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AI-Driven Search, Social Proof, and the Evolution of SEO: How Automation, Personalised Algorithms, and E-E-A-T Shape Digital Consumer Behaviour and Business Performance in the Modern Marketing Landscape

La ricerca guidata dall'intelligenza artificiale, la riprova sociale e l'evoluzione della SEO: come l'automazione, gli algoritmi personalizzati e l'E-E-A-T plasmano il comportamento digitale dei consumatori e le performance aziendali nel panorama del marketing moderno

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ABSTRACT

This thesis examines the transformation of search engine optimisation (SEO) within a digital marketing landscape increasingly shaped by artificial intelligence, personalised algorithms, and evolving frameworks of digital trust. As search engines have moved from keyword-based retrieval toward semantically aware, intent-sensitive, and machine-learning-governed systems, the criteria by which digital content achieves visibility have shifted in fundamental ways implicating organisational credibility, subject-matter expertise, and authentic community endorsement alongside conventional technical configuration.

The study adopts an exploratory mixed-methods research design. A conceptually oriented review of the literature, drawing on peer-reviewed scholarship from information retrieval, digital marketing, consumer behaviour, and strategic management and complemented by authoritative industry documentation, builds the theoretical framework; this is then examined empirically through a structured practitioner questionnaire and a semi-structured expert interview with WhitePress, a European content-marketing and publisher-network platform used as a contextual practitioner reference. The literature review integrates the evolution of search and SEO, the role of digital trust, the E-E-A-T quality framework, social proof in shaping consumer behaviour and algorithmic visibility, and the organisational implications of SEO automation and AI-assisted content production into a single literature review and conceptual framework. The study then sets out the research methodology, presents and discusses the empirical findings, interprets them in the discussion, and draws the analysis together in the conclusion.

The thesis argues that AI-driven search has made digital visibility simultaneously more technically sophisticated and more dependent on fundamentally human qualities genuine expertise, reputational authority, and authentic social validation. For businesses, this demands organisational capabilities in editorial depth, cross-functional coordination, and adaptive performance measurement that traditional SEO practice was not designed to develop. The European regulatory context, shaped by the General Data Protection Regulation and the Digital Services Act, further conditions how personalisation and algorithmic visibility can be pursued within EU markets, creating both compliance obligations and strategic opportunities that the existing literature has underexplored. Drawing the theoretical and empirical strands together, the thesis offers a set of evidence-

based strategic recommendations for firms operating in AI-mediated digital markets and identifies priority directions for further research.

Keywords: search engine optimisation, artificial intelligence, E-E-A-T, personalised algorithms, digital trust, social proof, consumer behaviour, organisational strategy, platform ecosystems

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INTRODUCTION

For the last thirty years, search engines have evolved from just simple information-retrieval systems that matched keywords into very sophisticated, AI-driven platforms that can understand user intent, the context of meaning, and even behavioural signals. Ranking criteria have profoundly changed with the ranking moving from mere lexical matching to semantic interpretation and finally to machine-learned and generative synthesis; nowadays, visibility of digital content depends much less on technical compliance with algorithmic requirements and much more on demonstrated expertise, reputational authority, and authentic social validation. At the same time, the search ecosystem is fragmenting and dispersing itself to social platforms, marketplaces, and AI-native interfaces, each governed by its own relevance logic. For companies working in European markets, these developments take place against a background of regulation determined by the General Data Protection Regulation and the Digital Services Act, which set limits on the ways in which personalisation and algorithmic visibility can be carried out. Together, these developments have turned search engine optimisation from mainly a technical task into a strategic organisational capability through which companies establish visibility, authority, and competitiveness within digital ecosystems.

Even though practitioners have been consistently interested, academic literature has looked at the transformation of search mostly through disciplinary boundaries-information retrieval, digital marketing, consumer behaviour, and strategic management-and the organisational and strategic dimension of AI-driven search, especially within the European regulatory context, has hardly been discussed. In fact, the existing literature only leaves a major tension at this point: while AI tools become almost universally available, using them can no longer be considered a source of competitive advantage; however, it is still a mystery what distinguishes companies that simply get these tools from those that truly change their capabilities, governance, and routines around them. So, the research question of this thesis is hiding behind the adoption of AI in search and organisational adaptation that converts adoption into durable advantage- a gap that existing accounts acknowledge in general terms but have not examined directly in the specific domain of AI-driven search.

This dissertation sets four research objectives that break down the overall purpose of the dissertation into concrete and manageable pieces of research: first, to trace the evolution of search and SEO and interpret its strategic significance (O1); second, to analyse how digital trust and the E-E-A-T framework act as gatekeepers for visibility and what they require from organisations (O2); thirdly, to study how personalisation and social proof influence consumer behaviour across distinct platforms (O3); and finally, to determine the organisational capabilities and structural changes necessary for achieving and maintaining competitive visibility (O4).

The research aims are achieved by four research questions, which are carried forward unchanged into the empirical chapters so that the theoretical and empirical strands of the thesis remain aligned:

RQ1. In what ways have the embedding of machine learning and large language models in search engine architectures caused fundamental changes in the rules of digital content visibility, and what are the resulting strategic and organisational implications for companies?

RQ2. How does the E-E-A-T framework implement digital trust in AI-powered ranking systems, and to what extent do organisations need to change their strategies and build new capabilities to meet these quality standards?

RQ3. How do personalised algorithms and social proof jointly influence the behaviour of digital consumers on different platforms that are characterised by distinct relevance logics?

RQ4. What are the organisational capabilities and structural changes companies need to make to be able to leverage AI-generated content outputs, meet E-E-A-T standards, and adapt cross-platform fragmentation so as to achieve and sustain competitive digital visibility?

The thesis is based on an exploratory mixed-methods research design, which is philosophically oriented from pragmatism. This philosophy of pragmatism views methodological decisions as being primarily driven by the research questions and not by a previous epistemological position to which one is committed. A conceptually driven review of the peer-reviewed literature in the fields of information retrieval, digital marketing, consumer behaviour, and strategic management along with the analysis of authoritative industry documents constitutes the theoretical framework on which this study is based. Then, onto the empirical examination, this theoretical framework is looked at through two research instruments that have been developed from it to serve the purpose of this research. One is a structured questionnaire given to practitioners, particularly digital marketing and SEO specialists, of which twenty-eight professionals actually completed it. The other instrument is a single, semi-structured interview with an expert from WhitePress, a European content marketing and publisher networking platform, who is used throughout the thesis as a contextual and practitioner reference. The survey maps the distribution of practices, beliefs, and adaptations in a variety of organisations. At the same time, the interview provides the interpretative depth necessary for explaining the mechanisms behind those patterns. These two sources of evidence, when taken in combination, are interpreted against the conceptual framework rather than separately.

CHAPTER 1: LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

The transformation of search has generated a growing body of research spanning information retrieval, digital marketing, consumer behaviour, and strategic management. While these disciplines have contributed valuable insights, they have often examined the phenomenon from distinct perspectives, resulting in a fragmented understanding of how AI-driven search influences both digital visibility and organisational strategy. This chapter integrates these strands of literature into a unified conceptual framework that explains the evolution of search, the increasing importance of trust and social validation, and the organisational capabilities required to compete effectively in AI-mediated digital environments. By bringing together these complementary perspectives, the chapter establishes the theoretical foundation for the empirical investigation presented later in the thesis.

1.1 Approach to the Literature Review

The review presented here is a narrative, integrative review of a conceptual kind rather than a systematic literature review in the formal, replicable sense associated with protocols such as PRISMA (Snyder, 2019; Torraco, 2005). The choice follows from the object of study. A systematic review is designed to identify, appraise, and aggregate an exhaustively defined body of evidence in answer to a tightly bounded question, and is most powerful where a mature literature has accumulated around a stable construct (Tranfield, Denyer, & Smart, 2003). The task here is different: to synthesise scholarship from information retrieval, digital marketing, consumer behaviour, and strategic management into a coherent theoretical account of a phenomenon that none of these fields, on its own, fully describes. Integrative reviews are the appropriate instrument when the objective is conceptual synthesis across disciplinary boundaries rather than the statistical aggregation of comparable studies (Snyder, 2019; Webster & Watson, 2002). The subject matter reinforces the point: AI-driven search is an emergent and fast-moving field in which commercial development has consistently outpaced systematic academic coverage, so that a procedure designed for stable literatures would systematically exclude the most current and relevant material.

A narrative review is not an unstructured one, and its conduct can be described transparently. The review drew on peer-reviewed scholarship identified through the major academic databases relevant to the constituent disciplines: Google Scholar for broad cross-disciplinary discovery, complemented by Scopus, the ACM Digital Library, IEEE Xplore, and SpringerLink for the information-retrieval, computer-science, and management literatures. Searches were built iteratively around clusters of terms corresponding to the core themes of the thesis, summarised in Table 1.1. Because the foundational concepts have long theoretical lineages while their application to AI-driven search is recent, two time horizons were combined: seminal theoretical contributions were admitted regardless of date, in order to establish the conceptual scaffolding, whereas literature on AI-driven search, generative systems, and platform-based discovery was concentrated on the period from 2015 onward, when the developments of central interest entered commercial deployment. Sources were selected on the basis of conceptual relevance to the research questions, scholarly standing as indicated by venue quality and citation impact, and, for fast-moving subtopics, recency.

Table 1.1. Thematic clusters and representative search terms

Thematic cluster	**Representative search terms**	**Primary section**
Search evolution and SEO	search engine optimisation; ranking algorithms; learning-to-rank; semantic search; intent classification; generative engine optimisation	1.3
Digital trust and credibility	digital trust; online credibility; source evaluation; E-E-A-T; brand reputation; authority signals	1.4
Social proof and consumer behaviour	social proof; online reviews; electronic word-of-mouth; influencer marketing; parasocial interaction; information cascades	1.4
Personalisation and platform ecosystems	recommender systems; collaborative filtering; personalisation; filter bubbles; platform governance; algorithmic visibility	1.3–1.4
SEO automation and organisational adaptation	marketing automation; generative AI in marketing; dynamic capabilities; digital transformation; organisational learning; AI governance	1.5

Note. The clusters are analytical rather than mutually exclusive; many sources informed more than one theme.

A distinction between academic and industry sources was maintained throughout. Peer-reviewed scholarship supplies the conceptual and theoretical content and carries the analytical weight of the thesis. Authoritative industry material, including Google’s published

Search Quality Evaluator Guidelines, survey research from Gartner, market analyses from SEMrush, and the global digital reports compiled by DataReportal, is treated as contextual evidence that illustrates how the mechanisms identified in the academic literature manifest in measurable practice, with its methodological basis and limitations noted where it is cited. Academic work thus provides depth and industry material provides currency, allowing the thesis to address a fast-moving subject without overstating the maturity of the evidence on which its claims rest. The principal limitation of a narrative review follows from its nature:because the search was not exhaustively protocol-driven, it cannot claim to have captured every relevant contribution, and the selection and interpretation of sources reflect the researcher's analytical judgement. These limitations are mitigated, though not eliminated, by the transparency of the selection criteria, by the triangulation of academic and authoritative industry sources, and by the explicit organisation of the review around the conceptual framework set out below.

1.2 Conceptual Framework

A review that integrates four disciplines requires an integrating logic, or it collapses into a sequence of disconnected summaries. The framework adopted here supplies that logic through two groups of theoretical lenses, one drawn from strategic management and one from the study of trust and social influence, and a single integrating proposition that the whole thesis is built to examine: that in an AI-mediated search environment the adoption of technology is increasingly a condition of mere participation, whereas durable competitive advantage derives from the organisational capabilities that determine whether that technology is used well. This proposition locates the study within the field of business organisation and strategy rather than within digital marketing alone, and the lenses below are the means through which it is analysed.

1.2.1 Strategic Management Perspectives

The first lens is the resource-based view of the firm, which holds that sustained competitive advantage derives not from any product or market position but from resources that are valuable, rare, imperfectly imitable, and non-substitutable (Barney, 1991). Its relevance to digital visibility is direct. The qualities that AI-driven ranking systems increasingly reward, demonstrated expertise, reputational authority, and accumulated digital trust, are precisely the kind of resources the resource-based view identifies as strategically significant: path-dependent, socially complex, and built only through sustained investment over time, they cannot be acquired quickly or copied cheaply. Where earlier, technically derived ranking advantages could be replicated by any sufficiently motivated actor, reputational and expertise-based advantages resist imitation in the way the resource-based view describes.

The second lens, dynamic capabilities, explains how firms sustain advantage in environments that change faster than any fixed resource endowment can accommodate. Teece, Pisano, and Shuen (1997) define dynamic capabilities as the firm's capacity to integrate, build, and reconfigure internal and external competences in response to rapidly changing environments, a capacity later decomposed into the abilities to sense environmental change, seize the opportunities it presents, and reconfigure the organisation's assets accordingly (Teece, 2007). Eisenhardt and Martin (2000) add that such capabilities are themselves more or less effective depending on the volatility of the environment. Applied to AI-driven search, the framework predicts that the firms best positioned to sustain visibility are not those optimised for the requirements of any single algorithmic configuration, which will change, but those that have built the organisational capacity to detect algorithmic and behavioural shifts, respond to them, and reorganise around them.

The third lens, organisational learning, addresses how that adaptive capacity is developed and maintained. Cohen and Levinthal's (1990) concept of absorptive capacity, the firm's ability to recognise, assimilate, and apply new external knowledge, explains why two firms with access to the same tools and the same information about algorithmic change may nonetheless respond very differently. March's (1991) distinction between exploration and exploitation, and O'Reilly and Tushman's (2008) treatment of the capacity to pursue both simultaneously as itself a dynamic capability, illuminate a tension that runs through the analysis: the firm must exploit established content and reputation assets while continuing to explore the requirements of an evolving search environment. These learning constructs connect to the broader digital-transformation literature, which cautions consistently that the accumulation of technology does not by itself produce organisational change, and that the decisive variable is the reconfiguration of processes and decision rights around new tools rather than their adoption alone (Kane et al., 2015; Verhoef et al., 2021; Vial, 2019).

1.2.2 Trust and Social Influence Perspectives

The strategic-management lenses explain why visibility-relevant resources are durable and how they are built; the second group explains what those resources consist of in the specific domain of search. Trust is the central construct. Organisational research has long modelled trust as a function of perceptions of a counterpart's ability, benevolence, and integrity (Mayer, Davis, & Schoorman, 1995), and information-systems research has adapted these foundations to the online setting, distinguishing institution-based trust in the structures within which a transaction occurs from interpersonal trust in the specific actor (McKnight, Choudhury, & Kacmar, 2002; Pavlou, 2003). Complementary work on web credibility examines the cues, source type, design quality, third-party endorsement, and accumulated experience, through which users form rapid credibility judgements under uncertainty (Fogg, 2003; Metzger, 2007). Together these literatures ground the later analysis of how Google's E-E-A-T framework operationalises digital trust as a search-quality standard.

The final lens is social influence, and within it the principle of social proof: the tendency, identified in classic social-psychological research, for individuals to infer appropriate behaviour from the behaviour of others, particularly under uncertainty (Cialdini, 1984; Deutsch & Gerard, 1955). Economic models of information cascades extend this insight, showing how early signals can produce self-reinforcing concentrations of attention that may diverge from underlying quality (Bikhchandani, Hirshleifer, & Welch, 1992), while research on parasocial interaction explains the quasi-relational trust that audiences extend to creators and influencers (Horton & Wohl, 1956). These constructs underpin the account of how social proof functions simultaneously as a behavioural influence on consumers and as an algorithmic signal that ranking systems treat as evidence of quality. Table 1.2 summarises the framework and its links to the research questions stated in the Introduction.

Table 1.2. Theoretical lenses and their application in the thesis

Theoretical lens	Core proposition	Application in this thesis	Linkage
Resource-based view (Barney, 1991)	Advantage derives from valuable, rare, inimitable, and non-substitutable resources	Expertise, reputation, and trust treated as strategic resources, not tactical configurations	RQ1, RQ4; §1.3–1.5
Dynamic capabilities (Teece et al., 1997; Teece, 2007)	Advantage in volatile environments rests on sensing, seizing, and reconfiguring	Framework for analysing organisational adaptation to algorithmic change	RQ4; §1.5

Organisational learning and absorptive capacity (Cohen & Levinthal, 1990; March, 1991)	Firms differ in their capacity to recognise and apply new knowledge	Explains divergent responses to identical tools and information	RQ4; §1.5
Digital trust (Mayer et al., 1995; McKnight et al., 2002)	Trust is multidimensional, relational, and accumulated	Theoretical grounding for the analysis of E-E-A-T as a quality standard	RQ2; §1.4
Social influence and social proof (Cialdini, 1984; Bikhchandani et al., 1992)	Behaviour is inferred from others, especially under uncertainty	Explains social proof as both consumer influence and algorithmic signal	RQ3; §1.4

Note. RQ references correspond to the research questions stated in the Introduction.

1.3 Evolution of SEO and AI-Driven Search

Over the past three decades, search engines have developed from relatively simple information-retrieval systems based on keyword matching into AI-driven platforms capable of interpreting user intent, contextual meaning, and behavioural signals. Read through the lenses set out above, this technical trajectory is significant less as a sequence of engineering advances than for what it has done to the basis of competition: it has transformed search engine optimisation from a predominantly technical optimisation activity into a broader strategic capability that shapes how organisations establish visibility, authority, and competitiveness within digital ecosystems. Visibility is no longer determined solely by technical compliance with algorithmic requirements but by an organisation's ability to create relevant, credible, and user-centred digital experiences that satisfy the evolving demands of both algorithmic systems and human audiences. At the same time the search ecosystem has fragmented, dispersing across social platforms, marketplaces, and AI-native interfaces, each governed by its own relevance logic, so that visibility now depends on a combination of technological, behavioural, and strategic factors that earlier frameworks of SEO were not designed to address.

1.3.1 Definition and Key Concepts of SEO

Search engine optimisation emerged as a response to a practical business problem: in an environment where information is ranked by algorithms rather than humans, how can organisations ensure that their content is found by relevant audiences without paying for every interaction? At its simplest, SEO is the set of practices through which organisations seek to improve the visibility of their digital assets in organic (unpaid) search results. This operational definition, however, has proved too narrow to capture the strategic realities of contemporary, AI-driven search.

The academic literature reflects the multidimensional character of SEO. Within information retrieval it is often described as a form of adversarial interaction in which practitioners attempt to satisfy or reverse-engineer ranking criteria while providers continuously redesign those criteria to resist manipulation (Brin & Page, 1998; Lewandowski, 2012). In marketing research it is framed as a channel within the broader digital marketing mix, evaluated alongside paid search, display, and social advertising in terms of acquisition cost and long-term brand impact. More recent management scholarship conceptualises SEO as a dynamic organisational capability: the ability to interpret evolving algorithmic quality standards, coordinate content and technical resources, and consistently signal expertise and trustworthiness across multiple platforms (Chaffey & Ellis-Chadwick, 2022). For the purposes of this thesis the capability-based view is most directly relevant. SEO is not merely a checklist of technical tasks but an organisational competence at the intersection of content strategy, user experience, analytics, and reputation management, a reading consistent with the resource-based perspective on competitive advantage (Barney, 1991), under which durable positions rest on resources that are path-dependent, socially complex, and difficult to imitate.

Several conceptual distinctions clarify this expanded understanding. It remains useful to differentiate on-page optimisation (content structure, headings, metadata, internal links), off-page optimisation (inbound links, brand mentions, reviews, and other external authority signals), and technical SEO (crawlability, indexability, site performance, structured data); these domains have always co-existed, but their relative importance has shifted as ranking systems have moved from lexical matching toward machine-learned models of relevance and credibility. A second distinction separates SEO as a tactical activity, discrete actions such as writing title tags or acquiring a backlink, from SEO as a strategic, ongoing capability concerned with aligning content production, technical infrastructure, and brand positioning with evolving algorithmic expectations and user behaviour across platforms. The transition to AI-driven, trust-sensitive ranking makes the strategic conception not merely desirable but necessary: firms that optimise for the technical requirements of a particular configuration, without building the underlying capabilities that configuration rewards, remain vulnerable to the next update. This framing is not universally shared, some practitioners still treat SEO as a cost-efficient acquisition tactic measured by short-term traffic, and others argue that the opacity of AI-driven ranking has reduced its controllability relative to paid channels, but precisely because ranking systems now encode broader notions of quality, expertise, and trust, they reward firms that invest in long-term brand and content assets rather than in short-term arbitrage.

