is large or not is an effect size issue, not a *p*-value issue.

Analysis of Moderator Variables. Much useful data other than main effects are often ignored in narrative reviews. An advantage of meta-analysis is the availability of finding moderator variables. Moderator variables are different from mediator variables. Moderator variables change the relations between the independent and dependent variables, where as mediator variables "lie casually in between" (Hall & Rosenthal, 1991). As such, moderators in meta-analysis are identical to the interaction terms in a factorial analysis of variance (ANOVA). This allows the meta-analyst to directly compare results across studies of different kinds, and allows the testing of hypotheses that were not tested in primary studies (Cooper, 1998).

Conclusion

The cognitive style of field independence-dependence has been researched as an influence on how learners perform in both traditional and technology-based learning environments because it describes the visual perceptiveness and analytical abilities of learners. Conflicting research results suggest that how field articulation influences a learner's experience is not a clear-cut problem. The confusing state of the research literature commonly leads to the call for more research to resolve the issue.

Meta-analysis offers a solution to this problem. The introduction of meta-analysis as a research procedure has had a positive impact on synthesis by offering answers to questions of how to best summarize the results of a number of studies and provides statistical procedures for computing effect sizes. By using carefully constructed methodology, comprehensive coding and accurate accumulation procedures (see Chapters 3-Method and 4-Results), research questions that cannot be answered in a single study may be resolved using meta-analysis.

CHAPTER 3

Methodology

This chapter provides a description of the methodology used for this study. As discussed in Chapter 2, the method of meta-analysis is a set of statistical procedures designed to accumulate experimental and correlational results across independent studies that address a related set of research questions (Lyons, 2003). The primary purpose of this meta-analysis was to determine whether there are differences in learning achievement in technology-based environments based upon the learner's field articulation (FD/FI) type. Specifically, meta-analytic methods were selected to answer two related questions:

1. What is the effect of field dependent and field independent cognitive styles on student achievement in technology-based environments?
2. How do these differences vary according to study characteristics, methodology characteristics, and treatment characteristics?

The meta-analysis method chosen to investigate the research questions is based on statistical procedures developed by Hunter, Schmidt, and Jackson (1982), and Hunter and Schmidt (2004; 1990). This chapter presents their formulas and steps which were used to analyze the individual and pooled data in this study. The chapter concludes with a description of the meta-analyses software programs selected to analyze the data.

Steps in the Meta-Analytic Process

The Hunter-Schmidt approach to meta-analysis is unique in that their methods allow the scientist to determine how much of the variance in findings across studies is due to sampling error and other artifacts, and how to adjust for the effects of these artifacts. The end result is an estimate of the true population variability of study outcomes. "This true variance is often either remarkably small or zero, indicating that many of the apparent disagreements among different studies are illusory" (Hunter & Schmidt, 2004, p.xxx).

This approach is particularly well suited to the studies under consideration which were prone to sampling error, measurement error, imperfect construct validity, and inconsistent applications of the GEFT instrument. As discussed in Chapter 2, artifactual study errors have likely contributed to the conflicting results presented in the body of literature. In order to clarify the debate and address the research questions, a set of statistical and methodological procedures were conducted as shown in Table 6 .

Table 6

Steps in the Meta-Analysis Process Lyons (2003)

Level of Analysis	Step
Planning	1. Define the domain of research
	2. Establish criteria for including studies in the review
	3. Determine the type of effect size to use
	4. Search for relevant studies
Individual Study	5. Extract data on variables of interest, sample sizes, effect sizes, reliability of measurement and other noteworthy characteristics of each study
	6. Code each study for characteristics that might be related to the effect size (moderator variables)
	7. Conduct reliability checks on the coding procedures
	8. Correct individual study artifacts (measurement error, dichotomization, construct validity)
Meta-Analysis	9. Calculate study weights and sampling error variance
	10. Calculate the average correlation, the variance of correlations and the average sampling error variance
	11. Decide whether to search for moderator variables
	12. Determine the mean and variance of effect sizes within moderator subgroups

Planning Phase

Domain of Research

The focus of this examination was research where the achievement of field independent learners was compared to that of field dependent learners in technology-based learning environments. Although meta-analytic methods are often used to express the difference between treatment and control groups in experimental studies, they can also be used to express the difference between any two groups (Cooper, 1998). Differences between naturally occurring groups, such as field dependent and field independent learners, are often very informative in their own right, and can direct future research (Hunter & Schmidt, 2004). Hence, this meta-analysis was essentially a main effects analysis, with moderator variables (e.g., coded study, methods and treatment characteristics) treated as equivalent to the interaction terms in a factorial analysis of variance (ANOVA).

Inclusion Criteria

For a study to be included in this meta-analysis, it had to have met specific inclusion criteria. This review and subsequent investigation focused on a total of 35 studies which met all of the inclusion criteria. The following criteria were established for the identification of studies:

1. Studies had to be retrievable without cost from local university libraries or through interlibrary loan (within a four week period), electronic journals, electronic library database access, or the internet.
2. Studies were published between 1990 and 2009.

3. Studies had to either compare or provide sufficient data to calculate the differences in achievement between field dependent and field independent groups in technology-based environments.
4. Technology-based environments included distance learning (eLearning), web-based learning, and computer-assisted learning technologies.
5. Achievement was reported as either post test study results or course grade assignments.
6. Studies demonstrated valid sampling techniques.
7. Studies provided quantitative results and/or sufficient quantitative data to calculate effect sizes. For example, studies had to be excluded if only interaction statistics were reported.
8. Studies took place in an educational setting or reflected interest in informing educational practices.

In addition, two other considerations were relevant to the identification of studies in this analysis, specifically the inclusion of methodologically weak studies, and the inclusion of unpublished research.

Inclusion of 'weak' studies. The inclusion of studies in this meta-analysis was quite tolerant. Although many reviewers wish to eliminate from their analyses studies that they perceive as having methodological inadequacies, these assertions are always dependent on theoretical assumptions about what might be true in a study. To make such decisions, evaluators must judge and rate each study on methodological quality. These assumptions may be false and are subject to researcher bias. According to Hunter and

Schmidt (1998), the hypothesis of methodological inadequacy should only be tested after two prior hypotheses have been rejected:

1. The variation across studies cannot be accounted for by sampling error and other artifacts.
2. Moderator variables cannot account for nonartifactual variance.

In accordance with these two hypotheses, potential threats to internal validity were tested empirically rather than excluding the questionable studies. The study characteristics that might produce inadequacy were coded as moderator variables and subsequently tested in the event that a relationship between effect sizes and these threats existed.

Inclusion of unpublished research. Some critics of meta-analysis suggest that the studies available for analysis will typically be a biased sample of all existing studies. In particular, it is often suspected that published studies will show results that are more often statistically significant and have larger effect sizes than unpublished studies (Lyons, 2003). It may be that bias differences in mean effect sizes by source (e.g., journals, reports) may partly reflect the artifactual effects of differences in average methodological quality among sources. Should this be the case, this analysis - which corrected for methodological weaknesses (e.g., sampling, measurement error, etc.) - will also account for these artifactual effects. It should also be reiterated that the research included in this meta-analysis was representative of both published and unpublished research.

However, should there be further reason to suspect availability or reporting bias, there are methods available to detect these effects. To determine whether or not availability bias was a problem for this set of studies, the 'File Drawer Analysis' formula based upon effect sizes was selected (Hunter & Schmidt, 1990). This formula is presented in Appendix A (Appendix A, Formula 1) and was used to determine how many missing studies averaging null findings would have to exist to bring the average effect size down to the smallest mean value that would be considered practically significant.

Establish Effect Size Parameters

In statistics, a meta-analysis combines the results of several studies that address a set of related research hypotheses. This is normally done by identification of a common measure of effect size, which is modeled using a form of meta-regression. According to Cooper (1998) the effect size recommended for a study in which two groups are compared on a quantitative variable is *d*, a standardized difference between the means of the two groups. Therefore, the *d* metric was selected to quantify the differences in achievement between field dependent and field independent learners.

Selection of effect size type. As discussed in Chapter 2, the variant of the effect size statistic used in this study was the pooled within-group standard deviation used in analysis of variance. This is due to the within-group standard deviation having approximately half the sampling error of the control group standard deviation (Appendix A, Formula 2).

Unfortunately, few of the primary research studies provided the descriptive data necessary to calculate *d* as an effect size; therefore, effect sizes had to be derived by the researcher from *t* and *F* statistics. In situations where the means and standard deviations were not reported for the separate groups, a formula for the *d* index that does not require this information was used (Appendix A, Formula 3).

Adjustment of Small-Sample Effect Sizes. Some researchers will exclude studies with sample sizes of less than 20 participants, as the *d* index may be a slight overestimate the size of an effect in the entire population. As well, when samples are small, a single extreme value can create an exceptionally large effect size. Since six studies in this analysis included sample sizes less than 20, rather than exclude the studies, a correction factor was applied based upon Hedges' (1980) formula. This calculation adjusts for the known biases that occur because effect size estimates based on samples are not always true reflections of their underlying population values (Appendix A, Formula 4).

