

Streamlining Observations, Feedback, Reflection, and Professional Development: Are You Ready to be COACHED?

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ABSTRACT

Special education teacher preparation programs vary in their usage of practices (e.g., modeling and performance feedback) that have consistently been shown to effectively coach pre-service teachers to sustain high-quality implementation of teaching practices. Research even suggests that some pre-service special education teachers may not receive any of these coaching practices during their field experiences. In this article, we describe a feasible multimedia coaching option for teacher educators and teacher candidates to use to streamline the observation and coaching process using effective coaching practices and improved consistency. Specifically, this multimedia tool can be used to document pre-service teacher practice, generate feedback, deliver targeted instruction, and provide the opportunity for structured self-reflection.

KEYWORDS

Coaching, multimedia, preservice teachers, special education

A well-prepared and qualified special education teacher is one of the most important school-related factors for increasing academic achievement for students, including those with disabilities (Darling-Hammond & Berry, 2006; Harris & Sass, 2011). Teacher use of high-quality practice is a key component impacting students' academic success (Kane et al., 2011; Stronge et al., 2011). Evidence suggests that (a) teacher preparation programs impact what practices teachers use during their teaching career (Maheady et al., 2013), and (b) teachers will, to a large extent, use the same practices and strategies they use during their first year of teaching throughout the rest of their career (Griffin & Kilgore, 1995).

The use of practices within teacher preparation programs such as observation (Stormont & Reinke, 2012), modeling (including video modeling; Brock et al., 2017), performance feedback (Cornelius & Nagro, 2014), and self-reflection (Nagro & deBettencourt, 2019) have shown in a range of empirical studies to

be effective for supporting pre-service teachers' learning and implementation of high-quality practices (Cusumano & Preston, 2018; Stormont & Reinke, 2012). However, research suggests that pre-service teachers do not consistently receive the type of practice and feedback required to acquire skills to implement high-quality practices (Grossman et al., 2009; Scheeler et al., 2016). In fact, special education teacher preparation programs vary significantly in how, and how often, they employ essential coaching practices (e.g., Mathews, 2021; Nagro & deBettencourt, 2017).

To illustrate, when Nagro and deBettencourt (2017) reviewed the literature (i.e., 36 publications including 107 teacher preparation programs) about field experiences for special education teacher candidates, they documented that special education preparation programs differed in practices used during teacher candidates' field experiences. Specifically, Nagro and deBettencourt reported how each program assessed and guided their teacher candidates. Although some programs noted that supervisors would

use modeling as a strategy for candidates, it was not reported as a strategy used during candidates' field experiences for most programs. Further, some programs reported using feedback forms to deliver verbal and/or written feedback to their candidates. Some programs noted that they provided verbal and/or written feedback to their candidates but did not mention using a specific/standardized form. Yet other programs did not mention providing any specific or organized feedback to candidates during field experiences. In sum, there was limited consistency of practices reported across the various programs.

Research suggests that one barrier for many university supervisors utilizing effective coaching practices is a lack of time (Hobson et al., 2009; Vertemara & Flushman, 2017). For example, university supervisors have reported that the geographic locations of teacher candidates' placements impede their ability to conduct as many observations as they would like during clinical supervision (Range et al., 2013). After conducting observations and analyzing observational data it is important to promptly provide feedback. The immediacy of feedback is critical for candidates (Burns et al., 2016), yet with supervisors facing difficulties with time, this may not always be possible. In sum, in addition to barriers such as time and money, there is a lack of consistency in the type of coaching practices and feedback teacher candidates receive (Grossman et al., 2009; Mathews, 2021; Nagro & deBettencourt, 2017).

Although special education teacher preparation programs do not need to be the same, there is a need for consistency in each program. Specifically, programs should focus on utilizing effective coaching practices to support teacher candidates' use of evidence-based teaching practices with fidelity and to sustain the usage of these practices throughout their teaching careers (Brownell et al., 2010).

The technology-based tool discussed in this article called Capturing Observations And Collaboratively sHaring Educational Data (COACHED) was designed to be an efficient way to address these core components of effective coaching to enhance pre-service teachers' implementation of evidence-based practices (EBPs) and other high-quality practices (Kennedy & Kunemund, 2020; Kunemund et al., 2021).

