

Using Generative Artificial Intelligence (GenAI) to Monitor the Progress of IEP Goals: A Proposed Framework

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Abstract

Special education teachers are responsible for developing and monitoring the progress of Individualized Education Programs (IEPs). This has contributed to high levels of stress and unmanageable workloads. With access to Generative Artificial Intelligence (GenAI) tools, such as ChatGPT, Google Gemini, and Claude, special education teachers may benefit from using these tools to support ongoing documentation. While current research has demonstrated that GenAI can be used to write high-quality IEP goals in less time than traditional methods (Rakap, 2024), limited attention has been given to its application in progress monitoring. This article offers a practice-oriented framework for using GenAI to support this process. While this framework has not been researched, it offers a practical model for integrating GenAI into required administrative practices. This article reinforces the need for continued professional learning of GenAI tools.

Keywords: Generative artificial intelligence (GenAI), Individual education program (IEP)

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Introduction

An Individualized Education Program (IEP) includes measurable academic and functional goals designed to assess students' progress toward the general education curriculum and other identified areas of need, and these goals must be monitored throughout the school year (U.S. Department of Education, 2017). This is such an essential aspect of an IEP that the Supreme Court ruled school districts were obligated to “offer an IEP that is reasonably calculated to enable the child to make progress appropriate in light of the child’s circumstances” (Endrew F. v. Douglas County School District, 2017, p. 11). Although this is a legal requirement for all students with disabilities, most educators are overworked by this mandatory documentation (Ruble et al., 2023), resulting in high levels of stress and unmanageable workloads (Bettini et al., 2017).

While the IEP writing process is a highly collaborative effort by all members of the IEP team, including the special/general education teacher[s], related service provider[s], the parent/guardian, the student [when applicable/appropriate], and the school psychologist [when applicable], it is still a rigorous process. The emergence of Generative Artificial Intelligence (GenAI) in education may help IEP teams complete required documentation and meet federal mandates more efficiently and consistently. GenAI has been defined as “a field of AI that utilizes machine learning algorithms to generate human-like content, such as texts, images, and sound” (Moundridou et al., 2024). Language Models (LLMs) are a type of machine learning designed to process context and generate language (Cain, 2024). GenAI tools, such as ChatGPT, Google Gemini, and Claude, are LLMs that may support educators by organizing, summarizing, and translating IEP-related information, including goals, to create documentation that shows growth over time. As this new technology becomes more prevalent in classrooms, it is also critical to understand its limitations and the essential role of human judgment in its use with IEPs.

IEPs and Progress Monitoring

A student’s IEP must include their Present Levels of Academic Achievement and Functional Performance (PLAAFP), which describe how their disability affects their involvement and progress in the general education curriculum, based on assessment data (U.S. Department of Education, 2017). This information is used to develop measurable annual goals to address a student’s academic and functional needs, which must be monitored for progress (U.S. Department of Education, 2017). Under the Individuals with Disabilities Education Act (IDEA), schools are expected to specify how, and how frequently, IEP goals will be measured (for example, quarterly or with report cards) (U.S. Department of Education, 2017). It is imperative that the PLAAFP has sufficient data to provide adequate services and to form clear, specific goals (Swain et al., 2022). While not required, many states use the SMART goal framework to write their student’s IEP goals, ensuring that goals are: Specific, Measurable, Attainable, Realistic, and Time-Bound (Jung, 2007). While it is at the discretion of the educator to choose how to monitor progress towards IEP goals, a common strategy is to use curriculum-based measurements, or *CBM* (Deno, 1985).

