Transformation of Search Engine Optimization Strategies from Keyword-Based to Search Intent Approaches in the Era of Generative AI: A Scoping Review and a Framework for Measuring Visibility in Answer Engines

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ABSTRACT

Generative artificial intelligence (AI) is changing web search from ranked lists of links into synthesised, cited answers, which weakens search engine optimization (SEO) practices built on keyword density and raises the question of how visibility should be measured. This study maps how SEO strategy has moved from keyword-based to search-intent approaches, identifies the influence of generative AI on SEO practice, and proposes a framework for measuring visibility in answer engines. A scoping review was conducted following the PRISMA ScR guidance, with explicit eligibility criteria based on the Population-Concept-Context framework and a PRISMA-style flow of records. From 44 records, 27 sources were included: 25 peer-reviewed journal articles, conference papers, and book chapters, and two working papers that are used only as supplementary evidence and are accompanied by explicit risk parameters. Fifteen sources were published between 2024 and 2026. Four findings emerge. First, SEO has evolved through three phases, namely keyword-based, intent-based, and generative, in which the unit of optimisation shifts from keywords to user needs and then to information worth citing. Second, evidence indicates that extractable evidence such as citations, quotations, and statistics improves visibility in generative engines, whereas keyword stuffing does not. Third, answer engines show weaknesses in citation accuracy, source concentration, and market bias, and early field evidence reports fewer outbound clicks when AI summaries appear. Fourth, because click-through rate alone cannot capture visibility in answer engines, the study proposes a five-stage framework that combines LLM Citation Rate, Brand Mention Frequency, Share of Model, and Entity Association Strength with traditional traffic indicators. The framework is conceptual and requires empirical validation, particularly in Indonesian-language contexts.

Keywords: Search Engine Optimization, Search Intent, Generative AI, Generative Engine Optimization, Digital Marketing

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INTRODUCTION

Digital technology has changed the way people search for, access, and use information. Search engines have become the main gateway through which internet users find products, services, and knowledge, so a website's visibility on search result pages largely determines its digital business opportunities. Within this context, search engine optimization (SEO) has grown into both a practical discipline and an important field of study in digital marketing (Ziakis et al., 2019; Giomelakis & Veglis, 2016).

In its early phase, SEO practice was closely tied to keyword matching. Site managers placed keywords in titles, meta tags, and page text, and then reinforced them with backlinks. Studies of Google ranking factors show that technical components, page structure, and content do contribute to a site's position (Ziakis et al., 2019), and similar findings have been reported for media websites (Giomelakis & Veglis, 2016). This approach is often called keyword-based, because keywords are treated as the primary unit of optimisation.

As search engines became better at understanding language, attention shifted to the goal behind a query. Broder (2002) introduced a taxonomy of web queries that distinguishes navigational, informational, and transactional goals, and this classification was later developed into methods for determining intent automatically from search logs (Jansen et al., 2008). The concept of search intent is the foundation for the shift in SEO from merely matching words to serving user needs.

This shift has been accelerated by generative AI. Generative search systems no longer merely display a list of links; they compose contextual answers that can be continued as a conversation (Aliannejadi et al., 2024). Experimental studies show that users of search based on large language models can complete tasks faster with fewer queries (Spatharioti et al., 2025). In Indonesia, similar patterns are beginning to appear in the information-seeking behaviour of technology practitioners, who combine conventional search engines with generative AI (Hibatulwafi & Laksmi, 2024). The consequence for site owners is that visibility is increasingly a matter of whether a source is cited inside a generated answer, rather than only where it is ranked (Popescu, 2026).

For SEO practitioners, this change has two consequences. First, there is a need to be cited and summarised by generative engines, not merely to be ranked. The idea of generative engine optimization (GEO) was proposed to address this need (Aggarwal et al., 2024). Second, concerns have arisen regarding the reliability, bias, and authority of answers produced by generative systems (Li & Sinnamon, 2024; Shah & Bender, 2024; Narayanan Venkit et al., 2025), together with the reminder that searching remains important even as AI is used more widely (Hersh, 2024). A third consequence is practical and concerns measurement: when answers are synthesised inside the interface, click-through rate and ranking position no longer describe visibility adequately, and generative search providers offer no public interface for tracking citations (Roumeliotis et al., 2026).

Although the literature on these topics is growing rapidly, it remains scattered across information retrieval, human-computer interaction, and digital marketing. Existing reviews tend to cover only part of the picture. A recent integrative review proposes a business intelligence lifecycle for SEO in the generative era (Roumeliotis et al., 2026), and a bibliometric analysis maps research on SEO and GEO (Popescu, 2026), but a synthesis that links the evolution from keyword-based to intent-based to generative optimisation with concrete, intent-aligned measures of visibility is still lacking, particularly with reference to the Indonesian context. This review seeks to fill that gap.

Based on the above, this study aims (1) to analyse the transformation of SEO strategies from keyword-based to search-intent approaches; (2) to identify the influence of generative AI on modern SEO practice; (3) to formulate the challenges and opportunities of implementing SEO in the era of artificial intelligence; and (4) to propose a framework for measuring visibility in answer engines that goes beyond click-through rate. The expected contribution is a conceptual framework of three SEO evolution phases, together with adaptation strategies and a set of testable visibility metrics that can serve as a reference for practitioners and as a basis for hypotheses in subsequent empirical research.

