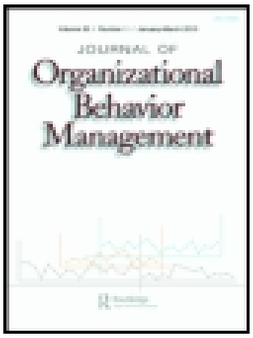

Journal of Organizational Behavior Management

ISSN: 0160-8061 (Print) 1540-8604 (Online) Journal homepage: http://www.tandfonline.com/loi/worg20

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To cite this article: Joshua D. Sleeper, Linda A. LeBlanc, Jonathan Mueller, Amber L. Valentino, Daniela Fazzio & Paige B. Raetz (2017): The Effects of Electronic Data Collection on the Percentage of Current Clinician Graphs and Organizational Return on Investment, Journal of Organizational Behavior Management, DOI: 10.1080/01608061.2016.1267065

To link to this article: http://dx.doi.org/10.1080/01608061.2016.1267065

Published online: 10 Jan 2017.

JOURNAL OF ORGANIZATIONAL BEHAVIOR MANAGEMENT
http://dx.doi.org/10.1080/01608061.2016.1267065

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The Effects of Electronic Data Collection on the Percentage of Current Clinician Graphs and Organizational Return on Investment

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ABSTRACT
Behavior analysts rely on frequent access to graphed data to facilitate clinical decision making and enhance their programming. Several new electronic data collection (EDC) products have recently been developed and marketed to behavior analysts. We evaluated the effects of an EDC software system on the percentage of current graphs. We also evaluated the potential return on investment (ROI) of the tool for a large human services agency. During baseline, graphs were seldom updated at the designated time the supervisor examined the file. When the EDC software was implemented, 100% of graphs were updated at all checks for all consumers with minimal or no corresponding increase in clinician hours. A comprehensive index of ROI was calculated using various costs of implementation and observed and estimated savings. Implementing the EDC software across the human services agency resulted in a projected cumulative positive average ROI of 59% over five years. These results are discussed in terms of strategies for systematically evaluating the costs and benefits of organizational efforts to use technology to enhance staff performance in human service settings.

KEYWORDS
Data collection; electronic data collection; graphing; return on investment; technology

Early intensive behavioral intervention (EIBI) is the most strongly supported evidence-based treatment for autism spectrum disorders (Eldevik et al., 2009; LeBlanc & Gillis, 2012; LeBlanc, Parks, & Hanney, 2014; Reichow, 2012; Reichow & Wolery, 2009). This intervention can involve up to 40 hours per week of intensive instructional programming (i.e., thousands of learning trials) across many different target areas (e.g., social behavior, language). The behavior analyst who oversees the intervention services creates instructional programs, monitors performance on the goals, and modifies the programs as needed to maximize the rate of progress (LeBlanc & Gillis, 2012). Careful and frequent measurement of behavior (i.e., data collection) is foundational to the

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delivery of applied behavior-analytic services (Baer, Wolf, & Risley, 1968; Sidman, 1960) and should be used to guide practitioner's choices about program implementation, modification, and introduction of new goals.

The authors of many curriculum manuals and guides recommend recording data for every learning trial with a summary of performance across blocks of learning trials (Leaf & McEachin, 1999; Lovaas, 2002). These data are compared to a mastery criterion to guide decisions about progress and potential program changes (Maurice, Green, & Luce, 1996). As the volume of services increases, collection and analysis of all relevant data may prove logistically difficult, resulting in a decrease in the frequency of graphing or data collection.

Technology can be used to automate or simplify data collection and analysis to save time. Several new products are designed to electronically capture and synthesize data so that practitioners can remotely access consumer performance data immediately.

The usefulness of technology products could potentially extend to training staff, documentation of clinical activities, and analysis of company-wide performance. As a result, human services agencies may decide to invest in infrastructure and equipment to automate data collection and analysis if the technology saves time and allows continued frequent analysis of data. Electronic data collection (EDC) has the potential for direct and derivative benefits for human services agencies, though no studies have explicitly demonstrated these benefits in the area of behavioral treatment of autism. Clinical staff may directly benefit from remote access to data and automatic graphing, allowing for more frequent analysis and faster data-based decision making. Potential derivative benefits of EDC might include improved consumer outcomes, increased staff efficiency, increased consumer and staff satisfaction, and positive perception of the human services agency in the field. However, use of these products requires investment in hardware, software, mobile device management software for security, monthly wireless data plans, and time and effort for change implementation. These investment dimensions increase the importance of systematic evaluation of costs and return on investment (ROI) in any change initiative (Wells, Reimer, & Houmanfar, 2013).