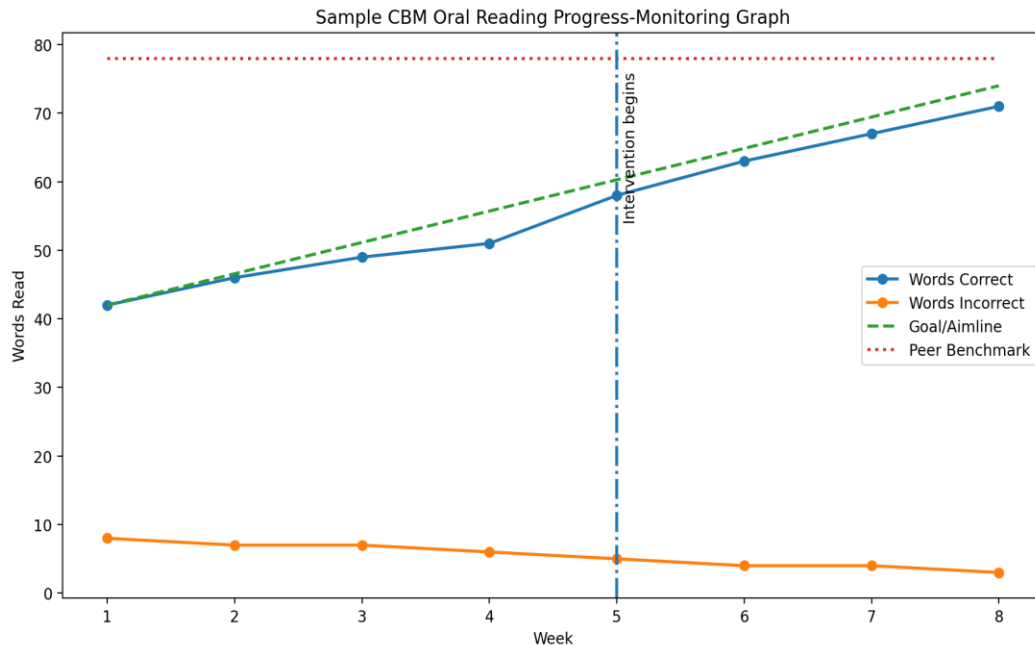
Curriculum-Based Measurements of IEP Goals. The purpose of a CBM is to ensure that educators integrate data into their daily instructional practice to make instructional shifts for students, rather than relying on informal observations (Deno, 1985). It established a standardized procedure for collecting data in reading, writing, math, and spelling (Cusumano, 2007). The

outline below describes the characteristics and structures of a CBM (Dino, 2003; Hosp & Hosp, 2026):

- Repeated sampling on core reading, writing, and math skills
- Using standard tasks
- Using stimulus materials
- Within an efficient and specific duration of time (1-3 minutes with a timing device)
- Standardized directions/guides for testing administrators
- Student directions
- Scoring guidelines (counting the number of correct and incorrect responses within a set timeframe)
- Standards for performance
- Repeating the samples across time (use a different passage out of the same resource)
- Record forms/charts
- Easy to teach

CBMs are simple to administer, valid, reliable, and cost-effective; and allow educators to see small growth over time (Deno, 1985). Prior to computers, these were often administered with paper and pencils. Today, CBMs are also administered both on paper and digitally.

CBMs naturally align with IEP goals as they provide ongoing evidence of progress or need for additional instructional support. For example, if a special educator needs to monitor a student's reading progress, the scores are graphed to show progress over time (van den Bosch et al., 2017). For example, if a student is reading fewer words correctly per minute than their peers, the teacher may choose an oral reading fluency measure to monitor student progress (Stecker et al., 2008), which could then be graphed. In alignment with CBM graphing practices, data would include the baseline (current level of performance), expected performance levels (to show discrepancies), a goal line, data points indicating correct and incorrect responses, growth lines to show progress, and instructional changes (van den Bosch et al., 2017). Figure 1 presents a sample CBM oral reading progress-monitoring graph created with fictional data based on common CBM graphing conventions.

Figure 1*Sample CBM Oral Reading Progress-Monitoring Graph*

Note: Created with ChatGPT.

Concerns with Monitoring IEP Goals. Effective monitoring of IEP goals is critical in determining whether students are making adequate progress; however, educators face several barriers to implementing these practices with fidelity. Research indicates that a primary obstacle is a lack of administrative time, combined with the need for professional development in administering and analyzing CBM data, and inconsistencies among educators (Swain et al., 2022). While these barriers exist, student outcomes may suffer. For example, limited implementation of evidence-based practices to address IEP goals has resulted in IEP goals remaining unchanged for three years or more (Brock et al., 2020). This suggests a misalignment between goals and progress monitoring, which will negatively impact student growth.

For schools to provide a Free Appropriate Public Education (FAPE), it is critical that progress toward IEP goals and objectives be appropriately documented (Rotter, 2014), and that educators select measures aligned with those goals to achieve the best outcomes for students. These persistent barriers—limited time, inconsistent implementation, and misaligned measures—suggest that educators need additional support in managing the monitoring process. Emerging GenAI tools may offer a practical solution to address these challenges.

