CROSS-CULTURAL VALIDATION OF THE WILL, SKILL, TOOL MODEL OF TECHNOLOGY INTEGRATION

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The teacher professional development component of the will, skill, tool model of technology integration was tested for predictive validity in the cross-cultural context of data from Texas, USA, and data from Mexico City, Mexico. Structural equation modeling (SEM) analysis, path analysis, and multiple regression analysis, were statistical procedures employed. The analyses yielded positive results for the model's validity and reliability. The resulting model was found to be a reliable tool to evaluate technology integration among elementary and middle school teachers in Texas and in Mexico City.

For the purposes of this study, the teacher professional development component of the will, skill, tool model of technology integration is referred to as the will, skill, tool model of teacher integration (WiSTTI). This was one of the seven alternative models tested for goodness of fit across a total of 7 data samples. The structural equation modeling approach proved to be a good technique to find the best fit model in a cross-cultural environment. Latent variables and a set of parameters to judge the validity and reliability of each model were set for testing and retesting in an iterative process. Eventually a "new" modified version of the WiSSTI model was found to fit the data for all samples studied from both countries. From a theoretical perspective, the variation of the WiSTTI model found to be the best fit to the data indicates that increased teacher willingness to integrate technology brings about increased skill, and increased skill leads to more advanced technology integration, if access to technology is available for instruction.

Results derived from the model with respect to the evaluation of technology integration for teachers from Texas and Mexico City suggest a differential effect by country, with the Texas

teachers (representing USA) currently more advanced in technology integration than their colleagues from Mexico. No large effect was found for educational level, with elementary school teachers and middle school teachers at approximately equivalent levels of technology integration in both countries.

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CHAPTER 1

INTRODUCTION

Under the No Child Left Behind Act (Committee on Education and the Workforce, 2001) and the recent revision of the national technology plan, technology integration has become a major concern in searching for the real impact of technology implementation in schools (Cavanagh, 2004). The large expenditures on technology that governments and international agencies have allocated in schools reached a delicate point where future technology infusion could be negatively affected if no tangible evidence on teaching practices and student achievement are foreseen in the near future. Reputable voices in the educational arena call for a moratorium on buying any more computers for K-12 schools, after observing weak results on teaching and learning (Cuban, 2001, p. 192). This situation is particularly serious in developing countries, where resources for education are scarce or poorly administered (de Ferranti et al., 2003, pp. 83-85). The long expected effects of technology in education proclaimed in the 1980s, including higher overall performance and reaching higher standards due to the use of technology are overdue. In taking a glimpse at how they perceived education and technology would be by the year 2000, Percival and Ellington (1984) wrote:

> By the time they reach the end of their primary schooling, children will probably vary greatly in the academic level that they have reached – almost certainly much more so than today because of the greatly increased learning opportunities that new information technology will make available to the 'high fliers'. Nevertheless, we expect the overall standard to be significantly higher than today, with virtually all children being brought to a level where they can benefit from the more advanced

> education that they will receive in secondary schools (Percival & Ellington, 1984, p. 155).

It is in this regard that technology integration has become important in recent years (Sheekey, 2003, pp. xiii-xiv). A certain degree of integration is expected, wherever technology is available. There is no need to invest in technology for education if educators are not willing to use it, or as it happens they misuse it. Cuban (2001) boldly contends that

> teachers at all levels of schooling have used the new technology basically to continue what they have always done: to communicate with parents and administrators, prepare syllabi and lectures, record grades, assign research papers. These unintended effects must be disappointing to those who advocate more computers in schools (Cuban, 2001, pp. 178-179).

Although it is an extreme point of view, Cuban's contention was certainly a call for attention that led to serious research on technology integration from the evaluation perspective. For example, after a five-year evaluation of a Technology Innovation Challenge Grant, researchers found, among other results, that high technology integration teachers made a critical difference for students with no access to computers at home, and that technology-enriched reading activities accounted for approximately 10% of reading achievement gains among first and second graders (Knezek & Christensen, 2004). They reached this conclusion after constructing sophisticated tools for measuring and analyzing technology integration.

In this regard, researchers and practitioners need the best tools available for evaluating the best teaching practices using technology, the results of professional development programs, and ultimately, the strategies for effectively learning with technology. One such tool, the Will, Skill, Tool model (Knezek, Christensen, Hancock, & Shoho, 2000) has been under careful construction, from the selection of the best measures available, to the building of new measures, to their groupings into meaningful combinations to best explain what was expected of technology integration in schools. At the time this research began, the model was ready to be tested in different settings and cultural practices, in different languages, and in different school systems.

Research conducted in Mexico has relied on some of the measures developed in the framework of the Will, Skill, Tool model. Surveys have helped to measure the willingness of teachers and students to work with technology, as well as the level of technology adoption perceived by teachers (Morales, Campos, Lignan, & González, 2001). Results in these areas have led to specific recommended practices for in-service teacher training and professional development, such as needs-assessment training groups, depending on the level of technology adoption, and the school model of technology use (Morales et al., pp. 84-85; Morales, Campos, Lignan, González, Medina, & González, 1999, p. 99). Nevertheless, much more is needed in terms of research, to secure resources, and help teachers find their most suitable educational practice using technology. There is a need for explanatory research that can lead to the design of the best standards for technology integration for in-service teachers, and the best teacher preparation practices for pre-service teachers. In this regard, there existed an opportunity to apply the Will, Skill, Tool model, in order to replicate previous results and to address further research from a broader explanatory perspective.

Differences in Technology Access: Mexico versus United States

It has been said that for the past 50 years, Mexico’s economy has steadily remained at one quarter of the United States’ economic wealth (Prawda & Flores, 2001, p.47). The enormous difference in wealth between Mexico and the United States makes any comparison between the two countries appear senseless or biased. Nevertheless, it could be useful in understanding the context for technology integration among teachers on both sides of the border.

It is important to note that among 30 nations of the Organization for Economic Cooperation and Development (OECD), Mexico's Gross Domestic Product (GDP) is next to the bottom, only higher than Turkey (National Center for Education Statistics, 2003), and even though Mexico is the third most populated country of the OECD (after the United States and Japan), expenditures per student in elementary and secondary education are only 17% of equivalent expenditures in the United States, and 22% of equivalent expenditures in Japan (National Center for Education Statistics, 2003).

In a recent study on availability of technology in basic education in Mexico (ILCE, 2003), one of the clearest results was that federal and state policy on technology across the country was aimed at furnishing all primary and secondary schools in Mexico with technology, demonstrating that access to information technology is still an important priority (Avila, Morales, Soto, González, García, & Alvarado, 2003, p. 7). Some states such as Nuevo León and Distrito Federal (Mexico City) have already equipped all secondary schools with technology, but elementary schools still represent a powerful challenge. It is estimated that only 10 to 19 percent of the nearly 70,000 elementary schools in the country are equipped with computers (Cavanagh, 2004; Cano, López, Pérez, & Rosas, 2003).

A dramatic difference between Mexico and the United States regarding access to technology becomes clear when the student-per-computer ratio is compared: During the time when the ratio in the United States elementary schools was six students per computer, the ratio in Mexico was 256 to one (Cano et al., 2003, p. 10).

Nevertheless, important initiatives are under way to consolidate access to technology in schools in Mexico. Based at ILCE's headquarters, a federal program called *Enciclomedia* is intended to provide computers and educational software to all fifth and sixth grade classrooms in the country during 2005 (Cavanagh, 2004). Furthermore, Mexico's teacher union (the largest in Latin America) has strongly supported technology for teachers by guaranteeing loans from banks for teachers to buy computers (Ornelas, 2003, p. 16). Therefore, a rise in technology availability and use is expected in elementary and middle schools in Mexico in the near future (Avila et al., 2003).

In the United States, the challenge has moved from access to impact (Cavanagh, 2004). The National Education Technology Plan (United States Department of Education, 2004) calls for a new generation of students and teachers, more proficient in managing technology, and more efficient in using it. In order to comply with the No Child Left Behind Act (Committee on Education and the Workforce, 2001), a transformation of the school organization and practice is needed. The Plan advocates that only through new models of education facilitated by educational technology (e.g. e-learning and virtual schools), the students will have "the knowledge and competence to compete in an increasingly technology-driven world economy" (United States Department of Education, 2004). Teachers need to be provided with examples and best practices using technology, based on research, in order to use technology effectively to enhance learning. In the end, "public schools that do not adapt to the technology needs of students risk becoming increasingly irrelevant. Students will seek other options" (United States Department of Education, 2004).

In terms of technology access, the current trend in the United States is toward "one-to-one" computer access, and ubiquitous computing (Muir, Knezek, & Christensen, 2004). This is unthinkable for the near future in Mexico.

Research Problem Statement

The search for a positive impact of technology use in the classroom on student achievement has led to focusing on the best indicators/predictors of technology integration (Vannatta & Fordham, 2004). It is likely that teachers' willingness to use technology plays a major role on technology integration, but as psychologists may argue, the will must at least be integrated to the skill in self-regulated tasks to be effective (McCombs & Marzano, 1990). The will to use technology is pointless, if it is not supported by the necessary skill to use it. Successful technology integration also depends on external factors that provide the teacher with the necessary tools in terms of the technology available, training, and support (Rogers, 1999).

Thus, the problem of finding the best predictors of technology integration becomes multidimensional (Bebell, Russell, & O'Dwyer, 2004). It implies an individual level of integration, a group level of integration, and an institutional level of integration. The individual level presupposes a personal commitment to use technology as a professional tool to enhance learning. The group level refers to the commitment of groups of people such as faculty, parent associations, or school boards, to promote the use of technology within the contextual realm of the schools. The institutional level assumes the commitment of society through government agencies, financial institutions, and educational associations to provide the educational system with the best technology available, the best tactics for promotion and advocacy, and the stakeholder training to create an enduring tradition of technology use.

Some models of technology integration may be narrow in their scope, in that the indicators refer to only one dimension of analysis, whereas others refer to more than one dimension (Bebell el al., 2004). Both scope and depth of analysis are important in identifying the best variable selection to ensure validity for a model, and the most reliable measures defining each variable (Schumacker & Lomax, 1996, pp. 37-38), in order to ensure a solid theoretical ground for the best prediction regarding technology integration practices. The Will, Skill, Tool Model of Technology Integration is a structural model intended to provide in-depth analysis in a multidimensional approach. The source of information for the model is the teacher's self perceptions (his/her reflections, or standpoint) on technology integration, based on his/her own needs: it assumes that the teacher's Will (attitude toward technology), Skill (his/her technology competency), and Tools (ready access to technology tools) are "…three key elements for successful integration of technology" (Knezek et al., 2000). The model also assumes that successful technology integration positively impacts the student's achievement. Each one of the model components is defined by various measurable indicators, reflecting the multiple dimensions under which technology integration should be explained.

The model has been under development for several years, and it has been used to comprehensively explain the reality of technology integration of various school districts in Texas. It was learned that approximately 40% of the measured technology adoption among Texas teachers could be attributed to Will, 30% to Skill, and nearly 14% to Tool access (Knezek et al., 2000). Furthermore, using the model as a predictor of student achievement, Christensen and Knezek (2001a, p.157) found that 12% of student gains in reading achievement could be attributed to the teacher's technology integration, a finding recently replicated (Morales, 2005b).

Nevertheless, international collaboration has been an important component in the refinement of ideas to explain technology integration, and the testing of individual measures (Knezek & Christensen, 2001, p. 276). Furthermore, the assumptions underlying the model have been observed in other contexts and cultural backgrounds different from Texas. For example, positive attitudes toward technology have been observed across different nations, even in regions where technology resources are limited (Knezek, Christensen, & Morales, 2001, p. 295), and attitudes in turn, seem to be influenced "…by extent of training or level of technology integration development, rather than nation or culture" (Knezek et al., 2001, p. 280). Isolated components of the model have been tested in Mexico in the past, mostly exploring the attitudes and dispositions of teachers toward technology, and their willingness to adopt technology into their teaching practices (Morales et al., 1999; Morales, González, Medina, & González, 2000; Morales et al., 2001; Morales, 2001a). Still, there are a number of gaps in the conceptualization and research data available in order to fully explain integration of technology in Mexico (Morales, 2001b; Ornelas, 2003, pp. 53-54). Replicating in Mexico those studies carried out in Texas would be beneficial for the theoretical foundation of the Will, Skill Tool Model, as it could then be tested in a cross-cultural framework. It was conjectured to also be important for the consolidation of technology integration efforts such as the Red Escolar in Mexico (de Alba, 2004) by improving the understanding of federal and local authorities, researchers, and teachers on the decisive factors to integrate technology.

Purpose of the Study

The purpose of this study was to explore the relationships between the teacher's dispositions toward technology (Will), the ability to use technology (Skill), and the available technology tools (Tool) on the integration of technology in the classroom. Derived from this general purpose, three particular goals were targeted:

1. To test the validity of the Will, Skill, Tool Model of Teacher Integration (WiSTTI Model) in a cross-cultural context. The infusion of technology into Mexican schools and the teacher access to technology at home are markedly different from the situation in Texas (Avila, et al., 2003). Only 57% of Mexican teachers reported having access to a computer at home, and 19% reported having access to the Internet at home in 2001 (Avila, et al., 2003, p. 44). Meanwhile, a corresponding sample in rural Texas showed that 85% of teachers reported having computer access at home, and 56% of them had access to the Internet at home (Christensen & Knezek, 2001a, p. 120). In terms of technology access in the schools, technology infusion programs in Mexico have traditionally overlooked elementary schools. Although it has been reported that all middle schools in Mexico City are equipped with technology (Observatorio Ciudadano de la Educación, 2003) it is worth noting that rough calculations conferred an average of 20% of elementary schools equipped in Mexico City, and 19% of those schools for the whole country in 2001 (Cano et al., 2003, p. 8). On the other hand, it is assumed that all K-12 schools in Texas are equipped with computers.
2. To compare the relative contributions of model components in varying educational contexts. In a comprehensive study using structural equation modeling (SEM) (Schumacker & Lomax, 1996) to test the Will, Skill, Tool Model in 2004 (Morales, 2005a), results supported the structural composition of the model, and a differential effect of Will, Skill, and Tool on technology integration, depending on the educational

level studied and the degree of technology infusion in schools. One goal of this study was to replicate the earlier study using data to be collected from teachers in Mexico City.

3. To compare the profiles of teacher's technology integration in Mexico and Texas, using the WiSTTI model. Previous measurement of technology integration in Mexico (Morales & Avila, 2003) showed that the highest frequencies of elementary and middle school teachers were in stages of adoption 1, 2, and 3, whereas equivalent measurement in Texas showed that teachers were in stages 4, 5, and 6 (Christensen & Knezek, 2001a). Nevertheless, those results have not been discussed in a comparative study. The use of an entire model to measure technology integration, and not just a single measure would serve also to cross-validate those previous results.

Significance of the Study

Conducting a cross-cultural validation of the Will, Skill, Tool Model of Teacher Integration (WiSTTI) would produce a unique methodological approach, validated across nations, for researchers and practitioners to explore and use to evaluate technology integration into the classroom. Specifically, four areas of potential benefit to research knowledge were identified in this study:

The Theoretical Foundations of the WiSTTI Model

Testing the model in a radically different contextual condition would strengthen its explanatory power to identify the best indicators for technology integration in the classroom. As stated before, the willingness to integrate technology among teachers appears to be free of cultural binding, thus, a factor to differentiate between populations is more likely to be found within the teacher's skills. But as more and better training is provided to Texas teachers, a tendency to upgrade technology adoption to higher stages has been observed among K-12 teachers who have undergone steady and more advanced training (26.2% of teachers perceived themselves in stage 5 of adoption, and 39.3% perceived themselves in stage 6, as measured among elementary school teachers from a large school district in North Texas; Knezek & Christensen, 2002, pp. 8.) It was believed that technology integration was far from being upgraded to a high uniform stage among teachers in Mexico (only 8% of the teachers perceived themselves in stage 5 of adoption, and 4% of them in stage 6, as measured among middle school teachers of public schools across Mexico in 2001-2002; Soto & González, 2003.) If the suspected difference in skills held true, and its effects were combined with the observed difference in access to technology, the composition and distribution of the WiSTTI model's main predictor constructs (Will, Skill, Tool) for technology integration might change as a result of this study.

The Methodological Ground to Explore the WiSTTI Model

A cross-cultural validation of the model required a special methodology that implied the equivalence of the constructs under investigation in different cultures, the consideration of "style" in responding to surveys when administered to individuals of different cultural backgrounds, and the resolution of the problems related to the validity of measures across cultures (van de Vijver, & Leung, 1977). For example, there are known to be three common ways to adapt an instrument originally written in English to Spanish, each affecting the instrument's validity: simple instrument *translation* into Spanish, *adaptation* of the measure, using different wording, and additional content that is more closely related to Spanish speaking teachers, and *assembling* a new instrument when the original measure is inappropriate (van de Vijver & Leung, 1997, p. 36). Each one of the adaptations is known to contain a series of advantages and disadvantages. As a measure becomes more exclusive to one culture (i.e. it is adapted or assembled) the less chance it has to yield comparisons across cultures. Practical considerations regarding the piloting of measures dictated translation as the course of action for the instrumentation in this study.

Tailored Data Analysis Techniques

Structural equation modeling was one of the methods of data analysis proposed for this study. It is an *ad hoc* methodology for cross-cultural studies (van de Vijver & Leung, 1997, pp. 99-107; Cheung & Rensvold, 2000) and comprehensive in nature to test the entire model at once. SEM is the only approach to data analysis that can test theoretical constructs such as Will, Skill, and Tool directly from the data. The mathematical model underlying this approach is the linear structural relationship between the variables (Jöreskog & Sörbom, 1993). A linear structural equation can explain the relationships between the variables, and the analysis is intended to test how well the theoretical model represents (approaches) the set of data. Thus, a substantial contribution in the methodological area was expected to provide the foundation for further studies on the WiSTTI model and similar theoretical proposals.

Assessment Capabilities of the WiSTTI Model

A fourth area targeted for potential contributions by this study focused on practical issues. The WiSTTI model can be viewed as a framework, a comprehensive evaluation tool for schools districts and technology-enriched educational programs, and also as an instrument to measure the teacher’s self-perceived technology integration. For example, Knezek et al. (2000) reported using the model components to test the degree of technology adoption among 39 teachers from Northern Texas. They found that 40% of the variance in stage of adoption could be attributable to Will, an additional 30% of the variance could be attributed to Skill, and 14% of the variance attributed to Tool. On the other hand, Morales (2005a) found a differential effect of

Will, Skill, and Tool, on technology integration, depending on educational level (elementary schools vs. middle schools vs. high schools), and technological environment (technology-enriched schools vs. schools equipped at typical levels). The present study expanded the assessment capabilities of the model, by requesting technology integration information from teachers in Mexico, in a disadvantaged environment with respect to teacher skills and technology access.

Research Questions and Hypotheses

There were three major research questions in this study:

1. Will data gathered from elementary and middle school teachers in Mexico City produce technology integration findings similar to those in Texas?
2. What are the best indicators of Will, Skill, and Tool for technology integration?
3. Are there models other than Will, Skill, Tool, that better explain the WST teacher professional development component (WiSTTI) results of data gathered from Mexico City and Texas?

The null hypotheses stated that:

1a. No difference in level of technology integration exists between Texas teachers and teachers from Mexico City.

1b. No difference in level of technology integration exists between elementary school teachers and middle school teachers.

2. There is no differential effect of Will, Skill, and Tool on technology integration across level of education or culture-differentiated samples.
3. There will be no differences in goodness of fit nor total variance accounted for among the seven technology integration models tested.

Limitations of the Study

Two main areas of concern were taken into consideration, to minimize the possible threats to the validity of the study. The first area was the *equivalence* of data from both Texas and Mexico City teachers, related to construct bias, item bias, and administration bias in cross-cultural studies (van de Vijver & Leung, 1997, pp. 140-141), and the second area was the selection of the samples, related to the limitations on the *generalizability* of the results (Campbell & Stanley, 1963, p. 5) to the populations of both Texas and Mexico City teachers.

Precautions were taken to minimize bias in the possible perceptions of the constructs involved in the survey administered to Mexico City teachers, although there is no ultimate guaranteed equivalence with the perceptions of teachers from Texas. It was assumed the same factorial composition of the measures existed for both cultural groups, and this assumption was confirmed for most of the measures in the pilot study. One indicator that did not meet conventional reliability standards was discarded altogether. Items were carefully translated by the author of this study, and given to experts in the field for revision. The pilot study also provided helpful insight on the wording of some items, which were changed for the final study.

The survey administration procedure was different in Mexico City than the procedure followed in Texas. In the latter, administration was entirely online, whereas in the former there was a need for a mixed procedure. About 15% of the middle school teachers who had the technology and an adequate speed connection available, were surveyed online, although a researcher was present to explain the procedure for the online survey. The rest of the middle school teachers and the entire sample of elementary school teachers who had no access conditions to answer an online survey, were surveyed using a paper and pencil procedure. The extent to which differences in administration procedures affected the data collected will remain unknown for the results of this study. Furthermore, data gathering from elementary school teachers was made during training sessions for *Enciclomedia,* a major technology infusion program for elementary schools being launched in 2005. Ministry of Education officials scheduled the survey administration onsite, based on their own criteria. The effect of this contextual difference in survey administration is also unknown.

The issue of the generalizability of results affects both the Texas sample and the Mexico City sample. The Texas sample was gathered through an invitation to all teachers in a School District of Northern Texas, and response to the survey was discretionary, although school district officials urged teachers to participate. The initial selection of schools for Mexico City was a random selection, but the final list of survey administration sites was provided by Ministry of Education officials, based on their own criteria. The middle school teacher sample was assembled through invitations to selected schools to participate in the study. Ministry of Education officials sent letters to the school principals, requesting the participation of the teachers. Survey administration for the elementary level was not conducted at school sites, but at five teacher training centers distributed across Mexico City: North, South, East, West, and Downtown.

Considering the administration conditions, the resulting samples can be classified as "convenience samples" (Gall, Gall, & Borg, 2003, p. 175). In order to ameliorate the negative effect of this type of sampling on the generalizability of results, efforts were made to ensure a large sample for each condition (e.g. elementary vs. middle school teachers; Texas teachers vs. Mexico City teachers).

Concept Definitions

Cross-Cultural Study

When research is directed toward analyzing a phenomenon across cultures, often it is worth considering some particular issues that might be important in applying methods and measures. One of the main problems in conducting cross-cultural research is the equivalence of constructs, methods, and measures (van de Vijver & Leung, 1997, p. 8).

Bias is a constant threat in cross-cultural studies. Measurement artifacts are common in cross-cultural measures, and precautions have to be taken in each one of the steps involved in a research project. The theoretical constructs to be examined may not be similarly defined in all cultural groups. A construct that is said to be common across cultures is called *etic,* whereas a culture-specific construct is called *emic* (Triandis, 1995, p. 189). Regarding the measures involved, it is necessary to decide if a standardized instrument is needed or not. If it is standardized for each culture, the comparison across cultures becomes cumbersome. If no standardization is required, then the aim is to reach validity across cultures, by making sure that the construct means the same for both groups, i.e. constructs to be compared need to be on the *etic* side. Van de Vijver & Leung (1997) describe in detail the different techniques used (Chapter 4, pp. 59-129) such as factor analysis, structural equation modeling, multidimensional scaling, cluster analysis, regression, and others.

Impact of Technology in Education

Hard data on the impact of technology in education is not common. It has been indicated that the effects of technology in education cannot be measured under the same standards of traditional assessment for a regular classroom (Haddad & Jurich, 2002a, p. 39).

Nevertheless, educational technologists have taken the initiative of comparing technology-driven classrooms and regular classrooms on certain specific effects on the learning process. In a comprehensive meta-analysis of the contribution of information technology to learning, Grégoire, Bracewell, and Laferrière (1996) selected studies with solid methodological foundation and reported positive results on student motivation (such as the interest in a learning activity, or the time and attention devoted to learning activities), student's relation to knowledge (including the development of a research spirit, a broader cooperation between students, and a more integrated and better assimilated learning), specific learning achieved (e.g. the development of various intellectual development skills, or the acquisition of knowledge and related learning). Furthermore, on the side of teachers, they found a positive impact of information technology on teaching, on the relationship between teachers and students, on the orientation of planning, and on learning assessment (Grégoire, Bracewell, & Laferrière, 1996, pp. 1-8).

Structural Model

In structural equation modeling, the structural model comprises the latent variables and the hypothesized relationships involved (Schumacker & Lomax, 1996, p. 83). In the case of the Will, Skill, Tool Model, it is hypothesized that the latent independent variables Will, Skill, and Tool influence the latent dependent variable Technology Integration. In terms of the resulting equation, it is hypothesized that Technology Integration is some function of Will, Skill, and Tool (Schumacker & Lomax, 1996, p. 84).

Skill

For the purpose of this study, Skill is the perceived proficiency of technology use. The construct is related to the degree of confidence when using technology (production and communication tools), and not just the actual proficiency, as measured by competence tests. In a broader sense, skill is a competency that develops with practice (McCombs & Marzano, 1990).

Structural Equation Modeling

Hoyle (1995, p. 1) defines structural equation modeling as "a comprehensive statistical approach to testing hypotheses about relations among observed and latent variables". In the present study, the latent variables were depicted by the constructs Will, Skill, Tool, and Integration, whereas the observed variables were the measures associated to each construct. The SEM approach to testing structural models includes five steps, (Schumacker & Lomax, 1996, p. 63; Hoyle, 1995, pp. 2-9):

- *Model specification*: This is the initial model the researcher formulates, including the variables and the relationships involved. It is a theoretical model.
- *Identification*: This concerns the specification of the observed data in terms of the covariances among the indicators. Typically one begins with a correlation or covariance matrix, in order to obtain the parameters necessary to test the model.
- *Estimation*: The employment of different iterative methods (Maximum Likelihood, Least-Squares, etc) to obtain estimates of the free parameters implied in the model.
- *Evaluation of fit*: A model fits the observed data when the estimated covariance matrix resembles the original observed covariance matrix. There are several fit tests, the most common being the Chi-Square goodness-of-fit.
- *Model modification (re-specification)*: Involves decisions regarding parameter modification, by adding or deleting correlation paths and error variances. The *modification indices* provide information on the resulting model fit.

One of the most popular statistical packages to test structural models is LISREL (Jöreskog & Sörbom, 1993). LISREL 8.54 was used in this study.

Technology Access

From the broad perspective, access is a result of infrastructure, costs, financing, and legal frameworks (Haddad & Jurich, 2002b, pp.43-50). Infusion of hardware, software, networking, and connectivity are basic conditions for technology access, but the allocation of those resources greatly depends on what the costs and sustainability for a technology program will be. For example, in establishing a large technology program in Mexico in the 1980's, it was estimated that cost-effectiveness was more advantageous for developing the program in middle schools, thus, elementary schools were neglected for two decades (Prawda & Flores, 2001, p. 143).

Nevertheless, technology access also depends on the model of technology use within the schools. The prevalent model of technology use in Mexico is the computer lab, or "technology room", which is advantageous for students, but in terms of access is detrimental for teachers, who usually are excluded from those rooms, or confined to the role of mere spectators.

Technology Integration

Educational technologists define technology integration as the "process of determining where and how technology fits" (Roblyer & Edwards, 2000, p. 2). The dynamic aspects of this process relate to integration strategies to meet specific instructional needs in curriculum planning for remedial instruction, prerequisite skills, motivation to learn, creativity, or transferring knowledge to problem solving (Roblyer & Edwards, 2000, p. 2). Several models of technology integration are addressed in this study.

Technology Infusion

Technology infusion means the allocation of technology resources, especially hardware, software, networking and connectivity, into the schools. Technology infusion is best understood in terms of creating technology infrastructure in the school. Although infusion cannot be separated from educational needs, and technology access for teachers and students, cost-effective criteria often prevail in decision making to provide infrastructure (Rusten & Hudson, 2002, p. 77).

Tool

For the purpose of this study, Tool is the self-reported access and extent of use of technology in educational settings and at home. Constraints to access may exist when the actual technology programs at schools favor one stakeholder over another, for example, scheduling the use of computers for students in the lab, with no related activities scheduled for the teacher. Therefore, the meaning of Tool necessarily refers to the teacher's point of view on access.

Will

For the purpose of this study, Will conveys the attitudes and dispositions toward using technology in the classroom. The broader psychological construct refers to a "self-actualized state of motivation, an internal self-generated desire resulting in an intentional choice" (McCombs & Marzano, 1990), which is also an important aspect of the conjectured role for Will in this study.

CHAPTER 2

LITERATURE REVIEW

There is no single definition of technology integration, although it refers to meeting specific instructional needs using technology in curriculum planning (Roblyer & Edwards, 2000, p. 2). The theoretical models addressing the issue propose the measurement of different variables allegedly responsible for integrating technology into the classroom.

Different Approaches to Technology Integration

Research on technology integration into the classroom has been addressed under different approaches. From the practical side, models of technology integration tend to be tailored to specific needs, and applied to a specific context. More often than not, models tend to consider a series of technological resources as necessary conditions to affect the stakeholder needs, and his readiness to use technology.

An applicative model of technology use at the school level might include: identification of the best equipment, software and other resources for the school needs, and a training strategy for teachers, and principals (Hall & Mantz, 2000). In doing so, it is expected to affect the educator's dispositions toward technology, and his actual technology adoption stage.

Results are usually more than satisfactory through the beginning stages of technology programs, as the morale of teachers and students consequently rises, but once a specific technology deployment project comes to an end, the enthusiasm declines to a "commodity" level, that could be rated as a midrange between total enthusiasm and indifference. For example, in their study on stages of concern, Atkins and Vasu (2000) found a positive correlation between the degree of school involvement with technology and technology integration. They studied three schools: the highest scores for technology integration were observed in a school with a full time technology support person, more funding, and more overall resources; the second best integrators were found in a school which received a technology grant ten years before the observation, when technology specialists worked along with the teachers for the period of the grant, and although no longer stayed in the school, the integration of technology into the curriculum was still visible; the lowest scores were found in a rural school, with no technology program, and no technology-related grants, or support personnel for technology.

Data based on direct observation are the primary source for constructing a technology integration model tailored to specific school needs. Nevertheless, advanced models that apply to more than one case are constructed on the basis of a more extensive research.

Based on their experience working with teachers and technology, Bitner and Bitner (2002) proposed eight "keys" to successful integration: (1) overcoming fear of change, (2) technology training in basics, (3) personal use of technology, (4) provision of teaching models with technology, (5) emphasis on a learning approach to teaching, (6) flexible climate to experience technology, (7) motivation, and (8) technical and curricular support. In this vision, all proposed areas of concern are external factors affecting technology integration, and it is the task of the school administrator to identify them, in order to provide support to the teacher.

On the contrary, other approaches emphasize the internal factors that must be overcome in order to integrate technology. Using the *Perceptual Control Theory (PCT)*, Zhao and Cziko (2001) proposed that technology integration should be a part of the teacher's goals in order to endure. To integrate technology, the teacher must analyze pros and cons, anticipating consequences for existing goals. The process would entail three decisions the teacher must go through, in order to integrate technology or not, as shown in Figure 1.

