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Rogers was Right:

A Predictive Model of the Diffusion of Technology

Into the K-12 Classroom

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Abstract

This study examines the factors contributing to the successful diffusion of technology innovations in the K-12 classroom. A series of potential diffusion factors were identified from the diffusion and implementation literature and peer-reviewed. A rubric was then developed to quantify each diffusion factor identified in an innovation.

A predictive model was constructed by examining data on 43 educationally-situated innovations into those diffusion factors using the rubrics. A multiple feed forward neural network was trained using 37 of the innovations, with 6 innovations withheld for model testing.

The neural network was used to predict the market success of the remaining 6 innovations based on the 16 diffusion factors. The network was able to predict the market success of the 6 innovations withheld with a high rate of accuracy. Regression collinearity analysis suggested that an equally predictive network could be achieved with five innovation factors advocated by Rogers's (1995) research on the diffusion of innovations.

A model built on those five factors was highly predictive (93% successful predictions) in determining the degree of market success. Innovations not included in the initial training were also highly predictable by the model (83% successful predictions). The congruence between traditional statistical analysis and neural network analysis suggests that neural networks can play a larger role in social science research.

Rogers was Right:

A Predictive Model of the Diffusion of Technology into the K-12 Classroom

A review of 30 years of educational technology for American K-12 schools suggests a poor return for the billions of dollars spent, from the standpoints of both classroom adoption and student learning (Cuban, 2001). There have been attempts to explain the failure of widespread classroom use in terms of misplaced theoretical underpinnings (Clark & Feldon, 2005) or as poorly designed technological solutions (Oppenheimer, 2003). It is as difficult to successfully introduce and cultivate the adoption of new technology into the classroom as it is to create it, perhaps even harder.

A large body of research investigates the diffusion of innovations into society at large, but the K-12 classroom is a constrained market when compared with consumer markets, both because of economic limitations and an odd combination of control issues. Although potential adopters (teachers) theoretically are masters of their own classrooms (Huberman, 1993), they themselves serve many masters, including parents, principal, school district, state standards, and federal mandates (Fullan, 2001).

This study sought to gain a better understanding of the diffusion and adoption process of introducing technology into the K-12 classroom environment and identify where it is similar to the diffusion studies conducted in business and industry and where new factors must be considered. A classroom-specific model of diffusion and adoption was built and tested using real-world data from classroom technology innovations.

This is a unique time for technology in education because of the confluence of three enabling factors: access, ability, and opportunity. To take advantage of these new capabilities, schools need to adopt these new developments at a pace faster than their early 19th century predecessors, who took 40 years to widely adopt the chalkboard (Anderson, Finn, & Campion, 1963). A systematic examination of the diffusion process might expedite the use of potentially beneficial innovations to be used in schools.

Theoretical frameworks for Studying Diffusion

Rural sociologist Everett Rogers emerged as the de facto head of the "invisible college" guiding diffusion research. He provided a framework allowing the comparison of a large number of innovations to be compared. using a common vocabulary and set of metrics. Rogers (1995, p. 5) defined *diffusion* as "the process by which an innovation is communicated through certain channels over time among the members of a social system." He saw it as a special kind of communication used to create and share ideas. It is not simply a one-way street as we have the experienced in the television era, but it reflects a conversation between two or more parties. Rogers defined five attributes thought to be important in the successful diffusion on any innovation:

1. Relative advantage is the degree to which an innovation appears to be better than other alternatives, measured in terms of economics, convenience, satisfaction, and social prestige. It is the personification of Emerson's "better mousetrap" and has been identified as the most important predictor of an innovation's adoption rate.
2. Compatibility is the degree to which the innovation is seen as consistent with existing values, previous experiences, and needs of the user. Innovations do not exist in a vacuum and rest on the experiences potential adopters have had with other innovations and their personal values and beliefs.

3. Complexity is the degree in which the innovation is perceived as difficult to understand or use.

4. Trialability is the degree in which the innovation can be experienced firsthand on a limited basis. For example, pills for weight control are more trialable than having one's stomach surgically tied.

5. Observability is the degree in which the innovation or its results can be seen by others likely to adopt it.

Rogers (1995) reported that the results from a series of diffusion studies in multiple areas have suggested strong relationships between these factors and successful diffusion. Innovations that have high relative advantage, compatibility, trialability, observability, and low complexity are likely to succeed over innovations that possess higher levels of those attributes.