GenAI for Monitoring IEP Goals

Emerging research indicates that using GenAI tools, such as ChatGPT, can help teachers write IEP goals more efficiently and to a higher standard. For example, Rakap (2024) found that using ChatGPT to develop IEP goals, compared with traditional methods, reduced the time required to write the goals, improved quality, and reduced inconsistencies by providing real-time feedback to

educators. These findings are similar to those of other special educators who used ChatGPT to evaluate the quality of IEP goals, stating that using this tool saved time and increased efficiency and effectiveness (Waterfield, 2026). Beyond outcomes, Rakap & Bilicki (2024) offer practical, step-by-step guidance on using ChatGPT to support the goal writing process, including asking ChatGPT if it understands what a SMART goal is and how to use it to write high-quality IEP goals, provide explicit examples, insert a PLAAFP, identify strengths and needs, suggest three priority goals, review the suggested goals, and revise or adjust as needed. This IEP goal-writing process may be useful when using GenAI to support monitoring progress. As stated by one participant in Waterfield (2026), “If it can make progress monitoring tools for me too, that would be great too!” (p. 64).

Proposed Framework for Progress Monitoring IEP Goals with GenAI. While current research has primarily focused on GenAI for IEP goal development, there is less attention to how special education teachers can use GenAI to monitor these goals. By using Claude (Anthropic, 2026) as a thought partner, this framework is offered as a practice-oriented, illustrative model rather than an evidence-based intervention. Its purpose is to demonstrate how educators might use GenAI to create data-collection tools aligned with IEP goals, organize data, quickly and easily display progress using CBM, and draft summaries for reports and families.

Step 1 – Input the Student’s IEP Goal. In addition to the IEP goal, include the accuracy, frequency, duration, and method of measurement. Do not include any personally identifiable information (PII) to protect student privacy. Prompt GenAI to create a data collection sheet that is specific to the goal, a progress-monitoring form that includes the exact skill, opportunities for recording correct and incorrect responses, percentage calculations, and weekly summary fields.

Example Prompt. “I am a second-grade special education teacher. This is the IEP goal of one of my students. Given a list of 10 consonant-vowel-consonant (CVC) words, the student will decode the words by identifying each sound and blending the sounds to read the whole word, in 4 out of 5 trials, with 80% accuracy, over 4 consecutive weeks, as measured by a data collection sheet. Create a data collection sheet specific to the goal, and a progress-monitoring form that includes the exact skill, opportunities to record correct and incorrect responses, percentage calculations, and weekly summary fields. Include a CBM graph that shows the baseline, the typical performance of their peers, a goal line, data points indicating correct and incorrect responses, growth lines showing progress, and instructional changes. For each trial, I want to record it as C (correct) or I (incorrect). I only want to record the data for lowercase letters. Connect all information so that data only needs to be entered once to create the CBM graph.”

Claude will create a labeled, three-tab Excel sheet (Data Collection, CBM Graph, and Weekly Summary) that a special educator can use to enter student data. See Figure 2 for an example of the Data Collection tab.