A diagram may illustrate this process:

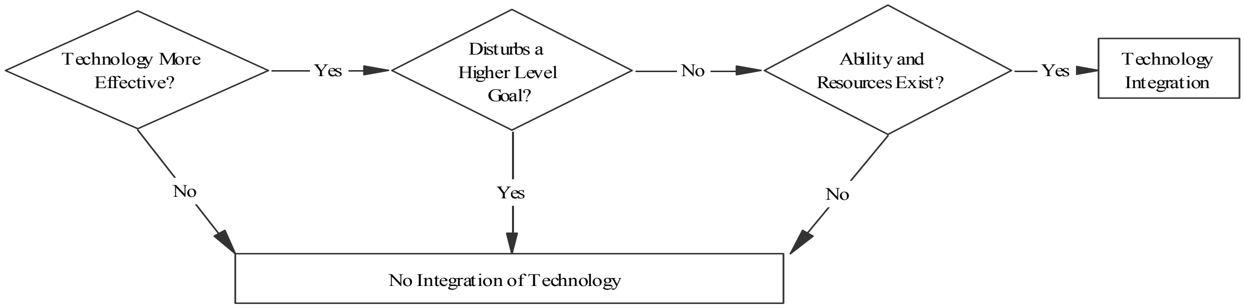


Figure 1. Model of technology integration based on Zhao and Cziko (2001).

Decision making entails a previous judgment on the effectiveness of technology to enhance learning or other important goal related to achievement, and consideration of possible conflicting disturbances with already existing goals, such as discipline, and the teacher's self-confidence that he or she can use technology effectively. In this view, teachers must believe that:

1. "…technology can more effectively meet a higher level goal than what has been used". When there is a discrepancy between a desired condition (e.g. delivering quality instruction to students), and the perceived present condition (e.g. a teaching practice "challenged" by students or peers), teachers might start using technology believing that it will help in achieving the desired goal. If the teacher perceives that the present teaching practice is the desired condition, no innovation, including technology is likely to be adopted.
2. "…using technology will not cause disturbances to other higher-level goals that he or she thinks are more important than the one being maintained". Technology enthusiastic teachers tend to be those who hold a student-centered approach to learning, thus, it would be only natural to adopt technology to enhance individual, and peer-to-peer learning, without much intervention from the teacher. More traditional teachers tend to maintain their authority through a teacher-centered practice, and the provision of technology

means a threat to the control of the class, and an occasion to change a practice with which they feel comfortable.

3. "…he or she has or will have sufficient ability and resources to use technology". If a teacher leans toward using technology to achieve a higher-level teaching goal, he must focus on a lower-level goal, to ensure that control over technology is not an obstacle to reach the ultimate goal. If the ability to use technology is considered as a barrier, provision of resources, such as training, peer-support or technical support is likely to be sought in order to integrate technology into the classroom. Of the three conditions, this is the easiest one to overcome.

A different approach takes into consideration both internal and external factors regarding technology integration. Vannatta and Fordham (2004) searched for the best predictors of technology use in the classroom. They found that among nine variables, the best predictors were (1) technology training, as measured by the number of hours of training related to technology, taken in the last two years; (2) number of extra hours working for class, as the number of hours beyond the teacher's contractual work week, to fulfill his teaching responsibilities with the class; and (3) openness to change, as "one's comfort and excitement when trying new methods of instruction as well as willingness to take risks and make mistakes" (Vannatta & Fordham, 2004). The resulting arrangement of the variables involved would yield the model in Figure 2.

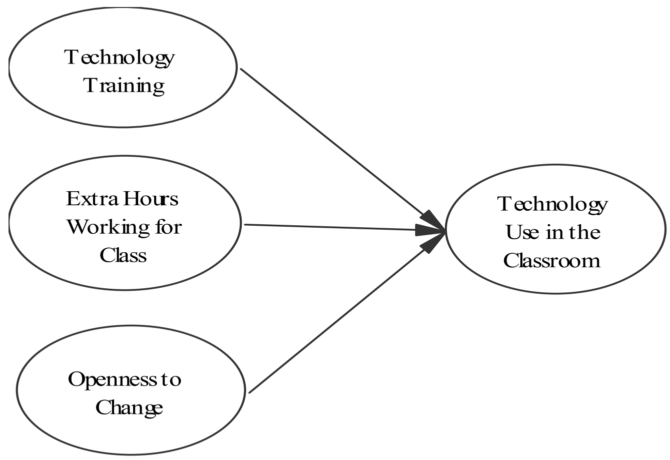


Figure 2. Model of technology use based on Vannatta and Fordham (2004).

It can be argued that in order to be useful, research on technology integration must identify the barriers to technology adoption. The sources of those barriers are both internal and external (Rogers, 1999). Internal barriers are referred to *attitudes and perceptions* of technology, where teacher anxiety represents an important negative feeling toward adopting technology, especially among beginners, who often panic and display what is called the “fear factor”. The lack of positive feelings toward the potential benefits expected when using technology in the classroom represents a second major internal obstacle to technology integration. The barrier is represented by the “17 percent problem”, where only 17 percent of the population “see” the potential of technology, but the remaining 83 percent are not interested in trying, until they see a practical benefit (Rogers, 1999, p. 8).

External barriers fall into three categories: *Availability and accessibility,* including limited access to useful, relevant, and appropriate software and hardware; *institutional and technical support,* as the lack of encouragement and funding from the administration, and the limited number of technical support staff to assist on maintenance and teacher assistance; *and stakeholder development,* as the lack of a training program for specific teacher, student, and staff needs.

Two studies at the K-12 and higher education levels confirmed what Rogers (1999) had found in the literature: She identified three external barriers: (1) availability and accessibility, (2) stakeholder development, and (3) technical support, and one internal barrier (teacher's attitudes and perceptions) to technology adoption. The following representation is an adaptation of her model:

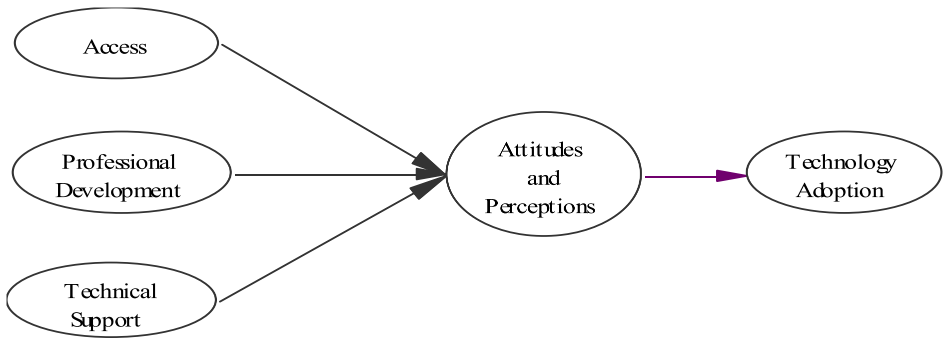


Figure 3. Model of technology adoption based on Rogers (1999).

An important assumption of this model is that the external and internal barriers affect each other, but the major barrier to technology adoption is internal (Rogers, 1999, p. 19). Another important assumption is the need to understand and measure the level of technology adoption by teachers, as a necessary first step in understanding barriers to technology adoption. Her contention, partially supported by the data, is that barriers become less relevant as the level of technology adoption increases from familiarization, to utilization, integration, and reorganization (Rogers, 1999, p. 21).

The Will, Skill, Tool Model of Technology Integration

Based on a view that encompasses internal and external factors affecting technology integration, a model involving the teacher's Will, Skill, and Tool has been developing for several years (Knezek et al., 2000; Knezek, Christensen, & Fluke, 2003; Hancock, Knezek, & Christensen, 2003). The entire model is broad in scope, as it includes student achievement. It is assumed that student achievement is affected by technology integration, which in turn is affected by the teacher's attitudes and dispositions (Will), abilities (Skill), and access to technology (Tool). The complete model can be referred as the structural WST model, whereas the teacher part of the model can be referred as the WiSTTI model (Will, Skill, and Tool for Teacher Integration). The present study will be devoted solely to the teacher part of the model. A representation of the WiSTTI model is:

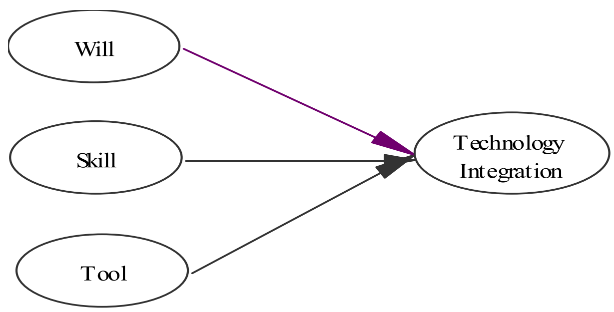


Figure 4. Teacher part of the WST model of technology integration (WiSTTI model). Adapted from Knezek et al., (2000).

If compared to the former models, WiSTTI presents a synthesis of the major features and the directionality of the effects: all models present a varying form of attitudes, dispositions, and abilities, as being the most important factors affecting technology integration (also named technology use, and technology adoption). They differ in some important ways: WiSTTI does not explicitly list technical support, or openness to change as important variables to consider, and it does not give priority to the internal factors (Will) over the external factors to explain technology integration, as other models do.

One of the most appealing features of the model is its simplicity. As a product of multiple observations and testing of different factors that appear to be important for technology integration, Knezek and Christensen have come to the point where reduction was necessary, and only a few of those components have remained as the most important and sufficiently comprehensive in their meaning. Therefore, the model Will, Skill, Tool is an example of "grounded theory", where each variable has undergone multiple testing through different hypotheses, in order to become part of the theoretical model. Only those three key factors have appeared over and over again as important determinants of a resulting technology integration experience.

The Combined Effect of Will, Skill, and Tool

Will and Skill are psychological constructs that must be defined within an educational framework. *Will* may be conceived as a "self-actualized state of motivation, an internal self-generated desire resulting in an intentional choice" (McCombs & Marzano, 1990). An active self is behind the will, in that the former acts as an "agent" of motivation and behavior. Self agency is in operation when individuals self-select and define those external influences that appear most nurturing of self, through intentional choices that are guided by positive feelings and desires (McCombs & Marzano, 1990, pp. 53-54). On the other hand, *Skill* may be defined as "an acquired cognitive or metacognitive competency that develops with training and/or practice" (McCombs & Marzano, 1990).

These variables must be interrelated within a person, to produce self-generated goals for professional development on technology. The awareness of a personal stage of technology mastery, and a self-determined teaching goal of becoming a "better teacher", may trigger the motivation to move forward to a new stage, thought of as a new desired self-actualized state. Therefore, awareness of a personal skill may influence the will to move forward to a new, more advanced skill. If awareness of the person's own skill is accompanied by the provision of additional aid, such as training and access to technology for immediate use, motivation may be enhanced, and become a powerful force for change. Although *Will* is the motivation force that impels the person to move forward, it is not activated by chance, but by a self-directed goal derived from the awareness of the person's own skill, and the provision of aids to accomplish the desired goal.

The Will, Skill, Tool model relies on the interrelation of these constructs to explain technology integration. Each element contributing to the model is an important piece of machinery to produce the resulting integration. They can be viewed as necessary forces to integrate technology, and contribute to strengthen the model. It has been empirically demonstrated the additive power of each one of the model elements by measuring the effect of Will (40%), then the effect of Will and Skill combined (70%), and finally the effect of Will, Skill, and Tool combined (84%) on technology integration (Knezek et al., 2000).

Recent Investigation on the Will, Skill, Tool Model

A particular study testing the model Will, Skill, Tool needs to be detailed at this point, since it was important for the planning of the present study. Information and excerpts were taken from Morales (2005a).

Data collected in 2003 and 2004 from elementary, middle school, and high school teachers from several school districts of Northern Texas as well as students from the University of North Texas were used as the basis for the model testing, using structural equation modeling (SEM) as the method of analysis.

Hoyle (1995, p. 1) defines SEM as "a comprehensive statistical approach to testing hypotheses about relations among observed and latent variables". In this study, the latent variables were the constructs Will, Skill, Tool, and Integration, whereas the observed variables were the measures associated with each construct, as it is depicted in the following theoretical model:

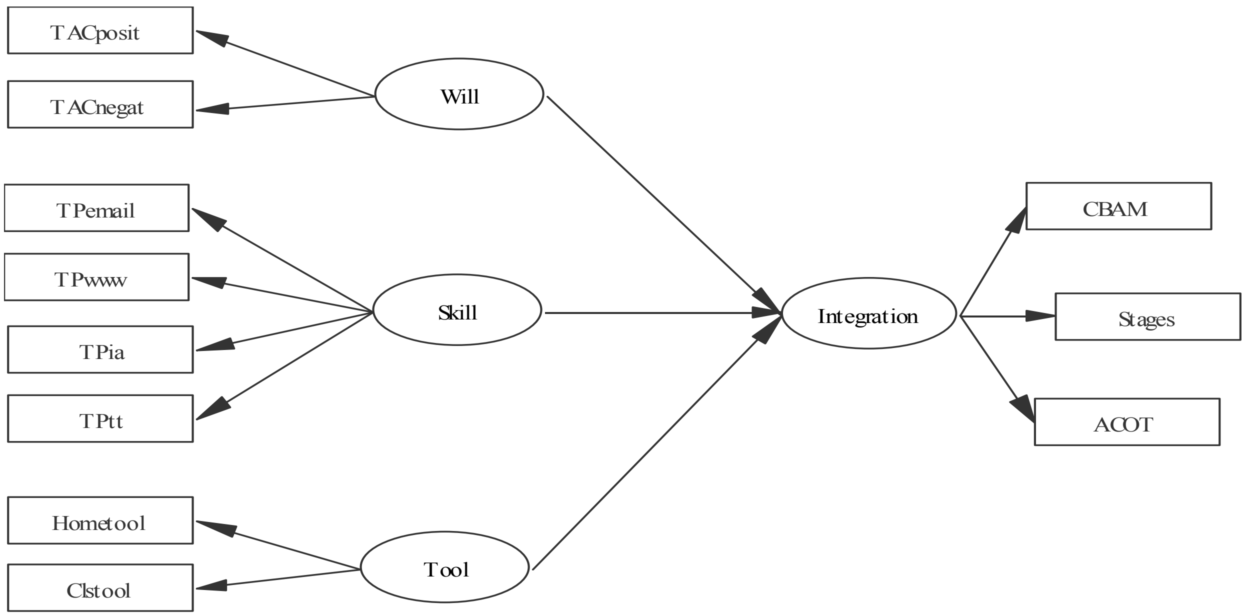


Figure 5. Basic structure and measures associated to test the Will, Skill, Tool, and Integration model from Morales (2005a).

The model depicted in Figure 5 contains two parts: the oval-shaped constructs in the central area, which are called the *structural model* (the latent variables Will, Skill, Tool, and Technology Integration), and the rectangle-shaped indicators in the outer area, called the *measurement model*, which consists of the subscales and composites from the Teachers' Attitudes toward Computers, the Technology Proficiency Self-Assessment, the Stages of Adoption of Technology, the Concerns-Based Adoption Model-Levels of Use of an Innovation, the Apple Classroom Of Tomorrow Teacher Survey, and direct questions comprising the indicators Hometool and Clstool.

Two research questions were studied by Morales (2005a): "Is the Will, Skill, Tool model of Technology Integration supported by data from different populations? Is there a differential effect of Will, Skill, and Tool on Technology Integration?"

The basis for the SEM analysis is a variance-covariance matrix obtained after all the variables from the measurement model are correlated. Each one of the samples and sub-samples provides a single variance-covariance matrix, thus, in the case of the Morales (2005a) study, ten different testing opportunities were provided for the model (see Table 1). On the other hand, the search for the best solution to the theoretical model becomes essential in SEM analysis, therefore a solution implies testing and re-testing the model through different variance-covariance matrices, until a single solution is found. In the Morales (2005a) study, the best solution found is depicted in Figure 6.

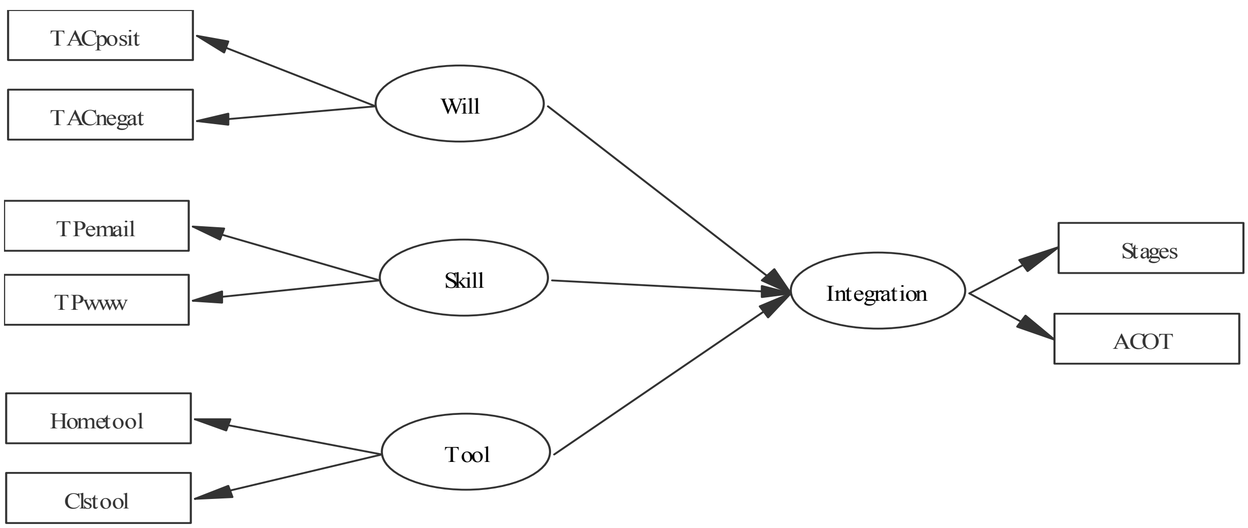


Figure 6. Resulting model for elementary through high school teachers from Texas, and student teachers from the University of North Texas (Morales, 2005a).

Although the structural model stayed intact, the measurement model changed, as some of the measures disappeared. This model was also considered the most parsimonious, since only two measures were attached to each latent variable. The results also showed a differential effect of Will, Skill, and Tool on technology integration, as it is presented in Table 1.

Table 1

Technology Integration in Different Education Levels as Predicted by Will, Skill, and Tool (Morales, 2005a)

Sample	District 1 2003	District 1 2004	District 2 2004	UNT
All Grade Levels	W= .045 S= .178 T= .610 Totvar= .834	W= .092 S= .333 T= .371 Totvar= .797		
Elementary	W= .288 S= .203 T= .267 Totvar= .758	W= .381 S= .124 T= .186 Totvar= .691		
Middle School	W= .068 S= .228 T= .498 Totvar= .794	W= .098 S= .330 T= .212 Totvar= .641		
High School	(No possible solution was found)	W= .006 S= .316 T= .377 Totvar= .699	W= .202 S= .486 T= .023 Totvar= .712	

(table continues)

Table 1 *(continued)*

Sample	District 1 2003	District 1 2004	District 2 2004	UNT
Preservice				W= .153 S= .247 T= .009 Totvar=.409

As shown in Table 1, the model worked better in elementary through high school environments, where the total variance explained by Will, Skill, and Tool ranged from 64% to 83%, whereas for preservice teachers, the variance explained by the model was only 40%. Furthermore, the relative weight of each variable was different, depending on the grade level, and also on the amount of technology available, since it was known that high school teachers from District 2 had more technology available, at least for their students, compared to teachers in District 1.

While the results of the Morales (2005a) study were interesting, a number of problems had to be addressed in this study, mainly due to the use of SEM as the only method of analysis. These drawbacks were discussed within the framework of Loehlin's (1987) "six caveats", five of which were directly related to the validity and reliability of the model resulting from the study:

1. Finding a good model fit does not mean that we have the best possible one. There is no doubt that the incorporation of additional variables, or the removal of some of them would change the solution. In this case, it took the testing of at least 60 different models to reach a fairly good solution, still with no model fit for most of them.

2. Latent variables depend on actual measures to develop into something meaningful. But, what is the limit for the number of indicators (measures) to define a latent variable? When is this variable 100% well defined? At least, we need the most valid and reliable measures, because for any model, there must be many other highly reliable indicators (measures) that may be part of the same variable. In the case of this study, the measures for Tool were highly unreliable, and should be replaced by more consistent measures, resembling more the scales used for Will, and Skill.
3. Once the model has been modified, its condition is always precarious. It only holds for the sample from which the data were drawn. If it holds for another sample of the same population, then the model might be legitimate. In this study, any promising model was tested until it failed for more than two samples. The last model held for all samples, except one (high school teachers from District 1 - 2003).
4. With these models, there is always a matter of "if". If all assumptions and conditions from the SEM methodological approach in the five basic steps of model specification, identification, estimation, fit, and modification are met, the resulting model can be trusted. As Loehlin (1987, pp. 216-217) demonstrated, a model can work well under an assumption of a latent dependent variable, and still work well if an independent latent variable is converted into the dependent variable. In Morales (2005a), the latent variables remained the same throughout the testing, but some of the measurement variables originally from the *x* (independent variable) side of the equation (Tpia, and Tptt from Skill) worked better for the *y* (dependent variable) side of the equation (Integration). This fact brought into the discussion the plausibility of integrating into the resulting model other variables and their relationships, when they are found to be important, such as those

portrayed in Roger's (1999) model previously shown. The possibility that Tool and Skill also determine the Will to use technology, and that technical support play a role in the Tool part of the model, was also discussed.

5. When latent variables are explored, large samples are the best choice. Correlation is affected by sample size, thus, some authors argue that under the best conditions, at least ten cases for each variable in the measurement model should be required (Schumacker & Lomax, 1996, p. 20). On the other hand, Chi-Square, as an index for model fit is also sensitive to sample size, with large samples standing a better opportunity to fit. Thus, no rule of thumb exists for sample size, but less than 100 cases to test a latent variable model would not be advisable. In the case of the Morales (2005a) study, samples were all above 100 teachers.

In summary, many different approaches to technology integration have been described in the literature with alternative approaches hypothesizing different collections of essential conditions as well as internal versus external barriers and/or concerns that must be overcome. The primary model chosen for testing in the cross-cultural context of this study is the Will, Skill, Tool Model of Technology Integration (Knezek et al., 2000) which is a "grounded theory" model based on the minimal components the authors have found to be essential conditions for integration across numerous studies. Other models that have a strong conceptual rationale and/or a published credibility base were also tested for goodness of fit to the existing data. Procedures for carrying out these tests will be described in the next chapter.

CHAPTER 3

METHODOLOGY

Need for Replication

This study is a replication of the study of the Will, Skill, Tool Model conducted in 2004 (Morales, 2005a), described in the literature review section. According to Gall, Gall, and Borg (2003), studies need to be replicated before the scientific community accepts the results as valid. Furthermore, "the need for replication is even more critical in education and other social science disciplines, because studies often have weaknesses in methodology or very limited generalizability" (Gall et al., p. 42). The call is to replicate in order to improve the original results, thus, the replication actually becomes an "extension" of the original study. Gall et al., (pp. 42-44) discuss five types of extensions, two of them important for the present study. The two main reasons to conduct a replication for the testing of the Will, Skill, Tool Model were:

1. "To check the validity of research findings across different populations" (Gall et al., 2003, p. 42). Although the samples of the previous study were large (more than 1000 teachers in two consecutive years), the populations belonged to the same cultural background. The intention for a replication (extension) was to cross-culturally validate the model, using the point of view of teachers from Mexico. Attending to the results of the referred study, it was believed that the reduction of the range of educational levels included in this study to only elementary and middle school could bring more control over the populations involved (in Mexico compulsory education ranges from grade 1 to grade 9, encompassing elementary and middle school), thereby enhancing the feasibility of finding the best model for these populations. Precautions were also taken in order to ensure the equivalence of the measures administered across populations.

2. "To check important findings using different methodology" (Gall et al., 2003, p. 43). As important as they are, results from the 2004 study were marked by what Loehlin, (1987, p. 216) calls "precarious" condition, until the model could be tested on a new set of data that were not part of the adjustment. It is in this regard, and also after the literature review, that the following changes in the methodology were introduced.
    - To control for generalizability, only teachers from elementary and middle school in Mexico City were invited to participate in the study. The comparison data were collected in 2004 from a Texas School District in the Dallas-Fort Worth Metroplex area.
    - To include relevant variables found in the literature for the model, a measure on openness to change (attached to the construct Will), and a measure on technical support, as well as the number of hours using the computer to prepare classes (for measuring the construct Tool) were added to the survey.
    - To avoid a unilateral testing of the model due to the sole use of structural equation modeling and its constraints, not always compatible with the use of real world data, other methods of data analysis (path analysis, factor analysis, and multiple regression) were introduced in this study to provide a more solid basis for the results.

Instrumentation

The variables Will, Skill, Tool, and Technology Integration were measured through a series of instruments and direct questions to the teachers. To analyze the variable *Will*, two measures were employed:

1. Teachers' Attitudes toward Computers (TAC). Version 6.1.

Likert type scale with nine subscales and 54 items. Developed by Christensen and Knezek (1996) from the University of North Texas. This extensively validated measure has undergone a parsimonious phase, which resulted in a shortened version. Validation of version 6.1 is presented in Table 2.

Table 2

Reliabilities for TAC 6.1 Subscales (Christensen & Knezek, 2001a, p. 74)

Subscale		Alpha	No. of items	*N*
Part 1	Interest	.92	5	300
Part 2	Comfort	.92	5	306
Part 3	Accommodation	.86	5	304
Part 4	Email	.94	5	303
Part 5	Concern	.90	8	297
Part 6	Utility	.92	8	299
Part 7	Perception	.97	5	293
Part 8	Absorption	.88	5	304
Part 9	Significance	.89	5	302

Although the TAC has been validated in Mexico (Morales, González, Medina, & González, 2000), the resulting 6-subscale version was clearly different from the 9-subscale version administered to the samples in Texas. Therefore, it was not considered for the present replication. Nevertheless, the wording of particular items in Spanish was taken from the previously validated version in Mexico.

2. Openness to Change.

A five-item Likert type scale was developed by Vannatta and Fordham (2004) from Bowling Green State University, as a subscale of the "Teacher Attribute Survey". Openness to change was defined as the "willingness to take risks and learn from mistakes". The reported alpha for the subscale was .69, and it was administered to 177 K-12 teachers.

No validation of the Openness to Change measure is known in Mexico, thus, the resulting alpha is reported in this study. The measure was partially modified for its presentation to teachers in Mexico: The original six-point scale was reduced to a five-point scale, to assure a similar range of perception to other Likert type scales administered in this study. It was administered to 100 elementary and middle school teachers (see results of the pilot study in Appendix A.)

3. To measure the variable *Skill*, the Technology Proficiency Self-Assessment (TPSA) was employed.

This is a Likert type scale with 20 items distributed in four subscales. It was developed by Ropp (1999) from Michigan State University. Subscale reliabilities for Texas teachers, as reported in Christensen and Knezek (2001a), are presented in Table 3.

Table 3

Reliabilities for TPSA Subscales (Christensen & Knezek, 2001a, p.37)

Subscale	Alpha	No. of items	*N*
TP Email	.73	5	426
TP WWW	.78	5	426
TP Integrated Applications	.86	5	426
TP Teaching with Technology	.87	5	426

This scale has not been validated in Mexico, therefore, the resulting alphas are reported in this study (see pilot study, Appendix A.) Two of the items (# 7 – "search for and find the Smithsonian Institution Web site", and # 11 "use a spreadsheet to create a pie chart of the proportions of the different colors of M&Ms in a bag") were changed in their content to a more contextually and culturally meaningful form.

To test the variable *Tool*, two sets of items were employed. In the first set, a composite of the teacher's answers to direct questions was employed:

4. Access to computer at home, access to WWW at home, number of hours using the computer at home, number of computers in the classroom, frequency of computer use for student learning, number of hours using the computer in the classroom, number of hours using the computer to prepare classes.
5. A second set of items comprised a measure on Technical Support.

   A ten-item Likert type scale was developed for this study. The intention of the scale was to evaluate the level of technical support the teacher perceived existed in his/her school. The items were administered to 100 elementary and middle school teachers in Mexico (see results of the pilot study, Appendix A.)

To assess the variable *Integration*, three measures were employed:

6. Stages of Adoption of Technology.

   This single item measure was developed by Christensen (1997) from the University of North Texas. The stages of this self-assessment measure are: Stage 1 – Awareness, Stage 2 – Learning the process, Stage 3 – Understanding and application of the process, Stage 4 – Familiarity and confidence, Stage 5 – Adaptation to other contexts, and stage 6 – Creative applications to new contexts. Although internal consistency reliability could not be calculated because its single-item condition, test-retest reliability was superior (.91), when the scale was administered to 525 K-12 teachers from Texas in 1999 (Christensen & Knezek, 2001b).

A Spanish version of the Stages of Adoption measure was administered to middle school teachers in Mexico in 1999 and again, an adjusted version in 2000 in Mexico City (Morales, 2001a, p. 71). The latter version was employed in this study.

7. Concerns-Based Adoption Model. Levels of Use of an Innovation (CBAM-LoU).

This single item measure was adapted by Griffin and Christensen (1999) from the work of Hall, Loucks, Rutherford, & Newlove (1975). The levels of use for this self-assessment instrument are: Level 0 – Non-use, Level 1 – Orientation, Level 2 – Preparation, Level 3 – Mechanical use, Level 4A – Routine, Level 4B – Refinement, Level 5 – Integration, Level 6 – Renewal. The measure was positively related to Stages of Adoption (r = .64), as reported by Christensen and Knezek (2001b).

The measure has not been administered in Mexico, therefore, a correlation analysis between CBAM-LoU and Stages of Adoption was performed, and the resulting correlation coefficient of $r = .61$ ($p < .0005$) was computed for this study (see pilot study, Appendix A.) The content of the levels of use were simply translated into Spanish.

8. Apple Classroom of Tomorrow Teacher Survey (ACOT).

This single item measure was adapted from teacher stage descriptions developed in the midst of a long-term collaborative project between Apple Computer, Inc., public schools, universities, and research agencies, that begun in 1985 and ended in 1998. (http://images.apple.com/education/k12/leadership/acot/pdf/acotover.pdf).

The measure was the result of an in-depth qualitative research project involving 32 teachers and 650 students from four public elementary and one high school (Dwyer, Ringstaff, & Sandholtz, 1990). The results of the study supported five stages of evolution in technology integration: Stage 1 – Entry, Stage 2 – Adoption, Stage 3 – Adaptation, Stage 4 – Appropriation, and Stage 5 – Invention. The measure used in this study was adapted by T. Clark (personal communication, April 20, 2005) from the work led by Dwyer (Dwyer et al., 1990).

No report of ACOT's use in Mexico is available, thus, a correlation coefficient of r = .63 ($p < .0005$) between ACOT and Stages of Adoption is reported in this study (see pilot study, Appendix A.) The descriptions of the ACOT teacher stages were directly translated from the original in English into Spanish.

All measures, except Technical Support, Openness to Change, and some demographic questions, had been previously administered to elementary and middle school teachers from a School District of the Dallas-Fort Worth Metroplex area in 2003 and 2004. The data from 2004 were used as the Texas sample. Therefore, administration of instruments was performed solely in Mexico City.

Research Design

This was a predictive model study, involving four latent variables: Will, Skill, Tool, as the predictor variables, and Technology Integration as the criterion variable. The study aimed at identifying the best model for the data from Mexico and Texas, and determining the amount of the technology integration variance accounted for by Will, Skill, and Tool. The proposed theoretical model for testing is depicted in Figure 7.

