Article

Journal of Special Education Technology
2023, Vol. 38(2) 146–160

DOI: 10.1177/01626434221085554
journals.sagepub.com/home/jst
Sage

Increasing On-Task Behavior Using Technology-Based Self-Monitoring: A Meta-Analysis of I-Connect

Gretchen Scheibel, MS, OTR, BCBA[1], Kathleen N. Zimmerman, PhD, BCBA-D[1], and Howard P. Wills, PhD, MBA, BCBA[1]

Abstract

Self-monitoring is a promising evidence-based intervention for students who benefit from supplemental supports to stay on-task during academic periods. I-Connect, a technology-based self-monitoring intervention with a substantial body of research, allows students to discretely recognize and record their behavior on a mobile or desktop app at scheduled intervals, to improve positive behavior and increase inclusion opportunities. This meta-analytic review examined the effect of I-Connect on the on-task behavior of students with or at risk for disabilities to determine the omnibus effect of using I-Connect across students and intervention packages. Students received 20–45 minutes of training before using I-Connect and most students monitored their on-task behavior every 30-seconds during 10-minute monitoring sessions. Under these conditions, I-Connect was found to demonstrate strong functional relations, an abrupt increase in on-task behavior and consistently positive parametric effects across all 14 elementary and secondary students receiving special education.

Keywords

self-monitoring, technology-based self-monitoring, academic engagement, on-task behavior, I-Connect

Increasing On-Task Behavior Using Technology-Based Self-Monitoring: A Meta-Analysis of I-Connect

Self-management interventions represent a broad class of interventions which allow the student to act as their own intervention agent to employ monitoring, assessment, instructional, and reinforcement strategies toward changing their own behavior (e.g., self-monitoring, self-evaluation, self-instruction, and self-reinforcement; (Cooper et al., 2020). Four decades of empirical investigations of self-management interventions have provided a substantial literature base cataloging strong positive outcome for students with disabilities (e.g., Briesch et al., 2019; Carr et al., 2014) and classification as an evidence-based practice (EBP) for students with autism spectrum disorder (ASD) and other behavioral disorders (Hume et al., 2021; Maggin et al., 2016). Further, self-management interventions appear to be popular among educators who report self-management interventions as socially valid and frequently implemented in their classrooms (McNeill, 2019; Morin et al., 2020). Much of this popularity may be due to the versatility of these interventions which can be implemented separately (e.g., self-monitoring or self-evaluation) or as a broader treatment package (e.g., self-monitoring with self-instruction and self-reinforcement). Self-management interventions are considered to be effective for students across special education eligibility categories to target individualized academic, behavioral, or adaptive outcomes (Briesch et al., 2019; Carr et al., 2014).

Self-Monitoring

Self-monitoring is the most frequently used self-management intervention (Briesch et al., 2019) where the student observes and records their own behavior during a specified interval to increase or decrease occurrences of that behavior (Cooper et al., 2020). Self-monitoring is considered to be effective for students across various special education eligibility categories (e.g., autism spectrum disorder, specific learning disability, emotional disturbance, other health impairment), instructional settings, and outcomes (Bruhn et al., 2020; Davis et al., 2016).

[1]University of KansasUniversity, Lawrence, KS, USA

Corresponding Author:
Gretchen Scheibel, Department of Special Education, University of Kansas, 1122 W Campus Rd., Joseph R. Pearson Hall, 531, Lawrence, KS 66045, USA.
Email: gscheibel@ku.edu

Self-monitoring has been found to be effective in general and special education settings, though the implementation setting appears to produce differential effects for various outcomes and disability categories (Bruhn et al., 2020; Davis et al., 2016). For example, students demonstrating challenging behavior (with and without special education eligibility) who used self-monitoring in general education settings demonstrated a stronger increase in academic engagement than students who self-monitored in special education settings (Bruhn et al., 2020). Alternatively, students with challenging behavior who used self-monitoring in special education settings demonstrated a stronger decrease in disruptive behavior (Bruhn et al., 2020). Further, students with ASD appear to benefit most from self-monitoring implemented in the individualized context of pull-out intervention (strong effects) and the least from general education settings (moderate effects) though no statistically significant difference in intervention effect was detected between settings (Davis et al., 2016). Despite moderate effects reported in general education settings, implementation in general education with supports produces strong intervention effects (Davis et al., 2016) indicating self-monitoring can facilitate inclusion in general education settings for students with ASD (Crosland & Dunlap, 2012). Additionally, some research indicates that elementary-aged male students in general education settings are most likely to benefit from self-monitoring to address challenging behavior, however, these findings may be limited by small female and secondary-age sample sizes (Bruhn et al., 2020).

Self-monitoring is typically implemented as a standalone intervention or as the core component of a larger intervention package which may include other self-management interventions (e.g., self-evaluation, self-graphing) or supplemental interventions (e.g., reinforcement, peer-mediated intervention; Briesch et al., 2019). Though self-management interventions are considered to be an evidence-based practice, self-monitoring has not been evaluated independently of self-management interventions to determine evidence-based status. Despite this, the overall intervention effect of self-monitoring is consistently positive in two recent meta-analyses (Bruhn et al., 2020; Davis et al., 2016). These findings are consistent with a meta-analysis of self-management interventions published by Briesch et al., (201) indicating self-management interventions, the majority of which include self-monitoring as a base intervention, are consistently effective. The collective findings of Briesch et al., 2019, Bruhn et al., 2020; and Davis et al., 2016 appear to establish the efficacy of self-monitoring when implemented in isolation. However, less is known about the differential effect of discrete self-monitoring components (e.g., student training methods, interval duration, accuracy checks) or the inclusion of supplemental interventions (e.g., visual supports or reinforcement; Briesch et al., 2019; Davis et al., 2016). For example, reinforcement is most often included as a supplement to self-monitoring (Briesch et al., 2019) though this addition does not consistently produce additional positive effects beyond those anticipated for self-monitoring alone (Bruhn et al., 2020; Davis et al., 2016).

Self-monitoring has demonstrated substantial meta-analytic evidence of positive effects for various academic and behavioral outcomes for students with and at risk for disabilities (Briesch et al., 2019), and social and adaptive outcomes for students with ASD (Carr et al., 2014; Davis et al., 2016). Among these meta-analyses, several note on-task behavior during academic tasks is one of the most commonly targeted by self-monitoring (Briesch et al., 2019; Bruhn et al., 2020). Self-monitoring demonstrates consistently strong, positive effects on on-task behavior across edibility categories (Briesch et al., 2019; Bruhn et al., 2020; Carr et al., 2014; Davis et al., 2016). One study found students exhibiting challenging behavior demonstrate an increase of 3.4 min of on-task academic engagement behavior and a decrease of 2.9 min of disruptive behavior for every 10 min the student spent self-monitoring (Bruhn et al., 2020). The versatility of targeted outcomes coupled with wide applicability across disability categories makes self-monitoring a valuable tool for educators in the classroom.

Technology-Based Self-Monitoring

Self-monitoring represents the implementation of the most basic form of self-management, when student monitoring is prompted at scheduled intervals to observe and record their own behavior with the purpose of increasing or decreasing the occurrence of this behavior over time (Cooper et al., 2020). Self-monitoring implementation has historically relied on timers to prompt students to monitor their behavior using analog recording methods (e.g., pen and paper, chips moved to a cup). While positive outcomes were recorded using these methods, the last decade has seen an increase in the use of technology to engage in self-monitoring (Bruhn et al., 2020). Technology-based self-monitoring has developed rapidly over the last decade (Chia et al., 2018), with the use of mobile and web applications which allow students to record their behavior on phones, tablets, and laptops (e.g., Wills & Mason, 2014). This form of self-monitoring provides a unique advantage over traditional pen-and-paper based self-monitoring in the collection of monitoring data within software which can then be graphically displayed to allow for simple and efficient progress monitoring and data-based decision making (Kumm et al., 2021). Similar to the recent findings regarding the benefit of technology-based interventions to support academic skills (Kiru et al., 2018), adaptive behavior (Delisio & Isenhower, 2020), and academic engagement (Shanley et al., 2020), the integration of technology into self-monitoring provides additional value to self-monitoring beyond the effect of the intervention (Crossland & Dunlap, 2012). First, technology-based self-monitoring has the benefit of being integrated into existing instructional technology (e.g., tablets or laptops), allowing for covert and efficient self-monitoring during instructional or adaptive tasks in inclusive settings (Crossland & Dunlap, 2012). Second, the streamlined process of monitoring, collecting, and graphing data on an electronic database eases instructional preparation demands on educators and enables sharing of information across special education team members (Kumm et al., 2021).

