

Revolutionizing Program Evaluation with Generative AI: An Evidence-Based Methodology

Drijesh Patel

Program Manager, IBM

Abstract

Generative Artificial Intelligence (AI) is revolutionizing program evaluation by enabling machines to autonomously create new data and information without human intervention. This paper explores the potential of Generative AI (GAI) in program evaluation and presents an evidence-based methodology to ensure accurate and valid results. GAI models, such as Generative Pre-Trained Transformers (GPTs), can generate human-like language, text, sketches, and software code. By leveraging GAI, program evaluations can be conducted more efficiently, providing objective feedback in less time compared to traditional manual evaluations. GAI can be applied in various domains, including medical interventions, statistical process control, traffic simulation, and AI algorithm evaluation. However, challenges exist in the implementation of GAI, such as language limitations, accuracy validation, and potential biases. To address these challenges, factors such as human input, language model optimization, and ethical considerations must be taken into account. The paper emphasizes the importance of integrating evidence-based approaches into program evaluation, ensuring accuracy, validity, and reliability. Strategies and techniques, such as independent reviews, standardized procedures, and ethical considerations, are discussed to enhance the accuracy and validity of program evaluations. The risks associated with GAI implementation, such as intellectual property rights and ethical concerns, are also highlighted. Finally, the implementation of generative AI in program evaluation involves considering the optimal context, legal issues, performance evaluation, and thorough review processes. Despite the challenges, generative AI holds great potential to transform program evaluation and improve outcomes through evidence-based methodologies.

Keywords: Program Management, Project Management, Generative AI, Artificial Intelligence

Overview of Generative AI

What is generative AI?

Generative Artificial Intelligence (GAI) is a leading technology that combines virtual and physical worlds to create new experiences [1]. It refers to the ability of machines to create new data or information on their own, without human intervention [1]. GAI models are capable of producing human-like language and generating new content without the need for explicit programming [2]. Generative language models are based on basic principles and are capable of producing new language similar to human language [3]. These models can be used to generate text, sketches, and software code [1], as well as create molecules with desired properties [4]. Generative AI has the potential to reduce the time and cost associated with drug discovery, as well as revolutionize Statistical Process Control practice, learning, and research [2]. To achieve this, large language models known as GPT (Generative Pre-Trained Transformers) are used [1]. These GPTs are trained on large, unstructured datasets and can handle various tasks such as searching and

analyzing large datasets, text translation, and creating new protein sequences [1]. However, GAI is still in the early stages of development and must be properly validated and used in combination with other methods to ensure accurate results [2][4]. OpenAI's Codex, DALL-E, and ChatGPT are some of the tools used for the GAI process, and GAI is expected to become a major tech trend in 2023 [1].

How is generative AI different from traditional program evaluation methods?

Generative AI (GAI) is a term that encompasses a wide range of Artificial Intelligence (AI) models and techniques. GAI stands for the ability of machines to create data and information autonomously, without any human intervention [5]. This is in stark contrast to traditional program evaluation methods, which require manual input from humans to assess the results [1]. In addition, GAI models can be used to generate data from a variety of sources, including literature reviews, mobile apps, and computer-aided systems [6], [7], [10], [8], [9]. GAI is increasingly being utilized in many different areas, from medical education to traffic simulation. For example, a mobile application such as TrafficGAN has been developed to generate realistic traffic data [7]. Moreover, GAI models are used in computer-aided systems to augment the training data and improve accuracy [8]. GAI is also used in the field of AI for training deep neural networks [9]. The key difference between generative AI and conventional program evaluation lies in the way data is generated [10]. Specifically, GAI models involve the estimation of distribution parameters and hypothesis [5], whereas traditional methods rely on manual input from humans [1]. To sum up, GAI is an emerging field that has the potential to revolutionize the way we evaluate programs and assess results.

What are the main advantages of using generative AI for program evaluation?

Generative AI (GAI) has the potential to revolutionize the way we evaluate programs, enabling us to develop more accurate and meaningful assessments. GAI can effectively analyze data and produce detailed reports, providing objective feedback in a fraction of the time it would take for manual evaluation [11]. However, it is important to consider the potential drawbacks of using GAI, such as its potential for bias and the subjective nature of the evaluation process [1]. Additionally, GAI can be used to evaluate the impact and effectiveness of medical interventions, offering users an insight into the potential benefits and risks of using AI in healthcare applications [12]. Generative chemistry methods are also being developed to take advantage of deep learning to predict molecular structures and enable more efficient and accurate evaluation of materials [13]. Furthermore, Generative Adversarial Networks (GANs) can be used to detect anomalies in data and provide more accurate evaluation of complex problems [5]. GANs can provide a number of advantages over other generative algorithms, such as better performance, quicker training, and more accurate results [14]. Mobile apps can also be used to evaluate medical treatments, providing users with a real-time assessment of their condition [3]. In addition, generative models can be used to evaluate different features of a medical condition, such as the uniformity of information in Cumulative Density Functions (CDFs) [15]. Deep Dirichlet Process Mixtures (DDPMs) are an example of a generative model that can offer a range of advantages over other generative models [16]. Finally, generative models can be used to evaluate AI algorithms, providing a more accurate and comprehensive assessment of AI performance [17]. In conclusion, GAI has the potential to provide a range of advantages to program evaluation, providing users with faster, more accurate, and more reliable results.