Estimation of effect sizes with more than two groups. A challenge that arose during effect size calculations from *F* statistics was that the conversion formula commonly used to transform *F* to *d* may only be used with an *F* score with one degree of freedom in the numerator. Many studies of field dependence as defined by use of the GEFT divided learners into more than two groups, for example, field dependent (FD), field neutral (FN), and field independent (FI). In these cases, Cooper (1998) does not recommend using an effect size metric associated with multiple-group inference tests, as the resulting effect size tells us nothing about which group has the highest mean. Because of this ambiguity, Cooper recommends that effect sizes be expressed as comparisons between two groups, between two continuous variables, or as the ratio of odds.

In light of this perspective, if sufficient descriptive data were reported in the study in order to compare FD and FI groups (means and standard deviations) then an effect size was derived from the data. However, if insufficient statistical data was reported for more than two groups ($df>1$), without subsequent single degree of freedom comparisons or t-tests, the study was excluded from analysis.

Transformation of effect sizes from d to r. Since the *d* index may leave something to be desired in terms of its intuitive appeal, Hunter and Schmidt (2004) recommend that the simplest way to do a meta-analysis which corrects for artifacts is to do the meta-analysis using correlations (*r)*. Relationships expressed in *d* form can be interchangeably expressed using the correlation metric *r*. Therefore, once the study database was assembled, the individual study statistic *d* was converted to a common metric *r* for subsequent artifact correction and later accumulation (Appendix A, Formula 5).

Determination of effect size significance. In social research it is quite common to apply words such as 'small', 'medium' and 'large' to the size of the effect. Cohen's (1988) conventional criterion of small, medium, or large have been adopted by many researchers. For example, an effect size of 0.2 to 0.3 might be a 'small' effect, around 0.5 a 'medium' effect and 0.8 to infinity, a 'large' effect. Using the conversion formula for transforming *d* to *r*, the small, medium and large standardized mean difference effect sizes were translated to *r*'s of .10, .25, and .37. These *r* values were used in this study as the criteria to classify the size of effects as small, medium or large.

Search for Relevant Studies

A comprehensive and methodical literature search was conducted to locate published and unpublished investigations using populations between 1990 and 2009 and based upon Witkin's FDI model. Studies were located through several approaches.

Electronic databases were systematically scanned using the terms 'field dependence' or 'GEFT' or 'field independence' AND 'achievement' or 'outcomes' or 'grades' AND 'cai' or 'computer' or 'internet' or 'web-based' or 'online' or 'distance education'. The computer-based search identified relevant studies contained in

PsycINFO, ERIC, Web of Science, Academic Search Complete, CBCA Education, EditLib Digital Library for Information Technology and Education, Education Research Complete, ProQuest Dissertations and Theses, ProQuest Education Journals, WorldCat, InGenta, and Masterfile Premier Education.

A computerized search of major educational technology journals was also conducted in the following journals: *British Journal of Educational Technology*, *Computers in the Schools, International Journal of Instructional Med*ia, and the *Journal of Computing in Higher Education*. Dissertations were obtained through the University of Alberta Interlibrary Loan Office or Proquest Dissertations and Abstracts.

In addition to using electronic and online indexes and databases, the Google Scholar search engine (http://scholar.google.com) was used to conduct searches of material on the World Wide Web through academic library access. The Google Scholar search engine was chosen because it is the most comprehensive search engine currently available for searching the internet. Studies normally not available to the public are accessible as many of the resources indexed by Google Scholar can only be accessed through subscriptions held by academic libraries.

After electronic databases were searched, an "ancestry analysis" was conducted by checking reference lists of retrieved publications. This process is also known as footnote chasing (Cooper & Hedges, 1994). Reference lists of research papers were searched to locate relevant studies.

Finally, a more traditional search of the literature using printed text volumes of the Education Index was conducted to locate additional studies.

Each study retrieved was subsequently examined to determine if it met all the necessary criteria to be included in this meta-analysis.

Study Analysis Phase

Extracting Data

The majority of the studies included in this review followed one of two prototypical formats. In the first situation, participants were given a test to measure FDI at the beginning of the study, then participated in a technology-based learning situation, and afterwards completed a post test designed to measure achievement. In the second situation, after administration of the FDI measure, students completed a technology-based course and were then assigned a course grade upon completion. An effect size was calculated for each post test or course grade outcome using the method of calculating *d* described earlier. The 35 studies produced 35 outcomes for which effect sizes were calculated - one effect size per study.

Moderator Variables

Two different types of variables were considered when coding studies for this meta-analysis. The dependent variables were the effect size values. The independent variables were study and design characteristics that may have influenced the magnitude of these effect sizes. The selection of possible moderator variables was based upon findings from prior meta-analysis reviews (Mangino, 2004; Hunter, 1994; Sullivan, 1993) and meta-analysis textbooks (Cooper, 1998; Hunter & Schmidt, 2004). Each study was coded study for characteristics that might be related to the overall effect size. The coded variables are summarized in Table 7. The coding form is located in Appendix B.

Table 7

Variables Coded for Each Study

Characteristics	Variables
Study Features	Year of Publication Type of Publication Sample Size Grade Level Study Location
Methodological Features	Pretest Equivalence Type of Inference Test Independent Variable Reliability of Measure (GEFT and PT or grade) Type of Research Design Dependent Variable
Characteristics of the Treatment	Treatment Duration Type of Application Student Context Academic Subject

Coding Reliability

As coding studies can be potentially subjective, efforts should be made to enhance coding reliability. To this end, a second investigator was not available to assist with the coding process and establish coding reliability. However, it should be noted that the categories presented are considered 'low inference codings'. The needed information was gathered from the study and simply transferred to a coding sheet. No inferential judgments were necessary which reduced the potential for coding bias (Cooper, 1998).

Artifact Corrections

As discussed in Chapter 2, there are often a number of study design features that can affect the size of a correlation coefficient. Hunter and Schmidt (2004, p. 35) provide a number of different procedures to attenuate these artifacts. For purposes of the current study, the artifacts selected to correct the individual study correlations are shown in Table 8.

Table 8

Study Artifacts Selected to Attenuate Outcome Measures

#	Artifact	Influence on Outcome
1	Error of measurement in the dependent variable	Study validity will be systematically lower than true validity to the extent that post test results are measured with random error.
2	Error of measurement in the independent variable	Study validity for a test will systematically understate the validity of the GEFT measure because the test is not perfectly reliable.
3	Dichotomization of the continuous GEFT variable	The GEFT test manual recommends the identification of a median split to separate FD from FI categories.
4	Deviation from perfect construct validity in the GEFT measure	Study validity will vary if the factor structure of the test differs from the usual structure of tests for the same trait.
5	Deviation from perfect construct validity in the post-test measure	Study validity will differ from true validity if the criterion is deficient.

These artifacts were chosen because they were directly applicable to corrections needed in the majority of studies, and the information required to correct the data was easily retrieved. A description of each of the attenuation factors follows. It should be noted that the calculations referenced in this section were applied to study data using Microsoft Excel 2002 software. The formulas used to calculate the attenuation factors are located in Appendix C.

Measurement error. The independent GEFT variable and the post-test dependent variable were not measured perfectly. Studies with reported reliability data were consistently less than 1. As such, the observed scores differed from the true scores, and determination of the "true population correlation" required a correction for attenuation procedure (Appendix C, Formula 1).

Attenuation for measurement error required the extraction of specific information from study data:

1. Where reliabilities of the GEFT were reported at the individual study level, these values were used in the correction formula; otherwise the reliability of .82 as reported in the test manual was used (Witkin, Oltman, Raskin & Karp, 1971).
2. For studies without a reported post-test reliability value, an artifact distribution based on the number of reliability coefficients available to the researcher was used. It was therefore possible to correct for measurement error for post-test results even when reliability information was incomplete (Lyons, 2003).

It should also be added that due to the lack of study information on the reliability of course grades, studies that reported grade-based achievement outcomes were not attenuated using this procedure. Rather, studies with grade outcomes were treated as a potential moderating variable.

Correction for dichotomization of the independent variable (GEFT). There were nineteen studies in this analysis which artificially dichotomized the GEFT results by dividing participants into two categories (FD and FI) at the median. This caused a downward distortion in the mean correlation and an upward distortion in the apparent real variation of the correlations across studies. Hunter and Schmidt (2004) provide a method for correcting this distortion in cases where the independent variable has been artificially dichotomized. This method was applied to individual study data, where applicable. The correction has been shown to be quite accurate for most research data, and makes it possible to yield unbiased estimates of mean population correlations despite the initial distortion in the correlations from individual studies (Hunter & Schmidt, 1990) (Appendix C, Formula 2).

Deviation from perfect construct validity. The construct validity of a measure is its true score correlation with the actual construct or trait that it is supposed to measure (Lyons, 2003). In the current study, both the independent and the dependent variables deviated from perfect construct validity. Imperfect validities of the GEFT and post-test scores were statistically corrected based upon path analysis logic (Hunter & Schmidt, 2004, p. 41-53)(Appendix C, Formula 3).

