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Do Traditional SEO Factors Matter in Answer Engines? An Empirical Study of AI-Based Voice Search Systems

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Abstract

Voice search systems powered by AI have redefined the concept of traditional use of SEO to switch the priority to the search optimization model based on answers, rather than the retrieval of the websites. In this paper, we studied the issue of whether the principles of foundational SEO as page score or domain score still have an impact on back link business in the environment of AE designs. To empirically test the relationships between backlinks and page-level and domain-level optimization metrics, we conducted a survey from 50 individual websites (n = 50). The findings showed that page score and backlinks had a strong positively significant relationship ($r_s(48) = 0.984$, $p < 0.001$), suggesting that a considerable proportion of the variance in our backlinks may be due to page-level optimization. Finally, the association between domain score and backlinks was highly weak and non-significant ($r_s(48) = 0.178$, $p = 0.217$). In light of the above findings, one could conclude that in environments influenced by AI based retrieval systems, content-level optimization has been found to outweigh the influence of domain-level authorities in environments where latter is affected. While the same traditional SEO signals are somewhat relevant it turns out that answer engines are more focused on structured, semantically optimal, content driven pages than domain authority. And the results find support for conventional SEO practices giving way to AEO in AI based voice search ecosystems.

Keywords: Search Engine Optimization, Answer Engine Optimization, Voice Search, Backlinks, Page score, Domain Authority, Artificial Intelligence, Answer Engines.

Introduction

The rapid use of AI has greatly impacted the way information is retrieved and the way people search digitally (Zhao et al.,2023). Traditional search engine optimization (SEO) strategies were developed primarily for conventional search engines. These businesses focused heavily on ranking algorithms based on backlinks, domain authority, and keyword optimization (Brin & Page,1998). Since the advent of AI driven question-answering engines and voice-search engines new dynamic results are being generated in how information is retrieved, interpreted and used by end users. Such systems are meant to provide short, simple answers rather than merely listing all the web pages for a search query for the same position on an index (Devlin et al.,2019) this affects traditional SEO ranking factors. In the past few years, AI-powered answer engines have been integrated more significantly into everyday digital interactions. Advanced natural language processing algorithms are deployed by several platforms capable of reading queries and producing accurate replies from the various points of the web (Karpukhin et al.,2020; Zhao et al.,2023). This suggests that the previous paradigm (link-based authority signals) will gradually evolve into content relevance, semantic alignment, and contextual knowledge (Lewis et al., 2020). This transition prompts us to question whether, with AI-mediated search, traditional SEO signals like backlinks and domain authority still impact visibility. The contribution of semantic similarity, contextual embeddings, passage-level ranking mechanisms, among others, to contemporary search architectures, has been the subject of previous information retrieval studies (Lewis et al., 2020).

Although AI-based search technologies have gained an increasing prominence, little research has been done empirically to investigate the effect of traditional SEO metrics in answer engine environments (First Page Sage, 2025). Existing literature mainly centers around algorithm development and retrieval performance but there are relatively few studies that explore how traditional website authority indicators interface with AI-generated answers (Mitra & Craswell,2018; Lin et al.,2021).The discovery of this relationship is important for both researchers in academic and practitioner of digital marketing, as it can be a game changer in finding an optimal optimization strategy in search engine systems. Therefore, the goal of the current research to determine whether the traditional SEO characteristics, namely page score, domain score, and backlink metrics, still perform an effective role in the context of AI AE (Yang et al.,2019; Gao et al.,2021).

The study investigates the correlation between these metrics and websites recommended by various AE systems using empirical data obtained from SEO analytical platforms. With the comparisons of results in three different AI powered retrieval environments, the researchers hope to find ways to explore how optimisation strategies might have to change at this stage of generative, and conversational search technology (Yates,A.2021).

The research results will enhance the existing literature on AE. Through an examination of traditional SEO criteria to emerging search environments, this analysis has tangible implications for digital marketers, website builders and academicassions who want to understand the emerging landscape of online search behaviour. Considering the existing literature on artificial intelligence driven search technologies and AE ecosystems, it is important to examine how conventional se SEO indicators perform within these emerging retrieval environments. Modern AI based AE increasingly depend on contextual interpretation, semantic matching, and passage level content extraction rather than relying exclusively on traditional ranking signals. Based on these considerations, the study was designed with the following objectives:1.) To create a standardized set of user queries and evaluate them across multiple AE to identify the websites referenced in their responses. 2.) To examine the AE related content characteristics of the websites recommended by different AE, including structural organization, keyword intent, answer formatting, and authority related signals and to compare optimization patterns across different answer engines and determine whether similarities or differences exist in the types of websites selected.