COACHED is intended to address many barriers encountered by teacher preparation programs and personnel. Described in more detail below, COACHED houses a library of self-reflection matrices and multimedia professional development (PD) videos with embedded modeling. COACHED also generates automated yet editable feedback which is intended to save time by removing the task of writing detailed feedback about specific practices. In the following sections, we introduce the individual components of COACHED that are intended to ease many of the obstacles faced by teacher preparation programs.

Welcome to COACHED

COACHED is a web app with evidence-based tools designed to provide practice-based feedback and PD to teacher candidates (<https://coachedweb.azurewebsites.net/>). COACHED has five key components that can function together or separately to provide PD:

1. The classroom teaching (CT) scan observation tool
2. Automated coaching feedback form
3. Content acquisition podcasts (CAPs)
4. Self-reflection matrices
5. A data dashboard

The CT Scan is an observational tool used to capture data-based information on teacher practices, classroom context, and student actions (Kennedy et al., 2017). After completing an observation, users receive an automatically generated but editable coaching feedback form that

includes all data captured using the CT Scan. Embedded within the feedback form are multimedia PD vignettes called CAPs which supervisors (e.g., faculty member or instructor) can refer or assign candidates (e.g., teacher candidates, pre-service teachers) to watch if needed (Kennedy et al., 2016a; Kennedy et al., 2016b). Within the feedback form, supervisors can also assign candidates self-reflection forms known as matrices to engage in deep reflection opportunities (Nagro et al., 2020). Finally, all these components are accessible through the main data dashboard hub where users can choose to view data and feedback, access the CT Scan to conduct an observation, or upload videos to their account or, if they are a supervisor, to the accounts of the candidates under their supervision. The COACHED app can be used to observe candidates in K-12 settings and across content areas. Supervisors and candidates can create free individual accounts linked to their institution by visiting and register at <https://coachedweb.azurewebsites.net/>.

There are several ways COACHED can be leveraged within teacher preparation programs to provide feedback and PD to candidates, such as a) supervisors can complete an observation cycle of the candidate; b) the candidate can complete a self-observation cycle; or c) the supervisor and candidate can complete an observation cycle together. In the next sections, we describe these components in detail and then review options for using COACHED in teacher preparation.

COACHED TOOLS AND EVIDENCE

Data Dashboard

The first component of COACHED is the data dashboard which serves as the central hub through which users can access data and feedback, conduct a CT Scan observation, and upload videos. Within COACHED, users can have

FIGURE 1: Data Dashboard

Please choose a person to view or begin a scan.
If the account is for a coach you will "drill down" to the accounts for which he/she is responsible.

A	B	C	User Name	D	Role	E	Institution	F
View Start Scan Upload Video			coach@greenvalley.edu			School Leader/Ship/Researcher/Teacher Educator	Green Valley Elementary	
View Start Scan Upload Video			sarahwells@greenvalley.edu			Teacher/Pre-service Teacher	Green Valley Elementary	
View Start Scan Upload Video			tbennett2@greenvalley.edu			Teacher/Pre-service Teacher	Green Valley Elementary	
View Start Scan Upload Video			tjohnson@greenvalley.edu			Teacher/Pre-service Teacher	Green Valley Elementary	
View Start Scan Upload Video			cmarcus@greenvalley.edu			Teacher/Pre-service Teacher	Green Valley Elementary	
View Start Scan Upload Video			sowers@greenvalley.edu			Teacher/Pre-service Teacher	Green Valley Elementary	

A. View list of feedback from previous observations for specific pre-service teacher
B. Begin a **CT Scan** for specific pre-service teacher
C. Upload a video for specific pre-service teacher
D. Pre-service teacher's or observer's username associated with their account
E. User's role they are assigned within the COACHED system
F. Institution each user is associated with

different roles which allow them different levels of access. To illustrate, a supervisor would have a *University Faculty/Staff* account and a candidate would have a *preservice teacher* account. The main difference is that the supervisor could see all their candidates' accounts and data while the candidate could only view their own account and data. In a University Faculty/Staff-level data dashboard (see Figure 1) the supervisor can locate the specific candidate they would like to observe on their dashboard and begin an observation or select an existing feedback form to view or edit. A preservice teacher-level data dashboard allows the user to start a CT Scan self-observation, view existing feedback, or upload an observation video.