Figure 2
Data Collection - Tab 1

CVC Word Decoding — Progress Monitoring & Data Collection																																			
GOAL: Given a list of 10 CVC words, the student will decode the words by identifying each sound and blending the sounds to read the whole word, in 4 out of 5 trials, with 80% accuracy, over 4 consecutive weeks.																																			
Student Name:		Grade:				Teacher:				School Year:				IEP Date:																					
SKILL: Phonemic Decoding of CVC (Consonant-Vowel-Consonant) Words TASK: Student identifies the initial consonant sound + medial vowel sound + final consonant sound, then blends all 3 sounds to produce the whole word SCORING: C = Correct (all 3 sounds AND blend correct) I = Incorrect or No Response CRITERION: ≥80% correct on 4 out of 5 trials, for 4 consecutive weeks																																			
#	CVC Word	WEEK 1								WEEK 2								WEEK 3								WEEK 4								Notes / Observations	
		Trial 1 Date:	Trial 2 Date:	Trial 3 Date:	Trial 4 Date:	Trial 5 Date:	Total Correct (C)	% Acc.	Trial 1 Date:	Trial 2 Date:	Trial 3 Date:	Trial 4 Date:	Trial 5 Date:	Total Correct (C)	% Acc.	Trial 1 Date:	Trial 2 Date:	Trial 3 Date:	Trial 4 Date:	Trial 5 Date:	Total Correct (C)	% Acc.	Trial 1 Date:	Trial 2 Date:	Trial 3 Date:	Trial 4 Date:	Trial 5 Date:	Total Correct (C)	% Acc.						
1	cat						0	0%						0	0%						0	0%						0	0%						
2	bat						0	0%						0	0%						0	0%						0	0%						
3	hat						0	0%						0	0%						0	0%						0	0%						
4	mat						0	0%						0	0%						0	0%						0	0%						
5	sat						0	0%						0	0%						0	0%						0	0%						
6	big						0	0%						0	0%						0	0%						0	0%						
7	pig						0	0%						0	0%						0	0%						0	0%						
8	hop						0	0%						0	0%						0	0%						0	0%						
9	sun						0	0%						0	0%						0	0%						0	0%						
10	bed						0	0%						0	0%						0	0%						0	0%						
WEEKLY SUMMARY																																			
Week Dates (Start – End)		0								0								0								0									
Total C (Correct) – out of 50		0								0								0								0									
Total I (Incorrect) – out of 50		50								50								50								50									
Overall % Accuracy		0%								0%								0%								0%									
# Words Meeting ≥ 80% (out of 10)		0								0								0								0									
# Trials with ALL Correct (5/5)		0								0								0								0									
GOAL MET? (80% accuracy, 4/5 trials)		✗ NO								✗ NO								✗ NO								✗ NO									
Teacher Initials & Date Recorded																																			
SCORING KEY: C = Correct — student correctly identified the initial consonant, medial vowel, AND final consonant, then blended all 3 sounds to read the whole word I = Incorrect or No Response Leave cell blank if the word was not assessed during that trial																																			

Step 2 – Enter Student Data. For the purposes of this example, fictional data was entered into the “Data Collection” tab (Tab 1) and was used to demonstrate how GenAI can create a tracking sheet to monitor student progress. Figures 3, 4, and 5 (CBM Graphs and Weekly Summary) demonstrate how, by prompting GenAI to connect these tabs, educators can enter a single dataset and review the generated data in multiple ways without needing to be an Excel formulas expert.

Figure 3
CBM Progress Monitoring Graphs - Tab 2

CBM Progress Monitoring Graph — CVC Word Decoding | Grade 2 Special Education

Student:0Teacher:0Grade:0

★ Data is automatically pulled from the "Data Collection" tab. Enter c / i / scores there — this graph and all calculations update instantly. Goal line = 80%. Peer norm = typical Grade 2 peer performance (~90%).

Session / Label	Student % Correct	Baseline	Goal Line (80%)	Peer Norm (~90%)	Aimline (Growth)	Instr. Change?	Instructional Change Notes
BASELINE (pre-intervention)		0%	80%	90%	0%		Enter baseline % correct before instruction begins
Week 1 — Trial 1	0%	0%	80%	90%	4%		
Week 1 — Trial 2	0%	0%	80%	90%	8%		
Week 1 — Trial 3	0%	0%	80%	90%	12%		
Week 1 — Trial 4	20%	0%	80%	90%	16%		
Week 1 — Trial 5	80%	0%	80%	90%	20%		
Week 2 — Trial 1	0%	0%	80%	90%	24%		
Week 2 — Trial 2	0%	0%	80%	90%	28%		
Week 2 — Trial 3	20%	0%	80%	90%	32%		
Week 2 — Trial 4	70%	0%	80%	90%	36%		
Week 2 — Trial 5	100%	0%	80%	90%	40%		
Week 3 — Trial 1	0%	0%	80%	90%	44%		
Week 3 — Trial 2	0%	0%	80%	90%	48%		
Week 3 — Trial 3	70%	0%	80%	90%	52%		
Week 3 — Trial 4	100%	0%	80%	90%	56%		
Week 3 — Trial 5	100%	0%	80%	90%	60%		
Week 4 — Trial 1	50%	0%	80%	90%	64%		
Week 4 — Trial 2	70%	0%	80%	90%	68%		
Week 4 — Trial 3	100%	0%	80%	90%	72%		
Week 4 — Trial 4	100%	0%	80%	90%	76%		
Week 4 — Trial 5	100%	0%	80%	90%	80%		