Traditional SEO: keywords, ranking factors, and technical optimisation. Historically, SEO was built around three pillars: keyword targeting, link-based authority, and technical compliance with crawler requirements. Early search engines were grounded in classical information-retrieval models that treated documents and queries as "bags of words", ranking pages by the statistical overlap between query and document terms (Salton et al., 1975). Practitioners could often improve rankings by increasing keyword density, with limited regard for stylistic quality or user experience, and the transparency of the system created strong incentives for manipulation through keyword stuffing, hidden text, and over-optimised meta tags. The introduction of PageRank, which modelled hyperlinks as a form of citation and used the structure of the web itself to infer authority (Brin & Page, 1998), improved matters but did not eliminate them, as an industry of link exchanges, paid networks, and content farms emerged to manufacture artificial authority at scale.

Search providers responded with successive counter-measures. Google's Panda update (2011) penalised thin or duplicate content, while Penguin (2012) targeted manipulative link patterns, shifting incentives away from surface-level optimisation toward editorial quality and natural linking. These updates marked the end of an era in which simple tactics could reliably generate disproportionate visibility gains. In parallel, technical SEO evolved from a marginal concern into a baseline requirement: as web usage shifted to mobile devices, factors such as secure connections (HTTPS), responsive design, site speed, and Core Web Vitals were codified within ranking systems, often as tiebreakers rather than primary signals. Technical optimisation today is less about gaming algorithms than about ensuring that high-quality content is accessible, fast, and interpretable by both crawlers and users. From a strategic standpoint, these developments changed who could compete: as quality and page-experience signals accumulated, sustainable performance increasingly required real editorial resources, brand reputation, and operational discipline, rebalancing the field toward organisations able to integrate technical, content, and reputational assets over the long term. Critics note, however, that the resources required to maintain high standards at scale may reinforce structural advantages for dominant players, making it harder for smaller sites to gain initial traction without paid support.

From keyword-based search to intent-based and semantic search: Keyword-centric ranking quickly ran into the inherent limits of human language. Synonymy, polysemy, and contextual nuance defeat systems that rely on exact term matching, which struggle to recognise equivalence ("car" versus "automobile") and to disambiguate identical terms used in different senses ("apple" the fruit versus "Apple" the company). Classical vector-space models and TF-IDF metrics were mathematically elegant but could not fully capture these subtleties (Deerwester et al., 1990), producing a retrieval system that could be gamed by surface manipulation precisely because it had no model of what queries meant. A conceptual breakthrough came from research on user intent: by classifying queries into navigational, informational, transactional, and commercial-investigation categories, Broder (2002) demonstrated that identical keywords could mask fundamentally different underlying goals. A search for "jaguar" might signal interest in the car, the animal, the football club, or the operating system, and a useful system needs to infer which interpretation is most probable given the user's context. Latent Semantic Analysis (Deerwester et al., 1990) and later neural word embeddings showed that semantic information is latent in large corpora and can be represented as relationships in high-dimensional vector spaces, providing the representational foundation for intent-aware retrieval.

Commercial search engines operationalised these insights gradually. Google's Knowledge Graph (2012) established explicit models of entities and their relationships, allowing the engine to understand "things" rather than just "strings", and the Hummingbird update (2013) enabled more holistic processing of natural-language queries as expressions of intent. This trajectory culminated in the integration of transformer-based language models into the ranking pipeline, most notably BERT (Devlin et al., 2019), deployed in 2019, and the Multitask Unified Model (MUM) in 2021, which represent each word in relation to its full context and capture syntactic and semantic nuance earlier systems could not detect. For practice, the semantic turn was transformative: optimisation ceased to be primarily about matching exact keywords and became about satisfying the informational need implied by a cluster of semantically related queries, prompting topic-cluster strategies built around comprehensive pillar pages supported by interlinked articles that map decision journeys and intent stages (Chaffey & Ellis-Chadwick, 2022).

The transition is not without complication. Intent classification and semantic-similarity metrics can misinterpret minority or emergent forms of language, slang, dialects, culture-specific references, thereby privileging dominant linguistic norms (Noble, 2018), and semantic clustering tends to favour sites able to produce large volumes of thematically coherent content, reinforcing the advantages of well-resourced media groups. From a measurement perspective, when a single page is designed to satisfy multiple related intents and is discovered through diverse long-tail queries, traditional keyword-level reporting provides only a partial view of performance, requiring analytics that combine behavioural metrics, engagement, task completion, session depth, with semantic analysis of topic coverage and internal linking. The reliability of these proxies is itself debated, since engagement measures such as dwell time can be noisy and easily influenced by interface design rather than genuine satisfaction. These challenges reflect a deeper shift in what it means to optimise effectively, and they demand closer collaboration between SEO specialists, subject-matter experts, and data analysts.

1.3.2 AI-Driven Search and Algorithmic Evolution

As semantic models improved and web content grew exponentially, providers were pushed toward more radical automation. Rule-based and feature-engineered approaches could no longer keep pace with the diversity of queries or the complexity of user expectations, leading to the progressive integration of machine learning into every layer of the ranking pipeline, so that search performance is now governed by models that learn from user behaviour, human quality ratings, and vast training corpora rather than by explicitly coded rules. Two consequences follow. Ranking behaviour is increasingly opaque, since even search engineers cannot always explain why a particular page outranks another, the decision emerging from complex interactions within neural architectures; and the interface itself is changing, as generative AI and retrieval-augmented generation move search from a list of ranked links toward conversational answers that synthesise information from multiple sources, often without requiring users to click through.

Machine learning in search engines: The integration of machine learning can be analytically divided into three overlapping phases, successive layers of capability that have accumulated within contemporary ranking systems. In the first, supervised learning was applied directly to ranking: rather than manually assigning weights to signals such as keyword placement or link counts, engineers trained models on human relevance judgements, allowing algorithms to learn which features best predicted satisfaction across large query sets. Learning-to-rank architectures such as RankNet (Burges et al., 2005) demonstrated that data-driven approaches could outperform static heuristics, particularly on ambiguous or rare queries. The practical consequence was that ranking factors became dynamic rather than fixed: the importance of a given signal could vary by query type, user context, or content category, undermining narratives about universally "most important" factors and placing a premium on experimentation, log-file analysis, and analytical capability within marketing teams.

The second phase, associated with BERT (Devlin et al., 2019) and later MUM, integrated deep contextual language understanding directly into the ranking pipeline. By representing each token in relation to its full context, these models capture syntactic and semantic nuance, prepositions, negations, idiomatic expressions, that bag-of-words approaches could not detect, allowing engines to interpret conversational queries, complex multi-part questions, and long-form content whose relevance depends on careful reading. The reward shifted strongly toward material that aligns with natural-language queries and offers comprehensive, well-structured answers, while thin, repetitive content written primarily for algorithmic consumption became easier to deprioritise.

The third, still-developing phase involves generative models that not only rank content but synthesise it into direct answers. Retrieval-augmented generation (RAG) architectures combine document retrieval with large language models (Lewis et al., 2020), enabling systems such as Google's AI Overviews to produce narrative responses grounded in cited sources, while agentic systems decompose complex tasks into multiple retrieval and reasoning steps. The result is a "zero-click" dynamic in which a growing share of informational intent is satisfied directly on the results page or within an AI interface (Chiou & Tucker, 2017). For businesses this changes the optimisation target fundamentally: visibility extends beyond earning a ranked position to being cited as a trustworthy source within AI-generated responses, an emerging practice sometimes termed generative engine optimisation (GEO) that places renewed emphasis on clarity of expression, explicit factual statements, and well-structured evidence that models can reliably retrieve and represent. The debate is unresolved: advocates suggest generative search can create visibility for high-quality niche content that might not have ranked prominently as a standalone result, while critics worry that AI interfaces may concentrate attention on a few consistently cited sources and that models may absorb knowledge from a site without sending measurable traffic, complicating return-on-investment calculations (Lewis et al., 2020).

Running through all three phases is the growing importance of demonstrated credibility as a basis for visibility. Google's E-E-A-T framework, Experience, Expertise, Authoritativeness, and Trustworthiness, formalises the quality standards that human raters apply when evaluating content, and the outputs of those evaluations serve as training data for the models that determine ranking behaviour (Google, 2023). E-E-A-T is not a direct algorithmic ranking signal in the sense of a single measurable variable but a normative standard that shapes how training data is constructed; its implications for content strategy and organisational credibility are developed in section 1.4. At this point it is sufficient to note that the progressive integration of machine learning has shifted the basis of effective SEO from technical configuration toward demonstrated substantive quality.

Personalised algorithms and user-centric ranking systems: Search systems have also become increasingly personalised. Rather than presenting a single universal ranking, modern systems adapt results to prior behaviour, device context, location, language, and inferred preferences, which renders the concept of a fixed ranking position misleading: different users encounter different search realities for the same nominal query. Technically, personalisation draws on a lineage of collaborative filtering and recommender-systems research that infers, from patterns of interaction, which documents are most likely to be relevant for a specific user at a specific moment (Goldberg et al., 1992; Sarwar et al., 2001), with recent advances encoding interaction histories as sequences processed by transformer-based models (Zhao et al., 2023). The consequences for measurement are significant: traditional rank-tracking, which assumes a single ranking per keyword and location, offers at best a rough approximation, since a domain may rank prominently for some cohorts while remaining invisible to others, necessitating more segmented, panel-based or user-centric measurement.

Personalisation also intersects with concerns about filter bubbles and informational diversity. The empirical picture is nuanced: while some studies document reduced exposure to cross-cutting perspectives, others find that the strongest drivers of selective exposure are users' own choices rather than algorithmic curation alone (Pariser, 2011; Guess et al., 2018), suggesting that filter bubbles are a joint product of platform design, business incentives, and user behaviour. The European regulatory context adds further complexity. The General Data Protection Regulation (EU Regulation 2016/679) and the Digital Services Act (EU Regulation 2022/2065) constrain the data-collection practices that underpin personalised ranking through restrictions on behavioural tracking, requirements to offer non-personalised alternatives, and obligations of algorithmic transparency, producing a privacy-utility tradeoff in which protecting user rights may reduce the precision of personalisation, particularly for smaller platforms with limited first-party data. For organisations, “doing SEO” in a personalised environment therefore requires designing content that performs robustly across diverse contexts, investing in cohort-level measurement, and building consent-based first-party data strategies, a cross-functional coordination challenge that reinforces the broader argument that contemporary search optimisation is a strategic organisational capability rather than a narrow technical task.

1.3.3 Search Beyond Google

Although Google remains the dominant gateway to the open web in most markets, focusing exclusively on its ecosystem obscures a structural change of strategic significance: consumer search behaviour is increasingly distributed across social platforms, e-commerce marketplaces, and AI-native interfaces, each governed by its own relevance criteria.

Consumers choose environments by goal, short-form video inspiration on TikTok, visual discovery and social validation on Instagram, product comparison and transactional search on Amazon, conversational synthesis on AI assistants, and each rewards different content, authority signals, and engagement behaviour. Search engine optimisation can therefore no longer be equated with Google optimisation; organisations must manage visibility across a portfolio of platforms and orchestrate consistent brand signals without over-reliance on any single intermediary, a challenge that is as much organisational as technical. Traditionally, search was conceptualised as a deliberately initiated, analytical activity and social media as passive browsing; as users have learned to treat platforms as purposeful tools for specific queries, the distinction between search and discovery has become difficult to sustain.

TikTok: interest graphs, short-form video, and creator authority. TikTok is emblematic of this shift. Its For You feed is driven less by explicit social-network connections than by an interest graph encoded from detailed user behaviour, what content users watch to completion, replay, share, or save, so that when users search within the platform the ranking reflects both keyword matching and accumulated behavioural signals. Authority is measured in engagement, narrative consistency, and resonance within interest clusters rather than the external links or formal credentials that shape Google’s assessments, and surveys suggest that a substantial share of younger users now treat TikTok as a primary or secondary search tool for lifestyle, fashion, and product discovery, even as Google retains dominance for more complex informational needs (DataReportal, 2024). Optimising for this discovery system is closer to programming for an entertainment algorithm than to conventional SEO: successful content combines an immediate narrative hook, demonstrative value, and an authentic creator persona, while social proof, comments, duets, stitches, and trend participation, signals what the community regards as credible. There are, however, legitimate concerns: recommendation systems that reward watch time create incentives for sensational or narratively simplified content, which for complex or sensitive topics can distort information quality and raise brand-safety risks.

Instagram: visual search, social graph, and shoppable discovery. Instagram occupies a distinctive position at the intersection of social networking, visual search, and commerce. Its Explore and Reels surfaces blend interest-based signals with social-graph connections, and search increasingly supports natural-language descriptions alongside hashtag and place queries, with visual content analysed not only through captions and metadata but also via computer-vision models that classify the semantic content of images and video. Visibility depends on the relevance of captions and keywords, the strength and breadth of engagement signals, the structure of the creator's social graph, and alignment with evolving Reels and Stories practices. Influencer partnerships are particularly consequential, because parasocial relationships between creators and audiences translate into trust and higher engagement on sponsored content, a dynamic that Cialdini's (1984) framework of social proof helps to explain, while integrated shopping and in-app checkout have compressed the path from discovery to purchase. The platform's emphasis on aspirational imagery has attracted criticism, and creates a strategic tension between the algorithmic appetite for polished, high-engagement content and a growing consumer desire for authenticity, prompting many brands to experiment with less produced, documentary-style formats.

Amazon: product-centric search and conversion-driven ranking. Amazon represents a fundamentally different type of search engine, one explicitly optimised for transactional intent and revenue rather than informational relevance. Its ranking prioritises products most likely to generate completed sales, with signals such as historical conversion rate, price competitiveness, stock availability, fulfilment method, and review volume and sentiment playing central roles (Ghose et al., 2019). Textual relevance still matters in titles, bullet points, and backend keywords, but topical authority and semantic comprehensiveness matter far less than the probability of purchase a product's profile signals, so that Amazon SEO is deeply intertwined with merchandising and operational management, inventory reliability, competitive pricing, customer-service performance, and active review management, rather than pure content strategy. Paid placements interact with organic visibility by influencing sales velocity, and for many categories Amazon has become the primary discovery interface. The model creates structural pressure on margins for smaller brands, which must compete with global incumbents and with Amazon's own private-label products, and raises ongoing debate about marketplace transparency, implying that Amazon should rarely be the sole environment on which a brand's visibility depends.

AI-native search: conversational retrieval and the citability imperative. AI-native search engines and conversational assistants add an emerging and strategically significant layer. Tools such as Perplexity, Microsoft Copilot, and Google's AI Overviews synthesise multi-source information into direct narrative responses, often with explicit citations and iterative refinement, and are particularly suited to complex tasks requiring synthesis across documents. Visibility within them depends less on traditional ranking positions and more on the citability of specific passages, clarity of factual expression, explicit attribution of evidence, and logical structure that models can reliably extract, pushing organisations to think of content as a set of granular, well-structured statements that systems can reassemble in response to prompts (Lewis et al., 2020). These systems also introduce distinctive risks: the tendency of large language models to produce confident but inaccurate statements means brands may be misrepresented in generated responses, creating a new category of reputation-management challenge, while the broader economics of zero-click AI search remain contested, with cited sources sometimes receiving disproportionate click-through even as publishers worry about aggregate traffic losses.

The fragmentation of search across algorithmically distinct platforms amplifies competitive pressure while creating new strategic options. Rather than competing solely for positions on a single results page, organisations must cultivate different types of visibility, topical authority and E-E-A-T alignment on Google, creator-centric credibility on TikTok and Instagram, product-level performance and review management on Amazon, and citation authority within AI-generated responses, each requiring a different combination of capabilities. The organisations best positioned to compete across them are those that have invested in the underlying assets, editorial depth, audience relationships, operational excellence, and genuine subject-matter expertise, that generate authentic authority across signal types. This has direct implications for structure: teams responsible for SEO, social media, content, public relations, and e-commerce can no longer operate in isolation, because algorithms increasingly interpret cross-channel signals as a unified representation of brand expertise, making cross-functional governance, shared editorial guidelines, integrated calendars, unified KPI frameworks, necessary rather than optional. Heavy reliance on any single channel also exposes organisations to sudden algorithm changes, policy shifts, or platform competition, so that a more resilient strategy diversifies discovery sources, invests in owned media, and builds the capability for rapid experimentation. As zero-click experiences and in-platform commerce spread, website traffic becomes an increasingly incomplete proxy for visibility, and organisations must complement traffic-based KPIs with measures of AI citation frequency and quality, branded-search trends, engagement depth, and conversion within third-party environments. Underlying all of these environments is the centrality of trust signals, which makes digital credibility a core competitive asset in a way earlier models of optimisation did not anticipate.

1.4 Digital Trust, E-E-A-T, Social Proof and Consumer Behaviour

The technical evolution traced in section 1.3 has an unavoidable human and organisational counterpart, because the systems described there are explicitly designed to approximate human judgement: to model what users find credible and helpful, and to surface content that satisfies not only informational needs but deeper requirements of confidence and reassurance. Within this setting digital trust functions simultaneously as a psychological, technological, and strategic phenomenon. Consumers depend on trust signals when assessing products, services, and information, while algorithms increasingly incorporate indicators of credibility, expertise, authority, and user satisfaction into their ranking decisions, and the interaction between these two layers of evaluation produces an environment in which trust shapes both what becomes visible and how audiences subsequently behave. Because both algorithms and consumers evaluate information through credibility, expertise, authority, reputation, and social validation, technical optimisation alone is no longer sufficient to secure sustainable visibility; the E-E-A-T framework represents the most explicit institutional formalisation of these principles, while social proof supplies the bottom-up signals through which trust is continuously confirmed.

1.4.1 Digital Trust

Digital trust is the confidence users place in online systems, information sources, and commercial actors to behave reliably, securely, and in their interests under conditions of uncertainty. The concept builds on long-standing work in organisational and interpersonal trust, which defines trust as a willingness to accept vulnerability based on positive expectations of another party's intentions or behaviour (Mayer, Davis, & Schoorman, 1995). What distinguishes the digital setting is the source of those expectations: where offline trust is scaffolded by physical presence, institutional routine, and repeated face-to-face interaction, online it must be inferred from mediated signals such as interface design, reviews, platform guarantees, and algorithmically curated reputations, all of which serve to bridge the information asymmetries that separate buyers from sellers (Akerlof, 1970). Research on electronic commerce has consistently shown that trust is a decisive antecedent of online transaction intention precisely because uncertainty is so much greater than in conventional exchange (Pavlou, 2003; Gefen, Karahanna, & Straub, 2003), and McKnight, Choudhury, and Kacmar (2002) show that initial trust in an unfamiliar online vendor depends heavily on institution-based assurances, the perceived safety of the broader environment, rather than on direct experience. Trust is therefore best understood as multidimensional and dynamic: it emerges from the interaction between institution-level assurances, such as platform policies, security infrastructure, and legal protections, and perceptions of specific brands or individuals framed in terms of competence, benevolence, and integrity (Mayer et al., 1995). For firms, the implication is that trust is not a marketing outcome to be communicated after the fact but a composite result of technical design, compliance practice, customer experience, and communication, each continuously interpreted by both human users and the algorithms that mediate their attention.

Trust, credibility, and authority in digital marketing: Trust has been operationalised through several complementary constructs. An influential distinction separates institution-based trust, confidence in the structural context within which a transaction occurs, from interpersonal trust, which rests on perceptions of the counterpart's competence, benevolence, and integrity (McKnight et al., 2002; Mayer et al., 1995). In online commerce the two operate at once: a consumer simultaneously assesses the reliability of the platform, for instance Amazon's fulfilment guarantees or Google's quality-evaluation systems, and the trustworthiness of the particular brand, so that search engines and marketplaces act as institutional guarantors whose perceived integrity is partially transferred to the actors within them. Closely related is credibility, which captures how believable and reliable a source appears. The classical communication literature traced credibility to perceptions of expertise and trustworthiness in the source (Hovland, Janis, & Kelley, 1953), and work on web credibility extended this to the digital interface: Fogg (2003) argued that users form credibility judgements largely through prominence and interpretation, drawing on whichever cues are most noticeable, while Metzger (2007) observed that, faced with abundant and unverified information, users rely on heuristics, source reputation, third-party endorsement, design quality, accumulated experience, rather than systematic verification. The strategic consequence is that surface cues can be engineered quickly, but durable credibility depends on consistent performance and honest communication over time.