The published literature indicates the importance of reporting ROI data to supplement intervention effectiveness and social validity data (Wells et al., 2013). Cost-benefit data are useful for determining the potential ROI of implementing an effective intervention or technology change. However, Wells et al. (2013) explain that authors may not report cost-benefit data to avoid giving financial information to competing organizations. For example, in a study by Goomas (2013) the analysis of the intervention results was limited to the cost of implementing the technology and the efficiency benefits of the intervention, which did not capture the potential ROI due to increased

productivity and decreased errors of staff. In Goomas (2012), only intervention effects of implementing the technology were reported, leaving questions about the ROI of purchasing the technology.

Understanding the ROI of change implementation of a technology, such as EDC, is critical for human services agencies that may have limited resources to invest in the product and tools without offsetting the investment or potentially increasing profit. Analysis of the effects of implementation of EDC may not provide all of the necessary information for analysis of the pros and cons of such a significant change initiative. The purpose of this investigation was to conduct a systematic evaluation of an EDC platform. We attempted to determine the utility of the product for enhancing consistency of data graphing as well as the potential companywide ROI for the product. A popular, commercially available, EDC software product was chosen for this investigation.

Method

Setting

This study was conducted in a large, multistate human services agency that provides applied behavior analytic treatment services to individuals with autism. Services are delivered through the efforts of bachelor level therapists and the oversight of master's or doctoral level clinicians. Therapy services are conducted in consumers' homes and agencies centers. Typically sessions range from 1.5 to 4 hours long. All consumers were supported by a therapy team consisting of a lead clinician responsible for developing programs, training staff, and evaluating the effects of programs on participant learning, and multiple therapists responsible for implementing direct sessions. Several consumers involved in the study had the support of a junior clinician who assisted the lead clinician with program development and staff training.

Participants

Three divisions participated in the evaluation. Each division had a PhD-level supervising clinician as divisional director (i.e., the last three authors). In each division, multiple clinicians were selected and multiple consumers were matched into dyads based on the type of programming, number of hours, and location of services. The experimenters reviewed the consumers for each clinician and categorized them based on type of programming (i.e., focused vs. comprehensive EIBI), number of hours per week, and location of services (i.e., agency's center or consumer's home). A total of five clinicians and nine consumer dyads participated in the study. Three of the five clinicians participated in a single subject design evaluation of the effects of the EDC product

Table 1. Demographic Information for Clinician and Consumer Participants and Summary Results of All Single Subject Design Analyses.

		Clinician	Consumers	Baseline average	Intervention average
Return on investment analysis	Single Subject Analysis	*Susan*: 27 years old, BCBA, 5 years of experience	WV -9 y	0%	
			RL -15 y	0%	100%
			SCR -2 y	0%	
			DR -2 y	0%	100%
			FT -2 y	42%	
			CV 2 y	0%	100%
		Kristina: 29 years old, BCBA, 8 years of experience	NNG -10 y	0%	
			DN -10 y	0%	100%
			KO -3 y	0%	
			TT -4 y	16%	100%
			GW 11 y	0%	
			RS 12 y	0%	100%
		Denise: 35 years old, BCaBA, 9 years of experience	IP -2 y	0%	100%
			KNE -2 y	0%	100%
		Sally: 36 years old, BCBA, 14 years of experience	AnTh -5 y		
			JaCo -9 y		
		Ashley: 33 years old, BCBA, 11 years of experience	LuRe -7 y		
			LeWo -6 y		

on the percentage of accurate and current program graphs and overall clinical hours of oversight effort. Seven consumer dyads, a total of 14 consumers, participated in the single subject analysis.