This attenuation factor was calculated based on the reliability information gathered under the scope of the error of measure factor. As was noted in that section, there was limited study information on the reliability of course grades. Without sufficient information to attenuate construct validity, the eight studies that reported grade-based outcomes were excluded from this procedure and grade-outcome was analyzed as a potential moderating variable.

Multiple Simultaneous Artifacts. Under most conditions, the effect of each correctable artifact is to reduce the correlation by an amount that can be quantified as a multiplicative factor less than 1.00. Once the individual artifacts were calculated, the total impact of the study imperfections was determined using two procedures:

1. *Artifact Attenuation Factor.* The overall attenuation factor is simply the product of each of the five factors, or, in the case of grade-based studies, the product of three factors (Appendix A, Formula 4).

2. *Linear Bias Attenuation Multiplier*. The sample correlation is not an 'unbiased' estimate of the population correlation; however, "the purely statistical bias in the sample correlation as an estimate of the population correlation is normally trivial in magnitude" (Hunter & Schmidt, 2004, p. 118). This bias is systematic and can be approximated using a linear equation to adjust the Attenuation Factor (Appendix C, Formula 5).

Correction of Individual Study Correlations. The adjusted total attenuation factor was then applied to each study correlation. According to Bobko (1983) this estimate of the corrected correlation (r_c) has a slight negative bias, but the degree of underestimation is very small (Appendix A, Formula 6).

Meta-Analysis Phase

After individual study correlations were corrected, meta-analytic statistics were used to combine the study results. The procedures at this level of analysis included the computation of certain critical averages: the average correlation, the variance of correlations, and the average sampling error variance. The formulas presented in this section were calculated by the Meta-analysis Programs Version 5.0 written by Ralf Schwarzer (1998).

Correction for sampling error. The first step was to compute a mean average correlation (population effect size). One difficulty with using the mean to summarize the effect size was that not all studies had the same sample size. A solution was to assign more weight to studies with larger sample sizes when calculating the overall mean. The rationale is that it is assumed that effect sizes of studies with large sample sizes should deviate less from the population effect size than small *N* effect sizes. Therefore, in combining all effect sizes, it is fair to assign more weight to large *N* studies (Appendix D, Formula 1). The weight is simply the product of sample size and the artifact attenuation factor. Therefore, the more extreme the artifact correction in a given study, the less the weight assigned to that study.

Pooled statistics. Once each study correlation was corrected for artifacts and weights were determined, three meta-analysis averages were computed using the corrected correlations: the observed variance of the correlations, $Var(r_c)$; the sampling error variance, $Ave(ve)$; and the population variance, $Var(p)$; (Appendix D, Formulas 2, 3, and 4).

The population variance is also called the residual variance, and its square root is called the residual standard deviation. The residual standard deviation also serves as the multiplier in the formula for the population effect size confidence interval (Appendix D, Formula 5). The 95% confidence intervals and Cohen's (1988) effect size definitions were used to interpret the mean effect-size values and to evaluate the significance of the average effect-size values.

Decide Whether to Search for Moderator Variables

A population effect size can only be interpreted reliably if the underlying data set is sufficiently homogeneous. Three tests of homogeneity were calculated by the Meta-analysis Programs software and used to evaluate the distribution of the underlying data (Schwarzer, 1989):

1. The residual standard deviation should be smaller than 25% of the population effect size;

2. The percentage of observed variance accounted for by sampling error should be at least 75%;
3. A chi-square test should not become significant.

If homogeneity is rejected by this statistical analysis of the effect size values, a search for variables that moderate the effect sizes is required.

Determine the Impact of Moderator Subgroups

To investigate the impact that each of the coded variables had on the population effect size, each variable was individually tested to determine characteristics of importance using the Statistics Software for Meta-analysis (Schwarzer, 1989). The same procedures previously described for calculating the weighted cumulative means, variance, and total heterogeneity were applied to the search for moderators. Moderator analysis required that the total heterogeneity be partitioned to explore the variation in effect sizes that was explained by the model and the residual variance that was not explained by the model. If homogeneity was rejected, the implication was that there is variability among the effect sizes that was not explained by the moderator.

Selection of Meta-analysis Software

In order to calculate individual study *d* statistics and conduct the transformations to *r*, the software package "ES: A Computer Program for Effect Size Calculation" (Shadish, Robinson & Lu, 1999) was selected. The ES program is a compilation of algebraic algorithms for calculating *d* from whatever information is available to the researcher. The ES program was chosen because it is accompanied by a user manual which contains numerous descriptions, formulas, and examples for each of the effect size calculation methods which support the Hunter-Schmidt method of meta-analysis.

The database of studies was coded and then maintained using Microsoft Excel 2002. This software was used to apply Hedges' (1980) formula to in order to adjust the *d* statistic associated with studies of less than 20 participants. Microsoft Excel was also used to apply the Hunter-Schmidt (2004) formulas to attenuate artifactual errors, where applicable, at the individual study level.

In order to calculate meta-analytic statistics the Meta-analysis Programs Version 5.0 written by Ralf Schwarzer was selected. Dr. Schwarzer is Professor of Psychology at the Freie Universität Berlin, Germany, and Adjunct Professor at York University, Toronto, Canada. The software is designed for IBM or compatible computers and is free of charge. According to the test manual, the software has become very popular with researchers since version 5.3 was released in 1989, and is probably still the most frequently used meta-analysis software in the world (Schwarzer, 1989).

Conclusion

This meta-analysis combined the results of several studies that addressed a set of related research questions. The overall objective required the completion of several sequential procedures based on the work of Hunter, Schmidt, and Jackson (1982), and Hunter and Schmidt (2004; 1990).

Activities carried out during the planning phase of this study included ascertaining the domain of research, establishing criteria for study inclusion, determining the effect size type, and identifying search techniques for finding relevant studies.

The establishment of a theoretical framework was followed by meeting objectives at the study level. These activities included extracting relevant study data, selecting and coding individual study characteristics, evaluating coding reliability, and correcting artifactual errors for individual correlations.

At the level of meta-analysis, three objectives were met. The first was to calculate and interpret the average-effect size and the overall shared variance. The second aim was to assess the homogeneity of the calculated mean effect size. The third was to search for moderating variables that influenced the variance of the relationships. The results of these measures are reported in the next chapter.

CHAPTER 4

Results

The purpose of this investigation was to conduct a meta-analysis of research that focused on Witkin's FDI theory and learning achievement in technology-based environments. This chapter provides a detailed review of the results and statistical analysis vis-à-vis the following two research questions:

1. Are there differences in achievement between field dependent and field independent learners in technology-based environments?

2. How do differences in achievement between field dependent and field independent learners vary according to study characteristics, methodology characteristics, and treatment characteristics?

A core element of this meta-analysis was the literature search and selection of studies to be included. The search was conducted in a methodical manner to ensure the same results could be replicated by a different researcher. A total of 35 studies were selected to answer the research questions. The entire sample size was 3,082 participants, and the number of effect sizes was 35. The 35 effect sizes range from -0.002 to .999. Following Cohen's definitions for small, medium, and large effect sizes, this analysis included 10 small, 9 medium and 16 large effect sizes. Table 9 provides a summary of the selected studies, their associated sample sizes, the correlation coefficients corrected using the procedures specified in Appendix B, and the variances for each of the studies calculated using the formulas provided in Appendix E.

Table 9

Corrected Correlations and Sampling Error for Individual Studies

Study	Author(s) and Publication Year	Sample Size (N)	Corrected Correlation (r)	Sample Error Variance (Var (e_c))
01	Abouserie, 1982	76	0.1089	0.0319
02	Archer, 2003	63	0.4479	0.0387
03	Buck, 2003	110	0.0485	0.0218
04	Cameron & Dwyer, 2005	300	0.5453	0.0079
05	Cao, 2006	156	0.4596	0.0153
06	Chou & Lin, 1998	121	0.6743	0.0310
07	Chuang, 1999	175	0.3285	0.0136
08	Daniels & Moore, 2000	80	0.2876	0.0303
09	Day, 1996	54	0.2444	0.0406
10	Fitzgerald & Semrau, 1998	23	0.9368	0.1122
11	Fullerton, 2000	62	0.6459	0.0393
12	Hall, 2000	102	0.2185	0.0236
13	Hsu & Dwyer, 2004	132	1.0000	0.0284
14	Hsu, Frederick & Chung, 1994	40	1.0000	0.0970
15	Katz, 1999a	56	-0.0648	0.0683
16	Katz, 1999b	63	0.1049	0.0604
17	Khine, 1996	76	0.7905	0.0421
18	Ku, 2000	180	0.2879	0.0274
19	Leader & Klein, 1996	75	0.9067	0.0667
20	Lee, 2006	52	0.2352	0.0472
21	Luk, 1998a	51	1.0000	0.0431
22	Luk, 1998b	113	0.8527	0.0190
23	Musgrove, 2002	108	0.0428	0.0199
24	Palmquist & Kim, 2000	48	0.0960	0.0801
25	Parcels, 2008	18	0.3272	0.1471
26	Roberts, 1999	29	-0.0029	0.0782
27	Shih & Gamon, 2002	74	0.1422	0.0293
28	Stegall, 1998a	26	0.0954	0.0879
29	Stegall 1998b	23	0.8863	0.1004
30	Summerville, 1997	177	0.0626	0.0211
31	Triantafillou et all, 2004	66	0.2905	0.0576
32	Umar, 1999	75	0.4857	0.0323
33	Weller 1995	22	0.7686	0.1178
34	Weymer, 2002	90	0.9626	0.0311
35	Yoon, 1993	166	0.2854	0.0284

The Statistics Software for Meta-analysis (Schwarzer, 1989) program was used to convert the individual findings into graphical representations of the data as shown in Figures 1 and 2.