The simplicity and efficiency of technology-based self-monitoring makes it an ideal intervention to target academic engagement behaviors. Academic engagement is one of the most common behaviors targeted using self-monitoring, with improved academic accuracy and completion reported in both participants with behavioral disorders, attention deficit hyperactivity disorder (ADHD), and those with ASD (Bruhn et al., 2020; Davis et al., 2016). Engagement in academic tasks has long been considered an essential skill for students with and at risk for disabilities to achieve positive outcomes later in life (Finn & Rock, 1997). Technology-based self-monitoring is uniquely suited to addressing academic engagement behaviors as they can easily be unobtrusively embedded into curriculums and instructional models and allow for covert and efficient behavioral intervention (Crossland & Dunlap, 2012). I-Connect is a technology-based self-monitoring intervention with a growing body of literature addressing academic engagement behaviors.

I-Connect is a self-monitoring system which allows students to monitor their behavior using a freely available mobile or desktop app available across Apple, Android and Chrome devices. As AA\ a fully customizable app, I-Connect I allows the educator to individualize the intervention to student's unique needs. Educators select a "prompt" based on the target behavior to be monitored (e.g., on-task behavior) and the interval when the prompts will occur (e.g., every 5 minutes). The prompts are then delivered to the student in the form of a pop-up notification (e.g., "Are you on-task?"), and can be scheduled to occur at an individualized fixed or variable interval. The student records their behavior by responding to this prompt using yes or no options). To evaluate student progress, educators set a "goal" for a targeted percentage of affirmative responses during a monitoring session (e.g., 80% yes responses during the session, indicating the student will be on-task for 80% of the session). Before using I-Connect, it is recommended students are trained to (a) identify when they are engaging in the target behavior, (b) accurately record behavior using the app, and (c) how to navigate the app to start, pause, and stop a monitoring session. During the training session, educators are encouraged to collaborate with the student to select a meaningful target behavior, customize wording for the prompt, select an interval corresponding to the student's baseline performance, and set a goal for affirmative responses that will encourage success. A full intervention description and implementation supports for I-Connect can be found in the Supplemental Materials available on Open Science Framework (OSF) https://osf.io/8xdv5/?view_only=da72d4a73d7142d282d1dbf20dd0ee41. Individual studies of I-Connect have demonstrated positive outcomes for students with or at risk for disabilities, especially when introduced to address academic engagement in the form of on-task behavior (Rosenbloom et al., 2019; Wills & Mason, 2014). While technology-based self-management interventions, including self-monitoring, are considered an EBP for students with ASD (Chia et al., 2018), syntheses of the research supporting this form of self-monitorng interventions, specifically I-Connect, are limited.

Purpose and Research Questions

Self-management interventions are effective and versatile interventions that can be implemented using resources available in most classrooms to address a variety of outcomes for students with unique learning needs (Briesch et al., 2019; Hume et al., 2021; Maggin et al., 2016). Self-monitoring is a popular form of self-management with evidence of effectiveness across disability categories to promote academic engagement or on-task behaviors (Bruhn et al., 2020; Davis et al., 2016). While previous syntheses of the self-monitoring literature have focused on the omnibus effects of self-monitoring across populations of students and intervention packages (Bruhn et al., 2020; Davis et al., 2016); less is known about the effects of technology-based self-monitoring on the frequently targeted outcomes of these interventions such as on-task behaviors (Chia et al., 2018). The purpose of this meta-analytic review is to examine the effect of a technology-based self-monitoring intervention with a substantial body of research, I-Connect, on the on-task behavior of students with or at risk for disabilities. The following research questions guided this meta-analysis: (1) For whom and under what task conditions and settings has I-Connect been used to improve on-task behavior for K-12 students with disabilities? (2) What intervention components were employed when implementing I-Connect to improve on-task behavior for K-12 students with disabilities? (3) What training components were employed to train K-12 students with disabilities to use I-Connect? (4) What are the outcomes of sufficiently rigorous studies that have evaluated the effectiveness of I-Connect as an intervention to improve on-task behavior for K-12 students?

Methods

A systematic literature search using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA; Page et al., 2021) guidelines was conducted to identify studies investigating the effect of I-Connect on the on-task behavior of K-12 students. Included studies were descriptively coded to determine for whom, in what settings, and under what conditions I-Connect has been used to target on-task behavior. Next, the methodological rigor of studies was analyzed to identify studies with sufficient rigor to evaluate outcomes. Two outcome analysis procedures were used to (a) determine the presence of a functional relation and (b) calculate a parametric effect size. Finally, parametric effect sizes were synthesized to calculate the omnibus effect of I-Connect on the on-task behavior of K-12 students.

Search Procedures and Inclusion Criteria

An electronic database search was conducted in April 2021 according to PRISMA guidelines (Page et al., 2021) using the following search terms: "*I-Connect*" AND "*education*" in the PsycINFO, ERIC and ProQuest Dissertations and Theses databases. The search was limited to studies published in English; no further exclusion criteria were applied. The following inclusion criteria were used to identify relevant records: (1) I-Connect was listed by name as a primary independent variable; studies that did not name "I-Connect" but instead described the independent variable as "technology-based self-monitoring" were not included; (2) on-task behavior was measured as a dependent variable; studies that included "task engagement" were considered for inclusion if the provided operational definition included a description of the participant attention or focus directed at an identified task; and (3) the study was conducted in a K-12 classroom setting. While on-task behavior is a valuable behavior in post-secondary, community, and home settings, these contexts were beyond the scope of this review. The initial search yielded 37 studies; seven duplicate files were removed resulting in 30 independent studies.

Studies were screened for inclusion in three waves: (1) use of an I-Connect self-monitoring intervention, (2) measurement of on-task dependent variables, and (3) implementation in a K-12 classroom. Twenty-one studies were removed after I-Connect intervention screening, two studies were removed for absence of measurement of on-task behavior as a dependent variable, and one study was removed for failing to meet the setting criteria. Six studies met all three inclusion criteria after title/abstract and full-text screening.

After included records were identified, a forward search to identify any additional relevant records that had cited included studies was conducted using Google Scholar; no additional studies were identified. Finally, the intervention developer was contacted to identify additional studies not located in the previous searches to ensure gray literature was adequately represented in the review. The intervention developer identified four master's level theses and one doctoral dissertation not returned in the electronic search. Two master's level theses were excluded due to the inclusion of data presented in peer-reviewed studies found in the initial pool (Beckman et al., 2019; Romans et al., 2020). The dissertation was excluded because it did not include an on-task behavior dependent variable, and a third unpublished thesis was excluded due to a non-school setting. The systematic search process yielded a total of six studies investigating the effect of I-Connect on the on-task behavior of K-12 student; a PRISMA diagram (Page et al., 2021) documenting the search process is available via Supplemental Materials ("I-Connect PRISMA Diagram," https://osf.io/8xdv5/?view_onlyda72d4a73d7142d282d1dbf20dd0ee41).

Variable Coding and Data Extraction

A three-part coding process was conducted to evaluate study characteristics, study quality and rigor, along with outcomes. All included studies were evaluated at the descriptive coding and quality and rigor analysis levels. The unit of analysis for study characteristics was the study (manuscript). The unit of analysis for quality and rigor analysis was the design (each single case design). A gating procedure was used between the quality and rigor analysis and outcomes analysis. Outcomes analyses were completed for designs that met quality and rigor standards. The unit of analysis for outcomes analyses was the design for visual analysis procedures and the A-B comparison for parametric effect size calculations. Coding procedures and variables for each level of coding are described below.

