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The Impact of Information Systems on End User Performance: Examining the Effects of Cognitive Style Using Learning Curves in an Electronic Medical Record Implementation

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The Impact of Information Systems on End User Performance: Examining the Effects of Cognitive Style Using Learning Curves in an Electronic Medical Record Implementation

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Abstract:

This study examines the relationship between cognitive style (adaptors versus innovators) and the learning curve when implementing new information technology. Kirton's proposition that adaptors and innovators find equally creative ways of solving problems based on cognitive preferences was tested using a longitudinal case study. Test subjects were paramedics from a large metropolitan area. Cognitive style of the paramedics was determined, along with their individual learning curve when transitioning from a paper medical record to an electronic medical record.

Results indicate Kirton's proposition of equal performance between adaptors and innovators was only supported during stable periods. There was no statistically significant difference between adaptors and innovators either before implementation of the new system or post-stabilization. However, following system implementation, adaptors and innovators differed significantly with regard to their initial change in task completion times, pattern of learning, and the number of days required to reach stabilization.

Keywords: user performance, cognitive style, learning curve, individual differences, end user performance, electronic medical record

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I. INTRODUCTION

Information systems are often implemented in order to increase the quality and/or quantity of work produced. However, when organizations implement new information systems, there is often a period of decreased performance and/or quality [Ramsay et al. 2000; Edmonson et al. 2003]. This period of decreased performance may be attributed to a variety of influences including the "learning curve" phenomena. Learning curve effects are evidenced by an initial increase in task time and/or decrease in performance, followed by gradual improvement with repeated usage [Wright 1936; McAfee 2002]. These effects are quantifiable and useful for measuring changes, such as time to complete a unit of work. However, this quantification does not address individual differences that might influence the learning curve. As discussed by Adler and Clark [1991], linking performance with cumulative experience only incorporates the end effects of learning. This does not explain individuality or the complex processes of first and second order learning such as training, managerial actions, or process changes.

Cognitive style is one important difference potentially related to performance. This personality trait refers to individual differences in information processing and relates to how people think and approach solving problems [Witkin and Goodenough 1981]. Cognitive style is also referred to as "learning style" [McLeod 1979; Honey and Mumford 1982; Allinson and Hayes 1990; Hayes and Allinson 1996; Haynes and Allinson 1996], "problem solving style" [Summers et al. 2000], "thinking style," [Leonard et al. 1999] or "cognitive work style" [Xu and Tuttle 2004b].

The original foundations of problem solving in the workplace as it relates to personality were based on work by Peter Drucker [1969]. He claimed that when managers and bureaucrats faced problems, two basic approaches emerged. Kirton [1976] proposed that this basic tenet applied to all people and that anyone could be located on a continuum ranging from "doing things better" (adaptors) to "doing things differently" (innovators). He suggested that personalities of people range from very adaptive to very innovative. Thus, some people habitually adapt (do things better) while some habitually innovate (do things differently).

Prior researchers have focused on organizational performance [Benbasat and Taylor 1978; Bariff and Lusk 1979; Banker et al. 1990]. It is well documented that software design and user training [Bostrom et al. 1990a; Davis and Bostrom 1993; Chen and Zhu 2004; Coskun and Grabowski 2005], as well as cognitive capacity and training success [Pearlman et al. 1980], impact performance. Other researchers have examined the impact of information technology on individual performance in the IT work place [Brynjolfsson 1993; Brynjolfsson and Hitt 1996; Napoleon and Gaimon 2004]. Another area of research focuses on individual differences and performance [Zmud 1979; Higgins 1996; Kirton 2003].

Theoretically, cognitive style is independent from individual capacity and uncorrelated with individual performance [Kirton 1976]. However, this relationship remains largely untested [Chan 1996; Fuller and Kaplan 2004]. If cognitive style affects an individual's performance, then there is a need to understand this phenomenon and its implications for systems and people. The impact on systems is important because employee management and training are expensive and time-consuming activities. The impact on people is important because this phenomenon affects both system developers and end users.

The purpose of this case study was to examine the relationship between cognitive style and the learning curve when implementing a new technology. There has been significant interest in cognitive variables [Bariff and Lusk 1977; Benbasat and Taylor 1978; Lusk and Kersnick 1979; Huber 1983; Green and Hughes 1986; Harrison and Rainer 1992; Clapp 1993; Hong et al. 2004; Santanen et al. 2004; Chilton et al. 2005; Khoumbati et al. 2006; Lee and Kwon 2006], learning curves [Howell 1980; Habermeier 1989; Saraswat and Gorgone 1990; Ramsay et al. 2001], and information systems in the literature, but no integration of these three subjects. These topics are important because systems take time to learn [Bostrom et al. 1990b; Davis and Bostrom 1993], and decreased performance generally results in increased operational costs. Therefore, the link between cognitive style and the learning curve needs further examination. We considered the following research questions: 1) What is the relationship between cognitive style and task performance when using information technology? 2) What is the relationship between cognitive style and an individual's learning curve components following implementation of an information technology?

II. LITERATURE REVIEW

While it is well known that cognitive ability impacts job performance, there exists only speculation that one's cognitive style has no impact on performance. There are no known studies integrating information technology with individual differences in cognitive style and individual performance, using learning curve analysis.

Cognitive Style Theory

Cognitive style and information systems are associated with a wide range of research topics such as the relation between cognitive style and system design [Bariff and Lusk 1977; Benbasat and Taylor 1978; Bariff and Lusk 1979; Huber, 1983], the fit between cognitive style and organizational climate [Kirton and McCarthy 1988; Spence and Tsai 1997; Chilton 2001; Chilton, Hardgrave et al. 2005], and the relation between cognitive misfit and task performance [Summers, Sweeney et al. 2000; Fuller and Kaplan 2004].

Benbasat and Taylor [1978] looked at differences in cognitive style and its effect on information system use and design. They suggested that cognitive style should be included in IS research, that research designs should be strengthened for studying the influence of cognitive styles on information systems, and that methods should be developed for studying cognitive styles, information systems use, and design. They also suggested that IS researchers pay more attention to the psychometric properties of instruments, have sufficient provisions to ensure generalizability, and use experimental controls.

Chilton [Chilton 2001; Chilton, Hardgrave et al. 2005] examined how individual differences in cognitive style affected system designers during paradigm shifts in the work environment. He modeled adaptors and innovators involved in radically changing job conditions and suggested that some work environments may not be well suited to an individual's problem solving preference. This would indicate that certain types of work might be better suited for certain cognitive styles. He termed this effect *cognitive misfit* and found that it increased stress, reduced performance, and increased turnover in object-oriented system designers [Chilton, Hardgrave et al. 2005].