Classroom Teaching (CT) Scan

Developed by Kennedy (2017), the CT Scan observation tool enables COACHED users to capture discrete instructional practices of the candidate across multiple content areas, student actions, as well as relevant contextual information (e.g., instructional grouping). The CT Scan is a low inference observation tool in the behaviorist tradition of process-product and attempts to document teacher practice with precision without forcing the observer to generate

an overall quality score or within specified domains. In other words, an observer uses this tool to document, not evaluate, teaching. The resulting data can be used to identify areas of strength and improvement. The CT Scan is flexible and can be used to capture data on live or recorded observations. Additionally, supervisors can conduct an observation of a candidate, or the candidate can complete a self-observation from a recorded video.

Categories. The CT Scan captures several levels of information related to the type of instruction the candidate is providing. First, the observer (i.e., university supervisor, teacher candidate) selects the broad category of instruction such as explicit instruction or vocabulary instruction the candidate is using at any given moment. The category can change multiple times within a lesson. For example, the candidate may begin with classroom management, then switch to general content instruction, and then to vocabulary instruction. There is no limit to the number of times the observer can change categories – they follow where the lesson leads. To change the category, the observer would click “set” in the top left corner. While instructional categories are helpful because they give a

general idea of the type of instruction the candidate is providing, it is not specific enough. To capture how the candidate is providing instruction, the observer next needs to determine the specific practice being used.

Practices. Each broad category (e.g., classroom management, vocabulary instruction, mathematics instruction) has a unique set of specific instructional practices that can be selected. Thus, once the observer decides about the broad category, they continue to watch the lesson to determine what specific practice is being used. The individual practices that make up the broader categories come from the literature related to that content area. The observer clicks “set new practice” in the top left-hand corner of the interface. For example, within the broad category of vocabulary, the candidate may be using a student-friendly definition, an example, having a discussion, or a demonstration. Once the category and practice are selected, the CT Scan tracks how long it is being used, and the observer can switch between practices and categories at any time. Therefore, at the end of the lesson, CT Scan data will report how long (to the second) each practice was used, overlaid with the other data being captured (see below). Lists of categories and practices are also customizable within COACHED.

Implementation Markers. Once the observer has determined the broad category of instruction and specific practice, the observer can capture the quality practice use. Each practice has a distinctive set of implementation markers (IMs) or quality indicators that the observer should look for. For example, the IMs for “modeling/I do it” are *clear and concise language, demonstrate skill, involves students, provides several models, and think aloud*. As IMs are observed and selected, they turn green, IMs that are not selected (i.e., not observed) remain black. IMs serve as the foundation for the

FIGURE 2: CT Scan Interface

A. Broad category being used by teacher
B. Specific practice being implemented
C. Implementation markers for practice (green observed, black not observed)
D. Time of observation (running clock)
E. Window to record content being taught
F. Document what students are supposed to be doing
G. Which teacher and group size
H. Co-teaching model being used
I. Visual aids being used (check = active)
J. Window to take qualitative notes
K. Count of deep, probing OTRs
L. Count of rote OTRs
M. Count of choral/group OTRs
N. Count of non-academic OTRs
O. Count of academic-specific Praise
P. Count of behavior-specific Praise
Q. Count of generic Praise
R. Count of prompts or pre-corrections academic
S. Count of behavior specific redirect
T. Count of error correction
U. Count of questions asked by students
V. Count of number of students asking questions
W. Custom buttons
X. Additional buttons can be requested

automated feedback sentences generated within COACHED following an observation. The IMs for each practice are also customizable by users.

Contextual Information. After the observer determines the instructional category and practice, they can focus on capturing contextual data that serves to provide a rich and detailed picture of the instructional session. By selecting from drop-down menus and checkboxes (see Figure 2) the observer can indicate: Student actions (e.g., answering ques-

tions, group discussion), instructional grouping size (e.g., small group, whole group), co-teaching model, visual aids (e.g., graphic organizer), and the vocabulary term/topic being taught. Each of these items can be changed and updated throughout the observation to reflect what is occurring in the classroom. There is a field in which the observer can type qualitative notes to capture any additional information. Numerous high-leverage practices (HLPs) can be documented using these options. For example, HLP 17,

Use Flexible Groupings, can be captured using the group size feature.

