





Charting a Course

Navigating to High Quality Learning Options

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Overview

A cross the country, many familiesⁱ are looking for greater personalization in their child's K-12 education. At the same time, innovative learning providers are creating a new ecosystem of flexible **learning options**. These learning options include any experience — whether provided by a school, community-based organization, local business, college or university, or online operator — designed to support the growth and development of children. Yet whether families want options that supplement a student's education or replace a traditional school experience, many face barriers to access.

Cost is a significant barrier for many families. To help, state legislators are using **direct funding policies** to create programs such as education savings accounts (ESAs), microgrants, or tax credits or deductions. These **direct funding programs** defray the costs of participation by giving families amounts ranging from \$500 to \$10,000 (or more) to spend on learning options. Even with these policies in place, however, families often have limited awareness of the opportunities that exist and need help navigating what is often a complex and confusing ecosystem.

Many turn to **navigation organizations**, which provide information and guidance for families. Navigation organizations typically include teams of **navigators** who build relationships with families to help them access learning options and direct funding programs to meet their child's needs. Several technology platforms have also emerged to aggregate information about learning options. These platforms provide families and navigators with centralized, searchable resources, and in some cases, they also allow families to receive and spend public funds.

Navigation organizations may not be able to keep pace with the demand for their services. Complex direct funding policies, a lack of information about learning options, and a resource-intensive service model all hinder their efforts to serve more families. Yet as direct funding programs grow and families' interest in personalized learning expands, navigation will increasingly be necessary to help families access the full potential of an expansive learning ecosystem. Meanwhile, new tools powered by artificial intelligence (AI) have the potential to advance navigators' efficiency, sustainability, and scale.

To better understand the challenges and opportunities ahead, the authors reviewed past research on navigation solutions; interviewed more than 30 experts in navigation, policy, and technology; and collected insights from Bellwether's work on the Filling the Gap and Assembly grant programs.^{II} <u>Charting a Course</u> is a series that unpacks the need for navigation services, details the challenges that limit their impact, and offers some solutions for how navigation organizations, policymakers, funders, and technology platforms can address these challenges to support more families and students.



i In this series, the term "family" refers to family or community members taking responsibility for the education and future of a child, including grandparents, foster parents, legal guardians, and other family members. Students are also included in this definition since they participate in educational decision-making, especially as they get older.

ii Because the focus on educational navigators is nascent, these analyses and recommendations should be interpreted as a synthesis of this research rather than as a definitive or comprehensive analysis of educational navigation services. For more, see <u>Charting a Course</u>: <u>Increasing Access to Learning Options Through Navigation</u> (Methodology).

Introduction

A key part of navigation is ensuring that families not only access learning options but also access learning options that are high quality. The question of how to define and assess the quality of a learning option doesn't have a clear or consistent answer, however.

Defining and assessing quality depends on more than the growth and proficiency rates commonly used to compare the quality of traditional K-12 schools. These measures are incomplete reflections of school quality and even less well-suited for comparing the quality of an increasingly diverse array of learning options. Tutoring programs, for instance, in which students participate for varying lengths of time and intensity, would be difficult to assess and compare with the same set of metrics. New ways to assess quality are needed.

Quality may also depend on students' needs and families' priorities. The same art program could be considered "high quality" for a student who is learning how to express themselves but not "high quality" for a peer who is developing a portfolio to apply for art school. Families also have different priorities, with some looking for learning options that provide a student with the opportunity to participate in advanced coursework, and others looking for options that provide culturally relevant instruction or build a student's sense of agency in their own learning.

The challenge of defining and measuring the quality of learning options has led to a general lack of data. In lieu of data, navigation organizations do their own research, collect word-of-mouth recommendations, and cultivate relationships with provider staff to understand what a provider is offering and how "good" it is. The work is time-consuming and still leaves gaps in navigators' knowledge. If others (e.g., technology platforms, intermediaries, state agencies) did more to collect data on a variety of quality indicators that could inform families' decisions, navigators could rededicate their resources to understanding families' needs and guiding them toward aligned options.