Authority adds a relational layer: in digital environments it is conferred when other actors, peer organisations, professional communities, reviewers, media outlets, consistently treat a source as a legitimate voice within a domain, with citation patterns, high-quality backlinks, and repeated brand mentions the visible residue of these collective judgements. The architecture described in section 1.3 was, in essence, an attempt to mechanise them: from the citation logic of PageRank onward, search engines have approximated social judgements of authority by weighting signals such as link quality, branded-search demand, and review portfolios, importing the editorial decisions of many independent actors into their rankings.

Trust, credibility, and authority are therefore best understood as three vantage points on a single underlying question, whether a source deserves to be relied upon, which both consumers and algorithms continually try to answer. A further consequence reframes where trust resides: when a platform vouches for a transaction through verified-purchase labels, secure-payment infrastructure, return guarantees, or the simple act of ranking one result above another, it lends a portion of its own institutional credibility to the actors within it, a process of trust transfer that is double-edged, since it lowers the barrier to a first transaction while positioning the platform as an indispensable intermediary able to revise the terms of visibility at will. Brands consequently cultivate trust on two fronts at once, with consumers who must be persuaded to act, and with the platforms whose evaluative systems decide whether that persuasion is ever given the opportunity to occur.

Brand reputation and online visibility: Brand reputation is the collective assessment of a firm's past conduct and future prospects relative to its competitors (Fombrun & Shanley, 1990). In pre-digital contexts this assessment evolved slowly; online, it is formed and revised almost continuously through search results, review scores, social commentary, user-generated content, and news coverage that can be indexed within seconds, increasing the upside of a positive reputation while sharply raising the speed at which failures propagate. The relationship between reputation and visibility is reciprocal rather than one-directional: strong brands generate high volumes of branded search and direct navigation, which signal to search engines that users actively seek them out, and that demand supports broader non-branded rankings, while repeated prominence then strengthens reputation further, since users read algorithmic visibility as an implicit endorsement. The outcome is a self-reinforcing loop that helps explain the persistent advantage of incumbents over newer entrants. Strategic theory clarifies why reputation has become such a durable digital asset: from the resource-based view, sustainable advantage derives from resources that are valuable, rare, and difficult to imitate (Barney, 1991), and reputational capital satisfies these conditions almost by definition, being path-dependent and built through a particular history of performance and relationships, with empirical work linking strong reputation to sustained superior financial performance (Roberts & Dowling, 2002). In AI-driven environments this advantage is amplified, as models trained to reward signals of genuine expertise tend to favour entities with long-standing positive footprints.

Online reviews are the most visible expression of this process. Studies across sectors find that higher average ratings and larger review volumes are associated with measurable increases in demand: the early analysis of online book reviews by Chevalier and Mayzlin (2006) showed that improvements in a title's reviews translated into relative sales gains, and later work on local-service platforms reported comparable effects, with each additional star on a restaurant's rating linked to meaningful revenue change (Luca, 2016). The same research documents clear manipulation risks, particularly on platforms with weak verification, where firms face incentives to post promotional reviews of their own offerings or disparaging reviews of rivals (Mayzlin, Dover, & Chevalier, 2014), to which search engines and marketplaces have responded by tightening guidelines and deploying fraud detection. The lesson for management is that sustainable reputational advantage depends on authentic, verifiable customer experience rather than engineered sentiment. A final feature is asymmetry: reputational capital accumulates slowly through many consistent interactions but can be depleted rapidly by a single visible failure that is indexed and shared within hours, which turns reputation management from a communications exercise into a question of operational reliability and makes crisis response a search-and-discovery problem as much as a public-relations one.

1.4.2 E-E-A-T

As search engines moved from retrieving documents to evaluating their usefulness and safety, they required a principled way to describe and train for content quality at scale. The concepts of trust, credibility, and authority examined above are intuitive to human readers but difficult to encode directly into a ranking system, and Google's E-E-A-T framework, denoting Experience, Expertise, Authoritativeness, and Trustworthiness, represents the most explicit institutional attempt to translate these qualities into operational guidance. Set out in the company's Search Quality Evaluator Guidelines, it functions as a bridge between how human evaluators judge credibility and how machine-learning models are subsequently trained to approximate those judgements (Google, 2023). An important clarification, frequently lost in practitioner discourse, concerns the framework's status within the ranking system: E-E-A-T is not a direct ranking factor in the sense of a measurable score the algorithm computes and applies, but a conceptual standard used by human raters whose assessments inform the training and evaluation of ranking models (Google, 2023). No single on-page adjustment can "set" a site's E-E-A-T; the framework describes the qualities that well-trained models are designed to recognise across many correlated signals, so that treating it as a switch to be flipped misreads its function. The standard acquires heightened importance in generative, AI-mediated search: as synthesised answers begin to satisfy queries without returning users to a ranked list, the question shifts from which page ranks first to which sources a model selects, trusts, and cites, and the well-documented tendency of generative systems to produce confident but inaccurate statements raises the premium on sources a model can rely upon without propagating error.

Experience, expertise, authoritativeness, and trustworthiness: The framework's four dimensions map closely onto the trust and credibility constructs outlined above. Experience, added to the model in 2022, requires that content be grounded, where appropriate, in first-hand engagement rather than purely secondary synthesis; in domains such as product reviews, travel, or practical instruction, lived experience often carries more evaluative weight than abstract knowledge and exhibits linguistic and structural patterns, concrete detail, situational specificity, evidence of direct use, that raters and trained models can distinguish from generic summary. The addition is significant in an era of large-scale automated content, since it privileges precisely the dimension that machine-generated text reproduces least convincingly. Expertise refers to the depth of subject-matter knowledge demonstrated in the content itself; formal credentials provide one set of signals, but demonstrated competence, the accuracy, nuance, and completeness of an explanation, remains central, echoing the source-expertise dimension of the classical credibility literature (Hovland et al., 1953). Authoritativeness introduces an explicitly relational element: a source is authoritative to the extent that others treat it as such, a judgement reflected in citations, high-quality backlinks, brand mentions in trusted outlets, and recognition within professional communities, thereby extending the citation-based logic described in section 1.3. Trustworthiness underpins the entire framework and is, in Google's own characterisation, its most important dimension, encompassing factual accuracy, transparency about authorship and intent, sound security practice, and the avoidance of deceptive design (Google, 2023); without it the other three dimensions lose their value. The standard is especially exacting in categories the guidelines label "Your Money or Your Life" (YMYL), where inaccurate information about health, finance, or safety can cause direct harm.

The framework is not analytically neutral. Because it relies heavily on signals legible to human raters and crawlers, it structurally favours institutional credentials, established publications, and well-resourced organisations, while community-based expertise, emergent voices, and marginalised perspectives may struggle to signal their value even when their practical knowledge is substantial, a concern that resonates with broader critiques of how algorithmic systems reproduce existing hierarchies of authority (Noble, 2018). The four dimensions are best read not as an additive scorecard but in terms of how they interact: experience and expertise are partly substitutable, yet both are ultimately gated by trustworthiness, which acts less as a fourth ingredient than as a precondition for the others to count at all, while authoritativeness is the most socially contingent, since it cannot be self-asserted and depends on recognition that accrues over time. Understood this way, E-E-A-T is an attempt to describe, in deliberately non-technical language, the configuration of qualities a credible source tends to exhibit, shifting the managerial question from "which boxes must be ticked" to "what kind of organisation reliably produces content with these properties."

Business implications of E-E-A-T for SEO strategies: In practitioner discourse, E-E-A-T is often reduced to a checklist: add author biographies, strengthen the "about" page, implement secure connections and structured data, and acquire links from authoritative domains. These steps are not without value, but treating them as sufficient misunderstands the framework's intent, since it is designed to surface genuine credibility rather than its appearance, and purely cosmetic compliance becomes progressively less effective as the underlying models improve. A more productive interpretation reframes E-E-A-T as an organisational capability challenge: building genuine experience, expertise, authoritativeness, and trustworthiness requires coordinated routines spanning hiring, content commissioning, editorial review, legal oversight, and reputation management. This framing aligns closely with the dynamic-capabilities perspective, under which competitive advantage in changing environments depends on the ability to integrate and reconfigure internal competences in response to shifting conditions (Teece, Pisano, & Shuen, 1997); firms with mature editorial cultures and disciplined governance often find that E-E-A-T alignment emerges as a by-product of how they already operate, whereas those without such foundations face higher costs and more fragile outcomes when they retrofit quality signals onto a low-quality content operation.

Practically, the implications unfold across several levels. At the level of authorship, brands benefit from associating topics with identifiable individuals whose expertise and experience are transparent and consistent across channels; at the level of content, depth and intent coverage are rewarded more reliably than sheer volume; and off the page, investment in earned authority, editorially justified coverage, genuine links, authentic reviews, provides more durable value than manufactured links or paid mentions. Across all three the connection to brand reputation is direct, since both E-E-A-T and reputation management concern how a source is evaluated across distributed signals and extended time horizons, and both reward consistency while penalising manipulation, so that budgets directed toward genuine expertise, editorial quality, and transparent communication tend to pay dividends simultaneously in search performance, AI-generated citations, and broader brand equity. This capability-based reading also clarifies a distributional concern: because the qualities E-E-A-T rewards accumulate slowly and depend on resources such as in-house experts and an existing reputation, the framework can place smaller and newer organisations at a structural disadvantage, producing a tendency toward authority concentration in which visibility accrues disproportionately to incumbents who are already visible (Noble, 2018). For such firms the strategic response is rarely to imitate the signal profile of large publishers but to build defensible authority within a narrower domain, concentrating on a specific topic or audience where genuine experience can be demonstrated convincingly and allowing recognition to accumulate from that base.

1.4.3 Social Proof

If E-E-A-T represents a largely top-down, institutional approach to evaluating trust, social proof represents the bottom-up, peer-driven mechanism through which consumers infer what is credible and desirable. The two are not independent: algorithms partially rely on social proof as evidence of quality, while users interpret algorithmic prominence as partial evidence that others have already validated a piece of content or a product. Understanding consumer behaviour in AI-mediated markets therefore requires examining how this peer-based logic operates and how platforms have embedded it into the architecture of discovery.

Reviews, engagement metrics, and popularity signals: The concept of social proof originates in social psychology, where it describes how individuals infer appropriate behaviour from the actions of others, especially under uncertainty. Cialdini (1984) identified it as one of the most powerful principles of influence, and earlier experimental work had distinguished two routes through which others' behaviour shapes our own: informational social influence, in which people treat the behaviour of others as evidence about reality, and normative social influence, in which they conform to gain acceptance (Deutsch & Gerard, 1955). The distinction maps cleanly onto digital marketing: informational influence is visible when consumers rely on review averages as quality indicators, normative influence when individuals engage with popular content or brands to signal group membership, and both are systematically embedded into platform design through visible metrics, from star ratings and review counts to follower numbers and engagement displays. Economic models of herd behaviour complement this account: once an option receives early positive signals, subsequent decision-makers tend to treat them as evidence of quality, sometimes discounting their own private information, the mechanism of an information cascade (Bikhchandani, Hirshleifer, & Welch, 1992). Online, bestseller lists, "trending" labels, and the initial distribution of reviews can trigger such cascades, and engagement-responsive ranking amplifies the effect, contributing to a "winner-takes-most" pattern of visibility, while the literature on electronic word of mouth confirms the substantial influence of reviews on attitudes and purchase intention (Cheung & Thadani, 2012).

Engagement metrics warrant particular scrutiny because they are simultaneously the most visible and the most ambiguous form of social proof. A high view count, a large follower base, or a dense thread of comments communicates popularity, but popularity is a noisy proxy for quality: it conflates genuine endorsement with mere reach and is comparatively easy to inflate through coordinated activity, purchased metrics, or content engineered for engagement rather than value. Platforms must therefore continually adjust which signals they expose and reward, lest visible metrics become targets that are gamed rather than indicators that are informative, while brands face a choice between pursuing the metrics that are easiest to influence and cultivating the deeper forms of engagement that are harder to fake but more closely correlated with trust. Influencer marketing introduces a further dimension by adding parasocial relationships to the picture: audiences frequently experience recurring exposure to a creator as a quasi-social relationship, first described in the context of broadcast media (Horton & Wohl, 1956), and attribute authenticity and expertise to creators in ways that exceed the credibility ordinarily granted to advertising, with research indicating that stronger parasocial bonds are associated with higher purchase intention, particularly when the creator's identity aligns with the product category (Lou & Yuan, 2019). This helps explain why micro-influencers, whose audiences are smaller but more engaged and tightly aligned with a niche, often deliver higher marginal impact than celebrities, and why follower counts interact in complex ways with perceived authenticity rather than simply increasing persuasive power (De Veirman, Cauberghe, & Hudders, 2017). It is worth considering the influencer ecosystem as a structured market in its own right, since platforms, creators, agencies, and brands pursue partly divergent objectives, and because recommendation algorithms reward watch time and interaction they tend to favour formats and emotional registers that sustain engagement, subtly steering creators toward particular styles of endorsement regardless of underlying product merit. Platform incentives are thus not a neutral backdrop to social proof but an active force in producing it.

Impact of social proof on consumer decision-making: Social proof does not operate in a neutral information environment. Personalised recommendation systems heavily filter which reviews, endorsements, and engagement signals an individual user actually sees, so that the social evidence reaching any given consumer is itself the product of prior algorithmic selection. The filter bubble that Pariser (2011) described applies directly: consumers encounter a curated subset of social proof reflecting both the aggregate behaviour of others and their own past interactions, rather than an unmediated picture of collective opinion. This recursive quality, social proof shaping the algorithm while the algorithm shapes the social proof on display, is a defining feature of behavioural influence in AI-mediated markets. When predictive recommendation is combined with social proof it produces powerful feedback loops: content that performs well initially is recommended more widely, accumulates further engagement, and appears even more credible to future users, while alternatives of comparable quality may remain effectively invisible, so that the reputation-visibility loop and the cascade dynamics described above converge into a single self-reinforcing system at the level of the individual feed.

Theories of persuasion clarify why personalisation intensifies these effects. The elaboration-likelihood model distinguishes a central route, in which people carefully evaluate arguments and evidence, from a peripheral route, in which they rely on simple cues such as source attractiveness or apparent popularity (Petty & Cacioppo, 1986). The design of most platform interfaces, fast-scrolling feeds, prominent engagement counts, recognisable creators, favours peripheral cues, and personalisation reinforces this by serving content aligned with existing interests, encouraging rapid, heuristic processing precisely under the conditions in which social proof exerts its strongest influence. The strategic implications follow directly: brands with strong existing social proof benefit disproportionately from personalised distribution, while new entrants confront a visibility barrier that product quality alone cannot overcome and must generate initial engagement through targeted sampling, niche communities, or creator partnerships that can trigger algorithmic amplification. These mechanisms also raise ethical and regulatory questions, since users rarely have full insight into how reviews are selected or why particular endorsements appear prominently, and emerging frameworks reflect a growing recognition that algorithmically mediated social proof constitutes a form of commercial influence warranting oversight: the Digital Services Act (Regulation 2022/2065) introduces transparency obligations for recommender systems and online platforms, while scholars argue that genuine accountability requires not only disclosure but contestability, the practical ability of users to interrogate and challenge the criteria by which content is selected for them (Helberger, Pierson, & Poell, 2018). The most durable approaches to cultivating social proof therefore work with the grain of the underlying mechanisms rather than attempting to short-circuit them, generating genuine early engagement by serving a defined community and partnering with aligned rather than merely large creators, and measuring results through the velocity and sentiment of reviews, the depth rather than the volume of engagement, and the consistency of a brand's representation across platforms rather than through vanity metrics whose ambiguity was noted above.

1.5 SEO Automation and Organisational Adaptation

The preceding sections establish why digital visibility has become a strategic rather than a narrowly technical concern: search has moved from keyword matching toward the machine-learning-governed interpretation of intent, and trust, demonstrated expertise, and authentic social validation have become the conditions under which visibility is granted. The question now is how organisations respond, and the technology that has moved fastest into the practice of search engine optimisation is automation and artificial intelligence. For a study situated in business organisation and strategy, the important question is not what the technology can do but what its adoption demands of the organisations that deploy it. AI and automation are transforming SEO from a specialised marketing activity into a broader organisational capability: as optimisation, content production, and performance analysis become automated, the work of remaining visible ceases to be the responsibility of a single technical specialist and becomes a matter of governance, coordination, and learning that runs across the firm. The competitive advantage available in an AI-mediated search environment does not come from acquiring the tools, which are largely available to everyone, but from the organisational adaptation that determines whether those tools are used well; technology adoption is increasingly a condition of participation, while organisational adaptation separates firms that merely keep pace from those that pull ahead (Kane et al., 2015; Iansiti & Lakhani, 2020).

1.5.1 Rise of AI and Automation

Automation is not new to marketing, and the present moment is better situated within a longer trajectory than treated as a sudden rupture. What has changed is less the fact of automation than its scope: where earlier systems automated the execution of decisions that people had already made, contemporary AI systems increasingly participate in the decisions themselves, and a technology that executes instructions and one that generates options and recommendations make very different demands on the structures around them.

The evolution of marketing automation: The first generation of marketing automation, which matured through the 2000s, was essentially rules-based. Email platforms, customer-relationship-management systems, and early campaign tools executed sequences specified in advance, removing repetitive manual work and allowing campaigns to operate at a scale human execution could not match, but they were deterministic, and the interpretive and strategic work, deciding what to say, to whom, and why, remained firmly with people. In SEO the equivalent early tools automated reporting, rank tracking, and technical auditing, surfacing information more quickly while leaving interpretation to the analyst. It is tempting to read the subsequent history as a smooth upward curve of ever more capable tools, but the digital-transformation literature cautions against equating the accumulation of technology with organisational change. A useful distinction separates digitisation, the conversion of analogue information into digital form, from digitalisation, the use of digital technologies to improve existing processes, and from digital transformation, a more fundamental reconfiguration of how an organisation creates and captures value (Verhoef et al., 2021; Vial, 2019). Much of what passes for transformation is in fact the first or second of these, with tools bolted onto existing structures and the underlying division of labour left untouched. The lesson that runs through this body of work is that the firms which benefited from each successive wave of automation were not simply those that adopted the newest systems but those that redesigned their workflows and decision rights around them: adoption was necessary; reorganisation was decisive. If earlier, far simpler automation already required organisational adjustment to deliver value, there is little reason to expect more capable and more autonomous systems to deliver value automatically; if anything, the organisational demands rise with the sophistication of the technology.

AI technologies in SEO and content production: The technologies now entering SEO practice differ from their predecessors in kind, not merely degree. Generative language models draft and rewrite content; natural-language-processing systems cluster topics, model search intent, and identify semantic gaps; predictive analytics forecast keyword opportunity and content performance; and automated systems handle technical auditing, internal linking, and large-scale localisation. These are not unrelated to the architectures discussed in section 1.3: the same transformer models that reshaped how search engines interpret queries (Vaswani et al., 2017) now power the tools that produce and optimise the content competing for visibility, so that the same family of technology operates on both sides of the ranking relationship. The qualitative change is that these systems generate and recommend rather than merely execute. A scholarly way of describing the trajectory distinguishes the kinds of intelligence AI can substitute for, mechanical tasks involving routine execution, analytical tasks involving the processing of information, and intuitive tasks involving empathy and judgement (Huang & Rust, 2021): marketing automation began by absorbing mechanical work and is now advancing into analytical work, so that activities once regarded as the core of a marketer’s expertise, interpreting data, drafting persuasive copy, identifying opportunities, are increasingly shared with machines. The strategic question is therefore not whether to adopt such systems, since competitive pressure makes adoption close to inevitable, but which tasks to delegate, which to retain, and how to govern the boundary between them (Davenport et al., 2020). Content-distribution and link-building platforms such as WhitePress illustrate the practical shape of this shift, allowing organisations to identify publishing opportunities, manage outreach, and coordinate content placement at a scale and speed manual processes could not sustain; used here as a contextual practitioner example rather than a formal case study, such platforms make the central tension concrete, since the very capability that allows content to be produced and distributed at scale is the one that most directly threatens the authenticity and expertise signals that algorithms and audiences increasingly reward.

