Analysis of Answer Engine Optimization (AEO) for E-Commerce Product Visibility A Study on Smartphones Under ₹30,000 in India

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Abstract- ***It examines how Answer Engine Optimization (AEO) can strengthen smartphone-related e-commerce visibility in India by comparing four query groups drawn from a secondary dataset: a broad budget query, a processor-focused feature query, a brand query, and a student use-case query. The findings show that brand-focused and user-need-focused queries outperform narrow feature queries across traffic, keyword breadth, page quality, domain strength, and backlink support. The study argues that answer-led visibility improves when content directly matches buyer intent, uses natural-language question framing, provides concise comparisons, and is structured for summarisation by answer engines and AI assistants. Although the data remain exploratory, the analysis suggests that AEO should complement SEO by improving answer extraction, trust, and recommendation readiness. The paper concludes that smartphone pages are more likely to be surfaced in answer-first search systems when they combine intent clarity, structured comparison, and clear product guidance.***

Keywords: Answer Engine Optimization, e-commerce, smartphone visibility, search intent, product relevance, voice search, India

I. INTRODUCTION

Search behaviour in e-commerce is changing from link-led browsing to answer-led discovery. Users increasingly expect short, reliable, and

comparison-ready responses before clicking through to long product pages. This shift is especially visible in smartphone shopping, where buyers often begin with conversational queries such as "best phone under a budget," "best Samsung phone," or "best phone for students."

The uploaded source report studies this transition through the lens of Answer Engine Optimization (AEO). While conventional SEO focuses on crawlability, indexing, and ranking, AEO

emphasizes whether content is easy for answer engines to interpret, summarize, and recommend. In practical terms, AEO asks whether a page can supply the best direct answer, not only whether it can appear somewhere in search results.

The study is built around a simple but timely problem: many product pages are optimized for keyword relevance yet remain poorly suited for answer extraction. Long blocks of unstructured text, weak comparison formatting, and limited intent matching reduce the chances that answer systems will select those pages as preferred responses. This issue matters for digital marketers, review publishers, e-commerce teams, and brands competing for visibility in AI-mediated search.

The source report therefore seeks to examine the role of AEO in smartphone product discovery, compare the performance of different query structures, connect the observed patterns to recent literature on relevance and conversational search, and derive practical suggestions for answer-first product content.

II. LITERATURE REVIEW

The literature reviewed in the source report can be grouped into five linked themes. First, semantic and personalized e-commerce search studies show that product discovery improves when search systems move beyond exact keyword matching and incorporate user preferences, query-product fit, and behavioural signals. This provides the conceptual base for AEO, which depends on relevance at the level of user intent rather than term frequency alone.

Second, research on keyword choice and SEO strategy highlights the importance of aligning optimization with the type of search being performed. Informational and transactional queries are not ranked in exactly the same way, and this matters for answer systems that often serve both roles at once: they explain options and guide purchase decisions.

Third, product relevance learning and re-ranking studies show that commercial search performs better when contextual meaning, user goals, and sometimes sentiment cues are taken seriously. In product discovery, the strongest results rarely come from isolated technical specification lists; they come from pages that interpret specifications in relation to user needs.

Fourth, voice search and conversational commerce studies reveal that users increasingly express search intent as full natural-language questions. This supports the use of direct question headings, concise answer blocks, FAQs, and conversational comparison formats in smartphone content.

Finally, recent large-language-model and multimodal search research suggests that modern retrieval systems favor content that is easy to parse, summarize, compare, and cite. The research gap identified in the source is therefore clear: although technical and marketing work exists, fewer applied studies examine answer-engine visibility using a small practical dataset tied to a specific product category such as smartphones.

Figure 1. Conceptual framework linking search intent, AEO content design, and visibility outcomes.

III. RESEARCH METHODOLOGY

The source study uses a descriptive and analytical research design based on secondary data rather than fresh survey collection. Its main evidence comes from a user-provided workbook containing four sheets, of which Key_Metrics and AEO_Benchmarks are central to analysis.

The unit of analysis is the smartphone query group. Four query groups are compared: Q1, a broad budget query about the best phone under ₹50,000; Q2, a feature-focused query about processor performance; Q3, a brand-focused query about Samsung phones; and Q4, a use-case query about phones for students. These four groups represent four different intent structures commonly seen in e-commerce search.

The main performance measures used by the source are organic traffic, paid traffic, organic keywords, paid keywords, and traffic-cost indicators. The benchmark sheet adds page score, domain score, and backlinks. Together these measures are treated as approximate indicators of visibility, reach, and search strength.