Study Characteristics. Included studies were coded to describe for whom, in which settings, under what conditions, and which I-Connect intervention components were introduced to address on-task behavior. Data on the following primary study variables were collected to determine the demographics of participants who received the intervention, instructional settings and task conditions under which the intervention was applied, self-monitoring intervention and training packages used to implement the intervention, and the study design information under which the outcomes were produced. Participant demographic data included the student's gender, age (years), ethnicity, medical diagnosis or special education eligibility, and education level. Instructional setting was classified as general education, special education, or both; special education settings included resource room, self-contained or specialized classrooms in neighborhood schools, or specialized schools. Task condition data included a description of the task the student engaged in during the intervention (e.g., individual instruction, independent work). Intervention package features were extracted to identify the intervention and training components used to implement I-Connect. Intervention component data included duration of self-monitoring session (minutes), schedule used to deliver the monitoring prompt (seconds), and the presence of supplemental intervention adaptations (e.g., reinforcement and accuracy checks). Training component data included the total number of training sessions (count) and duration of session (minutes), training topic (e.g., navigation of the I-Connect app, accurate discrimination of on-task behavior), and instructional method (e.g., explicit instruction, discussion, feedback) used during training. Finally, the study design of each study was recorded (e.g., multiple baseline across participants; A-B-A-B, alternating treatments design based on Ledford et al., [2018] single case design classifications), as well as primary (e.g., on-task behavior) and secondary (e.g., academic accuracy, disruptive behavior) dependent variable descriptions. Dependent variables were coded based upon study author description and were not analyzed by definition. The study characteristics codebook can be found in the Supplemental Materials ("I-Connect Meta Data OSF, https://osf.io/8xdv5/?view_onlyda72d4a73d7142d282d1dbf20dd0ee41).

Quality and Rigor Analysis. Research designs were initially reviewed to confirm the presence of at least three demonstrations of effect, designs that met this criterion were considered to be "experimental" and were evaluated for rigorous methodology using the What Works Clearinghouse Single Case Design Standards Version 4.1 (WWC; WWC, 2020). The following six criteria were applied at the design level: (a) data provided in graphical and/or tabular format; (b) included a systematic manipulation of the independent variable; (c) presented interassessor agreement for at least 20% of data points in each phase and for each condition; (d) the presence of residual treatment effects is not possible or unlikely; and (e) included sufficient data points at each phase in order to demonstrate effect over time (WWC, 2020, p. 82). The results were used to determine if the methodological rigor was sufficient to warrant analysis of study outcomes. Designs that met WWC Single Case Design Standards with or without reservations were considered to have sufficient rigor and included in the outcomes analysis (Moeyaert et al., 2018).

Outcomes Analysis. A two-part outcomes analysis was conducted: (1) visual analysis and (2) parametric effect size calculation. Each component is described below.

Visual analysis. A structured visual analysis protocol was used to evaluate the presence of a functional relation between I-Connect intervention and on-task behavior (Ledford et al., 2018). The visual analysis protocol evaluated quality of data across all phases, changes in level between adjacent conditions, immediacy and consistency of change, and degree of overlap between adjacent conditions (Ledford et al., 2018). If the presence of a function relation was identified, the relation was classified as "weak" if a delayed effect, overlapping data, or small change from baseline to intervention was present (Ledford & Pustejovsky, 2020). A relation was classified as "strong" if there was a consistent and clear positive effect (Ledford & Pustejovsky, 2020). Additionally, immediacy of change was analyzed at the initial intervention (B1), return to baseline (A2), and second intervention (B2) phases for the primary dependent variable (i.e., on-task behavior) to identify potential patterns of responding across participants. Immediacy of change was recorded as abrupt if the initial data points (e.g., 1–2 data points) indicated an immediate and clear change in level from the final data points (e.g., 1–2 data points) from the previous phase (Barton et al., 2018). If an abrupt change was not identified, the data were coded as "delayed" if the level of the initial data points were consistent with the final data points of the previous phase, but the remaining data points in the phase indicated a therapeutic trend. Phase data without a therapeutic trend or change in level were coded as "no change."

Parametric effect size. A parametric effect size was calculated for each A-B comparison in designs that met quality and rigor standards. A within-case log response ratio-increasing (LRRi; Pustejovsky, 2018) was selected as the parametric effect size because it is appropriate for the ratio scale used in the included designs, provides an outcome metric familiar to researchers and consumers (i.e., percentage of change between conditions), and is less sensitive to procedural variations (Moeyaert et al., 2018). LRRi is a version of a mean-based parametric effect size, log response ratio, that allows for the measurement of the proportional change between two adjacent conditions for behaviors expected to increase (Pustejovsky, 2018). To calculate LRRi, individual baseline (A) and intervention (B) data points were extracted from each phase of the included designs using Web Plot Digitizer, an open-source web-based software tool used to obtain numerical data from graphic displays with adequate reliability (Moeyaert et al., 2016). Data extraction yielded two sets of A-B comparisons for each design; these sets were not aggregated at the design level. In other words, an LRRi index was calculated for each A-B comparison, rather than each single case design. SingleCaseES (Pustejovsky & Swan, 2018), a web-based calculator, was used to calculate LRRi values, including standard errors and confidence intervals, for each A-B comparison.

Meta-Analysis. Effects were synthesized to calculate an overall average effect of I-Connect on on-task behavior across all studies and clusters of studies with common intervention and training components using a random effects multilevel meta-analysis (Moeyaert et al., 2018). Random effects were evaluated at the level of individual participant baseline time trends, as baseline effects trends were anticipated to vary across cases (Valentine et al., 2016). The meta-analysis was conducted in the R statistical environment (R Core Team, 2021) using the metaphor (Viechtbauer, 2010) to estimate meta-analysis models and clubSandwich (Pustejovsky & Swan, 2018) for obtaining cluster-robust variances. Raw data and the R script for replicating the meta-analysis are available in the Supplemental Materials ("I-Connect Meta R Code" and "I-Connect Data", https://osf.io/8xdv5/?view_only=da72d4a73d7142d282d1dbf20dd0ee41).

Interobserver Agreement. All data were coded by the first author, a doctoral student and Board Certified Behavior Analyst (BCBA©) with 17 years of experience in special education. The secondary coder was the second author, a doctoral level BCBA© with 10 years of experience in special education; this coder is also an expert in synthesis of single case designs. The primary coder coded all included studies independent of the secondary coder. The secondary coder was trained by the primary coder by reviewing coding manuals and analysis procedures. Following this training, the secondary

Table 1. Participants and Instructional Settings.

	Participant	Gender	Age	Diagnosis/Eligibility	Instructional Setting	Task
Rosenbloom et al. 2016	Participant 1	M	9	ASD	General education	Multiple formats
Beckman et al. 2019	Cody	M	11	ASD	Special education	Independent work
	Brian	M	10	ASD	Special education	Independent work
Rosenbloom et al. 2019	Carl	M	17	ASD	Special education	Independent work
	Stan	M	10	ASD	Special education	Independent work
	Colin	M	13	ASD	Special education	Independent work
	Jack	M	11	ASD	Special education	Independent work
Wills & Mason 2014	Student 1	M	15	SLD	General education	Multiple formats
	Student 2	M	14	ADHD	General education	Multiple formats
Clemons et al. 2016	Keith	M	17	SLD	Both	Multiple formats
	Brad	M	17	ASD	Both	Multiple formats
	Miranda	F	15	ID	Special education	Individual instruction
Romans et al. 2020	Jacob	M	17	ASD/ADHD	Special education	Independent work
	Zane	M	15	ASD/ADHD	Special education	Independent work

Abbreviation: M = Male; F = Female; ASD = autism spectrum disorder; ADHD = attention deficit hyperactivity disorder; ID = intellectual disability; SLD = specific learning disability.