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METHODOLOGY

Research Design

This study is a scoping review. A scoping review was chosen because the field is young, heterogeneous, and spread across disciplines, so the aim is to map concepts, evidence, and gaps rather than to estimate a pooled effect. The review follows the PRISMA extension for scoping reviews (Tricco et al., 2018), and the flow of records is reported in the style of the PRISMA 2020 statement (Page et al., 2021). Four review questions guided the work: (RQ1) how has SEO strategy moved from keyword based to search intent approaches; (RQ2) how does generative AI influence SEO practice and user search behaviour; (RQ3) what challenges and opportunities does this create; and (RQ4) how can visibility in answer engines be measured beyond click-through rate.

Eligibility Criteria

Eligibility was defined with the Population-Concept-Context framework recommended for scoping reviews and is shown in Table 1. Peer-reviewed sources were required for the evidence base. Because the field changes quickly, working papers and preprints were allowed only as supplementary evidence, and each such source had to be flagged and described with explicit risk parameters (Table 2). Classic sources before 2019 were retained only when they define the concepts of search intent and search behaviour on which later work builds.

Table 1: Eligibility criteria based on the Population-Concept-Context framework

Element	Inclusion criteria	Exclusion criteria
Population	Search engine users, website owners, SEO and digital marketing practitioners	Studies without a user, site-owner, or practitioner perspective
Concept	SEO, search intent, generative search, GEO, citation behaviour of AI search, and measurement of visibility	Paid advertising, ranking manipulation unrelated to content, and generic AI studies without a search link
Context	Web search and AI-based search, 2002 to 2026, with emphasis on 2019 to 2026	Domains without a web search context
Source type	Peer-reviewed journal articles, conference papers, book chapters; working papers only as flagged supplementary evidence	Blog posts, vendor reports, encyclopedia entries, and opinion pieces
Verification	Bibliographic metadata and DOI or stable link could be confirmed at the time of screening	Records whose metadata could not be confirmed
Language	English and Indonesian	Other languages

Information Sources, Search, and Selection

The update search was run on 25 October 2026 using 18 search strings, combining terms such as generative engine optimization, generative search, AI search, AI Overviews, search intent, query intent, citation, brand visibility, entity-based SEO, click-through rate, and zero-click search. Searches were run through web-based scholarly search and the websites of publishers and proceedings (Elsevier, Springer, ACM, Wiley, MDPI, and AAAI), and through arXiv and SSRN for working papers. The search extended an earlier corpus of 23 sources, which was re-screened against the criteria in Table 1. The updated search returned 21 candidate records, giving 44 records in total and no duplicates.

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Screening was carried out in a single pass on title, abstract, and bibliographic metadata, followed by confirmation of each included record against the publisher's page. Seventeen records were excluded: nine preprints (the three preprints of the earlier corpus, which were replaced by peer-reviewed sources, and six newly found preprints), seven records whose metadata could not be confirmed or whose focus was off-topic, and one encyclopedia entry. Twenty-seven sources were included, of which 25 are peer-reviewed and two are working papers. Figure 1 shows the flow of records.