Each of these clinicians had been employed with the organization for about one to six years, and were between the ages of 27 and 35 years old. Their consumers were diagnosed with autism spectrum disorder or developmental delay, and were between the ages of 2 and 15 years old. Susan was 27 years old, a Board Certified Behavior Analyst (BCBA) ™, and had five years of experience in the field. Kristina was 29 years old, a BCBA, and had eight years of experience in the field. Denise was 35 years old, a Board Certified Assistant Behavior Analyst (BCaBA) ™, and had nine years of experience in the field (see Table 1 for a summary of all consumer and clinician participant characteristics). In this agency, clinicians provide case management services, including developing consumer programs, analyzing data, and make data-based treatment decisions. Clinicians typically collect data during assessments and baseline phases of treatment. Therapists conduct therapy sessions and collect data during the sessions.

Materials

Software system and related materials

The software offers treatment planning and data analysis functionality via a web-based portal, and data collection functionality via common mobile devices (e.g., smart phones, tablets). The web portal is used by clinicians for client program creation and maintenance. Data are collected by therapists

during treatment sessions via a mobile app using a mobile device. Data are automatically accessible to clinicians via the web-based portal for analysis.

Web-based portal. The web-based portal is designed for clinicians and system administrators. The administrative features include maintaining active consumers and team members in the system, creating default settings, and paying subscription fees. Clinicians also used the web-based portal for entering client programs, adding program targets, and reviewing graphs. Specifically, clinicians entered programs for clients by specifying the discriminative stimulus, mastery criteria, prompt types and hierarchy, and targets.

EDC app. This app was used by therapists to collect data, write therapy notes, and sign into and out of therapy sessions. Therapists logged into the app, then selected a client's virtual program binder, which looks like a real notebook in the app, to gain access to program sheets and data collection features. Data collection consisted of tapping icons on the touchscreen to indicate the consumer's response and prompt level. The therapist also had the option of collecting live video, documenting observations, and implementing strategies, such as behavioral momentum or intermixing mastered and active targets. Selections made by the therapist were automatically saved and synchronized with the web-based portal. Once data collection was complete, the therapist logged out of the application or selected a virtual program book to collect data on a different consumer.

The EDC product included automatic graphing. During the evaluation the EDC software was loaded onto tablets and smart phones. Eighteen tablets were provided by the agency to therapists in the three participating divisions. Nine of the tablets were equipped with a cellular data plan for use in locations without access to a WiFi Internet connection. Eight of the tablets were basic WiFi models. Two therapists were reimbursed for using their personal smart phones during the pilot. Additionally, all tablets were equipped with MDMS (mobile device management software) to limit the functionality of the tablet to operating the EDC software, e-mail, and video recording. The MDMS is a software that ensures security of consumer personal health information by allowing monitoring of the location of the tablets, disabling of passwords, and remote installation of additional software.

Nonelectronic materials

During baseline, therapists collected data on child performance during learning trials using paper datasheets and pencil or pen. These datasheets were stored in a program binder at the service location after each session, to be retrieved and analyzed by the clinician at a later date. The clinician graphed the data using Microsoft Excel®.

Experimental design

A nonconcurrent multiple baseline design across consumers was used to evaluate the effects of the EDC platform with replication across multiple clinicians. Consumer dyads included one participant for whom programming was monitored using the EDC software and an age-matched consumer in similar programming who remained in the baseline phase (i.e., paper and pencil data collection) for monitoring of programming.

Measurement and data analysis

Single subject analysis

The dependent variable was the percentage of current program graphs for each consumer, defined as graphs that included current data from therapy sessions, but not including, the designated check day. The graph check occurred Friday at 5 p.m. Pacific Standard Time (PST). Program graphs containing data from the prior Friday to Thursday of that current week were counted as 100% current. The exception was the first week of implementation when data were gathered from Monday through Thursday, as the prior Friday was a washout day for implementation. Program graphs that did not contain data from a therapy session that occurred Friday to Thursday of that week were scored as not current. The percentage of current program graphs was calculated as the sum of current program graphs for a consumer divided by the total number of active consumer programs multiplied by 100%.

ROI analysis

The primary dependent variable for the ROI analysis was the number of nonreimbursable hours worked for each consumer by each clinician each week, which was incorporated into the ROI index in the return metric (see Table 2 for all formulas; Zerbe & Bellas, 2006). All five clinicians and all of their consumer dyads participated in the ROI analysis. Clinician hours were tracked for each consumer, Monday through Friday of each week. Work activities directly related to the consumers were tracked (e.g., program development, parent training, graphing and data analysis, transportation to the consumer's place of service). Clinician hours were tracked by type of activity and whether the work was reimbursable from a funding source.