Baseline Score:0%

Current Average % (all trials):49%

Best Single-Trial Score:100%

Trials at or Above Goal (80%):7

Trials Below Goal:13

Instructional Changes Made:0

Figure 4
CBM Progress Monitoring Graphs - Tab 2

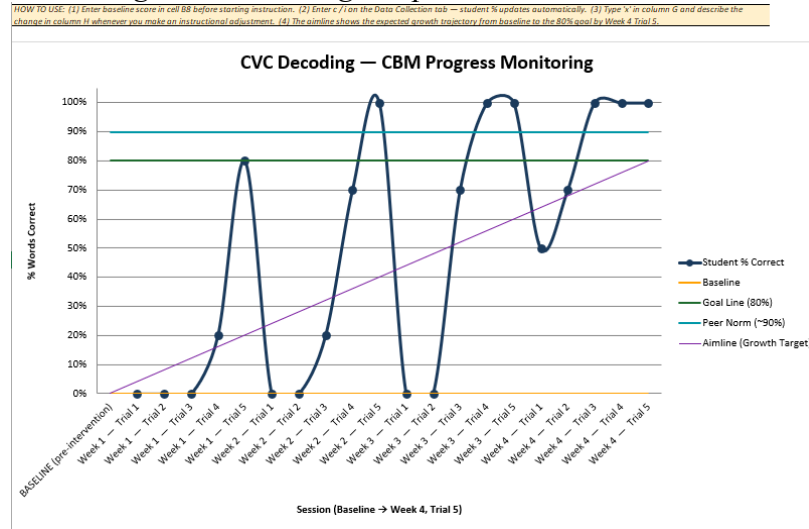


Figure 5
Weekly Progress Summary - Tab 3

Weekly Progress Summary — CVC Word Decoding Grade 2 Special Education					
Student:	0		Teacher:	0	
Grade:					
★ All values update automatically from the "Data Collection" tab. Only enter data in the yellow cells there.					
Metric	Week 1	Week 2	Week 3	Week 4	Observation Notes / Intervention Adjustments
Week Dates (Start → End)	0	0	0	0	
Total Correct (c) — out of 50	10	19	27	42	
Total Incorrect (i) — out of 50	40	31	23	8	
Overall % Accuracy	20%	38%	54%	84%	
# Words ≥ 80% Accuracy (out of 10)	0	0	0	7	
# Words ALL Correct (5/5)	0	0	0	5	
GOAL MET THIS WEEK?	NO	NO	NO	YES	
Teacher Initials & Date	0	0	0	0	
CONSECUTIVE WEEK GOAL ATTAINMENT TRACKER — 4 consecutive weeks at ≥80% = IEP GOAL MET					
WEEK 1: NO		WEEK 2: NO		WEEK 3: NO	
				WEEK 4: YES	
Consecutive Weeks at Goal → Circle one: 0 1 2 3 4 ◀ FOUR consecutive = IEP GOAL ACHIEVED ☒					
WORD-BY-WORD % ACCURACY (auto-updated — shows % per word per week for error pattern analysis)					
CVC Word	Week 1	Week 2	Week 3	Week 4	Error Pattern Notes (initial / medial / final / blend)
cat	20%	40%	60%	100%	
bat	20%	40%	60%	100%	
hat	20%	40%	60%	100%	
mat	20%	40%	60%	100%	
sat	20%	40%	60%	100%	
big	40%	60%	60%	80%	
plg	40%	60%	60%	80%	
hop	0%	20%	40%	60%	
sun	0%	20%	40%	60%	
bed	20%	20%	40%	60%	

Step 3 – Upload the Completed Data. Upload student data into GenAI to summarize it. Ensure that no PII student data is entered. Prompt GenAI to analyze the data and draft a narrative for progress reports, PLAAFP statements, or a progress report for families. Special educators can also prompt GenAI for ongoing areas of need based on the data. It is imperative that the educator review and edit the narrative to ensure it accurately reflects the data and the student. See Figure 6 for an example of a narrative generated by GenAI from data.

Figure 6

Narrative Example from GenAI

Progress monitoring data collected over four consecutive weeks in March 2026 indicates that the student has demonstrated meaningful growth in CVC word decoding, with a clear upward trajectory across the monitoring period. The student has not yet met the IEP goal, as the criterion requires 80% accuracy maintained across **four** consecutive weeks; the student reached the 80% benchmark in Week 4 only.