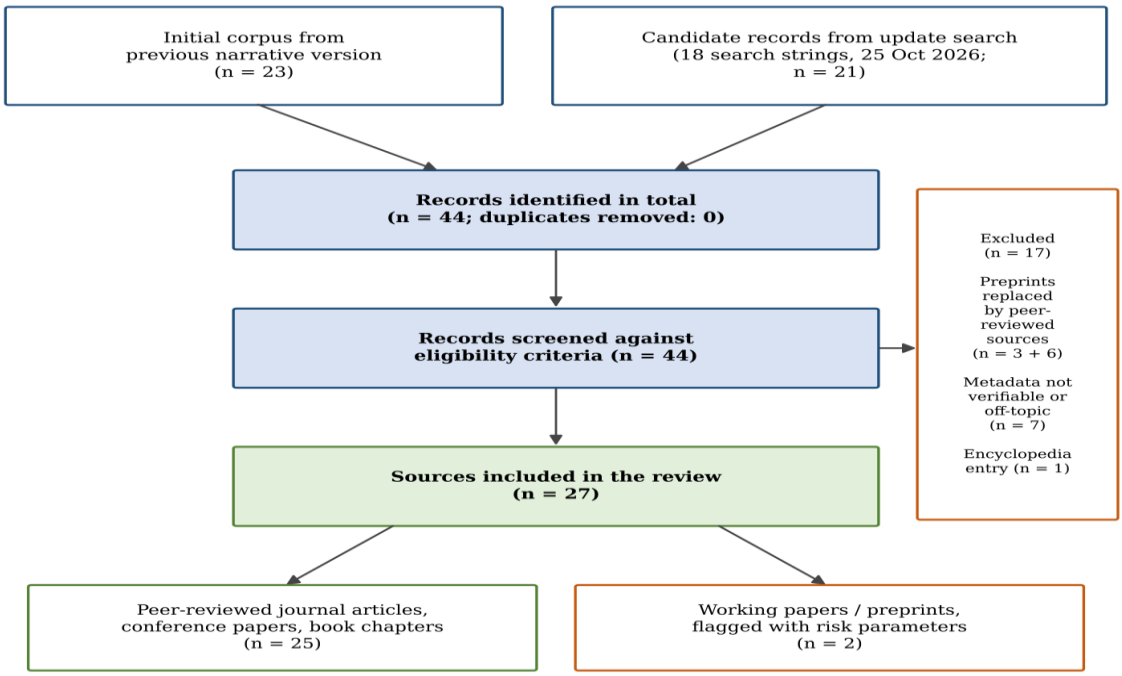


Figure 1: PRISMA-style flow of records for the scoping review

Of the 27 included sources, 22 (81%) were published between 2019 and 2026 and 15 (56%) between 2024 and 2026, while five classic sources provide the conceptual foundation. Figure 2 shows their distribution by publication period.

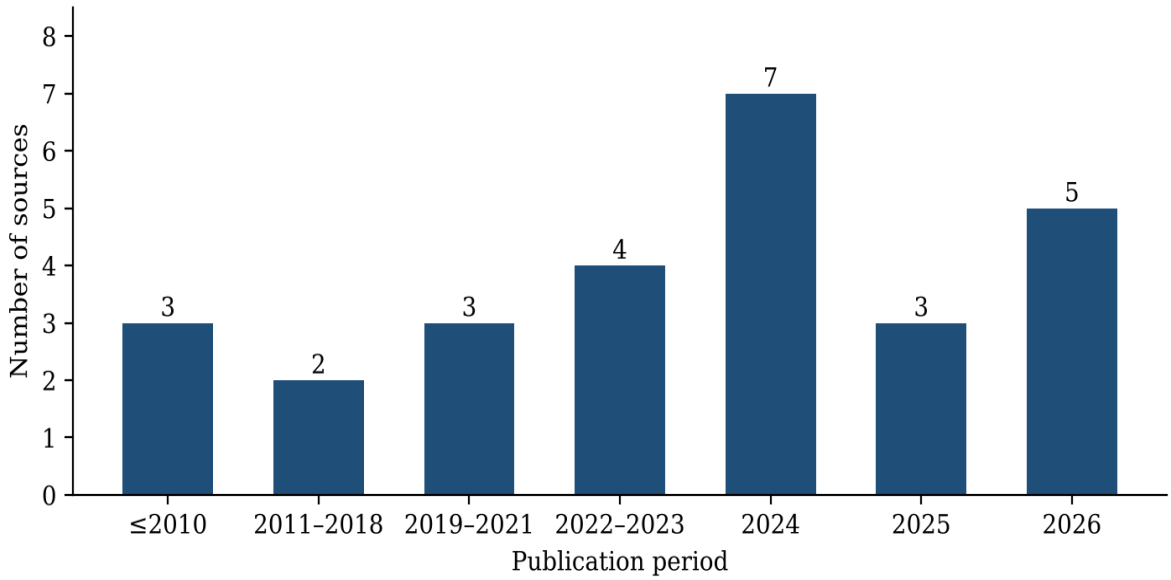


Figure 2: Distribution of the 27 included sources by publication period

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Data Charting and Synthesis

For each source, the authors, year, venue, source type, design, key finding, and relevance to the review questions were charted. Sources were then coded into five themes: (1) foundations of intent and search behaviour, (2) conventional SEO and AI in digital marketing, (3) generative AI and information seeking, (4) GEO and visibility measurement, and (5) risks, bias, and source quality. Consistent with the purpose of a scoping review, no formal quality scoring was applied to peer-reviewed sources, and findings were synthesised narratively. Figure 3 shows how the sources are distributed across themes.