Satisfaction survey

After participating in the study, therapists and clinicians completed a brief satisfaction survey (copy available upon request), which assessed preference for EDC compared to paper and pencil and effectiveness of training to use the EDC system.

Table 2. Dependent Variables and Calculation Formulas for All Analyses. ROI Calculations Are Based on Zerbe and Bellas (2006).

	Measure	Calculation
ROI	Clinician nonreimbursable hours	Sum of all nonreimbursable hours by clinician for all consumers
	Clinician hours saved per client/month	Nonreimbursable time saved per client that implemented EDC/month
	Total clinician time saved/month	Clinician hours saved/month * average clinician caseload
	Clinician increase in efficiency (%)	(Average # of clinician hours saved per month per consumer/ average # of clinician hours per consumer pre-EDC) * 100
	Increase in consumers served (#)	(Clinician increase in efficiency +1) * average TBH caseload
	Increased revenue($)	Average revenue per consumer * increase in consumers served
	Costs of implementation ($)	Sum of costs($): EDC software + mobile devices + MDM software + mobile device accessories
	ROI index (%)	(Increased revenue($) costs of implementation ($)/increased revenue)*100
SS	Percentage of current program graphs IOA percentage of current program graphs	([Sum of current program graphs for a consumer]/total open consumer programs)*l00 Agreements/(agreements + disagreements)*100

Note. EDC = electronic data collection; IOA = interobserver agreement; MDMS = mobile device management software; SS = single subject; TBH = trumpet behavioral health.

Training and support

Training on the EDC software was conducted for two levels of staff. Clinicians and their supervising clinical directors participated in a 1-hour training session conducted by the EDC company staff covering the use of the programming portal and the data collection app. Training consisted of instruction on how to navigate the software, create client programs, analyze data, and collect data using the app. Subsequent support was provided to clinicians and their supervisors by the EDC company's technical assistance feature and by the first author. Clinicians were able to access the EDC technical assistance feature through a chat option within the software. Clinicians were encouraged to contact the first author with questions and clarification on using the software. Clinicians consistently took advantage of both the technical assistance feature and support from the first author; however, no running log of assistance was kept. Before implementation of EDC with each consumer, clinicians entered all programs and ensured proper setup of the data collection app on the desired dimension(s) of the targeted behaviors.

Clinicians were given instructions, job aids, and a demonstration on uploading datasheets and graphs to the electronic database. This training primarily focused on orientation of the file structure and due date for uploading the materials, as clinicians had previous knowledge about using the electronic storage system.

Staff from the EDC company presented a 1-hour demonstration of the data collection application to all therapists involved in the study. Additionally, therapists participated in a 1–2 hour competency-based training session with a designated clinician. Each therapist was trained using Behavioral Skills Training (BST) to a criterion of 100% accurate and independent use of the mobile device and data collection software (e.g., operating the tablet, signing into the app, locating a consumer's program, collecting data, managing the tablet during a Discrete Trial Teaching session). The week before the implementation of the EDC software with a consumer, clinicians met with each therapist and reviewed the training on operating the mobile device and using the EDC software. All therapists were required to maintain the criterion-level performance from the previous competency-based training session prior to the software implementation.

Procedure

Baseline

Therapists collected consumer performance data using the paper datasheet templates provided by clinicians. The datasheets for each consumer were collected from the client binder by the lead clinician or the assistant clinician during regularly scheduled home visits or observations at the center. The clinicians were asked to upload any datasheets, updated data spreadsheets, and graphs for each consumer to the electronic database every Friday by 5 p.m. PST. There was no explicit contingency for doing so or failing to do so. The supervising clinical director checked the electronic database, and scored and logged the percentage of current program graphs for each consumer. Any consumer program graphs that were not uploaded by the Friday 5 p.m. PST deadline were scored as noncurrent. The clinicians notified the supervising clinical director on Friday at 5 p.m. PST to indicate if they uploaded or did not upload consumer program graphs. The purpose of this communication was to account for and track any technical difficulties with uploading graphs to the electronic database that might lead to an error in scoring of the current program graphs. Additionally, the clinician logged all work activities and uploaded the log to the electronic database every Friday by 5 p.m. PST.