Of course, collecting, analyzing, and publishing data on a variety of quality indicators for a multitude of learning options is a very tall order. But there are steps that policymakers, funders, technology platforms, and intermediaries can take in this direction. Policymakers can help by incentivizing more data collection and encouraging transparency. Funders can invest in partnerships among researchers and providers to create innovative ways to measure impact. Technology platforms can do more to aggregate data into usable tools and formats. Intermediaries can create systems for providing third-party quality ratings. Together, these steps would provide powerful tools for navigation organizations. Adding generative AI into the mix could further extend the impact of the data and how navigators use it to guide families in their decisions.

Navigation organizations lack access to information on learning options and must often collect it themselves

Several challenges contribute to the lack of information available on the quality of learning options, beginning with the lack of consensus regarding what constitutes a "quality" education. The diversity of learning options that eschew common measures, the limitations of using measures of family satisfaction as a proxy for quality, and the limited role of the state in assessing provider quality also contribute to significant gaps in the information available.

There is a lack of consensus on what constitutes a high-quality education. Many

Americans believe K-12 education should focus on a range of areas, such as math and English language arts (ELA) proficiency, social-emotional development, higher-order thinking skills, civic engagement, the arts and literature, college and career readiness, and many others.¹ Families' perspectives (let alone those of policymakers or system leaders) are far from monolithic, and each individual perspective on the goals of K-12 education suggests different measures of quality.

Interviewees also noted that "quality" can be subjective to a family's context and needs. As one navigator described, "Some parents' perception of quality is just whether or not their kid likes it and is engaged, whereas other parents need specific requirements to fit their child's situation, such as a math tutor who specializes in high-level math to meet specific high school graduation requirements."² In Arizona, NavigatEd's Founding Executive Director Kaitlin Harrier has found that, "There are parents who really value what that statewide assessment result looks like, and there are other parents who don't see value in that."³ Other aspects of quality might be meaningful to family members and students but ultimately hard to measure, such as cultural relevance. Billy Mawhiney, executive director of the South Dakota Afterschool Network, noted that sometimes providers create quality learning opportunities just by being a safe haven for students, especially if there aren't many other places for students to go.4

Perspectives on quality can also change over time. In an annual survey conducted by the Massachusetts-based think tank Populace, individuals stated their preferences (and what they perceive society's preference to be) on 57 distinct priorities for K-12 education. A comparison of the 2019 and 2022 surveys shows that only four priorities were in the Top 10 in both years: developing practical skills, thinking critically, demonstrating strong character, and choosing courses of study based on interests and aspirations.⁵ In 2022, new priorities for K-12 education had emerged, including students receiving unique supports for their learning needs and advancing only based on subject mastery.⁶ What families value in their child's education isn't monolithic — nor is it static.

The two decades since the No Child Left Behind Act (NCLB) provide another illustration of the variety of changing perspectives on the goals of education and how to measure progress. In 2002, NCLB put a stake in the ground in measuring school quality in terms of student growth and proficiency rates in math and ELA. Partially in response to criticisms that these measures were insufficient, the Every Student Succeeds Act (ESSA) of 2015 expanded the indicators that states must use to include English learner proficiency, graduation rates, and at least one other indicator of school quality.⁷ One analysis of 17 state ESSA plans found that states employed nearly 40 school quality indicators, showing that the debate on what constitutes school quality continues and isn't going away anytime soon.8 Recent calls to focus on students' social-emotional well-being, for instance, demonstrate priorities that families and other stakeholders want schools to support but aren't captured in measures of academic outcomes.⁹



The diversity of learning options compounds the challenge of defining or measuring quality. The debates over measures of school quality in NCLB and ESSA demonstrate the complexity of defining and assessing quality at the school level. But assessing school quality is relatively straightforward compared with defining and assessing quality across the wide range of learning options that have emerged and expanded in recent years.

Learning options vary greatly, from the frequency and length of time that students participate, to whether the experience is virtual or in-person, to the learning options' intended impact. **These factors all make measuring and comparing quality difficult**. For example, a tutoring program may focus on a specific subject over a limited duration (e.g., algebra tutoring one day a week for 12 weeks), whereas an after-school program might occur weekly for an entire year and focus on softer skills, like communication. Measuring the quality of just these two examples (among hundreds of others) will look vastly different, and comparing the two would be comparing apples to oranges.