The Adopter and Change Perspective on Diffusion

The adopter and change views the innovation diffusion and adoption process from the point of view of the adopter, and the focus is more on how to implement change into the organization once the decision to adopt has been made. This is not to imply that implementation is an after-thought to the adoption process. If an innovation is not successfully implemented, it will be discontinued and therefore not successfully adopted. “Implementation is the process of introducing an innovation and fostering its use” (Ensminger, Surry, Porter, & Wright, 2004). This change can occur from the top-down management in the organization or rise up from the lower levels of the hierarchy (Havelock & Zlotolow, 1995).

Although the focus will be Hall and Hord's Concerns Based Adoption Model (CBAM), a number of other models about organizational adoption from a change perspective can be found in the literature. Havelock and Zlotolow's (1995) CREATER model is designed to provide change agents in schools and a pragmatic guide for implementing change. The User Oriented Instructional Development model provides a process whereby formative assessment and feedback are used to assist the development and the change processes (Ensminger et al., 2004). This model began in business and was later adopted by schools, focuses on group rather than individual dynamics.

Methodology

The study employed a *mixed-method design*, using both qualitative and quantitative methodology to build a predictive model of technology diffusion into the K-12 classroom. A guiding framework, based upon the *diffusion of innovations* theory (Rogers, 1995) and the *concerns-based adoption model* (Hall & Hord, 1987) yielded a list of potential *primary diffusion variables* to describe the overall diffusion process. These variables describe a specific aspect of the innovation, the environment, or the potential user of the innovation. It is further broken down into discrete and independent *diffusion factors* that represent a continuous range of a factor, such as whether perceived trialability, complexity, or observability, is present or absent.

This collection of potential factors was organized and peer-reviewed by 19 scholars in the fields of education, diffusion, marketing, and psychology. The result was a vetted *model of diffusion factors*. A rubric was developed to guide the quantification of the qualitative data for each of the diffusion factors into a single real number indicating the degree of the factor as inhibitory or contributory.

Historical data was gathered from examples of innovations, both successful and unsuccessful, and coded into the model according to the rubrics. Data was gathered from public sources and interviews with the developers, teachers, administrators, teacher educators, and critics. This study was initially conducted with a small number of examples to refine both the diffusion factors and the effectiveness of the rubrics as a formative evaluation tool. Following this pilot, a larger number of innovations were analyzed, and a neural network model was constructed to suggest the relative probabilities between the independent variables.

Studied Innovation Sources

The data collection phase was conducted by seeking out representative examples of both successful and unsuccessful innovations in the K-12 classroom. The innovations to be studied fit the following criteria. Innovations were *educationally situated* and targeted at the K-12 classroom or school environment as adopters, innovations were focused on *technology related* efforts, and innovations were *accessible* to study. Forty-three innovations (see Table 3) were analyzed were analyzed from the following innovation categories:

- Graphing calculators
- Learning Management Systems
- Interactive Whiteboards
- Keyboarding software
- Content-Specific software in math, science, reading, and social studies.
- Concept mapping software

Neural Network Analysis

This study uses neural network analysis to determine which factors are most important in adoption of innovations. With neural networks, the principal elements of the brain are the inspiration for its model of computation and cognition in that they “learn” by exposure to new data. This learning is the adjustment of the weight values between nodes within the pathways in biological neurons, and is thought to be strengthened during learning (Pinker, 1997). Donald Hebb outlined the basic model of this associative memory in biology in 1949, and early neural net researchers have based their artificial neurons on this model, called Hebbian learning. Hebbian learning is the change of weights among all nodes in a network based on new data about one of them (MacKay, 2003, p. 505).

The data collected from each innovation was entered into a Microsoft Excel® spreadsheet on a computer with the NeuralTools™ neural network analysis software installed (Palisade Corporation (798 Cascadilla Street, Ithaca, NY 14850 www.palisade.com).

Model Testing Phase

To test the predictive power of the model, the dependent variable (Market Success) testing was withheld from some portion of the cases. With the neural network trained on the remaining cases, the software is asked to predict what the dependent variables of the withheld cases *should* be, based on their independent variables. Six innovations (14% of the total) were not included in the training to enable testing of the model’s predictive power. These six were randomly selected to reduce the internal validity risk of the researcher’s coding bias. Each innovation was analyzed independently as follows: (a) The neural net's node values were set using the untested diffusion factors and nothing set for the predicted success value; (b) the resulting conditional probability model was calculated to yield the expected diffusion success value; and (c) the expected diffusion success value was compared with the actual diffusion success value calculated in the manner described for the dependent variable.