Review Of Literature

Previous studies in information retrieval emphasize the importance of link-based ranking mechanisms in SE environments (Mint Position Research Team, 2025). Early search algorithms relied heavily on hyperlink structures to evaluate the authority and credibility of web pages. Pages receiving a higher number of links were assumed to provide more reliable and useful information, forming the foundation of modern search engine ranking systems (Brin & Page, 1998; Henzinger, 2001). Consequently, backlinks, domain authority, and keyword optimization became widely recognized as essential factors influencing the visibility of websites in search engine result pages (Mukaka, M. M. 2012).

Backlinks are often considered signals of credibility and trust, indicating that other websites acknowledge the value of a particular web page (Radford, A.,2019). Websites with stronger backlink profiles tend to achieve higher rankings because search engines interpret these links as endorsements of content quality. Domain level metrics further strengthen this evaluation by reflecting the overall reputation and authority of a website within a particular domain or industry (Manning et al., 2008). Together, backlinks and domain authority have long served as key indicators for assessing website performance in search results (Usmany, p., Rachmawati, R.,Rembe, 2024).

In addition to domain-level indicators, page-level optimization plays an important role in determining search visibility. Page score and related metrics measure the effectiveness of individual webpages in terms of structure, content relevance, and keyword alignment (Mukaka, M. M. , 2012). Properly optimized webpages that clearly address user queries are more likely to appear in search results, as search engines aim to deliver content that matches the intent of users. Structured content, relevant keywords, and well-organized information therefore contribute significantly to improving page visibility (Reimers, N., & Gurevych, I.2019).

With the increasing adoption of AI in search technologies, AE and conversational search systems have begun to influence how information is presented to users. Instead of simply listing web pages, these systems increasingly aim to provide direct and concise responses to user queries (Clarke.A, 2023). As a result, content that clearly answers questions and aligns closely with search intent is more likely to be selected as a source of information in these environments. This development highlights the growing importance of AEO, which focuses on structuring content so that it can be easily interpreted and referenced by answer-based search systems (Devlin, J., 2019).

Despite these technological advancements, traditional SEO indicators continue to play an important role in digital marketing strategies. Backlinks remain widely regarded as indicators of credibility and trust, suggesting that other websites recognize a page as a valuable source of information (Manning, C. D. , 2008). Domain authority metrics also reflect the overall strength and reputation of a website within a particular field. At the same time, page-level optimization ensures that web pages are properly structured and aligned with indexing requirements used by search systems (Lewis, 2020).

However, the emergence of AE raises important questions about the continued relevance of these traditional SE signals (Parth Gautam, 2025). Modern search environments increasingly emphasize content clarity, query relevance, and structured information rather than relying exclusively on domain-level authority indicators (Nogueira & Cho, 2019; Thakur et al., 2021). Consequently, page level optimization strategies such as clear content organization, semantic alignment, and structured presentation of information may play a more significant role in determining search visibility (Krasakis, 2024).

Although the integration of AI in search technologies has been widely discussed in the literature, empirical research examining the relationship between traditional SEO metrics and answer engine outputs remains limited (Yunyi Zhang, 2025). Most existing studies focus on algorithm development and retrieval performance rather than analyzing the role of classical SEO indicators in AE ecosystems (Ricardo Baeza Yates, 2022). Therefore, further research is required to determine whether metrics such as page score, domain score, and backlink counts continue to influence the websites recommended by AE (Dai, 2020).

Understanding this relationship is particularly important for researchers and digital marketing practitioners who seek to adapt optimization strategies to evolving search technologies (Brin & Page, 1998). By examining the interaction between traditional SEO metrics and AE outputs, this study aims to provide insights into how optimization practices may need to evolve within the emerging landscape of answer-based search systems(Baeza Yates & Ribeiro Neto, 2011).