Weekly Performance Summary:

- **Week 1:** The student scored 10 out of 50 opportunities correct (20% accuracy). No individual words met the 80% criterion, and no words were decoded correctly across all 5 trials. Performance was most consistent on *big* and *pig* (40% each), while *hop* and *sun* were the most challenging words, with 0% accuracy across all five trials.
- **Week 2:** The student scored 19 out of 50 opportunities correct (38% accuracy). While still below the goal, this represents a gain of 9 correct responses from Week 1. No individual words met the 80% criterion, though *big* and *pig* improved to 60% and the short /a/ words (*cat*, *bat*, *hat*, *mat*, *sat*) improved to 40% each.
- **Week 3:** The student scored 27 out of 50 opportunities correct (54% accuracy), continuing the upward trend. No individual words met the 80% criterion in isolation. The short /a/ words continued to improve (60% each), while *big* and *pig* held at 60%, and *hop*, *sun*, and *bed* showed gradual but still limited improvement (40%, 40%, and 40%, respectively).
- **Week 4:** The student scored 42 out of 50 opportunities correct (**84% accuracy**), surpassing the 80% goal for the first time. Seven of the 10 words met the >80% criterion, and five words (*cat*, *bat*, *hat*, *mat*, *sat*) were decoded correctly on all five trials (100%). The words *big* and *pig* reached 80%. The words *hop*, *sun*, and *bed* remained below criterion at 60% each.

Recommended Next Instructional Steps

1. **Continue progress monitoring for three additional weeks.** Because the student met the 80% criterion in Week 4 for the first time, the IEP goal requires four consecutive weeks at or above 80% before it can be considered mastered. Data collection should continue without interruption to confirm whether Week 4 performance is maintained.
2. **Provide targeted, explicit instruction on short /o/, /u/, and /e/ vowel sounds.** The three words that did not meet criterion (*hop*, *sun*, *bed*) each contain a different vowel sound. Direct instruction using sound-mapping or Elkonin (sound) boxes focused specifically on medial vowel discrimination would help the student solidify these sounds. Vowel picture cards or color-coded vowel referents may provide helpful scaffolding.
3. **Incorporate vowel contrast practice.** Because the student is strong on short /a/ but inconsistent across other vowels, explicit comparison activities — such as minimal pair sorting (*cat* vs. *cot*, *bat* vs. *but*, *hat* vs. *hit*) — can help the student attend to and distinguish medial vowel sounds more precisely.
4. **Expand the CVC word set once the goal is mastered.** Once the student achieves 80% accuracy across four consecutive weeks, the next instructional step should include a broader and more varied set of CVC words representing all five short vowels, followed by introduction of consonant blends or CCVC/CVCC word patterns, depending on the student's phonological readiness.
5. **Consider a brief fluency component.** As decoding accuracy strengthens, adding a timed or repeated reading component with CVC words will help the student move from effortful, sound-by-sound decoding toward more automatic word recognition, which supports reading fluency and comprehension at the second-grade level.

Summary of Progress: The student's accuracy improved from 20% in Week 1 to 84% in Week 4, a gain of 64 percentage points over the four-week period. The rate of growth was consistent week over week (+18 points, +16 points, +30 points), reflecting a strong positive response to instruction. The goal was met in Week 4 only; three additional consecutive weeks at or above 80% are needed to satisfy the full IEP criterion.

Pattern of Errors: Error analysis reveals a consistent pattern across all four weeks. The student demonstrated the strongest performance on short /a/ CVC words with familiar consonants (*cat*, *bat*, *hat*, *mat*, *sat*), suggesting that the short /a/ vowel sound is the most solidified. Words containing short /i/ (*big*, *pig*) were emerging and reached criterion by Week 4. The most persistent difficulty was with short /o/ (*hop*), short /u/ (*sun*), and short /e/ (*bed*), all of which ended the monitoring period at 60% and have not yet met the goal criterion. This pattern suggests the student may have stronger phonemic awareness of the short /a/ sound relative to other medial vowel sounds, and that errors are likely centered on medial vowel identification rather than initial or final consonant recognition.

This proposed framework illustrates how GenAI can support special education teachers in designing specific, effective monitoring tools aligned with a student's IEP goals, quickly graphing student performance, and drafting a narrative summary for classroom use, general education counterparts, or families. While there are clear advantages to using GenAI, there are also limitations and risks associated with these tools.