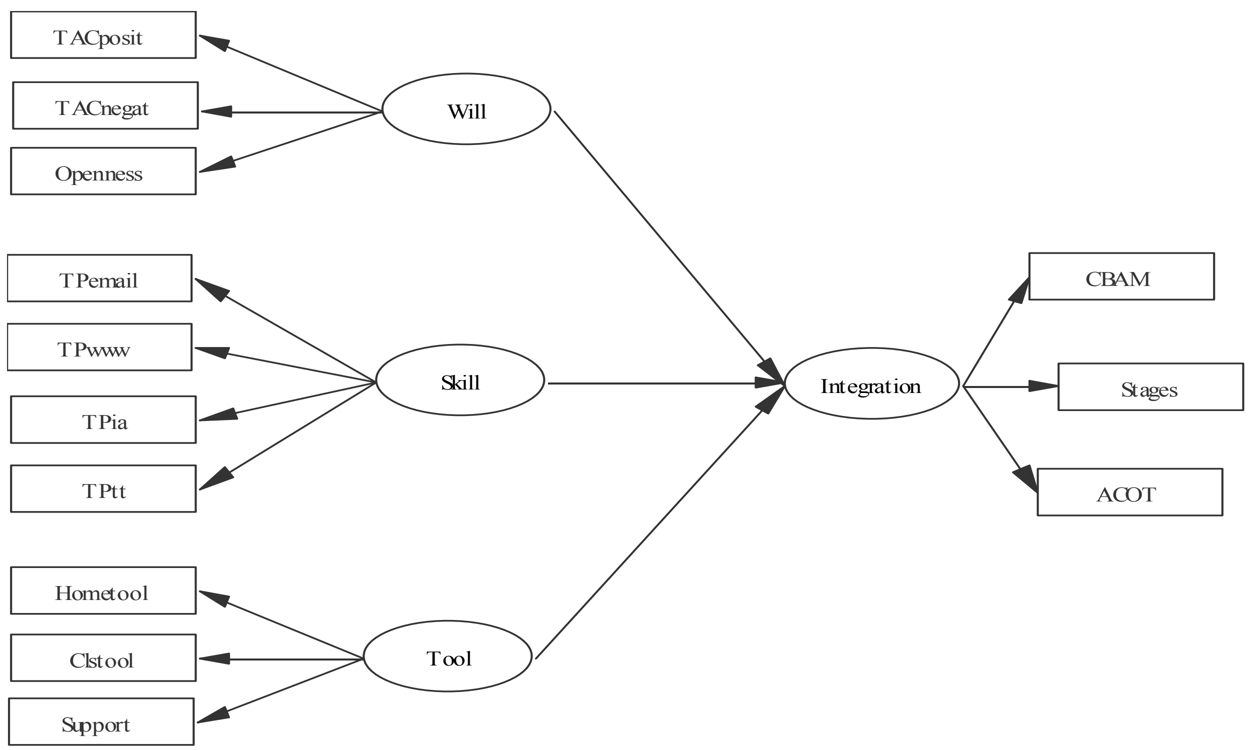


Figure 7. The structural will, skill, tool model of teacher integration (WiSTTI model), with the standard measures for each latent variable, proposed to be tested in this study.

The model depicted in Figure 7 shows two main parts: the constructs in the central part, which in structural equation modeling are called the *structural model*, comprising the latent variables Will, Skill, Tool and Integration, and the arrows indicating the direction of the influence, (i.e. Will, Skill, and Tool are the independent latent variables, influencing the latent dependent variable Integration.) The outer part of the model is called the *measurement model*, which consists of the indicators, in rectangles, comprising the measures of the latent variables, and the regression paths that connect each latent variable with their respective set of measures.

To the left, there are the *x* variables, or independent observed variables, and to the right there are the *y* variables, or dependent observed variables. The direction of the arrow is important: the variable at the end of the arrow is explained by the variable at the beginning of the arrow (Raykov & Marcoulides, 2000, p. 10), thus, Will, Skill, and Tool explain most of the variables in the model.

Correlations between all the variables from the measurement model were performed, and the association between each set of measures to the corresponding latent variable was tested. Also, the effect of each independent latent variable on the dependent latent variable was tested.

As for the origin of variable naming from the measurement model (see Figure 7), the predictor variable *Will* had three indicators attached:

- *TACposit* corresponded to five TAC subscales: TAC6 “Utility”, TAC9 “Significance”, TAC4 “Email”, TAC1 “Interest”, and TAC8 “Absoption”.
- *TACnegat* corresponded to four TAC subscales: TAC2 “Comfort (Anxiety)”, TAC3 “Accommodation”, TAC7 “Perception”, and TAC5 “Concern”.
- *Openness* referred to the measure “Openness to change”.

For the predictor variable *Skill*, the indicators were four Technology Proficiency Self-Assessment (TPSA) subscales:

- *TPemail*, Technology proficiency on Email.
- *TPwww*, Technology proficiency on World Wide Web.
- *TPia*, Technology Applications.
- *TPtt*, Teaching with Technology.

For the predictor variable *Tool*, the indicators were answers to single questions from the sociodemographics section of the survey:

- *Hometool* comprised (a) access to computer at home, (b) access to the WWW at home, (c) number of hours using the computer at home, and (d) number of hours using the computer to prepare classes.

- *Clstool* comprised (a) number of computers in the classroom, (b) frequency of computer use for student learning, and (c) number of hours using the computer in the classroom.
- *Support,* Technical Support.

For the criterion variable *Integration*, three one-item measures were selected:

- *CBAM*, Concern-Based Adoption Model. Levels of Use of an Innovation.
- *Stages*, Stages of Adoption of Technology.
- *ACOT*, Apple Classrooms of Tomorrow: Teacher stages.

Pilot Study

A pilot study was conducted to validate the measures employed in the study, and to test the feasibility of the online version of the survey. Four teacher training centers for elementary schools, and three middle schools were selected to administer the piloting survey. Detailed explanation of the pilot study results are presented in Appendix A. A brief summary of the major findings is presented in the following paragraph.

According to DeVellis' (1991) criteria there were two highly reliable measures in the pilot study data (TPSA, alpha = .96; and Technical Support, alpha = .93), four measures were "very good" (taken as a single measure, Stages of Adoption, CBAM, and ACOT resulted in an alpha = .83; and TAC, alpha = .89.) Openness to Change fell into the categories of "unacceptable" (alpha = .32), and "undesirable" (after removing two of five items, alpha = .62). Based on the results of the pilot study, the following changes to the survey were made for its use in the main study:

- Items TAC 227 ("Computers intimidate me"), TAC 280 ("The use of E-mail increases motivation for class"), and TAC 142 ("Computers are changing the world too rapidly") were eliminated.

- The measure “Openness to Change” was removed from the survey.
- Minor Spanish wording changes were performed on selected items identified by researchers.

Modification of the Theoretical Model

The removal of the measure “Openness to Change” from the study had a clear effect on the theoretical model, specifically on the number of indicators for the latent variable Will, which would be measured solely through the subscales of the TAC. The final theoretical model tested in this study is shown in Figure 8.

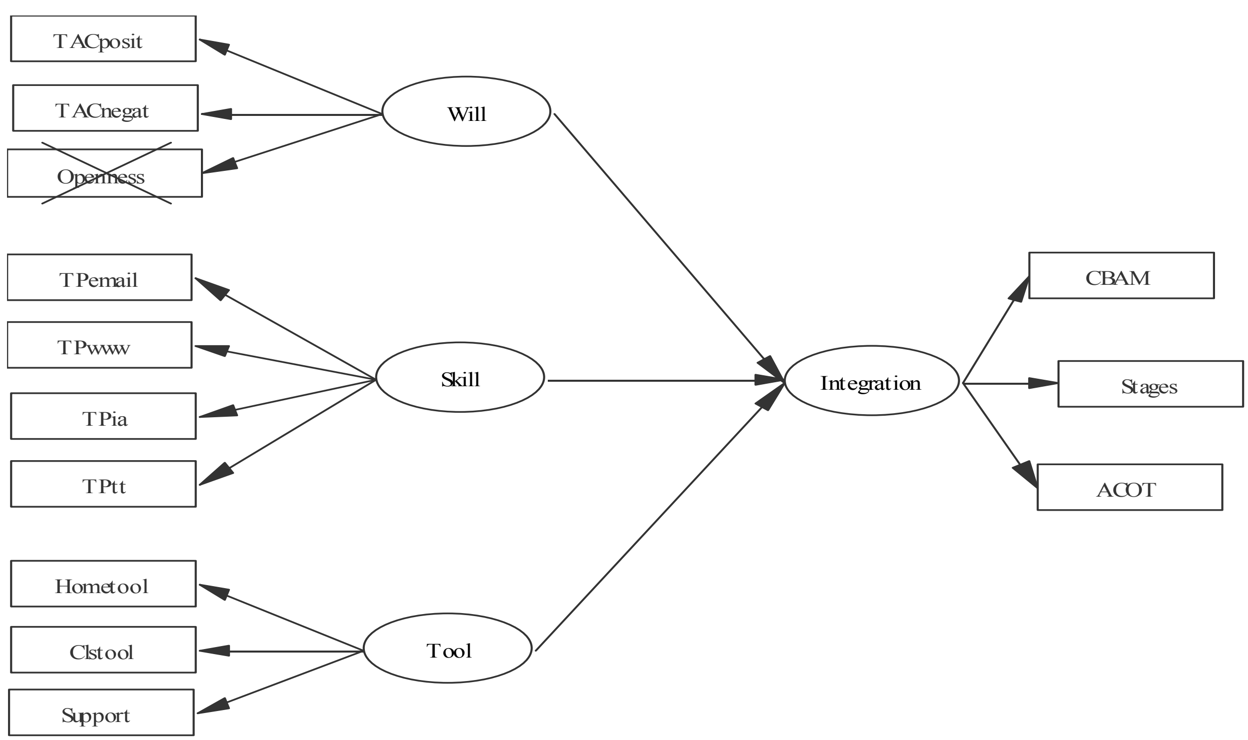


Figure 8. Resulting theoretical model after the pilot study.

As shown in Figure 8, the model that was actually tested resembles the one in Figure 7, except that the Openness to Change measure was removed from the model. It was also removed from the survey administered to the samples.

Selection of Schools and Samples

Selection of participating schools in Mexico City followed a set of procedures. The conditions for selecting a school were:

- To be a public school.
- To have a model of technology use for learning.
- To have access to the Internet

According to the Annex to 911 Questionnaire (2005) database for the school year 2003-2004, there were 720 primary schools, and 167 middle schools in Mexico City with those characteristics. In order to match the samples from Texas (612 elementary school teachers, and 320 middle school teachers), a total of 69 elementary schools, and 26 middle schools were needed, considering a faculty of 8.9 teachers per elementary school and 12.5 teachers per middle school.

A randomized procedure was followed to select the schools. Nevertheless, in the case of middle schools, Ministry of Education officials sanctioned the school selection by recommending the replacement of some schools for other more "convenient" ones, and at the same time, ensuring the participation of all political districts in the City, by selecting at least one school from each district. In the case of elementary schools, the random selection was disregarded by Ministry of Education officials, who recommended that the survey administration was conducted at five teacher training centers scattered throughout the City. Different cohorts of teachers participating in a major technology program called "Enciclomedia" gathered in those training centers on Saturdays throughout May 2005, and week days in July 2005, and a time slot was scheduled for the survey during the training sessions.

Thus, due to the selection of survey administration sites, the sample selection procedure was what has been called "convenience sampling" (Gall et al., 2003, pp. 175-176). All teachers available at selected schools and training centers were surveyed. Subjects were the most "convenient" to reach.

The school district that hosts the sample from Texas is located in a suburban area of the Dallas-Fort Worth Metroplex, with a high proportion of White teachers (86%), although only 33% of the students are also White. Furthermore, 41% of the students are Hispanic, but only 8.4% of the teachers are Hispanic. Twelve of the 38 schools in the district have 50% or more of their students on free or reduced lunches, and 22.9% of the families are Limited English Proficient. Teachers reported an average 10 years of experience in teaching, and 73% of the students met the standards for the Texas Assessment of Knowledge and Skills (TAKS) in 2004, a higher percentage compared to the State (68%) (Texas Education Agency, 2004).

Prior to any coding, or data processing, sample sizes were as follows:

- 413 elementary school teachers from Mexico City, all surveyed on site.
- 565 middle school teachers from Mexico City, 15% of them surveyed online.
- 612 elementary school teachers from Texas, all surveyed online.
- 320 middle school teachers from Texas, all surveyed online.

Data Collection

The Instituto Latinoamericano de la Comunicación Educativa (ILCE) provided the Web site, developed the database for data collection, and shared trained personnel to administer the survey. Research assistants met teachers at the site and explained the purpose of the project, introduced teachers to the survey, and detailed the answering procedure.

In consultation with the school technology coordinator, research assistants prepared the group of teachers for either answering the survey online, or on paper. Research assistants remained at the school campus until all teachers scheduled to answer the survey were finished. The main function of research assistants at that time was to ensure that all teachers understood the questions and the answering procedure, and solving any unexpected problems, especially with the online survey.

Instruments were administered on May 11 – July 8, 2005, with two different sets of dates for elementary schools, and for middle schools: Survey administration for elementary schools was conducted on May 14, May 21, May 28, and July 4-8 at five teacher training centers distributed across the city. Administration to middle schools was conducted on May 11-26 at school campuses.

Data Analysis

Data analysis was a major issue for the 2004 study (Morales, 2005a) intended to be replicated here. Discussion of the results showed particular problems for using structural equation modeling (SEM) as the only method of analysis. Real world data are difficult to confine as error-free, especially when the error is large in the original data set. This, and other necessary constraints for SEM, left inconclusive results regarding model fit in the earlier study. The goodness-of-fit analysis, important to SEM for finding the best model fit, showed that the theoretical model was different from the measurement model. Although it was clear that the measurement model (the composition of the measures attached to the four latent variables, Will, Skill, Tool, and Integration) had to be adjusted to yield better results, it was concluded that perhaps the use of SEM along with other statistical tools could have yielded clearer results.

Therefore, for this replication, a number of precautions regarding data analysis were taken:

1. All data were carefully coded and screened.
2. Four statistical methods were employed: Factor analysis, multiple regression, path analysis, and structural equation modeling.
3. All variables involved were subjected to an exploratory factor analysis, initially with a maximum likelihood method of extraction and oblimin rotation. However, a principal components method of extraction, and varimax rotation eventually proved to be better to determine the general tendency of variable clustering.
4. Composite variables using various subscales, and combinations of raw scores into variables were derived, when necessary. Subscales positive to the computer from the TAC resulted into the composite "TACposit", whereas subscales negative to the computer from the TAC resulted into the composite "TACnegat". On the other hand, the variables "Hometool" and "Clstool" resulted from a combination of raw scores, derived from dichotomous questions, as well as other categorical questions.
5. Following recommendation from Schumacker and Lomax (1996, p. 48), confirmatory factor analysis was performed to test whether a set of indicators (variables) effectively defined the constructs Will, Skill, Tool, and Integration, and also to assess the reliabilities of the variables.
6. All variables were searched for extreme skewness and kurtosis. Any skewness higher than 3.00 and kurtosis higher than 21.00 were unacceptable (Byrne (1998, p. 198). No indicators were adjusted or removed due to skewness and/or kurtosis parameters.

7. Regression analysis was performed for each of the criterion measures (Stages of Adoption, CBAM, and ACOT) to examine the variance that accounted for by each of the predictor measures (TAC, TPSA, Questions on access and extent of use of technology).
8. In performing the regression analysis, an additional query was the search for collinearities, and outliers. Any outlier greater than 3 standard deviations was removed. Three to five were deleted from the data sets from Mexico City as outliers. No outliers were found among the samples from Texas.
9. A correlation analysis was performed (bivariate Pearson correlation, or tetrachoric correlation), with a listwise deletion. The covariance matrix obtained was basic input for structural equation modeling analysis.
10. A structural equation was obtained for each sample or subsample analyzed, with an *R* square for technology integration as the total variance for the model, and Betas for Will, Skill, and Tool, as the basis to calculate the variance accounted for each predictor measure.
11. The Chi-square goodness-of-fit index was used to test the equivalence or non-equivalence of the structural model to the measurement model (i.e. the statistical correlation of the latent-variable theoretical model and the statistical model constructed with the data analyzed).

The analysis procedure detailed above was conducted to answer the research questions, as they imply model testing techniques. Summarizing, the data analysis techniques and procedures used in this study were divided into three categories:

- *For the total sample*. Data screening, exploratory factor analysis, production of composite scores, confirmatory factor analysis, and multiple regression.
- *For particular samples*. Bivariate correlation, path analysis, structural equation modeling, and tests of model significance (Chi-square goodness-of-fit index, standardized partial regression coefficients [Beta], and squared multiple regression coefficients [R^2]).
- *Hypotheses testing*. Two-way factorial ANOVA, and multiple regression with three independent variables.

All data analysis was performed using two statistical packages: SPSS 10.0, and LISREL 8.54.

Protection of Human Subjects, Sponsorship, and IRB Approval

Participants were adults to whom researchers explained the purpose of the study, emphasizing the importance of their participation to clarify the issue of technology integration in the school. An informed consent statement that included their voluntary participation and their right to withdraw from the study at any time was handed to teachers. Researchers made also clear that no harm, psychological or physical, was expected as a result of their participation in the study.

For the completion of this study, the researcher requested an endorsement from the Instituto Latinoamericano de la Comunicación Educativa (ILCE), as an institution with professional experience in the conduction of surveys in educational settings, and with the necessary relations with the Ministry of Education in Mexico City to ensure the feasibility of the survey administration. To ensure the anonymous participation of the subjects, each one of the surveys was coded, and written paper and pencil surveys as well as the first spreadsheet obtained from the online survey were secured and stored at ILCE.

The Institutional Review Board (IRB) at the University of North Texas approved the research proposal for the present study on April 6, 2005 (see Appendix B). Data collection started after the IRB approval. There is a possibility that the data generated by this study could be used for further research at ILCE.

CHAPTER 4

RESULTS

Sociodemographics

Participating teachers were numerous ($N = 1910$), and the total sample for each culture was nearly equivalent. Table 4 shows the distribution of the samples.

Table 4

Distribution of Samples from Texas and Mexico City

Grade Level	Texas	Mexico City	Total
Elementary	612	413	1025
Middle	320	565	885
Total	932	978	1910

Although the raw numbers indicate high *N*s for data analysis, missing values reduced considerably some of the samples for particular analyses (37%, and 39% missing for elementary and middle school teachers from Mexico City, respectively.) Table 5 shows the frequencies on access to technology, and technology use for each group of teachers involved in this study.

Table 5

Access to Technology and Technology Use by Sample

Sample	Home Computer	Home WWW	Classroom Computer	Home Hours	Classroom Hours	Frequency
Texas Elementary	571 $N = 612$ 93.3%	552 $N = 612$ 90.2%	561 $N = 604$ 92.9%	2-3 hrs.	4-7 hrs.	Weekly

(table continues)

Table 5 *(continued)*

Sample	Home Computer	Home WWW	Classroom Computer	Home Hours	Classroom Hours	Frequency
Texas Middle	301 *N* = 320 94.1%	294 *N* = 320 91.8%	209 *N* = 311 67.2%	4-7 hrs.	4-7 hrs.	Weekly
Mexico City Elementary	306 *N* = 412 74.3%	183 *N* = 405 45.2%	165 *N* = 413 39.9%	1 hour	2-3 hrs.	Occasion
Mexico City Middle	462 *N* = 559 82.6%	294 *N* = 553 53.2%	47 *N* = 565 8.3%	2-3 hrs.	1 hour	Occasion

Note: The meaning of the main categories are: Home Computer = Access to computer at home; Home WWW = Access to Internet at home; Classroom Computer = Access to computer in the classroom; Home Hours = No. of hours using the computer at home; Classroom Hours = No. of hours using the computer in the classroom; Frequency = Frequency of computer use for learning.

Table 5 shows a 12%-20% difference in computer access at home, and a 39%-47% difference in Internet access at home between teachers from Mexico City and Texas, favoring the latter group, whereas the difference in access to a computer in the classroom was 53% for elementary school teachers, and 59% for middle school teachers, with the higher percentages for Texas teachers.

Teachers in Texas were likely to spend up to 7 hours using technology at home or school on a weekly basis, whereas teachers in Mexico City reported up to 3 hours using technology at home or school on a more occasional basis.

Technology Integration Profile

Technology integration was measured through a composite of three measures, Stages of Adoption, CBAM, and ACOT, across seven groupings of data: Cross-Cultural sample, Texas sample, Texas Elementary School Teacher sample, Texas Middle School Teacher sample, Mexico City sample, Mexico City Elementary School Teacher sample, and Mexico City Middle School Teacher sample. The resulting measure comprised six levels of technology integration, similar to those defined for Stages of Adoption. Table 6 shows frequencies, and relative frequencies along six integration levels. Figures 9 to 15 graphically show the profiles corresponding to each sample.

Table 6

Frequencies and Relative Frequencies of Technology Integrators at Six Integration Levels in Seven Samples

Sample	Integr 1	Integr 2	Integr 3	Integr4	Integr5	Integr 6	Total
Cross-Cultural	48 (2.7%)	239 (13.3%)	313 (17.4%)	506 (28.2%)	567 (31.6%)	122 (6.8%)	1795 (100%)
Texas	2 (.2%)	22 (2.4%)	109 (11.8%)	285 (30.9%)	421 (45.6%)	84 (9.1%)	923 (100%)
Texas Elementary	2 (.3%)	9 (1.5%)	67 (11.1%)	204 (33.8%)	277 (45.9%)	45 (7.5%)	604 (100%)

(table continues)

Table 6 *(continued)*

Sample	Integr 1	Integr 2	Integr 3	Integr4	Integr5	Integr 6	Total
Texas Middle	0 (0%)	13 (4.1%)	42 (13.2%)	81 (25.4%)	144 (45.1%)	39 (12.2%)	319 (100%)
Mexico City	46 (5.3%)	217 (24.9%)	204 (23.4%)	221 (25.3%)	146 (16.7%)	38 (4.4%)	872 (100%)
Mex City Elementary	15 (4.0%)	116 (31.2%)	89 (23.9%)	84 (22.6%)	55 (14.8%)	13 (3.5%)	372 (100%)
Mex City Middle	31 (6.2%)	101 (20.2%)	115 (23.0%)	137 (27.4%)	91 (18.2%)	25 (5.0%)	500 (100%)

Note: The integration levels resulted from a composite of Stages of Adoption, CBAM, and ACOT.

As shown in Table 6, highest frequencies for the Texas sample and the Cross-Cultural sample tended to be concentrated in levels of integration 4 and 5, whereas highest frequencies for the Mexico City samples tended to be concentrated in levels of integration 2, 3, and 4.

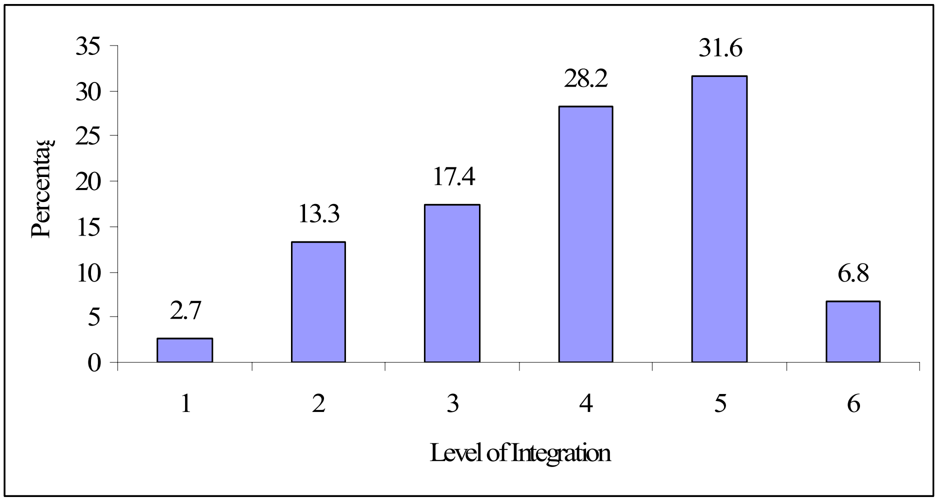


Figure 9. Integration profile for elementary and middle school teachers from Texas and Mexico City.

Considering that Mean = 3.93, and Median = 4.00, the distribution was negatively skewed, but skewness value was small (-.415).

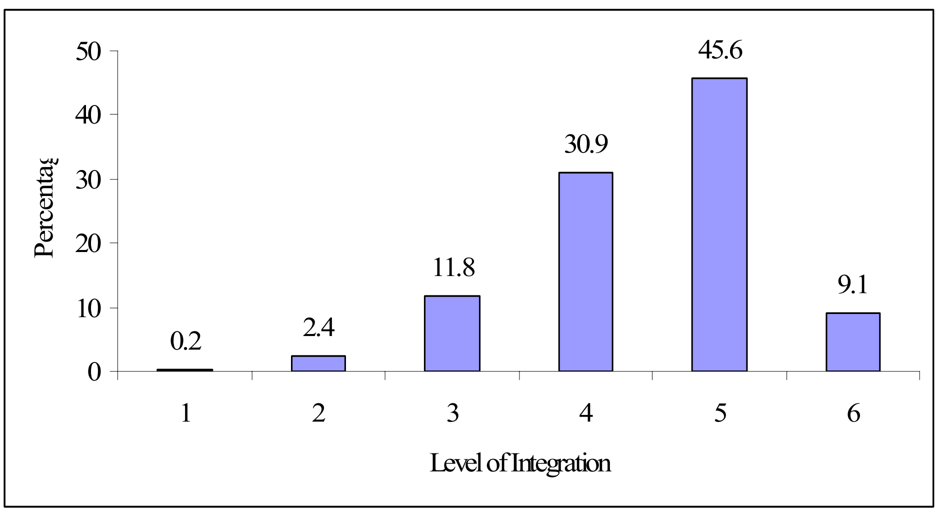


Figure 10. Integration profile for elementary and middle school teachers from Texas.

Considering that Mean = 4.46, and Median = 5.00, the distribution was negatively skewed, but skewness value was small (-.593).

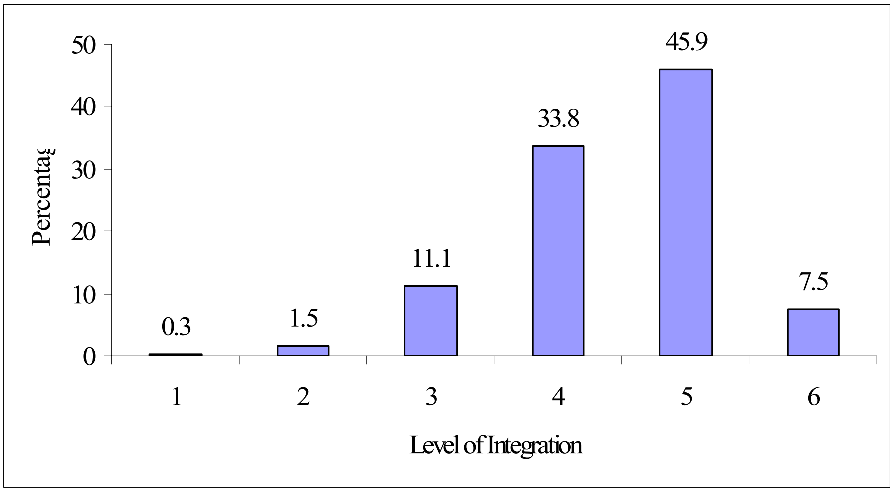


Figure 11. Integration profile for elementary school teachers from Texas.

Considering that Mean = 4.46, and Median = 5.00, the distribution is negatively skewed, but skewness value was small (-.598).

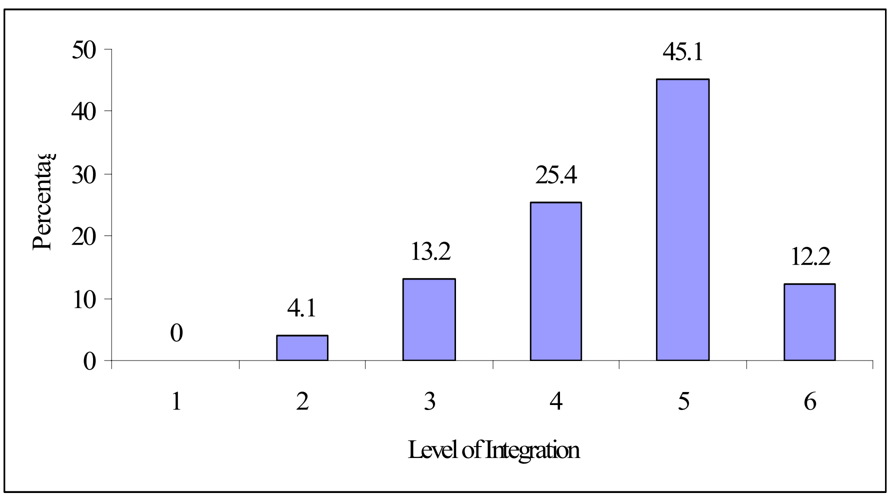


Figure 12. Integration profile for middle school teachers from Texas.

Considering that Mean = 4.48, and Median = 5.00, the distribution was negatively skewed, but skewness value was small (-.593).

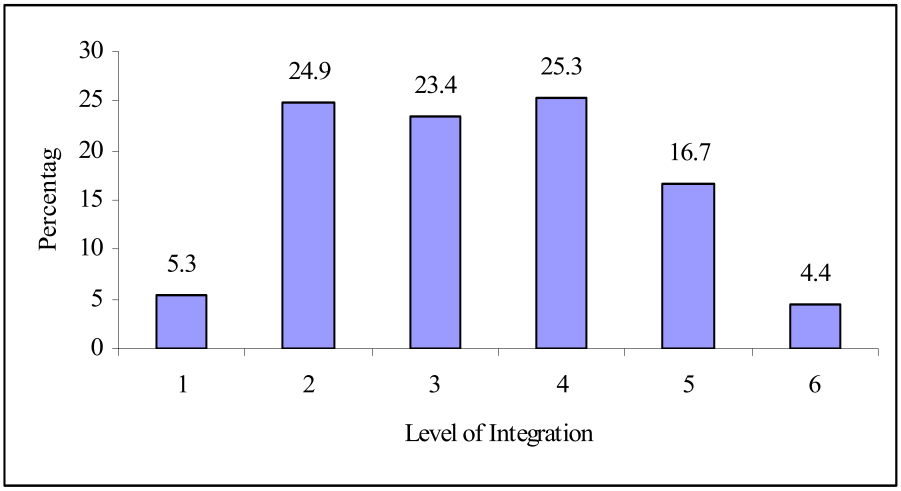


Figure 13. Integration profile for elementary and middle school teachers from Mexico City.

Considering that Mean = 3.36, and Median = 3.00, the distribution was positively skewed, but skewness value was small (.121).

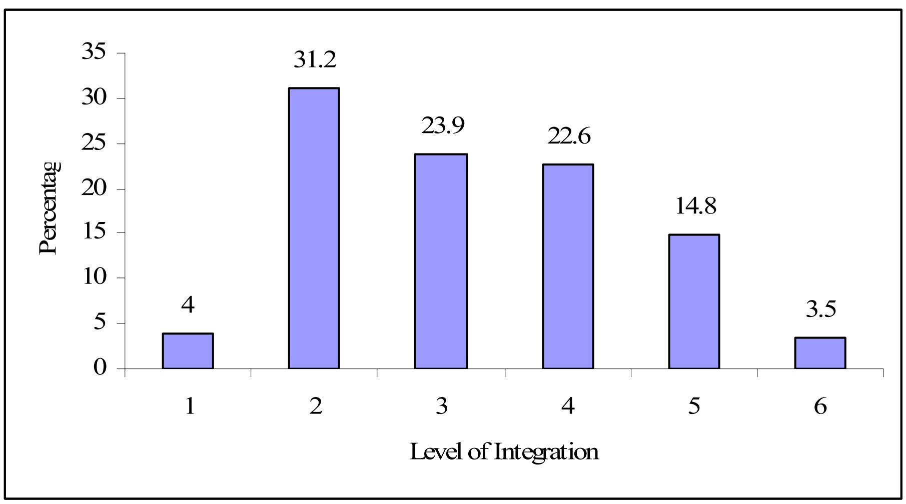


Figure 14. Integration profile for elementary school teachers from Mexico City.