Challenges with Generative AI

What are the challenges associated with using generative AI for program evaluation?

Generative AI has been used in program evaluation for a while now, however, there are many challenges associated with this process. For instance, the capability of Long-Short-Term Memory (LLMs) networks in understanding and generating languages other than English is still uncertain [18]. In spite of the immense progress that has been made in the field of natural language processing (NLP), generative LLMs are still not optimal for all languages [18]. This makes it difficult to determine the accuracy of such systems and how reliable they are for program evaluation [18]. Furthermore, the generation of natural language is a complex task and requires a deep understanding of the language, its grammar, and its semantics [18]. It is challenging to determine the accuracy of such a system and the reliability of the generated output. Thus, it is essential to develop a comprehensive evaluation system to determine the effectiveness of generative AI in program evaluation [18].

What factors should be taken into consideration when using generative AI for program evaluation?

There are a variety of factors to consider when using generative AI for program evaluation. [19] Such tasks may include writing an evaluation, responding to an argument or creating a report. Research has demonstrated that generative language models are not as accurate as other methods [18]. Therefore, it is necessary to review these discoveries and develop new approaches to generative AI [13]. This technology can be used to address educational-related problems and tasks [20], as well as generate molecules for review [21]. It is also important to incorporate human factors into the generative design process [22]. Additionally, mobile apps must be examined to determine their suitability for medical use [3]. Furthermore, when using generative AI for program evaluation, researchers must be aware of the existing open problems and future challenges [23]. To fully embrace these opportunities and challenges, one must consider various factors such as trust in AI systems [24] and the potential for unfair evaluation based on factors such as race [25]. Through proper evaluation and improvement, AI can be carefully deployed to ensure reliable results.

What are the potential risks of using generative AI for program evaluation?

The potential risks of using generative AI (GAI) for program evaluation are significant and should not be overlooked. Organizations should be aware that third-party developers may use GAI, and there is a possibility of using their output without knowing it, making it essential to consider governance practices of partners [1]. GAI tools have potential ethical risks that need to be considered carefully during program evaluation [1]. For instance, intellectual property rights, including copyright protection and ownership, may be affected due to the data used in developing GAI systems [1]. Additionally, some GAI models "reproduce" the content they draw from, potentially leading to mistaken generation of a new solution license for a particular piece of code [1]. Organizations should also conduct due diligence on the frameworks used to develop GAI tools to be aware of their potential shortcomings [1]. It is important to monitor the changes in the regulatory environment as they start experimenting with GAI models [1]. Despite the risks, GAI models can still be used safely, as long as the outputs are checked by a human before they are published or used [1]. To minimize the risks, organizations can customize the GAI tools to fit their requirements and avoid biases [1]. As the technology becomes more widely used, the regulatory environment will also change, and new models will be introduced and tested regularly [1]. Organizations

should also be aware that the landscape of GAI models is still very unpredictable, and they should ensure that the data they use for training their models are unbiased [1].

EvidenceBased Methodology

What is an evidence-based approach to program evaluation?

School systems must obtain evidence to maximize student achievement [26]. This requires an evidence-based culture of improvement in teaching and learning that utilizes the unique and specialized knowledge, skills, experience, and professional capacity of teachers [26]. To reach this goal, an evidence-based approach is used to inform and improve education [26]. Evidence can support the core business of schools, which is maximizing student learning and outcomes [26]. This is done by collecting data, analyzing it, and interpreting it to make informed decisions. Data collection can take many forms, from surveys and interviews, to focus groups and observation. Once the data is collected, it is analyzed to identify patterns, trends, correlations, and other insights. This allows for informed decision making on a range of issues, from curriculum design to teaching strategies. Finally, the evidence is strategically used to inform teaching and learning practices, and to measure the impact of programs and interventions [26]. This evidence-based approach to program evaluation is an effective way to improve education and ensure that students receive the best possible learning experiences.

What strategies and techniques can be used to ensure the accuracy and validity of program evaluations?