Figure 1 presents a stem and leaf display of the effect size data which serves to characterize the database. The Y-axis or the "stem" is made up by the first digit of correlations from - .9 to + .9. The second digits of the correlations are in the "leafs". They are ordered according to size within each category. The bimodal shape of the graph suggests the possibility that multiple groups may exist, and further investigation of the database distribution was necessary.

Stem	Leaf
(-).0	06
.0	456
.1	00014
.2	2446999
.3	33
.4	569
.5	5
.6	57
.7	79
.8	59
.9	1146999

Stem width: .1
Each leaf: 1 case

Figure 1. Stem and leaf display for effect sizes (corrected correlations).

Figure 2 displays a funnel plot of the data which is a measure of effect size against study size. This type of graph shows if there is a bias more toward one size study than another. It is expected that a symmetric, inverted funnel shape should arise from a ‘well-behaved’ data set (Light & Pillemer, 1984). The data in Figure 2 illustrates the expected shape, with a broad spread of points for the highly variable small studies at the bottom, and a decreasing spread as the sample size increases. This indicates that the data appear to be reasonably normally distributed, and confirms the appropriateness of meta-analysis of the data set.

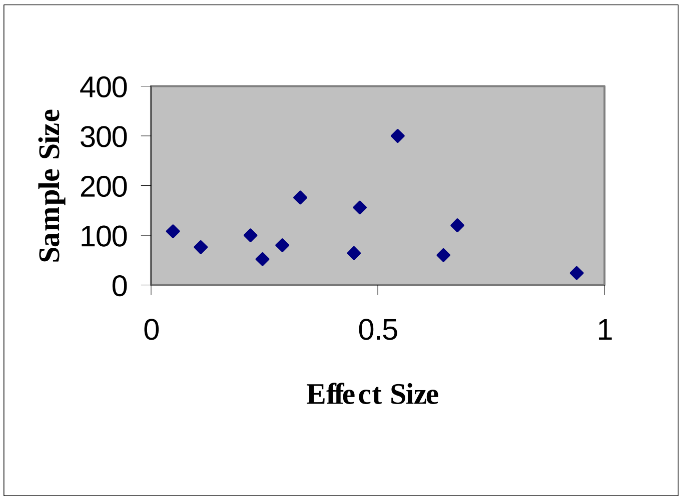

Figure 2. Funnel plot of effect sizes.

Meta-Analysis

Research Question 1

> Are there differences in achievement between field dependent and field independent learners in technology-based environments?

Using the Hunter and Schmidt (2004) random effects model and calculating the mean effect size "r" with the variance "Var (e_c)", the total mean weighted effect size (population effect size) for the meta-analysis was 0.4257, with an estimated pooled variance of 0.0969 and a 95% confidence interval from -0.15993 to 1.01151. Following Cohen's definitions for small, medium, and large effect sizes, the population effect size is considered large, indicating a significant difference in achievement between field dependent and field independent learners. However, three tests of homogeneity identified that the underlying population distribution was heterogeneous. The presence of 'unexplained' variance indicates that a search for moderators which may account for the remaining systematic variation is required. Results from the summary analysis are provided in Table 10.

Table 10

Summary Meta-Analysis

Summary Statistic	Value
Total N	3082
Number of Studies	35
Unweighted Mean r	0.44213
Population Effect Size (weighted mean r)	0.42579
Observed Variance of Effect Size	0.09692
Standard Deviation of Effect Size	0.31131
95% Confidence Interval	-0.15993 to 1.01151
Variance Due to Sampling Error	0.00761
Population or Residual Variance	0.08930
Residual Standard Deviation	0.016 → heterogeneous
Percentage of Observed Variance Accounted for by Sampling Error	7.85% → heterogeneous
Chi-square Analysis	445.628 → heterogeneous

Research Question 2

> How do differences in achievement between field dependent and field independent learners vary according to study characteristics, methodology characteristics, and treatment characteristics?

To explore the influence of moderators on the mean population effect size, two different variables were coded. The dependent variables were the effect size values (correlations) calculated from primary study statistics. The independent variables were moderator characteristics which may have influenced the magnitude of the effect sizes. A total of 14 moderator variables were examined. These variables were categorized into one of three subsets: study, methodology, or treatment characteristics. Within each subset, separate meta-analyses were computed to determine if the presence of the moderator can account for the unexplained variance. In order to classify a variable as a moderator, the following criteria were applied (Hunter et al., 1982):

1. The mean correlation varied from subset to subset.
2. The residual standard deviation was lower in the subsets than for the data as a whole (e.g., σ_p = 0.016).

Table 11

Coded Moderator Variables

Variables	Category/Range	# of Studies
Year of Publication	1990-1994	3
	1995-1999	15
	2000-2004	10
	2005-2009	7
Type of Publication	Journal Article	17
	Dissertation/Thesis	18
Sample Size:	15 – 50	8
	51 – 80	15
	81 – 110	4
	More than 110	8
Grade Level:	Primary	3
	Jr. High	1
	High School	4
	Undergrad	27
Location:	US	26
	Other	9
Methodology Variables	Category/Range	# of Studies
Pretest Equivalence	Unspecified or inadequate	8

Variables	Category/Range	# of Studies
	Random Assignment	19
	Pretest Scores	5
	Pretest Scores and Random Assignment	3
Type of Inference Test: (F, t, other)	F value for main effect	15
	Derived d statistic	14
	p	1
	t-Test	5
Independent Variable (GEFT)	Extreme Scores (.5 < sd; .5 >sd)	3
	Median FD/FI Split	19
	Categories FD/FN/FI	13
Dependent Variable	Final Class Grade:	8
	Post Test:	27
Treatment Features	**Category/Range**	**# of Studies**
Treatment Duration	Less than One Week	21
	1 – 4 weeks	2
	1 – 4 months	2
	longer than 4 months	10
Type of Instructional method:	Same treatment for all	8
	Same treatment with variations	27
Type of Application:	WEB	18
	CAI	17
Student Context:	Individual (Classroom-based)	14
	Research setting	14
	Distance Ed	7
Academic Subject:	Language/Reading/Writing	2
	Science/Medicine	20
	Social Science/Education	5
	Technology	5
	Other (ethics)	3

Study Characteristics. The five study characteristics examined as moderator variables included the Year of Publication; Type of Publication; Sample Size; Grade Level; and Study Location.

The Year of Publication variable was analyzed by partitioning the overall criteria range of 1990 to 2009 into four groups: 1990-1994; 1995–1999; 2000-2004; and 2005 - 2009. There were 3 studies from 1990-1994, 15 studies from 1995–1999, 10 studies from 2000-2004, and 7 studies from 2005 onward. Analysis of the data indicate an observed difference in mean correlations (r) between groups, with studies from 2005-

2009 indicating the highest mean correlation at $r = 0.510$, and studies from 1990-1994 indicating the lowest mean correlation at $r = 0.352$. In each range, the residual standard deviation is greater than the overall data set ($\sigma_{p} = 0.016$), indicating that the observed variance among effect sizes is not explained by the publication year variable. The summary results for the publication year moderator variable are shown in Table 12.

Table 12

Year of Publication Moderator Analysis

1990-1994	1995-1999	2000-2004	2005-2009
r = 0.352	r = .405	r = 0.399	r = 0.510
σ_r^2 = 0.113	σ_r^2 = 0.137	σ_r^2 = 0.093	σ_r^2 = 0.051
σ_e^2 = 0.012	σ_e^2 = 0.011	σ_e^2 = 0.008	σ_e^2 = 0.004
σ_p^2 = 0.101	σ_p^2 = 0.126	σ_p^2 = 0.092	σ_p^2 = 0.047
σ_p = 0.318	σ_p = 0.355	σ_p = 0.292	σ_p = 0.217
heterogenous	heterogenous	heterogenous	heterogenous

To facilitate the Type of Publication analysis, the variable was coded using two categories, unpublished dissertations and published articles. There were 18 dissertations and 17 articles included in this study. The mean correlation for Journal Articles is substantially larger at $r = 0.555$, than the effect size for Unpublished Articles at $r = 0.309$. The residual standard deviations (σ_p) are larger than the data set as a whole ($\sigma_{p} = 0.016$), which reveals there is continued variation in results between the two groups. The total heterogeneity was significant suggesting that the variance among effect sizes was greater than could be expected by sampling error and other variables may be affecting the result. The summary results for the publication type moderator variable are shown in Table 13.

