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DISCUSSION AND REVIEW PAPER

The Promises and Possibilities of Artificial Intelligence in the Delivery of Behavior Analytic Services

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Abstract

Artificial intelligence (AI) has begun to affect nearly every aspect of our daily lives and nearly every industry and profession. Many readers of this journal likely work in one or more areas of behavioral health. For readers who work in behavioral health and who are interested in AI, the purpose of this article is to highlight the pervasiveness of AI research being conducted around many facets of behavioral health service delivery. To do this, we first provide a brief overview of some of the areas within AI and the types of problems each area of AI attempts to solve. We then outline the prototypical client journey in behavioral healthcare beginning with diagnosis/assessment and ending with intervention withdrawal or ongoing monitoring. Next, for each stage in the client journey, we highlight several areas that parallel existing behavior analytic practice where researchers have begun to use AI, often to improve the efficiency of service delivery or to learn new things that improve the effectiveness of behavioral health services. Finally, for those whose appetite has been whet for getting involved with AI, we close by describing three roles they might consider trying out and that parallel the three main domains of behavior analysis. These three roles are an AI tool designer (akin to EAB), AI tool implementer (akin to ABA), or AI tool supporter (akin to practice).

Keywords Artificial intelligence · Behavioral health · Data science · Quality of life

Behavioral health is a term used to describe patterns of behaviors that have a known effect on the health and well-being of an individual. As a broad and general term, the behaviors targeted with a behavioral health intervention may span many areas of human behavior such as stress, depression, anxiety, interpersonal relationships, grief, addiction, learning disabilities, mood disorders, chronic disease management, diet, physical activity, and the use or misuse of substances (see Marsch et al., 2015, for a broad range of applications). Professionals working in the behavioral health realm may have education and training spanning many disciplines such as counseling, psychology, nursing, medicine, life coaching, and behavior analysis (Marsch et al., 2015). And, interventions may consist of a variety of methods and procedures such as behavioral therapy, counseling, and medication (Marsch et al., 2015).

As a profession, behavior analytic practitioners have worked and published in many areas and with many populations within the realm of "behavioral health." Arguably, the use of applied behavior analysis (ABA) for individuals with autism spectrum disorders (ASD) and developmental disabilities (DD) would fall within the above definition of behavioral health and is the most common area where board certified behavior analysts (BCBAs) work (Behavior Analyst Certification Board [BACB], n.d.). However, a smaller set of behavior analysts have also published and worked in areas spanning diet, physical activity, substance abuse and misuse, chronic disease management, and mental health (e.g., BACB, n.d.; Heward et al., 2022). Central to all areas of behavior analytic practice is the observation, measurement, and subsequent use of data collected on behavior-environment relations.

Behavior analysts working with individuals with ASD and DD have demonstrated how data collection on environment–behavior relations and the resulting functionally informed intervention for 20+ hr per week can lead

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to significant and socially important behavior change (e.g., Eldevik et al., 2009; Linstead et al., 2017). But, practitioners working in areas outside of ASD and DD are unlikely to get that same amount of direct 1:1 contact with their clients. Here, behavioral health practitioners may get 15–60 min with a client on a good week and, even then, those minutes are likely spent talking with one another rather than in direct observation and collection of data on behavior–environment relations. Thus, approaches to data collection, analysis, and functionally derived interventions practically have to look different than ABA interventions for individuals with ASD and DD.

One method whereby data collection, analysis, and intervention with behavioral health can more easily scale is through technology. For example, researchers have shown how technology allows practitioners and researchers to collect moment-by-moment data on the responses that people emit throughout their daily lives (e.g., Asch et al., 2012; Mehta et al., 2019). Further, researchers have also shown how technology can be used to collect data on the environment surrounding those responses at a similar moment-by-moment temporal scale (e.g., Bertz et al., 2018; Epstein et al., 2014; Kwan et al., 2018). As a result, behavioral health practitioners and researchers now have the ability to collect data on behavior–environment relations that span similar (or greater) proportions of time throughout the clients' day as ABA practitioners working with individuals with ASD or DD.

Using technology to collect data, however, requires that the researcher or practitioner can practically and efficiently access and analyze the data collected by that technology. Accessing and analyzing data collected by a technology is not always straightforward for a single technological device (e.g., FitBit, Apple Watch). As the number of data collection modalities increases, it becomes even more difficult to combine and display data in a single location so that the behavior analyst can analyze behavior–environment relations and effectively communicate with the client or patient. Further, large streams of data on many different variables requires the ability to sift through those variables, identify variables that are functionally related to behavior, sort out the probable degree of influence, and present the relations visually in a manner easily interpretable by the behavior analyst and client. One analytic approach increasingly being used by scientists to make sense of large datasets in this way is artificial intelligence (AI).