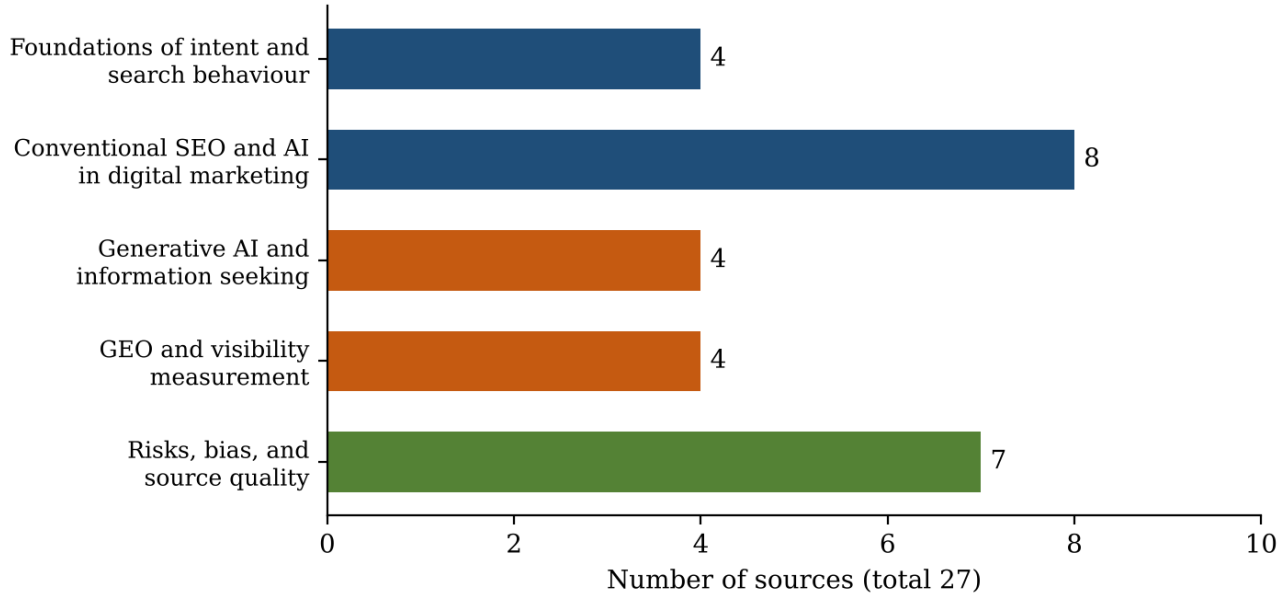


Figure 3: Distribution of the included sources by coded theme

Treatment of Non-Peer-Reviewed Evidence

Two working papers were retained because they report evidence that is not yet available in peer-reviewed form: a randomised field experiment on the effect of AI summaries on clicks (Agarwal & Sen, 2026) and a critical survey of GEO research (Martinez, 2026). To avoid weakening the rigour of the review, neither source is used as the sole basis for a conclusion. Table 2 states the risk parameters attached to each, and wherever they are cited in the text, they are identified as working papers.

Table 2: Risk parameters for the two non-peer-reviewed sources

Source	Type and design	Risk parameters	How it is used
Agarwal & Sen (2026)	SSRN working paper; randomised field experiment with 1,065 desktop Chrome users recruited through Prolific, two-week window in early 2026	Not peer reviewed; revised version may change; desktop-Chrome panel and short window limit generalisability; findings concern Google AI Overviews only	Indicative evidence of click loss; conclusions are framed as provisional
Martinez (2026)	arXiv preprint; critical scoping review of 45 studies published from late 2023 to mid-2026	Not peer reviewed; version dated July 2026; selection of included studies not independently verified here	Corroborates lever-level findings that also appear in peer-reviewed work; supports the metric hierarchy

RESULTS AND DISCUSSION

Conceptual Foundations: SEO and Search Intent

SEO is generally understood as a set of efforts to increase a website's visibility in organic search results. Evaluations of search engines show that the quality of search results cannot be separated from how users' queries are understood and matched with relevant documents (Lewandowski, 2015). Accordingly, the quality of SEO ultimately depends on the extent to which a page satisfies the need that lies behind a query.

This need is what is called search intent. Broder (2002) divided web queries into three classes: navigational (the user wants to reach a particular site), informational (the user wants to obtain information), and transactional (the user wants to perform an activity such as buying or downloading). Jansen et al. (2008) developed ways of determining these three types of intent automatically from large query datasets, and their report shows that most queries are informational. This three-class framework has since been widely extended in the digital marketing literature with a commercial investigation category, which describes users who are comparing options before making a transaction. In this review, the four categories are used as a practical working framework, with the caveat that the fourth category is a practical extension and not part of Broder's original taxonomy.

Characteristics of search behaviour are also relevant. A comparison of transaction logs from nine search engines shows that users tend to enter short queries and view only a few result pages (Jansen & Spink, 2006). This older finding explains why top positions were fiercely contested in the keyword-based era, and it also shows that short queries often conceal the user's real intent.

The Keyword-Based Era: Characteristics and Limitations

In the keyword-based era, SEO strategy centred on identifying high-volume keywords, placing them in page elements, and building backlinks. Studies of Google ranking factors confirm that technical and on-page content factors play a role in determining the position of search results (Ziakis et al., 2019). Research on Greek media websites likewise examined the SEO factors applied by media organisations and showed that, in practice, SEO implementation is strongly influenced by the editorial and technical decisions of site managers (Giomelakis & Veglis, 2016).

The limitation of this approach lies in its assumption that term matching is identical to relevance. A single keyword can serve different intents, and conversely a single intent can be expressed through many keywords. As a result, a page optimised solely for keywords may fail to meet user needs. Keyword stuffing is an extreme form of this weakness and, as discussed below, has been shown to yield no meaningful improvement in generative search engines (Aggarwal et al., 2024).

The Shift Towards Search Intent

The shift towards search intent is marked by a change in the unit of optimisation, from keywords to user needs. Consequently, keyword research no longer stops at search volume but continues with questions about what the user actually wants to achieve and which form of content suits that goal best. Research on ranking factors for voice queries is a good example. Saeed et al. (2024) examined the SEO factors that influence voice queries using a machine learning approach, and voice queries typically take the form of natural-language questions rather than the short strings typical of text queries. This is consistent with the argument that the more natural the language users employ, the more important the understanding of intent becomes relative to term matching.