Adaptor–Innovator Theory

Kirton developed the Adaptor–Innovator theory [Kirton 1976] based on the earlier work of Peter Drucker [1969]. Points of interest related to Kirton's Adaptor-Innovator (KAI) theory include the following:

- Cognitive styles are common to everyone.
- Cognitive styles are separate and distinct from cognitive ability.
- Cognitive styles manifest where creativity, problem solving and decision making take place.
- Adaptation-innovation is a basic dimension of one's personality that is relatively stable.
- There is no correlation between occupational status or educational level and cognitive styles.

Adaptor characteristics include precision, reliability, and efficiency. Adapters are concerned with resolving problems rather than finding them and seeking solutions within existing paradigms thus being safe, sound, and reliable.

Personalities of Innovators include a desire to approach tasks from unusual angles. They tend to discover problems and prefer thinking in unconventional ways. They will take control in unstructured situations and have low tolerance for routine work, challenging rules.

Kirton developed and validated the KAI scale from a descriptive typology, yielding 32 items. Each item used a five-point Likert scale; Adaptors scored on the lower end and innovators scored on the higher end of the continuum. KAI scores range from 32 to 160 with a theoretical mean of 96. The KAI has a substantial history, has been refined and updated and is increasingly viewed as important in work performance [Kirton and McCarthy 1988; Summers, Sweeney et al. 2000; Xu and Tuttle 2004a; Xu and Tuttle 2004b]. Kirton's AI theory provides the initial foundation for the cognitive style continuum further developed by Xu and Tuttle [2004a] that is used in this study.

In subsequent research, Kirton [1978] addressed whether adaptors and innovators were equally capable of creatively approaching and solving work problems. Specifically, he proposed that adaptors and innovators vary on their perception and approach to work problems but that there should be no difference in their abilities to do the same work. Innovators and adaptors display the same degree or level of creativity, and organizations need both types. While Kirton points to the potential for differences between disparate groups, the underlying assumption triggers a question within groups. If adaptors and innovators vary in their perception and approach to solving problems, why should there be no difference in their level of creativity in solving problems? In addition, if adaptors and innovators do vary then does this difference affect individual performance? This research attempts to address these questions.

Building on the work of Kirton [1976; 1978; 1980] and others [Goldsmith 1984; Flynn and Goldsmith 1993; Rogers1995], Agarwal and Prasad [1998] explored the role of personal innovativeness in the domain of information technology. However, these researchers looked at personal innovativeness in terms of information technology acceptance. Our research focuses more specifically on how cognitive style affects user performance when new information systems are implemented.

Learning Curve Theory

Learning curve phenomena reveal the rate at which learning from repeated usage takes place. Researchers have studied the learning curve phenomenon in efforts to enhance production, reduce costs, and predict manufacturing events. Wormer [1984] suggested that the learning curve model was valuable both for description and prediction. Studies in this area have explored different units of analysis in a multitude of settings using an assortment of populations. Units considered in studies included individuals [Mazur and Hastie 1978], groups [Leavit 1951; Epple and Argote 1991], and organizations [Argote and Epple 1990; Ramsay, Grant et al. 2001].

The learning curve was first documented by Wright [1936] while working in the aircraft construction industry. Wright noticed that as assembly workers repeated work functions their speed or unit rate increased. His learning curve measures revealed how individual performance improved with repeated tasks. The cost of learning can be calculated as a function of the length of time for tasks to be learned if other variables remain fixed [Kilbridge 1962]. This phenomena and its associated costs have been found to exist when new information systems are implemented [Waldman et al. 2003].

Performance

Previous researchers have studied the effects of IT implementations on performance [Fudge and Lodish 1977; Banker, Kauffman et al. 1990; Mukhopadhyay et al. 1997]. Their results suggest that new IT implementations positively influenced performance. In one of the few examples of research involving users and performance, Gray et al. [1993] examined the effect of a new information system and workstations that were expected to reduce operating costs and improve performance The project champion, New England Telephone (NYNEX) expected decreases in average work time per call handled by an operator. However, using a Goals, Operators, Methods and Selection (GOMS) model to analyze the project, the researchers accurately predicted that the new system would actually require more time and introduce greater costs ($2M/year) to the telephone operator function. Post implementation learning curve results indicated that using the new system did indeed take longer than the old system and that the average work time per call varied by call category. They also provided proof that the average work time stabilized after the first month.

In a more recent example, McAfee [2002] focused on the performance dip that typically follows IT change. He structured his study using a longitudinal quasi-experiment in a natural business setting. Time-series analysis of the learning curve determined the impact of the information system implementation. Results suggested a causal link between adoption and performance improvement after a period of learning.

III. HYPOTHESES

Figure 1 portrays the various measurement components of learning curves and their associated measurement points. The learning curve has several extractable components, including the intercept, slope, and continuity. These components correspond to interrupted time series effects, as discussed in Cook and Campbell [1979]. The Y-axis represents the average completion time prior to the system change (Point 1 on Figure 1). The height of the learning curve signifies the maximum completion time when using the new system (Point 2 on Figure 1). The next component looks at the area under the curve (Area 3 on Figure 1). This area represents the individual's "Learning Pattern," defined as the interaction of the difference between baseline and maximum completion time (height), rate of change (slope), and number of days to equilibrium. In most cases, the learning curve flattens, indicating improved proficiency with the system. The number of days to equilibrium, or the end of the learning curve, plots on the X-axis (Point 4 on Figure 1). The average completion time after system change is also located on the Y-axis (Point 5 on Figure 1). In the graphic example (Figure 1), the learning curve improves over time and completion time decreases post system implementation compared to baseline performance. The difference between baseline and post-implementation completion time plots on the Y-axis (Point 6 on Figure 1). The points on Figure 1 also coincide with the hypotheses discussed following.