The purpose of this article is to provide examples for how AI is being used to help behavioral health practitioners and researchers better help their clients and patients. To do so, we begin with a high-level primer on some of the subdomains of AI. We then step through the prototypical patient journey from diagnosis through treatment and discharge. At each step, we provide examples of how researchers have introduced AI to help them better provide services for their clients. Here, it also seems helpful to discuss what this manuscript is not. First, this manuscript is not an in-depth overview of how AI works. Covering the nuts and bolts of the many different areas of AI discussed in this article would require a book long treatment. Second, this article does not provide a comprehensive review of all past research at each stage in the client journey because that likewise would require a book long treatment. Rather, we hope to show behavioral health scientists and practitioners how their peers currently use AI so they can learn how adding AI as a tool might improve the work they do. For the interested, we close by highlighting three broad roles behavioral health scientists and practitioners can take if they are interested in getting started with AI.

Relevant Areas of Artificial Intelligence

AI is a broad branch of computer science whose goal is often to create nonbiological systems that can mimic intelligent behavior, often the behavior of humans.[1] Whereas humans are decent at learning patterns in data that involve two and three dimensions (e.g., Vanderveldt et al., 2015), computers can learn patterns in data that involve hundreds or thousands of dimensions. Computers can also efficiently complete complex mathematical computations well beyond the average human's ability. This ability allows computers to efficiently analyze large, multidimensional datasets to identify patterns, detect relationships, and make predictions far beyond what humans are capable of.

Table 1 shows a high-level overview of some of the many subdomains that comprise AI and organized around the human ability they attempt to mimic (e.g., Ramesh, 2017). For example, many humans use their eyes to differentially respond to stimuli within their visual field. The branch of AI that creates systems that mimic this ability is called *computer vision*. Humans can also move through their environment without running into things and getting injured. The branch of AI that attempts to mimic this ability is called *robotics*. Robotics and computer vision have historically

[1] Like behavior analysis, artificial intelligence (AI) is comprised of a broad set of behaviors implemented by many different people and toward many different applications. Thus, no section in a single article is likely to fully encompass all methods, approaches, applications, and technical specifications required to fully define AI; especially considering that the definition of what counts as "intelligent" is currently debated. Compounding this complexity is that building and deploying AI systems is often highly interdisciplinary further making it difficult to comprehensively define the totality of what "counts as AI." Readers interested in diving more into the technical details are encouraged to read Müller and Guido (2016), Everitt et al. (2011), Goodfellow et al. (2016), and Sutton and Barto (1998).

Table 1 High-level overview of the subdomains of AI

Human Ability Attempting to Mimic	Subdomain of AI
Use eyes to differentially respond to stimuli	Computer Vision
Move around environment without running into things	Robotics
Emit and respond to vocal-verbal behavior	Speech Recognition
Read and write text; Behavior influenced by textual symbols	Natural Language Processing
Respond to symbolic representation of the world	Symbolic Learning
Emit responses based on learned relations among large sets of varied stimuli	Machine Learning
Emit response via networks of neurons firing	Deep Learning; Neural Networks

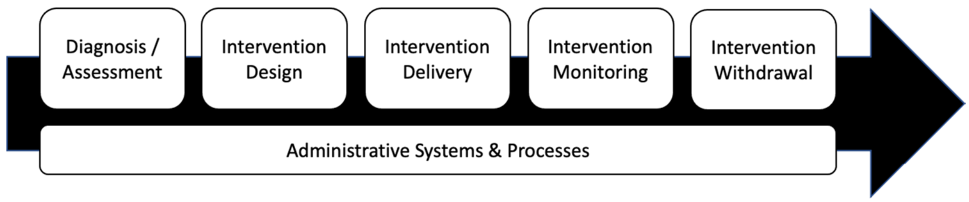

Fig. 1 High-level overview of the prototypical client journey in behavioral health

advanced by improving how these systems learn the shapes and features of objects in two- and three-dimensional arrays. This approach can be called *symbolic learning* because the computer systems are learning about the environment by encoding a symbolic representation of the environment with which it then interacts (although nonsymbolic approaches to robotics and computer vision also exist and, arguably, currently dominate this landscape).

Machine learning is an alternative approach to symbolic learning that teaches computer systems to mimic human behavior by learning associations in data (Table 1). In the supervised machine learning approach, researchers feed the computer system a lot of data and provide feedback following its predictions so that it learns spatial and temporal associations between the variables in the dataset. In the unsupervised machine learning approach, researchers feed the computer system a lot of data and then review the associations and groupings identified in the dataset. One popular way that machine learning is being used is with verbal behavior. For example, humans can emit and respond to vocal-verbal behavior. AI systems that focus on this area fall within the field of *speech recognition* and are present in many of the devices you likely have around your house (e.g., Amazon's Alexa) or carry in your pocket (e.g., Apple's Siri). Humans can also read and write text from a given language and those textual symbols can influence the behavior of the reader. The branch of AI that attempts to mimic this ability is called *natural language processing* (NLP). Finally, humans can engage in complex tasks involving response chains, problem solving, and sophisticated verbal relations. Though many traditional machine learning algorithms have been successful in this domain, recent advances in *deep learning* and *neural networks* allow computer systems to make complex conditional discriminations and to engage in complex chains of behavior well beyond the average human.