Table 13

Type of Publication Moderator Analysis

Dissertations	Journal Articles
r = 0.309	r = 0.555
σ_r^2 = 0.062	σ_r^2 = 0.107
σ_e^2 = 0.010	σ_e^2 = 0.005
σ_p^2 = 0.051	σ_p^2 = 0.102
σ_p = 0.227	σ_p = 0.320
heterogenous	heterogenous

The Sample Size of the studies in this meta-analysis varied from 16 to 300 participants. For coding purposes, the overall range was broken into four arrays: 15 – 50 (8 studies); 51-80 (14 studies); 81-110 (5 studies); and 111-300 (8 studies). The data indicate an observed difference in mean correlations (*r*), with sample sizes between 81 – 110 indicating the highest mean correlation at $r = 0.503$, and studies with samples between 51 - 80 displaying the lowest mean correlation at $r = 0.400$. The residual standard deviations (σ_p) reveal there is continued variation in results within each of the four ranges, indicating that the observed variance among effect sizes is not explained by the sample size variable. The summary results are shown in Table 14.

Table 14

Sample Size

15 – 50	51 - 80	81 - 110	> 110
r = 0.528	r = 0.400	r = 0.503	r = 0.424
σ_r^2 = 0.166	σ_r^2 = 0.094	σ_r^2 = 0.154	σ_r^2 = 0.074
σ_e^2 = 0.019	σ_e^2 = 0.011	σ_e^2 = 0.005	σ_e^2 = 0.004
σ_p^2 = 0.147	σ_p^2 = 0.083	σ_p^2 = 0.149	σ_p^2 = 0.070
σ_p = 0.383	σ_p = 0.289	σ_p = 0.386	σ_p = 0.265
heterogenous	heterogenous	heterogenous	heterogenous

Grade Levels for this study were grouped into one of three categories: Primary (4 studies); High School (4 studies); and Post Secondary (26 studies). The Primary category has the highest mean correlation at $r = 0.496$, and the High School category displays the lowest correlation at $r = 0.366$. The residual standard deviations (σ_p) reveal there is continued variation in results within each of the three ranges, indicating that the observed variance among effect sizes is not explained by the grade level variable. The summary results are shown in Table 15.

Table 15

Grade Level

Primary	High School	Post Secondary
$r = 0.496$	$r = 0.366$	$r = 0.436$
$\sigma_r^2 = 0.084$	$\sigma_r^2 = 0.077$	$\sigma_r^2 = 0.105$
$\sigma_e^2 = 0.006$	$\sigma_e^2 = 0.009$	$\sigma_e^2 = 0.008$
$\sigma_p^2 = 0.078$	$\sigma_p^2 = 0.068$	$\sigma_p^2 = 0.097$
$\sigma_p = 0.278$	$\sigma_p = 0.262$	$\sigma_p = 0.312$
heterogenous	heterogenous	heterogenous

The Location moderator was analyzed by splitting the variable into two groups: United States (27 studies) and Other (8 studies). The observed mean correlations are very similar, indicating that the studies in this meta-analysis were congruent across location, at $r = 0.446$ for US students, and $r = 0.440$ for students in other countries. The residual standard deviations (σ_p) reveal there is continued variation in results between the two groups, indicating that the observed variance among effect sizes is not explained by the location variable. The summary results are shown in Table 16.

Table 16

Location

United States	Other
r $= 0.446$	r $= 0.440$
$\sigma_r^2 = 0.113$	$\sigma_r^2 = 0.102$
$\sigma_e^2 = 0.009$	$\sigma_e^2 = 0.010$
$\sigma_p^2 = 0.104$	$\sigma_p^2 = 0.092$
$\sigma_p = 0.322$	$\sigma_p = 0.303$
heterogenous	heterogenous

Methodology characteristics. The four methodology characteristics examined as moderator variables included Pretest Equivalence, Type of Inference Test, Independent Variable Measure, and Dependent Variable Type.

Pretest Equivalence was examined by grouping the studies into one of four categories: Unspecified or Inadequate (8 studies); Random Assignment (19 studies); Pretest Scores (5 studies); and Pretest Scores and Random Assignment (3 studies). The studies that employed Random Assignment to treatment groups have the highest mean correlation at $r = 0.463$, with the lowest mean correlation associated with the Pretest group at $r = 0.351$. The residual standard deviations (σ_p) reveal there is continued variation in results within each of the four ranges, indicating that the observed variance among effect sizes is not explained by the pretest equivalence variable. The summary results are shown in Table 17.

Table 17

Pretest Equivalence

Unspecified	Random	Pretest	Pretest & Random
r = 0.420	r = 0.463	r = 0.351	r = 0.373
σ_r^2 = 0.163	σ_r^2 = 0.090	σ_r^2 = 0.033	σ_r^2 = 0.092
σ_e^2 = 0.008	σ_e^2 = 0.006	σ_e^2 = 0.010	σ_e^2 = 0.022
σ_p^2 = 0.155	σ_p^2 = 0.084	σ_p^2 =0.023	σ_p^2 = 0.081
σ_p = 0.393	σ_p = 0.290	σ_p = 0.152	σ_p = 0.266
heterogenous	heterogenous	heterogenous	heterogenous

The Type of Inference Test was analyzed by grouping the moderating variable into three categories: *d* Statistics (14 studies); *F* Statistics(15 studies) and *t* Statistics (5 studies). The studies for which field dependent and field independent learners were compared based upon *t* statistics displayed the highest mean correlation at $r = 0.500$, with the other direct measure of comparison between groups, *d,* indicating the lowest mean correlation at $r = 0.416$. The residual standard deviations (σ_p) reveal there is continued variation in results within each of the three ranges, indicating that the observed variance among effect sizes is not explained by the pretest equivalence variable. The summary results are shown in Table 18.

Table 18

Type of Inference Test

d Statistics	*F* Statistics	*t* Statistics
r = 0.416	r = 0.437	r = 0.500
σ_r^2 = 0.101	σ_r^2 = 0.072	σ_r^2 = 0.198
σ_e^2 = 0.008	σ_e^2 = 0.008	σ_e^2 = 0.008
σ_p^2 = 0.094	σ_p^2 = 0.064	σ_p^2 = 0.190
σ_p = 0.306	σ_p = 0.253	σ_p = 0.436
heterogenous	heterogenous	heterogenous

The Independent Measure variable was analyzed by grouping the potential moderator into three categories: GEFT Median Split (18 studies); GEFT – Field Neutral

Excluded (12 studies) and GEFT-Other (4 studies). The studies for which data was extracted based upon extreme scores of the GEFT-Other displayed the lowest mean correlation at $r = 0.320$. The highest mean correlation is associated with the Field Neutral Excluded category at $r = 0.477$. The residual standard deviations (σ_p) reveal there is continued variation in results within each of the three categories, indicating that the observed variance among effect sizes is not explained by the GEFT variable. The summary results are shown in Table 19.

Table 19

Independent Measure (GEFT)

Median Split	FN Excluded	IV Other
r = 0.424	r = 0.477	r = 0.320
σ_r^2 = 0.144	σ_r^2 = 0.056	σ_r^2 = 0.042
σ_e^2 = 0.008	σ_e^2 = 0.006	σ_e^2 = 0.011
σ_p^2 = 0.136	σ_p^2 = 0.050	σ_p^2 = 0.031
σ_p = 0.369	σ_p = 0.224	σ_p = 0.175
heterogenous	heterogenous	heterogenous

The Dependent Measure was analyzed by splitting the variable into two categories: Post-test results (27 studies) and Grade results (8 studies). The mean correlations for each of the categories is comparable at $r = 0.434$ for the Post test, and $r = 0.423$ for the Grade variable. The residual standard deviations (σ_p) reveal there is continued variation in results within each of the two ranges, indicating that the observed variance among effect sizes is not explained by the dependent variable. The summary results are shown in Table 20.

Table 20

Dependent Measure

Post-Test	Grade
r = 0.434 σ_r^2 = 0.088 σ_e^2 = 0.007 σ_p^2 = 0.081 σ_p = 0.285 heterogenous	r = 0.423 σ_r^2 = 0.154 σ_e^2 = 0.012 σ_p^2 = 0.014 σ_p = 0.378 heterogenous

Treatment characteristics. The five treatment characteristics examined as moderator variables included Treatment Duration, Type of Instructional Method, Type of Application, Student Context and Academic Subject.

The Treatment Duration variable was analyzed using three different categories: Less than 1 Day (21 Studies); 1 Day to 1 Month (4 Studies); and Course Term (10 Studies). The students involved in studies which lasted less than one day showed the highest mean correlation at r = 0.452, with students in the treatment duration category of 1 Day to 1 Month displaying the smallest mean correlation at r = 0.231. The residual standard deviations (σ_p) reveal there is continued variation in results within each of the three ranges, indicating that the observed variance among effect sizes is not explained by the treatment duration variable. The summary results are shown in Table 21.