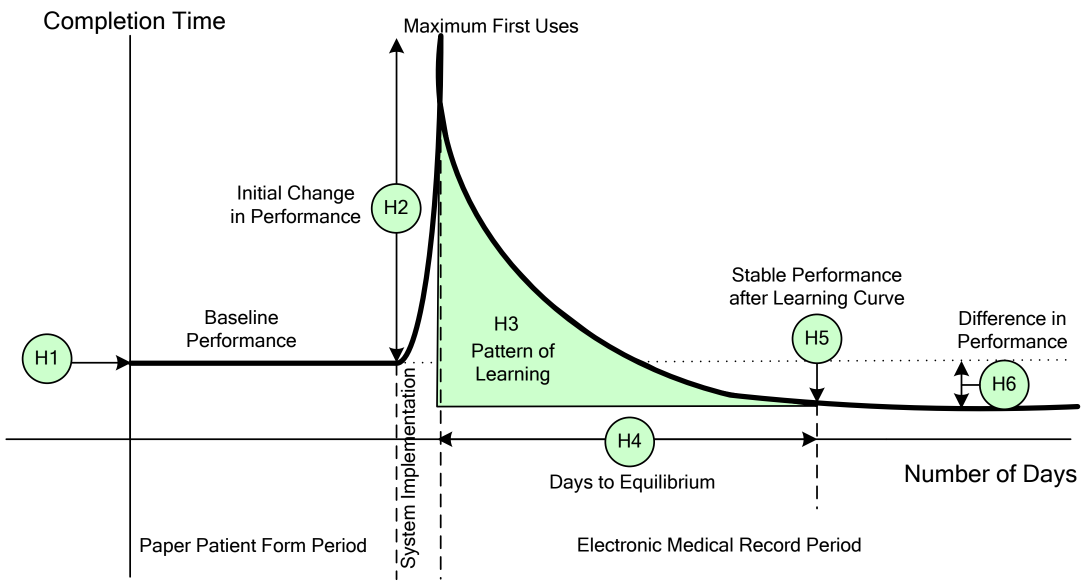

Figure 1. Measurement Points

Baseline Completion Time

Adaptors (as conformists) characteristically are concerned with solving problems in established ways. Innovators are viewed as non-conforming, less disciplined, yet more concerned with uncovering problems and finding new avenues for solution. Although their cognitive styles vary considerably, Kirton [1976] theorized that both styles find equally creative ways of solving problems. Thus:

H1: There is no statistically significant difference in baseline completion time of adaptors and innovators.

Change in Task Completion Time

The difference between an individual's baseline and their maximum completion time when first using the information system represents the amount of change in performance that the individual first experiences. Both groups would initially require more time to complete the task. However, we propose that the difference in completion times may be greater in the adaptor group. This is based on the premise that adaptors favor structure and dislike change, whereas Innovators favor change and lack of structure. Thus:

H2: The change in task completion times (HEIGHT) of adaptors will be significantly greater than innovators when first learning to use the information system.

Learning Pattern

We propose that adaptors might require more time to assimilate and place technological changes in suitable frameworks. Incremental improvement of Innovators could occur at a quicker rate than adaptors because of their willingness to adapt to change. Innovators might display greater slopes (e.g. rate of change) in their learning curves, thus affecting the learning pattern, whereas adaptors could exhibit a slower rate of change. Thus:

H3: The difference in learning pattern is significantly greater for adaptors than innovators.

Time Required to Master the System

Learning to correctly use a new information system takes time [Bostrom, Olfman et al. 1990b]. Adaptors might anticipate that the new information system threatens the existing paradigm, while innovators may wish to exploit advances in technology [Kirton 2003]. Thus:

H4: The difference in time required to master the new information system is significantly greater for adaptors than innovators.

Changes in Completion Time Post Learning

The effect of adaptor-innovator workplace style on individual performance has not been tested in the IT setting. Although adaptors and innovators approach problem solving differently, we propose that these differences are reflected in other components of the learning curve. We did not expect any significant differences in the completion times of Adaptors and Innovators at stabilization. Thus:

H5: There is no statistically significant difference in completion time post learning curve of adaptors and innovators.

Baseline versus Stable Task Completion Times

The final hypothesis considered the Adaptor-Innovator theory's contention that both styles are equally successful in organizations [Kirton 1978]. Although they approach problem solving in a different manner, neither style is considered superior. We propose that there should be no statistical significance in the difference in baseline performance and post system implementation. Thus:

H6: There is no statistically significant change in task completion times (DIFF) of adaptors and innovators when comparing the differences between BASELINE and STABLE task completion times.

IV. CASE DESCRIPTION AND HISTORY

As a result of the Omnibus Health Care Rescue Act, the Department of Health notified all Emergency Medical Service (EMS) agencies and hospitals throughout the state that the Department of Health was creating a trauma registry and that EMS agencies were mandated by law to submit data related to patient trauma to the state. Instead of sending aggregated data on multiple patients, all EMS agencies and hospitals were required to submit medical record data on a per patient basis in a prescribed data set to the Department of Health trauma registry. Transmittal of the prescribed data set was a prerequisite to licensure, so the agencies had little choice but to comply.

Prior to this legislative mandate, most EMS agencies relied upon manual documentation of patient charts and were only required to submit summary statistics on a quarterly basis. As a result, EMS agencies and hospitals were required to modify their information systems, making it possible to provide more detailed data on a per run basis.

An EMS agency located within a large metropolitan fire department was the subject of our study. Specifically, documentation procedures one year prior to and three years following implementation of an electronic patient documentation system were analyzed.

Initially, paramedics manually charted patient information and dropped off the completed forms at the end of their shift. Clerical personnel at the administrative offices manually checked the paper patient forms for errors or missing information, then separated, collated, and stored the forms for future use by patients, law enforcement, insurance companies, and the judicial system. They then forwarded other copies to the medical director's office and the billing company. Occasionally a clipboard was lost containing completed medical records and sometimes a record was accidentally destroyed in the field. EMS administration had to deal with these anomalies. Overall, the manual system was functional for many years but placed a clerical burden on administrative personnel, medical quality control evaluators and billing transcription clerks.

In their search for potential information system solutions, EMS administrative personnel visited other agencies to explore "in place" technologies and learn from others' experiences. Other EMS agencies planned to hire data entry clerks to transcribe each patient form into databases. EMS considered meeting the mandate in this fashion via the contract billing company. However, they were dissuaded by increased costs associated with this option. Other EMS agencies considered using electronic medical record software and pen-based computers to capture the data at or near real time. This seemed viable since the billing company could then extract the required data set from the server and upload it to the department of health. this system had the advantage of meeting the department of health mandate with fewer personnel and allowing contractual flexibility with the billing company. This system 1) eliminated the need to pick up the patient forms from the stations and deliver them to the administrative offices; 2) eliminated the need for administrative staff to separate and file the patient forms; 3) improved data quality for the billing contractor who transcribed paper patient forms on a daily basis, and often had difficulty interpreting handwriting; and 4) increased the speed of medical quality control through triggers and exception reporting and improved emergency nurse availability.