Considering that Mean = 3.23, and Median = 3.00, the distribution was positively skewed, but skewness value was small (.321).

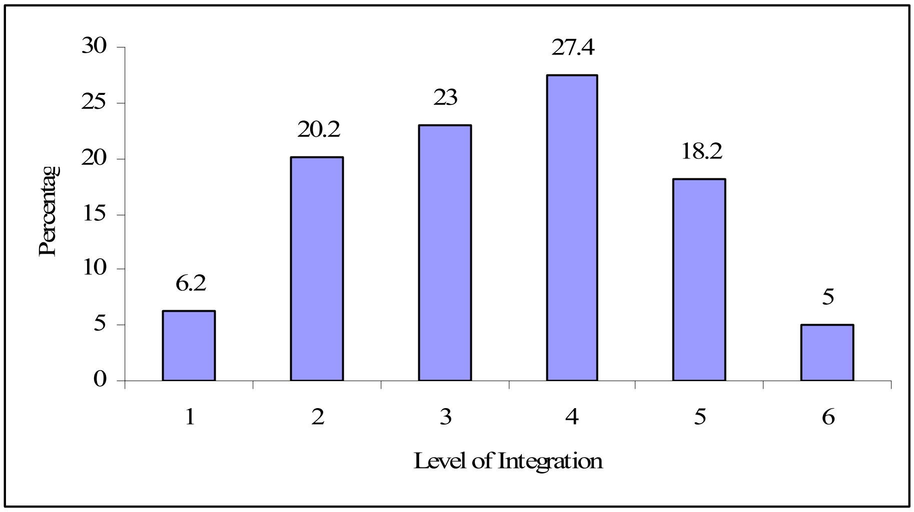


Figure 15. Integration profile for middle school teachers from Mexico City.

Considering that Mean = 3.46, and Median = 4.00, the distribution was negatively skewed, but skewness value was small (-.026).

Selection of Best Measures for the Model

Factor analysis and multiple regression were performed to explore research question 2: "What are the best indicators of Will, Skill, and Tool for technology integration?"

Factor Analysis

Exploratory and confirmatory factor analyses were performed on the data, preserving the original measures (no composites) for each variable:

Will = TAC1, TAC2, TAC3, TAC4, TAC5, TAC6, TAC7, TAC8, and TAC9.

Skill = TPemail, TPwww, TPia, and TPtt.

Tool (Texas) = Home Computer, Home WWW, Hours at Home, Hours in Classroom, # of Computers in Classroom, Frequency of Computer Use.

Tool (Mexico City) = Home Computer, Home WWW, Hours at Home, Hours in Classroom, # of Computers in Classroom, Frequency of Computer Use, Class Preparation Using Computer, Technical Support.

Integration = Stages of Adoption, CBAM, ACOT.

For the first run, no predetermined number of factors was set for the extraction, resulting in one factor for Skill, one factor for Integration, and multiple factors for Will, and Tool.

For the second run, the extraction of the measures of Will and Tool was set at two factors, resulting on some measures that would not load in any of the factors, particularly TAC4, Hours in the Classroom, and Technical Support, as shown in the following example.

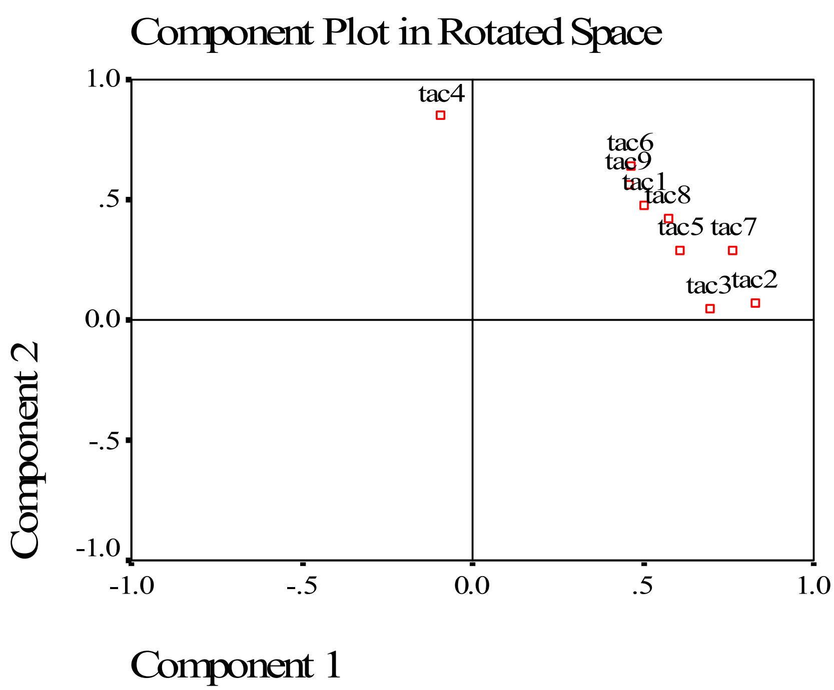


Figure 16. Loadings of TAC subscales (varimax rotated). Extraction was set at two factors.

For the third run, the extraction was set at three factors for the variables Will, and Tool. Not surprisingly, those measures that did not load in any of the previous factors but did load in a third factor this time. The overall results of the factor analysis for all the variables are shown in Table 7.

Table 7

Resulting Factors (Varimax Rotated Factor Loadings) for Four Variables Across Different Samples

Sample	Will			Skill	Tool			Integrat
	Fact 1	Fact 2	Fact 3	Factor 1	Fact 1	Fact 2	Fact 3	Factor 1
Cross-Cultural	TAC3 TAC2 TAC5	TAC8 TAC1	TAC6 TAC9	TPemail TPwww TPia TPtt	Hmcmp Hwww Hmhrs	Clshrs Clscomp	Frqlrn	Stages CBAM ACOT
Texas	TAC2 TAC8 TAC7 TAC1	TAC9 TAC6 TAC3 TAC5	TAC4	TPemail TPwww TPia TPtt	Hmcmp Hwww Hmhrs	Clscomp Frqlrn	Clshrs	Stages CBAM ACOT
Texas Elementary	TAC3 TAC9 TAC5 TAC6	TAC8 TAC2 TAC7 TAC1	TAC4	TPemail TPwww TPia TPtt	Hmcmp Hwww Hmhrs	Frqlrn Clscomp	Clshrs	Stages CBAM ACOT

(table continues)

Table 7 *(continued)*

Sample	Will			Skill	Tool			Integrat
	Fact 1	Fact 2	Fact 3	Factor 1	Fact 1	Fact 2	Fact 3	Factor 1
Texas Middle	TAC2 TAC7 TAC8 TAC1 TAC5	TAC9 TAC6	TAC4	TPemail TPwww TPia TPtt	Hmcmp Hwww Hmhrs	Clscomp Frqlrn	Clshrs	Stages CBAM ACOT
Mexico City	TAC3 TAC2 TAC5	TAC6 TAC9 TAC4	TAC7 TAC1	TPemail TPwww TPia TPtt	Clshrs Clscomp Freqlrn Prephrs	Hmcmp Hwww Hmhrs	Supprt	Stages CBAM ACOT
Mexico City Elementary	TAC9 TAC6	TAC1 TAC7	TAC5 TAC3 TAC2	TPemail TPwww TPia TPtt	Freqlrn Clscomp Clshrs	Hmcmp Hwww Hmhrs	Supprt	Stages CBAM ACOT
Mexico City Middle	TAC4 TAC6 TAC9 TAC1 TAC8	TAC2 TAC3 TAC5	TAC7	TPemail TPwww TPia TPtt	Clscomp Clshrs Prephrs	Hmcmp Hwww Hmhrs	Supprt	Stages CBAM ACOT

Note: See factor loadings in Appendix C.

As shown in Table 7, the composition of the factors for the variable Will was unique for each sample, although there was at least one regular pattern: for all the samples, TAC6 and TAC9 loaded within the same factor, and TAC2 loaded in a different factor. Table 7 also shows the factor composition for the variables Skill and Integration, with measures loading in one factor. Finally, Table 7 shows a variety of factor compositions for the variable Tool, although Home Computer, Home WWW, and Hours at home always loaded in one factor. Detailed information about factor analysis, including factor loading values, is included in Appendix D.

Regression Analysis

Multiple regression analysis was performed to answer the questions: What are the best predictors of Will, Skill, Tool, and Integration? Are the predictors the same as the best measures obtained from factor analysis?

All measures were forced to be as equivalent as possible. The first set of transformed measures was that from the variable Tool. The values from these measures were transformed into z-scores, due to the nature of the raw scores (i.e. Homecomp, Homewww, and Clscomp were categories, whereas Homehrs, Clshrs, and Freqlrn were continuous scores). After testing the overall equivalence of results yielded by *z*-scores and raw scores (see the R^2s of regression equations 1 and 2 below), it was decided to continue using raw scores in the following analyses.

Structural Equations

Raw Scores

(1)

Stages = - 0.0656*hcomp + 0.491*hwww + 0.284*hhrs + 0.275*clshrs + 0.137*clscomp + 0.0855*freqlrn, Errorvar.= 1.213, R^2 = 0.430

Z-scores

(2)

Stages = - 0.00549*hcomp + 0.165*hwww + 0.267*hhrs + 0.303*clshrs + 0.133*clscomp + 0.0576*freqlrn, Errorvar.= 0.541, R^2 = 0.449

In order to make the input data as uniform as possible, three of the measures were transformed into different scales:

- TAC7, from a 7-point scale, to a 5-point scale, conforming to the rest of the TAC subscales.
- CBAM, from an 8-point scale, to a 6-point scale, conforming to the Stages of Adoption scale.
- ACOT, from a 5-point scale to a 6-point scale, conforming to the Stages of Adoption scale.

Table 8 shows the results of the most solid measures obtained after regressing Will, Skill, and Tool, on Integration. The criterion for choosing a "strong" measure was that its standardized regression weight β was greater than 0.10.

Table 8

Strongest Measures According to the Regression Weights Obtained from Regression Analysis on Integration

Sample	Will	Skill	Tool
Cross-Cultural (N = 1444)	TAC2, TAC3, TAC6, TAC7, TAC9 R^2 = .293	TPemail, TPwww, TPtt R^2 = .370	Homewww, Homehrs, Clshrs, Freqlrn R^2 = .410

(table continues)

Table 8 *(continued)*

Sample	Will	Skill	Tool
Texas (N = 890)	TAC2, TAC6, TAC7, TAC8, TAC9 R^2 = .386	TPwww, TPia, TPtt R^2 = .455	Homecomp, Homewww, Homehrs, Clshrs, Clscomp R^2 = .203
Texas Elementary (N = 586)	TAC2, TAC3, TAC6, TAC7, TAC8 R^2 = .388	TPwww, TPia, TPtt R^2 = .447	Homecomp, Homewww, Homehrs, Clshrs, Clscomp, Freqlrn R^2 = .159
Texas Middle (N = 304)	TAC2, TAC3, TAC5, TAC6, TAC8, TAC9 R^2 = .423	TPemail, TPwww, TPia, TPtt R^2 = .509	Homecomp, Homewww, Homehrs, Clshrs, Freqlrn R^2 = .304
Mexico City (N = 476)	TAC2, TAC3, TAC7, TAC8 R^2 = .249	TPemail, TPwww R^2 = .205	Homecomp, Homewww, Homehrs, Clshrs, Clscomp, Prephrs, Freqlrn R^2 = .438 ($\beta_{support}$ = 0.0731)

(table continues)

Table 8 *(continued)*

Sample	Will	Skill	Tool
Mexico City Elementary (N = 210)	TAC2, TAC4 TAC6, TAC7, TAC8 , TAC9 R^2 = .282	TPemail, TPwww, TPia, TPtt R^2 = .211	Homecomp, Homewww, Homehrs, Clshrs, Clscomp, Freqlrn R^2 = .403 ($\beta_{support}$ = 0.0556)
Mexico City Middle (N = 266)	TAC1, TAC2, TAC3, TAC7, TAC8 , TAC9 R^2 = .226	TPia, TPtt R^2 = .212	Homecomp, Homewww, Homehrs, Clshrs, Prephrs, Freqlrn R^2 = .479 ($\beta_{support}$ = 0.0919)

Note: See regression weights in Appendix D.

It is worth noticing from this analysis that the regression weight for Technical Support do not reach the critical point of Beta = .1 in any of the samples from Mexico City analyzed. The rank order of the measures in terms of the number of samples in which they appeared, is shown in Table 9. Details of the regression analysis summarized in Tables 8 and 9 are provided in Appendix D.

Table 9

Rank Ordered Measures After the Regression Analysis

Will		Skill		Tool	
TAC2	7 samples	TPwww	6 samples	Homewww	7 samples
TAC7	6 samples	TPtt	6 samples	Homehrs	7 samples
TAC8	6 samples	TPia	5 samples	Clshrs	7 samples
TAC3	5 samples	TPemail	4 samples	Homecomp	6 samples
TAC6	5 samples			Freqlrn	6 samples
TAC9	5 samples			Clscomp	4 samples
TAC1	1 sample			Prephrs (Mex)	2 samples
TAC4	1 sample				
TAC5	1 sample				

Based on the results of the regression analysis, the best measures for the model were found to be: TAC2, TAC7, TAC8, TAC3, TAC6, and TAC9 for the variable Will; TPwww, and TPtt for the variable Skill; Homewww, Homehrs, Clshrs, Homecomp, and Freqlrn for the variable Tool.

Nevertheless, the final selection of the best measures for the model should come from a combination of these results with the results from the factor analysis presented in Table 6. The measures resulted from regression analysis, that also appeared to have loaded in one of the factors are presented in Table 10.

Table 10

Measures that Overlap Between Table 6 and Table 7 as Resulting from Factor and Regression Analyses

Sample	Will		Skill		Tool	
Cross-Cultural (N = 1444)	TAC2, TAC3, TAC6, TAC9 R^2=.268	Factor 1 Factor 1 Factor 3 Factor 3	TPemail, TPwww, TPtt R^2=.370	Factor 1 Factor 1 Factor 1	Homewww, Homehrs, Clshrs, Freqlrn R^2=.410	Factor 1 Factor 1 Factor 2 Factor 3
Texas (N = 890)	TAC2, TAC7, TAC8, TAC6, TAC9 R^2=.386	Factor 1 Factor 1 Factor 1 Factor 2 Factor 2	TPwww, TPia, TPtt R^2=.455	Factor 1 Factor 2 Factor 2	Homecomp, Homewww, Homehrs, Clscomp, Clshrs R^2=.203	Factor 1 Factor 1 Factor 1 Factor 2 Factor 3
Texas Elementary (N = 586)	TAC3, TAC6, TAC2, TAC7, TAC8 R^2=.388	Factor 1 Factor 1 Factor 2 Factor 2 Factor 2	TPwww, TPia, TPtt R^2=.447	Factor 1 Factor 1 Factor 1	Homecomp, Homewww, Homehrs, Clscomp, Freqlrn, Clshrs R^2=.159	Factor 1 Factor 1 Factor 1 Factor 2 Factor 2 Factor 3

(table continues)

Table 10 *(continued)*

Sample	Will		Skill		Tool	
Texas Middle	TAC2,	Factor 1	TPemail,	Factor 1	Homecomp,	Factor 1
(N = 304)	TAC5,	Factor 1	TPwww,	Factor 1	Homewww,	Factor 1
	TAC8,	Factor 1	TPia,	Factor 1	Homehrs,	Factor 1
	TAC6,	Factor 2	TPtt	Factor 1	Freqlrn,	Factor 2
	TAC9	Factor 2	R^2=.509		Clshrs	Factor 3
	R^2=.414				R^2=.304	
Mexico City	TAC2,	Factor 1	TPemail,	Factor 1	Clshrs,	Factor 1
(N = 476)	TAC3,	Factor 1	TPwww	Factor 1	Clscomp,	Factor 1
	TAC7	Factor 3	R^2=.205		Prephrs,	Factor 1
	R^2=.173				Freqlrn,	Factor 1
					Homecomp,	Factor 2
					Homewww,	Factor 2
					Homehrs	Factor 2
					R^2=.438	

(table continues)

Table 10 *(continued)*

Sample	Will		Skill		Tool	
Mexico City Elementary (N = 210)	TAC6,	Factor 1	TPemail,	Factor 1	Clshrs,	Factor 1
	TAC9,	Factor 1	TPwww,	Factor 1	Clscomp,	Factor 1
	TAC2,	Factor 2	TPia,	Factor 1	Freqlrn,	Factor 1
	TAC7	Factor 3	TPtt	Factor 1	Homecomp,	Factor 2
	R^2=.252		R^2=.211		Homewww,	Factor 2
					Homehrs	Factor 2
					R^2=.403	
Mexico City Middle (N = 266)	TAC1,	Factor 1	TPia,	Factor 1	Clshrs,	Factor 1
	TAC8,	Factor 1	TPtt	Factor 1	Prephrs,	Factor 1
	TAC9,	Factor 1	R^2=.212		Homecomp,	Factor 2
	TAC2,	Factor 2			Homewww,	Factor 2
	TAC3,	Factor 2			Homehrs	Factor 2
	TAC7	Factor 3			R^2=.452	
	R^2=.226					

In a similar array as in Table 9, the new set of measures derived is shown in Table 11.

Table 11

Rank Ordered Measures After Results from Factor Analysis and Regression Analysis

Will		Skill		Tool	
TAC2	7 samples	TPwww	6 samples	Homewww	7 samples

(table continues)

Table 11 *(continued)*

Will		Skill		Tool	
TAC6	5 samples	TPtt	6 samples	Homehrs	7 samples
TAC7	5 samples	TPia	5 samples	Clshrs	7 samples
TAC9	5 samples	TPemail	4 samples	Homecomp	6 samples
TAC3	4 samples			Freqlrn	5 samples
TAC8	4 samples			Clscomp	4 samples
TAC1	1 sample			Prephrs (Mex)	2 samples
TAC5	1 sample				

Therefore, based on the results from factor analysis and multiple regression, the best measures for the WiSTTI model in this study were:

- TAC2 (Comfort/Anxiety), TAC6 (Utility), TAC7 (Perception), and TAC9 (Significance), for the variable Will
- TPwww, TPtt, and TPia, for the variable Skill
- Homewww, Homehrs, Clshrs, Homecomp, and Freqlrn for the variable Tool
- Stages, CBAM, and ACOT for the variable Integration

Path Analysis

Path analysis was performed to explore research question 3: “Are there models other than Will, Skill, Tool, that better explain the WST teacher professional development component (WiSTTI) results of data gathered from Mexico City and Texas?”

For each sample and subsample, seven models were tested, depicted in Figures 17-23:

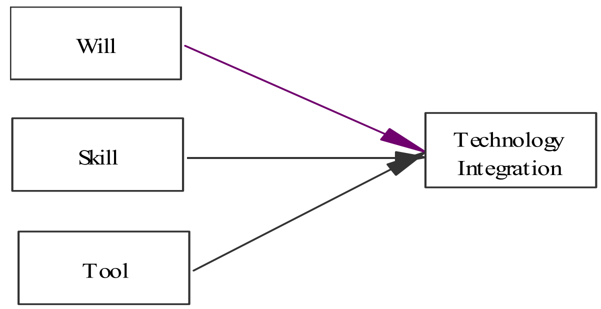


Figure 17. Path model 1: Will + Skill + Tool = Integration

For the model in Figure 17, it is hypothesized that the constructs Will, Skill, and Tool, directly affect the construct Integration. The disposition of the variables and the direction of the paths indicate that the model entails three independent variables and one dependent variable.

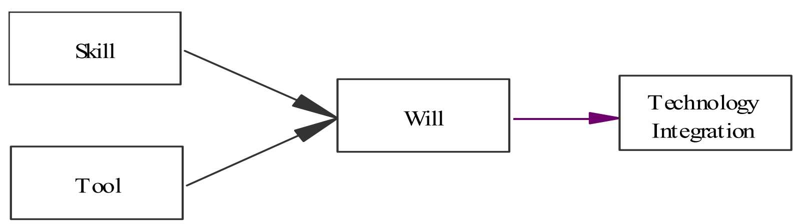


Figure 18. Path model 2: Skill + Tool = Will = Integration

For the model depicted in Figure 18, Will directly affects Integration. Additionally, Skill and Tool affect Will, and, indirectly, affect Integration. Another way to see it is that the model assumes two independent variables, Skill and Tool, affecting two dependent variables, Will, and Integration.

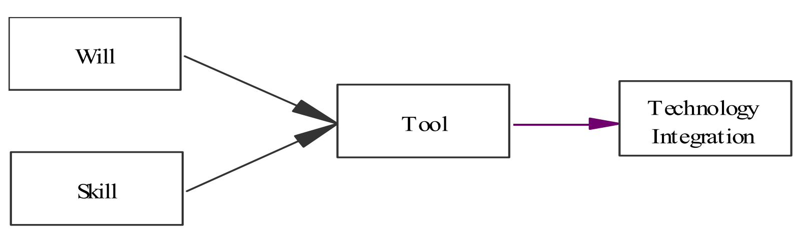


Figure 19. Path model 3: Will + Skill = Tool = Integration

For the model depicted in Figure 19, Tool directly affects Integration. Additionally, Will and Skill affect Tool, and, indirectly, affect Integration. Another way to see it is that the model assumes two independent variables, Will and Skill, affecting two dependent variables, Tool and Integration.

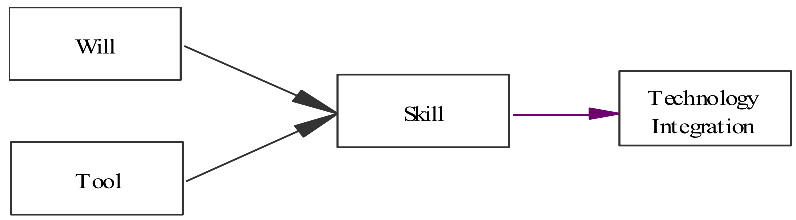


Figure 20. Path model 4: Will + Tool = Skill = Integration

For the model in Figure 20, Skill directly affects Integration. Additionally, Will and Tool affect Skill, and, indirectly, affect Integration. Another way to see it is that the model assumes two independent variables, Will and Tool, affecting two dependent variables, Skill and Integration.

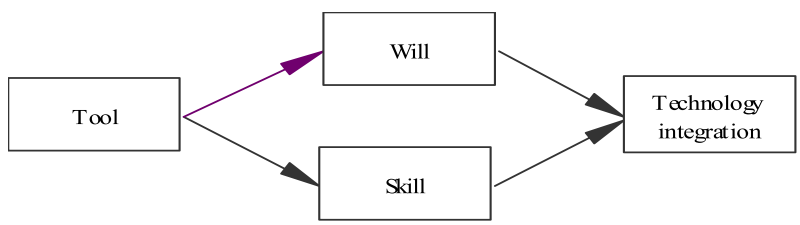


Figure 21. Path model 5: Tool = Will + Skill = Integration

For the model in Figure 21, Will and Skill directly affect Integration. Additionally, Tool affects Will and Skill. Therefore, it is hypothesized that Tool only indirectly affects Integration. Another way to see it is that the model assumes one independent variable, Tool, and three dependent variables, Will, Skill, and Integration.

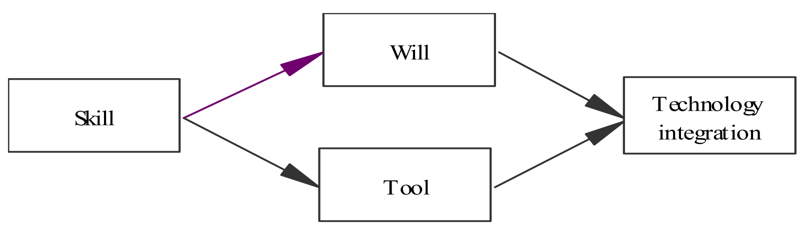


Figure 22. Path model 6: Skill = Will + Tool = Integration

For the model shown in Figure 22, Will and Tool directly affect Integration. Additionally, Skill affects Will and Tool. Therefore, it is hypothesized that Skill only indirectly affects Integration. Another way to see it is that the model assumes one independent variable, Skill, and three dependent variables, Will, Tool, and Integration.

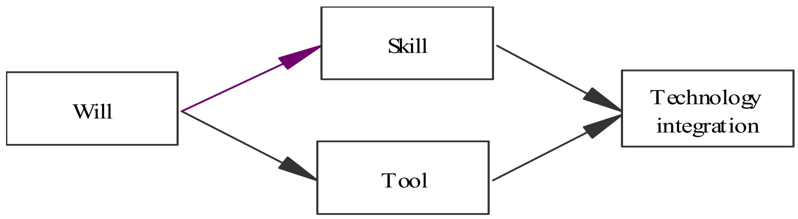


Figure 23. Path model 7: Will = Skill + Tool = Integration

For the model in Figure 23, Skill and Tool directly affect Integration. Additionally, Will affects Skill and Tool. Therefore, it is hypothesized that Will only indirectly affects Integration. Another way to see it is that the model assumes one independent variable, Will, and three dependent variables, Skill, Tool, and Integration.

In summary, the path models tested for validation included three independent variables, two independent variables, and one independent variable.

According to Schumacker and Lomax (1996, p. 44) path models are tested for significance through the *t*-test for testing path coefficients (the standardized partial regression coefficients β), and the Chi-square statistic for testing model fit. The seven models depicted above were tested for each of seven samples: Cross-Cultural, Texas, Texas Elementary, Texas Middle School, Mexico City, Mexico City Elementary, and Mexico City Middle School. A total of 49 models were tested.

Results

Results on model fit are presented in Table 12. A Chi-square value near 0.00 indicates a good model fit. Conversely, a large Chi-square value indicates lack of model fit.

Table 12

Chi-Square Statistic and Significance for Seven Models Tested on Path Analysis

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Cross-Cultural	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2=769.36$ $p = 0.000$	$\chi^2=284.09$ $p = 0.000$	$\chi^2=126.78$ $p = 0.000$
Texas	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2=302.71$ $p = 0.000$	$\chi^2=272.91$ $p = 0.000$	$\chi^2=86.95$ $p = 0.000$
Texas Element	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2=186.22$ $p = 0.000$	$\chi^2=162.05$ $p = 0.000$	$\chi^2=68.86$ $p = 0.000$
Texas Middle	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2=133.19$ $p = 0.000$	$\chi^2=111.44$ $p = 0.000$	$\chi^2=21.37$ $p = 0.000$
Mexico City	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2=312.07$ $p = 0.000$	$\chi^2=51.28$ $p = 0.000$	$\chi^2=35.72$ $p = 0.000$
Mex City Element	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2=116.63$ $p = 0.000$	$\chi^2=28.30$ $p = 0.000$	$\chi^2=19.49$ $p = 0.000$
Mex City Middle	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2 = 0.00$ $p = 1.00$	$\chi^2=203.26$ $p = 0.000$	$\chi^2=21.55$ $p = 0.000$	$\chi^2=24.88$ $p = 0.000$

As shown in Table 12, a three-independent variable model and a two-independent variable model fit the data for all the samples tested. A one-independent variable model did not fit the data.

Regarding path coefficients, Table 13 presents the decomposition of each path, tested for statistical significance. Paths with associated *t*-values higher than 1.96 were considered statistically significant at the .05 level (Schumacker & Lomax, 1996, p. 37). A low value on the standard error of the estimate was also sought.

Table 13

Path Coefficient, t*-Value, and the Standard Error of the Estimate for Each Path. Cross-Cultural Sample (N = 1516)*

Paths	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Will on Integr	p = .191 t = 8.93 SE = .02	p = .191 t = 8.93 SE = .02	p = .191 t = 8.93 SE = .02	p = .191 t = 8.93 SE = .02	p = .305 t =14.96 SE = .02	p = .343 t =18.07 SE = .02	
Skill on Integr	p = .312 t =14.77 SE = .02	p = .312 t =14.77 SE = .02	p = .312 t =14.77 SE = .02	p = .312 t =14.77 SE = .02	p = .397 t =19.49 SE = .02		p = .402 t =22.07 SE = .02
Tool on Integr	p = .435 t =22.87 SE = .02	p = .435 t =22.87 SE = .02	p = .435 t =22.87 SE = .02	p = .435 t =22.87 SE = .02		p = .485 t =25.59 SE = .02	p = .475 t =26.04 SE = .02
Skill on Will		p = .475 t =21.23 SE = .02				p = .545 t =25.29 SE = .02	
Tool on Will		p = .207 t = 9.31 SE = .02			p = .368 t =15.40 SE = .02		

(table continues)

Table 13 *(continued)*

Paths	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Will on Tool			p = .261 t = 9.31 SE = .03				p = .368 t =15.40 SE = .02
Skill on Tool			p = .196 t = 6.96 SE = .03			p = .338 t =13.97 SE = .02	
Will on Skill				p = .486 t =21.23 SE = .02			p = .545 t =25.29 SE = .02
Tool on Skill				p = .159 t = 6.96 SE = .02	p = .338 t =13.97 SE = .02		

As shown in Table 13, all the paths in these models for the cross-cultural sample were statistically significant, i.e. a significant correlation existed between each pair of variables depicted in the models. Ultimately, the hypothesis on the direction of the path was supported. Nevertheless, the direction of the path does not necessarily indicate causation, because all measures were acquired at the same time. Will, Skill, and Tool may not cause Integration, rather, the implication is that they directly or indirectly *influence* Integration.

Similar analyses for the rest of the samples indicated that all paths were statistically significant. Therefore, results from model fit testing, and path coefficient testing suggest that two-independent and three-independent variable models were the most reliable versions of the WiSTTI model for this study. Null hypothesis 3 of no differences in goodness of fit among the seven models is rejected on the ground that a one independent variable type of model did not fit the data for any of the samples studied, while several two and three independent variable models performed reasonably well, but only one had satisfactory goodness of fit characteristics across all samples examined. Was there a single model to explain integration for these samples? The next set of analyses was focused on that question.

Structural Equation Modeling (SEM) Analysis

The methodological approach for SEM analysis of the WiSTTI Model was a combination of the *confirmatory mode*, and the *exploratory mode* (Raykov & Marcoulides, 2000, p. 6) in which the theoretical constructs Will, Skill, Tool, and Integration were tested for confirmation of interdependence, but were also subjected to exploration for a plausible set of relationships (paths) defining the model.

Prior to model testing, a number of target conditions were set:

- Maximum variance explained would be sought, i.e. a model would be chosen when showing the highest R^2 from a specific sample.
- Only acceptable solutions indicating a good model fit (χ^2 with $p > .05$) would be accepted as valid outcomes.
- Only reliable paths between the measures and the latent variables, and especially between Will, Skill, Tool, and Integration would be acceptable.
- Any parameter estimates including correlations exceeding 1.00, a Heywood case (negative variance), or a non-positive definite matrix, would not be accepted.

Results

Results of SEM analysis indicated that the best single structural model for all the samples analyzed was a two-independent variable model, as depicted in Figure 24.