coder demonstrated initial reliability by coding an included study randomly selected using a random number generator, 100% agreement was observed for this initial coding. Finally, they coded the remaining randomly selected studies and designs for reliability. Reliability estimates at each stage of the coding process were calculated by point-by-point interobserver agreement (IOA) using the following formula: ([total number of agreements/total number of agreements and disagreements] × 100) (Ledford et al., 2018). Reliability of screening and coding procedures was estimated at the initial study screening, study inclusion, descriptive coding, quality and rigor coding, and outcomes coding (data extraction, visual analysis, and parametric effect size calculation) levels. The secondary coder screened 100% of studies at both the study screening and inclusion levels; average agreement was 100% across both levels. The secondary coder coded 67% of studies during descriptive coding; average agreement was 96% (range 90–100%). Forty-two percent of designs were coded during the quality and rigor analysis by the secondary coder; average agreement was 98% (range 87.5–100%). Forty-two percent of designs were evaluated using the structured visual analysis protocol by the secondary coder; average agreement was 89% (range 50–100%). Low agreement occurred in one design due agreement found on two of four variables resulting in 50% agreement, all other designs showed agreement on three or four of the four variables (i.e., above 75%). The secondary coder extracted data from 43% of designs; average agreement was 100%. Finally, the secondary coder calculated LRRi for 43% of A–B comparisons; average agreement was 91.7% (range 20–100%). Low agreement occurred in the data extract phase due to a coding error made by the secondary coder, both coders reviewed the data and determined the disagreement was an error.

Results

Systematic search procedures yielded six studies that met inclusion criteria: Beckman et al., 2019; Clemons et al., 2016; Romans et al., 2020; Rosenbloom et al., 2016; Rosenbloom et al., 2019; and Wills & Mason, 2014. These studies were coded at the participant level to explore study characteristics, then on-task and generalized designs for each participant were individually coded for quality/rigor and outcomes analyses. Results can be found below.

Study Characteristics

Participant Demographics. A total of 14 participants in elementary ($n = 5$) and secondary ($n = 9$) settings were included in the review, see Table 1 for participant *and* instructional settings data. When reported individually the average age of elementary and secondary students was 10.2 years (range = 9–11 years) and 15.6 years (range = 13–17 years), respectively. Gender was reported for all students and the vast majority of participants were reported to be male ($n = 13$). Autism spectrum disorder was the most common medical diagnosis or special education eligibility reported for elementary students ($n = 5$) and secondary students ($n = 5$). Two of these secondary students were described as carrying a dual diagnosis of ASD and ADHD. Additional common medical diagnoses or special education eligibilities reported among secondary students included: specific learning disability ($n = 2$), intellectual disability ($n = 1$), and ADHD ($n = 1$).

Instructional Setting and Task Conditions. All included studies were conducted in education settings in the United States. One elementary student was reported to use I-Connect in a general education class (Participant 1, Rosenbloom et al., 2016), while the remaining four used I-Connect in special education classrooms (Cody and Brian, Beckman et al., 2019; Stan and Jack, Rosenbloom et al., 2019). Instructional setting varied more in secondary settings, with two students reported to use I-Connect in general education classrooms (Students 1 and 2, Wills & Mason, 2014) and two students in both special and general education environments (Keith and Brad, Clemons et al., 2016). The remaining five secondary students were reported to use I-Connect in special education classrooms (Miranda, Clemons et al., 2016; Jacob and Zane, Romans et al., 2020; Carl and Colin, Rosenbloom et al., 2019). The majority of students using I-Connect monitored their on-task behavior during independent work in exclusively special education settings (64.3%, n = 9). Three students using I-Connect in general education settings self-monitored during multiple instructional formats (e.g., lecture, small group instruction, independent work etc.; Student 1 and 2, Wills & Mason, 2014; Participant 1, Rosenbloom et al., 2016). Two students who utilized I-Connect in both special and general education environments also engaged in self-monitoring during multiple instructional formats (Keith and Brad, Clemons et al., 2016) and one student utilized I-Connect to self-monitor during an individualized reading instruction task in the special education setting (Miranda, Clemons et al., 2016).

Self-Monitoring Intervention Components. Data were collected to examine the intervention and training packages I-Connect was implemented under, all self-monitoring interventions include a target behavior, recording method, monitoring interval and some form of training to accurately record behavior. The average monitoring session across participants was 17 min (range = 10–30 min) with 10 min sessions being the most common. All students received the prompt to monitor their on-task behavior on a fixed schedule, meaning the prompt was presented at consistent time intervals (e.g., every 15 sec). The most frequently used schedule was every 30 sec (range = 15 sec–5 min). All but two students received a prompt from the I-Connect app to monitor their on-task behavior at least once per minute (Student 1 and 2, Wills & Mason, 2014). Eight participants from four studies utilized I-Connect as a self-monitoring intervention without a supplemental intervention (Beckman et al., 2019; Clemons et al., 2016; Rosenbloom et al., 2016; Wills & Mason, 2014). The remaining seven participants from two studies utilized I-Connect to engage in self-monitoring and received reinforcement following monitoring sessions when they achieved an established goal (Romans et al., 2020; Rosenbloom et al., 2019). Additionally, accuracy checks were performed by classroom teachers or research staff for students who received reinforcement to ensure they were monitoring accurately and achieved their goal.

Self-Monitoring Training Components. Self-monitoring training components appeared to vary across participants, but were largely consistent within a study indicating training packages were not individualized at the participant level. Of the studies reporting component information for the training students received to engage self-monitoring, five students from two studies were trained to use I-Connect in a single session lasting either 20 or 45 min (Rosenbloom et al., 2019; Wills & Mason, 2014). Four participants provided three 20 min training sessions (Clemons et al., 2016; Rosenbloom et al., 2016). Eight participants from three studies received training in only target behavior discrimination, and one participant was trained only in app navigation (Beckman et al., 2019; Romans et al., 2020; Rosenbloom et al., 2019), while five participants from the remaining three studies were trained on both (Clemons et al., 2016; Rosenbloom et al., 2016; Wills & Mason, 2014). Training methods to instruct students in app navigation and/or target behavior discrimination varied across participants but appeared to be consistent within studies. All studies used some or all components of a behavior skills training model (i.e., rationale, modeling or example/non-examples, practice and feedback), while a few studies include the use of online modules for self-paced instruction and video self-models; see Table 2 for greater detail.

Study Design Information. All studies utilized single case, A-B-A-B withdrawal designs to investigate the functional relation between the use of I-Connect and on-task behavior. All designs included three potential demonstrations of effect between baseline and intervention conditions. All studies measured on-task behavior as a primary independent variable using momentary time sampling for direct observational measurement. Though all studies labeled the primary dependent variable as "on-task," it is important to note the topography of this behavior varied across study definitions. For example, Rosenbloom et al., (2019) reported an on-task definition focused on task engagement behaviors: "engaged with instructional content in the form of reading, writing, and/or actively completing an assigned task" (p. 5050). Alternatively, Beckman et al. (2019) reported on-task definition directed toward physical behaviors: "sitting in their seat, making eye contact with the teacher or looking at work, utilizing the pencil to write, and talking about the task at hand." (p.230). Only one study reported the use of on-task definitions individualized by participants, the remaining studies used a standard on-task definition across participants. The six studies included 14 individual designs, with total number of potential functional relations for on-task behavior of 14. Five studies included secondary dependent variables to measure generalized outcomes (i.e., classroom behaviors that were not monitored for during the sessions but hypothesized to increase contingent upon the use of I-Connect). Eight designs in three studies investigated academic generalized outcomes (e.g., task completion, academic accuracy), and nine designs in three studies investigated generalized behavioral outcomes (e.g., disruptive behavior).

Table 2. Study Characteristics: Intervention and Training Packages.