Counter Buttons. Below the contextual items are a series of counter buttons that track frequencies of different events. The observer can track the type and number of opportunities to respond (OTRs) provided: Deep OTRs, rote OTRs, choral OTRs, and non-academic OTRs. When a candidate provides feedback to students, the observer can keep count of the number and type of feedback statements provided (academic-specific, behavior-specific, and generic) and redirects and corrections (i.e., behavior redirect, error correction, and pre-corrections). Additionally, the observer can track the number of questions students ask throughout the lesson and how many students are asking these questions. To use this feature, the observer simply clicks the button indicating the type of event (e.g., behavior-specific OTR), if they made a mistake they can hover over the button until they see a “-” symbol and click to subtract an instance of the event. Each question, feedback statement, and other information is time synced at the second of occurrence and overlaid with the category and practice being used. To illustrate, the supervisor and candidate will be able to see the candidate taught a student-friendly definition for 3:45 seconds and provided 5 deep questions, 10 rote questions, 2 academic-specific feedback statements, and 7 generic feedback statements during that time.

Data Outputs. Data from the CT Scan generates two main outputs that the observer can use to provide feedback to the candidate: The CT Scan Timeline and the coaching feedback form. The CT Scan Timeline displays the observation in a rich visual format that allows the candidate and supervisor to see how various practices and other captured items co-occur with one another during the observation. Each data point captured

(e.g., practice) by the CT Scan is included on the CT Scan in a timeline format that shows the order in which events occurred overlaid with co-occurring items (e.g., student actions). For example, a candidate could easily view how many OTRs a candidate used when modeling a new skill and how many OTRs the candidate followed up with feedback. The feedback form is discussed in detail in the following section.

Automated Coaching Feedback Form

A barrier to many supervisors and candidates is time, as analyzing observational data and generating meaningful feedback is not a quick (or easy) task. Fortunately, COACHED does substantial work to get the observer started. As each practice is observed the COACHED app generates a “practice box” that provides detailed information about the practice and what was occurring when it was observed. Specifically noted are when and for how long the practice was used as well as which IMs were observed. The IMs are used to generate automated feedback sentences to the right of each practice box. COACHED maintains a database of multiple feedback sentences for each IM and whether it was observed and will pull randomly from these to create detailed narrative feedback. Each sentence was written to reflect best practice in delivering feedback by not only acknowledging whether the IM was observed but also providing corrective feedback about using that specific practice and IM (Cornelius & Nagro, 2014). For example, when using modeling during explicit instruction, if a candidate did not use the IM “think aloud”, feedback would read: “Providing modeling to students is a terrific use of time, and I was glad to see you doing so today. When you model, be deliberate in terms of explaining what you are doing and why you are doing it so students can hear your expert thinking

and they can replicate when it is their turn to do the task. This is hard to do because so many of the tasks we demonstrate we are able to do automatically but think back to when you first learned to do this task and break it down orally for your students.”

Each practice box displays the frequency and types of OTRs, feedback statements and corrections, student actions, visual cues, and any qualitative notes the observer took. For example, if the supervisor notices that the candidate was not following up student responses to OTRs with feedback they may add a note “Nice work providing students with plenty of OTRs, make sure to follow up student responses with some specific feedback to let them know what they got right or correct any misconceptions.” Once the CT Scan observation is saved, COACHED automatically generates a detailed yet objective coaching feedback report. Kennedy and colleagues (2017; 2018) found that this type of objective data-based feedback is preferred by those receiving the feedback.

In addition to the data displayed in each practice box, an associated multimedia PD vignette is automatically loaded to the right (Content Acquisition Podcasts – see below). For example, if the candidate was observed using “modeling,” the modeling vignette would be loaded to the right of the practice box. At the bottom of the coaching feedback form, the observer can write a brief narrative report of the observation as well as goals for the candidate to focus on. Here the observer can also assign the self-reflection matrix, determine how the candidate will access the feedback form (e.g., emailed link, printed PDF), and view the timeline. Once the feedback is edited and complete, the observer can save the form.