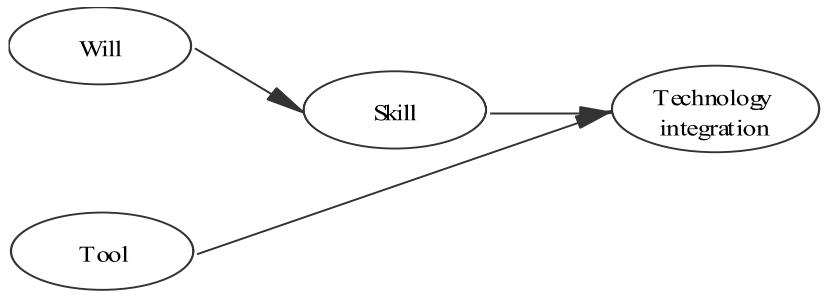


Figure 24. Structural model resulted from SEM analysis.

As shown in Figure 24, the resulting model was a linear model with two independent variables, Will and Tool, and two dependent variables, Skill and Integration. It resembles path model 4, depicted in Figure 20, with a change in the path departing from Tool. The fact that this model was the best fit for all samples, with the highest variance explained compared to the other two-independent variable and three-independent variable models, is strong evidence to reject null hypothesis 3 of no differences in total variance accounted for among the models. Detailed results including the path model and the structural equations for each sample are presented in the following section.

Research question 1: "Will data gathered from elementary and middle school teachers in Mexico City produce technology integration findings similar to those in Texas?" can be properly addressed through the integration variance explained by Will, Skill, and Tool across the samples from both countries.

Cross-Cultural Sample

As shown in Figure 25, the structural model fits the Cross-Cultural data ($\chi^2 = 22.88$, $p =$ .117). As shown in Table 14, Will predicted 56% of the variance of Skill ($R^2 = 0.561$, $t = 24.86 >$

1.96), whereas Skill predicted 33% of the variance of Integration ($R^2 = 0.327$, $t = 9.89 > 1.96$), and Tool predicted 49% of the variance of Integration ($R^2 = 0.497$, $t = 12.23 > 1.96$). Although according to the model Will only predicts integration through Skill, its indirect effect on integration can be calculated as 24% ($R^2 = 0.240$, $t = 9.56 > 1.96$).

Following the procedure from Schumacker and Lomax (1996, p. 44), the R^2 for the entire model would be derived from:

$$R^2_m = 1-(1- R^2_1)(1- R^2_2)\ldots(1- R^2_p) \tag{1}$$

where R^2_m is the total variance explained for the model (total effects), R^2_1 is the variance explained for Skill, and R^2_2 is the variance explained for Integration.

$$R^2_m = 1-(1- .561)(1- .824) = .923$$

Using Equation 1, total R² for the model was $R^2_T = 0.923$, i.e. the model significantly predicted 92% of the variance attributed to Integration.

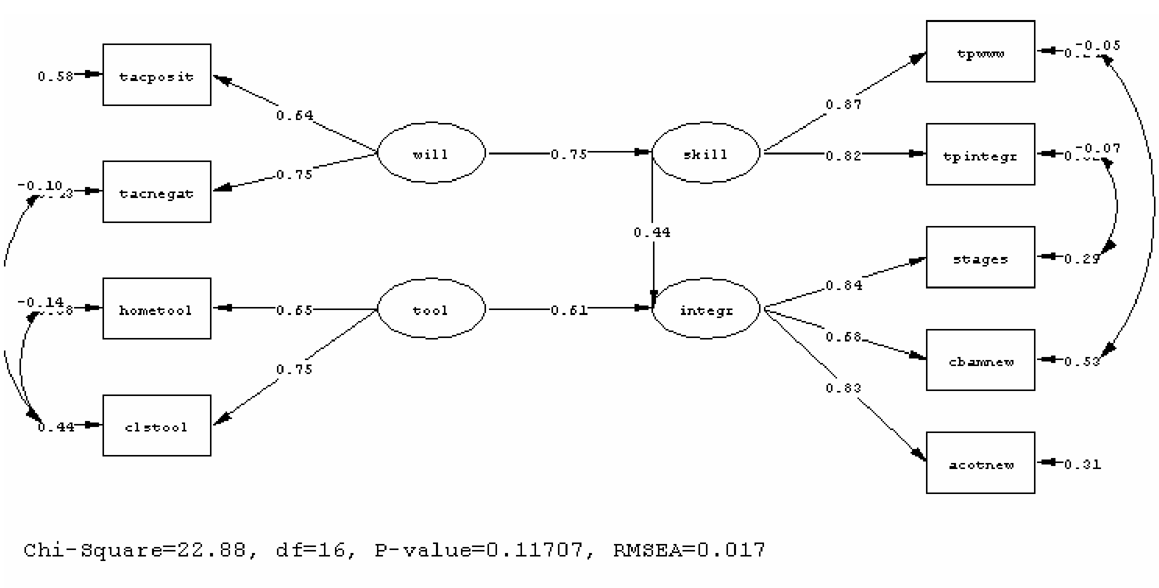


Figure 25. Path diagram of the WiSTTI model for the Texas-Mexico City sample (N=1504).

Table 14

Structural Equations and Correlation Matrix to Calculate the Effect of Will, Skill, and Tool on Integration for the Cross-Cultural Sample

Structural equations	skill = 0.749*will, Errorvar.= 0.439, R^2 = 0.561 (0.0301) (0.0359) 24.864 12.252 integr = 0.445*skill + 0.606*tool, Errorvar.= 0.176, R^2 = 0.824 (0.0449) (0.0495) (0.0339) 9.894 12.237 5.204
Reduced form equation	integr = 0.333*will + 0.606*tool, Errorvar.= 0.263, R^2 = 0.737 (0.0348) (0.0495) 9.562 12.237
Correlation matrix	skill integr will tool -------- -------- -------- -------- skill 1.000 integr 0.736 1.000 will 0.749 0.722 1.000 tool 0.481 0.820 0.643 1.000

Texas Sample

As shown in Figure 26, the structural model fits the data from the Texas sample (χ^2 = 18.10, p = .382). As shown in Table 15, Will predicted 52% of the variance of Skill (R^2 = 0.519, t = 18.19 > 1.96), whereas Skill predicted 48% of the variance of Integration (R^2 = 0.481, t = 12.31 > 1.96), and Tool predicted 33% of the variance of Integration (R^2 = 0.329, t = 8.76 > 1.96). Although according to the model Will only predicts integration through Skill, its indirect effect on integration can be calculated as 32% (R^2 = 0.316, t = 11.31 > 1.96).

Total variance explained by the model was R^2_m = 1-(1- .519)(1- .809) = .908, i.e. the model significantly predicted 91% of the variance attributed to Integration.

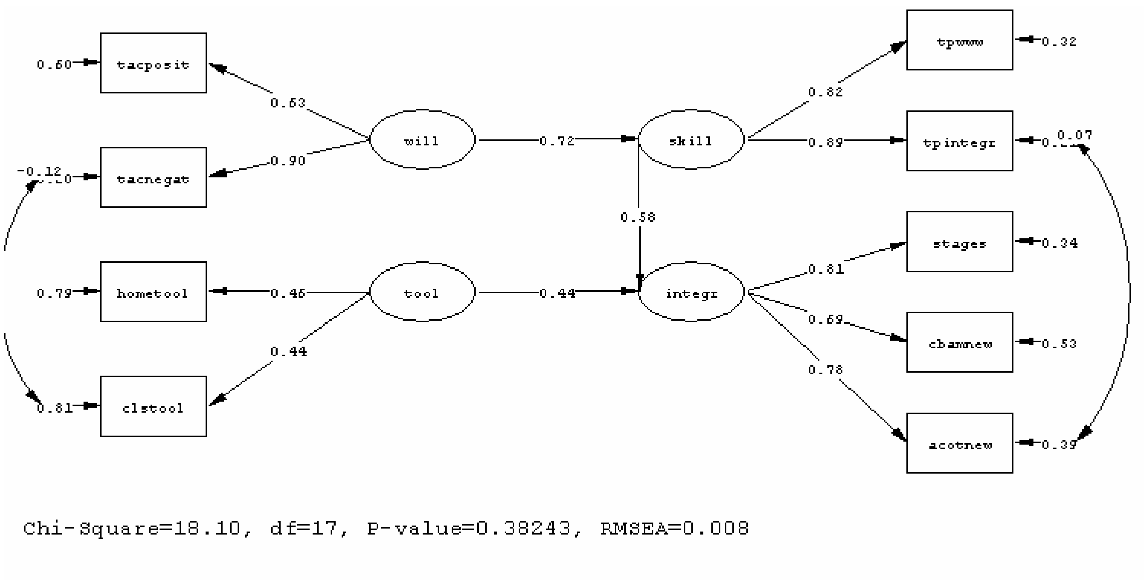


Figure 26. Path diagram of the WiSTTI model for the Texas sample (N=901).

Table 15

Structural Equations and Correlation Matrix to Calculate the Effect of Will, Skill, and Tool on Integration for the Texas Sample

Structural equations	skill = 0.720*will, Errorvar.= 0.481, R^2 = 0.519 (0.0396) (0.0436) 18.196 11.029 integr = 0.585*skill + 0.436*tool, Errorvar.= 0.191, R^2 = 0.809 (0.0475) (0.0497) (0.0335) 12.315 8.762 5.696
Reduced form equation	Integr = 0.421*will + 0.436*tool, Errorvar.= 0.355, R^2 = 0.645 (0.0372) (0.0497) 11.313 8.762
Correlation matrix	skill integr will tool -------- -------- -------- -------- skill 1.000 integr 0.822 1.000 will 0.720 0.750 1.000 tool 0.544 0.754 0.756 1.000

Texas Elementary School Teacher Sample

As shown in Figure 27, the structural model fits the data from the Texas elementary school teachers sample ($\chi^2 = 25.72$, $p = .106$). As shown in Table 16, Will predicted 54% of the variance of Skill ($R^2 = 0.540$, $t = 14.71 > 1.96$), whereas Skill predicted 51% of the variance of Integration ($R^2 = 0.512$, $t = 9.77 > 1.96$), and Tool predicted 28% of the variance of Integration ($R^2 = 0.281$, $t = 5.77 > 1.96$). Although according to the model Will only predicts integration through Skill, its indirect effect on integration can be calculated as 34% ($R^2 = 0.337$, $t = 8.96 > 1.96$).

Total variance explained by the model was $R^2_m = 1\text{-}(1\text{-} .540)(1\text{-} .793) = .905$, i.e. the model significantly predicted 90% of the variance attributed to Integration.

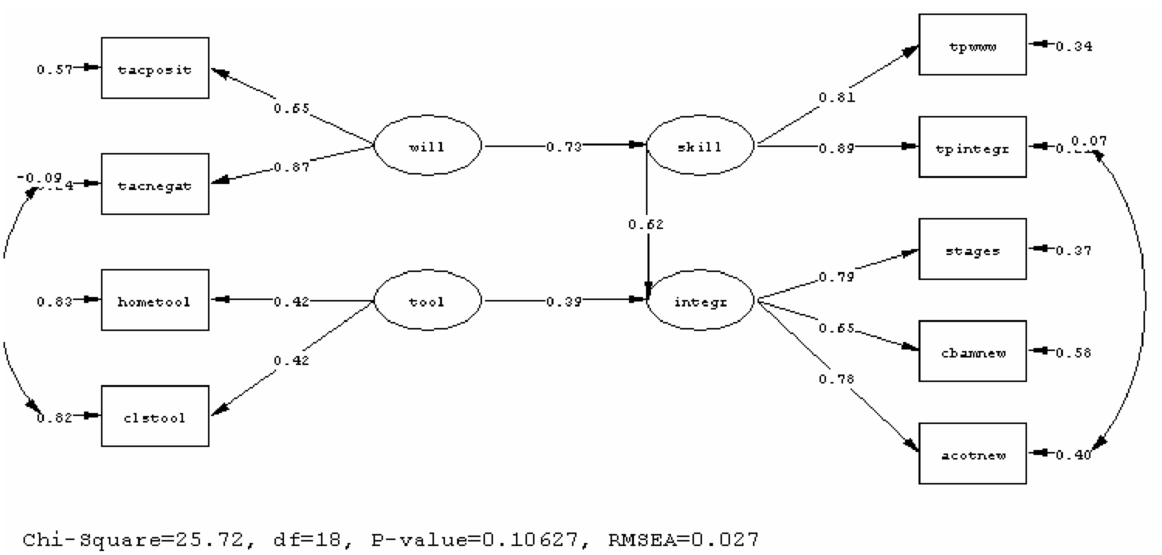


Figure 27. Path diagram of the WiSTTI model for the Texas elementary school teacher sample (N=589).

Table 16

Structural Equations and Correlation Matrix to Calculate the Effect of Will, Skill, and Tool on Integration for the Texas Elementary School Teacher Sample

Structural equations	Skill = 0.735*will, Errorvar.= 0.460, R^2 = 0.540 (0.0499) (0.0541) 14.713 8.507 integr = 0.616*skill + 0.385*tool, Errorvar.= 0.207, R^2 = 0.793 (0.0631) (0.0668) (0.0431) 9.769 5.774 4.801
Reduced form equation	integr = 0.453*will + 0.385*tool, Errorvar.= 0.381, R^2 = 0.619 (0.0505) (0.0668) 8.961 5.774
Correlation matrix	skill integr will tool -------- -------- -------- -------- skill 1.000 integr 0.831 1.000 will 0.735 0.745 1.000 tool 0.558 0.729 0.760 1.000

Texas Middle School Teacher Sample

As shown in Figure 28, the structural model fits the data from the Texas middle school teachers sample (χ^2 = 30.89, p = .056). As shown in Table 17, Will predicted 57% of the variance of Skill (R^2 = 0.574, t = 10.86 > 1.96), whereas Skill predicted 51% of the variance of Integration (R^2 = 0.515, t = 8.05 > 1.96), and Tool predicted 38% of the variance of Integration (R^2 = 0.383, t = 5.95 > 1.96). Although according to the model Will only predicts integration through Skill, its indirect effect on integration can be calculated as 36% (R^2 = 0.356, t = 7.28 > 1.96).

Total variance explained by the model was R^2_m = 1-(1- .574)(1- .899) = .957, i.e. the model significantly predicted 96% of the variance attributed to Integration.

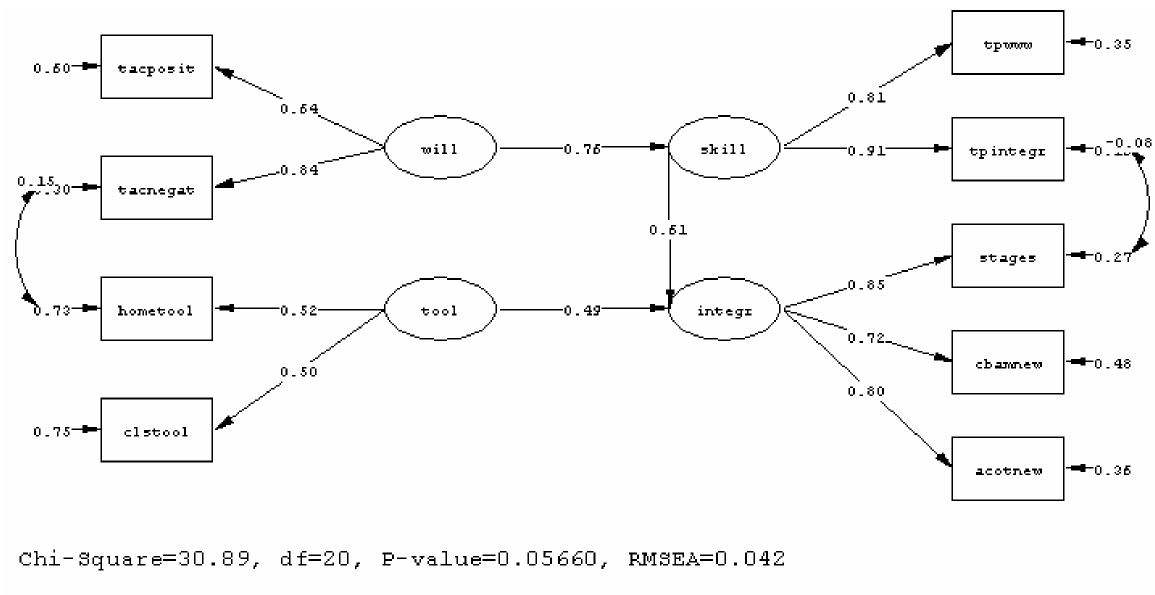


Figure 28. Path diagram of the WiSTTI model for the Texas middle school teacher sample (N=312).

Table 17

Structural Equations and Correlation Matrix to Calculate the Effect of Will, Skill, and Tool on Integration for the Texas Middle School Teacher Sample

Structural equations	skill = 0.758*will, Errorvar.= 0.426, R^2 = 0.574 (0.0697) (0.0735) 10.865 5.791 integr = 0.610*skill + 0.491*tool, Errorvar.= 0.101, R^2 = 0.899 (0.0758) (0.0826) (0.0527) 8.056 5.952 1.919
Reduced form equation	integr = 0.463*will + 0.491*tool, Errorvar.= 0.260, R^2 = 0.740 (0.0636) (0.0826) 7.280 5.952
Correlation matrix	skill integr will tool -------- -------- -------- -------- skill 1.000 integr 0.844 1.000 will 0.758 0.770 1.000 tool 0.475 0.781 0.626 1.000

Mexico City Sample

As shown in Figure 29, the structural model fits the data from the Mexico City sample ($\chi^2 = 24.55$, $p = .105$). As shown in Table 18, Will predicted 50% of the variance of Skill ($R^2 = 0.498$, $t = 11.89 > 1.96$), whereas Skill predicted 9% of the variance of Integration ($R^2 = 0.089$, $t = 3.84 > 1.96$), and Tool predicted 89% of the variance of Integration ($R^2 = 0.892$, $t = 16.15 > 1.96$). Although according to the model Will only predicts integration through Skill, its indirect effect on integration can be calculated as 7% ($R^2 = 0.068$, $t = 3.82 > 1.96$).

Total variance explained by the model was $R^2_m = 1\text{-}(1\text{- }.498)(1\text{- }.982) = .991$, i.e. the model significantly predicted 99% of the variance attributed to Integration.

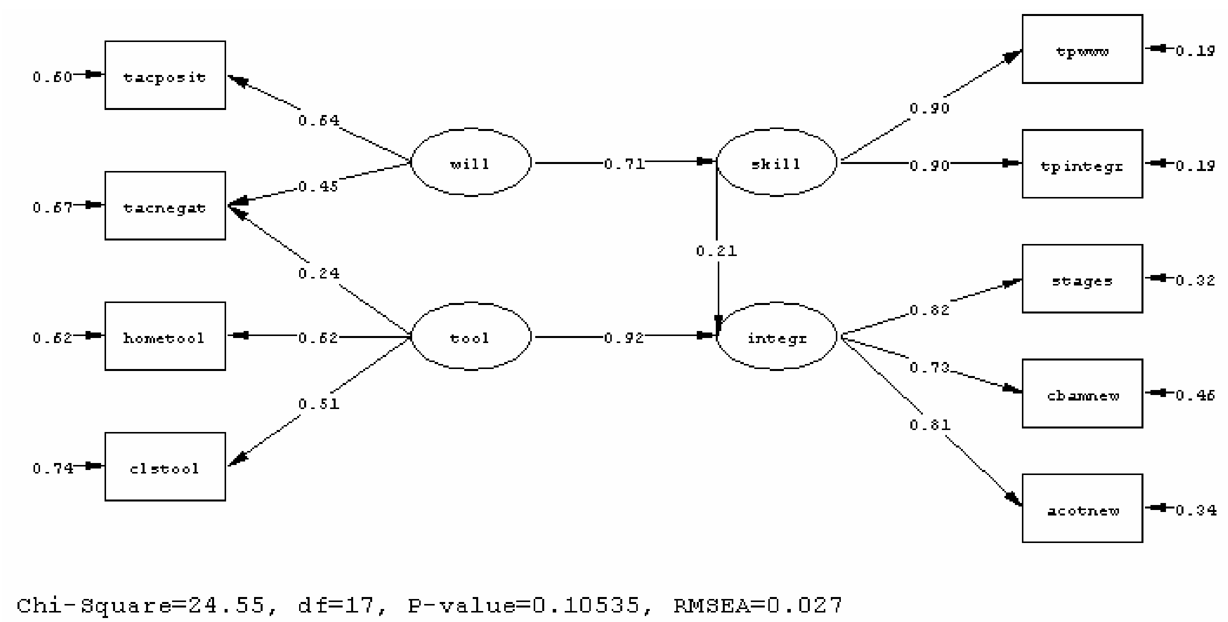


Figure 29. Path diagram of the WiSTTI model for the Mexico City sample (N=603).

Table 18

Structural Equations and Correlation Matrix to Calculate the Effect of Will, Skill, and Tool on Integration for the Mexico City Sample

Structural equations	skill = 0.706*will, Errorvar.= 0.502, R^2 = 0.498 (0.0594) (0.0797) 11.887 6.298 integr = 0.207*skill + 0.920*tool, Errorvar.= 0.0181, R^2 = 0.982 (0.0539) (0.0569) (0.0664) 3.839 16.155 0.273
Reduced form equation	integr = 0.146*will + 0.920*tool, Errorvar.= 0.0396, R^2 = 0.960 (0.0381) (0.0569) 3.827 16.155
Correlation matrix	skill integr will tool -------- -------- -------- -------- skill 1.000 integr 0.433 1.000 will 0.706 0.467 1.000 tool 0.246 0.970 0.349 1.000

Mexico City Elementary School Teacher Sample

As shown in Figure 30, the structural model fits the data from the Mexico City elementary school teacher sample (χ^2 = 23.48, p = .374). As shown in Table 19, Will predicted 44% of the variance of Skill (R^2 = 0.439, t = 7.16 > 1.96), whereas Skill predicted 10% of the variance of Integration (R^2 = 0.096, t = 3.33 > 1.96), and Tool predicted 79% of the variance of Integration (R^2 = 0.789, t = 10.84 > 1.96). Although according to the model Will only predicts integration through Skill, its indirect effect on integration can be calculated as 7% (R^2 = 0.066, t = 3.09 > 1.96).

Total variance explained by the model was R^2_m = 1-(1- .439)(1- .886) = .936, i.e. the model significantly predicted 94% of the variance attributed to Integration.

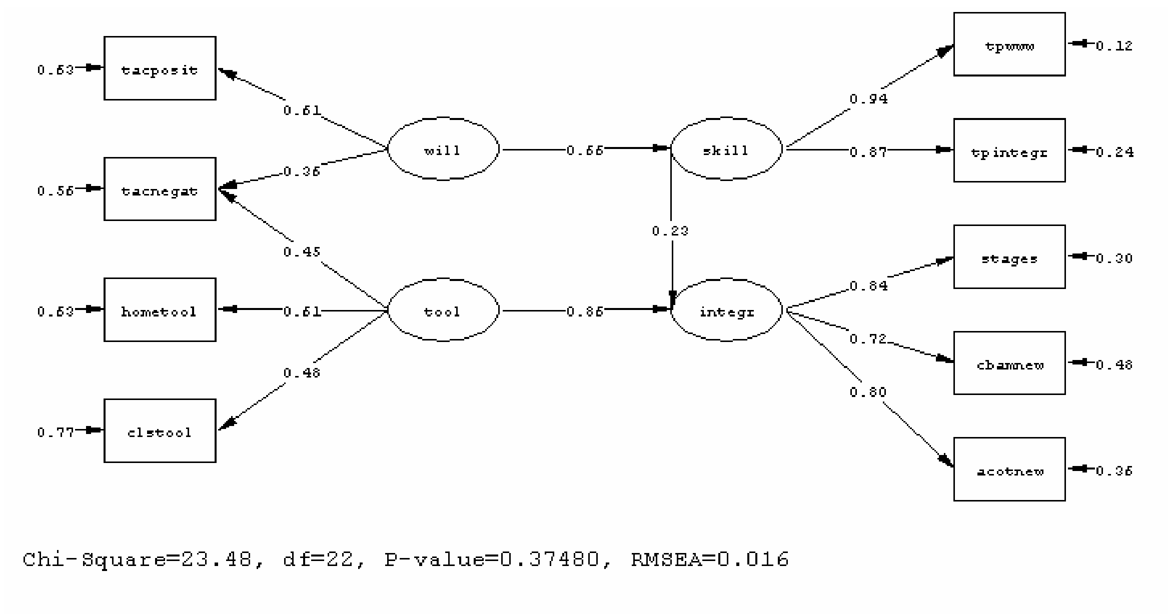


Figure 30. Path diagram of the WiSTTI model for the Mexico City elementary school teacher sample (N=260).

Table 19

Structural Equations and Correlation Matrix to Calculate the Effect of Will, Skill, and Tool on Integration for the Mexico City Elementary School Teacher Sample

Structural equations	skill = 0.662*will, Errorvar.= 0.561, R^2 = 0.439 (0.0925) (0.122) 7.163 4.599 integr = 0.230*skill + 0.864*tool, Errorvar.= 0.114, R^2 = 0.886 (0.0690) (0.0797) (0.0877) 3.334 10.839 1.302
Reduced form equation	integr = 0.152*will + 0.864*tool, Errorvar.= 0.144, R^2 = 0.856 (0.0493) (0.0797) 3.091 10.839
Correlation matrix	see below

Correlation matrix:

	skill	integr	will	tool
skill	1.000			
integr	0.418	1.000		
will	0.662	0.435	1.000	
tool	0.217	0.914	0.327	1.000

Mexico City Middle School Teacher Sample

As shown in Figure 31, the structural model fits the data from the Mexico City middle school teacher sample ($\chi^2 = 26.31$, $p = .194$). As shown in Table 20, Will predicted 59% of the variance of Skill ($R^2 = 0.592$, $t = 11.04 > 1.96$), whereas Skill predicted 6% of the variance of Integration ($R^2 = 0.057$, $t = 2.08 > 1.96$), and Tool predicted 84% of the variance of Integration ($R^2 = 0.845$, $t = 11.90 > 1.96$). Although according to the model Will only predicts integration through Skill, its indirect effect on integration can be calculated as 5% ($R^2 = 0.050$, $t = 2.09 > 1.96$).

Total variance explained by the model was $R^2_m = 1-(1- .592)(1- .902) = .960$, i.e. the model significantly predicted 96% of the variance attributed to Integration.

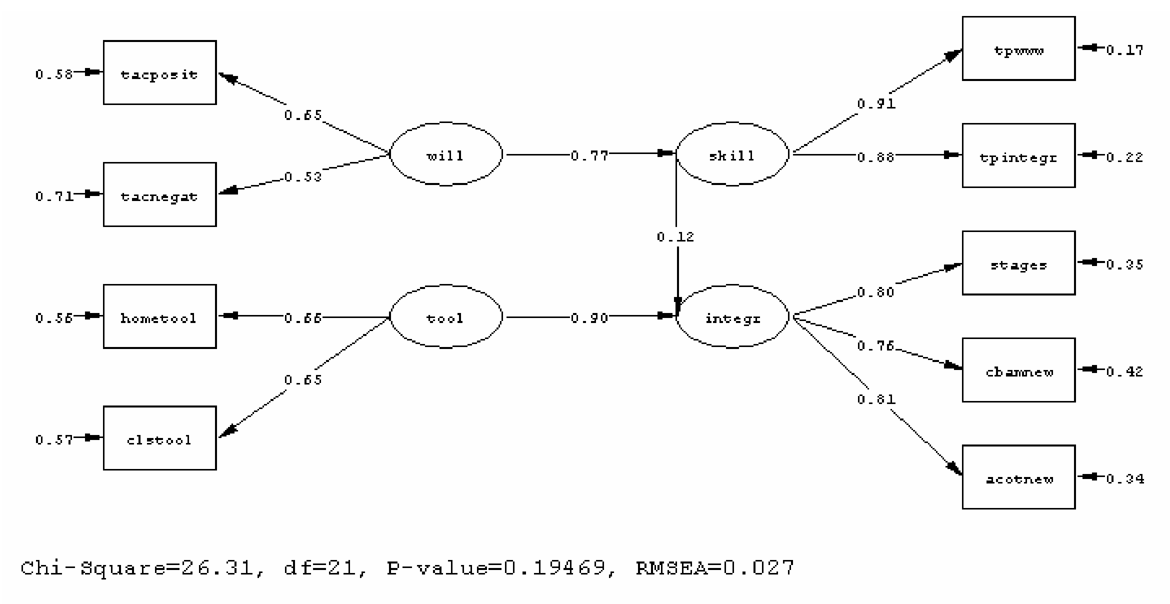


Figure 31. Path diagram of the WiSTTI model for the Mexico City middle school teacher sample (N=344).

Table 20

Structural Equations and Correlation Matrix to Calculate the Effect of Will, Skill, and Tool on Integration for the Mexico City Middle School Teacher Sample

Structural equations	skill = 0.769*will, Errorvar.= 0.408, R^2 = 0.592 (0.0697) (0.0858) 11.043 4.755 integr = 0.124*skill + 0.896*tool, Errorvar.= 0.0984, R^2 = 0.902 (0.0594) (0.0753) (0.0699) 2.088 11.905 1.408
Reduced form equation	integr = 0.0954*will + 0.896*tool, Errorvar.= 0.105, R^2 = 0.895 (0.0455) (0.0753) 2.098 11.905
Correlation matrix	skill integr will tool -------- -------- -------- -------- skill 1.000 integr 0.458 1.000 will 0.769 0.530 1.000 tool 0.373 0.943 0.485 1.000

Results from SEM analysis indicate that the WiSTTI model was a reliable tool to evaluate data from Texas and Mexico City. Will, Skill, and Tool showed a differential effect on integration depending on the country. Therefore, results derived from the SEM analysis suggested that the WiSTTI model yielded differential results for technology integration among teachers from Mexico City, as compared to technology integration from Texas teachers.

Hypotheses Testing

To test the Hypothesis 1a, of no difference in the level of technology integration between teachers from the Texas and Mexico City, and the Hypothesis 1b, of no difference in the level of technology integration between elementary school teachers and middle school teachers, a two-way (country by teaching level) ANOVA was conducted. The variable "Integration" was a composite of three measures: Stages of Adoption, CBAM, and ACOT, as discussed earlier.

Two-Way Factorial ANOVA

Table 21 shows the results of a two-way factorial analysis of variance to contrast means of technology integration when the data had been grouped by country and by grade level. In this analysis, the individual effect for country and for grade level as well as the combined effect for country by grade level were being examined.

Table 21

Summary of a Two-Way Factorial ANOVA Contrasting Country and Grade Level

Source	Sum of squares	*df*	Mean square	*F*	*Sig.*	Eta squared	Model R^2
Model	563.77	3	187.93	156.59	.000	.208	.208
Intercept	25619.68	1	25619.68	21347.37	.000	.923	
Country	540.38	1	540.38	450.27	.000	.201	
Grade level	7.11	1	7.11	5.93	.015	.003	
Country by Grade Level	4.09	1	4.09	3.40	.065	.002	
Error	2149.44	1791	1.20				

Note: Dependent variable: Integration

Results presented in Table 21 showed a significant main effect for the model, not only statistical, but also practical, with an effect size of R^2 = .21, which according to Cohen (1968), falls between a "medium" and a "large" effect. The effect for country was large, and highly significant (F = 450.27, p < .0005), and explained most of the variance attributed to the model

($\eta^2 = .20$), whereas the effect for grade level, although statistically significant ($F = 5.93$, $p = .015$), did not contribute meaningfully to the variance attributed to the model ($\eta^2 = .003$). The effect for the interaction between country and grade level was not significant.