Various measurement approaches can be used to assess the quality of different learning options, such as traditional student assessments (e.g., standardized, performance-based, or portfolios of student work), surveys of student and family experiences, and formal evaluations of individual programs. **All come with trade-offs**. The more tailored the approach to measurement, the more resource-intensive it is. And the variety of approaches makes comparisons difficult, if not impossible.

Family satisfaction ratings and word-ofmouth recommendations are potential, but flawed, proxies for the quality of

learning options. In lieu of clear definitions or measures of the quality of learning options, some organizations have sought to better understand program quality by relying on measures of family satisfaction, such as word-of-mouth recommendations. One navigator pointed out that education "will always be a social endeavor" and found that parental recommendations held more sway with the families they served than catalogs of resources did.¹⁰ Another navigator reported an explicit preference for providers that are frequently used by other families they serve, since they know those families have had good experiences.¹¹

Others have created systems that collect and communicate ratings. GreatSchools is perhaps the most well-known example. On its website, families can provide and access school ratings on a scale of one to five stars on a variety of factors, such as learning, family engagement, and safety.¹² Elliot Beaudoin, chief product officer for GreatSchools, noted that parent recommendations are more likely to reflect regional preferences and may therefore be better tailored for families than other resources lacking the same community context.¹³

Parent ratings and recommendations aren't a perfect solution, however. Research shows that people are typically motivated to rate something only when they have a particularly good or bad experience.¹⁴ One interviewee questioned whether user ratings and recommendations accurately reflect whether a provider is effective and using evidence-based strategies.¹⁵ Others pointed out that customer ratings may reflect cultural biases and that some communities are more engaged in making recommendations than others.¹⁶ For all these reasons, using family satisfaction to measure provider quality is imperfect and incomplete.

Some platforms are leaning away from customer ratings because, as one administrator put it, "in the education space, ratings seem to always be negative, and I don't know that that's fair when it's all very personal."¹⁷ Another navigation organization collects parent recommendations but keeps them internal to mitigate the potential for bias or undue influence from outliers.¹⁸ This increases their confidence in the integrity of their recommendations but requires greater capacity from staff to collect, review, and analyze the data.

While states implementing direct funding programs evaluate learning options, they focus mostly on student safety and provider eligibility, not

quality. Perhaps due to the complexity of and lack of consensus on what constitutes quality, direct funding programs largely steer clear of provider quality and instead focus on provider *eligibility*. Programs' authorizing statutes typically charge administrators with ensuring that approved providers complete background checks and provide assurance of basic safety measures, and that the services families purchase from them are included within the law's definition of eligible expenditures. Program administrators execute these requirements, reviewing purchases or conducting audits to prevent fraud and protect taxpayer dollars, but they stop short of collecting or analyzing information about whether a provider offers high-quality services.

Some program administrators, navigators, and advocates don't think it's the state's responsibility to vet provider quality; since every family has a different perspective on quality, it isn't within the state's purview to interfere in that vision. For these advocates, direct funding policies work best when they trust family members to make decisions with the least amount of state influence possible. Others worry that state involvement might bias how navigators present options to families: As one interviewee summarized, "When the state gets over-involved in [vetting providers] ... you lose the true spirit of what the navigator is supposed to be doing, which is providing unbiased information about every possibility, whether it's state-funded or not."19 In essence, navigators might focus on the elements of quality that the state has assessed (e.g., whether a tutor is a certified educator) but undervalue the elements of quality important to a particular family (e.g., whether a tutor can serve as a role model for a student from a similar background). Finally, state administrators have limited administrative funding²⁰ and may lack the capacity to vet provider quality given their many other responsibilities.