To ensure accuracy and validity of program evaluations, various strategies and techniques can be employed. For instance, two independent reviewers can be used for data abstraction, and the reviewers must be provided with training and feedback to guarantee accuracy and validity [27]. Moreover, standardized forms and procedures can be developed to provide consistency in program evaluations, and such standardization of forms and procedures can help reduce bias [27]. Additionally, reviews should maintain a focus on medical outcomes that matter to patients, as well as consider a range of specific family and societal outcomes when appropriate to ensure accuracy and validity [28]. Furthermore, developing and optimizing methods for assessing individual study quality, adequacy of evidence for each component of the analytic framework, and certainty of the overall body of evidence is a strategy to ensure accuracy and validity of program evaluations [28]. Furthermore, consideration of ethical, legal, and social implications should be an integral part of all components of evaluation to ensure accuracy and validity [28]. Additionally, formal assessment of analytic validity is a strategy to ensure accuracy and validity of program evaluations, and use of unpublished literature can be used as an evaluation component when published data are lacking or of low quality [28]. Moreover, use of questions from the ACCE analytic framework can be used to organize collection of information and ensure accuracy and validity of program evaluations [28]. Additionally, focusing on summarization and synthesis of the evidence and identification of gaps in knowledge is a technique to ensure accuracy and validity of program evaluations [28]. Furthermore, providing a foundation for evidentiary standards that can guide policy decisions is a strategy to ensure accuracy and validity of program evaluations, and multidisciplinary independent assessment of collected evidence is a strategy to ensure accuracy and validity of program evaluations [28]. Moreover, the consistency and generalizability of results, and understanding of other factors or contextual issues that might influence the conclusions, are also important considerations [28]. Additionally, key questions address the components of evaluation as links in a possible chain of evidence [28]. Furthermore, analytic

validity and clinical validity are important components that determine the test's ability to accurately and reliably identify or predict the disorder of interest, and clinical utility, which is the balance of benefits and harms when the test is used to influence patient management, is also an important component of evaluation [28]. Moreover, the USPSTF has updated its methods and terminology, which can provide consistency for shared audiences, and the quality of individual studies, the adequacy of evidence for each link in the evidence chain, and the certainty of benefit based on the quantity and quality of studies are important considerations for determining whether a chain of indirect evidence can be applied to answer the overarching question [28].

How can evidence-based methodology be used to improve program evaluation outcomes?

Evidence-based methodology is an effective approach to improving program evaluation outcomes [29]. This is done by using systematic reviews to identify consistencies between different studies and to assess the robustness of the program evaluation [29]. Evidence synthesis likewise combines multiple studies to determine if the findings are consistent and reliable [29]. Furthermore, the methodological quality of SCED meta-analyses has increased over time, although there is still room for further improvement [29]. In addition, the evidence base for public health effectiveness is not uniform across policies and programs targeting leading causes, and the Task Force has reviewed over 175 interventions for program effectiveness and practice recommendations [29]. Finally, there is an extensive literature for assessing a variety of intervention strategies [29]. Small-N designs are another way of using evidence-based methodology to improve program evaluation outcomes [29]. These designs involve focusing on 10 or fewer participants whose outcomes are measured repeatedly and compared over time [29]. While small-N designs can provide useful insights into evaluation outcomes, they also have some disadvantages that should be taken into account [29]. Examples of these designs can be seen in rehabilitation literature, where they are used to supplement traditional research methods, as well as to provide more accurate results [29]. However, care should be taken to avoid relying on single studies of varying quality [29], as this can lead to bias and inaccurate outcomes.

Implementation of Generative AI

What steps are involved in implementing generative AI for program evaluation?

AI-based generative models have become an integral part of program evaluation, as they are able to create new content and insights. This requires a comprehensive evaluation of the deep generative models through metrics and review processes. To facilitate this process, the implementation of generative AI needs to take into consideration various factors such as the optimal context, legal issues and performance evaluation. Additionally, there is a need to review the AI generated insights before they can be used in the real world. Various research studies have employed generative AI for de novo design, drug discovery and AI-guided generative chemistry. Furthermore, professors, postdocs and doctoral students have experience in using generative AI tools for teaching-related activities such as planning, implementation and evaluation [24]. Finally, artificial intelligence has been applied to the generalized learning of generative dynamic models [30]. Overall, there is an increasing trend in the use of generative AI models for program evaluation, but the process requires careful consideration of the various aspects involved [21][19][31][32][33][34][35][36].

How can generative AI be used to generate evidence-based program evaluation results?