Table 21

Treatment Duration

< 1 Day	1 Day – 1 Month	Course Term
r = 0.452 σ_r^2 = 0.089 σ_e^2 = 0.006 σ_p^2 = 0.083 σ_p = 0.288 heterogenous	r = 0.231 σ_r^2 = 0.107 σ_e^2 = 0.010 σ_p^2 = 0.972 σ_p = 0.312 heterogenous	r = 0.335 σ_r^2 = 0.130 σ_e^2 = 0.015 σ_p^2 = 0.115 σ_p = 0.339 heterogenous

The Instructional Method variable was analyzed using two categories: Different Treatments for each condition (27 Studies), and Same Treatment for all learners (8 Studies). The results indicate that there are much larger differences in achievement between field dependent and field independent learners when the studies involved more than one treatment condition (r = 0.457) as compared to learners exposed to one treatment condition (r = 0.329). The residual standard deviations (σ_p) reveal there is continued variation in results within each of the two ranges, indicating that the observed variance among effect sizes is not explained by the instructional method variable. The summary results are shown in Table 22.

Table 22

Instructional Method

Same Treatment	Different Treatments
r = 0.329	r = 0.457
σ_r^2 = 0.161	σ_r^2 = 0.080
σ_e^2 = 0.011	σ_e^2 = 0.007
σ_p^2 = 0.150	σ_p^2 = 0.073
σ_p = 0.388	σ_p = 0.270
heterogenous	heterogenous

The Type of Application variable was split into two categories: Web-based applications (17 studies) and CAI applications (18 studies). There was a noticeable difference between application environments, with the highest mean correlation found for Web-based Applications at r = 0.433, and CAI applications displaying a mean correlation of r = 0.370. The residual standard deviations (σ_p) reveal there is continued variation in results within each of the two ranges, indicating that the observed variance among effect sizes is not explained by the type of application variable. The summary results are shown in Table 23.

Table 23

Type of Application

Web-Based Application	CAI Application
r = 0.433 σ_r^2 = 0.120 σ_e^2 = 0.008 σ_p^2 = 0.112 σ_p = 0.334 heterogenous	r = 0.370 σ_r^2 = 0.115 σ_e^2 = 0.010 σ_p^2 =0.105 σ_p = 0.324 heterogenous

The Student Context variable was analyzed using three different categories: Distance Learning (7 studies), Individual Context (14 studies), and Research Context (14 studies). The highest mean correlation is found for the Research Context at $r = 0.422$, and the smallest difference between FD and FI learners is displayed in the Distance Learning Context at $r = 0.337$. The residual standard deviations (σ_p) reveal there is continued variation in results within each of the three ranges, indicating that the observed variance among effect sizes is not explained by the student context variable. The summary results are shown in Table 24.

Table 24

Student Context

Distance	Individual	Research
r = 0.337 σ_r^2 = 0.157 σ_e^2 = 0.011 σ_p^2 = 0.146 σ_p = 0.393 heterogenous	r = 0.395 σ_r^2 = 0.146 σ_e^2 = 0.010 σ_p^2 = 0.136 σ_p = 0.369 heterogenous	r = 0.422 σ_r^2 = 0.089 σ_e^2 = 0.007 σ_p^2 = 0.082 σ_p = 0.287 heterogenous

The last moderator variable analyzed was Academic Subject. This variable was divided into 4 categories: Language & Other (5 studies); Science (20 studies); Social Science (5 studies); and Technology (5 Studies). The studies with Social Science content displayed the highest mean correlation at 0.643, and the studies which utilized Language-based content had the lowest mean correlation at r = 0.018. The residual standard deviations (σ_p) reveal there is continued variation in results within each of the four ranges, indicating that the observed variance among effect sizes is not explained by the academic subject variable. The summary results are shown in Table 25.

Table 25

Academic Subject

Language	Science	Social Science	Technology
$r = 0.018$	$r = 0.460$	$r = 0.643$	$r = 0.327$
$\sigma_r^2 = 0.042$	$\sigma_r^2 = 0.099$	$\sigma_r^2 = 0.088$	$\sigma_r^2 = 0.060$
$\sigma_e^2 = 0.018$	$\sigma_e^2 = 0.006$	$\sigma_e^2 = 0.006$	$\sigma_e^2 = 0.008$
$\sigma_p^2 = 0.023$	$\sigma_p^2 = 0.093$	$\sigma_p^2 = 0.082$	$\sigma_p^2 = 0.052$
$\sigma_p = 0.152$	$\sigma_p = 0.304$	$\sigma_p = 0.287$	$\sigma_p = 0.227$
heterogenous	heterogenous	heterogenous	heterogenous

Conclusion

This chapter summarized the data obtained from a meta-analysis that attempted to answer the question of whether or not achievement differences exist between FDI learners in technology environments. The statistics results were obtained using the Meta-analysis Programs Version 5.0 (Schwarzer, 1989). Tables providing information on effect sizes, variances, and heterogeneity for moderator variables were presented in this chapter.

Overall, the total mean weighted effect size for the 35 studies indicated a large difference between field dependent and field independent learners. However, the presence of 'unexplained' variance in the main analysis indicated that a search for moderators to explain the size of the effect was required. *None of the variables subsequently tested met the criteria for moderator status.* Although significant results were not obtained, a descriptive highlight of outcomes from the subset analyses may prove purposeful for future research:

1. Studies published in the most recent range of 2005 – 2009 indicated the largest difference in achievement between FDI learners as compared to older studies.
2. Articles published in journals demonstrated a higher mean effect size than unpublished dissertations, suggesting the presence of publication bias.
3. Studies with smaller sample sizes tended to have higher correlations than studies with more participants.
4. Studies which reported t-statistics had unusually high mean correlations in comparison to *d* and *F* statistics.
5. Participants in primary grades displayed the largest difference in achievement between field dependent and field independent learners.
6. When participants in the Field Neutral category were removed from primary study analyses, the extension of range produced a higher mean effect in moderator analysis than studies which split the GEFT at the median.
7. Treatment durations of less than one day indicated a higher difference in achievement between FD/FI learners than studies which lasted longer.
8. Distance Learning contexts produced lower mean correlations than students who were exposed to individual class study or research settings.
9. Studies which utilized social science and science-based content indicated greater effect sizes than studies which used language or technology content.

These points of interest, as well as the overall statistical results of this meta-analysis, will be discussed further in the next chapter.

CHAPTER 5

Discussion

This chapter provides an interpretation of the meta-analytic results reported in Chapter 4. While this meta-analysis explored many issues and attempted to answer two specific research questions, a thorough understanding of the impact of field dependency on achievement in technology environments is extremely complex and requires a more detailed investigation than can be achieved in this meta-analysis. Conclusions which can be drawn from the data analysis, limitations of the current study, and recommendations for future research are discussed in this final chapter.

Research Question 1

> Are there differences in achievement between field dependent and field independent learners in technology-based environments?

The results of this meta-analysis did find a considerable difference in achievement outcomes between field dependent and field independent learners when learning with technology tools. The total mean weighted effect size was 0.426 with a 95% confidence interval and a pooled standard deviation effect size of 0.311. Although the population effect size is considered large by Cohen's (1988) criterion, a strict interpretation of this value would be irresponsible without also considering the large proportion of 'unexplained' variance which was not accounted for through statistical corrections. The existence of nonartifactual variation was likely caused by some aspect of the studies that varied from one study to the next. As a result, the existence of moderators was investigated to determine whether the variance of study effect sizes is larger than can be accounted for by the presence of variance-generating artifacts.

Research Question 2

> How do differences in achievement between field dependent and field independent learners vary according to study characteristics, methodology characteristics, and treatment characteristics?

To answer this question, moderator variables were analyzed according to study characteristics, methodology characteristics, and treatment characteristics.

Study Characteristics

Several study characteristics yielded interesting results; however, none of the variables investigated met the requirements of a moderator (Hunter, Schmidt & Jackson,1982). However, there are a number of observations which can be tentatively made regarding the data set for purposes of future research.

First, studies published in the most recent range of 2005 – 2009 indicated the largest difference in achievement between FDI learners as compared to older studies. There were no obvious indications as to why this range was more significant than the others. However, it could be speculated that a greater number of studies in this range used a research design strategy of aptitude-treatment-interactions. This practice deliberately matches or mismatches learners to technology environments based upon their field articulation type. This manipulation may create larger distinctions in achievement between field types than would be found from more naturally occurring observations. In fact, many of the primary studies reported significantly lower performances by field dependent participants in learning situations where they were mismatched with the technology presentation (Ku, 2000; Archer, 2003; Cameron & Dwyer, 2005). However, as was discussed in the literature review, many researchers have indicated a lack of theoretical linkage between aptitudes and information processing requirements which complicates the research findings.

Second, articles published in journals demonstrated a higher mean effect size than unpublished dissertations, suggesting the presence of publication bias. Although the data exploration using the funnel plot yielded a "normal" graph, the findings obtained when coding publication type as a moderator variable suggest the evidence of bias. Since journals typically publish studies with significant results, this likely explains the larger effect sizes associated with published works. This finding is consistent with criticisms of prior meta-analysis studies which have focused solely on published findings (Cooper, 1998).