Intervention

During intervention the EDC software and mobile device replaced the paper and pencil data collection and the program binder for the consumer. Therapists collected data using the EDC software application and those data automatically uploaded to the programming portal within 10–15 min of the data entry by the therapists when the mobile device was connected to a Wi-Fi or cellular network for Internet access. Clinicians had access to the

programming portal at all times to review automatically updated graphs for consumer performance data. Clinicians updated consumer programs as they typically would in their standard clinical practice, within the EDC programming platform. Clinicians tracked work activities and uploaded their work effort logs to the shared electronic file database. Clinicians were aware that every Friday at 5 p.m. PST, the supervisor would log into the programming portal and score the percentage of current consumer program graphs, which are automatically generated as data are collected using the app. No other contingencies were in place for having up-to-date graphs or failing to do so.

Due to the complexity and time requirements to implement the EDC software, a "washout week" was inserted between baseline data collection and intervention implementation. This allowed for the clinicians to notify team members and families of the implementation start date, ensure programs were entered into the software, and assign therapists their mobile devices. During the washout week the percentage of current consumer program graphs was not scored; however, work activities were tracked and uploaded to the shared electronic database.

Interobserver agreement

A second independent observer scored all graphs and compared the scores for each graph to those of the participant scores for 100% of opportunities. Every Friday at 5 p.m. PST the second observer scored graphs uploaded to the electronic database (i.e., during baseline) and graphs within the EDC software (i.e., during intervention) in comparison to consumer response data for programs conducted the prior week. The scoring of the first and second observers was compared for each instance and agreement was calculated by dividing the total number of agreements by the total number of graph agreements plus graph disagreements, and multiplied by 100%. Interobserver agreement was 97% across all participants.

Results

Single-subject analysis

Figure 1 shows the percentage of current program graphs (closed squares) and the number of clinician hours per week (closed circles) for Susan's consumer for whom EDC was implemented. The results for Susan are very similar to all other results and are presented as an example. All remaining data are summarized in Table 1 and graphs are available upon request. Her consumers had 0% current program graphs during baseline. Upon implementation of the EDC software, all three consumers had 100% current program graphs throughout the duration of the study.

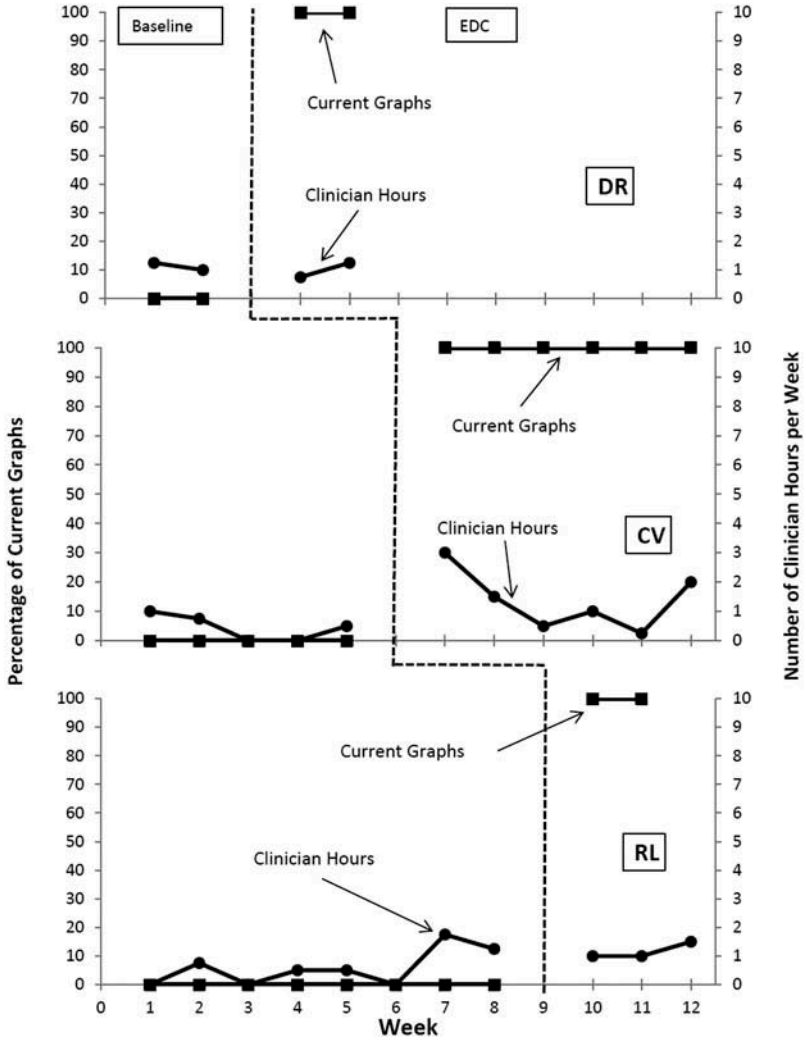

Figure 1. The percentage of current graphs (closed squares) and the number of clinician hours per week (closed circles) for Susan.