In sum, the areas of AI noted above and that are relevant below all attempt to identify patterns in datasets so that computer systems can mimic the behavior of humans. Many humans use their eyes to see and their body to subsequently move around their environment. Many humans are able to respond to the verbal behavior that contacts their senses through a variety of stimulus modalities. And, many humans are able to make sense of the plethora of current and past stimuli–environment–behavior relations to behave effectively within their daily lives. In what follows, we provide examples for how researchers and practitioners are leveraging computer vision, robotics, speech recognition, NLP, deep learning, and machine learning to improve the set of behaviors labeled within the broad area of behavioral health.

AI along the Patient Journey

Figure 1 provides a simplified overview of the prototypical client journey within behavioral health systems. To begin, an individual often has some inclination that something is not quite right with their overall health and well-being. The individual then has a conversation with a behavioral health professional (BHP) and that something might get a label (i.e., a diagnosis). The BHP likely conducts an assessment to determine exactly what is going on and potential areas that can be targeted for improvement. Using the assessment information along with client input, the BHP will likely design an intervention to improve those areas for the client and, once consent or assent is attained, deliver that intervention. For some period of time, that intervention is implemented, monitored,

Table 2 Overview of AI use cases relevant to behavioral health practitioners and the prototypical patient experience

Area	Use Case
Diagnosis & Assessment	Biological Conditions / Diseased Organs
	Clinically Significant Patterns of Behavior
	Improve Assessment Design/Implementation
	Predicting Low-Rate, High-Intensity Behavior
	Generating Diagnostic Reports
Intervention Design	Predicting Response-to-Intervention
	Efficient Use of Resources
	Patient-Provider Matching
Implement Intervention	Patient Engagement & Adherence
	Analysis of Intervention Effects / Response-to-Intervention
	Predict and Analyze Clinical Decision Making
	Analyzing Behavior During Sessions
Intervention Withdrawal & Monitoring	Automated Hovering, Ambient Intelligence
	Use Diagnosis & Assessment Tools to Predict or Prevent Relapse
Administrative Systems & Processes	Decision Aides via Research Literature Summarization
	Improving Patient Experience while Maintaining or Reducing Cost
	Staff Scheduling
	Performance Management for Practitioners

and modified based on the effect the intervention has on the client's overall health and well-being. For chronic conditions, this step may last indefinitely. For some, however, formal intervention within a client-practitioner relationship may come to an end and the intervention as monitored by the BHP is withdrawn. Lastly, wrapping around all steps within this chain, are a series of administrative systems and processes that may involve data collection, analysis, record updating and review, report writing, billing for services, and so on. In this second section, we provide several examples of how AI is touching every stage of the prototypical patient journey (see Table 2 for a summary).

AI to Improve Diagnosis and Assessment

Diagnosing Diseased Organs

As AI is used in healthcare right now, diagnosis and assessment are often interwoven. For example, the research that often grabs headlines involves using computer vision to analyze images and detect the presence or absence of diseased organs such as cancer (e.g., Erickson et al., 2017; Giger, 2018; Suzuki, 2017). This research often gets attention because the algorithms and resulting technologies repeatedly outperform medical experts in the diagnosis of diseased organs from medical images. It should be noted, however, that these are in proscribed instances of diagnosis. An AI tool that is great at identifying cancerous lung cells is unlikely to automatically be good at identifying cancerous heart cells, cancerous brain cells, or predicting pneumonia.

Diagnosing ASD

More directly in the behavioral health realm and specific to many practicing behavior analysts, researchers have begun to develop AI-based tools to diagnose ASD (e.g., Erden et al., 2021; Song et al., 2019). To reduce assessment time, machine learning has been used to identify which assessment questions are the greatest predictors of ASD (e.g., Choi et al., 2020; Kosmicki et al., 2015). In turn, shorter assessment durations may increase the rate at which assessments can be completed and increase overall access to care. Researchers have also evaluated the efficacy of machine learning to analyze motor movements that are indicators of ASD (e.g., Crippa et al., 2015). These two strategies have been combined in mobile apps that include an abbreviated assessment and video recording of the child (Abbas et al., 2020; Duda et al., 2016). Yet the most advanced use of AI in diagnosis can be seen in Autism AI (Shahamiri & Thabtah, 2020), a screening tool that uses deep learning algorithms that take data from users to inform predictions, as opposed to static algorithms based on assessment items.

Functional Assessment of Behavior

As another example relatable to many practicing behavior analysts, researchers have used wearable sensors and video cameras placed in heavily outfitted therapy rooms to collect data on multiple people's movement within a room over time (e.g., Plotz et al., 2012). Once these data on the behavior and the environment have been collected, AI can be used to automatically detect and quantify behavior (Plotz et al., 2012). Specific to diagnosis and assessment, Cantin-Garside et al. (2020) used AI to detect and classify types of self-injurious behavior (SIB). Overall, these researchers were able to detect the occurrence of SIB with high accuracy. However, accuracy varied substantially when attempting to classify the type of SIB with hair pulling being classified most accurately (97.2%) and pulling teeth with an object being classified least accurately (74.8%). AI has also been used to detect motor (Fasching et al., 2013) and vocal stereotypy (Dufour et al., 2020); and to inform conditions to include in functional analyses (Bailey et al., 2021). If embedded into clinical contexts, such technologies could reduce the burden of manual data collection by humans. In turn, automated data collection could free up their attention to respond to other clinical behaviors, reduce errors from manual data collection, and provide more accurate and immediate detection and assessment of ongoing behavior leading to more immediate intervention.