Limitations and Concerns

To ensure student privacy and data protection, educators should be aware of the potential for bias and the importance of accuracy and accountability in its use (Harkins-Brown et al., 2025). GenAI platforms are trained on data entered by humans, and human bias is reflected in them. This may cause groups to be under- or over-represented (Ntoutsis et al., 2020), result in unfair outcomes

(Chen et al., 2023), and lead to discrimination against individuals with disabilities (El Morr et al., 2024). Mitigating these biases requires a critical approach to engaging with AI-generated output to ensure fair and inclusive practices for students.

A secondary risk is that GenAI platforms rely on large datasets to predict their responses to users (i.e., the outputs they produce). A limitation of using these datasets is that they can produce inaccurate responses, even when they sound credible, a phenomenon known as hallucinations (Montenegro-Rueda et al., 2023). This poses a substantial risk to the required level of accuracy when working with students with special needs. The information used to support IEPs needs to be precise to make informed decisions and remain in compliance with federal mandates. Including invalid information may present legal and ethical risks, further demonstrating the need for critical evaluation.

An additional concern regarding the data is knowing where it is stored, how long it is stored for, how it is deleted, and who has access to it (U.S. Department of Education, Office of Educational Technology, 2023). Since IEPs include sensitive student information, any use of GenAI must be guided by student privacy protections, including the Family Educational Rights and Privacy Act (FERPA) policy on disclosing personally identifiable information from education records without consent (U.S. Department of Education, n.d.-a) and Children’s Online Privacy Protection Act (COPPA) protections related to the online collection of PII from children under 13 (Federal Trade Commission [FTC], n.d.). Educators need to be knowledgeable about how to engage with platforms in ways that align with IDEA and FERPA.

IDEA, FERPA, and GenAI Impact. Educators have a legal and ethical responsibility to their students and their families, and IDEA and FERPA serve as cornerstones for understanding those responsibilities. Together, these laws aim to protect student data and privacy while upholding equity for students. It is imperative that special educators have a clear understanding of how these two laws overlap to remain compliant, especially when interacting with GenAI. For example, entering confidential student information into an unauthorized platform could violate one or both laws. Based on the framework provided by the U.S. Department of Education (2022), the adapted table below (Table 1) outlines the provisions of IDEA, Parts B (early intervention services) and C (school-age services) combined, and FERPA, as well as how the inappropriate use of GenAI may violate these regulations.

Table 1
IDEA, FERPA, GenAI Impact

	IDEA (Part B/Part C)	FERPA	GenAI Impact
Educational Records	Education records/early intervention records are required to be maintained.	Records directly related to the student that are maintained by the educational agency/institution and include information recorded in handwriting, print,	If educational records are entered into a GenAI platform, this may directly violate established educational record laws.

		computer media, videotape, audiotape, film, microfilm, or microfiche. Records may be kept solely in the maker's possession to support memory and are not accessible to anyone except a temporary substitute for the maker.	No specific student educational records may be entered into an LLM, as doing so would mean the records are not kept in the sole possession of the maker.
Participating Agency/Educational Agency or Institution	An agency, institution, individual, or entity that collects, maintains, or uses PII.	Educational agency or institution.	An LLM is not an educational agency or institution and should not collect, maintain, or use PII.
Confidentiality	Ensures the confidentiality and protection of PII: name, parents' name, other family members, address, social security number, student identification number, and personal characteristics that would make it possible to identify the student.	Ensures the confidentiality and protection of PII: date of birth, place of birth, mother's maiden name, and other information that would allow an individual to link the information to the student. This may be through any exchange, such as oral, written, or electronic means.	Entering PII into an LLM platform would violate IDEA and FERPA, as it is an open platform and constitutes an electronic exchange.
Requirement of Consent	Parental consent must be obtained to disclose any PII (other than participating agencies).	Parental consent must be obtained to disclose any PII, except in the cases of disclosing to school officials, another school system to enroll a student, appropriate parties for financial aid, authorized representatives, state and local authorities	The disclosure of any PII within an LLM platform would violate the requirement of parent consent and does not meet the criteria for FERPA.

		pursuant to the juvenile justice system, organizations conducting studies on behalf of the educational agency, accrediting organizations, judicial order/subpoena, health or safety emergency, or directory information (in which the parent is eligible to opt-out).	
Access Rights	Parents have the right to inspect and review education records collected, maintained, or used by the educational agency and to request copies of the information, including early intervention records.	Parents have the right to inspect and review education records collected, maintained, or used by the educational agency and to request copies of the information. The agency may not destroy any records while an outstanding request is pending.	Entering educational records into an LLM platform violates IDEA and FERPA. This includes—but is not limited to—student transcripts, schedules, health records, and behavior records (U.S. Department of Education, n.d. -b).