According to these results, both country and grade level made a statistically significant difference in technology integration, and each measure was largely independent of the other. However, from an amount-of-variance accounted for perspective, the differences in the data were overwhelmingly due to country (20% of 21% total variance accounted for) while the differences due to grade level were trivial (.3%). Therefore, the null hypothesis of no differential effect on the level of technology integration between Texas teachers and Mexico City teachers is rejected (Hypothesis 1a). A Post Hoc test was conducted to locate the mean differences in teaching level. Table 22 shows the results.

Table 22

Post Hoc Pairwise Test to Contrast Grade Level from Texas and Mexico City

Group	Mean Difference	Standard Error	*Sig.*
Texas Elementary – Texas Middle	.031	.076	.976
Texas Elementary – Mexico City Elem.	1.230	.072	.000
Texas Elementary – Mexico City Middle	1.002	.066	.000

(table continues)

Table 22 *(continued)*

Group	Mean Difference	Standard Error	*Sig.*
Texas Middle – Mexico City Elem.	1.261	.083	.000
Texas Middle – Mexico City Middle	1.033	.078	.000
Mexico City Elem. – Mexico City Middle	.228	.075	.013

Note: Post-hoc test: Tukey

With regard to Hypothesis 1b, as shown in Table 22, the mean difference between integration of elementary school teachers, and middle school teachers from Texas was not statistically significant (Mean Difference = .031, p = .976) according to the post hoc analysis. This finding, combined with the trivial amount of variance found to be explained by grade level on the cross-cultural context, led to the conclusion that Hypothesis 1b could only be partially rejected at best. Therefore, the conclusion is that we fail to reject the null hypothesis stating no differential effect on integration between elementary school teachers and middle school teachers (.3%). Significant differences by grade level were only found in Mexico City (Mean Difference = .228, p = .013) not in Texas.

Regression Analysis with Three Independent Variables

To test the Hypothesis 2 of no differential effect of Will, Skill, and Tool on Integration, a series of regression analyses with three independent variables combined with ANOVA (a regression model with three independent variables) were conducted on seven samples and subsamples: Cross-Cultural, Texas, Texas Elementary School Teachers, Texas Middle School Teachers, Mexico City, Mexico City Elementary School Teachers, and Mexico City Middle School Teachers. Tables 23 to 28 show the results.

Cross-Cultural Sample

Table 23 shows a significant main effect for the model (F = 626.29, p = .000), that explained 55% of the variance of the dependent variable. The effect for each independent variable was large, and statistically significant (F = 78.81, p = .000 for Will; F = 212.20, p = .000 for Skill; F = 574.07, p = .000 for Tool), but the variables did not contribute equally to explain the variance (η^2 = .050 for Will; η^2 = .123 for Skill; and η^2 = .276 for Tool). Therefore, to explain integration for the Cross-Cultural sample, the highest contributor was Tool, then Skill, then Will.

Table 23

Regression Model with Three Independent Variables for the Cross-Cultural Sample

Source	Sum of squares	*df*	Mean square	*F*	*Sig.*	Eta squared	Beta	Model R^2
Model	1136.89	3	378.96	626.29	.000	.555		.555
Intercept	40.53	1	40.53	66.99	.000	.043	-1.36	
Will	47.69	1	47.69	78.81	.000	.050	.412	
Skill	128.39	1	128.39	212.19	.000	.123	.452	
Tool	347.36	1	347.36	574.07	.000	.276	.755	
Error	911.87	1507	.60					

According to the parameter estimates, the regression equation for estimating the value of technology integration was: Integration = -1.363 + .412Will + .452Skill + .755Tool.

Texas Sample

Table 24 shows a significant main effect for the model (F = 349.62, p = .000), that explained 54% of the variance of the dependent variable. The effect for each independent variable was large, and statistically significant (F = 71.01, p = .000 for Will; F = 260.07, p = .000 for Skill; F = 71.73, p = .000 for Tool), but the variables did not contribute equally to explain the variance (η^2 = .073 for Will; η^2 = .224 for Skill; and η^2 = .074 for Tool). Therefore, to explain integration for the Texas sample, the highest contributor was Skill, then Tool and Will.

Table 24

Regression Model with Three Independent Variables for the Texas Sample

Source	Sum of squares	*df*	Mean square	*F*	*Sig.*	Eta squared	Beta	Model R^2
Model	392.25	3	130.75	349.62	.000	.538		.538
Intercept	10.36	1	10.36	27.71	.000	.030	-1.03	
Will	26.56	1	26.56	71.01	.000	.073	.452	
Skill	97.26	1	97.26	260.07	.000	.224	.602	
Tool	26.82	1	26.82	71.73	.000	.074	.354	
Error	337.34	902	.37					

According to the parameter estimates, the regression equation for estimating the value of technology integration was: Integration = -1.027 + .452Will + .602Skill + .354Tool

Texas Elementary School Teacher Sample

Table 25 shows a significant main effect for the model (F = 207.33, p = .000), that explained 51% of the variance of the dependent variable. The effect for each independent variable was large, and statistically significant (F = 58.96, p = .000 for Will; F = 150.09, p = .000 for Skill; F = 18.99, p = .000 for Tool), but the variables did not contribute equally to explain the variance (η^2 = .091 for Will; η^2 = .203 for Skill; and η^2 = .031 for Tool). Therefore, to explain integration for the Texas elementary school teacher sample, the highest contributor was Skill, then Will, then Tool.

Table 25

Regression Model with Three Independent Variables for the Texas Elementary School Teacher Sample

Source	Sum of squares	*df*	Mean square	*F*	*Sig.*	Eta squared	Beta	Model R^2
Model	217.87	3	72.62	207.33	.000	.514		.514
Intercept	2.16	1	2.16	6.18	.013	.010	-.591	
Will	20.65	1	20.65	58.96	.000	.091	.496	
Skill	52.57	1	52.57	150.09	.000	.203	.539	
Tool	6.65	1	6.65	18.99	.000	.031	.226	
Error	206.31	589	.35					

According to the parameter estimates, the regression equation for estimating the value of technology integration was: Integration = -.591 + .496Will + .539Skill + .226Tool.

Texas Middle School Teacher Sample

Table 26 shows a significant main effect for the model (F = 161.43, p = .000), that explained 61% of the variance of the dependent variable. The effect for each independent variable was statistically significant (F = 10.82, p = .001 for Will; F = 129.35, p = .000 for Skill; F = 60.24, p = .000 for Tool), but the variables did not contribute equally to explain the variance (η^2 = .034 for Will; η^2 = .295 for Skill; and η^2 = .163 for Tool). Therefore, to explain integration for the Texas middle school teacher sample, the highest contributor was Skill, then Tool, then Will.

Table 26

Regression Model with Three Independent Variables for the Texas Middle School Teacher Sample

Source	Sum of squares	*df*	Mean square	*F*	*Sig.*	Eta squared	Beta	Model R^2
Model	186.29	3	62.10	161.43	.000	.610		.610
Intercept	11.54	1	11.54	30.00	.000	.089	-1.81	
Will	4.16	1	4.16	10.82	.001	.034	.308	
Skill	49.75	1	49.75	129.35	.000	.295	.812	
Tool	23.17	1	23.17	60.24	.000	.163	.536	
Error	118.86	309	.38					

According to the parameter estimates, the regression equation for estimating the value of technology integration was: Integration = -1.815 + .308Will + .812Skill + .536Tool

Mexico City Sample

Table 27 shows a significant main effect for the model (F = 177.55, p = .000), that explained 47% of the variance of the dependent variable. The effect for each independent variable was large, and statistically significant (F = 19.15, p = .000 for Will; F = 43.60, p = .000 for Skill; F = 294.87, p = .000 for Tool), but the variables did not contribute equally to explain the variance (η^2 = .031 for Will; η^2 = .068 for Skill; and η^2 = .329 for Tool). Therefore, to explain integration for the Mexico City sample, the highest contributor was Tool, then Skill, then Will.

Table 27

Regression Model with Three Independent Variables for the Mexico City Sample

Source	Sum of squares	*df*	Mean square	*F*	*Sig.*	Eta squared	Beta	Model R^2
Model	456.03	3	152.01	177.55	.000	.470		.470
Intercept	12.09	1	12.09	14.12	.000	.023	-1.106	
Will	16.40	1	16.40	19.16	.000	.031	.334	
Skill	37.33	1	37.33	43.60	.000	.068	.325	
Tool	252.44	1	252.44	294.87	.000	.329	1.001	
Error	514.53	601	.85					

According to the parameter estimates, the regression equation for estimating the value of technology integration was: Integration = -1.106 + .334Will + .325Skill + 1.001Tool.

Mexico City Elementary School Teacher Sample

Table 28 shows a significant main effect for the model (F = 68.74, p = .000), that explained 45% of the variance of the dependent variable. The effect for each independent variable was large, and statistically significant (F = 18.25, p = .000 for Will; F = 21.48, p = .000 for Skill; F = 86.89, p = .000 for Tool), but the variables did not contribute equally to explain the variance (η^2 = .067 for Will; η^2 = .077 for Skill; and η^2 = .253 for Tool). Therefore, to explain integration for the Mexico City elementary school teacher sample, the highest contributor was Tool, then Skill, then Will.

Table 28

Regression Model with Three Independent Variables for the Mexico City Elementary School Teacher Sample

Source	Sum of squares	*df*	Mean square	*F*	*Sig.*	Eta squared	Beta	Model R^2
Model	176.21	3	58.74	68.74	.000	.446		.446
Intercept	12.65	1	12.65	14.81	.000	.055	-1.901	
Will	15.59	1	15.59	18.25	.000	.067	.548	
Skill	18.35	1	18.35	21.48	.000	.077	.342	
Tool	74.24	1	74.24	86.89	.000	.253	.859	
Error	218.73	256	.85					

According to the parameter estimates, the regression equation for estimating the value of technology integration was: Integration = -1.901 + .548Will + .342Skill + .859Tool.

Mexico City Middle School Teacher Sample

Table 29 shows a significant main effect for the model (F = 115.71, p = .000), that explained 50% of the variance of the dependent variable. The effect for each independent variable was statistically significant (F = 8.96, p = .003 for Will; F = 14.30, p = .000 for Skill; F = 219.28, p = .000 for Tool), but the variables did not contribute equally to explain the variance (η^2 = .026 for Will; η^2 = .040 for Skill; and η^2 = .391 for Tool). Therefore, to explain integration for the Mexico City middle school teacher sample, the highest contributor was Tool, then Skill, then Will.

Table 29

Regression Model with Three Independent Variables for the Mexico City Middle School Teacher Sample

Source	Sum of squares	*df*	Mean square	*F*	*Sig.*	Eta squared	Beta	Model R^2
Model	289.05	3	96.35	115.71	.000	.504		.504
Intercept	3.83	1	3.83	4.60	.033	.013	-.783	
Will	7.46	1	7.46	8.96	.003	.026	.291	
Skill	11.91	1	11.91	14.30	.000	.040	.254	
Tool	182.59	1	182.59	219.28	.000	.391	1.104	
Error	283.95	341	.83					

According to the parameter estimates, the regression equation for estimating the value of technology integration was: Integration = -.783 + .291Will + .254Skill + 1.104Tool.

Table 30 summarizes the results from Tables 23 – 29, on the contribution of Will, Skill, and Tool to explain integration.

Table 30

Summary of Eta Squared for Will, Skill, and Tool Across Samples

Sample	Hill	Skill	Tool
Cross-C.	0.050	0.123	0.276
Texas	0.073	0.224	0.074
Tex. Elem.	0.091	0.203	0.031
Tex. Mid.	0.034	0.295	0.163

(table continues)

Table 30 *(continued)*

Simple	Hill	Skill	Tool
Mexico City	0.031	0.068	0.329
Mex. C. Elem.	0.067	0.077	0.253
Mex. C. Mid.	0.026	0.040	0.391

Figure 32 graphically displays the contribution of Will, Skill, and Tool to explain integration across the samples studied.

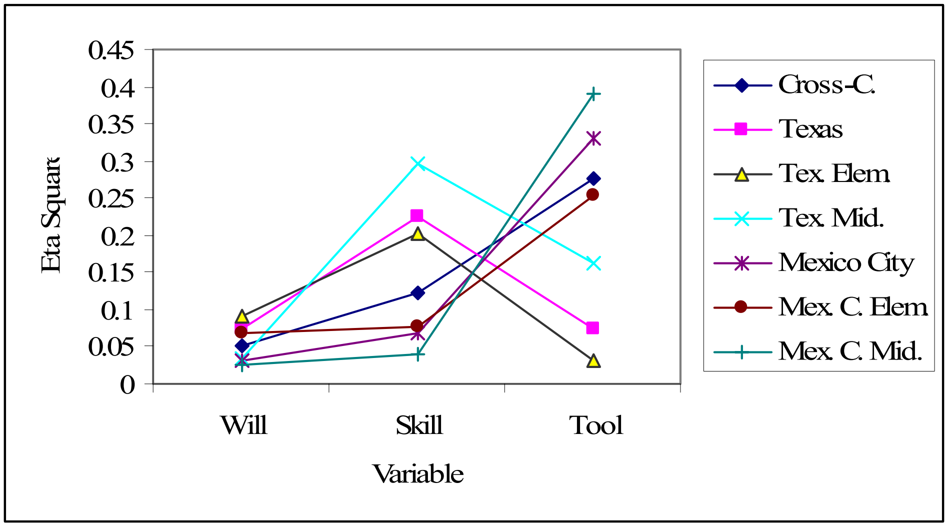


Figure 32. Eta squared values for will, skill, and tool across samples.

Table 30, and Figure 32 show a small effect of Will across samples, whereas Skill and Tool show a differential effect depending on the sample and the country. For the Texas samples, a large effect of Skill and a small effect of Tool appear to prevail, whereas for the Mexico City samples a large effect of Tool and a small effect of Skill appear to prevail. Therefore, the null hypothesis of no differential effect of Will, Skill, and Tool on Technology Integration is rejected. Although with a different tendency on the variance explained by Will across the samples, the overall results of hypotheses testing also supported the results on SEM analysis from a different perspective.

Summary

In summary, the most important finding of the study is that a single model of technology integration (with a differential explanatory contribution of Will, Skill, and Tool) could be shown to have good fit characteristics for all seven sample tested. Table 31 shows the individual R^2 for each variable, and the total R^2 for the model, derived from the structural equations.

Table 31

Total Integration Variance Explained and Variance Explained by Will, Skill, and Tool Across Seven Samples

Sample	Total R^2	Will	Skill	Tool
Cross-Cultural	0.923	0.240	0.327	0.497
Texas	0.908	0.316	0.481	0.329
Texas Elementary	0.905	0.337	0.512	0.281
Texas Middle	0.957	0.356	0.515	0.383
Mexico City	0.991	0.068	0.089	0.892
Mexico City Elem.	0.936	0.066	0.096	0.789
Mexico City Mid.	0.960	0.050	0.057	0.845

As Table 31 shows, the total variance explained by the model was more than 90% in all cases, and individual variables resulted in different variance explained, although there was a trend in the distribution by country. Derived from these data, Table 32 shows ranks of variance explained by each variable.

Table 32

Rank Order of Will, Skill, and Tool According to Their Relative Importance to Explain Technology Integration

	First	Second	Third
Cross-Cultural	Tool	Skill	Will
Texas	Skill	Tool	Will
Texas Elementary	Skill	Will	Tool
Texas Middle	Skill	Tool	Will
Mexico City	Tool	Skill	Will
Mex City Elementary	Tool	Skill	Will
Mexico City Middle	Tool	Skill	Will

As table 32 shows, there was a clear strongest contributor for each country: Skill was the strongest predictor of technology integration in Texas, whereas Tool was the strongest predictor in Mexico City. These results were paramount to define the status of the model as a plausible explanation of the technology integration process, as it is discussed in the next chapter.

CHAPTER 5

DISCUSSION AND CONCLUSIONS

The original Will, Skill, Tool model assumes that "enhancing an educator's will, skill, and access to technology tools will in turn lead to higher stages of classroom technology integration" (Knezek & Christensen, 2002, p. 111). The statement implies an equal predictor status for the three variables, and in fact the original model involves three independent variables (Will, Skill, and Tool), and one dependent variable (Integration). Findings from this study suggest an alternative distribution of the variables, and consequently, a different assumption on their status as predictor or criterion, as shown in Figure 33.

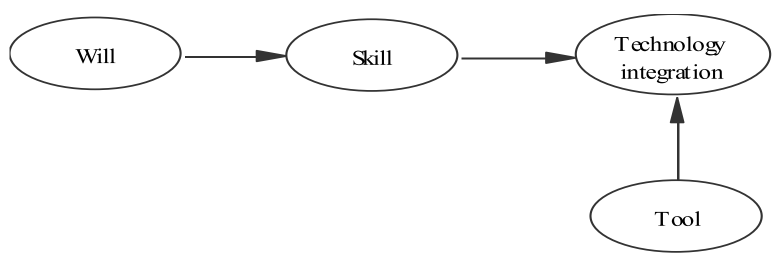


Figure 33. WiSTTI model derived for elementary and middle school teachers from Texas and Mexico City.

As seen in Figure 33, this modified version of the original model assumes that Will affects Skill, and in turn, Skill affects Integration, while Tool independently, and directly, affects Integration. In this case, the only true predictors are Will and Tool, whereas Skill plays a mediator role (criterion and predictor) affecting the only true criterion variable, Integration. Observing the composition of the model, it is important to keep in mind that, although Will is a true independent variable (it is not being influenced by any other variable), it only indirectly affects integration, as it covaries with Skill.

These results support the strength of Will, Skill, and Tool to predict technology integration. What will be discussed in this chapter is not a new model, but a strengthened version of the original teacher professional development component of the Will, Skill, Tool model, referred to as the Will, Skill, Tool Model of Teacher Integration (WiSTTI). The version resulting from this study has not added new variables to the model, rather it only changed the set of relationships between some of the variables.

Of particular importance for the discussion are the dispositions of Will, and Skill. During the testing, the only plausible direction of the path went from Will to Skill, not the opposite direction. Alternative arrangements of the variables were tested as well, such as Will as predictor of both Skill and Integration; Tool as predictor of Skill and Integration; or Tool as predictor of Will and Integration, but the only version that preserved all the conditions established before beginning SEM analysis (maximum variance explained, good model fit, reliable paths, and normal parameter estimates), and at the same time was a good fit for all the samples involved, was the one discussed here.

As noted in Chapter 3, this study started as an extension of a study carried out in 2004, with data from a Dallas-Fort Worth Metroplex school district, and using the original version of the Will, Skill, Tool model. To test if the original model composition would produce results similar to the version discussed here, and to directly address the first research question: "Will data gathered from elementary and middle school teachers in Mexico City produce technology integration findings similar to those in Texas?", SEM analysis was applied to the data from seven samples used throughout this project. The outcomes revealed that resolvable solutions could be found for the original WST model for only five of the seven data samples, including all the samples from Texas, but only one from Mexico City. Furthermore, the resulting solutions were not satisfactory in terms of two of the conditions established for the analysis:

1) *Solutions to the original model did not reach a maximum of variance explained*. For four of the five solutions brought about by the procedure, variance explained was considerably below the variance explained for the "new" version (Cross-Cultural R^2 = .85 vs R^2 = .92; Texas Teachers R^2 = .73 vs R^2 = .91; Texas Elementary R^2 = .74 vs R^2 = .90; Mexico City Middle R^2 = .87 vs R^2 = .96). Although for Texas middle school teachers variance explained was R^2 = .93, this value was still bellow the R^2 = .96 found for the modified model version.
2) *Solutions to the original model did not have reliable paths (*t*-value > 1.96).* None of the solutions showed a complete set of reliable paths within the structural model: Cross-Cultural, Will *t*-value = <u>.982</u>, Skill *t*-value = 4.941, Tool *t*-value = 11.655; Texas Teachers Will *t*-value = <u>.534</u>, Skill *t*-value = 4.345, Tool *t*-value = <u>1.863</u>; Texas Elementary Will *t*-value = <u>.366</u>, Skill *t*-value = 6.620, Tool *t*-value = <u>1.885</u>; Texas Middle Will *t*-value = <u>.292</u>, Skill *t*-value = 2.848, Tool *t*-value = 3.561; Mexico City Middle Will *t*-value = <u>.637</u>, Skill *t*-value = <u>.417</u>, Tool *t*-value = 10.278. As shown in these results, the path from Will to Integration was not reliable for any of the samples.

The unreliable paths on the part of Will could have affected the amount of variance explained by this variable in the original model, because it remained low across samples, as shown in Table 33.

Table 33

Differential Effect of Will Yielded by the Original Model and the Modified Version

Sample	Original model	Modified version
Cross-Cultural	$R^2 = .039$	$R^2 = .240$
Texas	$R^2 = .050$	$R^2 = .316$
Texas Elem.	$R^2 = .051$	$R^2 = .337$
Texas Middle	$R^2 = .022$	$R^2 = .356$
Mex City Middle	$R^2 = .049$	$R^2 = .050$

As shown in Table 33, the original model reduced the explanatory power of Will as a predictor of integration. As will be discussed later, there seems to be a more powerful role for Will, especially at higher stages of adoption, which is contrary to the overall findings reported here. Having a set of reliable paths, the modified version only kept a low profile on Will for the samples from Mexico City.

From these results, it was clear that the original composition of the model was not a reliable tool to cross-culturally address the research question. The modified reliable version of the model yielded results that clearly support the existence of a difference between teachers of Mexico City and Texas on Will, Skill, Tool, and Integration, as will be discussed in this chapter.

Other versions of the WiSTTI model were tested as well, particularly those two-independent variable versions that resulted in reliable solutions according to path analysis. Path model version 2 (see Figure 18) resulted in two good solutions, one of them with a higher R^2

than the version discussed here (R^2 = .96 vs. R^2 = .90 for the Texas Elementary School Teacher Sample). Path model version 3 (see Figure 19) resulted in three good solutions, two of them with equal or higher R^2s than the one produced for the version discussed here (R^2 = .97 vs. R^2 = .92 for the Cross-Cultural Sample; R^2 = .99 vs. R^2 = .99 for the Mexico City Sample). Path model version 4 (see Figure 20) resulted in three good solutions, one of them with higher R^2 than the one produced for the version discussed here (R^2 = .95 vs. R^2 = .90 for the Texas Elementary School Teacher Sample). Nevertheless, a closer analysis of the results revealed that, except for the Mexico City Sample, the solutions for path model versions 2, 3 and 4 presented unreliable error covariances, which were necessary for model fit. For the Mexico City Sample, both solutions (path model version 3 and the modified model) were nearly equivalent.

From these results, it is clear that the version found most suitable for Texas teachers and Mexico City teachers is the "average", but not the only possible one. Thus, at this point the third research question is in place: "Are there models other than Will, Skill, Tool that better explain the WST teacher professional development component (WiSTTI) results of data gathered from Mexico City and Texas?" This question has theoretical as well as methodological and practical implications.

Theoretical Consequences of Findings

The results of the study support the existence of two predictors of integration, Will and Tool, and Skill acting as a mediator between Will and Integration. The structural equations showed that this two-independent variable model had more predictive power than a three-independent variable model (the original Will, Skill, Tool model).

In terms of the integration process, the new version of the model prescribes that increased Will brings about increased Skill, which in turn leads, jointly with Tool, to higher integration.

The original model indicates that increased Will, Skill, and Tool, together would lead to higher integration. According to the results of this study, Will and Skill do not act separately, but jointly, as McCombs and Marzano (1990) would contend, and as it was discussed in Chapter 2. Although Will is the inner force that impels the teacher to integrate technology, its effectiveness depends on the accompanying confidence that enough skills are already in place and conducive to integration. In turn, the self-perception of high skill disentangled from an integration goal would be ineffective to support technology integration.

On the other hand, it is clear that technology integration is a process (see concept definitions in Chapter 1), which cannot be accomplished in the short term, as it needs the development of the teacher's skills to use technology at a regular rate, to face the problems inherent to use technology in the classroom, to enroll in training sessions, to exchange ideas and seek advice from more advanced integrators, and to reflect on his/her own integration efforts. Thus, it has to be conceived as a progressive stage process (Christensen & Knezek, 2001c, p. 27).

The stages of technology adoption measure developed by Christensen (1997) and used in this study, serves the purpose of reflecting on the alternative versions of the model that resulted in good solutions for some of the samples studied here. As a reminder of what was discussed in the instrumentation section of Chapter 3, the Stages of Adoption proposed are six: Stage 1- awareness; Stage 2 – learning the process; Stage 3 – understanding and application of the process; Stage 4 – familiarity and confidence; Stage 5 – adaptation to other contexts; Stage 6 – creative applications to new contexts. Analysis of means revealed that while teachers from Mexico City perceived themselves at lower Stage 3 (Stage mean = 3.13 for elementary school teachers; Stage mean = 3.50 for middle school teachers), teachers from Texas perceived themselves at upper Stage 4 (Stage mean = 4.91 for elementary school teachers; Stage mean = 4.96 for middle school teachers). In other words, while teachers from Mexico City were still in the process of understanding the meaning of technology integration, teachers from Texas were already confident in using technology, and moving toward adapting the use of technology to other contexts. The differences between the means of the two countries on stages of adoption were statistically significant ($t = 27.34$, $df = 1837$, $p < .0005$) and such differences can easily be corroborated by any observer.

The important consequence of the resulting stage means for this discussion is that the WiSSTI model revealed these differences along the variables Will and Skill. Table 34 summarizes the variance explained by Will, Skill, and Tool, from the structural equations presented in Chapter 4.

Table 34

Variance Explained by Will, Skill, and Tool, Total Variance Explained by the Model, and Related Means Across Seven Samples

Sample	Will	Skill	Tool	Total R^2	Integration (composite) mean	Stage mean
Cross-Cultural	0.240	0.327	0.497	0.923	3.93	4.14
Texas	0.316	0.481	0.329	0.908	4.46	4.93
Texas Elementary	0.337	0.512	0.281	0.905	4.46	4.91
Texas Middle	0.356	0.515	0.383	0.957	4.48	4.96
Mexico City	0.068	0.089	0.892	0.991	3.36	3.34

(table continues)

Table 34 *(continued)*

Sample	Will	Skill	Tool	Total R^2	Integration (composite) mean	Stage mean
Mex City Elem.	0.066	0.096	0.789	0.936	3.23	3.13
Mexico City Mid.	0.050	0.057	0.845	0.960	3.46	3.50

The data presented in Table 34 support the contention that low coefficients for Will and Skill mean low Integration. A dramatic change occurs when the stage of adoption shifts from 3 to 4, reflected in the variance explained by Will and Skill. Two conjectures could be derived from these data:

1. Perhaps at lower stages Skill has not been developed, and the dual effect of Will and Skill has not been consolidated. The lack of a strong Will and a strong Skill leaves Tool as the only plausible explanation for technology integration. Table 33 shows a dramatic reduction in the variance explained by Tool from Stage 3 to Stage 4, indicating that at lower stages variance explained by Tool is high, and at higher stages variance explained by Tool is low. Furthermore, path model version 3 (Figure 19), with Tool as the immediate antecedent of integration was found to be viable among the samples from Mexico City, where the lowest stages of adoption are found, but not among the samples from Texas.

2. A second conjecture involves a differentiation between stages of adoption and technology integration. Perhaps at lower stages integration is not possible. As stated in the Stages of Adoption measure, Stage 1 refers to the awareness of the existence of technology, and Stage 2 refers to learning the process. At those stages there is no actual teaching practice using

technology, or exploration of technology tools for learning. It is at Stage 3 when the application of the integration process begins. A side effect of testing different versions of the WiSTTI model that could apply to higher Stages of Adoption gave way to an unexpected result: no version of the model could be brought to a solution at Stages 1 and 2. A solution could only be found at the mean stage for the sample and above, for example, for the Mexico City samples an acceptable solution could only be found at Stage 3 and above, whereas for the Texas samples, a solution could only be found at Stage 4 and above. This would imply that the integration process only begins when accompanied by a strong will, and advanced skills.

At higher stages, when Will and Skill are also high, the most important variables to integrate technology would be the coupled combination Will-Skill. An indication of this assumption is that path model version 2 (Figure 18), with Will as the immediate antecedent of integration, and path model version 4 (Figure 20), with Skill as the immediate antecedent of integration, were only found among the samples from Texas, where teachers perceived themselves as much as 1.83 Stages of Adoption higher (in the extreme case) compared with their colleagues from Mexico City.

The appearance of model version 2 indicates the possibility that at higher integration stages, Will also could be a single independent force toward integrate technology. This would indicate additional support for the “barriers” model advocated by Rogers (1999). Was there a possibility that model version 2 could explain integration better than the model version found for this study?

To test model version 2, SEM analysis was conducted using the score from Stages of Adoption as the selector, specifically to select groups of teachers at stages 4-5, and 5-6. Results are shown in Table 35.

Table 35

Integration Variance Explained by Model Version 2 at Stages 4-6 Across Seven Samples

Sample	Stages 4-5	Stages 5-6	Modified model
Cross-Cultural	No solution	$R^2 = .987$	$R^2 = .923$
Texas	$R^2 = .972$	$R^2 = .968$	$R^2 = .908$
Texas Elementary	$R^2 = .938$	$R^2 = .960$	$R^2 = .905$
Texas Middle	No solution	No solution	$R^2 = .957$
Mexico City	No solution	No solution	$R^2 = .991$
Mexico City Elementary	No solution	$R^2 = .982$	$R^2 = .936$
Mexico City Middle	No solution	No solution	$R^2 = .960$

As shown in Table 35, acceptable solutions were found mainly at stages 5-6, with more variance explained than the modified average version found in this project. Nevertheless, the analysis of paths revealed that only the solution for the Texas sample at stages 5-6 also had a complete set of reliable paths. Additional SEM analyses revealed that this model was the best solution, better than the modified model. The complete solution is shown in Figure 34, and the following equations in Table 36.

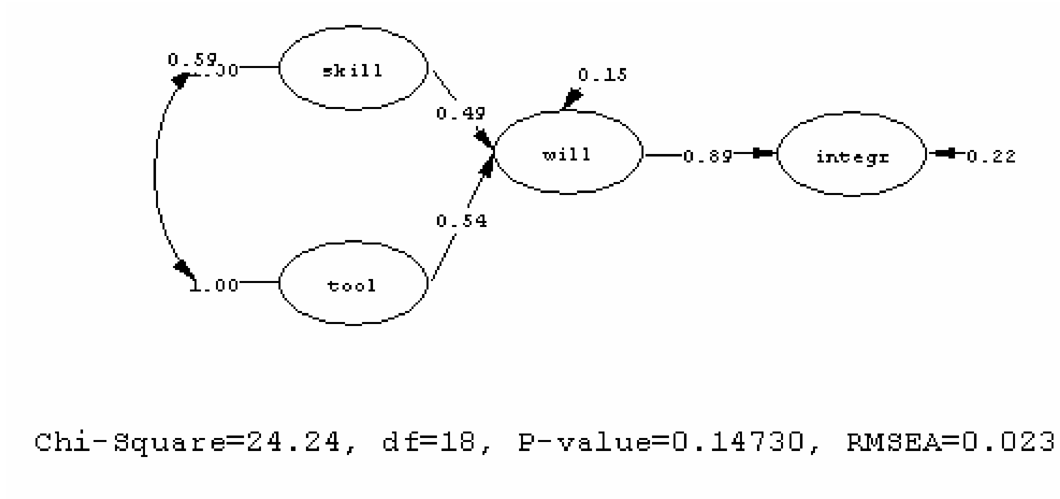


Figure 34. Path diagram of the model version 2 for the Texas sample at stages 5-6 (N=646).