1.5.2 Opportunities

The benefits of automating SEO are genuine, but their strategic value is conditional. A benefit equally available to every competitor changes the terms on which firms compete without, in itself, advantaging any of them, and a benefit an organisation cannot absorb into its processes and judgement is a benefit only on paper.

Efficiency and scalability: The most immediate benefit is efficiency. Tasks that once consumed substantial analyst time, technical audits across large sites, the drafting of routine content, the assembly of performance reports, the adaptation of material for multiple languages and markets, can now be performed in a fraction of the time and cost, which for organisations operating at scale can change what is feasible, allowing a small team to maintain a presence that would previously have required a large one. Yet efficiency of this kind is competitively self-neutralising when it becomes widely available. The resource-based view holds that a resource confers sustained advantage only when it is valuable, rare, difficult to imitate, and not readily substitutable (Barney, 1991); automation tools are valuable but neither rare nor difficult to imitate, since they are sold as a service to anyone willing to pay, so that as adoption spreads the efficiency they provide migrates from a source of advantage to a condition of remaining in the game. The firms that gain durable advantage are rarely those that adopt earliest but those that reorganise the surrounding work so that the technology's potential is realised (Brynjolfsson & McAfee, 2014). Seen in this light, the strategic value of efficiency lies less in cost reduction than in reallocation: when automation absorbs the routine, it frees scarce expert attention for the work that is hardest to automate and most closely tied to durable advantage, developing subject-matter depth, exercising editorial judgement, building relationships, and cultivating the authentic expertise and authority identified above as the foundation of trust. Whether a firm captures that value depends entirely on whether it redirects the freed capacity or simply does the same volume of low-value work more cheaply.

Data-driven decision-making: A second benefit concerns the quality and timeliness of decisions. AI-enabled analytics surface patterns across volumes of data that would overwhelm manual analysis, monitor performance in close to real time, forecast the likely return on particular opportunities, and automate the experimentation through which strategies are refined, in principle allowing decisions to be made on firmer evidential ground and adjusted more quickly. The organisational implications are more demanding than the promise suggests, because data and analytical tools do not interpret themselves; their value depends on the organisation's capacity to absorb and act on what they produce. Absorptive capacity captures this directly: a firm's ability to recognise the value of new information, assimilate it, and apply it depends on prior related knowledge and is itself an organisational achievement rather than an automatic consequence of having data available (Cohen & Levinthal, 1990). Without the analytical capability to interpret model outputs and the judgement to act on them, an abundance of data produces noise rather than insight, and the speed of automated analysis simply accelerates the rate at which poor decisions can be made. A related risk is the false objectivity that quantified outputs encourage, since dashboards and predictions present themselves with an air of precision that can crowd out the qualitative judgement they were meant to support, tempting managers to optimise for what is easily measured rather than for what matters strategically. The more rigorous response is to treat artificial intelligence not as a technology that produces value on its own but as one element in a bundle of resources, data and infrastructure, human skills, and the intangible assets of coordination and learning, whose combination determines performance (Mikalef & Gupta, 2021).

1.5.3 Risks and Challenges

If the benefits of automation are conditional, its risks are equally organisational in character. Each is sometimes presented as a technical problem with a technical solution, but on closer inspection each is a problem of governance, judgement, and strategic design, and the same capabilities that generate efficiency and scale, if left ungoverned, threaten the quality, distinctiveness, and accountability on which long-term visibility depends.

Content quality and authenticity: The most widely discussed risk of generative automation is the production of content that is fluent but shallow, derivative, or factually unreliable. Large language models can generate plausible text at scale, but they can also reproduce inaccuracies with the same fluency, and content produced primarily to satisfy an algorithm rather than to serve a reader tends toward a generic competence that adds little. This collides directly with the quality standards examined in section 1.4: the E-E-A-T framework rewards demonstrated experience and genuine expertise, qualities mass-produced content struggles to convey (Google, 2023), and platform guidance increasingly distinguishes helpful, people-first material from scaled low-value content created mainly to manipulate rankings.

Automation that ignores quality is therefore not merely risky but self-defeating, optimising for a target the ranking systems are designed to discount. There is a deeper, paradoxical implication: as the cost of producing content that imitates expertise falls toward zero, the value of genuinely demonstrated expertise as a distinguishing signal rises rather than falls. The logic is the one Akerlof (1970) identified in markets where buyers cannot easily verify quality: when low-quality output is cheap to produce and superficially indistinguishable from high-quality output, credible signals of genuine quality become more valuable precisely because they are harder to fake. The organisational response this calls for is not a better tool but a stronger process, editorial governance, human review of machine-generated material, clear accountability for accuracy, and a willingness to treat expertise as something to be cultivated rather than simulated.

Over-reliance, homogenisation, and strategic risk: A second cluster of risks concerns what happens when automation is relied upon too heavily or uncritically. If many organisations draw on the same underlying models, trained on overlapping data and prompted in similar ways, their outputs tend to converge, and the predictable result is homogenisation: a landscape of content that is competent, similar, and undifferentiated, the opposite of the distinctiveness on which competitive advantage depends. A firm that automates its way to the same output as its rivals has improved its efficiency while eroding its differentiation. Over-reliance carries a subtler cost, since delegating judgement to automated systems can, over time, atrophy the human expertise that constitutes the firm's durable asset; the classic account of organisational learning warns that an excessive tilt toward exploitation, the refinement of existing competencies, at the expense of exploration can trap an organisation in capabilities that are efficient but increasingly obsolete (March, 1991), leaving a marketing function that has automated all of its routine work efficient under stable conditions but poorly placed to adapt when the environment shifts. To these capability risks must be added dependence on third-party platforms and models whose behaviour the firm does not control and cannot fully observe, which concentrates strategic risk, and questions of accountability and compliance that cannot be delegated to the technology: within the European context, the General Data Protection Regulation conditions how the personal data underpinning personalisation may lawfully be used, and the Digital Services Act imposes transparency and accountability obligations on how content is handled and surfaced (European Union, 2016, 2022), so that automated decision-making without governance exposes the firm to regulatory as well as reputational risk.

1.5.4 Organisational Adaptation

The preceding analysis leads to a single conclusion: the benefits and risks of SEO automation are both real, and both conditional on the organisation. The decisive variable is not the technology a firm acquires but the capability it builds to absorb that technology, govern its use, and learn from its results, so that effective SEO in an AI-mediated environment is best understood not as a set of tasks but as a dynamic organisational capability. The framework of dynamic capabilities is well suited to this purpose: it distinguishes a firm's ordinary capabilities, which allow it to perform current activities efficiently, from its dynamic capabilities, which allow it to sense changes in the environment, seize the opportunities they present, and continually reconfigure its resources in response (Teece et al., 1997; Teece, 2007). In rapidly changing settings the dynamic capabilities matter most, since the value of any fixed set of routines erodes as conditions shift, although scholars have rightly debated how far such capabilities can themselves be reduced to identifiable routines rather than remaining partly tacit and firm-specific (Eisenhardt & Martin, 2000). Read through this lens, maintaining visibility under AI-driven search is a continuous exercise in sensing algorithmic and platform change, seizing the openings new technologies create, and reconfiguring content, processes, and roles accordingly: the tools are inputs to this capability, not the capability itself, and because the capability is socially complex and path-dependent it is far harder to imitate than the tools, which returns the analysis to the resource-based observation that durable advantage rests on what is rare and inimitable rather than on what can be purchased (Barney, 1991).

Governance, coordination, and the reconfiguration of roles: One of the clearest organisational consequences of AI-driven SEO is that visibility ceases to be the property of a single function. Producing authoritative content requires subject-matter expertise that often sits outside marketing; interpreting performance data requires analytical capability; implementing technical recommendations requires engineering; and protecting the brand and meeting regulatory obligations requires brand, public-relations, and legal involvement. Visibility now depends on coordination across functions that were historically siloed, and the quality of that coordination becomes a determinant of competitive performance in its own right: as the cost of producing content falls, the binding constraint shifts from production to coordination, and the firms that design for it are advantaged. Governance is the mechanism through which this coordination is made reliable, and also the means by which trust is operationalised internally, editorial standards specify what quality means and who is accountable for it; policies on generative models define where automation is permitted and where human authorship or review is required; data-governance practices keep personalisation and analytics within legal and ethical bounds; and brand-safety and compliance procedures translate external obligations such as those imposed by the Digital Services Act into internal routines. Governance is frequently treated as a constraint on speed, but it is more accurately the infrastructure that allows a firm to automate without forfeiting the authenticity and accountability on which its visibility rests. The same shift reconfigures roles: the work of the SEO specialist moves from the manual execution of technical tasks toward the orchestration of human-and-machine workflows, deciding what to delegate, reviewing and improving output, and integrating it with the contributions of other functions, consistent with the broader pattern by which AI shifts human effort toward interpretive, relational, and strategic work (Huang & Rust, 2021).

Organisational learning and managerial competencies: If the environment changes faster than any fixed playbook can accommodate, the capacity to learn becomes more valuable than any particular set of practices. Research on organisational learning emphasises that knowledge is accumulated, retained, and transferred through routines and structures, so that a firm's ability to improve is a property of how it is organised rather than of the talent of any individual (Argote & Miron-Spektor, 2011), while research on absorptive capacity adds that the ability to exploit new external knowledge depends on the stock of related knowledge a firm already holds (Cohen & Levinthal, 1990). Together these suggest that advantage accrues less to the firm that adopts a given technique first than to the firm that learns from each change most effectively. A particular form of this capacity is organisational ambidexterity, the ability to exploit current capabilities efficiently while simultaneously exploring emerging ones (March, 1991; O'Reilly & Tushman, 2008), which here means capturing the efficiency today's automation offers while continuing to experiment with new platforms, formats, and models whose importance is not yet established, maintaining performance on established channels while building competence in the social and conversational discovery environments examined in section 1.3. Balancing the two is a problem of organisational design and managerial attention rather than a technical one. The competencies that matter are therefore no longer primarily technical; they are the capacity to interpret algorithmic and platform change in strategic terms, to govern the division of labour between people and machines, to resist the false economy of automating work whose value depends on human judgement, and to recognise what should deliberately not be automated. The broader evidence on digital transformation supports this conclusion: studies of digital maturity find consistently that the organisations which derive the most value from digital technologies are distinguished not by the sophistication of their tools but by the clarity of their strategy and the adaptiveness of their organisation, captured in the observation that it is strategy, not technology, that drives digital transformation (Kane et al., 2015), and research on the business value of artificial intelligence locates the source of performance gains in the organisational and process changes that surround AI adoption rather than in the technology in isolation (Mikalef & Gupta, 2021). The implication for SEO is direct: the firms that will sustain visibility are those that treat automation as an occasion to build organisational capability, not as a substitute for it.

CHAPTER 2: RESEARCH METHODOLOGY

The literature reviewed in Chapter 1 established a set of theoretical propositions about how AI-driven search reshapes the determinants of digital visibility and about why competitive advantage in this environment derives from organisational capability rather than from tool adoption alone. Those propositions were developed through the synthesis of existing scholarship; they have not yet been examined against the experience of the practitioners who operate within the environment the literature describes. The empirical strategy through which that examination is conducted is set out below. It is concerned exclusively with the primary investigation, the research design, the instruments, the sample, and the procedures for collecting and analysing data, and is kept analytically distinct from the conceptually oriented review that precedes it: where Chapter 1 asked what the literature implies, the empirical study asks whether those implications are recognisable in practice.

2.1 Research Design

The study adopts a mixed-methods design that combines a quantitative practitioner survey with a qualitative expert interview. The choice is grounded in a pragmatist research philosophy, which treats methodological decisions as a function of the research questions rather than of a prior commitment to a single epistemological tradition, and which legitimises the integration of quantitative and qualitative evidence where each addresses a dimension of the problem the other cannot reach (Johnson & Onwuegbuzie, 2004; Creswell & Plano Clark, 2018). The research questions of this thesis are of exactly this dual character. They concern, on one side, the distribution of practices, beliefs, and adaptations across a population of digital-marketing and SEO professionals, a matter of breadth that a structured survey is well suited to capture; and, on the other, the mechanisms through which AI adoption, content governance, trust, and competitive positioning actually operate inside an organisation, a matter of depth that is accessible only through the detailed account of an informed practitioner.

The design is convergent and complementary rather than sequential. The survey and the interview were developed from the same conceptual framework and conducted in the same period, and their results are brought together at the interpretation stage so that each illuminates the other. The complementarity is substantive, not merely additive. The survey measures how far a cross-section of organisations has moved from AI adoption toward genuine organisational adaptation, but it cannot explain why particular boundaries between automated and human work are drawn where they are, or how an intermediary operationalises E-E-A-T and trust in day-to-day editorial practice. The expert interview supplies precisely this interpretive depth, and it also reaches forward-looking questions, notably the response to generative, zero-click search, that have no stable equivalent in a closed-format questionnaire. Combining the two allows the analysis to triangulate: where survey patterns and expert testimony converge, confidence in a finding is strengthened; where they diverge, the divergence itself becomes an object of analysis. This integrative logic is appropriate to a phenomenon that is simultaneously widespread, registering across many firms, and concentrated, observable in its most developed form within specialist intermediaries such as the one examined here.

2.2 Research Objectives and Research Questions

The empirical investigation is organised around four research objectives that translate the thesis's overarching aim into discrete, investigable tasks. The objectives are to trace the evolution of search and SEO and interpret its strategic significance (O1); to examine how digital trust and the E-E-A-T framework condition visibility and what they demand of organisations (O2); to analyse how personalisation and social proof shape behaviour across platforms governed by distinct relevance logics (O3); and to identify the organisational capabilities and structural adaptations required to achieve and sustain competitive digital visibility (O4). The first objective is addressed primarily through the literature and the expert interview, while the remaining three are examined through both instruments, with the survey establishing distribution and the interview establishing mechanism.

These objectives are pursued through four research questions, carried forward unchanged from the Introduction so that the theoretical and empirical strands of the thesis remain aligned:

RQ1. How has the integration of machine learning and large language models into search engine architectures transformed the criteria by which digital content achieves visibility, and what are the strategic and organisational implications for firms?

RQ2. In what ways does the E-E-A-T framework operationalise digital trust within AI-driven ranking systems, and what does meaningful alignment with these quality standards require of organisational strategy and capability?

RQ3. How do personalised algorithms and social proof together shape digital consumer behaviour across platforms governed by distinct relevance logics?
RQ4. What organisational capabilities and structural adaptations are required for firms to achieve and sustain competitive digital visibility in a search landscape defined by AI-generated answers, E-E-A-T standards, and cross-platform fragmentation?

The empirical design connects to these questions through a deliberate division of labour between the two instruments. The questionnaire generates evidence on practitioners' AI maturity, their beliefs about trust and E-E-A-T, the concrete adaptations their organisations have made, and their expectations of future visibility drivers, addressing RQ2, RQ3, and RQ4 across a range of organisations. The expert interview probes the organisational mechanisms behind these patterns and extends the analysis to questions of governance, publisher-network trust, competitive positioning, and generative search that bear most directly on RQ1 and RQ4. Neither instrument is expected to answer any question in isolation; the contribution of the empirical chapter lies in reading them together against the framework established in Chapter 1. Because the empirical design engages practitioners and an industry expert rather than end users, the consumer-behaviour dimension of RQ3 is approached through the literature and through practitioners' accounts of consumer response rather than through direct consumer data.

2.3 Questionnaire Development

The questionnaire was developed directly from the conceptual framework set out in Chapter 1, so that each thematic block operationalises a construct the literature identifies as consequential. The instrument was designed to measure constructs, AI maturity, trust and E-E-A-T beliefs, organisational adaptation, governance, and expected future drivers of visibility, without naming the underlying theories in the wording presented to respondents, a standard precaution that avoids priming participants toward theoretically 'correct' answers and keeps the language accessible to busy practitioners. The instrument comprises twenty-five questions organised into six thematic sections, followed by a short block of four optional open-ended questions, and was implemented and distributed through Google Forms. A range of closed formats was used as appropriate to each construct:

single-answer multiple choice for categorical and profile variables, checkbox items for activities and practices where more than one response is valid, five-point Likert grids for belief and capability statements, linear scales for the two anchor variables, and a ranking item for expected future drivers of visibility. The questionnaire was reviewed for clarity, length, and face validity before distribution, and the small number of required items was limited to those essential for segmentation and analysis in order to protect the completion rate.

Two items function as cross-cutting analytical variables that bind the six sections into a single argument. The organisation's AI maturity stage (Q7) positions each respondent on a five-point continuum from no use to strategic embedding, and organisational preparedness for AI-driven search (Q13) records how ready the organisation considers itself to be. These two variables provide the principal axes against which trust beliefs, adaptation actions, governance safeguards, and future expectations are cross-tabulated, allowing the analysis to test the thesis's central proposition that advantage flows not from adopting AI but from the depth of organisational integration around it.

Section 1 – Respondent Profile (Q1–Q6): The opening section establishes professional context and generates the segmentation variables used throughout the analysis: role, years of experience, organisational sector, organisational size, the respondent's involvement in search-visibility and content decisions, and the respondent's personal use of AI tools. These items do not test a research question directly; they make it possible to read every subsequent result against the characteristics of the respondent, and so support interpretation across all four research questions.

Section 2 – AI Adoption and AI Maturity (Q7–Q10): The second section locates each organisation on the adoption-integration continuum. It records the maturity stage (Q7), the frequency of AI use in search, content, and marketing activities (Q8), the specific activities to which AI is applied (Q9), and the depth of integration into standard workflows as opposed to ad hoc use (Q10). The section provides the evidence on which RQ1 and RQ4 draw, distinguishing organisations that have merely acquired AI tools from those that have embedded them in routine practice.

Section 3 – Digital Trust, E-E-A-T and Visibility (Q11–Q12): The third section captures practitioner beliefs about trust, credibility, authority, and social proof as determinants of visibility. A five-point Likert grid (Q11) tests whether practitioners recognise demonstrated expertise, author authority, organisational trustworthiness, social proof, and long-term trust-building as genuine drivers of ranking and performance, while a checkbox item (Q12) maps these beliefs onto the concrete practices through which organisations signal expertise and trustworthiness. Comparing stated beliefs with operational behaviour, this section speaks directly to RQ2 and contributes to RQ3.

Section 4 – Organisational Adaptation and Capability Development (Q13–Q16): The fourth section is the analytical core of the survey. It records organisational preparedness (Q13), the extent of specific capability-building actions such as training, AI-literacy development, workflow redesign, role creation, cross-functional collaboration, and the establishment of internal guidelines (Q14), the concrete structural and governance changes actually made (Q15), and the locus of responsibility for AI-in-search decisions (Q16). Together these items reveal whether organisations have moved from awareness to genuine reconfiguration, and whether adaptation has reached the structural and governance levels, providing the principal evidence for RQ4 and a substantial part of RQ3.

Section 5 – Opportunities and Challenges (Q17–Q19): The fifth section balances the benefits of AI in search against its risks and the safeguards organisations have established. It records the benefits realised or expected (Q17), the single challenge perceived as the greatest organisational risk (Q18), and the extent to which governance safeguards, human review, editorial standards, approval workflows, AI-use disclosure, and compliance checks, are in place (Q19). This section supports RQ4 and, through the safeguards grid, tests whether governance investment is keeping pace with AI adoption.

Section 6 – Future Outlook (Q20–Q21): The sixth section is forward-looking. A ranking item (Q20) asks respondents to order seven candidate factors, including AI adoption, content quality, human expertise, E-E-A-T, brand authority, customer reviews, and technical SEO, by their expected importance for future visibility, testing directly whether practitioners expect quality- and trust-related factors to outweigh purely technical or adoption-based ones. A single-answer item (Q21) captures the expected strategic trajectory of AI within the organisation. The section feeds RQ1, RQ2, and RQ4 and provides practitioner-level evidence on the thesis's central normative claim.