		SMI intervention package				SMI training package												Generalized outcome	
		Training components												Instructional methods					
Study	Participant	Session duration	Monitoring Schedule	Reinforcement	Accuracy checks	Sessions	Duration	App navigation	Behavior discrimination	Discussion	Online module	Explicit instruction	Examples/ Non-Examples	Modeling/ role play	Video self-model	Practice	Feedback	Academic	Behavioral
Rosenbloom 16	Participant 1	15 min	F30 s	No	No	3	20	Yes	Yes	X			X			X			BD
Beckman 19	Cody	20 min	F20 s	No	No	3	NR	No	Yes				X		X	X	X	A	
Beckman 19	Brian	20 min	F15 s	No	No	3	NR	No	Yes				X		X	X	X	A	
Rosenbloom19	Carl	10 min	F30 s	Yes	Yes	1	45	No	Yes		X	X						TC	BDV
Rosenbloom19	Stan	10 min	F30 s	Yes	Yes	1	45	No	Yes		X	X						TC	BDV
Rosenbloom 19	Colin	10 min	F30 s	Yes	Yes	1	45	No	Yes		X	X						TC	
Rosenbloom 19	Jack	10 min	F30 s	Yes	Yes	1	45	No	Yes		X	X						TC	BDV
Wills 14	Student 1	15 min	F5 min	Yes	Yes	1	20	Yes	Yes			X		X		X			BV
Wills 14	Student 2	15 min	F5 min	Yes	Yes	1	20	Yes	Yes					X		X			BD
Clemons 16	Keith	30 min	F60 s	No	No	3	20	Yes	Yes			X	X	X	X	X	X		
Clemons 16	Brad	30 min	F60 s	No	No	3	20	Yes	Yes			X	X	X	X	X	X		
Clemons 16	Miranda	30 min	F30 s	No	No	3	20	Yes	Yes			X	X	X	X	X	X		
Romans 20	Jacob	10 min	F30 s	Yes	Yes	1	NR	No	Yes			X	X			X		A	
Romans 20	Zane	10 min	F30 s	Yes	Yes	1	NR	No	Yes			X	X			X		A	

Abbreviation: F = Fixed interval; s = second; min = Minute; NR = Not reported; A = Academic Accuracy, TC = Task Completion, BD = Disruptive Behavior, Disruptive Verbal Behavior; BDV = Disruptive Behavior and Disruptive Verbal Behavior.

Table 3. On-Task Visual and Outcomes Analysis.

Study	Design	Participant	On-Task Visual Analysis			On-Task Outcomes Analysis			
			Visual Analysis	Comparison	Immediacy of Change	LRRi (SE)	95% CI	% Change	95% CI
Rosenbloom16 16	ABAB	Participant 1	FR (4)	A1B1	Abrupt	1.25 (0.35)	(0.35, 0.57)	249%	(77, 590)
Rosenbloom 16				A2B2	Abrupt	1.04 (0.28)	(0.28, 0.49)	183%	(63, 390)
Beckman 19	ABAB	Cody	FR (4)	A1B1	Abrupt	0.8 (0.07)	(0.07, 0.67)	123%	(95, 154)
Beckman 19				A2B2	Abrupt	0.67 (0.17)	(0.17, 0.35)	96%	(41, 171)
Beckman 19	ABAB	Brian	FR (4)	A1B1	Abrupt	2.23 (0.44)	(0.44, 1.38)	834%	(297, 2097)
Beckman 19				A2B2	Abrupt	1.58 (0.19)	(0.19, 0.2)	385%	(231, 610)
Rosenbloom 19	ABAB	Carl	FR (4)	A1B1	Abrupt	1.78 (0.47)	(0.47, 0.86)	495%	(136, 1398)
Rosenbloom 19				A2B2	Abrupt	1.93 (0.38)	(0.38, 0.19)	587%	(228, 1338)
Rosenbloom 19	ABAB	Stan	FR (4)	A1B1	Abrupt	1.78 (0.22)	(0.22, 0.34)	490%	(282, 812)
Rosenbloom 19				A2B2	Abrupt	0.52 (0.1)	(0.1, 0.33)	68%	(39, 104)
Rosenbloom 19	ABAB	Colin	FR (4)	A1B1	Abrupt	0.98 (0.16)	(0.16, 0.67)	167%	(95, 266)
Rosenbloom 19				A2B2	Abrupt	0.57 (0.1)	(0.1, 0.37)	77%	(45, 115)
Rosenbloom 19	ABAB	Jack	FR (4)	A1B1	Abrupt	1.19 (0.36)	(0.36, 0.48)	230%	(62, 573)
Rosenbloom 19				A2B2	Abrupt	1.07 (0.24)	(0.24, 0.61)	193%	(84, 365)
Wills 14	ABAB	Student 1	FR (4)	A1B1	Abrupt	0.6 (0.11)	(0.11, 0.39)	83%	(47, 127)
Wills 14				A2B2	Abrupt	0.82 (0.09)	(0.09, 0.64)	126%	(88, 172)
Wills 14	ABAB	Student 2	FR (4)	A1B1	Abrupt	1.21 (0.31)	(0.31, 0.6)	236%	(82, 518)
Wills 14				A2B2	Abrupt	0.76 (0.21)	(0.21, 0.35)	113%	(41, 221)
Clemons 16	ABAB	Keith	FR (4)	A1B1	Abrupt	0.7 (0.2)	(0.2, 0.31)	101%	(36, 197)
Clemons 16				A2B2	Abrupt	0.37 (0.07)	(0.07, 0.24)	45%	(27, 67)
Clemons 16	ABAB	Brad	FR (4)	A1B1	Abrupt	0.52 (0.09)	(0.09, 0.35)	68%	(41, 100)
Clemons 16				A2B2	Abrupt	0.35 (0.11)	(0.11, 0.13)	42%	(14, 76)
Clemons 16	ABAB	Miranda	FR (4)	A1B1	Abrupt	0.94 (0.14)	(0.14, 0.67)	156%	(95, 237)
Clemons 16				A2B2	Abrupt	0.6 (0.08)	(0.08, 0.44)	82%	(56, 112)
Romans 20	ABAB	Jacob	FR (4)	A1B1	Abrupt	0.72 (0.19)	(0.34, 1.1)	105%	(41, 200)
Romans 20				A2B2	Abrupt	0.17 (0.08)	(0.01, 0.34)	19%	(1, 40)
Romans 20	ABAB	Zane	FR (4)	A1B1	Abrupt	0.71 (0.09)	(0.09, 0.53)	103%	(70, 142)
Romans 20			FR (4)	A2B2	Abrupt	0.63 (0.16)	(0.16, 0.31)	87%	(37, 157)

Abbreviation: FR = Functional relation; CI = Confidence interval.

Quality and Rigor Analysis

Twenty-nine single case designs found in six studies were analyzed individually for rigor and outcome analysis. All 29 were found to demonstrate at least three potential demonstrations of effect and were included in the quality and rigor analysis. For the six studies, 12 designs from five studies (Beckman et al., 2019; Clemons et al., 2016; Rosenbloom et al., 2016; Rosenbloom et al., 2019; Wills & Mason, 2014) met the WWC design standards without reservations while two designs from one study (Romans et al., 2020) met WWC design standards with reservations due to the presence of four data points in intervention conditions. As all 14 on-task designs from the six included studies met WWC design standards, all designs were determined to be of sufficient rigor for further analysis of outcomes. Six of the eight academic generalized outcomes (Brian, Beckman et al., 2019; Jacob, Romans et al., 2020; Carl, Stan, Colin, and Jack, Rosenbloom et al., 2019) and all nine behavior generalized outcome designs met WWC design standards with or without reservations. Two academic generalized outcome designs did not meet WWC standards due to insufficient data points (Cody, Beckman et al., 2019) and presence of treatment effects (Zane, Romans et al., 2020), and were not included in the outcomes analysis.