3. Materials and Methods

The present study was conducted in Department of Marketing, Mittal School of Business at Lovely Professional University, Phagwara, Punjab, India from October- March 2026. To test the hypothesis of the possible relevance of conventional metrics of SEO to maintain predictive validity in AE, AI environments, a quantitative empirical framework was implemented to assess the connection between the two procedures (Brin & Page,1998; Manning et al.,2008).

The study was initiated by performing systematic eliciting of key words with the aim of establishing commercially important, high-intent, search terms in the sport utility vehicle/SUV sphere. The five keywords were chosen based on the search intent, relevancy, and relevance to the user queries, these were best SUV, affordable SUV, best SUV on Indian roads, etc. These words were incorporated into a standardised query that tries to simulate the real user behaviour: List the 5 best SUV in India that is both affordable and is suitable on Indian roads (Fishkin & Hogenhaven, 2013; Bansal . D, 2024).

The specified query was sent to two AI based AE systems, which would be referred to as AE 1, AE 2. All the SE were responding to the same query prompt and generated a ranked list of suggested websites. The URLs provided by each AE model were noted separately so as to ensure the data sets are independent to be compared.

The URLs were then obtained and studied through the SEMrush SEO analytics system per the AE system. SEMrush was selected because of its approached scoring model (Erdmann,A.,& Ponzoa, J. M.,2022), its distinct backlink indexing platform, and its extensive use in SE research results. The specific quantitative measures were gathered on each of the websites found through the AE results (Page score, a page-level optimisation performance measure), Domain Score (a domain-level authority measure, which is the cumulative number of backlinks), and total Backlinks (the absolute number of inbound links) (Patel,2016; Fishkin & Hogenhaven,2013). All the data have been exported to structured Microsoft Excel spreadsheets in order to facilitate a systematic data management and statistical processing.

In both the AE, 50 observations were retained so that there is sufficient statistical representation and consistency between comparative analyses. All datasets had a similar extraction arrangement and definition of metrics. The data sets were filtered by their completeness, consistency, and duplications before subjecting them to statistical testing. There were no missing values and all variables were numerically proved.

The rank-order correlation coefficient (r_s) of Spearman was chosen to evaluate the monotonic correlations between Backlinks and Page Score, between Domain Score and Backlinks, respectively, in each of the AE models (Spearman,1904).

All the statistical calculations were done with the Statistics Kingdom online statistical analysis tool (George Casella, 2021). The alpha value used was 0.05 to establish the statistical significance. Separate correlation assessments were conducted on AE 1 and AE 2, which allowed to comparatively assess the effectiveness of conventional metrics of SEO in the operational behavior of individual AI based AE.

Results and Discussion

The relationship of backlinks with page score and domain score in Answer Engine 1

The data from AE1 analysis revealed a strong, significant relationship between backlinks and page score [$r_s(48) = 0.992$, $p < 0.001$] (Fig. 1). This indicates that higher page-level optimisation is associated with backlink acquisition. However, the relationship between backlinks and domain score was weak and non-significant,[$r_s(48) = 0.093$, $p = 0.519$](Fig.2).

Recent studies demonstrates that semantic matching significantly improves ranking effectiveness (Guo et al.,2016). Several studies further show that models prioritise contextual semantic similarity over traditional link-based metrics (Thakur et al.,2021). Recent developments in AI-powered search systems show that AE prioritise semantically structured content and contextual relevance within webpages, reinforcing the significance of page-level optimisation in AE Optimisation (Karpukhin et al.,2020). While traditional ranking systems relied heavily on link-propagation algorithms, recent neural models reduce dependence on global domain authority and instead emphasise contextual relevance (Hofstätter et al., 2021). These results may provide further evidence that the most recent environments for answer engines place greater emphasis on contextual and semantic relevance than traditional domain-wide authority metrics (Trabelsi et al., 2021; Pan et al.,2024). Whereas domain score has traditionally been linked to the accumulation of backlinks in classical SEO models, AI-driven retrieval systems seem to assess content at a more granular level (Khattab & Zaharia, 2020). Page-level optimisations, such as architectural clarity and semantic congruence, may therefore be more influential on not just visibility but also backlink performance (Khattab & Zaharia,2020). The results imply a change in structural approach from authority-based ranking to relevance-based evaluative frameworks. With the growing dependence of data retrieval architectures on contextual embeddings and passage-level matching (Nogueira & Cho, 2019), it seems that domain-level authority signals are receiving less attention (Farivar, 2025). This shows the progress of optimisation strategies for AI mediated search ecosystems.