Use of the CT Scan and resultant coaching feedback reports has been associated with increased use of targeted evidence-based explicit instruction

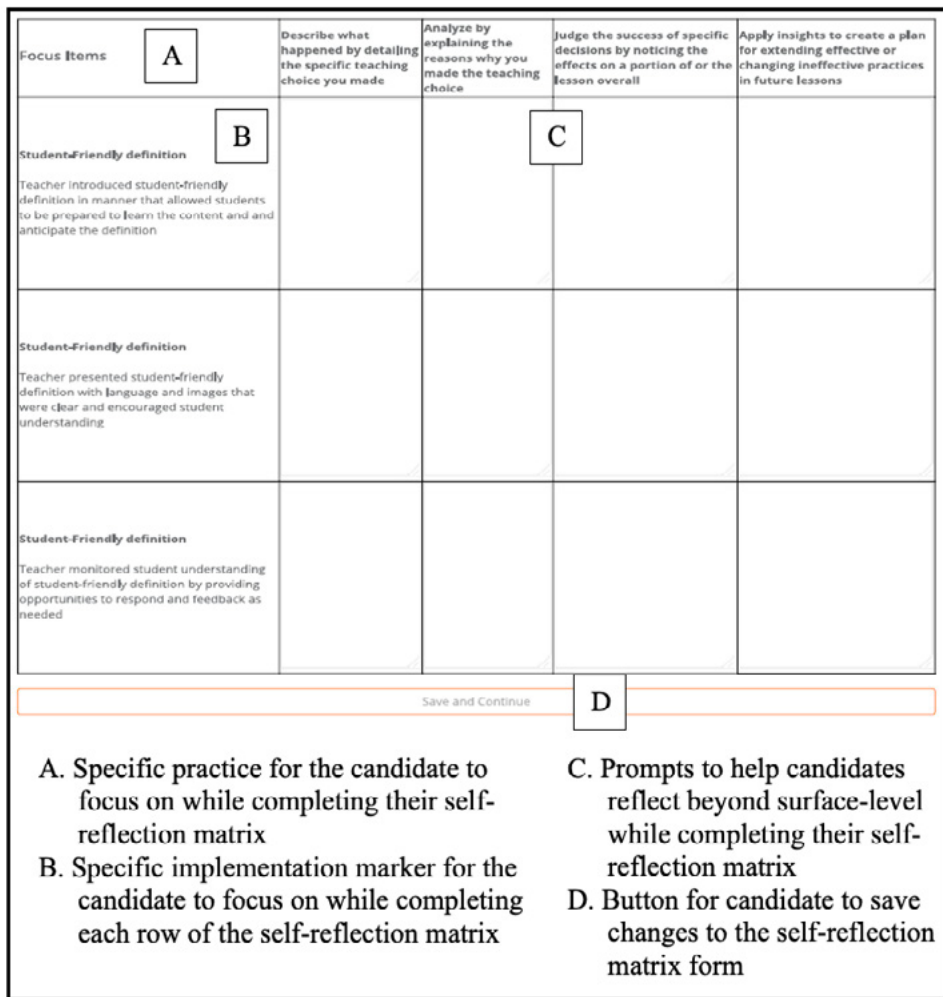
among candidates (Peeples et al., 2018). Specifically, candidates who received feedback from the CT Scan used more explicit vocabulary instruction practices compared to their peers who did not receive CT Scan feedback (Peeples et al., 2018). Kennedy and colleagues (2017, 2018) found that this type of objective data-based feedback is preferred by those receiving the feedback.

CAPs Multimedia Vignettes

Content Acquisition Podcasts (CAPs) are multimedia PD modeling videos embedded within the coaching feedback form that provide instantaneous and targeted PD to users (Kennedy et al., 2016a; Kennedy et al., 2016b). Centered around Mayer’s (2020) cognitive theory of multimedia learning (CTML), CAPs are designed to minimize cognitive load (DeLeeuw & Mayer, 2008) while maximizing learning and knowledge acquisition. Over the last decade CAPs have repeatedly been demonstrated to be effective in improving the declarative, procedural, and conditional knowledge of candidates across various instructional strategies within special education (Daley, 2020).