The source organizes the analysis in five steps: reviewing the workbook, arranging query-level values, calculating benchmark averages, interpreting the patterns with support from recent literature, and developing practical recommendations. Because the workbook is limited in size, the results should be interpreted as exploratory signals rather than universal market rules.

Component	Summary
Data source	Secondary workbook with Key_Metrics and AEO_Benchmarks sheets.
Unit of analysis	Four smartphone query groups representing different buyer intents.
Performance metrics	Organic traffic, paid traffic, keyword counts, traffic value.
Benchmarks	Page score, domain score, backlinks.

Analytical purpose	Identify which query structures align most strongly with visibility.

Table 1. Summary of design and variables used in the source report.

IV. DATA ANALYSIS AND INTERPRETATION

The results show a clear hierarchy among the four query types. Q3 and Q4 are strongest across almost every visibility measure. Both attract the highest organic traffic and paid traffic, the widest organic keyword coverage, the strongest domain scores, and the highest backlink averages. This suggests that brand intent and user-need intent are especially compatible with answer-first visibility.

Q1, the broad budget query, performs well but remains below Q3 and Q4. This indicates that price-led discovery remains commercially important, especially for users beginning a general buying journey. However, it is still somewhat weaker than content anchored in a specific brand or a concrete user problem.

Query	Intent type	Organic traffic	Organic keywords	Avg. backlinks
Q1	Budget	54,680	12,980	651.43
Q2	Processor	41,780	9,460	545.00
Q3	Samsung	69,420	15,860	783.75
Q4	Students	69,420	15,860	783.75

Table 2. Condensed query-level visibility profile from the uploaded source report.

Q2, the narrow processor-focused feature query, is weakest across the dataset. It records the lowest traffic, smallest keyword footprint, and weakest benchmark profile. The implication is not that processor content lacks value, but that feature-only content may not gain strong answer-engine visibility unless it is embedded within broader buying scenarios such as gaming, battery life, or student needs.

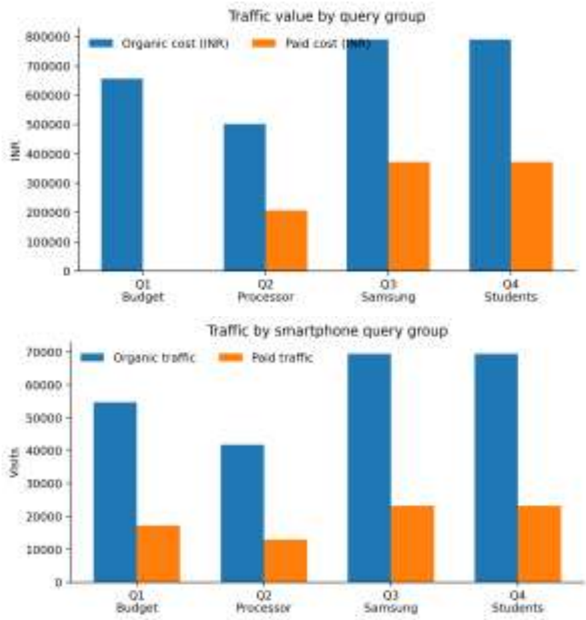

Figure 2. Organic and paid traffic by smartphone query group.

The traffic comparison reinforces the narrative above. Q3 and Q4 dominate both organic and paid activity, while Q2 trails the field. This suggests that answer-led systems favor content attached to recognizable shopping missions rather than narrowly technical queries.

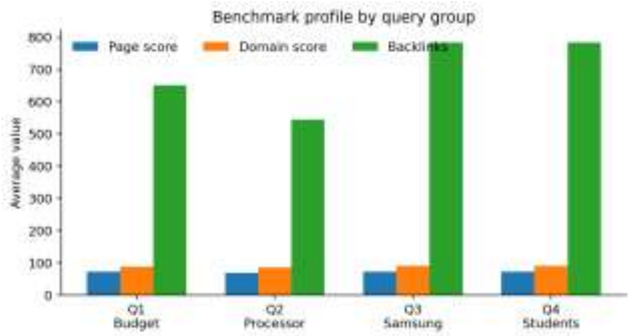

Figure 3. Benchmark profile by query group using page score, domain score, and backlinks.

Benchmark indicators tell the same story. Q3 and Q4 are backed by stronger domains and stronger link profiles, which means their intent advantage is reinforced by authority advantages. Q2 not only has weaker intent framing, but also weaker benchmark support.