Recent integrative work places intent at the start of the optimisation cycle. The Signal-Structure-Surface-Score (4S) lifecycle proposed by Roumeliotis et al. (2026), built on an integrative review of 70 studies, begins with conversational intent capture and proceeds to entity-based data architecture, content optimisation for retrieval by large language models, and attribution metrics for zero-click environments. The same review reports that users write longer, more conversational queries in LLM-based search than in

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traditional search, which makes intent identification both harder and more valuable. A bibliometric analysis conducted under PRISMA 2020 likewise describes the field as moving from visibility based on rankings to visibility based on citations (Popescu, 2026).

The influence of generative AI on search behaviour

Generative AI changes the form of search interaction. Aliannejadi et al. (2024) explain that interaction with generative information retrieval systems is conversational, allows users to clarify their needs gradually, and produces answers that have already been synthesised. In the Indonesian context, Hibatulwafi and Laksmi (2024) describe how technology practitioners use generative AI in their information-seeking behaviour, not to replace search engines entirely but to complement them according to the needs of the task.

Experimental evidence shows two sides. On the one hand, Spatharioti et al. (2025) report that search based on large language models allowed participants to complete tasks faster with fewer queries than traditional search. On the other hand, the same study found a risk of overreliance, in which users tend to accept incorrect answers when the system provides wrong ones. From the standpoint of reliability, Hersh (2024) emphasises that searching remains important in the era of generative AI, among other reasons because of the limited ability of language models to guarantee accuracy, particularly in fields that demand precision such as health informatics. This argument matters for SEO because it shows that credible source content remains the raw material of the search ecosystem, even though the way it is presented is changing.

Table 3: Summary of key studies and their relevance to the transformation of SEO

Source	**Focus of study**	**Relevant finding or argument**
Broder (2002)	Taxonomy of web queries	Three intent classes: navigational, informational, transactional
Jansen et al. (2008)	Determining query intent	Intent can be determined automatically; most queries are informational
Ziakis et al. (2019)	Google ranking factors	Technical and content factors play a role in ranking
Saeed et al. (2024)	Ranking factors for voice queries	Natural queries demand an understanding of intent
Aggarwal et al. (2024)	Generative engine optimization	Citations, quotations, and statistics raise visibility; keyword stuffing is ineffective
Spatharioti et al. (2025)	LLM-based search	Faster tasks, but a risk of overreliance on incorrect answers
Narayanan Venkit et al. (2025)	Answer engines versus traditional search	Sixteen limitations identified; a share of statements not supported by listed sources
Brantner et al. (2025)	Sourcing in AI-powered search	Citations to news media often erroneous; English-language outlets dominate
Allaham & Diakopoulos (2026)	Audit of generative search citations	AI-generated sources appear among cited sources; citations concentrate on few domains
Roumeliotis et al.	Integrative review of 70	4S lifecycle; attribution and brand-mention metrics for

(2026)	studies	zero-click settings
Popescu (2026)	Bibliometric analysis (PRISMA 2020)	Shift from ranking-based to citation-based visibility

Generative Engine Optimization as a Continuation of SEO

Aggarwal et al. (2024) introduced GEO as a framework to help content creators increase their visibility in generative engines. Testing on a broad set of queries, they report that several methods, such as adding source citations, quotations, and statistics to content, could raise visibility by up to about 40 percent under their experimental conditions, whereas keyword stuffing produced no meaningful improvement. These figures cannot, of course, be generalised automatically to all engines and sectors, but the direction is clear: generative engines reward content that is easy to verify and easy to cite. A critical survey of 45 GEO studies, available as a working paper, reaches a consistent picture at the level of individual levers, rating extractable evidence such as statistics, definitions, and quotations as moderately to strongly supported and keyword stuffing as null or negative (Martinez, 2026). Because that survey is not peer reviewed, it is used here only to corroborate the peer-reviewed finding.

These findings have important implications. First, a content strategy that relies on keywords without substance is no longer adequate. Second, the quality of evidence in content, namely data, references, and traceable statements, becomes an optimisation asset. Third, success is no longer measured only by position in a list of links but also by how often the content is referenced in the answers composed by the engine. GEO should therefore be understood as a continuation of SEO, not its replacement, since both depend on content quality and an understanding of intent.

Challenges of implementing SEO in the AI Era

The first challenge concerns bias and authority. An audit of generative search engines shows that such systems act as arbiters of public knowledge authority, so that questions of source bias and representation become relevant (Li & Sinnamon, 2024). Shah and Bender (2024) add that replacing traditional search with generative systems can weaken users' ability to trace sources and understand the search process, so system designs that preserve transparency are needed. For site managers, this means that reputation and source traceability must be built deliberately.

The second challenge concerns the quality and distribution of cited sources. A qualitative and automated evaluation of answer engines found that participants judged answers to be shallow, overconfident, and sometimes supported by citations that did not support the attached claims, and the automated evaluation reported that roughly a quarter to a third of statements were not supported by any listed source, with citation accuracy ranging from about 49 to 68 percent across the engines tested (Narayanan Venkit et al., 2025). An audit of four generative search engines on 712 real-world queries found that AI-generated sources made up roughly 16 percent of cited sources and that citations concentrated on a narrow set of domains (Allaham & Diakopoulos, 2026). For site owners, concentration implies that entering the small set of repeatedly cited domains is difficult, which raises the value of distinctive, verifiable content.