Outcomes Analysis

Visual Analysis. Visual analysis was conducted for 14 on-task, six academic and nine behavior designs from six studies to determine the presence of a functional relation for on-task behavior (the primary dependent variable) and generalized outcomes (the secondary dependent variable). A functional relation was identified for the increase in on-task behavior and the use of I-Connect for 14 designs. An abrupt immediacy of change of on-task behavior (i.e., an immediate increase in the level of the initial intervention data from the level of the final baseline data points) was identified upon the initial and second introduction of I-Connect for all 14 designs. Three designs were identified as having a delayed increase in on-task behavior following a return to baseline condition, see Table 3 for greater detail. Further visual analysis was conducted for generalized outcomes designs. A functional relation was identified for all six academic generalized outcome designs, and six of the nine designs investigating behavior generalized outcomes. An abrupt immediacy of change was noted in all six academic generalized outcome designs, but only five of the nine behavior generalized outcomes designs (Participant 1's disruptive behavior, Rosenbloom et al., 2016; Stan's disruptive and verbal behavior and Jack's verbal behavior, Rosenbloom et al., 2019; Student 2's disruptive behavior, Wills & Mason, 2014).

On-Task Effect Size Estimate. Effect size estimates using LRRi can be found in Table 3. On-task effect size estimates ranged from .17 to 2.23, and which corresponded to percent changes with a range of 19–834%. All AB conditions resulted in a positive LRRi value, indicating all AB comparisons demonstrate an increase in on-task behavior when I-Connect was introduced. No outlier data was present. See Table 3 for LRRI and percentage change estimates.

On-Task Meta-Analysis. The results of the univariate meta-analysis can be found in Table 3. The average effect of I-Connect on on-task behavior is LRRi = 0.86 (95% CI = [0.68, 1.04]). An unweighted average percent change across conditions was found to be 198% (range = 19–834%). See Figure 1 for a Forest Plot Summary. Secondary meta-analyses were run for designs with unique training or intervention components. The average effect of I-Connect when implemented with reinforcement is LRRi = 0.88 (95% CI = [0.63, 1.13]). The average effect of I-Connect when implemented without reinforcement is LRRi = 0.83 (95% CI = [0.53, 1.14]). The average effect of I-Connect when students received app navigation and target behavior discrimination training is LRRi = 0.67 (95% CI = [0.51, 0.84]). The average effect of I-Connect when students received only target behavior discrimination is LRRi = 1.00 (95% CI = [0.70, 1.30]). See Supplemental Materials for a forest plot of intervention and training components, "I-Connect Intervention and Training Forest Plot" (https://osf.io/8xdv5/?view_only=da72d4a73d7142d282d1dbf20dd0ee41).

Discussion

The purpose of this review was to examine the evidence base and the overall effectiveness of I-Connect on the on-task behavior of students with or at risk for disabilities. I-Connect has a research base of nine peer-reviewed studies, including six that that investigated the effect of I-Connect on on-task behavior. These six studies include 14 single-case designs which met WWC Standards indicating a sufficiently rigorous body of literature provides evidence that I-Connect produces consistent and substantial increases in on-task behavior to double the rates demonstrated in baseline. Positive outcomes were seen with all generalized academic and some behavioral outcomes, though students did not appear to demonstrate as immediate improvement in these outcomes.

RQ (1) For Whom and Under What Task Conditions and Settings

I-Connect on-task studies included positive outcomes for students from upper-elementary school through high school who received special education services or were in the referral process, and consistent with Chia et al., 2018 all but one participant were male students. These outcomes were found in both general and special education environments and were consistent with previous systematic reviews of self-monitoring (Bruhn et al., 2020; Davis et al., 2016). Unlike

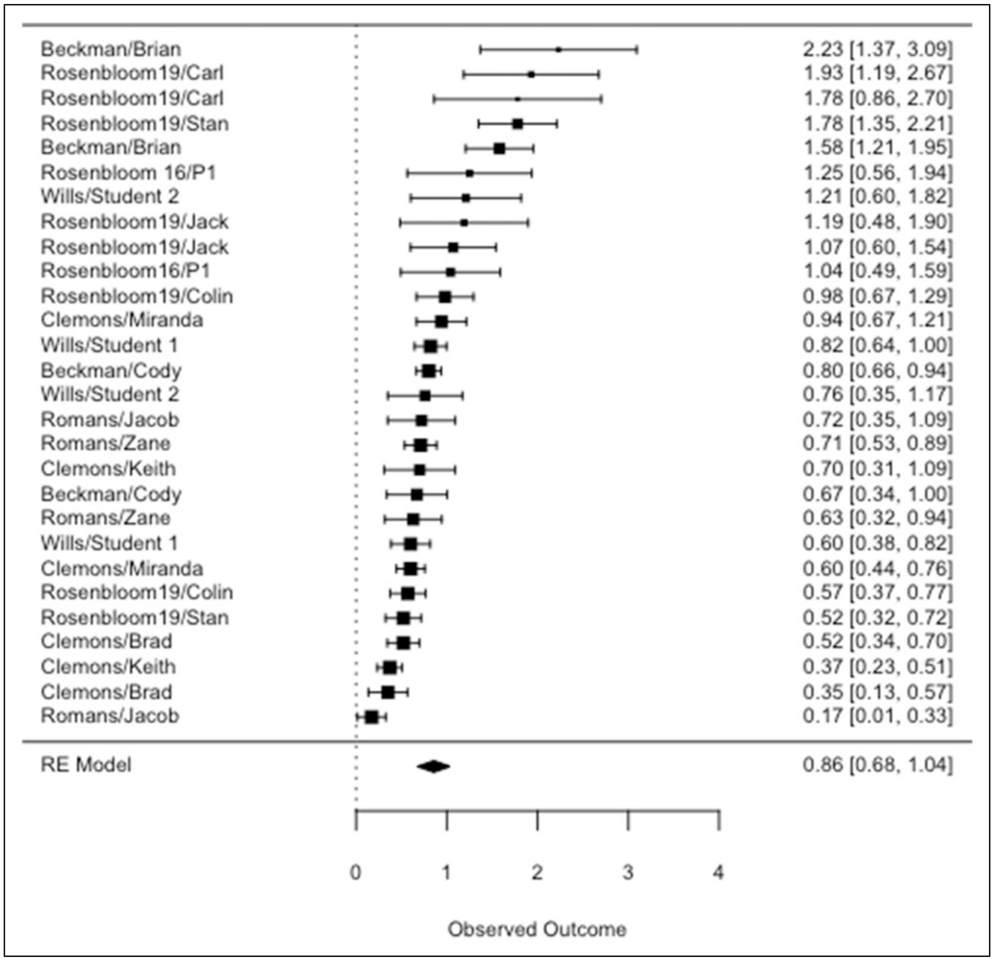

Figure 1. Forest plot of I-Connect effect sizes.

the broader self-monitoring literature reported by Bruhn et al. (2020) and Davis et al. (2016), the I-Connect literature represents a greater percentage of middle and high school aged students (n = 64%). The I-Connect literature base includes students from multiple special education eligibility categories suggesting the effects of I-Connect are generally applicable across students who receive special education. However, it should be noted that all five elementary-aged students were reported to have a medical diagnosis or special education eligibility of ASD, as did five of the nine secondary students. These findings are useful for special educators who support students with ASD, as this group reports using self-monitoring or self-management interventions frequently (McNeill, 2019; Morin et al., 2020)

While most students utilized I-Connect to monitor on-task behavior during independent work, positive outcomes were noted across task formats and were consistently effective when students engaged in multiple task formats throughout the intervention in general education. These results suggest I-Connect may be well suited to supporting inclusion in general education environments where various tasks are expected (Crosland & Dunlap, 2012). Further, I-Connect demonstrated initial effectiveness for students receiving instruction in either general or special education environments, however, two participants demonstrated positive outcomes using I-Connect across environments.

RQ (2) I-Connect Intervention Components

Most students using I-Connect demonstrated increases in on-task behavior using intervals between 15-60 seconds, consistent with findings that smaller intervals were correlated with the largest rates of academic engagement during intervention (Bruhn et al., 2020). However, two participants (Wills & Mason, 2014) demonstrated positive effects using 5-min intervals. Intervals ranged widely across participants, suggesting that the interval length is determined by individual student need. Reinforcement and accuracy checks were used to supplement I-Connect for 50% of the students using I-Connect, however, these participants did not demonstrate larger gains in positive effects than their peers who did not receive reinforcement. Meta-analytic results indicate I-

Connect with supplemental reinforcement produced only slightly larger outcomes (LRRi = .88) than when implemented alone (LRRi = .83), though the increases were slight. This finding differs from Bruhn et al. (2020) who found the addition of reinforcement produced the largest intervention effect on academic engagement for students with EBD and ADHD and Davis et al. (2016) who reported differentiated effects across self-monitoring treatment packages for students with ASD.