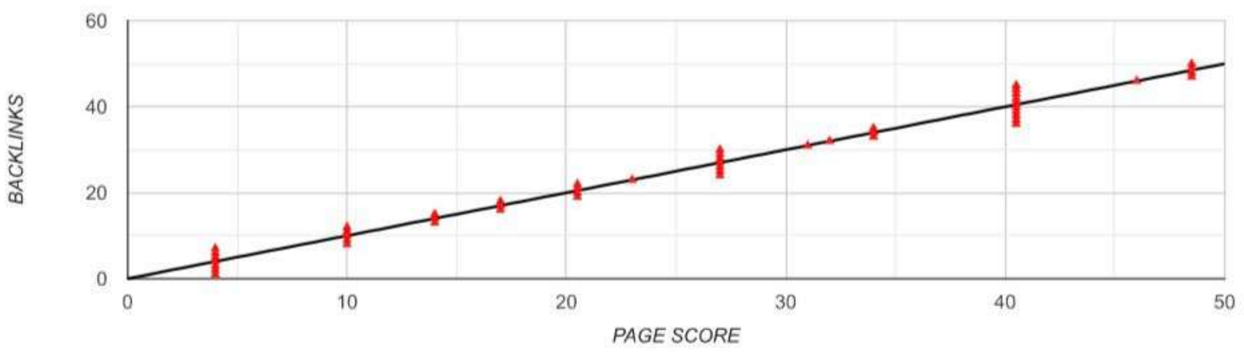

Figure 1: Scatterplot showing the relationship between page score and backlinks in AE1

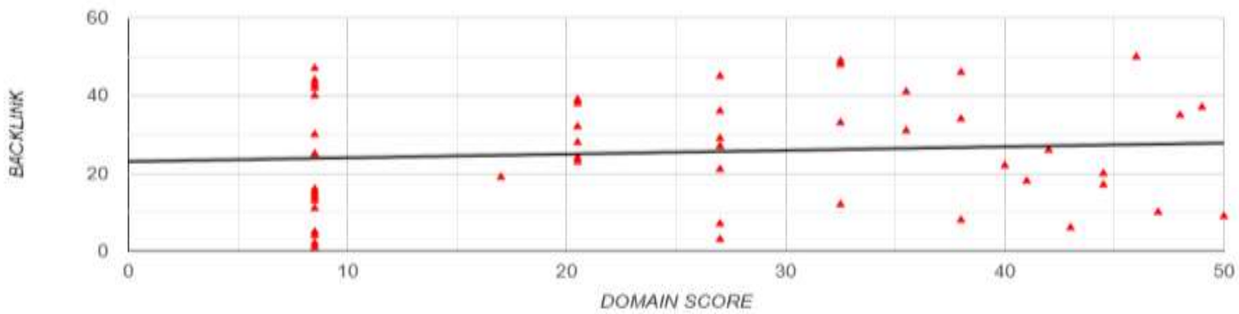

Figure 2: Scatterplot showing the relationship between domain score and backlinks in AE1

Relationship of backlinks with page score and domain score in AE 2

The AE 2 analysis indebated significant relationship between backlinks and page score,[$r_s(48) = 0.984$, $p < 0.001$] (Fig. 3). However, the relationship between backlinks and domain score was weak and non-significant, [$r_s(48) = 0.178$, $p = 0.217$](Fig. 4).

Ranking architectures enhance the contextual understanding of keyword intent within page content (Nogueira & Cho, 2019; Khattab & Zaharia, 2020). Study further illustrates how passage-level interaction improves semantic ranking accuracy (Khattab & Zaharia, 2020). Data retrieval models demonstrate that embedding similarity and semantic precision often outweigh macro-level domain authority signals (Xiong et al., 2021). These results reflect the evolution from hierarchical SEO structures to context-sensitive ranking systems. Accordingly, relevance is now driven more by semantic alignment between query intent and page-level content than by aggregated domain-wide authority metrics (Devlin et al.,2019; Reimers & Gurevych,2019). While ranking systems do not ignore contextual coherence or passage-level interaction, page optimisation strategies seem to perform better on visibility metrics (Reimers & Gurevych,2019). The weaker contribution of the domain score also suggests that AI-mediated answer systems rely less on cumulative backlink strength. Instead, their focus is on content clarity (Karpukhin et al.,2020). The findings indicate a broader shift toward AE practices, in which AI-based answer engines rely more on semantically relevant and well-structured content rather than traditional link-based ranking mechanisms (Thakur et al.,2021; Lin et al,2021)