The neural network software randomly chose the six innovations (listed in Table 1) to be withheld from the training process. The independent variables were added to the data set, withholding the dependent factor (Market Success); and the software used the network to predict what those dependent factors should be, based on the independent variables and the training from the other 37 innovations. The results are shown in the columns labeled "Using 16 Factors" in Table 1 and suggest good predictive power of the neural network.

Table 1
Prediction Test Results

Innovation	Actual Value	Predicted Variable and Residual From Actual			
		Using 16 Factors		Using 5 Factors	
		Predicted	Residual	Predicted	Residual
1. PolyVision whiteboard	**0.53**	**0.79**[a]	**-0.26**	0.54	-0.01
2. TI calculator	**0.95**	**0.41**[a]	**0.54**	0.76	0.19
3. Cabri geometry software	0.33	0.40	-0.08	0.40	-0.07
4. Blackboard,com LMS	0.90	0.79	0.11	0.76	0.14
5. Moodle LMS	0.50	0.53	-0.03	**0.29** [a]	**0.21**
6. ExploreLearning manipulative	0.53	0.66	-0.13	0.73	0.20

[a]indicates a poor prediction (residual > 20)

Data Reduction

To find the parsimony that William of Ockham advocated, the collected factor data were analyzed by the use of linear regression statistical techniques to determine what factors actually contributed to the model and which might be eliminated. A *collinearity* *analysis* was undertaken using SPSS statistical software to determine whether some of the correlation between the factors and the dependent variable were related to other factors.

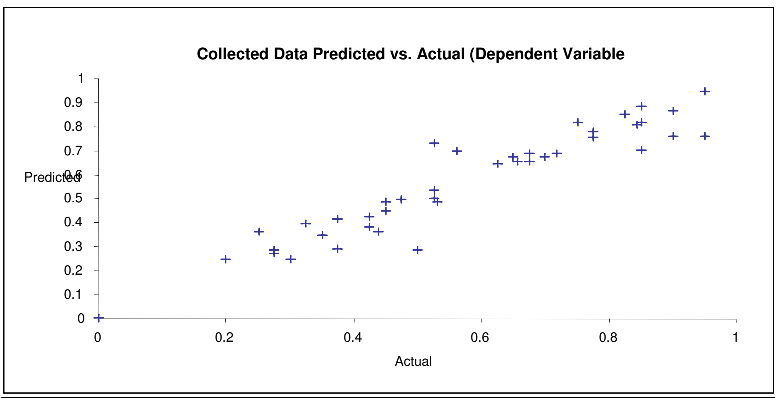
Table 2
Diffusion Factors Listed by Degree of Collinearity Probability

Low Probability	Medium Probability	High Probability
Relative Advantage Compatibility Lack of Complexity Trialability Observability Ease of Use	Implementation Reqs. Efficacy Existence of Skills Congruence Reliability Show Stoppers	Features Relative Cost Product Maturity Market Phase

Some judges considered the *Ease of Use* and *Complexity* factors measured the same attribute during the diffusion factor peer review phase. The two factors were highly correlated ($r = .737$, $p < .001$) across the 43 innovation cases, and the confidence index was very close to the 15 cutoff for probable collinearity ($ci = 14.730$). Regression analysis showed a highly correlated value in the multiple r-square when removed ($r = .470$, $p < .001$) vs. ($r = .471$, $p < .001$). The *Ease of Use* diffusion factor was then eliminated since it assumed to be measuring the same phenomenon as the *Complexity* factor. This left the following five diffusion factors as potentially independent and contributory to innovation success: Relative advantage, Compatibility, Lack of Complexity / Ease of Use, Trialability, and Observability.

Reduced Factors Neural Network Analysis

The same three groupings were trained using neural network analysis and yielded relatively high predictive powers with the accuracy dropping as more factors were removed. (See Table 3 and Figure 1.) The full group of 16 diffusion factors yielded a 7% bad prediction rate with an RMS error of .10, removing the four highly collinear factors yielded a 21% bad prediction rate with an RMS error of .15, and removing all suspected collinear factors and ease of use yielded a 9% bad prediction rate with an RMS error of .08. The reduction in the number of factors to a more parsimonious set of five increased the bad prediction rate 2%, and the *r*-square from regression analysis went from of r^2 = .649 to of r^2 = .470, but the smaller number of factors will make further analysis and future replication more efficient.