CAPs typically follow the same general format designed to maximize knowledge acquisition while reducing cognitive load. Each brief video begins with an explanation of the practice and direct instruction on using that practice followed by a modeling video of a teacher using that practice with high-quality in a classroom setting (Kennedy et al., 2016a; Kennedy et al., 2016b). The specific format of the CAPs is intended to build the candidate’s declarative knowledge through direct instruction while the modeling segment provides an initial step in forming both procedural and conditional knowledge (Alexander, et al., 1991; Kennedy, Rodgers, et al., 2017). Hirsch and colleagues (2015) provide additional information about how CAPs can be used.

FIGURE 3: Self Reflection Matrix



Self-Reflection Matrix

Self-reflection activities are common in teacher preparation (Nagro & deBettencourt, 2017), and for good reason. Candidates will be expected to reflect on their decision-making in every teaching role they transition into because teaching is an iterative process. Meaningful self-reflection goes beyond surface-level summarization of a lesson and includes recognizing pertinent teaching choices, analyzing why such choices were made, judging the success of these choices based on student outcomes, and applying these insights to decision-making in future lessons. Meaningful self-reflection is challenging, and candidates benefit from structure and guidance during reflection activities (Nagro et al., 2017).

Self-reflection activities can include the use of a graphic organizer to help candidates organize their thinking. One such graphic organizer is the reflection matrix (see Figure 3). This matrix includes both approaches and topics for self-reflection. The four approaches to self-reflection, describe, analyze, judge, apply (Nagro, 2020) can be combined with any focus topics for reflection such as (a) elements of asking open-ended questions (e.g., O’Brien et al., 2021), (b) elements of communicating with students (e.g., Nagro et al., 2017), (c) elements of promoting expressive language in students (e.g., Coogle et al., 2019), and (d) elements of classroom management (e.g., Nagro et al., 2020). A reflection matrix does not take as long as an essay style self-reflection to complete and candidates are more

on topic with their reflective practice (deBettencourt & Nagro, 2019; Nagro, 2020). The graphic organizer is laid out in a matrix so that candidates can describe an occurrence of each focus item, analyze why they made the described teaching choice, judge the strength of their choices by using student outcomes as evidence of success, and then apply these insights to plans for increasing, decreasing, or maintaining the described choice. Although the four approaches to reflection stay the same, the focus items can change as candidates shift their professional goals or can remain the same so that candidates can notice growth in their teaching decisions over time.

Candidates can use video evidence to review their instructional decision-making and complete a reflection matrix. Using video evidence helps candidates reflect with concrete data rather than relying on memory alone. Memory-based self-reflections tend to be feelings driven (i.e., it felt good when...I felt frustrated when...) rather than evidence driven (i.e., I asked seven close-ended questions, but no open-ended questions.). Nagro’s *record, review, reflect, revise* video analysis cycle (see Nagro et al., 2020) fits well within the larger COACHED model because candidates can review video evidence they have uploaded into COACHED to reflect using the integrated reflection matrix all with the goal of refining their practice. The additional supports built into COACHED compliment the video analysis process by including additional data, feedback, and content acquisition all aimed at a seamless learning experience.

COACHED MODELS IN TEACHER PREPARATION

Supervisor feedback, self-observation, and self-reflection are powerful tools for improving candidate practice (Benedict et al., 2016). One of the strengths