Figure 4. Organic and paid traffic value by query group.

Traffic value analysis highlights the commercial strength of brand and use-case queries. Their higher estimated traffic value suggests that these query types are important not only for visibility volume but also for commercially meaningful discovery.

V. RESULTS AND FINDINGS

The main substantive finding is that answer-engine visibility is strongly linked to intent framing. Queries reflecting a recognizable buyer mission perform better than narrowly technical queries. A page answering "best Samsung phone to buy now" or "which phone under ₹50,000 is best for students" offers a clearer decision context than a page focused only on processor quality, and answer engines appear to reward that clarity.

A second finding is that broad budget queries remain useful discovery gateways. Q1 suggests that early-stage searchers still rely heavily on price ceilings when beginning the buying journey. For AEO, this means budget pages should not be generic listicles; they should offer direct answer summaries, ranked shortlists, and comparison-ready tables that support rapid decision making.

A third finding is that technical feature content needs contextual packaging. Processor queries may be important to advanced users, but on their own they appear less competitive in visibility terms. Feature content works better when translated into user outcomes such as gaming performance, speed, multitasking, or long-term value.

In practical terms, the study supports the view that AEO is a content design strategy. It encourages publishers to write around intent clusters, use direct answers near the top of the page, structure comparisons clearly, and reduce the friction between a user's question and the page's response.

Priority area	Recommended AEO action	Expected value
Budget pages	Use direct answer snippets, price filters, and ranked comparison blocks.	Improves broad discovery and early-stage guidance.
Feature pages	Embed processor content within gaming, performance, and multitasking comparisons.	Makes technical content easier for answer systems to recommend.
Brand pages	Maintain current best-pick modules and model-level answer sections.	Supports high-intent brand traffic with stronger recommendation readiness.
Use-case pages	Write plain-language recommendations for students and other buyer groups.	Aligns with conversational search and decision intent.

Table 3. Practical AEO implications derived from the observed query patterns.

VI. DISCUSSION AND PRACTICAL IMPLICATIONS

The study's contribution is not to claim that AEO replaces SEO, but to show that SEO without answer-readiness is increasingly incomplete. Strong pages still need authority, topical relevance, and backlink support. Yet answer engines also require pages to be recommendation-friendly: they must be easy to quote, compare, and summarise.

This insight matters for modern smartphone content because user journeys are increasingly fragmented across search engines, AI answer systems, shopping assistants, and voice interfaces. In these environments, winning visibility depends less on the number of keywords inserted into a page and more on whether the content resolves the user's intent in a structured way.

The findings also help explain why use-case content is powerful. Queries linked to students, gaming, creators, or budget-conscious buyers are easier to answer in plain language than highly abstract specification questions. That makes them more compatible with conversational search and answer extraction workflows.

For e-commerce teams, the practical lesson is to build pages that combine decision intent, trust signals, and comparative structure. Model comparisons, FAQ blocks, summary tables, short answer modules, and update-ready recommendation sections are likely to perform better than unstructured specification-heavy pages.

VII. LIMITATIONS AND FUTURE SCOPE

The source study has clear limitations. The dataset is small and based on an extracted workbook rather than a large market-wide panel. The query set is also not strictly limited to under-₹30,000 smartphones in every case, even though the broader framing points in that direction. In addition, some benchmark entries appear as dataset-derived references rather than fully validated competitor observations.

These limitations do not erase the value of the study, but they do mean that the results should be treated as directional. Future work could use a larger smartphone-only dataset, compare more query families, and incorporate answer-engine outputs directly from AI search summaries or shopping assistants.

Future research could also examine content structure more closely by auditing schema markup, FAQ usage, review blocks, page freshness, and multimodal elements such as images or short videos. Another useful direction would be user testing to determine which answer formats buyers trust most when narrowing phone choices.

VIII. CONCLUSION

This paper shows that the uploaded AEO report can be meaningfully reframed as a publication-style argument about intent and visibility. Across the four query groups, brand-focused and use-case-focused searches consistently outperform narrow feature-focused searches on traffic and benchmark indicators.

The key implication is that answer engines favor content that resolves buyer questions directly. Pages designed around recognizable purchase intent, such as budget guidance or student recommendations, are easier to summarize and recommend than pages built around isolated technical signals.

The evidence therefore supports a balanced conclusion: AEO should be treated as an applied extension of SEO. It strengthens product visibility not by replacing traditional optimization, but by improving answer extraction, recommendation readiness, and trust in modern answer-led search ecosystems.

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