Training cases	*37*
Independent variables	*5*
Topology	*MLFN*
Nodes	*3*
Bad predictions (30%)	*9.3%*
RMS error	*0.075*
Mean absolute error	*0.050*
Std. dev. abs error	*0.056*

Figure 1. Results from neural net trained on 5 factors

Table 3

Actual Success vs. Predicted Success (16, 12, and 5 Factors)

Innovation	Market Success	Predicted Variable and Residual from Actual					
		Using 16 Factors		Using 12 Factors		Using 5 Factors	
		Pre	Res	Pre	Res	Pre	Res
MIA - Mimeo attachment	0.00	0.05	-0.05	-0.03	0.03	0.01	-0.01
MIB - Mimeo whiteboard	0.35	0.29	0.06	0.31	0.04	0.35	0.00
HIT - Hitachi whiteboard	0.28	0.27	0.00	0.31	-0.03	0.28	0.00
PLY - Polyvision whiteboard	0.53	[a]**0.79**	**-0.26**	[a]**0.25**	**0.28**	0.54	-0.01
PRO - Promethean whiteboard	0.78	0.66	0.11	0.77	0.00	0.76	0.02
SMA - Smart whiteboard	0.90	0.90	0.00	0.81	0.09	0.87	0.03
NUM - Numonics whiteboard	0.28	0.29	-0.01	0.31	-0.03	0.29	-0.01
TI - TI calculator	0.95	[a]**0.41**	**0.54**	[a]**0.46**	**0.49**	0.76	0.19
HP - HP calculator	0.25	0.25	0.00	0.25	0.00	0.36	-0.11
CAS - Casio calculator	0.45	0.43	0.02	0.46	-0.01	0.49	-0.04
INS - Inspiration	0.95	0.90	0.05	0.95	0.00	0.95	0.00
KIN - Kidspiration	0.75	0.75	0.00	[a]**0.52**	**0.23**	0.82	-0.07
MND - Mind Matters	0.20	0.20	0.00	0.19	0.01	0.25	-0.05
GSP - Sketchpad	0.85	0.85	0.00	0.85	0.00	0.70	0.15
CAB - Cabria	0.33	0.40	-0.08	0.33	0.00	0.40	-0.07
ULT – Ultra-Key Typing	0.84	0.84	0.00	0.79	0.05	0.81	0.04
TYT - Typing Time	0.44	0.41	0.03	0.44	0.00	0.36	0.07
MAV - Mavis Beacon	0.72	0.66	0.06	0.72	0.00	0.69	0.03
TY2 - Type to Learn	0.53	0.66	-0.13	0.53	0.00	0.49	0.04
BLK - Blackboard	0.90	0.79	0.11	0.90	0.00	0.76	0.14
MOO - Moodle	0.50	0.53	-0.03	0.47	0.03	[a]**0.29**	**0.21**
SAK - Sakai	0.30	0.29	0.01	0.30	0.00	0.25	0.05
WEB – Web-CT	0.70	0.70	0.00	0.70	0.00	0.67	0.03
DEC - Decisions, Decisions	0.65	0.65	0.00	0.80	-0.15	0.68	-0.03
ORE - Oregon Trail	0.85	0.85	0.00	0.81	0.04	0.89	-0.04
TIM - Timeliner	0.68	0.67	0.00	0.68	0.00	0.69	-0.01
CAR - Carmen San Diego	0.48	0.47	0.00	0.47	0.00	0.50	-0.02
EXP - Explore Learning	0.53	0.66	-0.13	0.58	-0.05	0.73	-0.20
NLM – Natl. Manipulative Lib	0.28	0.29	-0.01	0.30	-0.02	0.29	-0.01
DES - Destination Math	0.43	0.42	0.00	0.42	0.00	0.42	0.00
UNI - United Streaming	0.83	0.91	-0.08	0.79	0.03	0.85	-0.02
ANN - Annenberg Video	0.43	0.40	0.02	0.30	0.13	0.38	0.04
POP - Brain Pops	0.53	0.53	0.00	0.52	0.00	0.50	0.02
IND - Inspiration Data	0.68	0.66	0.01	0.80	-0.13	0.65	0.02
GM2 - Graph Master 2	0.38	0.38	0.00	[a]**0.81**	**-0.43**	0.42	-0.04
CLB - Graph Club 2	0.38	0.41	-0.03	0.37	0.00	0.29	0.08
TNK - TinkerPlots	0.63	0.66	-0.04	0.69	-0.06	0.64	-0.02
BLS - Math Blaster	0.66	0.65	0.01	0.66	0.00	0.66	0.00
ALG - Algebra Tutor	0.56	0.56	0.00	[a]**0.79**	**-0.23**	0.70	-0.14
MIL – Millie's Math House	0.38	0.41	-0.03	[a]**0.16**	**0.22**	0.42	-0.04
GOB - Green Globs Graphing	0.45	0.45	0.00	0.45	0.00	0.45	0.00
STR - Starry Night	0.78	0.78	0.00	0.78	0.00	0.78	0.00
QX3 - Intel QX3 Microscope	0.85	0.85	0.00	[a]**0.31**	**0.54**	0.82	0.03