After several attempts, EMS contracted a software company to develop the system. Although the new information system would provide a different method of capturing the medical information, the required fields would be as similar as possible. Both manual and electronic forms had 107 required observation or data entry fields.

A small group of field paramedics trained on the new electronic medical record system. They became the system champions and reported the system was easy to use. The amount of work required to complete a record was similar to a paper patient form. Although both systems required the same fields, data entry for the electronic medical record system was split over twelve tabbed screens. The navigation requirements appeared to increase the amount of time to complete a form, particularly until paramedics became familiar with the location of the fields in the system. This potential increase in completion time was thought to be insignificant compared to the improvements in the back office and the ability to meet the department of health mandate.

Initially, paramedic supervisors were trained on system usage and support, followed by field paramedics. They received an initial four hour training session after which they received a tablet PC for documentation purposes. The following shift paramedics took part in a second four-hour training session where they could discuss problems they encountered during the initial shift of usage. A parallel rollout strategy ensured continued service during training. After one month, the majority of paramedics had completed training and were becoming more proficient with the new electronic medical record.

Both manual and electronic systems relied upon a series of timestamps to record the time required to complete each segment of an emergency call, beginning with the telephone call to the dispatch center. When paramedics arrive at the hospital, they transmit a timestamp from their mobile digital terminal, deliver the patient to the emergency room, and document the call. Upon completion of documentation, another timestamp signals departure from the hospital.

At the EMS administrative offices, the electronic medical record system provided several back office benefits. Clerical personnel were no longer required to check forms for errors or missing information, nor separate, collate, and store the forms for archival purposes. The system provided a search interface where records were retrieved and printable on demand. In addition, a daily missing record list was output for managerial investigation. Search capabilities also provided management improved access to run data for performance measures and budgeting. The system eliminated many of the mundane record handling tasks and provided EMS administration more information for managerial purposes. Therefore, in addition to meeting the requirements of the state mandate, the electronic medical record system increased data, information, and knowledge production

V. RESEARCH METHODOLOGY

Cognitive style in this model was determined using Xu and Tuttle's (2004a) adaptor-innovator in the workplace (AI-W) instrument. Only those paramedics working during the four-year period across both the paper and the electronic systems were included in the study. Individual performance was determined using the average completion time as a baseline prior to system implementation. Completion time was again measured post implementation after mastery of the system. Measurements of individual differences between baseline and post implementation times serve as the operationalization of the individual performance construct. Figure 2 shows the relation between cognitive style, information technology, and performance. Operationalized variables included cognitive style and individual performance. Information technology represented the treatment in this study.

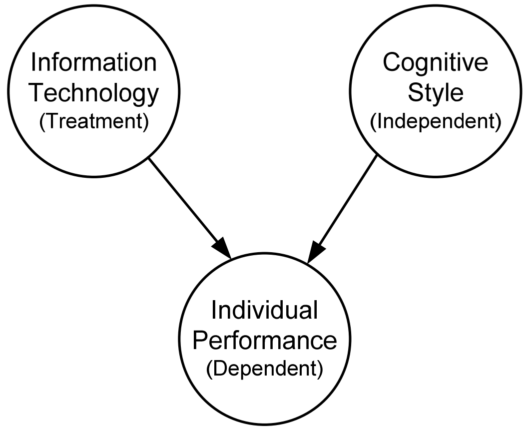

Figure 2. Research Diagram

Data Collection

After soliciting management support, we sent paramedics requests for participation via email. A link to the online survey was included with the invitation. Subjects included paramedics working within the system from 2000 through 2004. Of the 368 assigned paramedics, 195 actively used the paper-based system, received training, and switched over to the new electronic medical record system. The initial pool of respondents consisted of these 195 paramedics. Of the 195 subjects, 95 completed the demographic and cognitive style survey, resulting in an initial response rate of 48.72 percent. Of the 95 respondents, 34 failed to complete the cognitive style portion of the survey, or entered an invalid identification number, eliminating their data from consideration. Both of these requirements were necessary for inclusion in the study. Therefore, 60 respondents were found suitable for analytical purposes, yielding a sample response rate of 31.28 percent. Further review of this data indicated no missing data values or data entry errors.

The range for the continuum of the AI-W survey was 9 to 81. Score results for the paramedics ranged from 9 to 59, with a mean of 38.49. Of the 61 participants, 29 scored as adaptors and 32 scored as innovators. Adaptor scores averaged 27.29, whereas innovators averaged 48.16.

Fifty-four (88.5 percent) of the participants were male, and seven (11.5 percent of the participants were female. The disparity between males and females was expected. The distribution of males and females across adaptors and innovators was relatively equal with 27 male adaptors, 27 male innovators, 2 female adaptors, and 5 female innovators. The majority of participants (59 percent) ranged in age from 41-50 years of age, with the second highest ranging from 51-60 (34.4 percent). Bracketing of education level split potential responses into six categories: High School/G.E.D; Some College; Associates Degree; Bachelors Degree; Masters Degree; and Doctorate Degree. The organization requires a high school diploma for entry and provides financial benefits for additional education. Therefore, it was not surprising that 26 of the 61 (42.6 percent) respondents had some college. Another 17 (27.9 percent) held an associate degree and 13 (21.3 percent) held bachelor degrees. Respondent's computer work experience was bracketed by year into the following six categories: 0-1; 2-3; 4-5; 6-7; 8-9; and >10. Given the respondents' average ages, it was not surprising that the majority reported greater than 10 years of computer work experience. Twenty-five (41 percent) of the 61 users who answered this question reported more than 10 years experience. All other categories ranged from five (8.2 percent) to eight (13.1 percent) years of computing experience.

Data were obtained from four years of emergency transports to hospitals. During this time, there were 138,138 hospital transports of which 113,445 were Code 2 transports. Code 2 transports are medically serious transports with less performance variance. By focusing on Code 2 patient documentation, medical severity and its affect on documentation was controlled for in this study. Plotting Code 2 completion times over four years provided the information for the learning curve analysis. Of these 113,445 Code 2 transports, a total of 35,627 were evaluated. (The remaining calls were completed by paramedics that either did not respond to the study, or were not eligible to participate in the study). Adaptors documented 17,083 calls, and innovators documented 18,544 calls. The number of cases completed per user ranged from a minimum of 224 to a maximum of 1099. The average number of cases completed per paramedic was 584.