In lieu of data on learning options, navigation organizations often do their

own research. In a system without adequate data, navigators must independently develop familiarity with provider landscapes. If a navigator isn't already familiar with a learning option, they must do their own research. For instance, over several months, NavigatEd Arizona developed an inventory of learning options formatted in a spreadsheet. It includes information on learning options such as geography and grade levels served, as well as the degree of flexibility in programming and the "kind of anecdotal description that could serve as a school's 'elevator pitch' to parents."21 This level of detail might not be easily accessible for families otherwise, but it's critical to determining whether something is the right fit for a family. Constant change, however, makes it challenging for navigators to keep information updated. Programs open or close, points of contact turn over, and websites go out of date. Some navigation organizations, such as Boston After School & Beyond, have dedicated personnel who are continuously in touch with programs to update their information.²²

Even in states with direct funding programs, where administrators have compiled a list of approved providers, **navigators struggle to grasp the entire landscape**. For Virginia's Learning Acceleration Grant program, the list of approved tutors was a "3,000-row Google Sheet."²³ Outbridge navigators eventually developed a searchable website based on the list, which required extra time and resources.²⁴ Similarly, Colorado's list of training providers for the state's Path4ward program was "huge" and "a hard list to navigate," requiring navigators to spend precious time combing through the various options.²⁵

Technology platforms provide helpful information but are still limited. In Texas and Arizona, navigation organizations partner with GreatSchools and Schoolahoop to embed tools on their websites that help families find schools in their area.²⁶ Platforms such as Schoolahoop, GreatSchools, MySchoolOptions, and others provide information on school options, while regional third parties like Boston After School & Beyond and South Dakota Afterschool Network host databases of other learning providers. These online platforms must collect data on available options through public databases, private school associations, web-scraping technology, or provider-reported data. Yet similar to the challenges faced by navigation organizations, providers aren't always fastidious about keeping their websites or profiles on platforms up to date. The information isn't always complete or accurate and requires extra time to verify.²⁷ In addition, many platforms are just in the beginning stages of including a broader array of learning options beyond specific types of programs or schools of choice.²⁸



As these platforms continue to develop, they have the potential to be powerful tools for navigators, allowing them to spend less time finding and verifying provider data themselves. In the meantime, **navigators must rely on "folk knowledge"** that's hard-earned through outreach, research, and cultivation of relationships.²⁹

Navigation organizations must provide families with guidance on options that best match students' needs

Families "desire tailor-made experiences reflective of their child's interests and needs ... [and have a] pronounced belief in student-centric experiences: learning that adapts to their child's interests, preferred schedule, and personal needs."³⁰ Navigation organizations, therefore, have an essential role not only in understanding what options are available and how good they are, but also in helping families understand the options that align with their child's needs, interests, and goals. As summarized by Tyton Partners, "Parents crave two types of knowledge: 1) information on their child's specific learning needs and, 2) educational programs available to meet these needs."³¹ The process of matching families to learning options is multifaceted. Navigators get to know a family's logistical capacity (e.g., budget, location, transportation availability, and/or schedule) to understand what options are feasible. They help families understand students' performance and goals, including helping families understand student test scores or report cards.³² **They discuss students' needs and families' preferences**, such as curricular model, cultural relevance, and type of programming.³³ And they search among the provider landscape for the possibilities that best match what a student and their family needs.

In subsequent conversations, **the navigator and family might refine the list of possible providers**, with navigators potentially handling provider outreach to ask questions on behalf of a family. Once a provider is chosen, the navigator may also guide a family through the enrollment process and continue to provide personalized support as new educational needs arise.

As one navigator said, "Navigation isn't just, 'I'm pointing you in this direction.' It's also understanding the fit for a student and being able to unpack, assess, and evaluate the student's strengths and where the student is going to thrive."³⁴ This process of matching families and learning options can vary in degrees of complexity according to the level of personalization a family needs. For example, navigating the transition to high school or finding a specialized tutoring provider may require a higher degree of personalization than finding a summer camp.³⁵

As students grow older, navigators must also balance the relationship between students and parents, all while being careful to stay as impartial as possible. Navigators may engage directly with older students to discuss their goals and aspirations, cultivating their sense of agency while supporting them on their journey to adulthood. For instance, high school students who are considering learning options in the career pathways space can benefit from a navigator's guidance about the programs or public funding available, but navigators may need to tread carefully if students and their parents have different ideas about what their future plans should include.³⁶ Navigators must be able to put aside their own instincts and center both the

Student Success Agency (SSA)

SSA, a national nonprofit that works with schools and districts to digitally connect students to services like tutoring, mental health support, and career advising, centers the voices and perspectives of students.