Open-ended questions (Q22–Q25): Four optional open-ended questions close the instrument, placed last so as not to deter completion. They ask respondents to describe, in their own words, the most significant change their organisation has made because of AI (Q22), how they maintain content quality and trust when using AI (Q23), the biggest organisational challenge they face in integrating AI (Q24), and the capabilities they believe organisations will most need to build (Q25). These responses are coded thematically and integrated with the closed-question results to add interpretive depth across RQ1, RQ2, and RQ4. Table 2.1 summarises the mapping of sections to objectives and research questions. The full questionnaire, as administered, is reproduced in Appendix A.

Table 2.1. Questionnaire structure and links to objectives and research questionsSection (items)	**Analytical focus**	**Question formats**	**Objective(s)**	**Research question(s)**
1. Respondent Profile (Q1–Q6)	Professional context and segmentation variables	Single-answer multiple choice	O1–O4 (segmentation)	All RQs
2. AI Adoption and AI Maturity (Q7–Q10)	Adoption–integration continuum; maturity anchor (Q7)	Single choice; checkboxes; linear scale	O1, O4	RQ1, RQ3
3. Digital Trust, E-E-A-T and Visibility (Q11–Q12)	Beliefs about trust, authority, social proof; signalling practices	Likert grid; check boxes	O2	RQ2, RQ3
4. Organisational Adaptation and Capability Development (Q13–Q16)	Preparedness anchor (Q13); capability-building and structural change	Linear scale; Likert grid; checkboxes; single choice	O4	RQ3, RQ4
5. Opportunities and Challenges (Q17–Q19)	Benefits, greatest perceived risk, governance safeguards	Checkboxes; single choice; Likert grid	O2, O4	RQ4

6. Future Outlook (Q20–Q21)	Expected future drivers of visibility; strategic trajectory of AI	Ranking; single choice	O1, O4	RQ1, RQ2, RQ4
Open-ended block (Q22–Q25)	Organisational change, quality maintenance, challenges, future skills	Long-answer text (optional)	O2, O4	RQ1, RQ2, RQ4

Note. Objectives: O1 evolution of search/SEO and its strategic significance; O2 digital trust and E-E-A-T as conditions of visibility; O3 personalisation and social proof; O4 organisational capabilities and adaptation.

2.4 Interview Design

The qualitative component consists of a single semi-structured expert interview conducted with a specialist at WhitePress, the European content-marketing and publisher-network platform used throughout the thesis as a contextual practitioner reference. The semi-structured format was chosen because it secures comparability and thematic coverage through a prepared guide while preserving the flexibility to follow the informant's reasoning and to pursue unanticipated lines of insight, a combination well suited to eliciting expert knowledge about processes that are not directly observable from outside the organisation (Kvale & Brinkmann, 2009; Bogner, Littig, & Menz, 2009). The informant was approached as a positional expert: that is, as a person whose value to the research lies not in personal opinion but in privileged knowledge of how decisions are actually made within an organisation that occupies a strategically informative position in the content-marketing ecosystem.

The rationale for selecting a WhitePress specialist follows from the structure of the research problem. As an intermediary that connects clients to a curated network of publishers, WhitePress sits precisely at the junction of the processes the thesis examines: it has adopted AI across parts of its operation while deliberately retaining human judgement in others; it operationalises E-E-A-T and content quality through an editorial governance process applied at scale; it manages digital trust directly through the admission and monitoring of publishers; it advises clients on authority and social-proof signals across fragmenting platforms; and it must adapt a business model built on link-based authority to the rise of generative, zero-click search. These are not topics on which a generalist practitioner could speak with comparable authority, and several of them, the governance of AI-generated content, the assessment of publisher trust, and the strategic response to generative search, are observable only from inside such an intermediary. A single information-rich case of this kind yields more analytical insight into the mechanisms in question than a larger number of less well-positioned informants would provide.

The interview was guided by a protocol comprising twelve core questions preceded by a warm-up question that establishes the informant's role and scope of responsibility, organised across five analytical themes, with optional probes attached to each question for use where the informant did not spontaneously address the relevant ground. The five themes correspond to the empirical heart of the thesis: AI adoption and its organisational consequences; content-quality governance and E-E-A-T; digital trust and publisher-network management; social proof, client outcomes, and competitive positioning; and future outlook and strategic adaptation, closing with a catch-all question designed to surface themes outside the guide. The interview objectives were, accordingly, to test the central distinction between technology adoption and organisational adaptation in a concrete operational setting, to examine how an intermediary translates abstract quality standards into editorial routines, and to capture an expert reading of how the competitive logic of the field is changing. Table 2.2 sets out the thematic structure of the protocol and its links to the research questions.

Table 2.2. Interview protocol: thematic structure and links to research questions

Theme (items)	Analytical focus	Conceptual lens	Research question(s)
Warm-up	Establishes the informant's role, scope, and positional knowledge	-	-
Theme (items)	**Analytical focus**	**Conceptual lens**	**Research question(s)**
1. AI Adoption and Organisational Consequences (Q1–Q2)	Where automation has and has not been adopted; how roles and skills changed	Dynamic capabilities; organisational learning	RQ1, RQ4
2. Content-Quality Governance and E-E-A-T (Q3–Q4)	How content is judged publishable; how E-E-A-T is operationalised in editorial practice	E-E-A-T as quality standard; governance	RQ2, RQ4

3. Digital Trust and Publisher-Network Management (Q5–Q6)	How publisher trust and authority are assessed; genuine versus nominal link authority	Digital trust; resource-based view	RQ2, RQ4
4. Social Proof, Client Outcomes and Competitive Positioning (Q7–Q8)	Role of social-proof signals; sources of distinctiveness under automation pressure	Social proof; resource-based view	RQ3, RQ4
5. Future Outlook and Strategic Adaptation (Q9–Q11)	Adaptation to generative/zero-click search; the capability that sustains visibility	GEO and zero-click; dynamic capabilities	RQ1, RQ4
Closing (Q12)	Surfaces themes outside the guide; corrects framing assumptions	-	All RQs

Note. Probes attached to each core question were used flexibly and only where the informant did not spontaneously address the relevant ground.

The interview complements the survey in three specific ways. First, it converts the survey's categorical measures of adaptation and governance into an account of how those changes are actually enacted, explaining the reasoning behind decisions that the questionnaire can only record as outcomes. Second, it addresses dimensions of the trust argument, the assessment of publisher authority and the distinction between genuine and merely technical link signals, that cannot be captured by self-report from a general practitioner sample. Third, it reaches the forward-looking question of generative search, for which the questionnaire has no equivalent item, drawing on expert knowledge to interpret a development still too recent for settled practice. Read alongside the distribution of practitioner responses, the interview thus supplies the mechanism behind the pattern. The complete interview guide, including the warm-up question and all twelve core questions, is provided in Appendix B.

2.5 Sampling Strategy

Both components rely on non-probability, purposive sampling, a standard and appropriate choice for research that seeks analytical insight into a defined professional practice rather than statistical representation of a general population (Patton, 2015). The two instruments, however, apply the logic of purposive selection in different ways.

The survey targeted professionals with direct working knowledge of search visibility and content strategy: SEO and search specialists, content strategists and managers, marketing managers and directors, digital-marketing specialists, and agency consultants and account managers, operating across marketing and SEO agencies, B2B services, B2C and e-commerce, media and publishing, and technology and SaaS organisations of varying size. This population was chosen because the research questions concern organisational adaptation to AI-driven search, a phenomenon that only practitioners working in or adjacent to the function can report on credibly. Twenty-eight valid responses were collected. The sample is therefore modest in size and self-selected, which has direct consequences for analysis and is addressed explicitly in the limitations below; it is treated as a basis for descriptive characterisation and analytical interpretation rather than for statistical generalisation to the wider professional population.

The interview applied purposive selection at the level of the single, strategically informative case. Rather than seeking a representative cross-section of intermediaries, the study deliberately selected one expert occupying a position that renders the mechanisms of interest, AI governance, E-E-A-T operationalisation, publisher-network trust, and adaptation to generative search, directly observable. In expert-interview research, this concentration on an information-rich informant is a recognised and defensible strategy, since the value of the data derives from the depth and positional authority of the account rather than from the number of interviews conducted (Bogner et al., 2009). The single expert interview is consequently understood not as a representative sample of practitioner opinion but as an in-depth window onto practice within a particularly revealing organisational setting, to be triangulated against the survey and the literature.

2.6 Data Collection Procedures

The questionnaire was administered online through Google Forms, which provided a single, accessible point of entry and structured the export of responses for analysis. The link was distributed through professional networks, including relevant LinkedIn communities and the researcher's industry contacts, and through contacts associated with WhitePress, in order to reach practitioners with genuine exposure to AI in search and content work. Participation was voluntary and responses were collected anonymously, with no personally identifying information required. The form was structured so that only the items essential to segmentation and core analysis were mandatory, the four open-ended questions were optional, and respondents could complete the instrument at a time of their choosing, a design intended to support completion among time-constrained professionals.

The expert interview was conducted remotely by video call, lasting approximately fifty minutes within the planned forty-five-to-sixty-minute window. With the informant's prior consent the interview was audio-recorded and subsequently transcribed for analysis, the recording serving to preserve the detail and accuracy of the account and to allow the researcher to engage fully in the conversation rather than relying on contemporaneous notes. The semi-structured guide was followed flexibly, with probes used selectively and the order of questions adjusted to the natural flow of the discussion. The research observed standard ethical principles for studies involving human participants. Participation in both components was voluntary and based on informed consent: survey respondents were told the purpose of the study, the academic context, and the anonymous and confidential treatment of their answers before proceeding, and the interview informant gave explicit consent to participation and to recording, having been informed of how the material would be used. No special-category or sensitive personal data were collected. Data were stored securely and used solely for the academic purposes of this thesis, in line with the data-protection expectations of the European context and the General Data Protection Regulation, and the interview material was handled so as to respect the professional position of the informant and the commercial sensitivity of the organisation discussed.

2.7 Data Analysis Procedures

Prior to analysis, the exported survey data were screened and prepared. Of the thirty responses received, two were removed: one respondent declined the participation item that functioned as consent, and one returned non-substantive (gibberish) text across all open-ended fields together with extensive item non-response, indicating a non-genuine submission. This yielded an analytic sample of twenty-eight. Two export artefacts were then corrected at the label level only, without altering any recorded response: the Google Forms export had concatenated two response labels for the AI-maturity item (Q7), which were resolved to the single intended option, consistent with the fact that no respondent selected the option indicating no current use of AI tools, and a duplicated column header for the safeguards item (Q19) was de-duplicated.

Given the size and non-probability character of the sample, the quantitative data were analysed using descriptive statistics only. The analysis reports frequencies and percentage distributions for the categorical and checkbox items, summarises the Likert-grid items through response distributions and average levels of agreement, and reports the ranking item through the aggregate ordering of factors. The two anchor variables, AI maturity stage (Q7) and organisational preparedness (Q13), are used to structure the interpretation through cross-tabulation: trust beliefs, adaptation actions, governance safeguards, and future expectations are read against an organisation's position on the adoption-integration continuum, allowing the analysis to examine whether AI-mature organisations have also adapted more deeply or whether adoption and adaptation diverge. No inferential or advanced statistical testing was undertaken; with twenty-eight responses, significance testing would convey a false precision, and the descriptive approach is the methodologically honest one, suited to characterising patterns and informing interpretation rather than to confirming hypotheses. The four open-ended responses were coded thematically and integrated with the closed-question results to add interpretive depth.

The interview was analysed using thematic analysis, following the established sequence of familiarisation with the transcript, the generation of initial codes, the collation of codes into candidate themes, and the review and refinement of those themes against the data (Braun & Clarke, 2006). The procedure combined deductive and inductive elements. The five themes of the protocol provided an initial deductive framework derived from the conceptual chapters, ensuring that the analysis engaged directly with the thesis's constructs; within that frame, inductive coding remained open to ideas the informant raised that the guide had not anticipated, including any surfaced by the closing question, so that themes were identified both from the theoretical framework and from the data itself rather than imposed wholesale. The resulting themes were then related to the survey findings so that the two strands could be interpreted together.

Integration occurs at the interpretation stage, where quantitative patterns and qualitative themes are synthesised against the literature. Throughout, the analysis follows a consistent interpretive sequence, moving from the empirical result to its interpretation, to comparison with the theoretical framework established in Chapter 1, and finally to its managerial implication, so that the survey and interview evidence build cumulatively toward the discussion and conclusions that follow.

2.8 Research Limitations

The design has limitations that should be stated plainly and borne in mind when reading the findings. The first is the modest size of the survey sample. Twenty-eight responses are sufficient to describe patterns and to support cautious, analytically framed interpretation, but they do not permit statistical generalisation to the wider population of digital-marketing and SEO professionals, and they preclude inferential testing; the quantitative findings are accordingly presented as descriptive and indicative rather than confirmatory.

The second limitation concerns the composition of the sample. Respondents were reached through professional networks and self-selected into the study, which is likely to bias the sample toward practitioners already engaged with, and favourably disposed toward, AI in search and content. The sample is also industry-specific by design, drawn from professionals working in or close to the SEO and content-marketing function, so that its findings speak to that community rather than to organisations in general. These features sharpen the relevance of the data to the research questions while limiting its breadth.

The third limitation is the reliance on a single expert interview. While the informant was selected precisely for the strategic value of their vantage point, one account inevitably reflects the perspective and circumstances of one organisation and cannot represent the full diversity of practice across intermediaries and in-house teams. This limitation is mitigated, though not removed, by triangulating the interview against the survey and the literature, and by treating it as an interpretive instrument rather than as a representative one.

The fourth limitation concerns the survey instrument itself. Two items did not function exactly as intended. The greatest-risk question (Q18) was designed as a single-answer item but was rendered as a multiple-selection field, so the risk figures reported in Chapter 3 denote the share of respondents who flagged each risk rather than a single most-important risk, and the percentages consequently sum to more than one hundred. The ranking question (Q20) used an internally inconsistent scale and many respondents returned flat or identical rankings, so its results are interpreted only directionally and no precise rank means are reported. Neither issue affects the integrity of the recorded responses, but both qualify the precision with which the corresponding items can be read.

A final limitation is contextual. AI-driven search is evolving rapidly, and several of the developments examined here, particularly generative and zero-click search, are changing as this research is conducted. The findings therefore represent a time-bound snapshot of practitioner experience and expert practice at a specific moment, and their currency should be weighed accordingly. Taken together, these limitations define the appropriate register of the empirical claims that follow: the study offers grounded, theoretically informed insight into how organisations are adapting to AI-driven search, not statistically generalisable measurement of that adaptation, and the findings are interpreted in that spirit.

CHAPTER 3: EMPIRICAL FINDINGS

3.1 The Practitioner Survey

This chapter reports the findings of the practitioner survey, the quantitative component of the empirical investigation set out in Chapter 2. Its purpose is to establish, against the experience of professionals who operate within the AI-mediated search environment, how far the propositions developed in the literature are recognisable in practice. The analysis is descriptive throughout: it reports frequencies, percentage distributions, and average levels of agreement, and it reads these patterns against the two cross-cutting variables that the methodology designates as analytical anchors, the organisation's AI maturity stage (Q7) and its self-rated preparedness for AI-driven search (Q13). Consistent with the modest, non-probability character of the sample, no inferential testing is undertaken; the findings are presented as indicative rather than confirmatory, and each result is interpreted, compared with the conceptual framework of Chapter 1, and related to the research questions it bears upon. The findings of the expert interview are reported separately and are not anticipated here. The full set of descriptive survey tables is also consolidated in Appendix D.

Twenty-eight valid responses were obtained. Because four of the open-ended items were optional and a small number of grid rows were left blank by individual respondents, the denominator for each item is stated where it departs from the full sample of twenty-eight.

3.2 Respondent Profile

The opening section of the questionnaire established the professional context of the sample and generated the segmentation variables used throughout the analysis. Six characteristics were recorded: current role, years of professional experience, organisational sector, organisational size, the respondent's involvement in search-visibility and content decisions, and the respondent's personal use of AI tools. These characteristics do not test a research question directly; rather, they make it possible to read every subsequent result against the composition of the sample, and so they condition the interpretation of all four research questions. Table 3.1 reports the distributions.

Table 3.1. Respondent profile (N = 28)

Characteristic	Category	n	%
Current role (Q1)	SEO / search specialist	3	11
	Content strategist or content manager	5	18
	Marketing manager or director	6	21
	Digital marketing specialist	5	18
	Agency consultant / account manager	1	4
	Business owner or founder	1	4
	Other (e.g., content creator, IT, finance, banking)	7	25
Experience (Q2)	Less than 2 years	14	50
Characteristic	**Category**	**n**	**%**
	2–5 years	10	36
	6–10 years	3	11
	11–15 years	1	4
Sector (Q3)	Marketing / SEO agency	6	21
	B2B services	9	32
	Technology / SaaS	4	14
	Media / publishing	4	14
	B2C / e-commerce	1	4
	Other / unspecified (finance, banking, healthcare)	4	14
Organisation size (Q4)	1–9 (micro)	7	25
	10–49 (small)	7	25
	50–249 (medium)	5	18
	250 or more (large)	9	32
Decision involvement (Q5)	Not involved	6	21
	Occasionally consulted	11	39
	Regularly involved	10	36

	I lead these decisions	1	4
Personal AI use (Q6)	Occasional / experimental	4	14
	Regular use for specific tasks	11	39
	Daily, integral to work	12	43

Percentages are rounded and may not sum to 100. No respondent reported "more than 15 years" experience or "I do not use AI tools."

Three features of the sample stand out and shape the reading of all later results. The first is its junior profile: fourteen respondents (50%) reported fewer than two years of professional experience and a further ten (36%) reported two to five years, so that eighty-six per cent of the sample had five years or less in the field, with only four respondents above that threshold (Figure 3.1). The second is the dispersion of organisational size, which is bimodal rather than concentrated: large organisations of 250 or more employees (32%) and micro organisations of fewer than ten (25%) together account for more than half (57%) of the sample, with small and medium organisations less represented. The third is the variation in decision involvement: while a combined forty per cent either lead or are regularly involved in search-visibility decisions, more than a fifth (21%) reported no involvement at all, indicating that a meaningful share of respondents observe rather than direct the practices the survey examines.

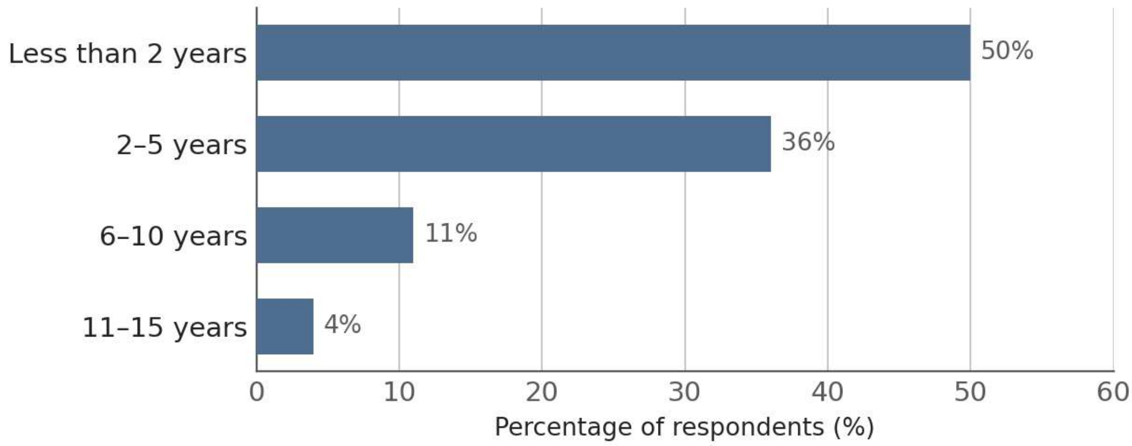

Figure 3.1. Respondent experience profile (Q2; N = 28).