VI. DISCUSSION OF RESULTS

Hypotheses were tested using a between groups comparison to determine if statistically significant differences in performance existed over six dependent variables. One-Way Analysis of Variance (ANOVA) was used to test differences between adaptor and innovator group means as a way to test the hypotheses. The following dependent variables were included.

BASELINE - the average completion time during the year prior to new system implementation
HEIGHT - the maximum completion time using the new system minus the average completion during the year prior to new system implementation (BASELINE)
LEARNING - the interaction of the initial change, the rate of change and the number of days to master the system
DAYS - the number of days to master the system
STABLE - the average completion time during the multiyear period post DAYS
DIFF - the difference between STABLE and BASELINE

The means of the dependent variables are summarized by cognitive style in Table 1.

When comparing groups, ANOVA assumes relatively equal group size. It also assumes that groups formed by the independent variable possess similar variance of the dependent variable. As can be seen in Table 1, group sizes were similar (29 vs. 32), validating the first assumption. The Levene test was used to examine homogeneity of variance for all variables. Table 2 reports the summary of the Levene tests by variable, with significance values

As shown, DAYS failed the Levene test of homogeneity. Further analysis of variance assumptions are provided when hypothesis three is discussed. Table 3 provides the ANOVA results for all hypotheses.

Table 1. Means of Dependent Variables by Group

Means	Adaptors	Innovators	Total
N	29	32	61
BASELINE	20.23	20.46	20.35
HEIGHT	22.70	26.84	24.87
LEARNING	11354	16413	14008
DAYS	431	632	537
STABLE	24.32	23.41	23.85
DIFF	4.09	2.95	3.49

Table 2. Homogeneity of Variance Tests

	Levene Statistic	Significance
BASELINE	0.002	.966
HEIGHT	1.537	.22
LEARNING	3.836	.055
DAYS	7.026	.01
STABLE	0.31	.58
DIFF	1.285	.262

Table 3. ANOVA Results for Hypotheses

		Sum of Squares	df	Mean Square	F	Sig.
BASELINE	Between Groups	0.80	1	0.80	0.117	0.734
	Within Groups	403.54	59	6.84		
	Total	404.34	60			
HEIGHT	Between Groups	260.68	1	260.68	4.888	0.031
	Within Groups	3146.23	59	53.33		
	Total	3406.91	60			
LEARNING	Between Groups	389343332	1	389343332	6.675	0.012
	Within Groups	3441553923	59	58331422		
	Total	3830897256	60			
DAYS	Between Groups	616973	1	616973	7.833	0.007
	Within Groups	4646964	59	78762		
	Total	5263938	60			
STABLE	Between Groups	12.62	1	12.62	0.465	0.498
	Within Groups	1602.25	59	27.16		
	Total	1614.87	60			
DIFF	Between Groups	19.77	1	19.77	0.859	0.358
	Within Groups	1358.79	59	23.03		

Hypothesis 1 examined the difference in baseline completion time of adaptors and innovators. Given the fact that the paper patient form system functioned long term, both styles should have mastered the system in their own way. The dependent variable was completion time during the paper form period (BASELINE). The independent variable was cognitive style (adaptor vs. innovator). As shown in Table 1, when completing the paper form, Adaptors and Innovators took approximately the same amount of time (20.23 vs. 20.46 minutes). The BASELINE difference was not statistically significant at the .05 level (p = .734). Thus, Hypothesis 1 was supported. Both groups performed equally well during the period preceding the information system implementation.

Hypothesis 2 states that the change in task completion times (HEIGHT) of adaptors would be significantly greater than Innovators when learning to use the information system. Since the subjects were learning a new method of documenting, it was expected that both adaptors and innovators would initially take longer to complete the task, but that task completion time would decrease over time, and eventually reach stabilization. It was also expected that, because Adaptors dislike change, a greater difference would be seen between the BASELINE and the initial maximum completion for adaptors than innovators.

The dependent variable was the difference between BASELINE completion time and the maximum completion time during post system implementation. This was represented by the variable HEIGHT, shown at H2 on Figure 1. The independent variable was cognitive style (adaptor vs. innovator). As shown in Table 3, the difference in completion time was statistically significant at the .05 level (p = .031). However, contrary to our expectations, Innovators experienced greater change between BASELINE and maximum completion time than Adaptors. Several reasons for this result are possible. Since innovators tend to avoid detail, they may be unaware of, or simply choose to ignore the rules (Kirton et al. 1991), potentially interjecting errors in their data entry when using the system. Thus, error correction may increase overall completion time. Another possibility is that since Innovators like to try many solutions [Alter 2001], they may experiment when first using the system and take a variety of completion paths to do things differently. This could increase their completion times when learning the new system. Adaptors, on the other hand prefer performing in situations where well-established rules exist. This preference may facilitate their work completion times, particularly when first using the system. By closely following the provided guidelines for completing the task [Kirton et al. 1991] adaptors may perform better.

Hypothesis 3 examined the difference in learning pattern for adaptors and innovators. The learning pattern was defined as the interaction between the initial change (HEIGHT), the rate of change or slope, and the amount of time (DAYS) required to master the new information system. This interaction produced a measurable area under the curve representing the subject's pattern of learning the new information system. It was expected that adaptors would take more time to assimilate the new system and that Innovators might display greater rates of change given their acceptance of new technology. In addition as proposed in Hypothesis 2, it was thought that adaptors would experience a greater initial change (HEIGHT) in performance of the new system. Therefore, the combination of these three variables was expected to produce a greater area (LEARNING) for adaptors than innovators. Because the homogeneity test for this hypothesis was marginally significant, an independent sample t-test without equal variances assumed was performed. Table 4 provides these results.