Justin Cyrus, head of agent success at SSA, recalled a navigator who was initially taken aback by a student in Las Vegas who had ambitions to be a janitor. Rather than dissuading or dismissing the student, the navigator realized that "it wasn't their job to make the student feel inadequate for what he wanted."³⁷

Instead, the navigator worked with the student and his family to understand how janitorial service was part of the student's broader interest in hospitality and could lead to career pathways in nearby resorts in the greater Las Vegas metro region.



family and student's best interests without making the final decision for them — an intensely personal process that requires building a strong relationship with both the family members and students involved.³⁸

Without valid and reliable provider data, this matching process is much harder and forces navigators to rely on their own research, relationships, and experience to help families — hard-won but imperfect resources.

Relying on personal experiences and relationships also raises concerns about equity. If navigators have uneven access to information about high-quality options, the families they serve will, in turn, lack awareness of and access to those options. Additionally, navigators who are stretched thin may inadvertently provide guidance that isn't well-tailored to the individual student. Research has shown that rushing, fatigue, and distraction can increase the risk of implicit bias affecting judgments and decisions.³⁹ As navigators' workload becomes unsustainable, they may fall into behavior patterns or read into assumptions that don't actually serve students' best interests.

Funders, intermediaries, researchers, and policymakers can help increase the information available

There are numerous ways in which sector leaders T can 1) support the creation of quality measures that can capture more information about a wider variety of learning providers and 2) enable the collection of data that navigators need to support families.

One approach is accreditation, which funders could accelerate by investing in third parties or intermediary organizations to develop provider certifications. Third-party certifications or endorsements of a provider can give navigators' recommendations credibility and help families understand why a provider was recommended.⁴⁰ For example, every educator who wants to teach an Advanced Placement (AP) course must receive authorization from the College Board (Disclosure). The AP Course Audit requires educators to submit syllabi and other course materials aligned with College Board curricular requirements for each course.⁴¹ Administered via the third-party company Inflexion, the AP Course Audit results in a vast database that enables postsecondary institutions to verify student transcripts and allows researchers to conduct studies on topics such as school accountability incentives.42 Accreditation systems like the AP Course Audit typically operate on program inputs rather than outcomes because they are easier to implement in the short term, but they could also serve as the foundation for future outcomes-based analyses.

The increasing variety of learning options necessitates new measurement approaches that are valid, reliable, and fair.^{III} A longer-term solution could be **investing in partnerships between providers and researchers to create new measures of program quality that include outcomes-based metrics**. Providers are inherently incentivized to capture and market their



iii Measures of quality are valid if they accurately measure the outcomes they aim for (e.g., algebra skills, coding ability, behavioral regulation). Measures are reliable if they are consistently accurate and fair if they are free from biases that disadvantage any group or individual. value, but self-reported outcome data can lack credibility, and many providers don't have the capacity or budget to self-evaluate, analyze, and report outcome data on a continual basis. An external research partner can work with providers to design analyses that independently verify program outcomes and provide data to inform a provider's continuous improvement. These processes are expensive to implement and require specialized expertise, but funding partnerships among researchers and providers could lead to high-quality measures that other providers can use and adopt to measure their own work. As more partnerships are formed and more research is done, they could collectively surface a variety of measurement approaches that are capable of capturing quality metrics for diverse learning providers.

Ideally, these partnerships lead to a repository of shared quality measures, associated measurement tools, and publicly reported data. Shared tools and infrastructure could scale the development and application of innovative quality approaches faster, helping more providers capture their effectiveness. An example of a similar system is the Johns Hopkins Institute for Education Policy's School Culture 360[™] Survey. The survey is designed for use in "all types of schools," and the institute has used the data to build dashboards and analyses for school leaders.⁴³ In the after-school sector, Boston After School & Beyond has created an exportable suite of tools and infrastructure for data collection and analysis.⁴⁴ Adapting these models to create a repository of data across providers would increase transparency for families and navigators by making key metrics publicly available and accessible.