Analyzing Patterns of Health Behavior

Many health behaviors and choices involve physical activity and movement throughout environments humans have built. In this article, AI has been used to analyze patterns in streaming physiological and behavior data via wearable technologies (Asch et al., 2012; Ed-daoudy & Maalmi, 2018; Jones et al., 2011; Nair et al., 2018). Baseline data can be gathered on physiological behavior (e.g., heart rate, skin conductance), operant behavior (e.g., daily steps, posture while seated at work, diet logs, CO submissions as proxy for cigarettes smoked), and environmental conditions contacted (e.g., neighborhoods traversed). For clients presenting with a pattern of health behavior they would like to change, these data may allow for a direct functional assessment of the time of day and environmental conditions that predict unhealthy and healthy behavior. For individuals without current concern for their behavioral health, deviations from typical patterns of baseline behavior might suggest a medical or behavioral issue in need of attention. Once identified or predicted, the individual or their BHP can be alerted so that appropriate action can be taken. Because AI can incorporate hundreds or thousands of variables with relative ease, predictive time-series analytics can be accomplished that are well above traditional visual analysis involving one, or perhaps a few, independent variables.

Predicting Low-Rate, High-Intensity Behavior

Another common challenge in the assessment of behavioral health are low-rate high-intensity responses (e.g., heart attack, suicide). Researchers working in preventive medicine or preventive behavioral health have begun to use AI to tackle the challenge of predicting and preventing these responses. For example, researchers have leveraged machine learning techniques on physiological data and data from other electronic healthcare records (EHRs) to predict one of the most common causes of death globally: heart attacks (e.g., Nasrabadi & Haddadnia, 2016; Srinivas et al., 2010). Such systems could be used by BHPs to proactively identify when interventions need to be inserted or modified as the risk of heart attack increases, and subsequently scaled back as risks decreased. In another example, AI has been used to predict suicidal behaviors (Carson et al., 2019; Ji et al., 2019; Walsh et al., 2017, 2018). Here, predictions were made via machine learning that analyzed EHR data, clinical notes, social media posts, the videos people had watched on the Internet, and peoples' search history. Facebook and Twitter already monitor their users' posts for suicidal thoughts with the aim to prevent attempts (Coppersmith et al., 2018; Ji et al., 2019). BHPs could similarly use those same data streams and analytic methods to focus on other health behaviors.

Generating Diagnostic Reports

Once a diagnosis has been made or an assessment completed, BHPs often need to write up their findings for several audiences. These audiences include the client or patient, the third-party payor likely to reimburse for the assessment and fund subsequent intervention, and other BHPs who may prefer detail and jargon outside what the client or payor wants to read. Here, AI can be used to reduce this administrative burden by automatically generating diagnostic reports where the content is specific to the client, the insurance company, and other BHPs (e.g., Luh et al., 2019). Further, when these reports use the diagnosis or assessment results produced via computer vision or machine learning algorithms, the confidence of a correct diagnosis can be precisely quantified—a feature that humans are unlikely to be able to accomplish with similar precision. In turn, the confidence and probabilities of various diagnoses and biobehavioral mechanisms that contribute to the behavioral health condition can be used to inform intervention design.

AI to Improve Intervention Design

Continuing along the prototypical patient journey (Fig. 1), once an assessment has been conducted, BHPs will then use that information to create an individualized therapeutic program. This program is typically tailored to the patient to maximize the probability that they obtain the best possible outcome as determined by evidence-based practice (Slocum et al., 2014) and the patient's own definition of health and well-being. In medicine, this is sometimes referred to as precision medicine, or the idea of tailoring an intervention to each unique individual based on the totality of presenting facts (Food & Drug Administration, 2018). Tailoring interventions is not novel for behavior analytic practitioners. However, AI offers the possibility to automate the tailoring process using a greater number of variables. For example, researchers have combined all available biological information about cancerous tissue and data about the individual's genetic makeup to identify the most advantageous treatment combination of which drugs to use and what dosage is likely to optimally treat the cancer (Adir et al., 2019).

Predicting Response-to-Intervention

Within the behavioral health realm, researchers have begun to use machine learning to predict a patient's response to intervention. For example, Cox et al. (2021) used NLP to numerically describe patients' written descriptions of their experience during a psychedelic-assisted therapeutic event. The output of these models was then used with a second set of machine learning algorithms to predict the degree to which the individuals successfully reduced or quit using alcohol, cannabis, opioids, or stimulants. More directly related to ABA for individuals with ASD, Linstead et al. (2015) used AI to predict goal mastery as a function of treatment hours, age, and gender.