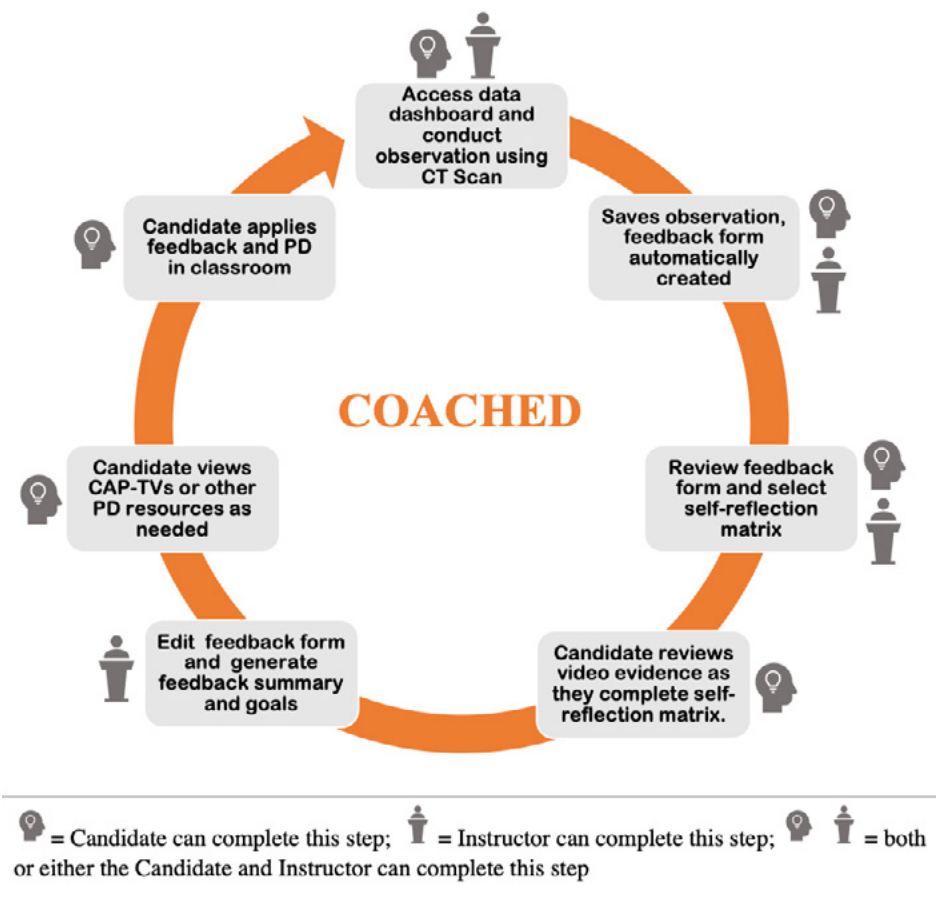
of COACHED is that it can be used in several ways to provide a flexible option for observing and providing feedback. COACHED can be used to complete any of three coaching models: traditional model, self-observation model, or co-observation model. Figure 4, on the next page, demonstrates how different components of a coaching cycle (e.g., observation) can be completed by either the candidate, instructor, or both to accomplish a full coaching cycle. Below, we describe in detail how each of these cycles can be completed dependent on the user.

Traditional COACHED Model

Supervisor observations of candidates during field experiences have long been a hallmark of teacher preparation. Traditionally, the supervisor would observe the candidate in the classroom or by viewing a recorded video, use a rubric or other instrument record notes and data, and then translate this recorded data into meaningful feedback for the candidate. Yet, often, candidates do not receive the high-quality feedback necessary (Grossman et al., 2009; Scheeler et al., 2016). The *Traditional COACHED Model* follows the same basic premise in terms of the supervisor completing the observation and providing feedback.

In the traditional COACHED model, the observation cycle begins with the supervisor conducting a CT Scan observation either live or using a candidate self-recorded video. Once the observation is complete, the supervisor saves the data, and the customizable feedback form is automatically generated. The supervisor opens the feedback form, reviews the quantitative data and automated feedback sentences, and uses this information to select a self-reflection matrix to send to the candidate. For example, the supervisor may have noticed that during the explicit instructional practice of “modeling” the candidate was only observed

FIGURE 4: Flexible Coaching Model



using two of the implementation markers. Therefore, the supervisor would select the “modeling” self-reflection matrix. Once the candidate logs into COACHED and completes their self-reflection matrix, the supervisor uses this information to finalize their narrative feedback summary and goals. Using the narrative summary, goals, and other data, the supervisor may also choose to assign the candidate a CAP-TV or other PD video to watch. Once the candidate reviews their feedback and PD, the goal is for them to apply this knowledge into their teaching and improvement will be noted in future observations. The traditional COACHED model is beneficial in that the supervisor can provide their expertise to the candidate when giving feedback. Although the candidate can complete a self-reflection matrix, in this model, the candidate does not have the opportunity to collect data on

their own practice as part of the process.

Candidate Self-Observation Model

COACHED can be leveraged by the candidates and used without direct supervisor interaction by completing a video self-observation. The *Candidate Self-observation Model* not only saves the instructor’s valuable time and enables candidates to receive more frequent feedback, it also provides quality learning and reflection opportunities. Video self-observation is a powerful tool; in observing their own teaching, candidates learn how to recognize practices they used, areas of needed improvement (Gaudin & Chaliès, 2015; Kleinknecht & Gröschner, 2016), and promote in-depth self-reflection of their own teaching (Nagro et al., 2017). Prior to beginning the instructional session, the candidate can also refer to the

CT Scan menu as a scaffold to determine which implementation markers should be used for specific practices. By scanning the menu ahead of time, the candidate can familiarize themselves with markers that make up a high-quality instructional practice.