[a]indicates a poor prediction (residual > 20)

Conclusions

This study builds on the long tradition of diffusion research (Fullan & Pomfret, 1977; Hall & Hord, 1987, Rogers, 1995; Surry, 1997; Ely, 1999) with a focus on technological innovations targeted for adoption in the K-12 school system. Often, a long delay occurs between the introduction and the adoption of classroom technology. The systematic examination of the diffusion process might expedite the use of potentially beneficial innovations to be used in schools.

The goal of this study is to build a predictive model of technology diffusion into the K-12 classroom by using a small number of quantitative diffusion factors that were qualitatively assessed by an examination of a group of innovations in the field. The results suggest that such a model can be constructed with a good degree of predictive power and offer a better understanding of which factors are important in adoption.

A predicative model should be able to take some data about a phenomenon and forecast the likelihood that some particular action will occur. The degree in which that likelihood occurs speaks to the power of the model's ability to predict, and the model's usefulness is contextually situated. Some problem domains, such as prediction of weather, have low probability rates for predicting the weather at any particular time and place; but are nonetheless overall useful. Domains such as medicine require higher degrees of confidence in the veracity of their predictions. The nature of the predictive power for the model in this study is closer to forecasting the weather than testing for a heart condition. Given an innovation rated on the model's diffusion factors, its similarity to other successful innovation factors will offer a generally accurate prediction for its success of adoption in the K-12 classroom.

The model led to successful predictions the likelihood of success for the six innovations tested to be 83%, with successful prediction defined as the difference between the actual success and the predicted success.

Validation of Rogers' Research in Education

The goal of this study was not to validate Rogers' (1995) findings in education, but to seek out what factors were salient in developing a model of technology diffusion into the K-12 classroom. The final five diffusion factors, *Relative Advantage, Compatibility, Lack of Complexity, Trialability,* and *Observability* were the same ones Rogers identified in the diffusion studies in contexts as varied as industrial products and animal husbandry (Rogers, 1995).

Rogers (1995) reported the results from a series of diffusion studies in multiple areas that suggested strong relationships between these factors and successful diffusion. Innovations with high relative advantage, compatibility, trialability, observability and low complexity are likely to succeed over innovations possessing the lower amounts of these attributes.

The study began with 16 factors and evidence from the systemic analysis of 43 innovations and offered evidence that, although there may be contributions from other factors in understanding diffusion, the primary predictors for success in the K-12 classroom are the same five Rogers (1995) identified from a lifetime of research as being important, and will enable future researchers to focus on those five with more confidence.

The diffusion literature provides a number of studies suggesting similar findings. Tornatzky and Klein (1982) performed a meta-analysis using 75 diffusion of innovation studies, and found 30 distinct factors. After analysis, these factors were reduced to ten more atomic factors that added the following five attributes to Rogers: *communicability, divisibility, profitability, cost, and social approval.* Later studies found these new factors to be sub-dimensions of Rogers' original set (Kshetri, 2005).

The Value of Artificial Intelligence Techniques

The artificial intelligence research (AI) tradition promised human-like knowledge representation in a computer (Kurzweil, 1990). The research efforts were unable to attract funding and were abandoned. In spite of this apparent failure, many of the techniques of AI, such as neural network analysis, are successfully used in a wide array of real-world applications.