Table 4. Independent Samples t-test

	t-test for Equality of Means	t	Sig.
DAYS	Equal variances assumed	-2.799	.007
	Equal variances not assumed	-2.829	.006

The dependent variable was for Hypothesis 3 was LEARNING, as shown at H3 on Figure 1. The independent variable was cognitive style (adaptor vs. innovator). The difference in LEARNING was statistically significant at the .05 level (p = .012). The next step was to determine the direction of the inequality of the means. Although it was expected that the area under the curve would be greater for adaptors than innovators, this was not the case. An analysis of the direction of the inequality provided interesting results. From Table 1, the area under the curve was considerably greater for innovators (16413) than adaptors (11354). One interesting explanation for this finding might be the effect of the business environment on individual work. Goodenough [1985] and later Chilton [2005] proposed that business environments might force people to work in ways that did not support or fit their preferred style. In contrast, the emergency environment requires a strong chain of command controlled by rules and regulations, standard operating procedures and medical control. Thus, EMS can be considered a paramilitary organization that is very structured, organized, and rule conforming. This might be why adaptors out-performed innovators. Another possibility is related to adaptor's preference to progress incrementally toward a defined goal within the existing structure [Xu and Tuttle 2004a; Chilton, Hardgrave et al. 2005], potentially affecting their learning rate. Because innovators are less comfortable following routines and structure, their incremental change may not be consistent in affecting their learning rate [Xu and Tuttle 2004a]. If adaptors look for structured change and prefer incremental improvements while being precise and methodical, they may have smaller learning patterns than innovators, who are less disciplined and look for larger improvements by doing things differently [Xu and Tuttle 2004a]. In addition, learning to use an information system may ultimately affect user performance [Parkinson and Redmond 2002]. It may be that the system design favored Adaptor's preferences during the learning curve. This idea is supported in the literature by Goodenough [1985] who states that the requirements of a specific problem may be related to a particular style. Work requirements are reflected in information systems and therefore, the system itself may produce differences in performance between adaptors and innovators. If the system design does not fit the cognitive preferences of the users, performance may be degraded [Chilton, Hardgrave et al. 2005; Coskun and Grabowski 2005].

Hypothesis 4 looked at the difference in days required to master the new information system for adaptors and innovators. Since the subjects were learning a new system, it was suggested that cognitive style might affect learning time and that adaptor preference to use the existing paradigm might cause them to take longer to learn the new system. Innovators' preference for doing things differently might enamor them to new technology, reducing the number of days needed to master the system. Therefore, it was expected that adaptors would take longer to learn the new system than innovators. DAYS were calculated by regressing each paramedic's performance and determining when the slope of the learning curve returned to zero indicating an equilibrium or end of learning. The dependent variable was time required to master the new information system (DAYS) as shown at H4 on Figure 1. The independent variable was cognitive style (adaptor vs. innovator). Because of the failed Levene test, an independent sample t-test to examine significance not assuming equal variances was conducted. Table 4 reports the results of the t-test for Hypothesis 4. A statistically significant difference at the .01 level was found ($p = .006$). Therefore, the t-test with equal variances not assumed supports the analysis of variance. As shown in Table 3 the ANOVA results for Hypothesis 4 were similar. The difference in DAYS was statistically significant at the .01 level ($p = .007$). The hypothesis that there is no statistically significant difference in the amount of time required to master the information system was therefore rejected. The means were compared to determine the relation of the inequality. As can be seen in Table 1, the number of days required to master the system for Innovators (632) was greater than the number of days to master the system for Adaptors (431). Two possible reasons for this long learning curve come from the psychology literature. The first is related to the paramedics' normal work pattern. They typically only work every fourth day, and do not always document patient charts each day they work. Thus, they may forget procedures during time off between uses. The second is concerned with the potential for employees to have cognitive failures and unintentionally produce errors.

Forgetting is an interesting concept associated with long learning curves affecting worker learning and retention. In real world systems, it is not uncommon for forgetting to occur following a break in attendance [Nembhard and Uzumeri 2000]. Arzi and Shtub [1997], Jaber and Bonney [1997] and Shtub et al. [1993] modeled the amount of learning following breaks. They found that workers who learn more rapidly also forget more rapidly for both manual and procedural tasks [Nembhard and Uzumeri 2000]. Wallace and Chen [2005] found that it was not uncommon for employees to forget important work-related procedures when distracted from work performance. Since the paramedics worked, on average, every fourth day, it was possible that learning and retention were negatively affected.

Cognitive failure might also help explain why the paramedics took so long to learn the new system [Broadbent et al. 1982; Wallace and Chen 2005]. Employees forgetting work related rules and procedures, failing to pay attention to requests from their coworkers, or unintentionally committing errors are examples of cognitive failure. These types of occurrences might have affected paramedics working with the electronic medical record system. Breaks in workdays or number of days missed have been found to be correlated with cognitive failure variables, failures of memory, attention and action [Wallace and Chen 2005]. It is possible that innovators had more cognitive failures than adaptors. This might explain differences in performance. Adaptors clearly mastered the system much earlier than innovators. One explanation for this difference, as suggested by Goldsmith [1984], is that adaptors focus on improving efficiency by conforming to rules and authority. This fundamental preference may equate to quicker learning and mastery of an information system that is bound by rules, logic and codes [Ella Miron 2004]. Conversely, Innovators will try to implement with "wide sweeps" rather than day-to-day precision [Goldsmith 1984]. This may cause the number of days required to master an information system to increase.

Education and training methods may have affected user performance. Alter [2001] found support for tailoring classroom instruction so that Adaptors and Innovators reap greater benefits from provided instruction. This point is echoed by several researchers, suggesting that novices should be allowed to experiment and that learning to use a new computer systems is best accomplished by actual use [Carroll and Olson 1984; Brown and Newman 1985] It is possible that system training on the system was unintentionally tailored to fit adaptors rather than innovators. If this occurred, training may have influenced time to master the system. Adaptors are most productive when receiving specific assignments, structure and support, whereas innovators do best if allowed to function independently and spontaneously [Alter 2001]. Within the confines of learning a new information system, there may be little flexibility to support Innovators desire to function independently. This system may not have allowed Innovators the flexibility to do things their way. A potential solution for this problem might be the use of continuing education for both adaptors and innovators to reduce learning forgetting and cognitive failure. By refreshing paramedics in the use, policies and procedures of the system, learning forgetting might have been mitigated. This could have benefited both cognitive styles by reducing the increase in performance time attributable to shift work and breaks in use.

Hypothesis 5 compared the differences in completion time post learning curve of adaptors and innovators. Hypothesis 5 is similar to Hypothesis 1, except it is measuring completion time after system implementation (STABLE). The independent variable was cognitive style (adaptor vs. innovator). Table 3 presents these results. The findings indicate no statistically significant difference at the .05 level (p = .498) and is consistent with Kirton's proposition that adaptors and innovators perform similarly. When using the new system post mastery, adaptors and innovators took approximately the same amount of time (24.32 vs. 23.41 minutes) to complete the task, and the difference was not statistically significant.

Hypothesis 6 considered the change in task completion times (DIFF) of adaptors and innovators, when comparing the differences between BASELINE and STABLE task completion times. This hypothesis questioned the adaptor-innovator contention that both styles are equally successful in organizations [Kirton 1978]. Both groups should have similar performance differences. Therefore, there should have been no statistically significant change in the task completion times (DIFF) in baseline performance and post system implementation.