To begin a COACHED self-observation cycle, the candidate records their lesson and then logs into their data dashboard to upload the video. Once the video is uploaded, they complete a CT Scan observation. COACHED enables the user to pull the uploaded video up on the same screen alongside the CT Scan. Not only does the CT Scan serve as a scaffold for candidates prior to the observation but it also gives candidates an opportunity to view and reflect on their own implementation of instructional practices by determining which IMs were and were not used. Once the observation is complete the candidate returns to the data dashboard and selects a self-reflection matrix based on their needs or supervisor direction and reflect on their lesson prior to viewing the video. The candidate then views their automated feedback form, resultant data, and views the CAPs or other PD for practices that had few or no IMs observed. With the self-observation model, the candidate can benefit from watching their own instruction and collecting data on the practices and IMs, noting which IMs they did not use. However, this model lacks the expert feedback of the supervisor. Yet, because the supervisor does not need to be directly involved in the observation, this is a great way to save already limited time.

Co-Observation Model

In the third COACHED observation model, the supervisor and candidate work together to complete an observation cycle. With the *Co-observation Model*, the candidate benefits from both the expert feedback and self-observation. Self-observation alongside expert feedback in

teacher preparation is an effective strategy for improving candidate's knowledge and practice (Nagro et al., 2017). When engaging in a co-observation cycle communication between the candidate and supervisor is essential; the candidate will receive the most benefit from the cycle if they look at their own observation feedback alongside that of the instructor.

Once the candidate has uploaded their video to COACHED the first step of the co-observation cycle is for both the candidate and supervisor to complete the CT Scan observation separately. As in the traditional observation cycle, the supervisor will use the automatically generated feedback form to determine which self-reflection matrix to send the candidate. The candidate completes the matrix, the supervisor finalizes their feedback form and submits it to the candidate. The supervisor should also assign either the embedded CAPs or other relevant PD to the candidate at this time. It is important to note that the supervisor can also rely on the CT Scan as a scaffold when completing observations. No one person is proficient in every content area across all grade levels; the CT Scan and its list of practices and associated IMs offer a guide during the observation, telling the observer what to look for. Next, the candidate reviews both the instructor's and their own feedback forms prior to engaging with the PD and applying their new knowledge in the classroom. The co-observation model combines the best of both worlds, in that the candidate can benefit from their self-observation and the supervisor's feedback.

Due to the flexible design of COACHED (i.e., three coaching models, ability to select components) it can easily be incorporated into teacher preparation field experiences. For programs engaging in more frequent coaching cycles (e.g., monthly) the ability to upload observation videos into COACHED reduces the time commitment and travel for supervisors.

However, for less frequent coaching cycles, live observations are beneficial in that you can capture more nuanced information using the CT Scan (e.g., student off-task behavior). Additionally, for preparation programs that may be completely online, the video upload capability along with the virtual CAPs videos, enable supervisors to engage in quality coaching.

CONCLUSION

Teacher preparation programs play a key role in preparing special educators for entering the workforce. In fact, when it comes to factors associated with academic performance for students with disabilities, high-quality and prepared teachers are key (Aaronson et al., 2007; Darling-Hammond & Berry, 2006). Research suggests observation (Stormont & Reinke, 2012), feedback (Cornelius & Nagro, 2014), opportunity for self-reflection (Nagro & deBettencourt, 2019), and modeling (Brock et al., 2017), are associated with increased teacher candidate use of quality instructional practices in the classroom (Cusumano & Preston, 2018; Stormont & Reinke, 2012). Despite this knowledge, there is an inconsistency in the type of training and feedback teachers receive in preparation programs (Nagro & deBettencourt, 2017). Moreover, teacher educators often do not have the time to consistently provide high-quality and meaningful data-based feedback to candidates. Fortunately, with COACHED candidates and their supervisors can engage in quality and time-saving observations, feedback, self-reflection, and modeling.

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