Policymakers could also **leverage this repository and encourage data collection in different ways**. In states where policymakers want a greater role in determining provider quality, they could require data collection. For example, in Massachusetts, after-school providers must report outcome data using a common measurement tool to receive state funding. Not only does this requirement incentivize providers to collect and report comparable data, but it also allows navigators or another third party to easily collect the reported data and use it to help families make decisions. In states where policymakers are less inclined to be the arbiter of provider quality, they could stop short of requiring data collection but create an opportunity for providers to include "badges" indicating third-party certifications or their impact on particular outcomes within state-created or state-facilitated databases. As more quality measures and measurement tools become available, policymakers can combine incentives for providers with a variety of measurement options that align with the diversity of providers' offerings.

Ultimately, having better access to more data on provider quality helps navigators, broadens access to high-quality options, and showcases the value of both individual providers and the ability to customize education.

Generative AI could help navigators curate options to share with families

G enerative AI has improved considerably over the last few years, driven by breakthroughs in large language models (LLMs) like OpenAI's ChatGPT (Sidebar). Within navigation, there is a growing consensus that generative AI can support navigators by reducing the burden of researching provider data and accelerating the process of curating options and matching families with providers. To reach this state, however, there are also several challenges to overcome, including the same lack of valid data on providers and provider quality that navigators currently face.

Generative AI models can drastically reduce the research burden on navigators, allowing them to focus on building relationships with families. One

of generative AI's unique strengths is its ability to take enormous amounts of unstructured data from disparate sources and turn it into something cohesive and easy to comprehend, like a set of recommended learning providers that fit a family's unique needs and preferences. To that end, generative AI is wellpositioned to drive the collection, analysis, curation, and matching of provider and family data. In essence, an AI model could become a navigator's superpowered assistant.

In this vision, navigators could give the AI model a family's profile, a description of what they are looking for, and other parameters such as budget or location. The AI model might even be able to reference which metrics or characteristics would make a provider "high quality" to a family and use the combined information to generate a list of five to 10 suggested providers that fit the requested parameters. A navigator could then take that list, review it for potential errors, and refine it to three to five prioritized options based on what they know of a family. Instead of doing hours of research and calling providers for information, the navigator almost immediately has a list of options they can share with a family.

The navigator can then focus on their

relational role in reviewing options with families and discussing additional context or considerations. This conversation might surface new preferences a family might not have initially articulated or spark ideas for other ways to customize the student's education. Even if the initial list doesn't immediately lead to enrollment with a provider, the recommended content could facilitate greater dialogue between the navigator and family, accelerating their ability to build trust and rapport.

Generative AI addresses the resource-intensive tasks and provides the initial "intelligence," while the navigator can focus on building trust and connection for greater customization.⁴⁵ With this model, generative AI might even expand a family's options beyond what a navigator alone might have suggested, as the curating algorithm can both access more information faster and maintain a neutral perspective more efficiently than a human.

Sidebar: What is Generative AI?

AI is an umbrella term for computer systems that "demonstrate human-like intelligence and cognitive abilities, such as deduction, pattern recognition, and the interpretation of complex data."⁴⁶ The term can also refer to the entire field of studying and building these systems.

To better understand how AI works, it may be helpful to understand some of the developments and processes that make AI possible.

Algorithms can be thought of as the "building blocks" of Al.⁴⁷ An algorithm simply describes a process, or "a set of instructions that end up in a desired conclusion."⁴⁸ Algorithms can be as simple as "if-then" statements but can also get infinitely complex as multiple algorithms build on one another to take in and put out increasing amounts of information.

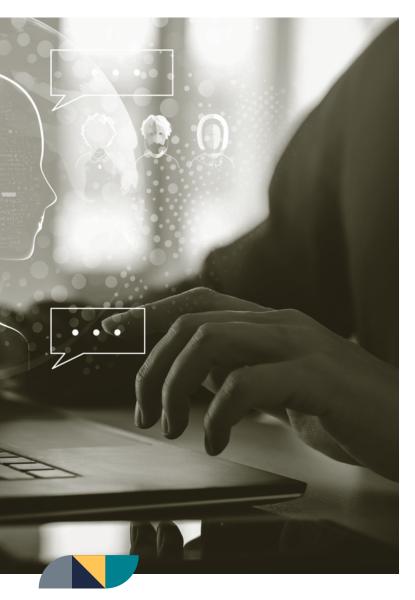
Machine learning describes "the intersection of computer science and statistics" where computers use algorithms to perform tasks "without being explicitly programmed."⁴⁹ Algorithms are used to recognize patterns and turn those into descriptions of data, predictions based on data, and/or prescriptions of what actions to take next.⁵⁰ Machine learning allows AI models to "teach themselves" and refine their outputs toward greater accuracy and relevance.