Generative AI has become increasingly popular in the field of evidence-based program evaluation [32]. It has been shown to be effective in collecting, interpreting and analyzing large amounts of data [37], as well as in identifying patterns and trends in data [12]. In addition, AI-generated literature reviews have been used to provide evidence-based insights into the effectiveness of programs [38]. Recently, a AI chatbot called "Familio" [39] was developed to help healthcare professionals to provide evidence-based care [40]. In addition, AI has been used to generate rephrased evidence-based insights [41] and to develop best practices for evidence-based medicine using AI [42]. There are also various methods of validating generative models that can be used to ensure accuracy [43], such as using evidence-based guidelines, best practices, and differential privacy for protected data [44]. While GAI offers many potential benefits, it is important to ensure that these technologies are used responsibly and ethically [37]. AI can be used to identify patterns and trends in data, but it can also be used to predict outcomes and inform decision-making [12], which requires careful implementation and evaluation in order to ensure accuracy and reliability.

What technologies are available to support the implementation of generative AI for program evaluation?

Generative AI (GAI) is becoming increasingly popular as a tool for program evaluation. GAI can provide a comprehensive analysis of the effectiveness of programs by objectively assessing the performance of program participants. However, the implementation of GAI can be challenging due to the complexity of the technology. To support the implementation of GAI for program evaluation, various technologies are available. Generative language models (GLMs) are one such technology that can be used to support the implementation of GAI for program evaluation [3]. GLMs are based on the concept of natural language processing (NLP) and machine learning algorithms. Among these algorithms, transformer-based models such as GPT (generative pre-trained transformer) are the most commonly used for program evaluation [3]. GPT is a machine learning model that uses a self-attention mechanism to capture the long-term dependencies present in data. Moreover, GPT models are capable of understanding the context of words and sentences in order to accurately evaluate the performance of program participants. In addition to GLMs, other technologies such as deep learning algorithms, natural language processing (NLP) and text mining are also available to support the implementation of GAI for program evaluation. These technologies can be used to generate meaningful insights from large datasets that can be used to evaluate the performance of program participants.

Future Directions

What are the potential applications of generative AI for program evaluation?

Generative AI has the potential to revolutionize many aspects of the construction industry, including program evaluation. A number of studies have discussed the potential applications of generative AI for program evaluation [45]. For example, AI-based program evaluation can be used to evaluate the cost-effectiveness of construction projects and to identify potential cost savings. AI-based program evaluation can also be used to identify areas of potential risk in construction projects, which can help to reduce the likelihood of costly errors and delays. AI-based program evaluation can also be used to identify potential improvements to the design of a construction project and to identify potential opportunities for innovation. Furthermore, AI-based program evaluation can be used to identify areas of potential savings in the construction process, such as reducing the cost of materials and labor. Additionally, AI-based program

evaluation can be used to identify potential areas of process optimization, such as reducing the time needed to complete a construction project. AI-based program evaluation can also be used to identify potential areas of improvement in the construction industry, such as reducing the environmental impact of construction projects [45]. All of these potential applications of generative AI for program evaluation have the potential to revolutionize the construction industry.

What new technologies are being developed to improve generative AI for program evaluation?

To ensure that generative AI is used efficiently and reliably in program evaluation, various technological advancements are being explored [45]. For instance, the introduction of new tools for AI-based data processing has enabled the automatic generation of data with minimum human intervention [45]. This helps to reduce the reliance on manual data generation and processing, thereby increasing the efficiency of the process [45]. Additionally, the development of AI-based techniques such as Reinforcement Learning and Deep Learning has resulted in improved generative models [45]. These models have the potential to produce high-quality results with greater accuracy and precision [45]. Furthermore, the implementation of AI-assisted algorithms and data analysis techniques can improve the accuracy of program evaluations [45]. This technology can reduce the amount of time and effort needed to detect and diagnose errors and anomalies within the data [45]. Finally, AI-based approaches to statistical process control (SPC) can help to identify patterns in data and identify patterns that may lead to poor program outcomes [45]. By utilizing these technological advancements, data scientists can ensure better accuracy in program evaluation and improve the quality of generative AI models [45].

What challenges remain to be addressed in order to fully realize the potential of generative AI for program evaluation?

Despite the potential of generative AI (GAI) for program evaluation, many challenges remain to be addressed. The key difference between conventional and generative AI is that the former is based on supervised learning, while the latter is based on unsupervised learning [46][47]. While GAI can be used to assess requirements, design solutions and evaluate outcomes, its effectiveness is limited by its lack of domain knowledge [48]. This means that GAI tools need to be designed to handle a variety of data types [49] in order to be more effective in tackling the challenges of program evaluation [45]. Additionally, GAI models need to incorporate explainable AI (XAI) in order to be better able to explain their decision-making process [50]. In order to make GAI more effective in program evaluation, researchers need to focus on developing algorithms that are able to capture important small details that might be missed by conventional AI [46]. Furthermore, there is a need for the development of metrics to evaluate the performance of GAI models [51]. Finally, GAI models need to be developed with proactive strategies to address potential issues [52] in order to fully realize their potential [53][54][55].

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