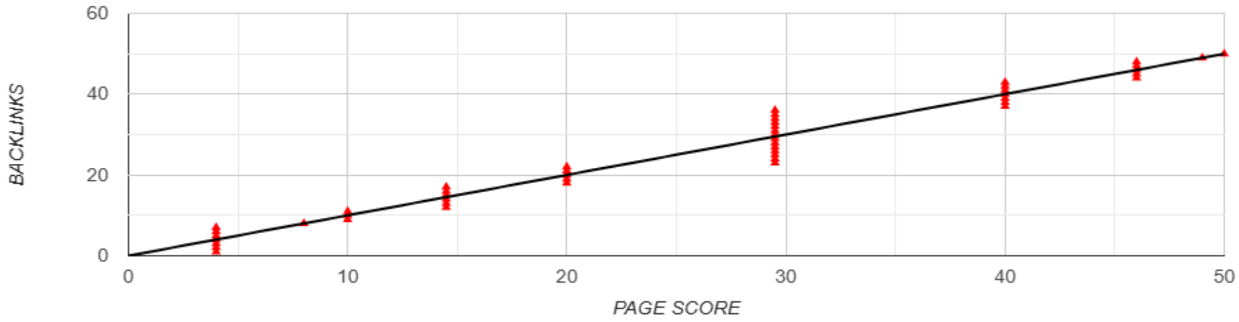

Figure 3: Scatterplot showing the relationship between page score and backlinks in AE 2

Figure 4: Scatterplot showing the relationship between domain score and backlinks in AE 2

Conclusion

In the current study, we assessed if traditional SEO metrics were relevant in answer engine scenarios by comparing backlinks, page score and domain score for multiple answer engine systems AE1 and AE2. This analysis utilized empirical data obtained from AE results to find out if conventional SEO indicators still play a significant role in website selection in AI based retrieval systems of the latest era. AE1 results showed significant positive correlation between backlinks and page score, showing the higher level of page-level optimisation leads to significant number of backlinks. In spite of this, the relationship of the backlinks with domain score in AE1 was weak and non-significant confirming that domain level authority was not major influence on backlink performance in answer engine responses. These results suggest the AE may be assessing content at a fine level, whereby quality of pages is prioritized over the richness of the domain itself. A similar trend was seen in AE2 where the relationship between backlinks and page score were both strong and statistically significant, while the relationship between backlinks and domain score was weak and not significant. The uniformity of these results between the two answer engines suggest that the degree of effect of page level optimisation is more important to answer engines in contrast to domain-level authority. This, which may suggest that AE pay more importance to well-formed, relevant, and contextually aligned content rather than traditional authority based signals. Comparison with AE1 and AE2 also shows that although old SEO metrics still are important, they have played a reduced role, since they focus from authority by domain and on page level optimisation. Backlinks still have a significant relationship with page score, although decreased between them and domain score implies that answer engines are now considering the importance of relevance and quality of content being used on each page. This is representative of the movement from previous rank based search models to retrieval mode oriented towards answer, in which semantic relevance and content clarity is expected to become more important. Taken together, the results of the study suggest that the conventional SEO indicators are still somewhat relevant in answer engine environments, but that their effect is uneven in practice in all measures. Page level optimisation seems to be more related to backlink performance than domain level authority, which suggests the tendency to move toward relevance-based benchmarking and evaluation in the modern world of search with ever evolving search environment. These findings indicate that optimisation strategies must be modified to accommodate AEO where the structure, semantics of the content and quality of the content may be more important than total domain authority. The contribution of the study is the empirical evidence on the performance of traditional SEO metrics in AE systems. Further research could also investigate the emergence of more ranking signals and content-level factors to understand optimisation strategies in AI mediated search environments.

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