Deep learning is an evolution of machine learning where the algorithms are structured and layered in a way "similar to how a human would draw conclusions," creating an "artificial neural network."⁵¹ The layers of machine learning algorithms act as feedback loops so that the network can "capture highly complex relationships" among large amounts of unstructured data.⁵² An artificial neural network can constantly refine itself, requiring little human intervention.⁵³

Generative AI models build on algorithms, machine learning, and deep learning to create entirely new content. These models use families of artificial neural networks in combination with techniques like natural language processing (which allows computers to process human language) and LLMs (which allow computers to respond in human language).⁵⁴ The result is a system that can generate new data in the form of "audio, code, images, text, simulations, and video."⁵⁵

Unfortunately, several constraints and risks prevent this vision of generative AI from being realized right now. The largest

constraint is the lack of provider data: A generative AI model is only as good as the data provided.⁵⁶ If an AI model is being asked to reference a set of providers and glean the relevant information necessary for curation, the provider data being referenced must be comprehensive, updated, and accurate. Yet, as discussed earlier, data sources on learning providers often don't exist or, if they do, have outdated, unreliable, or incomplete data. Until this problem is addressed, the lack of comprehensive, reliable data will make using an AI model to help curate options harder and riskier for navigators and families alike.



Another constraint is capacity and expense. While generative AI models are inherently self-iterating and learn quickly, building and training such a model requires specialized talent and a lot of money. Jared Chung, whose online platform CareerVillage.org recently launched an AI career coach, noted that "the way you have to make these applications these days is deeply layered, and you have to use multiple large language models. So, this is not just a wrapper on OpenAl's ChatGPT ... you have to make sure that you're using the right model for the right step, and you can't rely upon any single model for that."57 These technical intricacies can create nontraditional cost structures that make building and using generative AI models expensive.⁵⁸ An application that uses an existing model like ChatGPT would be less expensive; however, buying licenses and chat interactions, in addition to building the application, can also get pricey.⁵⁹

Creating an Al-powered navigation assistant would also require training both the AI model and the navigators using it. On the human side, some navigators might be uncomfortable or unfamiliar with using such new technology, so AI literacy would need to be a key component of managing the implementation of a new system.⁶⁰ Training navigators on how to prompt an AI model would also make the process more efficient, as well-crafted prompts create better results.⁶¹ On the machine side, there must be monitoring and guardrails constraining the model's response. For example, maybe the model should never choose a single learning option for a family; it should always try to generate a list of options unless impossible. Or perhaps the model should always alert a navigator when a suggested provider has missing information or flag a search chat if there's not enough information in a family profile to create a truly personalized list of suggestions. Creating these guardrails will require time and user testing, adding to the upfront capacity and expense needs.

Training the AI model on reliable data, creating guardrails, and doing extensive user testing are also key strategies **to mitigate the risk of the AI model making errors**, whether the errors are as small as listing the wrong phone number to as large as perpetuating societal inequities. Generative AI uses pattern recognition to understand data and create outputs based on those patterns. As a result, if the existing data contains inequitable patterns or stereotypes, a machine based on those patterns is vulnerable to replicating the same inequities.⁶² Past examples of this include skewed facial recognition technology, criminal justice algorithms, and recruitment tools, which have resulted in discrimination against women and Black individuals.⁶³

With navigation, **seemingly innocuous patterns might inadvertently limit or influence a family's choices**.