RQ (3) I-Connect Training Components

Students using I-Connect were most often trained using a portion of or a comprehensive behavior skills training model; (Cooper et al., 2020); though training methods, duration and topics varied widely across participants. The consistency of training methods within studies suggests the self-monitoring intervention was not individualized to the participant within the study but was treated as a standard treatment package. Meta-analysis results comparing two training packages (e.g., target behavior discrimination training with and without app navigation) found training with app navigation to be less effective than target behavior discrimination alone. However, caution is warranted when interpreting this result as these studies reported app navigation training occurring in three 20 min sessions, while the remaining studies with only target behavior discrimination training reported a single 45 min session or training duration was not reported. The variation in intervention effect across participants, training format and duration suggests further research is needed to examine the effect of individualized training methods.

RQ (4) I-Connect Effects on On-Task Behavior

The results of visual analysis indicate the use of I-Connect under research conditions often results in an immediate and large improvement in on-task behavior, resulting in a consistent positive increase in on-task behavior. This information may help guide educators in determining if a student is responding positively to I-Connect or if individualizations may be needed. For example, if an immediate response is not seen educators can work with the student to adjust the phrasing of the prompt, monitoring schedule, or consider the inclusion of reinforcement (Bruhn et al., 2016). Further, a residual increase in on-task behavior following the use of I-Connect was reported for 36% of participants, however, this increase dissipated to previous baseline levels within 1–2 monitoring sessions. Overall, I-Connect produced positive effects that ranged from a 19% to 834% increase in on-task behavior when introduced. As this is the first self-monitoring research synthesis to report the use of a within-case parametric effect size, these results cannot be compared to analog self-monitoring interventions or other technology-based interventions analyzed in previous syntheses. However, the I-Connect LRRi effect sizes demonstrate a consistent presence of positive outcomes when I-Connect is used across students with varying special education eligibilities, task formats, and settings using standardized intervention and training packages across students within a study. This finding has interesting implications for educators who are often instructed to individualize self-monitoring intervention components to unique student needs (Davis et al., 2016). A potential explanation for these consistent effects is the explicit instruction model used to train students to monitor and relatively short monitoring interval (e.g., 30 s), two components that may be considered an intensified form of self-monitoring (Bruhn et al., 2016). While most students may benefit from this form of self-monitoring, it is unclear if most students require this level of intervention. Further research is needed to examine the core components of self-monitoring interventions and the utility of individualized self-monitoring.

Visual analysis of on-task designs indicates a strong functional relation and an abrupt immediacy of change in on-task behavior occurred each time I-Connect was introduced, however, generalized academic and behavioral outcomes demonstrate a less consistent response to the instruction of I-Connect. Academic outcomes appeared to demonstrate some evidence of a generalized impact, with 66% of academic outcome designs demonstrating a strong functional relation (n = 4), a weak functional relation was present in a fifth study and only one design demonstrated no function relation. However, only two of the nine behavioral outcomes designs demonstrated a strong functional relation. The majority of behavioral outcome designs (44%, n = 4) demonstrated a weak functional relation and 33% demonstrated no functional relation (n = 3). This result is consistent with a recent moderator analyses of self-monitoring interventions (Bruhn et al., 2020). The inconsistent effects of improved on-task behavior on behavior outcomes is likely impacted by confounding variables such as persistent presence of setting or antecedent events or an unrelated function of on-task behavior. Further investigation into the generalized effect of on-task behavior on the reduction of academic and disruptive behavior is needed.

Limitations and Future Research

There are several limitations to the findings presented in this review. First, while every effort was made to locate all empirical studies using I-Connect it is possible some studies which did not identify I-Connect by name were not returned in the search or excluded during the screening process as it would be difficult to determine if the intervention applied was I-Connect or another technology-based self-monitoring intervention. To address this concern, authors conducted a forward search of all included studies in hopes of identifying additional studies, however, no additional studies were returned during this search. A secondary limitation of this study is the relatively small sample size of the I-Connect literature base which limited the quantitative analyses to a univariate meta-analysis and and hindered comparison of the I-Connect literature base to the broader self-monitoring literature. Further, a parametric effect size was used to estimate effect as parametric effect sizes provide the most robust estimate of effect, however, this deviation from the previous research syntheses (which employed calculation of Tau-U) limited further comparison.

Further research should expand the I-Connect literature base to examine the effect of I-Connect on the on-task behavior of female students and those without ASD (e.g., EBD, ID) especially those in upper-elementary school. Additionally, investigation into generalized academic and behavioral outcomes is needed, attention should be given to the generalized effect of I-Connect on the quality, accuracy and quantity of academic tasks and prosocial behaviors beyond the absence of disruptive behavior. Finally, I-Connect intervention packages appeared to vary across participants though limited information was provided within empirical studies about how components were individualized across participants. Comprehensive reporting of participant and setting characteristics is needed in the in the I-Connect and self-monitoring literature to include translational practice information (i.e., participant characteristics which guided the selection of interval length, task demand, and training methods) to better support educators seeking to individualize self-monitoring for students on their caseloads.

The results of this meta-analytic review provide a unique contribution to the literature by examining the literature base of a freely available, packaged self-monitoring intervention that can be individualized to meet the needs of many students with and at risk for disabilities. The results of this review indicate clear evidence that the use of I-Connect produces an increase on-task behavior for students with and at risk for disabilities. Continued research is needed to better understand the utility of individualizing I-Connect and other technology-based self-monitoring interventions to meet unique student needs and the generalized effect on on-task behavior to academic and behavioral outcomes.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by Office of Special Education Programs, Office of Special Education and Rehabilitative Services

ORCID iD

Gretchen Scheibel https://orcid.org/0000-0002-3047-910X

References

***Denotes studies included in this meta-analysis.**

Barton, E. E., Lloyd, B. P., Spriggs, A. D., & Gast, D. L. (2018). Visual analysis of graphic data. In J.R. Ledford, & D.L. Gast (Eds.), *Single case research methodology: Applications in special education and behavioral sciences* (pp. 179–214). https://doi.org/10.4324/9781315150666-8

*Beckman, A., Mason, B. A., Wills, H. P., Garrison-Kane, L., & Huffman, J. (2019). Improving behavioral and academic outcomes for students with autism spectrum disorder: Testing an app-based self-monitoring intervention. *Education and Treatment of Children*, *42*(2), 225–244. https://doi.org/10.1353/etc.2019.0011

Briesch, A. M., Daniels, B., & Beneville, M. (2019). Unpacking the term "self-management": Understanding intervention applications within the school-based literature. *Journal of Behavioral Education*, *28*(1), 54–77. https://doi.org/10.1007/s10864-018-9303-1

Bruhn, A., Gilmour, A., Rila, A., Van Camp, A., Sheaffer, A., Hancock, E., & Wehby, J. (2020). Treatment components and participant characteristics associated with outcomes in self-monitoring interventions. *Journal of Positive Behavior Interventions*, *24*(2), 156–168. https://doi.org/10.1177/1098300720946651.

Bruhn, A. L., Vogelgesang, K., Fernando, J., & Lugo, W. (2016). Using data to individualize a multicomponent, technology-based self-monitoring intervention. *Journal of Special Education Technology*, *31*(2), 64–76. https://doi.org/10.1177/0162643416650024

Carr, M. E., Moore, D. W., & Anderson, A. (2014). Self-management interventions on students with autism: A meta-analysis of single-subject research. *Exceptional Children*, *81*(1), 28–44. https://doi.org/10.1177/0014402914532235

Chia, G. L. C., Anderson, A., & McLean, L. A. (2018). Use of technology to support self-management in individuals with autism: Systematic review. *Review Journal of Autism and Developmental Disorders*, *5*(2), 142–155. https://doi.org/10.1007/s40489-018-0129-5

*Clemons, L. L., Mason, B. A., Garrison-Kane, L., & Wills, H. P. (2016). Self-monitoring for high school students with disabilities: A cross-categorical investigation of I-connect. *Journal of Positive Behavior Interventions*, *18*(3), 145–155. https://doi.org/10.1177/1098300715596134

Cooper, J.O., Heron, T.E., & Heward, W.L. (2020). *Applied Behavior Analysis* (3rd ed.). Hoboken, NJ: Pearson.