NLP could likewise be used at the onset and throughout behavioral interventions to provide useful information to BHPs. For example, NLP could be used to analyze patient intake interviews that could suggest treatment parameters (e.g., intensity, format) to a clinician. NLP could also be used to analyze clinical session notes. These data could be used to predict client performance or staff training needs. For example, if a RBT notes the client "did not sleep the night before," a notification could be sent to the team that there may be an increase in problem behavior or decreased performance during skill acquisition. NLP of session notes may also provide predictions of staff behavior. The words used or structure of sentences may indicate additional training is warranted. For example, notes that describe the client as "mad" may suggest a review of functions of behavior and/or operational definitions would be useful. If a note describes the client "didn't want to," the BCBA could be notified the client may be due for updated preference and reinforcer assessments, or the team might benefit from reviewing motivating operations.

Efficient Use of Resources

All healthcare practitioners have constraints to what they can do because of time, money, limits to human learning or physiological adaptability, or other resource limitations. In turn, by understanding how many different behaviors group together functionally, BHPs can use this information to determine exactly how they will allocate their limited clinical resources to maximize the therapeutic effects of their intervention. Here, researchers have begun to use machine learning to identify how different behaviors group together functionally (Cox et al., 2019). Once the similarity between responses or response classes are identified, BHPs can better determine how allocating clinical resources is likely to have the greatest impact and to design their intervention accordingly. As a question, if a practitioner can only focus their intervention on five things, which five things give them the greatest net impact to someone's behavioral repertoire?

Patient–Provider Matching

Human interactions are dynamic, socially nuanced, and include a host of variables that are not always observed or measured. That is, a behavioral or educational intervention delivered by one practitioner or teacher might look different than the same behavioral or educational intervention implemented by another person. Based on these differences, researchers can use AI to optimize the patients that are assigned to a healthcare practitioner based on the clients' presenting symptomatology and the doctors' demonstrated skill in treating different medical conditions or implementing different interventions (e.g., Field & Caetano, 2010; Zilcha-Mano et al., 2022). Optimizing a BHP's clinical caseload is likely to maximize their abilities to help their patients and also prevent burnout (e.g., Anderson et al., 2022; Hassanzadeh et al., 2022). On the flip side of that interaction, AI has also been used to match patients with a team of healthcare providers that are best suited to the totality of their presenting health concerns, their cultural background, and any other dimension along which the researchers have patient and provider data (Nie et al., 2017). Together, these allow optimal patient caseloads to be built for individual BHPs, and the optimal treatment team to be built for individual patients.

AI to Improve Intervention Implementation

Patient Engagement and Adherence

The third phase of the prototypical patient journey (Fig. 1) is the implementation of the designed intervention. One significant impediment to maximizing treatment outcomes stems from BHPs' struggle to keep clients engaged in an effective intervention and to maintain treatment fidelity once an intervention has begun. Patient engagement and adherence is important because the more patients proactively participate in their own well-being and care and the more likely patients are to adhere to recommended interventions, the better the health-care outcomes and the patient's overall experience (Davenport & Kalakota, 2019). As a result, AI has been used to provide real-time delivery of intervention-related content or intervention-related support that has been adapted or tailored based on the data collected from that individual. For example, these just-in-time-adaptive interventions (JITAIs) have been used to increase physical activity, improve dietary patterns and food consumption, and to improve health-related decision making in everyday environments (e.g., Hardeman et al., 2019; Rabbi et al., 2015; Van Dantzig et al., 2013; Van Dantzig et al., 2018). In this same area, AI has been used to provide individualized prompts to refill and take prescribed medication as well as prompts to make healthier decisions that decrease incidence of diseases such as cancer (Misawa et al., 2020), and to reduce addiction-related behaviors such as drug abuse and gambling (e.g., Carpenter et al., 2020).

Analysis of Intervention Effects

An important part of intervention delivery is the ongoing analysis of intervention effects. In this article, AI has been used to automatically analyze single-case intervention data with error rates lower than the best structured decision criteria (Lanovaz et al., 2020). At present, these tools might best be considered as supplemental aides to the visual analysis of data (Lanovaz & Hranchuk, 2021). However, if the models that result from these algorithms continue to improve and BHPs learn to use them well, AI with single-case intervention graphs could allow BHPs to automate routine clinical decisions across clients on their caseload. In turn, this would free up BHPs to spend more time on more difficult decisions or more challenging cases or to increase the overall number of client programs they supervise at any one point in time.

The analysis of within-subject time-series data could also benefit from AI through the inclusion of more variables. For example, data plotted over time is the primary method that many different industries use to think about and analyze their data. Adding AI to this mix would allow BHPs the ability to incorporate a greater number of biological, environment, and behavioral variables into their analyses to predict the multiple control of complex behavior over time (e.g., Cox, 2023). Behavior analysts that embrace computational techniques to analyze data over time are a short step away from powerful tools that can help them to better understand the complexity of multiply controlled and dynamic behavior change. And, the tools and computational techniques are often open source (i.e., free to use) that places like Facebook, Amazon, and Google make freely available for analyzing these types of data.