Two compositional characteristics qualify the inferences that can be drawn. The roles classified as "Other" (25%) include several positions outside the core digital-visibility population, among them credit analysis, banking, and information-technology consulting, and a corresponding 14% of the sample reported sectors, principally finance, banking, and healthcare, that fall outside the marketing, agency, media, and technology fields the instrument was designed to reach. These responses are retained because they were valid completions, but their presence reflects the self-selected, network-distributed recruitment described in the methodology and reinforces that the data characterise an engaged, AI-adjacent practitioner community rather than a representative cross-section. The strongly positive personal-use figures, with no respondent reporting non-use of AI tools and 82% using them regularly or daily, are consistent with this self-selection toward practitioners already disposed toward the technology.

These characteristics matter because the conceptual framework treats organisational adaptation as a function of accumulated, path-dependent capability rather than of individual familiarity with tools (Barney, 1991; Teece et al., 1997). A sample weighted toward junior practitioners, polarised between very small and very large organisations, and including a tail of respondents only loosely connected to the digital-visibility function is one in which both deep organisational capability and authoritative knowledge of firm-level governance are unevenly distributed. The profile therefore provides the necessary backdrop for the central analytical question of the chapter, pursued in section 3.5, of whether the depth of organisational adaptation tracks the depth of AI adoption, and it counsels caution in reading individual enthusiasm as evidence of organisational readiness.

3.3 AI Adoption and AI Maturity

The second section located each organisation on the continuum from tool acquisition to organisational integration. It recorded the maturity stage (Q7), the principal cross-cutting variable, the frequency of AI use (Q8), the specific activities to which AI is applied (Q9), and the depth of integration into standard workflows as distinct from ad hoc use (Q10). Together these items distinguish organisations that have merely acquired AI tools from those that have embedded them in routine practice, and they supply the evidence on which RQ1 and RQ4 draw. Table 3.2 reports the maturity, frequency, and integration distributions, and Table 3.3 the activities in which AI is applied.

Table 3.2. AI maturity, frequency of use, and workflow integration (N = 28)

Item	Category	n	%
AI maturity (Q7)	Experimental / individual use	6	21

	Used within selected teams	7	25
	Integrated across multiple departments	10	36
	Strategically embedded across the organisation	5	18
Frequency of use (Q8)	Daily	16	57
	Weekly	7	25
	Monthly	5	18
Workflow integration (Q10)	1 – Not at all integrated	2	7
	2	9	32
Item	**Category**	**n**	**%**
	3	7	25
	4	6	21
	5 – Fully integrated	4	14

No respondent selected "We do not currently use AI tools" (Q7) or "Never / Rarely" (Q8). Q10 mean = 3.04 on a five-point scale.

Table 3.3. Activities to which AI is applied (Q9; multiple responses permitted, N = 28)

Activity	n	%
Content creation / drafting	15	54
Keyword and topic research	12	43
Analytics and performance reporting	13	46
Workflow / task automation	9	32
Translation / localisation	10	36
Customer or audience insights	8	29
Technical SEO	6	21

Adoption across the sample is both widespread and frequent. Every respondent's organisation uses AI to some degree, more than half (57%) report daily use (Figure 3.3), and no organisation falls below monthly use. Just over half the sample (54%) places its organisation at one of the two highest maturity stages, integration across multiple departments (36%) or strategic embedding (18%), while the remainder is split between experimental, individual use (21%) and use confined to selected teams (25%; Figure

3.2). The activities to which AI is applied concentrate on content generation and discovery work: content creation (54%) and analytics (46%) lead, followed by keyword research (43%) and workflow automation (32%), while technical SEO (21%) is the least common application, a pattern consistent with the literature's account of generative tools displacing routine drafting and research before more specialised technical tasks (Verhoef et al., 2021).

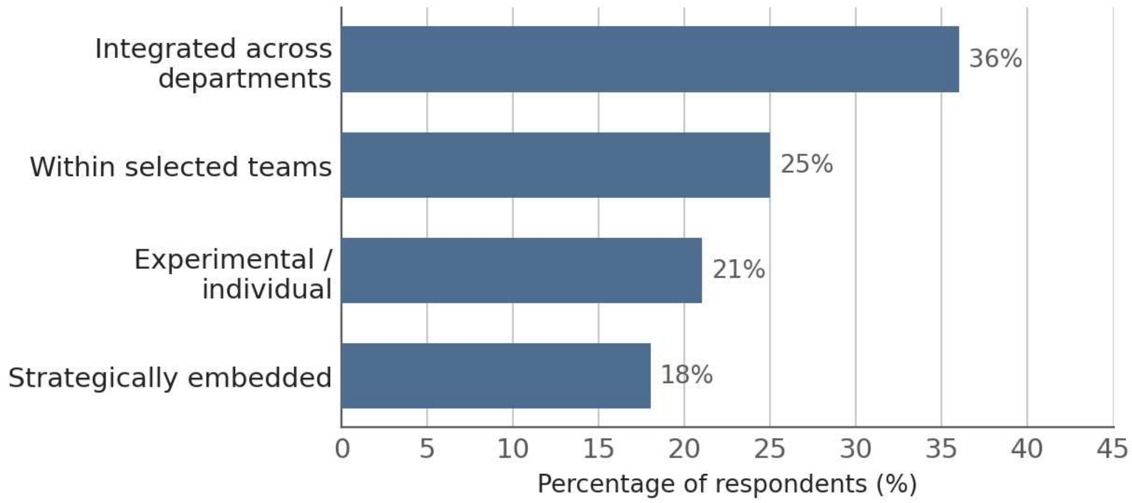

Figure 3.2. Organisational AI maturity stage (Q7; N = 28).

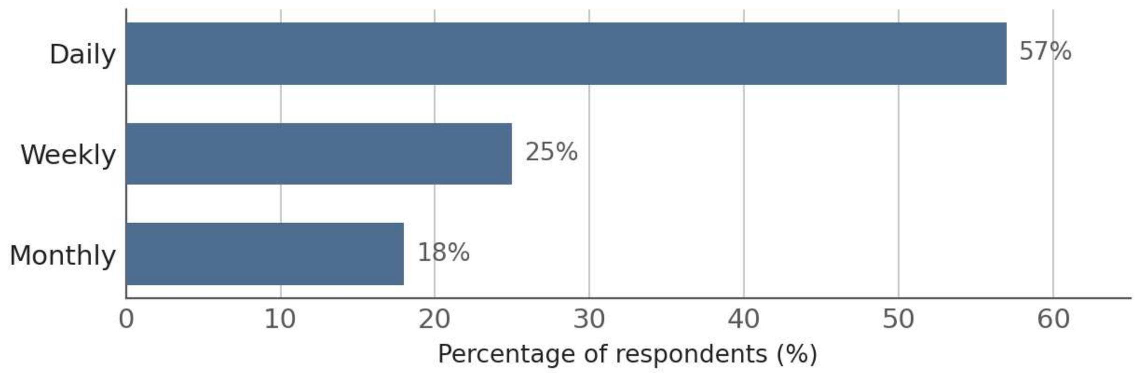

Figure 3.3. Frequency of organisational AI use (Q8; N = 28).

The decisive finding of this section, however, is the divergence between the frequency of adoption and the depth of its integration. Although more than half the sample reports daily use and just over half places itself at the higher maturity stages, the mean workflow-integration score (Q10) is only 3.04, and just ten respondents (36%) rate their integration at four or five on the five-point scale, with the modal responses clustered at the lower-middle of the distribution. The picture is therefore one of frequent but shallow integration: AI is used often, but for many organisations it remains layered onto existing processes rather than woven into standard workflows. This distinction is precisely the one the digital-transformation literature insists upon, between the use of digital technologies to accelerate existing processes and a more fundamental reconfiguration of how work is organised (Verhoef et al., 2021; Vial, 2019). The data suggest that a substantial part of the sample has digitalised its activities without yet transforming them. For RQ1, which concerns how the integration of machine learning into search has altered the determinants of visibility and the implications for firms, these results indicate that practitioners are responding to the shift primarily at the level of tooling and task execution. The concentration of AI use in content drafting and keyword research shows organisations adopting the technology where it most directly reduces production effort, consistent with the literature's observation that the immediate appeal of automation is efficiency (Brynjolfsson & McAfee, 2014). For RQ4, the gap between maturity self-classification and workflow integration provides the first piece of evidence for the chapter's central proposition that adoption and adaptation are distinct, a proposition examined directly in section 3.5.

3.4 Digital Trust and E-E-A-T

The third section captured practitioner beliefs about trust, credibility, authority, and social proof as determinants of visibility, and the concrete practices through which organisations attempt to signal these qualities. A five-point Likert grid (Q11) recorded agreement with five statements operationalising the trust constructs developed in Chapter 1, and a checkbox item (Q12) mapped these beliefs onto signalling practices. Comparing what practitioners believe with what their organisations do, this section speaks directly to RQ2 and contributes to RQ3. Tables 3.4 and 3.5 report the results.

Table 3.4. Beliefs about trust and visibility (Q11; five-point scale, N = 28)

Statement	Mean	% agree (4–5)
Visibility increasingly depends on demonstrated expertise and experience, not just technical optimisation	3.57	61
Content credibility and author authority materially affect where content ranks	3.96	75
An organisation's perceived trustworthiness affects its business performance online	3.71	68

Social proof (reviews, ratings, engagement) influences both rankings and customer decisions	4.00	79
Building trust and authority is a long-term organisational investment, not a quick technical fix	4.04	79

Table 3.5. Trust and expertise signalling practices (Q12; multiple responses permitted, N = 28)

Signalling practice	n	%
Customer reviews and testimonials	16	57
Named expert authors / stated credentials	10	36
Citations and reputable sources	10	36
Case studies and demonstrated results	11	39
Original research or proprietary data	9	32
Editorial or fact-checking standards	5	18
Does not actively signal expertise / trustworthiness	3	11

Practitioner beliefs align closely with the theoretical claims of Chapter 1. Agreement is strong and consistent across all five statements, with mean scores between 3.57 and 4.04 and majorities endorsing each proposition. The recognition that social proof influences both rankings and customer decisions attracts the widest agreement (79%), followed by the propositions that author authority affects ranking (75%) and that trust-building is a long-term investment (79%). Even the most demanding statement, that visibility now depends on demonstrated expertise rather than technical optimisation alone, secures a clear majority (61%). At the level of belief, therefore, the sample recognises trust, expertise, authority, and social proof as genuine determinants of visibility, corroborating the thesis's contention that the basis of effective search performance has shifted from technical configuration toward demonstrated quality (Google, 2023), and that social proof operates simultaneously as a behavioural influence and an algorithmic signal (Cialdini, 1984; Bikhchandani et al., 1992).

The signalling practices, however, reveal a marked gap between belief and behaviour. The most widely adopted practice is the collection of customer reviews and testimonials (57%), the signal most directly associated with social proof, which is also the belief most strongly endorsed; the alignment between the two is the clearest instance in the data of conviction translating into action. Beyond it, adoption thins. Although seventy-five per cent agreed that author authority materially affects ranking, only thirty-six per cent reported using named expert authors with stated credentials, and the practices most closely tied to the editorial substance of E-E-A-T are the rarest of all: original research is used by just under a third (32%), and documented editorial or fact-checking standards by only five respondents (18%). Three organisations (11%) reported that they do not actively signal expertise at all.

This belief-behaviour gap is the central finding for RQ2, which asks what meaningful alignment with E-E-A-T requires of organisational strategy and capability. Chapter 1 argued that E-E-A-T is not a checklist to be ticked but a description of the qualities a credible source reliably exhibits, and that genuine alignment is an organisational-capability problem requiring coordinated routines across authorship, editorial review, and reputation management (Google, 2023; Teece et al., 1997). The survey indicates that, within this sample, practitioners have internalised the belief that authority and expertise matter, but that the corresponding organisational machinery, named expertise, original evidence, and above all documented editorial governance, is largely absent. Practitioners more readily adopt the signal that can be gathered from outside the organisation (customer reviews) than the signals that require building internal editorial capability (named experts, original research, fact-checking standards). The data thus support the thesis's claim that the binding constraint on E-E-A-T alignment is not awareness but the capacity to operationalise it, and they anticipate the analysis of governance safeguards in section 3.6, where the near-absence of editorial standards reappears as a systematic weakness.

3.5 Organisational Adaptation and Capability Development

The fourth section is the analytical core of the survey. It recorded organisational preparedness for AI-driven search (Q13), the second cross-cutting variable; the extent of specific capability-building actions (Q14); the concrete structural and governance changes actually made (Q15); and the locus of responsibility for AI-in-search decisions (Q16). Together these items reveal whether organisations have moved from awareness to genuine reconfiguration, and whether adaptation has reached the structural and governance levels, providing the principal evidence for RQ4 and a substantial part of RQ3. The findings are interpreted through the dynamic-capabilities and organisational-learning frameworks established in Chapter 1.

Self-rated preparedness (Q13) is moderate and slightly positive, with a mean of 3.36. Eleven respondents (39%) rated their organisation at four or five, eleven (39%) chose the midpoint, and six (21%) rated themselves unprepared at one or two. The capability-building actions recorded in Q14, however, present a more sober picture. As Table 3.6 shows, the mean score for every adaptation action falls close to the midpoint of the scale, ranging from 3.00 to 3.36. Cross-functional collaboration (3.36) and the establishment of internal guidelines (3.22) are the most developed; the creation of new roles or the reassignment of responsibilities (3.00) is the least. The pattern indicates that adaptation, where it occurs, takes the least structurally disruptive forms, encouraging existing functions to work together and issuing guidance, rather than the more demanding forms of reorganisation, such as creating dedicated roles or rebuilding workflows.

Table 3.6. Extent of capability-building actions (Q14; five-point scale, mean of valid responses)

Adaptation action	Mean
Increased cross-functional collaboration	3.36
Established internal guidelines or oversight for AI use	3.22
Built AI literacy and understanding across the team	3.07
Redesigned workflows or processes	3.19
Invested in training or upskilling staff	3.11
Created new roles or reassigned responsibilities	3.00

Means computed over valid (non-blank) responses; between 24 and 25 respondents answered each row.

The concrete-changes item (Q15) is consistent with this reading. The most frequently reported changes are the formation of cross-functional working groups and the revision of performance metrics (both 32%), followed by dedicated AI or SEO teams (25%), formal training programmes (21%), and written AI-use policies and new hires (both 18%). Critically, a quarter of respondents (25%) reported that their organisation had made no concrete structural or governance change at all. The locus of responsibility (Q16), which respondents could assign to more than one party, is correspondingly diffuse: it rests most often with the marketing or SEO team (39%) or with individual employees (36%), followed by cross-functional groups (29%) and senior leadership (25%), while three respondents (11%) reported that no clear owner exists. No single locus commands a majority; decision authority for AI in search sits predominantly at the individual or single-team level rather than being governed as a cross-functional, strategically owned concern.

These results acquire their analytical force when read against the two cross-cutting variables. Table 3.7 cross-tabulates the adaptation and governance measures by AI maturity stage.

Table 3.7. Adaptation, governance, and preparedness by AI maturity stage (Q7)

Maturity stage	n	Pre-pared-ness (Q13)	Adapt-ation (Q14)	Govern-ance (Q19)
Experimental / individual	6	3.17	2.36	2.03
Within selected teams	7	3.14	3.11	2.83
Multiple departments / embedded	15	3.53	3.47	3.31

Cell values are group means on five-point scales. The two higher maturity stages are combined for legibility. “None yet” on concrete changes (Q15) was reported by four of six experimental-stage respondents, none of the selected-team respondents, and three of fifteen higher-maturity respondents.

Two patterns emerge, and together they constitute the most important finding of the chapter. The first is that genuine adaptation does rise with maturity. The mean adaptation score climbs from 2.36 among organisations at the experimental stage to 3.11 among those using AI within selected teams and 3.47 among those at the higher maturity stages, and governance safeguards rise in parallel, from 2.03 to 2.83 to 3.31. Organisations that have integrated AI more deeply have, on the whole, also built more of the surrounding capability and oversight, which is consistent with the thesis’s proposition that advantage flows not from adoption itself but from the depth of organisational integration around it.

The second pattern is more revealing and more troubling. Self-rated preparedness does not track actual adaptation. Organisations at the experimental, individual stage rate their preparedness at 3.17, close to the 3.14 reported by organisations using AI within selected teams and only modestly below the 3.53 reported by the most mature organisations, even though their actual adaptation (2.36) and governance (2.03) are by far the lowest in the sample and four of the six reported no concrete change whatsoever. The narrow spread in self-assessed preparedness contrasts with the much wider spread in demonstrated adaptation and governance, so that preparedness, as practitioners perceive it, appears only loosely coupled to the organisational capability that would substantiate it. The least adapted organisations feel nearly as ready as the most adapted ones.

This decoupling is precisely the phenomenon the conceptual framework predicts. The digital-transformation literature warns repeatedly that the accumulation of technology does not by itself produce organisational change, and that the decisive variable is the reconfiguration of processes and decision rights rather than adoption alone (Kane et al., 2015; Verhoef et al., 2021; Vial, 2019). Dynamic-capabilities theory locates competitive advantage not in the possession of tools but in the capacity to sense, seize, and reconfigure (Teece et al., 1997; Teece, 2007), and absorptive-capacity theory explains why organisations with the same access to tools and information may nonetheless adapt very differently, since the ability to assimilate and apply new knowledge depends on a prior stock of related capability (Cohen & Levinthal, 1990). The survey supplies a practitioner-level signature of all three claims: confidence in readiness is widely held, but it rests, for the least mature organisations, on adoption rather than on the reconfiguration of work, roles, and governance. The predominance of individual and single-team ownership (Q16) and the prevalence of the least disruptive adaptation forms (Q14) reinforce the point, indicating that for much of the sample AI has been absorbed into existing structures rather than occasioning their redesign, exactly the digitalisation-without-transformation pattern the literature cautions against.

For RQ4, which asks what organisational capabilities and structural adaptations are required to sustain competitive visibility, these findings are directly informative. They indicate that the sample's organisations have, in the main, not yet built the capabilities the framework identifies as decisive. Adaptation is real but shallow and concentrated in its least structural forms; governance is weak and improves only at the highest maturity stages; responsibility is diffuse; and self-assessed preparedness systematically overstates organisational readiness. The gap between felt preparedness and demonstrated capability is itself the principal empirical contribution of this section, and it frames the analysis of opportunities, risks, and safeguards that follows.

3.6 Opportunities and Challenges

The fifth section balanced the realised or expected benefits of AI against the risks practitioners perceive and the governance safeguards their organisations have put in place. Benefits were recorded through a checkbox item (Q17), the single greatest perceived risk through a further item (Q18), and the extent of safeguards through a five-point Likert grid (Q19). The section provides the principal evidence for the opportunity-risk dimension of RQ4. Tables 3.8, 3.9, and 3.10 report the results.

Table 3.8. Realised or expected benefits of AI (Q17; multiple responses permitted, N = 28)

Benefit	n	%
Efficiency / time savings	20	71
Higher output and productivity	16	57
Faster responsiveness to change	8	29
Better quality of decisions	6	21
Cost reduction	6	21
Scalability of content or campaigns	5	18
No clear benefits yet	3	11

Table 3.9. Greatest perceived organisational risk (Q18; responses recorded, N = 28)

Risk	n	%
Lack of employee skills	12	43
Compliance concerns	10	36
Content accuracy	8	29
Misinformation	7	25
Governance issues	7	25
Brand reputation risks	7	25
Risk	**n**	**%**
Data privacy concerns	6	21
Over-reliance on automation	6	21

Q18 was intended as a single-answer item but was rendered as a multiple-selection field; several respondents recorded more than one risk, so the column sums exceed the sample size and percentages denote the share of respondents flagging each risk.

Table 3.10. Governance safeguards in place (Q19; five-point scale, mean of valid responses)

Safeguard	Mean
Approval workflows before publishing	3.14
Compliance checks (data protection, regulatory)	2.93

Documented quality or editorial standards	2.89
Transparency or disclosure about AI use	2.71
Human review and fact-checking of AI-generated content	2.89

The benefits practitioners associate with AI are overwhelmingly operational. Efficiency and time savings (71%) and higher output and productivity (57%) are reported far more often than any other benefit, while faster responsiveness (29%), better decision quality (21%), and cost reduction (21%) trail well behind, and scalability is reported by only eighteen per cent. Three respondents (11%) perceived no clear benefit yet. The concentration of benefit on efficiency and throughput, rather than on decision quality or strategic scalability, corresponds closely to Chapter 1's argument that the most immediate gain from automation is efficiency, but that efficiency is competitively self-neutralising once the underlying tools are widely available, because a resource that anyone can purchase is neither rare nor difficult to imitate (Barney, 1991; Brynjolfsson & McAfee, 2014). The data suggest that the sample is realising precisely the kind of benefit the framework identifies as least durable, and is largely not yet realising the higher-order benefit, the reallocation of freed expert attention toward judgement-intensive work, that the literature identifies as the genuine source of advantage.