The third challenge is market and language bias. In a study of Microsoft Copilot answering political news prompts in five languages, nearly 40 percent of citations to professional news media were misattributed, erroneous, or both, and the engine relied disproportionately on UK and US outlets even for non-English queries; Swedish commercial outlets that blocked AI crawlers did not appear in Swedish-language answers (Brantner et al., 2025). The study concerns political news and a single engine, so it cannot be generalised directly. It does suggest, however, that language, market, and crawler policy can affect whether a publisher is cited, and this should be tested explicitly for Indonesian-language websites.

The fourth challenge is content saturation. Dwivedi et al. (2023) summarise multidisciplinary perspectives on the opportunities and challenges of conversational generative AI, including concerns about quality,

originality, and the spread of misinformation. Kasneci et al. (2023), in the educational context, also warn of the need for caution regarding the reliability and bias of large language models. When content production becomes very cheap, the main differentiator is no longer the ability to produce but the ability to present information that is original and accountable.

The fifth challenge is a possible loss of referral traffic. A randomised field experiment, available as a working paper, reports that when a Google AI Overview appeared, outbound organic clicks fell by 39.8 percent and zero-click searches rose by 34.5 percent among its desktop-Chrome participants (Agarwal & Sen, 2026). Given the risk parameters in Table 2, this result is treated as an indication of direction and not as a stable estimate. The sixth challenge is measurement opacity: generative search providers offer no public interface for tracking citations, so practitioners must rely on proxy methods such as auditing a panel of queries or using third-party tools (Roumeliotis et al., 2026). Section "Measuring visibility in answer engines" responds to this problem. Table 4 summarises the challenges together with their implications and strategic responses.

Table 4: SEO challenges in the era of generative AI and strategic responses

Challenge	**Implication for site managers**	**Strategic response**
Bias and authority of sources	Content that is not credible is unlikely to be cited	State authorship, references, and traceable data
Citation accuracy and concentration	Entry into the small set of cited domains is difficult; errors can attach to a source	Publish distinctive, verifiable content; monitor how the site is cited
Language and market bias	Local-language sites may be under-cited	Test visibility in local-language query panels; review crawler policy
Content saturation	Generic content is easily replaced	Offer analysis, original data, and a distinctive perspective
Loss of referral traffic	Ranking and click metrics alone are no longer sufficient	Add citation, mention, and conversion metrics
Measurement opacity	No public interface for tracking citations	Run a repeatable query-panel audit with logged answers

The role of AI in SEO and digital marketing practice

Besides changing search behaviour, AI has also become a tool for practitioners. A systematic review of AI in marketing shows its wide range of uses, from customer data analysis to personalisation (Verma et al., 2021), and another literature-based study summarises applications of AI across marketing functions (Haleem et al., 2022). Ziakis and Vlachopoulou (2023) specifically review the role of AI in digital marketing, which includes search engine optimisation. At a broader level, Dwivedi et al. (2021) emphasise that research on digital and social media marketing must continue to adapt to technological developments.

The use of AI in SEO includes keyword research, topic clustering, intent identification, and technical audits. Given the risks discussed above, however, AI is best positioned as a tool for analysis and initial drafting that still requires editing and verification by humans. Practices that hand all content production over to AI risk producing generic and erroneous content, which ultimately contradicts the very purpose of optimisation.

Comparison of the three SEO paradigms

The synthesis in the preceding sections can be summarised into three phases of SEO evolution. Figure 4

shows the flow of the three phases together with their implications for adaptation strategy, while Table 5 compares them across the main dimensions. It should be noted that the three phases do not replace one another sharply. In practice they coexist: users still use conventional search engines, while others switch to generative systems or combine the two.

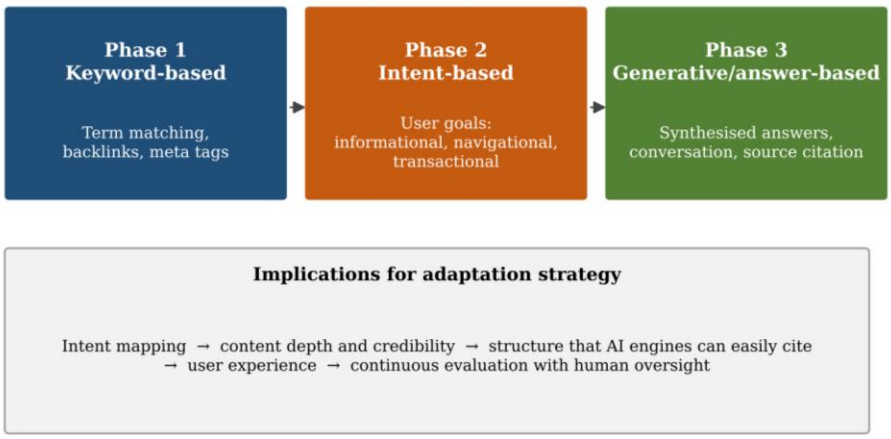


Figure 4: Framework of SEO evolution and implications for adaptation strategy (authors' synthesis of the reviewed literature)