Analyzing Behavior during Clinical Sessions

AI has also been used in areas more directly related to working one-on-one with someone with ASD or DD. One exciting area uses speech recognition devices that help individuals with speech disabilities communicate vocally and more clearly (Hawley et al., 2013). With skilled behavior analysts, these tools could be combined with simple shaping and chaining procedures to shift these tools from vocal amplification devices to therapeutic devices that increase the intelligibility and comprehensibility of someone's vocal speech.

Another really exciting area where AI is used in intervention implementation is facial recognition software. Researchers here are using AI to identify the emotions that someone displays in real-time (Flynn et al., 2020). Behavioral practitioners could use this technology in several ways. One way would be to help individuals learn to recognize the emotions that other people display—perhaps in a phone app or through augmented reality. In addition, this technology could be used to give a learner immediate biofeedback on the emotions they might be displaying and to help them better associate their facial expressions with their private events.

In total, AI is already being used to deliver or to improve the implementation of behavior-related interventions or to improve the efficiency of clinical decisions that are made relative to behavioral interventions. Several low-hanging AI fruits seem to exist in the areas of speech recognition and facial-emotion recognition. Both of which could seemingly be added as tools to improve existing verbal behavior or emotion-based intervention programs.

AI to Improve Intervention Withdrawal or Monitoring

At some point in time, some patients or clients may fade out their contact with intensive interventions. This may occur because an acute condition has gone into remission or because a chronic condition can be successfully self-managed. The majority of the work in this area has used some version of automated hovering or ambient intelligence to collect ongoing data about the person in many of the same ways we discussed in previous sections (e.g., Aziz et al., 2009; Jerez-Aragones et al., 2003; Salleh et al., 2017).

Automated Hovering and Ambient Intelligence

Automated hovering and ambient intelligence often involve wearable technology (e.g., FitBit, Apple watch) or environmental sensors and cameras. These devices are then used to collect data that allows researchers or BHPs to track and analyze patterns in what people are doing, where they are going, and their physiological state. In turn, these data can be used with AI to predict: if and when people will relapse to using drugs after they successfully quit (e.g., Asch et al., 2012; Budney et al., 2019; Dallery et al., 2015), when someone might experience a relapse of cancer following successful treatment and remission (e.g., Good et al., 2018), or when someone might relapse to severe depression and be at-risk of suicide following a successful behavioral intervention (e.g., Carson et al., 2019; Ji et al., 2019; Walsh et al., 2017, 2018). Of note, much of this work has been accomplished without the collaboration of BHPs or researchers who have a robust understanding of the behavioral processes likely to control the recurrence of clinical levels of physiological or behavioral phenomena (e.g., Greer & Shahan, 2019; Liggett et al., 2018; Muething et al., 2022). It is not hard to imagine how powerful these technologies might become if BHPs were to increase their collaboration with researchers on these technologies.

Prediction and Prevention of Relapse

Treatment withdrawal and avoiding relapse have arguably been considered a distinct piece of the intervention puzzle. However, when viewed through a different lens, it is hard to know whether someone is an ex-client or patient, a future client or patient, or whether these labels are being trivially applied. When viewed through this lens, the research and work related to intervention withdrawal and monitoring can be thought of similarly to the research and use cases described above relative to diagnosis and assessment. The main difference here being that the BHP or researcher would have much more baseline data about the individual as to the function of their behavior and what intervention components are likely to successfully lead to behavior change. In particular, using AI with automated hovering and ambient intelligence allows BHPs and researchers to take a more holistic view of this cycle as opposed to thinking about treatment as a linear pipeline with a clear beginning and end.

AI to Improve Administrative Systems and Process

Creating Decision Aides via AI Summaries of Research Literature

Wrapping around the entire prototypical client experience and treatment pipeline are a host of administrative systems and processes to support each of these steps. Here researchers are helping BHPs by using machine learning to automatically extract and synthesize the massive amounts of research literature that are being published (e.g., Marshall & Wallace, 2019). This condensed research can then be provided to BHPs in the form of easily accessible resources to aid their decision making and so that they can stay abreast of the literature. Also in this area, researchers have begun to use AI to try to predict the next major discoveries within different fields and to guide scientific researchers toward fruitful and powerful research topics (e.g., Rzhetsky et al., 2015). When spun toward behavioral health research, this same strategy could be used to summarize the published behavior analytic literature and to identify opportunities to enhance the clinical services BHPs deliver (e.g., Sosine & Cox, 2023).

Improving Patient Experience while Reducing Cost

AI has also been used to improve the patient experience with the healthcare system. For example, researchers have used AI to analyze patient flows through hospital administrative processes (e.g., Ellahham & Ellahham, 2019). Patient flow refers to how people move through a healthcare facility related to medical care, contact and use of physical resources, and the internal systems needed to move patients from admission to discharge (NEJM Catalyst, 2018). For example, AI has been used to optimize patient and staff scheduling based on forecasts of the times, days, and weeks when people are more likely to seek services (e.g., Jones et al., 2008). When combined with knowledge about staff availability, ideal schedules, and patterns of resource use, researchers can use such forecasts to improve service use and reduce cost (e.g., Tenhunen et al., 2018).