Neural networks offer social science researchers another tool to let the data directly suggest patterns of importance. Because there was good congruence between the neural network analysis and the more traditional regression analysis in this study, this suggests that neural networks may be effective in analyzing data of this type.

Implications

Gaining a better understanding of how technology is diffused in the K-12 classroom is useful from both economic and educational viewpoints. A better understanding of how the diffusion process actually works in the K-12 environment, from the various stakeholders' perspectives, will allow students and teachers to benefit from a more streamlined diffusion process because resources will reach them faster, administrators will waste fewer precious resources on unsuccessful diffusion efforts, and funding agencies and taxpayers will get a higher return on their substantial investments in technology.

This is a unique time for technology in education because of the confluence of three enabling factors: access, ability, and opportunity. At the turn of the millennium, almost every school in America (98%) had access to the Internet (Cattagni & Farris, 2001); a new generation of student ability has emerged, sometimes referred to as *digital natives* (Prensky, 2001), who use the Internet extensively for their schoolwork, at school, at home, and at the library (Levin & Arafeh, 2002); and finally, an explosion of software is being developed that reflexively builds upon itself and upon established standards that offer capabilities harnessing the massive numbers of people and amount of information (Weinberger, 2003). A better understanding of the factors that encourage the adoption of these promising technologies should foster more rapid diffusion of these technologies.

Educational Technology Developers

The developers of educational technology benefit from this empirical validation of the five diffusion factors suggested as being important in the adoption of technology in the K-12 classroom. A better understanding of the diffusion factors would be useful for technology developers in formatively assessing their own products, present or future, to encourage adoption.

A developer could use the model as an alternative to the traditional focus group product feedback procedure on an existing product to suggest changes in the product or the way it is marketed and supported. This procedure could be accomplished by putting together a representative panel of potential adopters and asking them to rate their product along the five dimensions. Using only the rubrics without performing neural network analysis, the results may suggest areas to be improved to encourage adoption. For example, if the *Trialability* numbers undesirably low, the developer could offer other kinds of access to their product and see if that improved diffusion.

Developers could use the model to a priori assess the potential success of future products while they are in the design phase, or even simply at the concept stage, giving them the opportunity to experiment with a virtual version of the products at low or no cost. Revisions could be iteratively made as a result of the factor assessment and subsequent success prediction from the neural network.

The potential adopters of new technology can benefit by having new and potentially valuable innovations available to the classroom earlier. While efficacy played a limited role as a factor in this study, it is logical to assume that increasing the number of otherwise valuable innovations will increase the number of educationally effective innovations as well.

Some of the diffusion factors speak directly to the quality of the innovation itself, such as *Lack of Complexity,* and improvements on that dimension will make classroom use more effective. Because that dimension appears to be important in promoting successful classroom adoption, developers will have a strong financial motivation to make their innovations more accessible.

Teacher and schools could potentially rely on publicly available diffusion factor data to inform future adoptions of highly rated innovations. Diffusion ratings could provide a more objective mechanism assessing innovations than anecdotal and subjective product reviews and offer common fabric on which these innovations can be contrasted and compared.

Suggestions for Further Study

The primary suggestions for further study revolve around some of the limitations of the study described in the previous section that would improve the study's internal and external threats to validity during replication. A larger number of innovations, such as 100 or 150 including both successful and unsuccessful innovations would help with generalizability. The use of more than one rater procedure would help ensure that the data will be as representational of the innovation as possible.

The Internet offers unprecedented capabilities to link people together for a common goal. A new trend in Internet-based applications is having the ability for people to easily rate items such as products, reviews, and media. This is consistent with the idea of "the wisdom of crowds" proffered by James Surowiecki (2004), where the aggregated knowledge of a wide variety of individuals can produce stronger results than a small group of experts. This concept could be extended to the rating of innovations according to the five identified diffusion factors to yield a larger variety of innovations on which to train the neural network and to provide an answer to the single rater threat to validity in this study.

U.S. schools are poised to achieve some of the long-promised benefits from the large sums invested in the physical infrastructure afforded by making computer hardware and Internet connectivity available to students and teachers. The entry barriers to creating effective learning technologies are steadily becoming lower, in particular, those that are primarily software based. A strong foundation consisting of tools, both commercial and free, sharable resources, and Internet distribution will make it possible for teachers to draw upon a wealth of technology—providing it can be effectively diffused.

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