Table 5: Comparison of keyword-based, intent-based, and generative-based paradigms

Dimension	**Keyword-based**	**Intent-based**	**Generative-based**
Unit of optimisation	Keywords and pages	User needs	Information worth citing
Main question	Which words are searched?	What is the searcher's goal?	What does the engine trust enough to summarise?
Main signals	Term matching, backlinks	Fit between content and intent	Evidence, citations, structural clarity
Form of output	List of links	More relevant list of links	Synthesised answers and conversation
Measure of success	Ranking and traffic	Relevance and engagement	Citation, mention, and conversion
Main risk	Keyword stuffing	Misinterpreting intent	Bias, errors, loss of visits

Adaptation Strategy Based on Search Intent

Based on the literature synthesis, an adaptation strategy can be organised into five steps. The first step is intent mapping, that is, grouping target queries into intent categories and assessing the content form that suits each best. The second step is strengthening the depth and credibility of content by including traceable data, references, and quotations, in line with the findings of Aggarwal et al. (2024). The third step is structuring content so that it is easy to understand and cite, for example through clear headings, a concise answer at the start, and supporting explanation below, together with an entity-based data architecture as proposed in the 4S lifecycle (Roumeliotis et al., 2026). The fourth step is maintaining user experience, including access speed and ease of navigation. The fifth step is continuous evaluation, for which the next section proposes concrete measures.

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Table 6: Content strategy derived from each type of search intent

Intent type	Suitable content form	Primary visibility indicator
Informational	Guides, concept explanations, concise answers with references	LLM Citation Rate
Navigational	Clear brand pages, tidy site structure	Brand Mention Frequency
Transactional	Product or service pages with complete information and a call to action	Conversion rate and click-through rate
Commercial investigation	Comparisons, reviews, and honest case studies	Share of Model and Entity Association Strength

Measuring Visibility in Answer Engines

Click-through rate (CTR) and ranking position remain useful, but they are insufficient in answer engines for two reasons. First, a user may read a complete answer without clicking, so a source can be influential and yet record no visit; the field experiment discussed above reports exactly this pattern, with more zero-click searches when an AI summary appeared (Agarwal & Sen, 2026). Second, ranking position has no direct equivalent inside a synthesised answer. The reviewed literature points to a more suitable family of measures. Roumeliotis et al. (2026) describe Share of Model, citation density, brand mention frequency, and answer sentiment, and distinguish impression-based, citation-based, and influence-based approaches to attribution, while the critical survey by Martinez (2026) organises metrics into a hierarchy that runs from retrieval and mention through citation and prominence to behaviour. Narayanan Venkit et al. (2025) add that the accuracy of citations should itself be measured.

Building on these sources, this review proposes a five-stage framework (Figure 5) in which each stage has its own metric, and in which three metrics are defined explicitly because they are the most actionable for site owners. The LLM Citation Rate (LCR) is the percentage of collected answers that cite at least one URL from the target domain. The Brand Mention Frequency (BMF) is the percentage of collected answers that name the brand, and the Share of Model (SoM) expresses the brand's mentions as a proportion of all mentions in a defined competitive set. The Entity Association Strength (EAS) is the proportion of answers in which the brand co-occurs with a target topic entity among all answers in which that entity appears; it can optionally be weighted by the order of mention. LCR, BMF, and SoM operationalise concepts in the reviewed literature, whereas EAS is the authors' own operationalisation and requires empirical validation. Table 7 gives the definitions.

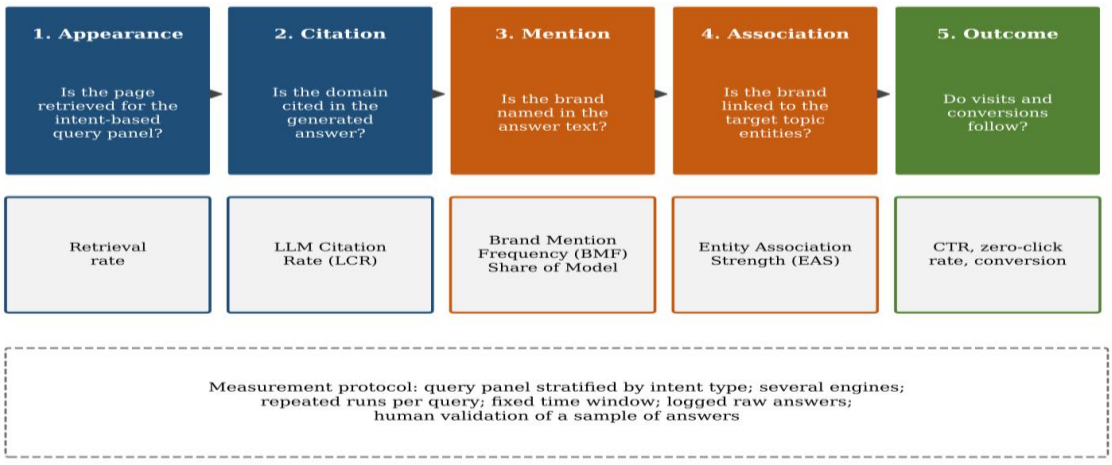


Figure 5: Five-stage framework for measuring visibility in answer engines (authors' proposal based on the reviewed literature)