For example, if an AI model notices that many Asian American families are interested in STEM tutoring for their children, the model may assume — whether it's in a family's profile or not — that all Asian American families need a STEM tutor on their suggested provider list. This would defeat the purpose of an education customized to individual learners' needs, interests, and goals. Generative AI adds another layer of risk because the output creation isn't a structured "if-then" process; in fact, the output creation has been called a "black box."⁶⁴ As a result, generative AI models can "hallucinate," or come up with new information that is entirely false, even when the data being referenced is verified or reliable.⁶⁵

Threaded throughout these constraints are also **concerns regarding data privacy**. While interviewees' responses were mixed on whether data privacy laws would prevent the development of an AI-powered navigation assistant, there is little doubt that developers will have to ensure that families' data and profiles are protected from misuse. Compliance with data privacy policies, as well as having comprehensive data, guardrails, and user testing, are all critical steps to ensure that generative AI does no harm in working for the navigators and families it's meant to serve.

Conclusion

T he lack of valid and reliable data about learning providers too often hinders navigators. They do the best with what they have — their research, experiences, and relationships — but it takes time and effort away from the relational work of navigators in understanding families' needs, building trusting relationships, and guiding them in their educational decisions.

More and better data on learning options is necessary, and there are ways that funders, intermediaries, researchers, and policymakers can help. Accreditation systems and input metrics can build the foundation for more robust measures. Tailored approaches to measure the quality of providers could surface new, valid, and reliable measures for others to adopt. Over time, improvements to data would allow navigators, families, and the field to better understand the learning options that best support students' success.

With more provider data at their fingertips, navigators might be able to find more opportunities for students or discuss them more in-depth with families. With the power of generative AI at their fingertips, navigators could also serve more families in less time and spend more time helping students and families find the learning options that fit them best.

Ultimately, increasing the amount of comprehensive, accurate provider data will allow more families to engage in the ecosystem of learning options and tailor unique, personalized learning experiences for their students.

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Beta by Bellwether is an initiative to jump-start bold solutions to structural problems in the education sector. Beta moves beyond imagining a new sector by bringing together viewpoint- and experience-diverse teams from across education to create blueprints and tools for leaders around the United States. Our goal is to help build an education system that better serves all young people — particularly those from systemically marginalized communities — and models a new way forward for the sector. For more, visit **bellwether.org/beta**.

Bellwether

Bellwether is a national nonprofit that exists to transform education to ensure systemically marginalized young people achieve outcomes that lead to fulfilling lives and flourishing communities. Founded in 2010, we work hand in hand with education leaders and organizations to accelerate their impact, inform and influence policy and program design, and share what we learn along the way. For more, visit **bellwether.org**.

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Disclosure

Bellwether works with organizations and leaders who share our viewpoint-diverse commitment to improving education and advancing equity for all young people regardless of identity, circumstance, or background. As part of our commitment to transparency, a list of Bellwether clients and funders since our founding in 2010 is publicly available on our website. An organization's name appearing on our list of clients and funders does not imply any endorsement of or by Bellwether.



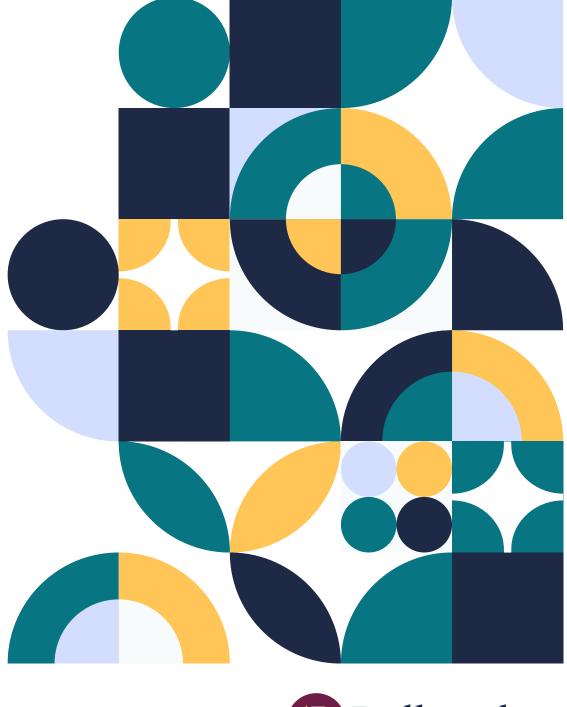
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