Table 36

Structural Equations for Model Version 2, Texas Sample at Stages 5-6

Structural Equations
will = 0.494*skill + 0.542*tool, Errorvar.= 0.146, R^2 = 0.854
(0.157) (0.182) (0.122)
3.151 2.974 1.200
integr = 0.885*will, Errorvar.= 0.216, R^2 = 0.784
(0.124) (0.0825)
7.139 2.622

As shown in Figure 34 and Table 36, this model illustrated a remarkable shift in the variance explained by Will. For this model, the R^2 = .784, whereas for the modified WiSTTI model, the variance explained was R^2 = .316.

Nevertheless, positive results for model version 2 would only be part of the answer to the question of how Will and Skill act at higher stages. SEM analysis was conducted to test model version 4 (Figure 20), using the same selector. In this model, Skill is the immediate predictor of Integration. Table 37 presents the results. Despite the fact that most of the solutions explained more variance than the solutions for the modified model, a closer analysis showed that all the solutions had unreliable paths.

Table 37

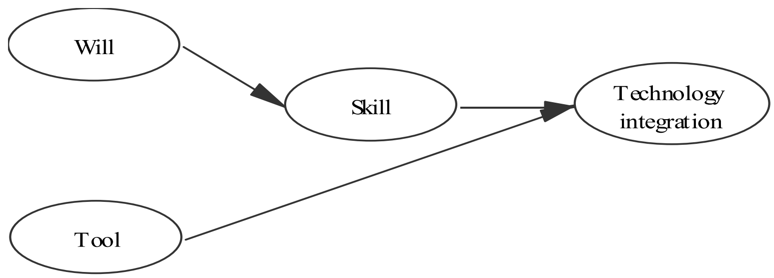
Integration Variance Explained by Model Version 4 at Stages 4-6 Across Seven Samples

Sample	Stages 4-5	Stages 5-6	Modified model
Cross-Cultural	No solution	$R^2 = .969$	$R^2 = .923$
Texas	$R^2 = .942$	$R^2 = .940$	$R^2 = .908$
Texas Elementary	$R^2 = .927$	$R^2 = .938$	$R^2 = .905$
Texas Middle	No solution	No solution	$R^2 = .957$
Mexico City	No solution	No solution	$R^2 = .991$
Mexico City Elementary	$R^2 = .406$	No solution	$R^2 = .936$
Mexico City Middle	No solution	No solution	$R^2 = .960$

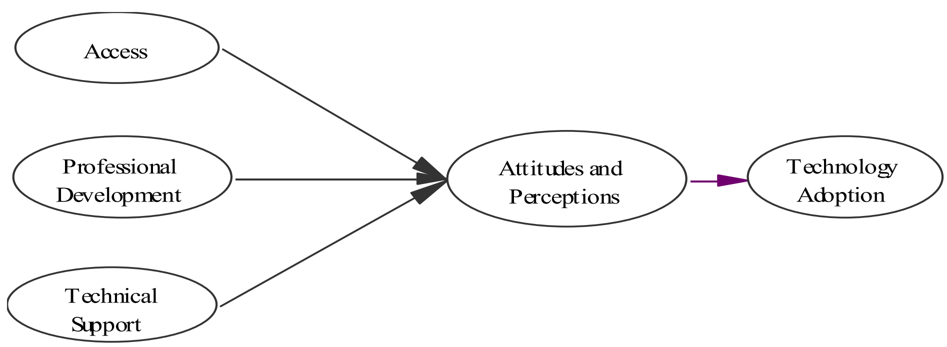
Although more conclusive evidence is needed, it is possible that alternative processes take place at higher stages of adoption regarding the influence of Will and Skill on integration. If Will and Skill are taken as a dual influence on integration, perhaps the idea of *turn-taking* between Will and Skill in order to explain integration is in place. At a certain point in the process, Will could become more important to integrate technology if, for example, a discrepancy between the present teaching condition and a more rewarding desired condition is perceived (Zhao & Cziko, 2001), or when teachers perceive a practical benefit when using technology (Rogers, 1999). It is also possible that the regulation of the will and the skill to integrate technology comes from a *self-agency* process (McCombs & Marzano, 1990) that is guided by positive feelings and desires toward using technology. The possibility that Will and Skill form a single force to integrate technology, as a *self-confidence* variable, is not unlikely. Further research is needed to explore the unique and joint values of Will and Skill for technology integration.

Technology Integration: Overcoming Barriers or Stepwise Development?

Although the findings and theoretical implications of this study are important, they are not conclusive evidence that alternative approaches, such as Roger's barriers model, might not better explain technology integration among Texas teachers, or Mexico City teachers. The findings address a deeper theoretical question: Is technology integration a process of overcoming barriers, or is it a process of reaching more advanced steps in technology proficiency and satisfaction? A barrier means an obstacle preventing the reaching of a goal, and it is understandable to think of external barriers when there is a lack of technical support or insufficient release time to explore and freely use technology. But what happens when those barriers are overcome? Maybe a new process begins, a process of progressive steps toward technology integration. A few of the findings from this study will serve as an argument for this claim. It is important, for the sake of argument, to recall Rogers' model and the modified WiSTTI model at this point. These are displayed in Figure 35.



Modified Knezek and Christensen (Knezek et al., 2000) WiSTTI Model Based on Stepwise Development



Rogers (1999) Model Based on Barriers to Technology Adoption

Figure 35. Two alternative models of technology integration.

Figure 35 shows two different ideas regarding technology integration, but both share the concepts (although with different nomenclature) involved. As stated before, Will refers to the attitudes and perceptions toward technology, Skill could be the basic outcome of professional development, and Tool refers mainly to access. The models start differing from each other as the relations between the variables involved in each model become clear.

Rogers' barriers model differs from the modified WiSTTI model in three important ways: First, for the WiSTTI model, it was found that attitudes and perceptions *precede* professional development, if this could be referred to as the skills gained through training. It was clear during the analysis that the direction of the influence was from attitudes to the perceived skills, not the other way around. Second, technical support did not appear to play an important role in explaining technology integration: Even though the scale for Technical Support was highly reliable (alpha = .93), no evidence from the regression weights indicated influence on technology integration. Third, access to technology was found to directly influence technology integration, and had no influence on attitudes. From these differences among the relationships involved, two important theoretical consequences follow:

1. Rogers explicitly contends that the first barrier that needs to be overcome is internal. Once past this barrier, external barriers become important. Nevertheless, as the results of the present study showed, it is unlikely that the integration process could be dependant on a single variable, otherwise, the single independent variable models tested (see Figures 21, 22, and 23) would not have been consistently rejected as non-fitting. It seems more likely that after the external barriers are resolved, a potential internal barrier such as the disposition to use technology becomes important. Then, it is perhaps at this point where the interrelated influence of Will and Skill on technology integration begins. The findings related to the ability of the construct Tool (access to technology and extent of use) to explain technology integration for beginners from Mexico City, and the fact that no solution to the model could be obtained for Stages of Adoption 1 and 2, seem to support this claim. There cannot be actual integration when teachers and school principals are still struggling with the problem of access.
2. If the process toward technology integration starts by removing external barriers, and progresses by moving toward integration while supported by Will and Skill, then models such as Rogers' barriers might work at lower stages of adoption, whereas stepwise

models such as the WiSTTI model might work at mid and higher stages of adoption. Perhaps it is important to note at this point that the path model version 3 (see Figure 19) with Tool as the immediate predictor of integration showed a good model fit for two of the samples from Mexico City, but none for the samples from Texas. These results could be interpreted as an access problem, which needs to be resolved first, in order for the teachers to reach a more advanced stage where integration might start becoming a reality.

Methodological Issues

What was the advantage of using structural equation modeling in testing the WiSTTI model? Could not the same results be reached by using a more "standard" statistical analysis, such as factor analysis? Although it can be said that confirmatory factor analysis is also a form of testing latent variables, it lacks some of the advanced features characteristic of structural equation modeling, which are drawn from path analysis and multiple regression. In fact, SEM analysis comprises the testing of the association between a set of measures and different constructs, but it goes a step further in testing the relationship between those factors, as it also allows calculations of direct and indirect effects on a factor (latent variable). This feature was especially useful for testing a three-independent variable version of the model, against a two-independent variable version. SEM is also grounded in regression analysis, thus, the resulting structural equations are similar to a regression equation, except that the regressed variables are theoretical constructs.

Nevertheless, the SEM procedure requires the active intervention of the researcher to set the condition for the analysis. The flexibility involved in the SEM approach has advantages and disadvantages. Besides the advantage of testing theoretical models directly from the data, SEM analysis allows the researcher to seek alternative solutions (models) that also might explain the data. Once basic conditions are set (in the case of this study, four conditions: maximum variance explained, model fit, statistically significant paths, and normal parameters) the researcher is allowed to do parameter modifications in order to search for the best solution to the model. The disadvantages of following this approach are many. As discussed in a previous study (Morales, 2005a), Loehlin (1987) holds an interesting, and admonitory view of SEM, and other latent variable models. He presents some “caveats” related to the validity and reliability of these models, which are worth addressing (Loehlin, 1987, pp. 214-218).

The Problem of Finding the Best Model

Finding a good model fit does not mean that we have the best possible one. There is no doubt that the incorporation of additional variables or the removal of some of them would change the solution. In this study, variables (measurement and latent variables) were not changed, nor were the original parameters. Nevertheless, paths were changed or added, and measurement errors for some variables were set to covary for each sample studied. Table 38 shows the particular paths and covariate errors added to the original parameters, in order to bring the best solution to the model.

Table 38

Added Paths and Correlated Errors Set for the Model Solution Across Seven Samples

Sample	Additional paths	Correlated errors between:
Cross-Cultural	No paths added	Clstool (T) and TPintegr (S) Stages (I) and TPintegr (S) Hometool (T) and TPwww (S) Clstool (T) and TACnegat (W) CBAMnew (I) and TPwww (S) Hometool (T) and Clstool (T) Clstool (T) and ACOTnew (I)
Texas	No paths added	Clstool (T) and CBAMnew (I) TPintegr (S) and ACOTnew (I) Clstool (T) and TACnegat (W) Hometool (T) and TPwww (S) TACnegat (W) and CBAMnew (I) Hometool (T) and TPintegr (S)
Texas Elementary	No paths added	Clstool (T) and CBAMnew (I) TPintegr (S) and ACOTnew (I) Hometool (T) and TPwww (S) Hometool (T) and TPintegr (S) Clstool (T) and TACnegat (W)

(table continues)

Table 38 *(continued)*

Sample	Additional paths	Correlated errors between:
Texas Middle	No paths added	Clstool (T) and CBAMnew (I) Hometool (T) and TACnegat (W) TPintegr (S) and stages (I)
Mexico City	From Tool to TACnegat	Clstool (T) and CBAMnew (I) TACnegat (W) and TPintegr (S) Clstool (T) and TPwww (S) Hometool (T) and TPwww (S) Hometool (T) and TPintegr (S)
Mexico City Elementary	From Tool to TACnegat	No error correlations were set
Mexico City Middle	No paths were added	Clstool (T) and CBAMnew (I) TACnegat (W) and Stages (I)

Of interest for the discussion is that the Tool measures were used more frequently as an originating point for a path, or as a covariate with other measures, especially with measures from Skill, and Integration. For example, “Clstool”, a composite involving the number of hours using technology in the classroom, and frequency of computer use for learning, was correlated to CBAM for five of the seven samples, and “Hometool”, a composite involving access to computers at home, access to Internet at home, and the number of hours using technology at home, was correlated to “TPwww” (TPSA subscale on proficiency of Internet use) for four of the seven samples. All the added paths and the error covariances were statistically significant, i.e. they all were reliable contributors to define the variance for the variables involved. It was unlikely that changing a path or adding new error covariances would substantially change the model *R* squared. Nevertheless, since all of these were new parameters added to the model, new values were expected for the existing parameters, resulting in possible threats to the model reliability on any of the four conditions set for a good solution. Although each possible path and error covariance was previously tested for negative consequences on the model, it has to be recognized that there were many other possible paths and error covariances which were not included in the final solution.

The Problem of Causation

Causation not only implies a significant directional correlation in a time frame, it has to be proved. In principle, causation implies a change on a variable by a demonstrated cause (particularly in an experimental design), as it is observed from one particular time to the next. In the case of the present study, SEM analysis and path analysis did not prove cause-effect results for any of the model solutions, even if the direction of the paths could lead to such an assumption.

As for the variables tested in this study, it is important to note that Will, Skill, or Tool did not necessarily cause integration, rather, they were strongly related to integration. The cause of technology integration might be the teacher's Will and Skill, but SEM results are not sufficient proof for this claim. Perhaps a longitudinal study, a time series experimental design involving all latent variables from this model would be effective in testing causal relationships. Although SEM and path analyses have been associated with the study of causal relationships (Gall et al., 2003, p. 347), the present study may be addressed as a correlational study (Gall et al., 2003), with an important outcome expressed in a regression equation. Thus, being aware that no time elapsed between the measure of Will, Skill, and Tool, and the measure of Integration, those measures are only part of a predictive model, not a causal one.

The Problem of Finding the Best Measures

Latent variables depend on actual measures to develop into something meaningful. But, what is the limit for the number of indicators (measures) to define a latent variable? When is this variable 100% well defined? These are different aspects of the second research question addressed in this study: “What are the best indicators of Will, Skill, and Tool for technology integration?” There is a need for the most valid and reliable measures, because for any model, there may be many other highly reliable indicators (measures) that are part of the same construct.

Before conducting the model testing, a prior step involving the selection of the best measures was followed. The cross-cultural validity of the model depended basically on these measures. Therefore, both, factor analysis and multiple regression were involved in the selection process. For the final selection, from 21 original measures 15 were selected which corresponded to the best factor loadings and also the highest regression weights. To reach these results, factor analysis was crucial. First, it was clear from the beginning that measures related to Skill and Integration were not a problem. Skill measures (subscales from the TPSA) loaded in one higher order factor, and Integration measures (Stages, CBAM, and ACOT) loaded in another. Cross-culturally, those were the most valid measures, since the selection analysis included all data from both countries.

Results on factor loadings for Will and Tool were not as straightforward. Several tests were conducted involving maximum likelihood (*ML*) and principal components (*PC*) as the method of extraction, and direct oblimin and varimax as the rotation method. Maximum likelihood extraction and oblimin rotation were originally intended to be used, but in searching for the most parsimonious solution, the best results were obtained using principal components extraction and varimax rotation. The regression weights also contributed to defining the best procedure for factor analysis. Some of the factor loadings using *ML* and oblimin rotation were quite different from the statistically significant regression weight that apparently predicted the variable. Thus, some of the best factor compositions had to be discarded. For example, in using *ML* with an oblimin rotation, it was learned that TAC2, and TAC3 always loaded in one factor, and TAC6, and TAC9 loaded in a second factor. Nevertheless, in looking at the regression weights, it was evident that TAC3 was not contributing to explaining the variance of the TAC in two of the samples, thus, it could not be taken as a good measure for the variable Will. TAC7 seemed the best second choice after using principal components and varimax rotation.

Despite the set of strong measures found, diversity appeared also to be important. Even though more than half (8) of the selected measures were present in all samples, a few other not-selected measures appeared in each sample as well (see Tables 7 and 8.)

The importance of the measure selection process became clear in the repercussions it had on model testing. The highest R^2s (squared multiple correlation coefficients) were those corresponding to Skill for the Texas samples, whereas the highest R^2s for the samples from Mexico City corresponded to the variable Tool. Based on these findings, it was expected that more variance from Integration could be attributed to Skill in the case of the Texas samples compared to samples from Mexico City. Conversely, it was expected that more of the variance from the Integration variable could be attributed to Tool in the case of the Mexico City samples, compared to samples from Texas. Variance differentially explained by each variable might have impacted the model composition in terms of the distribution of the variables as well (the WST model, the modified WiSTTI version, Rogers' model, and others).

Other measures, based on important theoretical constructs, were removed at different stages of the analysis. A measure on openness to change was not reliable, and it was dropped at the pilot stage. A measure on technical support was dropped at the regression analysis stage, since the resulting standardized regression coefficient was below a critical point to explain any meaningful variance. Nevertheless, further research should be conducted to test other measures of diverse constructs related to Will, Skill, and Tool, such as pedagogy (see Knezek & Christensen, 2002, p.111) and forms of support (technical, administrative) in order to strengthen the predictive power of the model.

Thus, by answering the second research question, and selecting the best measures for the study from the beginning, much of what followed, especially the finding of a valid cross-cultural version of the WiSTTI model, was already being set. Perhaps at another time (when conditions in Mexico could allow teachers to improve their skills), or with a different sample composition, the results could have been different.

The Problem of a Modified Model

Once the model has been modified, its condition is always precarious. It only holds for the sample from which the data were drawn. If it holds for another sample of the same population, then the model might be supported.

As stated at the beginning of Chapter 3, this study was intended as a replication of a study conducted in 2004, using basically the original Will, Skill, Tool model. As some changes were intended from the beginning, the study would actually be an "extension" of the first study. Nevertheless, the validation of the model for a cross-cultural sample took precedence, and, as SEM analysis became the most important tool for validation, the original model had to be modified in order to fit the data from the two countries. It also was evident from the beginning that the requirements for accepting a good solution (highest variance explained, and a "reasonable" model fit) were insufficient for testing a cross-cultural model. Therefore, despite using the same set of data, the lack of consistency in utilizing the same version of the model yielded different results, as shown in Table 39.

Table 39

Variance Yielded by the Original Version of the Model in 2004, Compared to the Variance Yielded by the Modified Model in 2005

Grade level	Original model (data analysis 2004)	Modified model (data analysis 2005)
Texas Elementary	Will R^2 = .381 Skill R^2 = .124 Tool R^2 = .186	Will R^2 = .337 Skill R^2 = .512 Tool R^2 = .281
Texas Middle	Will R^2 = .098 Skill R^2 = .330 Tool R^2 = .212	Will R^2 = .356 Skill R^2 = .515 Tool R^2 = .383

As shown in Table 39, the variances yielded by each model were quite different, although more consistency is observed in the variances from the modified version of the model. Prediction of technology integration yielded by the original model in 2004 appeared to be different for elementary school teachers, versus for middle school teachers. As a matter of fact, one of the ideas that triggered the realization of this study came from the alleged differential effect of Will, Skill, and Tool on integration, depending on the teaching level (see the purpose of the study in Chapter 1). Nevertheless, those results are questionable, because the regression paths on Skill and Tool were unreliable for the elementary school sample, and the paths on Will and Tool were unreliable for the middle school sample.

Although it appears that changing the version of the model was a necessary step, the shifting from one version to another has additional consequences for the problem of generalizability, addressed in the limitations of the study in Chapter 1. As discussed above, in the present condition, the model only holds for the samples that have been studied. In order to overcome this problem, the final test has to be performed on a different set of data drawn from the same populations involved in this study.

Practical Issues

The WiSTTI model can be regarded as more than a theoretical device to explain the integration process. It is also a tool to help practitioners and researchers to evaluate and predict integration. Although individual measures of the model were validated in the past in both countries, a comprehensive vision of what technology integration might be can only be possible when those measures are associated with meaningful constructs, and their relationships are analyzed through the magnification of a structural model. The tested WiSTTI model has yielded a set of path coefficients associated with Will, Skill, and Tool, which can be used as the parameters for calculating with more accuracy the level of technology integration among various groups of teachers from Texas and Mexico City.

A cross-cultural evaluation of technology integration was attempted using the model and its corresponding path coefficients. The problem of *equivalence* of measures listed as one of the limitations of the study from a cross-cultural perspective should be accounted for by using the model.

Having a cross-culturally validated model, the differences found between a sample from Texas and a sample from Mexico City can be regarded as real differences, because both samples are being measured with the same standards. It would not be fair to measure technology integration among elementary school teachers from Mexico City with the localized criteria being used to measure technology integration among elementary school teachers from Texas. From a cross-cultural perspective, and considering the uneven development of technology integration in both countries, evaluation standards may be easier to reach for Texas teachers, and harder to reach for Mexico City teachers, but they have to be reachable by both groups.

It is proposed that the standardized regression coefficients be used as the evaluation parameters of the model, as the real value of Will, Skill, and Tool. In this way it is assured there will be an underlying equal contribution from the three variables in explaining technology integration. Table 40 shows the set of Betas found for each sample.

Table 40

Standardized Regression Coefficients from Structural Equations Across Samples

Sample	Will	Skill	Tool
Cross-Cultural	0.333	0.445	0.606
Texas	0.421	0.585	0.436
Texas Elementary	0.453	0.616	0.385
Texas Middle	0.463	0.610	0.491
Mexico City	0.170	0.261	0.862
Mexico City Elem.	0.152	0.230	0.864
Mexico City Middle	0.095	0.124	0.896

The cross-cultural Betas are of particular importance for this study. As shown in Table 40, the cross-cultural regression coefficients appear to "balance" the other coefficients, as they stand in the middle of the values for Mexico City and Texas. Cross-cultural evaluation parameters would imply a third of Will ($\beta = 0.333$), around half of Skill ($\beta = 0.445$), and nearly two thirds of Tool ($\beta = 0.606$) can be used to accurately estimate the value of integration. It can be argued that these parameters may hinder the possibility of reaching a better level of technology integration for the Texas teachers, because they lower the proportion of Will and Skill going to integration; nevertheless, as a compensatory factor, they also augment the proportion of Tool going to integration. The opposite occurs for Mexico City teachers, who benefit from a higher proportion of Will and Skill going to integration, and a lower proportion of Tool applied to integration. It is only through this compensatory exchange of proportions that an even set of rules can be implemented for evaluating technology integration across cultures.

Ancillary Finding: An Evaluation Metric

A byproduct of this study was the realization the Betas combined with the means for each main construct can be used to produce a comprehensive metric to evaluate technology integration. The model can provide the Betas for each of the seven samples studied. The means for Will, Skill, and Tool, can be calculated as a composite of the individual indicators. Finally, adding the products of the Betas and means produces the metric. The general expression is the following:

$$IM = \beta_w * Mean_w + \beta_s * Mean_s + \beta_t * Mean_t \tag{1}$$

where IM is the integration metric, β_w is the standardized regression coefficient for Will, $Mean_w$ is the mean value for the variable Will, β_s is the standardized regression coefficient for Skill,

$Mean_s$ is the mean value for the variable Skill, β_t is the standardized regression coefficient for Tool, and $Mean_t$ is the mean value for the variable Tool.

At this point, the modified version of the model would imply that the scores of Will and Skill should be added to obtain a single score for the dyad Will-Skill. However, when the procedure using Equation 1 was tested against a composite of Will-Skill added to the score for Tool, the resulting value proved to be nearly equivalent. Therefore, for practical purposes, the computationally simpler 3-predictor additive model is recommended.

Using Equation 1, the Betas, and the means from the Cross-Cultural sample, it was possible to obtain the integration metric from equivalent conditions of Will, Skill, and Tool, and set the basis for a cross-cultural evaluation of technology integration. The new values of each predictor were added to obtain the integration metric, as shown in Table 41.

Table 41

Proportion of Will, Skill, and Tool Added to Integration, Calculated from the Cross-Cultural Standardized Regression Coefficients

Sample	Will (β=.333)	Skill (β=.445)	Tool (β=.606)	Integration Metric
Texas Elementary	β*4.43 = 1.47	β*4.07 = 1.81	β*2.77 = 1.68	4.97
Texas Middle	β*4.41 = 1.47	β*4.28 = 1.91	β*2.70 = 1.63	5.01
Mexico City Elementary	β*4.20 = 1.41	β*3.66 = 1.63	β*1.94 = 1.21	4.26

(table continues)

Table 41 *(continued)*

Sample	Will (β=.333)	Skill (β=.445)	Tool (β=.606)	Integration Metric
Mexico City Middle	β*4.04 = 1.35	β*3.79 = 1.70	β*1.86 = 1.17	4.22

The integration metric shown in Table 41, which was derived from the "corrected" scores, should approximate the scores obtained with the integration measures used in this study. Although the resulting Will, Skill, Tool, and Integration scores do not form a scale like the TAC or the Stages of Adoption, analysis revealed that the metric obtained from this procedure was strongly correlated to the composite integration score (r = .744, p < .01), and with Stages of Adoption (r = .703, p < .01). When the metric was obtained using Will-Skill as a single variable, similar correlation coefficients were obtained for the composite integration score (r = .694, p < .01) and for Stages of Adoption (r = .734, p < .01). Furthermore, as shown in Table 42, the contrasting of means revealed a similar discriminatory power for the new integration metric based on Will, Skill and Tool, versus the composite score produced from the self-reported direct measures of level of technology integration. Table 42 shows similar F value for both scores, and an improvement on the variance explained when using the integration metric. Several comparisons of this type can be made regarding the hypotheses in this study, based on the new metric. Those will be presented in the following sections.

Table 42

Contrasted Means for Texas Elementary, Texas Middle, Mexico City Elementary, and Mexico City Middle Using the Integration Metric and the Composite Integration Score

Source	*df*	*F*	*Sig.*	R^2	η^2
Integration metric	3	161.127	.000	.196	.236
Integration (composite)	3	156.587	.000	.155	.208

Results of Re-Examining Hypothesis 1 with New Metric

Hypothesis 1a of no difference in level of technology integration between teachers from the Texas and Mexico City, and hypothesis 1b of no difference in level of technology integration between elementary school teachers and middle school teachers were tested based on the new integration metric. The same procedure reported in chapter 4 (two-way factorial ANOVA) was used for the re-examination. Results are shown in Table 43.

Table 43

Summary of a Two-Way Factorial ANOVA Using Integration Metric Means to Contrast Country and Grade Level

Source	Sum of squares	*df*	Mean square	*F*	*Sig.*	Eta squared	Model R^2
Model	212.34	3	70.78	161.13	.000	.237	.237

(table continues)

Table 43 *(continued)*

Source	Sum of squares	*df*	Mean square	*F*	*Sig.*	Eta squared	Model R^2
Intercept	30717.44	1	30717.44	69925.40	.000	.978	
Country	202.88	1	202.88	461.83	.000	.228	
Grade level	.003	1	.003	.01	.928	.000	
Country by Grade Level	.479	1	.479	1.09	.297	.001	
Error	685.29	1560	1.20				

If the results from Table 43 are compared to those reported in Table 21 (Chapter 4), a large contrast between the original and the new metric outcomes for effect of grade level is perceived. Using the original integration composite measure, the effect for grade level was not large, but significant ($F = 5.93$, $p = .015$), whereas using the integration metric from the WiSTTI model, the difference between grade levels disappears ($F = .008$, $p = .928$). Perhaps this finding should not be surprising, since the reported Eta squared for grade level in Chapter 4 was very small (Eta squared = .003), and therefore, the alleged difference could not have a practical value (only .3% of the variance in integration was attributable to grade level). If based on the new results, null hypothesis 1a would be rejected, as there is a clear difference between countries ($F = 461.83$, $p = .000$, eta squared = .228), but hypothesis 1b would not be rejected, as there is no significant difference between grade levels.

Note that the difference in the new measure versus the old with respect to the impact of grade level only enters into the discussion of whether grade level differences reached the level of statistical significance ($p < .01$). From a practical perspective, the amount of variance attributable to grade level with the original measure (.3%) and the amount attributable to grade level with the new metric (approximately .01%) were both trivial. Especially compared to differences due to country (23%), any differences encountered due to grade level are negligible.

The conclusion about these hypotheses would be that technology integration was significantly higher among teachers from Texas, compared to integration among teachers from Mexico City. Nevertheless, within each culture, the level of technology integration was not found to be significantly different between elementary school teachers and middle school teachers.

Results of Re-Examining Hypothesis 2 with New Metric

Regarding hypothesis 2 of no differential effect of Will, Skill, and Tool on integration, based on the data presented in Table 34, the following Figure 36 shows a more defined differential effect by country than those effects reported in Table 30 and Figure 32, in Chapter 4.

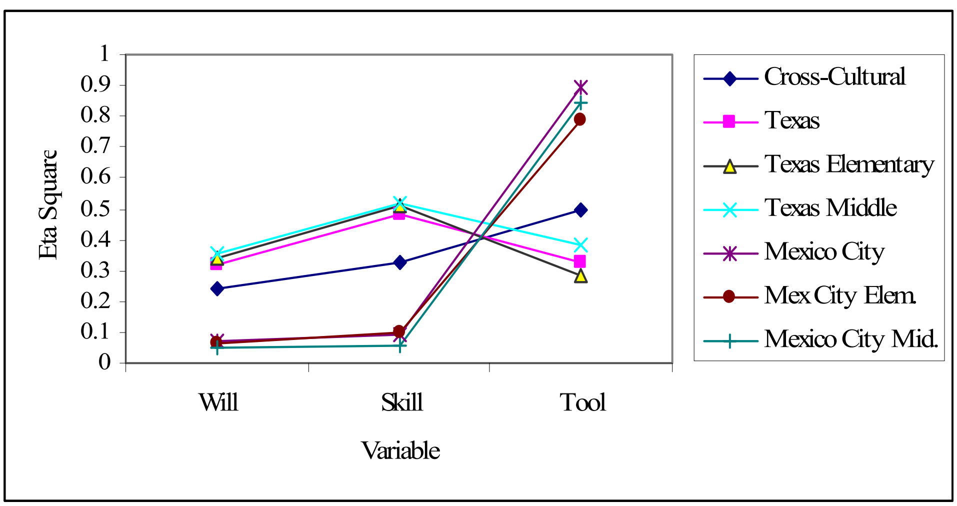


Figure 36. Variance explained by Will, Skill, and Tool using the modified version of the WiSTTI model.

As shown in Figure 36, there was a clear difference by country in the variance explained by each variable. Variance is aligned by country, with a predominance of variance explained by Skill in the case of the Texas samples, whereas the predominance of the variance explained by Tool is evident in the case of the Mexico City samples. The cross-cultural variance remains between both countries. These results suggest that the best predictor of integration was Skill in the case of samples from Texas, and the best predictor of integration for the Mexico City samples was Tool. Will maintained a lower profile as a second integration predictor, along with Tool in the case of the Texas samples, and pairing at the bottom with Skill in the case of the samples from Mexico City. Therefore, based on data from the modified model, hypothesis 2 is rejected, since a differential effect of Will, Skill, and Tool on integration can be observed.

It is important to note that even though the rejection of hypothesis 2 was reached using both the modified version of the model (Figure 36) and the original version (Figure 32), the quality of the outcome was different. As shown in Figure 32, when Will, Skill, and Tool are considered as three independent variables, variance explained by Skill and Tool was more sample-bound, resulting in a more diverse plot, whereas variance explained by Will remained low across samples, producing an average of $\eta^2 = .050$, the variance explained by this variable in the Cross-Cultural sample. Results for Will and Skill based on the original model perhaps could be supportive of the contention that willingness to integrate technology is culture free, and a factor to differentiate between populations is to be found in the teacher's skills (see significance of the study in Chapter 1). Nevertheless, what is seen using the original model is the near-null effect of Will on integration across samples. This is not the theoretical meaning of being "culture free". At any rate, a high effect of Will on integration across samples was expected, because the highest means for all samples were found among the Will indicators. On the other hand, the modified version of the model produced perhaps more “culture-oriented” variances explained (including Will variance explained), as they tended to cluster along a low or a high value, depending on the nation (see Figure 36). Thus, if measured within the modified WiSTTI model, Will is not culture free, but culture-bound, just as Skill and Tool are dependent on the culture. Perhaps the difference in the quality of the results from the original and modified versions of the model is due to the status of the variables: The original version of the model considers three independent factors (Will, Skill, and Tool) predicting integration; the modified version of the model considers two independent factors (Will-Skill, and Tool) differentially predicting integration in one culture or the other.