Last, studies with smaller sample sizes tended to have higher correlations than studies with more participants. Since waiting for studies with large samples may mean too long a wait and too few studies to analyze, the use of a correction factor for small study sizes was applied to the data (Hedges & Olkin, 1985). However, two of the studies included in the small sample analysis reported exceptionally large effect sizes (outliers). Therefore, the results of this subset analysis are not particularly meaningful. Increased statistical power could have been gained from the inclusion of more studies in this meta-analysis. Had primary researchers provided more detailed statistical data in their studies, the sample size for this study would have increased by 17, which may have provided additional findings beyond the conclusions presently made.

Methodology Characteristics

Coding of methodology characteristics also failed to account for the remaining population variance; however, three observations were noteworthy.

First, studies which reported *t*-statistics had higher correlations in comparison to *d* and *F* statistics. Since those studies that reported *t* statistics explored the relationship between FDI types and achievement in a more focused manner than those which used omnibus tests, it is not unusual that those studies indicated higher levels of significance for the main effect. However, it was noted that two of the studies which reported *t*-statistics had unusually large values ($t = 6.98$; $t = 6.94$), which negates any meaningful interpretation of this result.

Second, participants in primary grades displayed the largest difference in achievement between field dependent and field independent learners. Although this category included the smallest number of primary studies (3 out of 35 studies), it is interesting to note that younger participants displayed greater differences in achievement when compared on the basis of FDI types. A number of reasons for the difference could be speculated, such as different developmental trajectories of field types, the impact of prior computing experience, or differential reactions to the research process for young participants. Such ideas suggest the need for more longitudinal research – a point which was a raised as a criticism of technology-based research in the literature review.

Third, in primary studies where outcomes from the Field Neutral category were removed from analyses, the extension of range produced a higher mean effect in moderator analysis than studies which split the GEFT at the median. Although Hunter and Schmidt (1994) provide statistical methods to correct for the extension of range, there was insufficient information contained in the primary studies to implement the correction. The impact of the uncorrected artifact was to artificially inflate the size of effect in studies which excluded field neutral participants. The presence of this artifactual error likely also contributed to the size of the overall unexplained population variance.

Treatment Characteristics

While none of the treatment characteristics subjected to moderator analysis accounted for the remaining population variance, several observations may be of interest to future investigations.

First, treatment durations of less than one day indicated a higher difference in achievement between FD/FI learners than studies which lasted longer. Most of the studies in this analysis were conducted in less than one day within a research context. In many of the studies, the treatment was administered in one sitting, and then a post test administered afterward. Given the brief amount of time for instruction and the lack of opportunity to work with the technology, it may be that differences in field dependent and field independent learners are exacerbated by limited exposure and practice.

Second, distance learning contexts produced lower mean correlations than stations where learners were exposed to research-oriented settings. This outcome is in contrast to findings in the literature review which indicated that field dependent learners had lower achievement in distance learning (Thompson, 1988; Luk, 1998). It would appear that the lack of a face-to-face interaction and the need to structure their own learning did not adversely affect field dependent learners in this analysis. However, it should be noted that distance learning situations typically lasted the duration of a course term. In this case, the length of the treatment may be more relevant than the learning context. As stated previously, brief, research-oriented learning situations may tend to inflate achievement differences between field types.

Also contrary to information presented in the literature review was the finding that studies which utilized social science content displayed a larger mean effect size than studies which used science, language or technology content. According to Garger and Guild's (1987) summary of the literature on differences between field types, it is expected that field independent learners would perform better in science content subjects, and field dependent learners would perform better in socially-based subjects. However, this study found that material with social content resulted in the largest differences in achievement between field types. In an analysis of the primary studies which utilized social content (Archer, 2003; Daniels & Moore, 2000; Fitzgerald & Semrau, 1998; Leader & Klein, 1996; Hsu, Frederick & Chung, 1994), the results indicated that field independent learners typically had higher levels of achievement. Therefore, this study did not identify a performance advantage for field dependent learners in studies with social content.

Finally, it is interesting to note that web-based applications had a higher mean difference between field dependent and field independent learners than did CAI applications. According to Jonassen and Wang (1993), the link and node structure of web-based designs can benefit field independent learners who are more likely to impose a meaningful organization upon the learning material. It may be that the navigational demands of a web-based environment favor field independent learners. However, this result is confounded by the presences of other variables, such as the fact that this technology type was used exclusively in distance learning, which in turn, was associated with increased treatment duration. The analysis of multiple variables separately will be correct only if the moderator variables are independent - an assumption that does not appear to fit this case. The analysis of such correlated variables is better suited to hierarchical regression. Unfortunately, the difficulty in conducting a fully hierarchical moderator analyses is that there are too few studies in this meta-analysis to yield adequate numbers of studies in cells beyond the initial breakout (Hunter & Schmidt, 2004). This means that it is not possible to address all moderator hypotheses at this time.

Overall, the results of the subset analyses did not detect any significant moderator variables. Even after correction, the remaining variation across studies is probably due to uncorrected artifacts rather than to a real moderator variable. In the coming years, with further advances in meta-analytic techniques, there will probably be more correctable artifacts defined and quantified which would lead to a better understanding of this data set. As well, as more studies in this research domain accumulate over time, different statistical techniques can be used to gain a better understanding of the interaction of moderators in this analysis.

Limitations

Many of the studies included in this meta-analysis provided some kind of technology treatment with variations in the treatment groups. The contrast was minimal in some studies (e.g., Buck, 2003; Shih & Gamon, 2002; Luk, 1998; Abousserie, 1992), and substantial in others (e.g., Cameron & Dwyer, 2005; Archer, 2003; Katz, 1999; Summerville, 1997). In these cases, variations of technology treatments may have been too similar to affect students' cognitive styles, or too contrived for authentic analysis. Unfortunately, it is impossible to conduct a meta-analysis on interaction effects with technology treatments, as the independent variables involved vary from study to study, and common elements are not evident. However, the outcome of this study may have been improved by implementing a coding system to weight the impact of the range of treatment effects. This coding scheme could then be used in moderator analysis to determine the impact of various levels of technology-based interventions on learning performance. A potential treatment moderator of such importance could well have impacted the magnitude of the population variance observed in this study.

In addition to extreme variations in treatment types, researchers in this analysis also introduced many new variables in attempting to understand the relationship between achievement and technology-based learning. Many different independent variables were identified in the literature base, and include, but are not limited to: student rank, the provision of feedback, prior knowledge, verbal ability, motivation, social context, learning strategies, and anxiety. A potential end-user model will include some or all of these variables, and be very complex.

One of the more frustrating limitations of this study was the number of primary studies which did not provide sufficient results information. For this reason, 17 studies were excluded from this meta-analysis. As well, for the included studies, it was often difficult to correct artifactual errors, such as the extension of range, due to lack of data. Correction of artifacts requires auxiliary information such as study sample sizes, study means and standard deviations, estimates of reliability, and so on. Other researchers have reported similar difficulties with obtaining sufficient primary study data to conduct thorough analyses (Rosenthal, Rosnow & Rubin, 2000; Cooper, 1998). As researchers summarize and synthesize studies in their fields, research journals and other publications should be reminded that null results are as important as significant results to the contribution of knowledge, and should be reported alongside more detailed statistical findings for subsequent meta-analysis.

Finally, this study would have benefited from the presence of other meta-analyses in this research domain to aid in the definition of moderator variables that could be specified or hypothesized in advance by theory. As it was, coding was dependent on prior meta-analyses from other research areas and textbook examples. This resulted in the use of 'omnibus' tests to detect moderators by determining whether the variance of study effect sizes was larger than can be accounted for by variance generating artifacts. As it is impossible to code studies for all potential moderator variables, detecting them without *a priori* guidance is like finding a needle in the proverbial haystack. Although the outcomes of this study demonstrated a weak ability of meta-analysis to detect moderators, the overall objective was to contribute a piece of information to the research domain. According to Hunter and Schmidt (2004), the results of a meta-analysis should not be "interpreted in isolation, but rather in relation to a broader set of linked findings from other meta-analyses that form the foundation for theoretical explanations" (p. 205). Therefore, it is hoped that the results of this meta-analysis will contribute to a body of literature which will support the development of theory to generate future hypotheses about moderators.

Future Research

The findings of the meta-analysis offer several suggestions for future research. The FDI literature has produced many healthy debates in the past, and by all appearances will again in the future.

Findings presented in this meta-analysis demonstrate that there is evidence supporting the impact of cognitive styles on student achievement. Thus, as an important individual difference variable in student performance and behavior, Witkin's cognitive styles deserve the research attention that they have received from scholars in the past and should continue to be widely researched. In this respect, this author wishes to address three areas for future research planning and consideration.

First, educational planners should understand that meta-analysis is a method of reexamining existing research; it is not a forecaster of prospective developments in education. When examining the nature of cognitive styles, and in particular issue of academic value, this study looked closely at how cognitive styles relate to achievement performance. Such research implies that styles are not value-free because some styles are consistently associated with better academic performance, whereas their opposite styles are consistently associated with poor academic performance. In general, this study found there is a difference in achievement between field types that favored field-independent learners in limited technology-based learning situations. However, the supporting literature review suggests that this is a simplistic perspective. There are a number of learning-environment relevant factors, such as the nature of an academic discipline, the type of performance tasks, the learner's approach to the task, and the nature of student assessment that can allow the learner to adapt in different ways. Further investigation into the adaptive nature of field dependent and field independent cognitive styles, in the context of more natural and qualitative observations in educational settings, would contribute to a more comprehensive understanding of the educational value of styles research.