Table 7: Proposed metrics for visibility in answer engines

Metric	Operational definition	Stage	Conceptual basis
LLM Citation Rate (LCR)	Answers citing at least one URL of the target domain / total answers collected x 100	Citation	Citation-level metrics (Martinez, 2026; Roumeliotis et al., 2026)
Brand Mention Frequency (BMF)	Answers naming the brand / total answers collected x 100	Mention	Roumeliotis et al. (2026)
Share of Model (SoM)	Brand mentions / mentions of all brands in the competitive set x 100	Mention	Roumeliotis et al. (2026)
Entity Association Strength (EAS)	Answers in which brand and topic entity co-occur / answers in which the topic entity appears	Association	Authors' operationalisation; entity-based architecture in the 4S lifecycle
Citation accuracy	Claims supported by the cited source / claims checked in a sample	Citation	Narayanan Venkit et al. (2025)
Answer sentiment	Share of answers framing the brand positively, neutrally, or negatively	Mention	Roumeliotis et al. (2026)
Click effect of AI summaries	Relative change in outbound organic clicks per search when an AI summary is shown	Outcome	Agarwal & Sen (2026), working paper
CTR, zero-click rate, conversion	Traditional traffic and conversion indicators from site analytics	Outcome	Established analytics practice

A measurement protocol is needed to make these metrics comparable over time. The query panel should be stratified by the four intent types in Table 6, so that each intent is evaluated with its own primary indicator. Several engines should be queried, because citation behaviour differs across platforms. Each query should be run repeatedly within a fixed time window, because generated answers can vary between runs, and the raw answers should be logged so that the metrics can be recomputed. A sample of answers should be validated by a human coder, particularly for mentions and entity association. As a purely illustrative calculation, a panel of 50 queries run three times on each of three engines yields 450 answers; if the target domain is cited in 90 of them, the LCR is 20 percent. This arithmetic is not empirical data and only shows how the metric is computed. Because proportions from a limited number of runs are uncertain, they should be reported with confidence intervals.

IMPLICATIONS AND LIMITATIONS

Theoretically, this review brings together the literature on information retrieval, human-computer interaction, and digital marketing within a single evolutionary framework and links it to a measurement scheme. Practically, it gives direction to site managers, business owners, and educational institutions to view SEO as an effort to meet user needs with credible, citable content, and to track success with metrics that fit answer engines.

This review has several limitations. First, although it follows PRISMA-ScR guidance and uses explicit eligibility criteria, the search was run through web-based scholarly search and publisher websites rather than a structured export from Scopus or Web of Science, and screening was done in a single pass, so selection bias cannot be excluded. Seven records were set aside because their metadata could not be confirmed, which may have omitted relevant studies. Second, no formal quality appraisal was applied, in line with scoping

review practice, and two included sources are working papers whose findings are treated as provisional (Table 2). Third, the visibility gains reported by Aggarwal et al. (2024) arise from particular experimental conditions and cannot be generalised without testing on other engines and sectors. Fourth, the 27 included sources describe a field that changes quickly, so the review is a snapshot as of October 2026. Fifth, the proposed metrics, and especially the Entity Association Strength, have not been validated empirically, and literature in Indonesian on this topic is still limited. A structured update using a Scopus export and a second independent screener is recommended for future work.

CONCLUSION

This scoping review shows that SEO strategy has shifted from a keyword-based approach towards search intent and is now entering a new phase because of the arrival of generative AI. In the first phase, optimisation relied on term matching and backlinks. In the second phase, the unit of optimisation moved to user needs, as formulated in the intent taxonomy. In the third phase, generative search engines synthesise answers, so content is required not only to be relevant but also to be worth citing.

Generative AI offers opportunities in the form of faster and more personalised search, while also creating challenges such as the risk of overreliance, weaknesses in citation accuracy, concentration and market bias in cited sources, content saturation, and a possible loss of referral traffic. The available evidence indicates that content accompanied by citations, quotations, and statistics is more likely to improve visibility in generative engines than keyword stuffing. An adaptive SEO strategy therefore needs to combine intent mapping, content depth and credibility, structures that are easy to cite, user experience, and continuous evaluation with human oversight.

Because click-through rate cannot describe visibility inside synthesised answers, this review proposes a five-stage measurement framework built on LLM Citation Rate, Brand Mention Frequency, Share of Model, and Entity Association Strength, aligned with the four types of search intent and combined with traditional traffic indicators. Future research is advised to validate these metrics empirically, for example through repeated query panel audits of Indonesian language websites on several answer engines, to test the effect of citation-rich content on LCR and BMF, and to quantify changes in traffic. For practitioners, the main recommendation is to shift resources from simply producing more content towards improving the quality, originality, and traceability of information, and to start logging citation and mention metrics alongside conventional analytics.

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