Improving Direct Staff Schedules

Researchers studying the logistics of moving goods around the country have used AI to find optimal solutions to the traveling salesman problem (e.g., Karaboga & Gorkemli, 2019; Xing et al., 2008). That is, planning the optimal route to go from one location to another when certain stops must be made along the way. Combined with staff availability, these tools could be of tremendous help for ABA agencies trying to coordinate peoples' work and personal schedules with client session times to reduce the amount of time and distance their RBTs must travel each day. In fact, CentralReach has already incorporated AI in their scheduling system (CentralReach, 2020).

Feedback and Prompts for Providers

Researchers within the area of behavioral economics have demonstrated repeatedly that humans, including healthcare providers, do not always make the best decisions (e.g., Bickel et al., 2020; Makary & Daniel, 2016; Thompson et al., 2013). To help healthcare providers make better decisions, researchers have used AI to analyze and predict the clinical decisions that healthcare practitioners make (e.g., Ninness et al., 2021) to then determine the optimal intervention strategies based on the unique symptoms and backgrounds of different patients and their unique conditions (Komorowski et al., 2018).

Administratively, such research and tools could be used to help manage the performance of providers in at least two ways. First, once a likely optimal intervention path is known and the requisite systems built out, clinical decision-making aids can be created that prompt BHPs proactively on what decision is likely best. Second, where

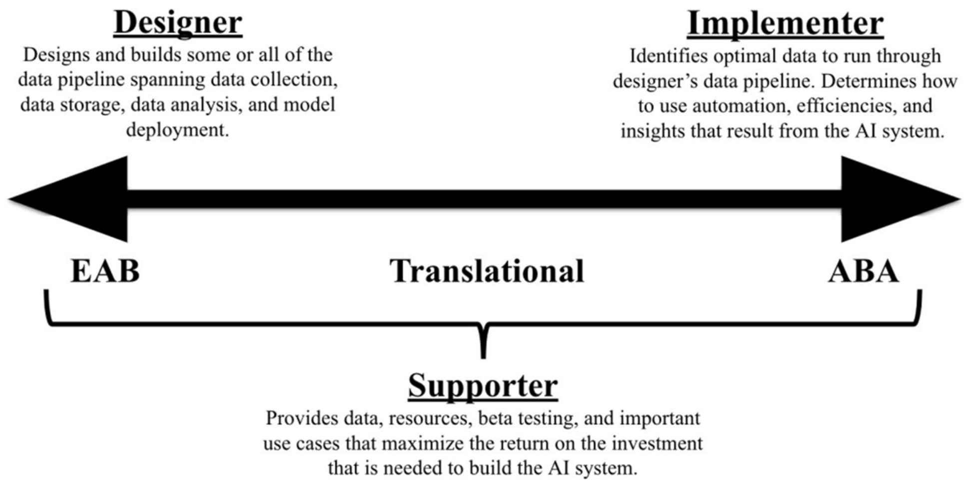

Fig. 2 Potential roles to get started with AI

real-time prompts are unavailable, ad hoc analyses could be conducted to determine what would have been the best decision to make and the resulting feedback could be provided to the healthcare providers to improve the interventions they deliver.

Lastly, many of the use cases described above are applicable to administrative use of AI tools. Administrative processes are often aimed at improving the efficient use of available resources while maximizing patient outcomes and the overall satisfaction of patients and employees. Many previously discussed topics relate to these objectives such as optimizing caseloads for a single healthcare provider, matching patients with the ideal provider, and automating report generation that are unique to distinct audiences. BHPs do not operate in a vacuum. They are embedded in larger, complex, and dynamic organizational systems. Organizational systems collect and use data to improve efficiencies. And, AI can or is being used to improve many of these areas of administrative systems and processes.

Finding a Role

To this point in the manuscript, we have described the many areas along the prototypical behavioral health patient journey wherein AI has been researched or successfully deployed. We hope many readers found at least one area interesting and directly applicable to their everyday work settings. We also hope that at least some of those readers are interested in learning how they might start to bring AI to behavioral health more broadly. In this final section we describe three potential roles that readers might take to begin working toward the inclusion of AI in behavioral health. We refer to these three potential different paths as the designer, the implementer, and the supporter (Fig. 2).

The Designer

The designer is someone who wants to bring AI to an area that is not currently represented or easily accessible, or who wants AI to play a primary role in their career. The designer would be someone who is interested in designing and building some portion of the data pipeline spanning data collection, data storage and transformation, data analysis via AI, and model deployment. Within behavior analysis, this role might be akin to the area of the experimental analysis of behavior (EAB) where the researcher is interested in basic questions about how things work and how they might translate that understanding for a specific research question or goal.