Second, it is recommended that a standardized practice of using the GEFT to reliably distinguish between field dependent and field independent learners be used. Such a consistent practice would greatly benefit the analysis of research outcomes based on Witkin's theory of FDI. Additionally, it would be beneficial to study cognitive styles as a continuum rather than a dichotomy. The distinction between approaches is that full use of a range would determine whether or not performance improves as the amount of field dependence/independence increases.

Finally, the number of studies exhibiting lower scores achieved by the field dependent groups is a concern. Additional research is needed to determine what factors might have influenced the cumulative difference in effect sizes. It is strongly recommended that future investigators of FDI consider statistically controlling for the influence of intellectual ability in the analysis of data. Although the intent of cognitive styles is to explain performance differences, the analysis herein identifies its value as a competence variable, and in this respect FDI appears indistinguishable from intelligence.

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APPENDIX A

Planning Analysis

Formula 1 – File Drawer Analysis:

$$x = k(d_k / .10 - 1)$$

Where:
k = the number of included studies
d_k = average effect size across studies
x = the number of missing studies needed to reduce the effect size to .10

Formula 2 – Effect Size d:

$$d = (M_1 - M_2) / SD$$

Where:
$M_1 - M_2$ are the means of group 1 and group 2
SD is $s^2 = ((n_e - 1)(s_e)^2 + (n_c - 1)(s_c)^2) / (n_e + n_c - 2)$

Formula 3 – Calculation of d from *t* or *F*:

$$d = 2t / \sqrt{df_{error}}$$

Where:
t = the value of the t test for the comparison; and
df_{error} = the error degrees of freedom associated with the t test

In situations where *F* tests with a single degree of freedom in the numerator were reported, the square root of the *F* value ($t = \sqrt{F}$) was substituted for the *t* value in the formula where the direction of the mean difference was known (Cooper, 1998).

Formula 4 – Correction for Samples < 20:

$$d \text{ (corrected)} = d * [1 - 3 / 4(n_1 + n_2) - 9]$$

Where:
n_1 and n_2 are the sample sizes for each condition (FI and FD)

Formula 5 – Calculation to convert *d* to *r*:

$$r = (d/2) / [(N-2)/N + (d/2)^2]^{1/2}$$

Where:
N = The total sample size of the group

APPENDIX B

Coding Form

STUDY FEATURES		
Year of Publication	1990-1994	OLD
	1995-1999	MED
	2000-2004	YNG
	2005-2009	NEW
Type of Publication	Journal Article	ATL
	ERIC	ERC
	Dissertation/Thesis	DIS
Sample Size:	20 – 50	S
	51 – 80	M
	81 – 110	L
	More than 110	XL
Grade Level:	Primary	ES
	Jr. High	JH
	High School	HS
	Undergrad	UN
	Graduate	GR
Location:	US	US
	Other	OT
METHODOLOGY FEATURES		
Pretest Equivalence	Unspecified or inadequate	UN
	Random Assignment	RA
	Pretest Scores	PR
	Pretest Scores and Random Assignment	PS
Type of Inference Test: (F, t, other)	F value for main effect	F
	Derived d statistic	D
	p	P
	t-Test	T
Independent Variable (GEFT)	Extreme Scores (.5 < sd; .5 >sd)	EXT
	Range FD/FI	RNG
Dependent Variable	Final Class Grade:	GR
	Post Test:	PT
CHARACTERISTICS OF THE TREATMENT		
Treatment Duration	Less than One Week	DY
	1 – 4 weeks	WK
	1 – 4 months	MO
	longer than 4 months	TM
Instructional method:	Same treatment for all	
	Same treatment with variations	
Type of Application:	WEB	WEB
	CAI	CAI
Student Context:	Individual (Classroom-based)	IND
	Small Group (<10)	SMG
	Research setting	RSC
	Distance Ed	DST
Academic Subject:	Language/Reading/Writing	RED
	Science/Medicine	SCI
	Social Science/Education	SOS
	Technology	TEC
	Other (ethics)	OTH

APPENDIX C

Study Analysis

Formula 1: Measurement Error:

$$p_{TU} = \frac{r_{xy}}{\sqrt{r_{xx}}\ \sqrt{r_{yy}}}$$

Where:

p_{TU} = correlation between true scores

r_{xy} = observed correlation

$\sqrt{r_{xx}}$ = sq rt of the reliability of GEFT scores

$\sqrt{r_{yy}}$ = sq rt of the reliability of post-test scores

Formula 2: Dichotomization of the Independent Variable

$$p_o = ap$$

$$a = \varphi(c) / \sqrt{PQ}$$

Where:

p_o = the observed correlation

p = the population correlation

a = depends on extremeness of the split induced by dichotomization

P = proportion in the high end of the split

Q = 1- P the proportion in the low end of the split

c = point in the normal distribution that divides the distribution into proportions P and Q

$\varphi(c)$ = the normal ordinate at c

Formula 3: Imperfect Construct Validity:

$$p_o = a_1 a_2 p$$

Where:

p_o = the observed correlation

p = the population correlation

a_1 = the square root of the reliability of the GEFT

a_2 = the square root of the reliability of the post-tests

Formula 4: Total Attenuation Factor

$$A = (a_1)(a_2)(a_3)(a_4)(a_5)$$

Where:
A = Total attenuation factor
a_i = Individual correction factor

Formula 5: Linear Bias Attenuation Factor

$$a = 1 - 1/(2N - 1)$$

Where:
N = Total sample size

Formula 6 – Correction of Study Correlations

$$r_c = r_o / A$$

Where:
r_c = Corrected correlation
r_o = Observed correlation
A = Total attenuation factor

APPENDIX D

Meta-Analysis

Formula 1 – Calculation of Individual Study Weights

$$w_{\mathrm{i}} = \mathrm{N_i A_i}^2$$

Where:
w_{i} = Weight for each study
$\mathrm{N_i}$ = Study sample size
$\mathrm{A_i}^2$ = Square of the artifact attenuation factor

Formula 2 – Calculation of Observed Variance

$$\mathrm{Var}(r_{\mathrm{c}}) = \sum w_{\mathrm{i}}\ [\mathrm{r_{ci}} - \mathit{Ave}\ \mathrm{r_c}]^2 / \sum w_{\mathrm{i}}$$

Where:
$\mathit{Ave}\ \mathrm{r_c} = \sum w_{\mathrm{i}}\ \mathrm{r_{ci}}\ / \sum w_{\mathrm{i}}$

Formula 3 – Calculation of Sampling Error Variance

$$\mathrm{Ave}(ve) = \sum w_{\mathrm{i}}\ ve_{\mathrm{i}} / \sum w_{\mathrm{i}}$$

Formula 4 – Calculation of Population Variance

$$\mathrm{Var}(p) = \mathrm{Var}(r_{\mathrm{c}}) - \mathrm{Var}(r_{\mathrm{c}})$$

Formula 5 – Calculation of Confidence Interval

$$\mathrm{P}\ (\ \mathit{Ave}\ \mathrm{r_c}\ - 1.96 * \mathrm{Var}(p)\ < \mathrm{rho} < \mathit{Ave}\ \mathrm{r_c}\ + 1.96 * \mathrm{Var}(p)\ ) = .95$$

APPENDIX A
Planning Analysis

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Where:
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x = the number of missing studies needed to reduce the effect size to .10

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Formula 3 – Calculation of d from *t* or *F*:

$$d = 2t / \sqrt{df_{error}}$$

Where:
t = the value of the t test for the comparison; and
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In situations where *F* tests with a single degree of freedom in the numerator were reported, the square root of the *F* value ($t = \sqrt{F}$) was substituted for the *t* value in the formula where the direction of the mean difference was known (Cooper, 1998).

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Where:
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$$r = (d /2) / [(N-2) / N + (d / 2)^2]^{1/2}$$

Where:
N = The total sample size of the group

APPENDIX E

Sampling Error Variance of Individual Study Correlations

The sampling error variance in the corrected correlation is computed in two steps (Hunter & Schmidt 1994b). First the sampling error variance in the uncorrected correlation is computed . Then the sampling error variance in the corrected correlation is computed from that.

<u>Step 1:</u>

$$\text{Var}\ (e_o) = [1 - r_{\text{o}}^{2}]^{2} / \text{N}_{\text{i}} - 1)$$

Where:

$\text{Var}(e_o)$= Variance of the uncorrected correlation
r_{o} = Mean of the uncorrected correlation across studies
N = Sample size of the study in question

The sample error variance in the corrected correlation is then given by:

<u>Step 2:</u>

$$\text{Var}\ (e_c) = \text{Var}\ (e_o)\ / \text{A}^2$$

Where:

$\text{Var}(e_c)$ = Variance of the corrected study correlation
A^2 = The compound attenuation factor for that study