Crosland, K., & Dunlap, G. (2012). Effective strategies for the inclusion of children with autism in general education classrooms. *Behavior Modification*, *36*(3), 251–269. https://doi.org/10.1177/0145445512442682

Davis, J. L., Mason, B. A., Davis, H. S., Mason, R. A., & Crutchfield, S. A. (2016). Self-monitoring interventions for students with ASD: A meta-analysis of school-based research. *Review Journal* of Autism and Developmental Disorders, 3(3), 196–208. https://doi.org/10.1007/s40489-016-0076-y

Delisio, L. A., & Isenhower, R. W. (2020). Using video prompts to promote independent behavior in students with autism spectrum disorder. *Journal of Special Education Technology*, *35*(3), 167–175. https://doi.org/10.1177/0162643420919179

Finn, J. D., & Rock, D. A. (1997). Academic success among students at risk for school failure. *Journal of Applied Psychology*, *82*(2), 221–234. https://doi.org/10.1037/0021-9010.82.2.221

Hume, K., Steinbrenner, J. R., Odom, S. L., Morin, K. L., Nowell, S. W., Tomaszewski, B., & Savage, M. N. (2021). Evidence-based practices for children, youth, and young adults with autism: Third generation review. *Journal of Autism and Developmental Disorders*, *51*(11), 1–20. https://doi.org/10.1007/s10803-020-04844-2

Kiru, E. W., Doabler, C. T., Sorrells, A. M., & Cooc, N. A. (2018). A synthesis of technology-mediated mathematics interventions for students with or at risk for mathematics learning disabilities. *Journal of Special Education Technology*, *33*(2), 111–123. https://doi.org/10.1177/0162643417745835

Kumm, S., Talbott, E., & Jolivette, K. (2021). A technology-based self-monitoring intervention for secondary students with high-incidence disabilities. *Journal of Special Education Technology*, *36*(3), 141–151. https://doi.org/10.1177/01626434211004450

Ledford, J. R., Lane, J. D., & Severini, K. E. (2018). Systematic use of visual analysis for assessing outcomes in single case design studies. *Brain Impairment*, *19*(1), 4–17. https://doi.org/10.1017/brimp.2017.16

Ledford, J. R., & Pustejovsky, J. E. (2020). Systematic review and meta-analysis of stay-play-talk interventions for improving social behaviors of young children. *Journal of Positive Behavior Interventions*. https://doi.org/10.1177/1098300720983521

Maggin, D. M., Wehby, J. H., Farmer, T. W., & Brooks, D. S. (2016). Intensive interventions for students with emotional and behavioral disorders: Issues, theory, and future directions. *Journal of Emotional and Behavioral Disorders*, *24*(3), 127–137. https://doi.org/10.1177/1063426616661498

McNeill, J. (2019). Social validity and teachers' use of evidence-based practices for autism. *Journal of Autism and Developmental Disorders*, *49*(11), 4585–4594. https://doi.org/10.1007/s10803-019-04190-y

Moeyaert, M., Maggin, D., & Verkuilen, J. (2016). Reliability, validity, and usability of data extraction programs for single-case research designs. *Behavior Modification*, *40*(6), 874–900. https://doi.org/10.1177/0145445516645763

Moeyaert, M., Zimmerman, K. N., & Ledford, J. R. (2018). Synthesis and meta-analysis of single case research. In J.R. Ledford & D.L. Gast (Eds.), *Single case research methodology: Applications in special education and behavioral sciences* (pp. 393–416). https://doi.org/10.4324/9781315150666-14

Morin, K. L., Sam, A., Tomaszewski, B., Waters, V., & Odom, S. L. (2020). Knowledge of evidence-based practices and frequency of selection among school-based professionals of students with autism. *Journal of Surgical Education*, *55*(3), 143–152. https://doi.org/10.1177/0022466920958688

Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., & McKenzie, J. E. (2021). PRISMA 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews. *British Medical Journal*, *372*. https://doi.org/10.1136/bmj.n160.

Pustejovsky, J. E. (2018). Using response ratios for meta-analyzing single-case designs with behavioral outcomes. *Journal of School Psychology*, *68*(x), 99–112. https://doi.org/10.1016/j.jsp.2018.02.003

Pustejovsky, J. E., & Swan, D. M. (2018). *Single case ES: A calculator for single-case effect size indices (R package version 0.4.0.4)*. x. https://github.com/jepusto/SingleCaseES.

R Core Team (2021). *R: A language and environment for statistical computing. R foundation for statistical computing*. Vienna, Austria. http://www.R-project.org/

*Romans, S. K., Wills, H. P., Huffman, J. M., & Garrison-Kane, L. (2020). The effect of web-based self-monitoring to increase on-task behavior and academic accuracy of high school students with autism. *Preventing School Failure*, *64*(3), 249–260. https://doi.org/10.1080/1045988X.2020.1732282

*Rosenbloom, R., Mason, R. A., Wills, H. P., & Mason, B. A. (2016). Technology delivered self-monitoring application to promote successful inclusion of an elementary student with autism. *Assistive Technology*, *28*(1), 9–16. https://doi.org/10.1080/10400435.2015.1059384

*Rosenbloom, R., Wills, H. P., Mason, R., Huffman, J. M., & Mason, B. A. (2019). The effects of a technology-based self-monitoring intervention on on-task, disruptive, and task-completion behaviors for adolescents with autism. *Journal of Autism and Developmental Disorders*, *49*(12), 5047–5062. https://doi.org/10.1007/s10803-019-04209-4

Shanley, L., Strand Cary, M., Turtura, J., Clarke, B., Sutherland, M., & Pilger, M. (2020). Individualized instructional delivery options: Adapting technology-based interventions for students with attention difficulties. *Journal of Special Education Technology*, *35*(3), 119–132. https://doi.org/10.1177/0162643419852929

Valentine, J. C., Tanner-Smith, E. E., Pustejovsky, J. E., & Lau, T. S. (2016). Between-case standardized mean difference effect sizes for single-case designs: A primer and tutorial using the scdhlm web application. *Campbell Systematic Reviews*, *12*(1), 1–31. https://doi.org/10.4073/cmdp.2016.1

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, *36*(3), 1–48. https://doi.org/10.18637/jss.v036.i03

What Works Clearinghouse. (2020). *What works clearinghouse: Standards handbook, version 4.1*. Institute of Education Sciences. https://ies.ed.gov/ncee/wwc/Docs/referenceresources/WWC-Standards-Handbook-v4-1-508.pdf.

*Wills, H. P., & Mason, B. A. (2014). Implementation of a self-monitoring application to improve on-task behavior: A high-school pilot study. *Journal of Behavioral Education*, *23*(4), 421–434. https://doi.org/10.1007/s10864-014-9204-x

Author Biographies

Gretchen Scheibel is a doctoral candidate in special education and Implementation Coordinator at Juniper Gardens Children's Project at the University of Kansas. Her work focuses on using rigorous research methods to support the selection and implementation of effective and feasible evidence-based practices for students with intensive support needs. She also employs economic evaluation methods to explore intervention cost of evidence-based practices for students with intensive support needs.

Kathleen Zimmerman is an Assistant Professor of Special Education at the University of Kansas. Her work focuses on supporting educators to implement evidence-based instructional practices to increase the engagement of young children with language and behavioral support needs. She also explores methods to improve the measurement and synthesis of single case research designs.

Howard Wills is a Professor in the Educational Psychology Department and a Senior Scientist at Juniper Gardens Children's Project at the University of Kansas. His research focuses on the development and evaluation of academic and behavioral interventions.