As a final word for this discussion, it is fair to say that perhaps results on technology integration would be nearly equivalent when obtained by using the WiSTTI model, or by using independent measures. The advantage of using the model is that there is a more comprehensive view of integration, due to the variety of measures involved, and also, a more precise understanding of the role played by Will, Skill, and Tool as integration facilitators.

Results of Re-Examining Hypothesis 3 with New Metric

Null hypothesis 3 of no differences in goodness of fit and variance explained among the seven models tested, was rejected on the ground that a one independent variable type of model did not fit the data for any of the samples involved, while several two and three independent variable models performed reasonably well, but only one had satisfactory goodness of fit characteristics across all samples examined. Furthermore, the fact that the modified version of the WiSTTI model presented the highest variance explained across samples is additional evidence for the rejection of hypothesis 3.

Conclusions

Results of this study imply that the modified WiSTTI model (vs. the original) is a closer approximation of the true relationships among the theoretical constructs of Will, Skill, Tool, and Integration. However, a research design that allows stronger verification of direction of causation would be required for this model to be presented with more certainty, for stronger theoretical statements to be made. For practical uses (such as evaluation measures in education) both the original and modified WiSTTI models have very good fit characteristics across numerous data sets (note computation example with values from the modified model, but treatment of Will, Skill, and Tool as independent variables in the original model). Although an integration metric based on the WiSTTI model proved to be more accurate to evaluate technology integration than a composite of independent measures, these are only preliminary findings, since the datasets used to test the new metric were the same from which the metric was derived. It would be necessary to replicate these results using new datasets from different samples, in order to strengthen the credibility of the new metric. Both the original and modified WiSTTI models appear to perform better with these data than the major professional development-oriented competitor (Rogers, 1999). These findings may have implications for alternative views of technology professional development, either as: a) technology adoption via removal of external/internal barriers (Rogers), vs. b) technology integration as a stepwise developmental process (Knezek, Christensen, Hancock, & Shoho, 2000).

APPENDIX A

DETAILED PILOT STUDY

The sample consisted of 36 elementary teachers, and 64 middle school teachers. Reliability analysis of the resulting 100 surveys is shown in Table A1.

Table A1

Reliabilities for the Measures Employed in the Survey

Scale	Alpha	Comments
Technical Support	.93	The intention of the scale was to evaluate the level of technical support the teacher perceived existed in his/her school. It was not intended to measure the ability of the teacher to provide technical support.
TAC (First round with all 51 items)	.72	Seeking to improve reliability, each subscale was separately analyzed.
TAC 1	.89	
TAC 2	.35	Unacceptable, according to DeVellis (1991), alpha raised to .96, when item TAC 227 (Part 2- Computers intimidate me) was eliminated.
TAC 3	.98	
TAC 4	.15	Unacceptable, the alpha increased to .90 when item TAC 280 (Part 4- The use of e-mail increases motivation for class) was eliminated.

(table continues)

Table A1 *(continued)*

Scale	Alpha	Comments
TAC 5	.75	Although this is a "respectable" scale, according to DeVellis' (1991) criteria, alpha increased to .92 when TAC 142 (Part 5- Computers are changing the world too rapidly) was eliminated.
TAC 6	.88	
TAC 7	.91	
TAC 8	.82	
TAC 9	.74	Although this is only a "respectable" scale, according to DeVellis (1991), there was no indication of improvement by eliminating any of the items.
TAC (Second round with 48 items)	.89	Reliability improved from "respectable" to "very good" by eliminating TAC 227, TAC 280, and TAC 142.
TPSA	.96	
TPemail	.92	
TPwww	.88	
TPia	.89	
TPtt	.92	

(table continues)

Table A1 *(continued)*

Scale	Alpha	Comments
Openness to Change	.32	Reliability was "unacceptable", according to DeVellis (1991). It improved up to alpha=.62 when both negative items (1-"When exploring new instructional methods, I try to find ones that require little change", and 3- "The instructional methods that I currently implement need little revision") were removed from the scale. Nevertheless, reliability was still "undesirable". Factor analysis showed two distinct factors with no correlation between them. The original source (Vannatta & Fordham, 2004) showed only a "minimally acceptable" reliability of alpha = .69.
Stages of Adoption CBAM ACOT	.83	Cronbach's alpha for these three scales cannot be computed individually, since each is a one-item scale. Nevertheless, assuming that these were all measures of the construct "Integration", they were grouped as one single scale with three items. The resulting alpha was "very good" according to DeVellis' (1991) criteria. Factor analysis showed a single factor and the scales highly correlated ($r1$ = .61, $r2$ = .63, $r3$ = .68, p = .0000).

Openness to Change Scale

The poor results on reliability for Openness to Change called for a closer look at the scale and the data analysis procedures. The following is the scale as it was presented to teachers. The name of the scale was changed to avoid possible bias in the teacher answers.

TEACHING METHODOLOGY

Instructions: Select the closest choice to what you think regarding each of the following statements.

TD=Totally disagree D=Disagree U= Undecided A=Agree TA= Totally agree

	TD	D	U	A	TA
1. When exploring new instructional methods, I try to find ones that require little change	①	②	③	④	⑤
2. I am comfortable trying new things even when I will probably make mistakes	①	②	③	④	⑤
3. The instructional methods that I currently implement need little revision	①	②	③	④	⑤
4. I feel excited when I try new instructional techniques	①	②	③	④	⑤
5. I don't mind making mistakes since I can learn from them	①	②	③	④	⑤

Openness to Change created by and used with permission of Dr. Rachel Vannatta and Dr. Nancy Fordham, Bowling Green State University.

For the analysis of the scale, items 1 and 3 were reversed, thus all items could be positive to the psychological object.

After obtaining an alpha = .32, factor analysis was conducted, resulting in two distinct factors, as shown in Table A2.

Table A2

Component Matrix for Five Openness to Change Items.

Extraction Method: Principal Components

Item	Component 1	Component 2
Op5	.816	.210
Op4	.644	.478
Op2	.595	.205
Op3	-.341	.788
Op1	-.497	.669

As shown in Table A2, two different components were extracted from factor analysis: Factor 1 comprising Op5, Op4, and Op2, and Factor 2 comprising Op1 and Op3, although the analysis of communalities showed that Op2 had not much in common with either factor. Table A3 shows the correlation values for all items.

Table A3

Correlation Matrix for Five Openness to Change Items and the Significance of Each Correlation

Item	Op1	Op2	Op3	Op4	Op5
Op1	1.000	p = .417	p = .000	p = .277	p = .013
Op2	-.023	1.000	p =.156	p =.018	p =.000
Op3	.433	-.109	1.000	p =.169	p =.254
Op4	-.064	.224	.103	1.000	p =.000
Op5	-.238	.346	-.072	.470	1.000

As shown in Table A3, there were only three statistically significantly correlated items: AC1 – AC3; AC2 – AC5; and AC4 – AC5. Total variance explained by the two factors was 63.6%. Analysis of components showed no statistically significant relationship between the two factors (*Corr* = .095).

Rotation requested was direct oblimin, assuming that the resulting factors could be related, but switching to varimax rotation assuming independent factors did not change the factor composition. Factor 1 comprised items 2, 4, and 5, whereas factor 2 comprised items 1, and 3.

Variations on the elimination of one item at a time to see the resulting alpha, showed that the only improvement for the scale in terms of reliability was by eliminating Factor 2 altogether (alpha = .62). Therefore, this measure was not included in the final survey.

Pilot Results on the Online Survey

Results on the feasibility of conducting an online survey showed that middle schools could handle an online survey with some difficulties, mainly due to connectivity problems. As most schools in the City use modem connectivity, problems arose when more than five teachers answered the survey at the same time. Training centers for elementary school teachers did not have connectivity available, thus, paper-and-pencil surveys were administered.

In the case of middle schools, some of the scheduled sites to have administered an online survey had to shift to a paper-and pencil procedure, due to problems derived from a slow connection to the Internet at the school site, or the way the school network was set, or an overload to either the school server, or the ILCE server. After those problems were detected, it was decided that research assistants would carry hard copies of the survey to all administration sites, and ensure that all scheduled teachers would answer the survey either online (provided a fast connection, and previously testing that no breakdown would occur to the servers), or on

paper. The online survey database was available during the administration period at:
http://capacitacion.ilce.edu.mx/tei/panel_control/track.asp?id=130

After analysis of these results, it was decided that for the main study, research assistants would carry hard copies of the survey for administration, and the survey would be administered online only when fast connectivity was available at the site.

APPENDIX B

INSTITUTIONAL REVIEW BOARD (IRB) APPROVAL OF RESEARCH PROPOSAL

UNIVERSITY *of* NORTH TEXAS

Office of Research Services

April 6, 2005

Cesareo Morales
Department of Management
University of North Texas

RE: Human Subjects Application No. 05-102

Dear Mr. Morales,

Your proposal titled "Cross-cultural Validation of the Will, Skill, Tool Model of Technology Integration" has been approved by the Institutional Review Board and is exempt from further review under 45 CFR 46.101. **Federal policy 45 CFR 46.109(e) stipulates that IRB approval is for one year only.**

It is your responsibility according to U.S. Department of Health and Human Services regulations to submit annual and terminal progress reports to the IRB for this project. Please mark your calendar accordingly. The IRB must also review this project prior to any modifications.

Please contact Shelia Bourns, Compliance Administrator, ext. 3940 or Boyd Herndon, Director of Research Compliance, ext. 3941, if you wish to make such changes or need additional information.

Sincerely,

Shelia Bourns

For: Scott Simpkins, Ph.D.
Chair
Institutional Review Board

SS:sb

P.O. Box 305250 ◆ Denton, Texas 76203-5250 ◆ (940) 565-3940
Fax (940) 565-4277 ◆ TTY (800) RELAY TX ◆ www.unt.edu

APPENDIX C

COMPONENT MATRICES AND FACTOR LOADINGS USED TO ISOLATE VALID INDICATORS OF WILL, SKILL, AND TOOL CONSTRUCTS

Cross-Cultural Sample

Will

Rotated Component Matrix

	Component		
	1	2	3
TAC1	.118	.804	.153
TAC2	.844	.224	4.215E-02
TAC3	.855	-8.600E-02	7.178E-02
TAC4	-.106	.443	.429
TAC5	.750	.164	.183
TAC6	.191	.170	.844
TAC7	.337	.460	.400
TAC8	.129	.826	.159
TAC9	.109	.175	.822

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 4 iterations.

Skill

Component Matrix

	Component
	1
TPEMAIL	.834
TPWWW	.916
TPIA	.865
TPTT	.881

Extraction Method: Principal Component Analysis.
1 component extracted.

Tool

Rotated Component Matrix

	Component		
	1	2	3
HOMECOMP	.872	-5.275E-02	.136

[1] Highest-loading indicators are compiled in Table 7.

HOMEWWW	.791	.291	-3.955E-02
HOMEHRS	.740	.211	.139
CLSHRS	.231	.849	.124
CLSCOMP1	7.945E-02	.840	.268
FREQLRN	.134	.294	.935

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 4 iterations.

Integration

Component Matrix

	Component
	1
STAGES	.891
CBAM	.832
ACOT	.896

Extraction Method: Principal Component Analysis.
1 component extracted.

Texas Sample

Will

Rotated Component Matrix

	Component		
	1	2	3
TAC1	.621	.233	.346
TAC2	.777	.331	-.145
TAC3	.313	.678	-.231
TAC4	.132	.113	.848
TAC5	.390	.579	5.803E-02
TAC6	.228	.722	.404
TAC7	.736	.392	7.294E-02
TAC8	.776	.121	.299
TAC9	.160	.756	.315

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 7 iterations.

Skill

Component Matrix

	Component
	1
TPEMAIL	.832

TPWWW	.893
TPIA	.891
TPTT	.865

Extraction Method: Principal Component Analysis.
1 component extracted.

Tool

Rotated Component Matrix

	Component		
	1	2	3
HOMECOMP	.905	3.276E-02	-8.173E-02
HOMEWWW	.893	3.118E-02	-7.444E-02
HOMEHRS	.717	-1.511E-02	.351
CLSHRS	9.609E-03	.119	.957
CLSCOMP1	-1.920E-02	.864	5.584E-02
FREQLRN	5.722E-02	.854	7.783E-02

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 4 iterations.

Integration

Component Matrix

	Component
	1
STAGES	.868
CBAM	.818
ACOT	.855

Extraction Method: Principal Component Analysis.
1 components extracted.

Texas Elementary School Teacher Sample

Will

Rotated Component Matrix

	Component		
	1	2	3
TAC1	.143	.663	.353
TAC2	.458	.702	-.153
TAC3	.706	.214	-.128
TAC4	4.723E-02	.135	.854
TAC5	.662	.242	9.569E-02
TAC6	.652	.228	.505
TAC7	.456	.666	9.526E-02

TAC8	.147	.811	.184
TAC9	.675	.188	.382

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 6 iterations.

Skill

Component Matrix

	Component
	1
TPEMAIL	.839
TPWWW	.892
TPIA	.893
TPTT	.857

Extraction Method: Principal Component Analysis.
1 component extracted.

Tool

Component Matrix

	Component		
	1	2	3
HOMECOMP	.879	-.209	-9.035E-02
HOMEWWW	.860	-.211	-.102
HOMEHRS	.758	2.618E-02	.232
CLSHRS	.144	.575	.770
CLSCOMP1	.137	.765	-.294
FREQLRN	.217	.724	-.365

Extraction Method: Principal Component Analysis.
3 components extracted.

Integration

Component Matrix

	Component
	1
STAGES	.848
CBAM	.798
ACOT	.855

Extraction Method: Principal Component Analysis.
1 component extracted.

Texas Middle School Teacher Sample

Will

Rotated Component Matrix

	Component		
	1	2	3
TAC1	.619	.394	.300
TAC2	.858	.105	3.788E-03
TAC3	.553	.528	-.284
TAC4	8.814E-02	.182	.867
TAC5	.592	.407	.127
TAC6	.277	.775	.244
TAC7	.831	.266	.127
TAC8	.641	.184	.483
TAC9	.177	.854	.172

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 6 iterations.

Skill

Component Matrix

	Component
	1
TPEMAIL	.806
TPWWW	.889
TPIA	.878
TPTT	.880

Extraction Method: Principal Component Analysis.
1 component extracted.

Tool

Rotated Component Matrix

	Component		
	1	2	3
HOMECOMP	.905	5.210E-02	-7.950E-02
HOMEWWW	.900	5.935E-02	-3.762E-02
HOMEHRS	.690	-4.530E-02	.408
CLSHRS	4.772E-03	.129	.947
CLSCOMP1	-8.613E-03	.881	3.520E-02
FREQLRN	7.049E-02	.865	.103

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.

Rotation converged in 4 iterations.

Integration

Component Matrix

	Component
	1
STAGES	.899
CBAM	.850
ACOT	.856

Extraction Method: Principal Component Analysis.
1 components extracted.

Mexico City Sample

Will

Rotated Component Matrix

	Component		
	1	2	3
TAC1	9.420E-02	.378	.611
TAC2	.877	2.430E-02	.121
TAC3	.887	9.115E-03	-1.385E-02
TAC4	7.298E-03	.720	7.687E-02
TAC5	.831	7.260E-02	.121
TAC6	9.418E-02	.788	.205
TAC7	7.813E-02	9.814E-02	.870
TAC8	.107	.531	.571
TAC9	-2.334E-02	.732	.242

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 5 iterations.

Skill

Component Matrix

	Component
	1
TPMAIL	.858
TPWWW	.934
TPIA	.923
TPTT	.908

Extraction Method: Principal Component Analysis.
1 components extracted.

Tool

Rotated Component Matrix

	Component		
	1	2	3
COMPCAS	3.638E-02	.807	6.562E-02
INTCAS	2.432E-02	.777	-.117
HORCASA	.358	.694	.174
HORESC	.800	.157	6.804E-02
COMPSAL1	.793	-.155	-6.451E-02
HORPRE	.635	.477	.136
FRECUSO	.661	.208	.119
SOPORTE	8.411E-02	2.229E-02	.976

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 4 iterations.

Integration

Component Matrix

	Component
	1
ETAPAS	.873
CBAM	.851
ACOT	.880

Extraction Method: Principal Component Analysis.
1 component extracted.

Mexico City Elementary School Teacher Sample

Will

Rotated Component Matrix

	Component		
	1	2	3
TAC1	.103	.718	1.734E-02
TAC2	-.134	.414	.679
TAC3	.296	-.206	.697
TAC4	.396	.409	-3.889E-02
TAC5	.113	.189	.732
TAC6	.755	.156	.178
TAC7	.155	.626	.313
TAC8	.511	.570	.150
TAC9	.835	.117	7.159E-02

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 8 iterations.

Skill

Component Matrix

	Component
	1
TPMAIL	.847
TPWWW	.936
TPIA	.922
TPTT	.894

Extraction Method: Principal Component Analysis.
1 component extracted.

Tool

Rotated Component Matrix

	Component		
	1	2	3
COMPCAS	4.680E-02	.796	4.757E-02
INTCAS	-1.433E-02	.783	-.115
HORCASA	.318	.677	.209
HORESC	.683	.310	.193
COMPSAL1	.792	-.181	-.162
HORPRE	.585	.471	.146
FRECUSO	.794	.113	.122
SOPORTE	7.865E-02	1.545E-02	.960

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 5 iterations.

Integration

Component Matrix

	Component
	1
ETAPAS	.880
CBAM	.841
ACOT	.888

Extraction Method: Principal Component Analysis.
1 component extracted.

Mexico City Middle School Teacher Sample

Will

Rotated Component Matrix

	Component		
	1	2	3
TAC1	.689	7.993E-02	.324
TAC2	4.613E-02	.922	2.894E-02
TAC3	-3.561E-02	.915	-1.087E-02
TAC4	.803	-2.768E-02	-.148
TAC5	3.658E-02	.866	7.316E-02
TAC6	.773	5.057E-02	.228
TAC7	.264	3.874E-02	.897
TAC8	.661	8.833E-02	.408
TAC9	.755	-7.000E-02	.159

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 5 iterations.

Skill

Component Matrix

	Component
	1
TPMAIL	.865
TPWWW	.932
TPIA	.924
TPTT	.919

Extraction Method: Principal Component Analysis.
1 component extracted.

Tool

Rotated Component Matrix

	Component		
	1	2	3
COMPCAS	-8.858E-03	.811	8.442E-02
INTCAS	2.546E-02	.755	-.118
HORCASA	.411	.697	6.638E-02
HORESC	.830	.144	9.905E-02
COMPSAL1	.834	-.119	-9.986E-03
HORPRE	.666	.496	9.792E-02
FRECUSO	.472	.404	.273
SOPORTE	9.482E-02	-1.653E-02	.968

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 5 iterations.

Integration

Component Matrix

	Component
	1
ETAPAS	.868
CBAM	.862
ACOT	.873

Extraction Method: Principal Component Analysis.
1 component extracted.

APPENDIX D

REGRESSION EQUATIONS USED TO SELECT BEST INDICATORS OF WILL, SKILL, AND TOOL CONSTRUCTS

Cross-Cultural Sample

Will

Estimated Equations

$$\begin{array}{llllll}
\text{INTEGR} = & -\,0.0578 & -\,0.0715*\text{TAC1} & +\,0.490*\text{TAC2} & -\,0.188*\text{TAC3} & -\,0.0347*\text{TAC4} \\
 & (0.275) & (0.0451) & (0.0422) & (0.0498) & (0.0320) \\
 & -0.210 & -1.586 & 11.619 & -3.768 & -1.084
\end{array}$$

$$\begin{array}{lllll}
-\,0.0950*\text{TAC5} & +\,0.340*\text{TAC6} & +\,0.205*\text{TAC7} & +\,0.0377*\text{TAC8} & +\,0.208*\text{TAC9} \\
(0.0407) & (0.0533) & (0.0303) & (0.0360) & (0.0590) \\
-2.334 & 6.376 & 6.753 & 1.048 & 3.520
\end{array}$$

$$+\ \text{Error},\ R^2 = 0.293$$

Skill

Estimated Equations

$$\begin{array}{llllll}
\text{INTEGR} = & 0.400 & +\,0.354*\text{TPEMAIL} & +\,0.290*\text{TPWWW} & +\,0.0328*\text{TPIA} & +\,0.235*\text{TPTT} \\
 & (0.130) & (0.0435) & (0.0576) & (0.0421) & (0.0471) \\
 & 3.068 & 8.134 & 5.033 & 0.779 & 4.984
\end{array}$$

$$+\ \text{Error},\ R^2 = 0.370$$

Tool

Estimated Equations

$$\begin{array}{lllll}
\text{INTEGR} = & 1.853 & -\,0.0830*\text{HOMECOMP} & +\,0.221*\text{HOMEWWW} & +\,0.263*\text{HOMEHRS} \\
 & (0.155) & (0.100) & (0.0715) & (0.0208) \\
 & 11.982 & -0.830 & 3.087 & 12.661
\end{array}$$

$$\begin{array}{lll}
+\,0.223*\text{CLSHRS} & +\,0.0904*\text{CLSCOMP1} & +\,0.150*\text{FREQLRN} \\
(0.0181) & (0.0238) & (0.0280) \\
12.340 & 3.790 & 5.366
\end{array}$$

$$+\ \text{Error},\ R^2 = 0.410$$

---

[2] Selections based on highest regression coefficients across samples are compiled in Table 8.

Texas Sample

Will

Estimated Equations

INTEGR = 0.344	+ 0.0687*TAC1	+ 0.436*TAC2	- 0.0886*TAC3	+ 0.0296*TAC4
(0.342)	(0.0416)	(0.0454)	(0.0755)	(0.0304)
1.005	1.650	9.600	-1.173	0.974

- 0.0722*TAC5	+ 0.248*TAC6	+ 0.0781*TAC7	+ 0.150*TAC8	+ 0.101*TAC9
(0.0400)	(0.0595)	(0.0385)	(0.0330)	(0.0637)
-1.804	4.171	2.028	4.542	1.590

+ Error, $R^2 = 0.386$

Skill

Estimated Equations

INTEGR = 0.920	+ 0.0734*TPEMAIL	+ 0.252*TPWWW	+ 0.160*TPIA	+ 0.377*TPTT
(0.195)	(0.0551)	(0.0608)	(0.0387)	(0.0421)
4.729	1.333	4.145	4.119	8.967

+ Error, $R^2 = 0.455$

Tool

Estimated Equations

INTEGR = 2.876	- 0.301*HOMECOMP	+ 0.217*HOMEWWW	+ 0.179*HOMEHRS
(0.246)	(0.171)	(0.140)	(0.0252)
11.673	-1.766	1.553	7.118

+ 0.175*CLSHRS	+ 0.109*CLSCOMP1	+ 0.0941*FREQLRN
(0.0227)	(0.0288)	(0.0348)
7.694	3.784	2.700

+ Error, $R^2 = 0.203$

Texas Elementary School Teacher Sample

Will

Estimated Equations

$$
\begin{array}{llllll}
\text{INTEGR} = 0.681 & + 0.0583*\text{TAC1} & + 0.390*\text{TAC2} & - 0.150*\text{TAC3} & + 0.00616*\text{TAC4} \\
(0.391) & (0.0434) & (0.0524) & (0.0825) & (0.0359) \\
1.744 & 1.343 & 7.448 & -1.812 & 0.172
\end{array}
$$

$$
\begin{array}{lllll}
+ 0.0158*\text{TAC5} & + 0.246*\text{TAC6} & + 0.104*\text{TAC7} & + 0.112*\text{TAC8} & + 0.0796*\text{TAC9} \\
(0.0454) & (0.0705) & (0.0433) & (0.0391) & (0.0747) \\
0.349 & 3.494 & 2.391 & 2.852 & 1.065
\end{array}
$$

$$+ \text{Error}, R^2 = 0.388$$

Skill

Estimated Equations

$$
\begin{array}{lllll}
\text{INTEGR} = 1.362 & + 0.0597*\text{TPEMAIL} & + 0.206*\text{TPWWW} & + 0.184*\text{TPIA} & + 0.319*\text{TPTT} \\
(0.220) & (0.0631) & (0.0675) & (0.0444) & (0.0468) \\
6.179 & 0.946 & 3.048 & 4.146 & 6.809
\end{array}
$$

$$+ \text{Error}, R^2 = 0.447$$

Tool

Estimated Equations

$$
\begin{array}{llll}
\text{INTEGR} = 2.876 & - 0.138*\text{HOMECOMP} & + 0.129*\text{HOMEWWW} & + 0.134*\text{HOMEHRS} \\
(0.298) & (0.204) & (0.164) & (0.0310) \\
9.648 & -0.678 & 0.787 & 4.309
\end{array}
$$

$$
\begin{array}{lll}
+ 0.129*\text{CLSHRS} & + 0.160*\text{CLSCOMP1} & + 0.113*\text{FREQLRN} \\
(0.0292) & (0.0433) & (0.0406) \\
4.437 & 3.689 & 2.790
\end{array}
$$

$$+ \text{Error}, R^2 = 0.159$$

Texas Middle School Teacher Sample

Will

Estimated Equations

INTEGR = - 0.797 + 0.0852*TAC1 + 0.523*TAC2 + 0.180*TAC3 + 0.0765*TAC4
(0.677) (0.111) (0.0864) (0.166) (0.0558)
-1.177 0.768 6.055 1.083 1.372

- 0.308*TAC5 + 0.268*TAC6 + 0.0439*TAC7 + 0.221*TAC8 + 0.119*TAC9
(0.0815) (0.108) (0.0807) (0.0609) (0.117)
-3.777 2.483 0.545 3.629 1.011

+ Error, R^2 = 0.423

Skill

Estimated Equations

INTEGR = - 0.329 + 0.115*TPEMAIL + 0.366*TPWWW + 0.142*TPIA + 0.508*TPTT
(0.385) (0.105) (0.125) (0.0749) (0.0862)
-0.855 1.091 2.936 1.894 5.897

+ Error, R^2 = 0.509

Tool

Estimated Equations

INTEGR = 2.739 - 0.545*HOMECOMP + 0.366*HOMEWWW + 0.241*HOMEHRS
(0.442) (0.305) (0.260) (0.0426)
6.193 -1.787 1.405 5.649

+ 0.215*CLSHRS + 0.0987*CLSCOMP1 + 0.119*FREQLRN
(0.0367) (0.0427) (0.0707)
5.856 2.312 1.680

+ Error, R^2 = 0.304

Mexico City Sample

Will

Estimated Equations

INTEGR = 0.327 + 0.0290*TAC1 + 0.443*TAC2 - 0.332*TAC3 + 0.0238*TAC4
(0.492) (0.0973) (0.0761) (0.0750) (0.0623)
0.665 0.298 5.819 -4.430 0.382

- 0.0211*TAC5 - 0.0453*TAC6 + 0.146*TAC7 + 0.507*TAC8
(0.0777) (0.0936) (0.0493) (0.0887)
-0.271 -0.484 2.963 5.714

+ 0.0364*TAC9 + Error, R^2 = 0.249
(0.105)
0.346

Skill

Estimated Equations

INTEGR = 1.161 + 0.277*TPMAIL + 0.248*TPWWW + 0.0979*TPIA + 0.0252*TPTT
(0.237) (0.0790) (0.120) (0.119) (0.105)
4.906 3.511 2.064 0.825 0.239

+ Error, R^2 = 0.205

Tool

Estimated Equations

INTEGR = 1.344 - 0.198*COMPCAS + 0.262*INTCAS + 0.332*HORCASA +
0.216*HORESC
(0.245) (0.143) (0.0990) (0.0416) (0.0391)
5.486 -1.387 2.647 7.995 5.539

- 0.116*COMPSAL1 + 0.117*HORPRE + 0.160*FRECUSO + 0.0731*SOPORTE
(0.0676) (0.0444) (0.0513) (0.0373)
-1.720 2.634 3.123 1.959

+ Error, R^2 = 0.438

Mexico City Elementary School Teacher Sample

Will

Estimated Equations

$$\begin{array}{lllll}
\text{INTEGR} = -1.709 & -\ 0.0269*\text{TAC1} & +\ 0.509*\text{TAC2} & -\ 0.000563*\text{TAC3} & +\ 0.121*\text{TAC4} \\
(0.995) & (0.143) & (0.112) & (0.172) & (0.0904) \\
-1.718 & -0.188 & 4.541 & -0.00327 & 1.338
\end{array}$$

$$\begin{array}{lllll}
+\ 0.0236*\text{TAC5} & -\ 0.212*\text{TAC6} & +\ 0.198*\text{TAC7} & +\ 0.355*\text{TAC8} & +\ 0.195*\text{TAC9} \\
(0.118) & (0.136) & (0.0828) & (0.142) & (0.160) \\
0.200 & -1.555 & 2.395 & 2.499 & 1.218
\end{array}$$

+ Error, $R^2 = 0.282$

Skill

Estimated Equations

$$\begin{array}{lllll}
\text{INTEGR} = 1.222 & +\ 0.153*\text{TPMAIL} & +\ 0.425*\text{TPWWW} & +\ 0.233*\text{TPIA} & -\ 0.192*\text{TPTT} \\
(0.350) & (0.117) & (0.172) & (0.175) & (0.160) \\
3.490 & 1.310 & 2.468 & 1.333 & -1.202
\end{array}$$

+ Error, $R^2 = 0.211$

Tool

Estimated Equations

$$\begin{array}{lllll}
\text{INTEGR} = 1.489 & -\ 0.189*\text{COMPCAS} & +\ 0.147*\text{INTCAS} & +\ 0.402*\text{HORCASA} & +\ 0.277*\text{HORESC} \\
(0.353) & (0.208) & (0.155) & (0.0716) & (0.0634) \\
4.223 & -0.910 & 0.951 & 5.611 & 4.371
\end{array}$$

$$\begin{array}{llll}
-\ 0.280*\text{COMPSAL1} & +\ 0.0566*\text{HORPRE} & +\ 0.138*\text{FRECUSO} & +\ 0.0556*\text{SOPORTE} \\
(0.148) & (0.0729) & (0.0813) & (0.0608) \\
-1.887 & 0.777 & 1.701 & 0.914
\end{array}$$

+ Error, $R^2 = 0.403$

Mexico City Middle School Teacher Sample

Will

Estimated Equations

IINTEGR = 0.535 + 0.150*TAC1 + 0.408*TAC2 - 0.328*TAC3 - 0.0684*TAC4
(0.614) (0.139) (0.109) (0.102) (0.0866)
0.872 1.083 3.736 -3.228 -0.790

- 0.0324*TAC5 + 0.0534*TAC6 + 0.103*TAC7 + 0.598*TAC8 - 0.112*TAC9
(0.105) (0.130) (0.0616) (0.114) (0.144)
-0.309 0.410 1.665 5.250 -0.774

+ Error, R^2 = 0.266

Skill

Estimated Equations

IINTEGR = 1.155 + 0.377*TPMAIL + 0.0921*TPWWW + 0.00378*TPIA + 0.188*TPTT
(0.323) (0.108) (0.169) (0.162) (0.141)
3.572 3.488 0.545 0.0233 1.330

+ Error, R^2 = 0.212

Tool

Estimated Equations

IINTEGR = 1.307 - 0.262*COMPCAS + 0.346*INTCAS + 0.279*HORCASA +
0.161*HORESC
(0.354) (0.201) (0.130) (0.0532) (0.0511)
3.691 -1.305 2.672 5.236 3.160

- 0.0489*COMPSAL1 + 0.163*HORPRE + 0.231*FRECUSO + 0.0919*SOPORTE
(0.0778) (0.0570) (0.0758) (0.0495)
-0.628 2.859 3.047 1.856

+ Error, R^2 = 0.479

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