The dependent variable was the difference between completion time in the paper form period and completion time in the post implementation period (DIFF) shown at H6 on Figure 1. The independent variable was cognitive style (adaptor vs. innovator). As shown in Table 3, ANOVA indicated no statistically significant difference at the .05 level (p = .358). Therefore, the hypothesis that there is no statistically significant change in task completion times of Adaptors and Innovators post system implementation cannot be rejected. Adaptors and innovators reach a similar equilibrium in performance, supporting Kirton's theory. Adaptors experienced a slightly greater change (4.09) while innovators experienced a (2.95) smaller change but the differences were not statistically significant.

VII SUMMARY OF RESULTS

The task completion times of adaptors and innovators were not statistically different either before implementation of the electronic system or after post-system implementation stabilization. However, the manner in which the adaptors and innovators learned and mastered the task was quite different. Contrary to initial expectations, innovators had a greater change in completion time when first learning to use the new information system. Additionally, their learning pattern was significantly greater than that of adaptors, and they required 46 percent more time to master the new information system. Table 5 provides a summary of all hypothesis tests.

Table 5. Summary of Hypothesis Tests

Hypotheses	Variable	p value	Expected	Result
One	BASELINE	.734	A=I	A=I
Two	**HEIGHT**	**.031**	**A>I**	**A<I**
Three	**LEARNING**	**.012**	**A>I**	**A<I**
Four	**DAYS**	**.007**	**A>I**	**A<I**
Five	STABLE	.498	A=I	A=I
Six	DIFF	.358	A=I	A=I

Prior research suggested that people performed work at equal levels and that cognitive style was not a predictor of performance [Kirton 2003]. However, these studies did not consider the relation between cognitive style and the learning curve. In this study, the performance of adaptors and innovators was comparable during stable periods, but significantly different while learning to master the system. Although it was expected that innovators would perform better than adaptors during the learning period, the results showed that adaptors experienced significantly shorter learning curves and task completion times while learning to use the system. Therefore, Kirton's propositions of equality were only applicable during stable periods.

While this work was an individual case study, it analyzed performance over a considerable period of time in a single organization, as well as the interaction with other organizations. Note that performance (as measured by the time to complete the electronic medical record) actually declined (Figure 3). Even following the learning period, completion times never approached those observed prior to implementing the electronic patient documentation system. Also, note that the actual time required for the paramedics to reach stabilization was much longer than presumed. This extensive time can be partially attributed to post-interruption learning [Bailey and Mc Intyre 2003]. On average, paramedics work once every four days. In addition, when they work, they do not always perform patient documentation. Therefore, they may have initially spent time relearning the system.

Although the paramedics actually required more time to complete the task, even after stabilization, and the learning curve was longer than expected, the system was still deemed successful. In addition to meeting the requirements of a state mandate, there was improved functionality within the affiliated organizations associated with the adoption of this technology.

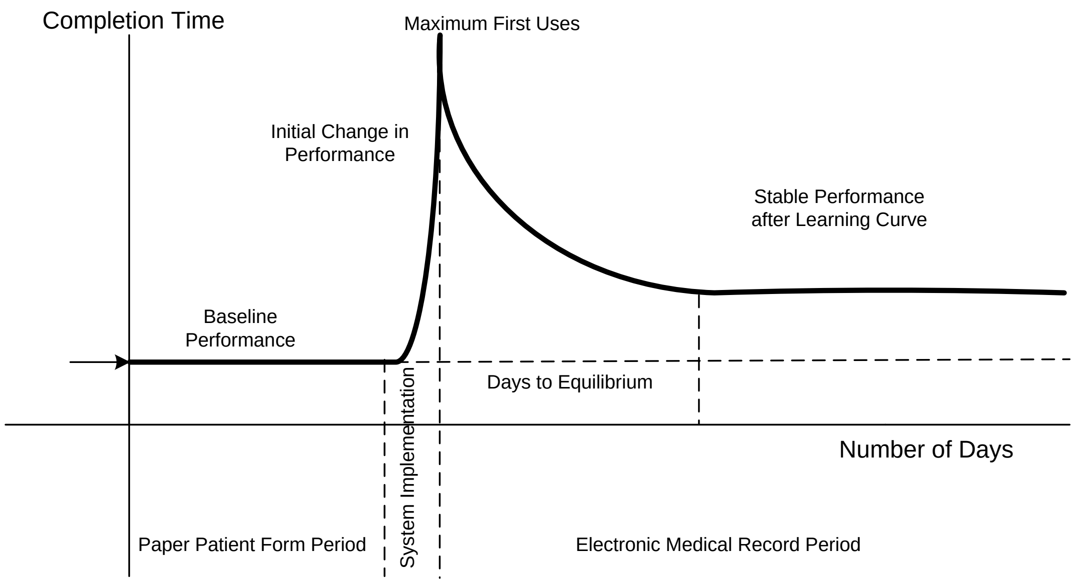

Figure 3. Medical Record Performance Decrease

VIII. DISCUSSION

This is the first known study to examine the relation between cognitive style, the learning curve, and individual performance when implementing an information system. The most significant finding in this study was the existence of differences in performance related to cognitive style *during* the learning curve.

Limitations

The quasi-experiment time series case study design for this study introduced strengths and weaknesses attributable to the design's lack of rigor and strength of relevance. The quasi-experiment research design varies from the true experiment in subject assignment. True experiments use random assignment whereas the quasi-experiment does not [Creswell 2003]. In this case, participants were assigned to groups based upon their responses to a cognitive style classification survey. While this is not as rigorous a method as random assignment, it is a suitable method for case research. Case research has been used in information systems research such as this for over 10 years [Dube and Pare 2003], and the results of this case study provide valuable insight into a working organization's adoption of technology.

One limitation introduced with the case study and time series interrupted design is that the implementation had already occurred. This is a limitation introduced by the design of the research. A strength of this study was the use of a very large number of performance data points over time across a substantial group of workers using a system. As is the situation in all case studies, the assumption is that confounding variables are present, creating alternate explanations. However quasi-experiments represent an improvement over pre-experimental designs [Campbell and Stanley 1966].

The time series design provides a major advantage over other forms of quasi-experiments in that it allows the assessment of trends prior to the treatment [Cook and Campbell 1979]. These types of designs are useful when the researcher is trying to determine the existence and magnitude of effects within a temporal sequence of events [Campbell and Stanley 1966]. This study looked at performance over four years; one year prior to the treatment and three years post treatment in an effort to decompose the learning curve and analyze user performance.