Readers of this journal who are interested in this role will likely have to learn some new skills. Depending on the area of the total data pipeline that they are interested in, the designer will likely have to improve (or dust off) their skills in mathematics, statistics, computer programming, and computer science. Readers interested in this path can do a quick internet search to find degree programs related to the job titles of data engineer, data scientist, data analyst, and machine learning engineer. Obtaining a formal degree in this area certainly would carry many benefits. However, aside from a formal degree, there are many opportunities to develop the same list of skills outlined in the degree programs through free courses and online tutorials, such as Coursera (https://www.coursera.org) and freeCodeCamp (https://www.freecodecamp.org). Readers who opt for this free course route would do well to find a mentor in this area as they develop their professional repertoire. There are also some related resources created specifically for behavior analysts. For example, Turgeon and Lanovaz (2020) wrote a step-by-step tutorial for using machine learning as it applies to behavioral research.

The Implementer

Another potential role readers might take would be as an implementer of AI solutions in their practice or research. That is, rather than focusing on the technical aspects of how to build data pipelines and analyze the data, the implementer would focus on how to use the AI tool effectively to improve patient outcomes. In loose analogy, the relationship between the designer and the implementer might be similar to the relationship between researchers pairing up from EAB and ABA. The designer is likely to spend more of their time developing their skills to perfect the AI tool. Whereas the implementer is likely to spend more of their time developing their skills to perfect the use of the tool within novel areas of service delivery.

Readers of this journal who are interested in this role will likely have to learn to think differently about their data and the delivery of behavioral health services. As noted above, AI technologies use a broad and large amount of data to improve the efficiency of systems and to identify novel patterns in datasets. Here, critical questions that the implementer would need to solve surround what data are and are not currently being collected, the best level to collect the data at based on a robust understanding of behavioral function and the data needed to describe it well, and how the efficiencies or insights gained from the use of the AI tool can be practically worked into the day-to-day behaviors of the practicing BHP.

The Supporter

As an alternative, behavior analysts may prefer to serve the role of the supporter. This role is likely best for those who may not be interested in learning new skills or figuring out how to implement AI tools within their practice, but who are interested in the promises and possibilities that AI as a tool has to improve behavioral healthcare. For these readers, there are at least three ways they can support the work of designers and implementers. One way to support designers and implementers is by providing data. AI tools require a lot of labeled data to build models of sufficient accuracy and generalizability to be used outside of the often highly circumscribed research settings. Data are expensive to collect and curate. Practicing behavior analysts as a field, however, collect massive amounts of labeled data on a daily basis. Potential supporters are sitting on troves of data that could be leveraged for many variations of AI research.

A second way to support designers and implementers is to help beta test AI tools and products outside of their development environments. Every instance of generalizing an AI tool with new people or to new situations is going to involve mistakes and errors that need to be corrected. Beta testing these tools as they are being developed helps the designer and implementers fix these bugs. This also carries the bonus that the supporter gets access to cutting-edge technological tools that are not yet widely available.

A final way to support designers and implementers is to provide feedback and specific use cases around their "pain points" where AI tools would lead to the greatest impact. Everyone has strengths and blind spots. The designers and implementers described above are likely to be people who have found a job where they can dedicate 40+ hr per week to thinking about, experimenting with, and solving practical problems related to the design and implementation of a specific AI tool. It seems likely that at least some of these individuals will not be adept at running ABA businesses, will not understand the practical constraints and logistics of implementing new technologies in a larger behavioral health clinical-business context, nor have a pulse on what areas of the behavioral healthcare could benefit most from improved efficiency and insight. Thus, potential supporters could play a significant role in helping to shape or guide what designers and implementers focus their efforts on.

For those interested in being a supporter, the next step would be to find and connect with a designer or implementer. This might be accomplished via a few relevant special interest groups through the Association for Behavior Analysis International such as *Behavior Analysis and Technology* or *Behavior Analysis and Selectionist Robotics*. Another community of behavior analysts interested in the relationship between computer science and behavior science is *Behavior Analysts Who Code*. Lastly, it seems apropos to point to additional guidance for developing competence in a new area such as that by LeBlanc et al. (2012) and Brodhead et al. (2018).

Conclusion

AI involves providing instructions to computers so they learn about patterns in datasets. Many of the behaviors, decisions, systems, and processes that BHPs engage in on a daily basis are being touched by AI. Many of these systems result in improved speed, accuracy, efficiency, reach, and scalability of access to high quality behavioral healthcare services. And, researchers have begun to demonstrate how AI can lead to improvements in all aspects of the prototypical client journey. Behavioral health providers and their employing organizations that learn to practically adopt AI will likely gain significant advantages in terms of improved patient outcomes and more cost-effective business operations. For those that are interested in helping to shape how AI will be used in ABA more specifically, several possible paths exist. These include working as a designer of AI systems, learning the most effective and practical way to implement AI systems in existing clinical processes and workflows, or in supporting designers and implementers by providing access to quality data, beta-testing AI tools, or helping to guide what the AI systems focus on to maximize the benefit gained from such efforts. In the modified words of William Gibson, AI for behavioral health is already here, it is just not very distributed (National Public Radio [NPR], 2018). We hope you join us in figuring out how to take advantage of the promises and possibilities of AI for ABA.

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Declarations

Conflicts of Interest The authors have no conflicts of interest to disclose.

IRB Note N/A.

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