The risks practitioners flag are, by contrast, organisational and qualitative rather than technical. The single most frequently cited risk is the lack of employee skills (43%), followed by compliance concerns (36%) and a cluster of content-integrity and oversight risks, led by content accuracy (29%), with misinformation, governance, and brand reputation each cited by a quarter (25%). That the skills gap is the foremost concern is significant: it is a direct practitioner acknowledgement of the absorptive-capacity constraint, the recognition that the value of AI depends on the organisation's capacity to interpret and apply it rather than on the technology itself (Cohen & Levinthal, 1990). The prominence of content accuracy and misinformation connects to the quality argument of Chapter 1, in which the falling cost of producing content that imitates expertise raises rather than lowers the premium on credible signals of genuine quality (Akerlof, 1970; Google, 2023).

The safeguards item exposes the gravest mismatch in the dataset. Every governance safeguard records a mean at or below the scale midpoint of three, with the single exception of approval workflows before publishing (3.14), which only marginally exceeds it. Compliance checks (2.93), human review and fact-checking of AI-generated content (2.89), and documented editorial standards (2.89) all fall below the midpoint, and transparency about AI use (2.71) is the least embedded safeguard of all, indicating that governance safeguards are, on average, only partially in place (Figure 3.4).

That the safeguards bearing most directly on content integrity, human review of machine-generated material and disclosure of AI use, should remain among the weakest is difficult to reconcile with the same respondents' ranking of content accuracy and misinformation among their leading risks. The recurrence here of weak editorial standards, already visible in the near-absence of editorial signalling practices in section 3.4, marks it as a recurring feature of the sample rather than an isolated result.

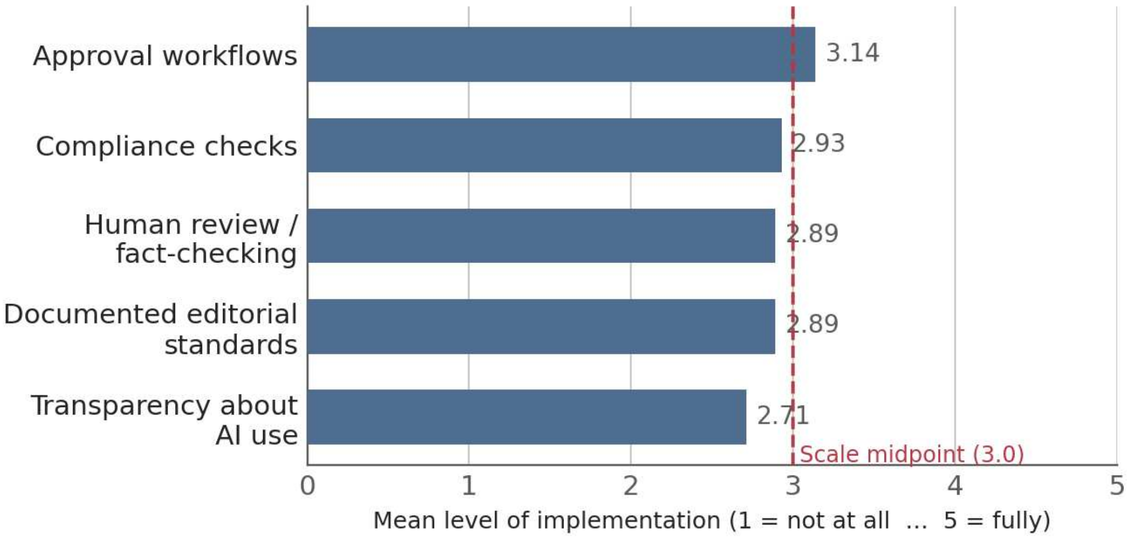

Figure 3.4. Mean implementation of governance safeguards (Q19; five-point scale, N = 28), with the scale midpoint (3.0) marked.

Read together, these findings describe a sample that is capturing the readily available efficiency benefits of AI while lagging conspicuously on the governance required to manage its risks, and doing so even though it identifies those very risks clearly. This is the practical manifestation of the adoption-adaptation gap established in section 3.5: organisations have adopted the technology and realised its operational dividend, but have not built the editorial and oversight infrastructure that Chapter 1 identifies as the means by which trust is operationalised internally and through which automation can be pursued without forfeiting accountability. For RQ4, the implication is that the binding organisational challenge is not the realisation of benefit, which is already occurring, but the construction of governance commensurate with the risks that practitioners themselves recognise.

3.7 Future Outlook

The final section recorded practitioners' expectations of the future drivers of digital visibility and the anticipated strategic trajectory of AI within their organisations. A ranking item (Q20) asked respondents to order seven candidate factors by their expected importance for future visibility, and a single-answer item (Q21) captured the expected strategic role of AI over the next two to three years. The section feeds RQ1, RQ2, and RQ4 and provides practitioner-level evidence on the thesis's normative claim that quality- and trust-related factors will outweigh purely technical or adoption-based ones.

Table 3.11. Expected strategic trajectory of AI over the next two to three years (Q21, N = 28)

Expected trajectory	n	%
Become central to strategy	10	36
Grow significantly	11	39
Grow moderately	5	18
Stay about the same	1	4
Decline	1	4

Expectations of the future trajectory of AI are emphatically expansionary. Thirty-nine per cent of respondents expect AI to grow significantly and a further thirty-six per cent expect it to become central to their organisation's strategy, so that three-quarters (75%) anticipate a substantial increase in its strategic role, while a further eighteen per cent expect moderate growth. Only one respondent each expected the role of AI to remain stable or to decline. The near-unanimous expectation of intensification is consistent with the strongly positive adoption and personal-use figures of sections 3.1 and 3.2, and it indicates that, whatever the current shallowness of integration, practitioners do not regard AI as a passing or peripheral development. For RQ1 and RQ4, this anticipated trajectory implies that the organisational pressures documented in the preceding sections, the demand for deeper integration, for editorial governance, and for cross-functional coordination, are likely to intensify rather than abate.

The ranking item (Q20) was designed to test directly whether practitioners expect quality- and trust-related factors, content quality, human expertise, E-E-A-T, brand authority, and customer reviews, to outweigh AI adoption and technical SEO as drivers of future visibility. The item must, however, be interpreted with considerable caution. A substantial number of respondents did not produce a valid ordering: several assigned the same rank to every factor, and others compressed all seven factors into one or two adjacent ranks, so that the responses cannot be aggregated into a reliable composite ordering without misrepresenting the underlying data. This is a measurement limitation of the ranking format rather than a substantive finding, and it accords with the methodology's decision to treat the quantitative data descriptively rather than to impute precision the responses cannot bear.

Where a clear ordering was discernible, the pattern nonetheless leaned in the direction the thesis anticipates. Among the respondents who differentiated their rankings, content quality, human expertise, E-E-A-T, and customer reviews recurred as the factors placed highest, while AI adoption itself was seldom ranked as the most important driver and was on several occasions ranked among the least important. This tendency, though it cannot be quantified responsibly given the data quality, is consistent both with the strong endorsement of trust and expertise beliefs recorded in section 3.4 and with the thesis's normative claim that, as AI tools become ubiquitous, the durable determinants of visibility will be the quality and trust signals that resist commoditisation rather than the adoption of the tools themselves (Barney, 1991; Google, 2023). The forward-looking evidence therefore complements the belief data of section 3.4: practitioners expect AI to grow in strategic importance while simultaneously, where they express a clear view, expecting the factors that determine visibility to be those of quality, expertise, and trust rather than tool adoption alone.

3.8 WhitePress Expert Interview Findings

The survey establishes how widely the patterns anticipated in the literature are recognised across the practitioner population; it cannot, by its nature, explain why those patterns take the forms they do, or how the work of adapting to AI-driven search is actually organised inside a firm. The expert interview supplies that interpretive depth. It was conducted remotely as a single semi-structured conversation with a senior WhitePress informant whose responsibilities span content-quality governance, publisher-network management, and strategic adaptation, a positional vantage point from which the mechanisms behind the survey's aggregate figures become visible. The account is treated as illustrative rather than representative, consistent with the expert-interview logic set out in Chapter 2: a single, well-placed informant offers access to specialised, positional knowledge that breadth-oriented instruments cannot reach. The transcript was analysed using the six-phase thematic procedure of Braun and Clarke (2006), and the seven themes reported below are read against the conceptual framework of Chapter 1 and related, where the evidence allows, to the survey findings of sections 3.1 to 3.6. The interview is used throughout not to restate what the survey already shows but to explain it, to convert pattern into mechanism, and belief into practice. A thematic summary of the interview is provided in Appendix C.

3.8.1 AI Adoption and Workflow Automation

The informant's account locates AI firmly within the operational layer of the organisation rather than its strategic core. AI tools are used to assist with content drafting, translation and localisation, categorisation, data processing, and the optimisation of repetitive workflow tasks; strategic marketing decisions, client relationships, and high-level content planning, by contrast, remain the province of human judgement. The distinction the informant draws is explicit: AI functions as an efficiency-enhancing technology, not as a substitute for professional expertise. Automation absorbs the tasks that are repetitive, scalable, and tolerant of standardisation, while the activities that depend on tacit knowledge, relational understanding, and contextual judgement are deliberately retained within human control.

This characterisation does more than corroborate the survey's adoption figures; it explains their shape. Section 3.3 found adoption to be universal and frequent, every organisation using AI, half doing so daily, yet shallow in its integration, with a workflow-integration mean of only 3.04 and AI use concentrated in content creation and keyword research rather than in technical or strategic functions. The interview supplies the rationale for that concentration. AI is adopted first, and most fully, precisely where it reduces production effort on routine tasks, because that is where its comparative advantage over human labour is clearest and its risks most easily contained. The augmentation logic the informant describes is the organisational principle underlying the survey's distribution: firms layer AI onto the operational tasks it performs well and withhold it from the judgement-intensive work it performs poorly. What the survey registers as frequent but shallow integration is, from the practitioner's vantage point, a considered division of labour rather than a failure of ambition.

Read against the conceptual framework, the finding refines the thesis's central distinction between adoption and adaptation. The literature treats the mere acquisition of widely available tools as competitively self-neutralising, since a resource that anyone can purchase is neither rare nor difficult to imitate (Barney, 1991; Brynjolfsson & McAfee, 2014). The informant's insistence that AI augments rather than replaces expertise implies that advantage accrues not to the firm that automates the most but to the one that automates the right tasks while protecting and redeploying the human expertise that automation cannot reproduce. For RQ1, which concerns how the embedding of machine learning in search alters the determinants of visibility and the implications for firms, the interview indicates that the operative organisational response is selective augmentation, the reallocation of human attention toward the strategic and relational work that remains scarce, rather than the wholesale displacement of labour. The augmentation boundary the informant describes is therefore not a transitional state but a deliberate and durable feature of how a capable intermediary organises its use of AI.

3.8.2 Organisational Adaptation and Capability Development

If the first theme concerns where AI is applied, the second concerns what its application demands of the organisation. The informant reported that WhitePress has not undergone major change in its formal job architecture, roles have not been wholesale created or abolished, but that substantial change has occurred beneath that architecture, in workflows, in the skills the work requires, and in the training needed to sustain them. Teams increasingly require AI literacy; continuous learning has become a condition of competence rather than an occasional supplement; new AI-related services have emerged from the reconfigured workflows; and, tellingly, resistance to change has become one of the organisation's principal challenges. The informant further observed that AI has lowered the value of certain operational tasks while raising the premium on creativity and strategic thinking, a redistribution of which capabilities matter rather than a reduction in their number.

This pattern speaks directly to the dynamic-capabilities and organisational-learning frameworks established in Chapter 1. Dynamic-capabilities theory locates advantage not in assets themselves but in the capacity to reconfigure them as the environment shifts (Teece et al., 1997; Teece, 2007). The informant's description of stable roles overlaying reconfigured workflows is an instance of reconfiguration occurring at the level of routines and competencies rather than of formal structure: the organisation chart is largely unchanged, but the work done within it, and the skills it presupposes, have been rebuilt. Organisational-learning theory adds the complementary insight that the capacity to absorb and apply new external knowledge depends on a prior stock of related capability (Cohen & Levinthal, 1990). The informant's emphasis on continuous learning and AI literacy describes precisely the cultivation of that absorptive capacity, and the identification of resistance to change as a leading challenge names its principal internal constraint: the binding limit on adaptation is not the availability of tools but the organisation's willingness and ability to learn.

The interview thereby illuminates the survey's most consequential result. Section 3.5 found that adaptation, where it occurred, took the least structurally disruptive forms, collaboration and guidance rather than the creation of roles or the redesign of workflows, and that self-rated preparedness was decoupled from demonstrated capability, with the least-adapted organisations feeling as ready as the most-adapted. The informant's account suggests why the most demanding forms of adaptation are the rarest: workflow redesign and capability-buildingare slow, contested, and dependent on overcoming internal resistance, whereas issuing guidance is comparatively costless. Where the survey sample largely stalls at the low-cost forms of adaptation, the interview describes an organisation that has pushed further into the costly ones, and that experiences, in its struggle with resistance to change, exactly the friction that the survey's less-adapted firms have not yet confronted because they have not yet attempted the deeper reconfiguration. For RQ4, the interview corroborates the proposition that competitive advantage resides in adaptive capacity rather than in tool adoption, and specifies the mechanism, continuous learning under conditions of internal resistance, through which that capacity is, and is not, built.

3.8.3 Human Oversight and Content Governance

The third theme exposes the sharpest contrast between the interview and the survey, and it is a contrast of capability rather than of belief. The informant described a governance architecture in which human oversight is not residual but constitutive. WhitePress maintains dedicated local-language content teams whose function is to review submissions, verify authenticity, and ensure that published material meets the quality and relevance standards of the network. Content is subject to human copywriting, editorial review, proofreading, and validation against user intent, and material identified as AI-generated is rejected. The informant stressed, in particular, that every piece of content passes through multiple reviewers before publication, oversight is distributed and redundant rather than vested in a single gatekeeper.

The analytical significance of this account lies in its juxtaposition with the survey's governance findings. Section 3.6 identified the governance of AI as the gravest weakness in the practitioner sample: every safeguard scored at or below the scale midpoint, with only approval workflows (3.14) marginally exceeding it, and the safeguards bearing most directly on content integrity, human review and fact-checking of AI-generated content (2.89) and transparency about AI use (2.71), remained among the weakest, even though the same respondents ranked content accuracy and misinformation among their leading risks. Section 3.4 had already shown documented editorial standards to be uncommon, used by only five organisations in twenty-eight (18%). The interview describes, in effect, the capability whose scarcity the survey documents. Where the broad practitioner population recognises the importance of editorial governance but has not built it, the intermediary has institutionalised it as a core operational function. The contrast is instructive precisely because it is not one of awareness (both populations understand that quality must be controlled) but of organisational investment: the survey sample holds the belief without the machinery, and the interview supplies a portrait of the machinery itself.

This finding connects governance to the trust and quality arguments of Chapter 1. The economics of information holds that as the cost of producing content that imitates expertise falls, the value of credible signals of genuine quality rises rather than falls, because the market must find means to distinguish substance from imitation (Akerlof, 1970; Google, 2023). The informant's rejection of AI-generated content and insistence on multi-reviewer human verification is the organisational expression of that logic: in an environment saturated with machine-produced text, demonstrable human editorial control becomes itself a source of differentiation and trust. For RQ2, which asks what meaningful alignment with E-E-A-T requires of organisational strategy and capability, the interview answers concretely, it requires the standing editorial infrastructure of dedicated teams, layered review, and explicit rejection criteria that the survey shows most organisations lack. Human oversight, on this account, is not a brake on automation but the precondition that allows automation to be pursued without forfeiting the quality on which visibility and trust depend.

3.8.4 Digital Trust, E-E-A-T and Authority

The fourth theme develops the interview's account of how authority is constituted in an AI-mediated search environment. The informant maintained that visibility now depends less on backlinks considered in isolation and more on a composite of brand perception, demonstrated expertise, experience within a niche, trustworthiness, and positive brand sentiment. Authority, in this view, is increasingly constructed through reputation and demonstrated knowledge rather than through the accumulation of technical signals. The framing maps closely onto the Experience, Expertise, Authoritativeness and Trustworthiness construct examined in Chapter 1, and the informant's stress on experience and demonstrated expertise echoes the framework's treatment of these as qualities a credible source reliably exhibits rather than attributes that can be manufactured through configuration.

Set against the survey, this theme both corroborates and explains the belief-behaviour gap identified in section 3.4. Practitioners overwhelmingly endorsed the proposition that author authority and demonstrated expertise govern ranking, seventy-five per cent agreed that content credibility and author authority materially affect where content ranks, yet the practices that would substantiate authority, named expert authors and original research, were adopted by only a minority, and documented editorial standards by fewer than a fifth (18%). The informant's account clarifies what the survey's believers have grasped in principle but not operationalised: that authority is not a property of an individual page but of a reputation built and maintained over time, and that signalling it convincingly requires sustained editorial and reputational investment rather than a discrete technical intervention. The intermediary's role, on this reading, is partly to supply the authority-building capability that resource-constrained clients cannot generate for themselves, a service that exists precisely because demonstrating E-E-A-T is difficult, capability-dependent, and therefore valuable.

Theoretically, the interview reinforces the thesis's conception of digital trust as multidimensional and cumulative, accruing through consistent behaviour over time rather than through any single signal (Mayer et al., 1995; Fogg, 2003). The informant's displacement of the backlink from the centre of authority assessment, in favour of brand perception and demonstrated experience, tracks the broader shift the literature describes from quantity-based to quality-based determinants of visibility (Google, 2023). For RQ2, the theme indicates that alignment with E-E-A-T is most accurately understood as an organisational-capability problem: authority is earned through the patient construction of reputation and expertise, and the firms, or the intermediaries acting on their behalf, that can orchestrate that construction hold an advantage that imitation of technical signals cannot erode.

3.8.5 Social Proof and AI Visibility

The fifth theme emerged as one of the strongest in the interview, and it extends the thesis's treatment of social proof into the domain of machine-mediated visibility. The informant reported that platforms carrying user-generated validation, Reddit, Trustpilot, LinkedIn, Google Reviews, and X, are increasingly drawn upon by AI systems when forming assessments of brands, and that community validation, customer reviews, and online sentiment now feed directly into how organisations appear in AI-generated search outputs and AI Overviews. Social proof, in the informant's framing, has acquired a dual function: it remains a behavioural influence on prospective customers and has additionally become an algorithmic input that AI-driven retrieval treats as evidence of standing.

This dual function is the conceptual hinge between the survey's strongest belief and the thesis's argument about AI visibility. Section 3.4 recorded that the proposition attracting the widest agreement across the entire sample, endorsed by seventy-seven per cent, was that social proof influences both rankings and customer decisions, and that the collection of reviews and testimonials was the single most widely adopted signalling practice, the one clear case of conviction translating into action. The interview explains why this belief is so firmly held and why the practice is so readily adopted: social proof is the trust signal that originates outside the organisation, generated by customers and communities rather than requiring the construction of internal editorial capability, and it is therefore both the easiest signal to gather and, increasingly, the one to which AI systems are most attentive. The informant's account thus elevates social proof from a marketing tactic to a visibility asset whose importance is amplified, not diminished, by the move toward generative search.

The theme connects to the social-influence literature of Chapter 1, in which individuals under uncertainty infer appropriate behaviour from the observed behaviour of others, and early signals can produce self-reinforcing cascades of attention (Cialdini, 1984; Bikhchandani et al., 1992). What the interview adds is the observation that AI-driven retrieval systems now participate in the same inferential logic: where human users read reviews and community discussion as proxies for quality, large language models increasingly mine the same sources for the same purpose, compounding the influence of social proof by routing it through both human and algorithmic channels. For RQ3, which concerns the role of social proof and trust signals in shaping consumer behaviour and visibility, the interview indicates that the influence of social proof is no longer confined to the consumer's decision but is increasingly encoded in the visibility mechanisms that determine which brands the consumer encounters at all.