ROI analysis

We calculated a monthly average time for each clinician. For all five clinicians the total monthly average time increased by about 4.25 hours after implementing the EDC software and the majority of that time was billable (i.e., 3.87). All 5 clinicians' data graphing and analysis improved upon implementation of the EDC software. The projected cumulative ROI was calculated based on projected increases in revenue generated by an increase in reimbursable hours per clinician over a five-year implementation period. Specifically, ROI was calculated by subtracting the costs associated with implementation of EDC (e.g., software subscription, mobile devices, MDM software) from the projected increased revenue generated and dividing the

difference by the projected increased revenue generated and multiplying by 100 (Zerbe & Bellas, 2006). The revenue and costs are included from prior years to project the total cumulative ROI during a five-year period of time. It is projected that the EDC implementation would generate a 58–59% return in each of the first five years.

The results of the satisfaction survey indicated that 87% of responding team members either preferred EDC or felt neutral about the trade off with paper and pencil data collection. In addition, 90% of team members indicated that they agreed or strongly agreed that the training was sufficient to prepare them for using EDC.

Discussion

Implementation of EDC resulted in immediate improvements in the percentage of current program graphs for consumers. Baseline graphing was consistently low due to logistical constraints associated with regularly traveling to clients' homes to obtain data and update graphs by the deadline. The EDC system solved this problem because of the automatic graphing feature, allowing for more frequent data analysis. Having graphs that are consistently up-to-date may allow clinicians to make more frequent data-based clinical decisions about programming (Carey & Bourret, 2014; Cummings & Carr, 2009; Lerman, Dittlinger, Fentress, & Lanagan, 2011). In addition to possible improvements in the clinical process and decision making, implementation of the EDC software increased the reimbursable hours provided by clinicians.

The increased capacity for data-based decision making has to be considered in the context of the cost of implementation to the company. Due to the relatively costly investment for EDC software and hardware, it is important to fully evaluate the potential ROI before deciding whether to make the investment. In this case, EDC adoption is a wise use of financial resources (Wells et al., 2013). The current ROI analysis indicates increased profitability upon implementing EDC, which offsets the cost of EDC and allows for investment in other initiatives designed to improve client outcomes, staff performance, and staff satisfaction.

Prior studies of the ROI of technology implementation have been limited to evaluation of costs of implementation and efficiency benefits of the intervention, but have not captured the potential ROI as a result of increased productivity and decreased staff errors (Goomas, 2012, 2013). This study advances the literature by presenting a more comprehensive analysis of ROI. The return occurred because the clinicians invested additional time into managing programming for their current clients and that time was usually billable. In other instances, clinician time might be saved that could be reallocated to other client services or other professional development activities.

Future studies should focus on a larger scale implementation of EDC with additional participants. In addition, research could examine the impact of policies and guidelines to enhance the utilization of the full functionality of the software. Additional consideration should be given to the impact of EDC on efficacy of staff training and procedural integrity with treatment implementation, and consumer outcomes. Finally, options for choosing EDC software continue to increase as new companies enter the market. It is reasonable to expect that any EDC product would result in increased completeness of graphs; however, it is not clear that the ROI for all products would be identical to the ROI for the product evaluated in this investigation (information about the specific product available upon request). Similar ROI analyses should be conducted for other EDC products to determine whether all products yield the same ROI. Factors such as complexity of the data collection system setup, time required for training, and direct product costs could alter the cost analysis, resulting in greater or less ROI compared to that reported here.

Acknowledgments

We thank Sarah Veazey, Kate Goldsmith, Danae Medrano, Lani Fritts, and Chris Miller for their assistance on the project. Access to the electronic data collection product was made available to Trumpet Behavioral Health free of charge by the electronic data collection company; however, no information about the findings of the study was conveyed to the company representatives prior to completion of the project.

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