Dube et al. [2003] examined positivist case studies finding that a large number of researchers failed to pose clear research questions, provide information about data collection methods, or discuss data analysis methods. This study clearly discusses research questions and hypotheses, supplies information concerning data collection methods and data analysis techniques, thereby improving its case research rigor as suggested by Dube et al. [2003].

A weakness of case studies such as this is that they cannot be generalized beyond cases that are similar to the one under consideration. However, they provide a starting point for future research with other populations and settings.

Suggestions for Future Research

This study involved a single longitudinal case study. Obviously, additional laboratory and field experiments are needed to be able to generalize these findings. To improve generalizability and further understanding of the relations found here, the following implications and suggestions for further research are provided.

Because of the very long learning curve discovered in this exploratory study, further study is needed to determine if this result is common. We therefore urge researchers and practitioners to closely examine learning and task completion times.

Individual Differences

The impacts of individual differences manifest themselves in external behaviors when confronting new information systems. Clearly, individual differences can affect behaviors and behaviors can affect performance. Paramedics who failed to follow procedures and methods delineated during training may have exhibited behavior associated with failure to accept the technology or they may simply have followed ingrained preferences for approaching new problems considered part of their cognitive style. There is a wide variety of cognitive style indices. This study focused on adaptors versus innovators. Other potential areas of interest might include: elements of the Five Factor Model such as openness to experiences [McCrae and Costa 1989], Miller's Innovation Styles Profile [1986], Witkin's field dependent-independent cognitive styles [1981], Allison and Hayes' cognitive style index [Allinson and Hayes 1996], and Basadur's creative problem solving profile [1989].

Person-Job Fit

Certain environments may not lend themselves to a variety of problem solving preferences. For example, the military or emergency worker environment may not accommodate the Innovator's desire to experiment. Task type in these situations may better fit one cognitive style over another. Adaptors may perform better because they fit the environmental demands. Research has shown that a cognitive misfit between the individual and the environment leads to increased stress, reduced performance, and increased turnover [Chilton, Hardgrave et al. 2005]. Cognitive misfit between the individual and the system may also introduce undesirable effects on employees. Can the fit be improved?

System Design

Another potential explanation related to paramedic performance is the effect of the target system. The fit between the system and the user can be an important aspect of learning [Bostrom, Olfman et al. 1990b; Shayo and Olfman 2000; Chilton, Hardgrave et al. 2005; Avital et al. 2006]. Research has shown that system design plays a role in influencing the user's experience and satisfaction [Chung and Tan 2004; Lin et al. 2005]. The interface provided in the case study might have fit adaptors better than innovators. Interfaces with greater user control afford the opportunity for experimentation or "playfulness" versus systems designed to control the learner [Martocchio and Webster 1992; Polys et al. 2005]. This may be why adaptors performed better during the learning curve. The design of the system may have strictly controlled the learner by requiring linear performance, which would be more suitable for adaptors. Future research might examine the role of cognitive playfulness and training methods on system design. In the laboratory, various system configurations might be used across adaptor-innovator groups to see the effects of playfulness. It may be that certain types of systems require less play and more control, or the reverse may be true.

Learning Curve Improvements

Since adaptors and innovators appear to learn and approach problems differently, learning may be facilitated by closely monitoring performance objectives post system implementation. Management should establish checkpoints, evaluate performance, and attempt to shift the performance curve with additional means of support.

The concept of learning cycles is useful to envision the effect of shifting the performance curve by using checkpoints and intervention training. Learning cycles can be thought of as the inverse of learning forgetting and cognitive failure as seen in Figure 4. Where learning forgetting and cognitive failure cause a decrease in performance, learning cycles coupled with checkpoint monitoring can increase performance. While learning forgetting and cognitive failure can be triggered by breaks in workdays, learning can be facilitated by implementing checkpoint monitoring and focused training sessions. Figure 4 shows the potential impact of check-point monitoring and focused training to shift and improve the learning curve.

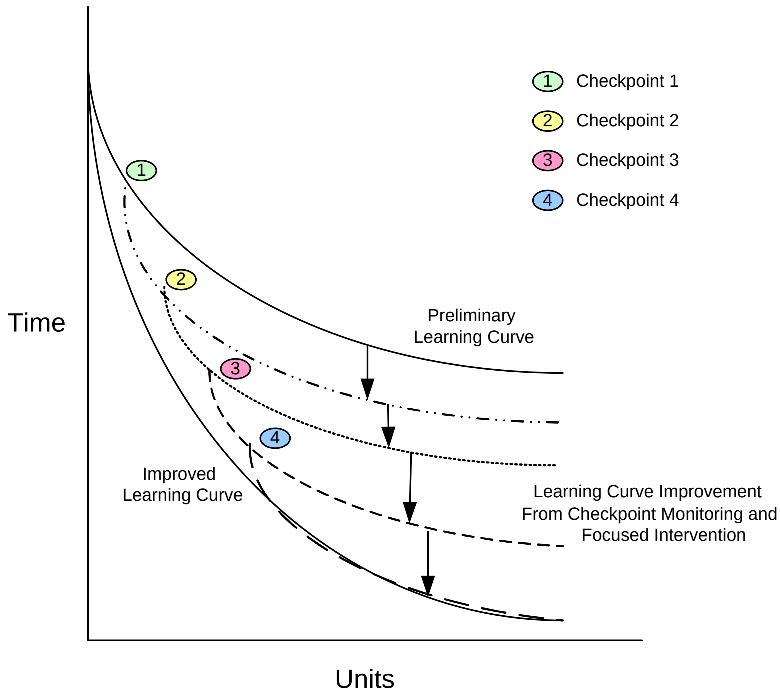

Figure 4. Check-Point Monitoring and Learning Curve Improvement

Because of the significant differences found during the learning curve, organizations may want to build and use mechanisms to support these implications such as performance awareness sessions, workplace tolerance and fit training, and intervention training. These may be supplemented with quality help systems, performance feedback loops, and system champions to assist users. These monitoring and coping mechanisms may facilitate performance and help reduce differences introduced by cognitive style.

IX. CONCLUSION

The objective of this research was to advance our knowledge of the relation between performance, cognitive style, the learning curve, and information technology. The study successfully tested how cognitive style affects individual performance when using information technology over time. Discovery of performance differences during the learning curve provided new insight into previous propositions of equal performance. These findings enhance our understanding of cognitive styles and learning curves, offering new explanations of how performance may be affected when learning to use information systems. Further study in this area is encouraged.

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