Note. Adapted from *IDEA and FERPA Crosswalk: A Side-by-Side Comparison of the Privacy Provisions Under Parts B and C of the IDEA and FERPA*, by K. S. Surprenant and F. Miller, 2022, U.S. Department of Education.

This reinforces the necessity of ongoing training and learning opportunities, as well as the active and intentional exercise of professional judgment.

Educator Training and Professional Judgment. As generative AI tools become deeply embedded in education, establishing structured professional learning pathways for educators has become an urgent priority. Developing AI literacy, or the “ability to understand the nature, opportunities, and challenges of AI technologies, to use and create with them wisely, effectively, safely, and responsibly, with respect for the rights and values of others,” (MacCallum et al., 2026, p. 2), will be critical in ensuring that AI is used responsibly and within the legal bounds of special education. Without proper training and development, IEP teams may inadvertently subject themselves and/or their students and families to violations of IDEA and FERPA regulations. Providing educators with professional learning opportunities, such as workshops that offer hands-on, authentic learning experiences with different GenAI platforms, will increase their competence, familiarity, and understanding of the benefits and challenges of these tools, as well as how to use

them appropriately (Ajlouni et al., 2025). These opportunities should also be structured to ensure educators can critically evaluate and defend their choices to accept, reject, or adapt AI-generated content (Larson & Morgan, 2026).

The importance of keeping human knowledge and judgment at the core of using artificial intelligence cannot be overstated. This needs to be a continuous part of the conversations surrounding GenAI so the knowledge and voices of educators (and students) are not overshadowed by technology. Maintaining a human-centered approach when using AI tools ensures that humans remain in control and are held accountable (UNESCO, 2024). While these GenAI platforms can quickly generate information, questions, suggestions, and feedback, they do not possess the ability to think as humans do. For example, if a teacher enters a prompt into GenAI for an IEP goal suggestion, the teacher needs to remain the ultimate decision-maker regarding the value, quality, and relevance of the suggestion and to critically evaluate the output. They need to ask themselves questions such as: Is this goal in alignment with my student's assessment results? Does this goal meet the student's needs? Does this goal provide the student with access to the general education curriculum? Is this attainable? Only the educator can answer these questions, not AI.

The WISE AI Literacy Framework (Vontz et al., 2026) exemplifies a human-centered approach to AI in education. Within this framework, human knowledge, judgment, and practical wisdom are at the core of AI literacy. The framework focuses on four human-centered areas: wisdom (practical wisdom), informed (understanding, critiquing, and applying knowledge), safe (ensuring student privacy, clear expectations, and academic integrity), and ethical (fairness, bias, transparency, and accountability) (Vontz et al., 2026). By grounding GenAI in this manner, educators preserve the essential expertise they bring to their students while leveraging technology to overcome barriers and better meet their students' needs.

Conclusion

The introduction of GenAI in education has the potential to change special educator teacher practices to better support student learning and administrative demands. As GenAI continues to shape teaching practices, special education must be thoughtfully and intentionally integrated into the conversation to ensure that students with disabilities are included. For example, the Ohio State Department of Education and Workforce has issued guidelines on the use of GenAI in their IEP writing process, such as generating initial drafts to reduce administrative tasks, summarizing multiple pieces of information for a cohesive PLAAFP, goal writing, and generating ideas for instruction (Ohio Department of Education and Workforce, 2025). GenAI can also serve as a tool to provide classroom paraprofessionals with outlines of IEP goals for small-group instruction and to quickly summarize progress for parents or guardians (Morgan & Larson, 2026). However, it is essential that educators remain the ultimate decision-makers. Although this model has not been used in research, it offers a practical example of how IEP teams can use GenAI to support student learning and administrative demands. Educators continue to require professional learning opportunities to become more proficient in using GenAI tools (Castro et al., 2025). Future research is needed to examine the effectiveness, accuracy, and usability of such workflows in authentic special education settings.

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