3.8.6 The Evolution of SEO and Search Visibility

The sixth theme addresses the trajectory of search optimisation itself, and the informant's position is unambiguous: SEO is evolving rather than disappearing. Traditional ranking signals retain their relevance, but visibility increasingly depends on the satisfaction of user intent, the authenticity of content, brand mentions, authority signals, and emerging practices of Generative Engine Optimisation and visibility within AI Overviews. The informant returned repeatedly to a single proposition, that content remains the foundation of both conventional search engines and large language models. The shift the informant describes is therefore one of mechanism rather than of substance: the channels and signals through which content earns visibility are changing, but the primacy of substantive, intent-satisfying content is not.

This account aligns the interview with the survey's forward-looking evidence and with the thesis's normative claim. Section 3.7 found practitioners to expect AI to grow in strategic importance while, where they expressed a clear view, expecting the durable determinants of visibility to be content quality, human expertise, E-E-A-T, and customer reviews rather than tool adoption, a tendency the ranking item's data quality prevented from being quantified but which leaned consistently in the direction the thesis anticipates. The informant supplies the practitioner rationale the survey could only infer: as AI tools for producing and optimising content become universally available, the act of optimisation ceases to differentiate, and competitive visibility migrates toward the qualities that resist automation, authenticity, demonstrated authority, and the satisfaction of genuine user intent. The emergence of Generative Engine Optimisation does not overturn this logic but extends it, transferring the contest for visibility onto new terrain while leaving its underlying currency, credible content, unchanged.

For RQ1, the theme indicates that the integration of machine learning into search reconfigures rather than abolishes the determinants of visibility: the firm must now optimise for generative synthesis and AI-mediated retrieval as well as for conventional ranking, but the foundational requirement of substantive content persists across both regimes. The continuity the informant insists upon is analytically important, because it implies that the capabilities a firm has built around content quality and authority, the path-dependent, difficult-to-imitate capabilities Chapter 1 identifies (Teece et al., 1997), transfer across the transition from conventional to generative search rather than being rendered obsolete by it. The evolution of SEO, on this account, rewards the organisations that have invested in durable quality capabilities and penalises those that have relied on the technical optimisation that automation has commoditised.

3.8.7 Competitive Advantage and Future Capabilities

The final theme assembles the interview's dispersed observations into an account of competitive advantage, and it is here that the analysis must work hardest, because several of the questions bearing on this theme, particularly those concerning what insulates the firm's offer from commoditisation and which capability separates firms that will remain visible from those that will not, were addressed only partially within the interview. The analysis therefore draws on the evidence the informant did provide, read in the light of WhitePress's documented business model and the broader arc of the conversation, and interprets it through the Resource-Based View developed in Chapter 1. Claims about future capabilities are presented as interview-informed industry developments and organisational priorities rather than as established outcomes.

The informant attributed the organisation's competitive position to a combination of resources and accumulated capabilities rather than to any single feature: an extensive publisher network

- reported to encompass in excess of two hundred thousand websites, together with international reach, long-standing publisher relationships, an automated content-distribution infrastructure, local-market expertise, and the organisational knowledge built up over years of operating in the field. The Resource-Based View holds that sustained advantage derives from resources that are valuable, rare, difficult to imitate, and non-substitutable (Barney, 1991). The informant's inventory maps onto these criteria with some precision. The publisher network is valuable because it grants clients distribution at a scale and across markets they could notassemble independently; it is rare because few intermediaries command comparable breadth; and it is difficult to imitate because it is the product of relationships and reputation accumulated over time rather than of capital that a competitor could simply deploy. The relational and reputational character of these assets is decisive: a new entrant could purchase software and hire staff, but could not instantaneously reproduce the trust, the local-market knowledge, or the publisher relationships on which the network depends, because these are path-dependent and socially complex, precisely the conditions the Resource-Based View associates with inimitability. The automated distribution infrastructure, by contrast, is the more replicable element of the offer, which is consistent with the informant's implicit recognition that technology alone, being purchasable, cannot constitute durable advantage; the protection against commoditisation lies in the relational and editorial assets that surround the technology rather than in the technology itself.

That interpretation supplies the answer the interview only partially articulated to the question of what resists commoditisation under conditions of widely available automation. If link-building tools are accessible to anyone, then the differentiating resource cannot be the capacity to place links but must be the quality, curation, and trustworthiness of the network through which they are placed, the editorial governance described under the third theme and the authority-building capability described under the fourth. WhitePress's advantage, on this reading, is the integration of a hard-to-imitate publisher network with the editorial capability to maintain its quality, a combination that automation commoditises in neither of its parts. This connects the theme to RQ4, which asks what organisational capabilities sustain competitive visibility: the interview, supplemented by the business model, indicates that the decisive capabilities are the relational and editorial assets that automation cannot reproduce, and that these are most valuable in precisely the environment, one of cheap, ubiquitous content generation, that might appear to threaten an intermediary's relevance.

On the organisation's forward trajectory, the informant identified a set of priorities that should be read as interview-informed industry developments rather than as settled commitments. Future capability investment was expected to concentrate on AI-visibility optimisation and Generative Engine Optimisation, on brand-authority monitoring and reputation management, on the deepening of AI literacy and data-analytics capability, and on cross-functional collaboration, a portfolio aimed at extending the firm's existing authority-and-distribution advantage into the emerging domain of AI-mediated search. The informant was candid that these directions are responses to uncertainty rather than the exploitation of a known opportunity: the single greatest strategic challenge identified was the opacity of AI ranking systems, the difficulty of optimising for retrieval mechanisms whose criteria are neither published nor stable. Framed through dynamic-capabilities theory, this is an account of sensing under conditions of genuine ambiguity (Teece, 2007): the organisation has detected the environmental shift toward generative search and begun to assemble the capabilities it judges necessary to meet it, while acknowledging that the precise form of the required response cannot yet be specified. The future capabilities the informant describes are therefore best understood not as predictions but as the priorities of a firm attempting to convert an established advantage in authority and distribution into a defensible position in a search environment whose rules are still being written. For RQ4, the implication is that the work of adaptation is continuous ratherthan terminal: even an organisation possessed of valuable and inimitable resources must keep reconfiguring them, because the value of those resources is contingent on an environment that AI-driven search is actively reshaping.

CHAPTER 4: DISCUSSION

4.1 Revisiting the Research Questions

The literature reviewed in Chapter 1 generated a set of theoretical propositions about how the embedding of machine learning in search has altered the determinants of digital visibility, and the empirical investigation reported in Chapter 3 examined how far those propositions are recognisable in the experience of practitioners and in the operation of a strategically placed intermediary. This discussion is interpretive rather than descriptive. It does not restate the survey distributions or the interview themes, which the preceding chapter has already established; it asks what they mean when read together against the conceptual framework, and it does so in order to answer the four research questions that have organised the study from the outset.

Those questions concern, first, how the integration of machine learning and large language models into search architectures has transformed the criteria by which content achieves visibility, and what this implies for firms (RQ1); second, how the E-E-A-T framework operationalises digital trust within AI-driven ranking, and what meaningful alignment with it demands of organisational strategy and capability (RQ2); third, how personalised algorithms and social proof together shape consumer behaviour across platforms governed by distinct relevance logics (RQ3); and fourth, what organisational capabilities and structural adaptations are required to achieve and sustain competitive visibility in a search landscape defined by AI-generated answers, trust-based quality standards, and cross-platform fragmentation (RQ4). A single proposition runs beneath all four and binds the discussion together: that in an AI-mediated search environment the adoption of widely available technology has become a condition of mere participation, whereas durable competitive advantage derives from the organisational capabilities that determine whether that technology is used well. The sections that follow interpret the empirical evidence through this proposition, integrating the survey and interview findings with the strategic-management and trust-based lenses introduced in Chapter 1, and answering the research questions through their combined reading.

4.2 AI Adoption Does Not Automatically Produce Organisational Transformation

The clearest pattern in the empirical evidence is also the most consequential for the thesis: the adoption of artificial intelligence has become close to universal among the organisations studied, while the organisational transformation that would convert adoption into advantage remains uneven and, for a substantial part of the sample, largely absent. Every respondent's organisation used AI to some degree, half did so daily, and none fell below monthly use; yet the depth of integration told a different story, with a workflow-integration mean of only 3.04 and barely a third of respondents rating their integration in the upper reaches of the scale. The activities to which AI was applied concentrated on content drafting and keyword research, the tasks where the technology most directly reduces production effort, while the capability-building actions that would embed it in the organisation clustered near the midpoint of the scale and took their least disruptive forms. Cross-functional collaboration and the issuing of internalguidance were the most developed adaptations; the creation of new roles and the redesign of workflows were the least; and more than a quarter of organisations reported no concrete structural or governance change whatsoever. The sample had, in the main, digitalised its activities without transforming them.

This distinction between digitalisation and transformation is precisely the one the digital-transformation literature insists upon, separating the use of digital technologies to accelerate existing processes from the more fundamental reconfiguration of how work is organised and how value is created (Verhoef et al., 2021; Vial, 2019). Read through the dynamic-capabilities framework, the survey describes organisations that have acquired ordinary capabilities, the means to perform current tasks more efficiently, without developing the dynamic capabilities through which firms sense environmental change, seize the opportunities it presents, and reconfigure their resources in response (Teece et al., 1997; Teece, 2007). The decisive theoretical point is that these are different kinds of achievement, accomplished by different means. Adoption is an act of procurement: the tools are sold as a service to anyone willing to pay, and acquiring them requires only a budget and a decision. Transformation is an act of reconfiguration: it requires the redesign of routines, the redistribution of decision rights, the cultivation of new skills, and the construction of governance, none of which can be purchased and all of which take time. The technology can be installed in an afternoon; the organisation that uses it well is built over years.

The survey supplies an unusually sharp signature of this divergence. When the adaptation and governance measures are read against the AI-maturity anchor, genuine adaptation does rise with maturity, climbing from a mean of 2.36 among organisations at the experimental stage to 3.47 among the most mature, with governance safeguards tracking the same ascent. But self-rated preparedness does not follow suit. Organisations at the experimental, individual stage rated their preparedness at 3.17, close to the 3.53 reported by the most mature organisations and marginally above the figure reported by those using AI within selected teams, even though their actual adaptation and governance were by far the weakest in the sample and most of them had made no concrete change at all. The least adapted organisations, in other words, felt nearly as ready as the most adapted. This decoupling of perceived readiness from demonstrated capability is the empirical heart of the section, because it is exactly what the conceptual framework predicts: absorptive-capacity theory holds that the ability to assimilate and apply new knowledge depends on a prior stock of related capability (Cohen & Levinthal, 1990), so that confidence resting on adoption alone is confidence without foundation. Felt preparedness, for the least mature firms, is an artefact of having tools rather than of having reorganised around them.

The expert interview converts this aggregate pattern into mechanism, and in doing so it refines rather than merely confirms the thesis's central distinction. The intermediary's account located AI firmly in the operational layer, applied to drafting, translation, categorisation, and the optimisation of repetitive tasks, while strategic decisions, client relationships, and high-level planning were deliberately retained within human judgement. What the survey registers as frequent but shallow integration is, from this vantage point, not a failure of ambition but a considered division of labour: the firm layers AI onto the tasks it performs well and withholds it from the judgement-intensive work it performs poorly. The augmentation boundary is a deliberate and durable feature of how a capable organisation deploys AI, not a transitional stage on the way to fuller automation. This selective augmentation has a precise strategic meaning. Because the tools are available to everyone, advantage cannot accrue to the firm that automates the most; it accrues to the firm that automates the right tasks while protecting and redeploying the human expertise that automation cannot reproduce (Barney, 1991; Brynjolfsson & McAfee, 2014). The operative organisational response to AI-driven search is therefore the reallocation of scarce human attention toward strategic and relational work, not the wholesale displacement of labour.

The interview also names the constraint that explains why the most demanding forms of adaptation are the rarest. The intermediary reported that its formal job architecture had changed little, but that substantial change had occurred beneath it, in workflows, in the skills the work requires, and in the continuous learning needed to sustain them, and that resistance to change had become one of its principal challenges. This is reconfiguration occurring at the level of routines and competencies rather than of the organisation chart, the very process dynamic-capabilities theory describes, and the friction it generates is instructive. Workflow redesign and capability-building are slow, contested, and dependent on overcoming internal resistance, whereas issuing guidance is comparatively costless. The survey sample largely stalls at the low-cost adaptations precisely because it has not yet attempted the costly ones; the intermediary has pushed further and consequently encounters the resistance that the less-adapted firms have not, because they have not yet confronted it. The binding limit on adaptation, on this account, is not the availability of tools but the organisation's willingness and capacity to learn. For RQ1 and RQ4, the conclusion is that the transformation of search visibility is being met, across most of the sample, at the level of tooling and task execution rather than of organisational redesign, and that the gap between the two is not a temporary lag but the central strategic problem the technology poses.

4.3 From Technical SEO to Authority, Trust and Reputation

If the first analytical thread concerns whether organisations have adapted, the second concerns the direction in which the determinants of visibility have moved, and the evidence converges on a single answer: away from technical optimisation and toward demonstrated authority, trust, and reputation. At the level of belief, the survey records this shift unambiguously. Practitioners endorsed, by clear majorities, the propositions that content credibility and author authority materially affect ranking, that an organisation's perceived trustworthiness affects its online performance, and that building trust and authority is a long-term organisational investment rather than a quick technical fix; even the most demanding statement, that visibility now depends on demonstrated expertise rather than technical optimisation alone, secured a clear majority. The practitioner community has internalised the central claim of Chapter 1, that the basis of effective search performance has migrated from configuration toward demonstrated quality (Google, 2023).

Belief, however, has not translated into the organisational machinery that would substantiate it, and the gap between the two is the section's principal finding. Although seventy-five per cent of respondents agreed that author authority materially affects ranking, only thirty-six per cent reported using named expert authors with stated credentials; original research was used by just under a third; and the practice that lies closest to the editorial substance of E-E-A-T, documented editorial or fact-checking standards, was reported by just five organisations in twenty-eight (18%). The signals that can be gathered from outside the organisation were adopted far more readily than those that require building internal editorial capability. This is the belief-behaviour gap that the survey makes visible, and it is precisely the gap the conceptual framework leads one to expect. Chapter 1 argued that E-E-A-T is not a switch the algorithm computes and applies but a normative standard describing the qualities a credible source reliably exhibits, and that genuine alignment is therefore an organisational-capability problem rather than a checklist (Google, 2023; Teece et al., 1997). What practitioners have grasped in principle but not operationalised is that authority cannot be configured into a page; it must be built into an organisation.

The expert interview supplies the operational portrait of what that construction involves, and in doing so it explains the survey's gap from the other side. The intermediary maintained that visibility now depends less on backlinks considered in isolation than on a composite of brand perception, demonstrated expertise, experience within a niche, trustworthiness, and positive brand sentiment, and that authority is increasingly constructed through reputation and demonstrated knowledge rather than through the accumulation of technical signals. The displacement of the backlink from the centre of authority assessment is significant, because the backlink was the most quantifiable and the most manipulable of the traditional signals; its relegation tracks the broader movement the literature describes from quantity-based to quality-based determinants of visibility (Google, 2023). Authority, on this account, is a property of a reputation built and maintained over time, not of a discrete intervention, which is exactly why the survey's believers have not operationalised it: the practices that would substantiate authority demand sustained editorial and reputational investment that most of their organisations have not made. The intermediary's own role is partly defined by this difficulty, since it exists to supply the authority-building capability that resource-constrained clients cannot generate for themselves-a service that is valuable precisely because demonstrating E-E-A-T is capability-dependent and therefore scarce.

Read through the resource-based view, this movement from technical to reputational determinants of visibility is a movement from imitable to inimitable resources, and it is this that gives the shift its strategic weight. Technical optimisations are valuable but neither rare nor difficult to copy; any sufficiently motivated competitor can replicate them. Reputational capital, by contrast, satisfies the conditions the resource-based view associates with durable advantage almost by definition: it is path-dependent, accumulated through a particular history of performance and relationships, and socially complex, and it therefore resists rapid imitation (Barney, 1991; Roberts & Dowling, 2002). The grounding of trust in the broader literature reinforces the point, since trust is multidimensional and cumulative, emerging from consistent behaviour over time rather than from any single signal (Mayer et al., 1995; Fogg, 2003). The answer to RQ2 follows directly. Meaningful alignment with E-E-A-T requires not the cosmetic compliance that practitioner discourse often reduces it to, but the standing organisational capability to produce content with genuine experience, expertise, authority, and trustworthiness, a capability built through coordinated routines spanning authorship, editorial review, and reputation management. Visibility has become harder to buy and easier to earn, and the firms that benefit are those whose ordinary way of operating already produces the qualities the quality standard rewards.

4.4 Social Proof as a Strategic Visibility Asset

Among all the determinants of visibility examined in the study, social proof occupies a distinctive position, because it is the one on which belief and behaviour most clearly coincide and the one whose strategic significance the move toward generative search most directly amplifies. The proposition that attracted the widest agreement anywhere in the survey, endorsed by more than three-quarters of respondents, was that social proof influences both rankings and customer decisions, and the collection of customer reviews and testimonials was the single most widely adopted signalling practice, the clearest case in the dataset of conviction translating into action. The alignment is not accidental. Social proof is the trust signal that originates outside the organisation, generated by customers and communities rather than requiring the construction of internal editorial capability, and it is therefore both the easiest credibility signal to gather and, as the interview makes clear, increasingly the one to which automated systems are most attentive.

The conceptual significance of social proof lies in its dual character, and the interview is what brings the second half of that duality into view. Chapter 1 established the first half: drawing on the social-influence literature, it described how individuals under uncertainty infer appropriate behaviour from the observed behaviour of others, through both informational influence, in which the conduct of others is treated as evidence about reality, and normative influence, in which conformity secures acceptance (Cialdini, 1984; Deutsch & Gerard, 1955), and how early signals can trigger self-reinforcing cascades of attention that concentrate visibility on a few options (Bikhchandani et al., 1992). This is social proof as a behavioural signal, directed at the consumer. The interview adds the algorithmic dimension. The intermediary reported that platforms carrying user-generated validation, among them Reddit, Trustpilot, LinkedIn, Google Reviews, and X, are increasingly drawn upon by AI systems when forming assessments of brands, and that community validation and online sentiment now feed directly into how organisations appear in AI-generated outputs and AI Overviews. Social proof has thus become an algorithmic input as well as a behavioural influence: where human users read reviews and community discussion as proxies for quality, large language models increasingly mine the same sources for the same purpose.

The argument this licenses is that social proof functions simultaneously as a behavioural signal and as an algorithmic signal, and that the two reinforce one another through a recursive loop the personalisation literature anticipates. Recommendation systems heavily filter which reviews and endorsements a given consumer actually encounters, so that the social evidence reaching any individual is itself the product of prior algorithmic selection (Pariser, 2011); social proof shapes the algorithm while the algorithm shapes the social proof on display, and the cascade dynamics described above converge with the reputation-visibility loop into a single self-reinforcing system. The move toward generative search does not weaken this mechanism but compounds it, routing the influence of social proof through both human and algorithmic channels at once. The consequence for RQ3 is that the role of social proof can no longer be confined to the consumer's decision: it is increasingly encoded in the visibility mechanisms that determine which brands the consumer encounters at all, so that a brand's standing in community and review environments shapes both whether it is recommended by other people and whether it is surfaced by the systems that mediate discovery.

This elevation of social proof from marketing tactic to visibility asset carries a strategic ambivalence that the analysis should not soften. Because the same metrics that signal quality are comparatively easy to inflate through coordinated activity or purchased engagement, social proof is simultaneously the most influential and the most manipulable form of credibility, and platforms must continually adjust which signals they expose lest visible metrics become targets that are gamed rather than indicators that are informative. The durable approach, consistent with the resource-based logic that runs through the thesis, is to cultivate social proof that is difficult to fake, generated by genuine engagement within a defined community and aligned creator partnerships, rather than to pursue the vanity metrics whose ambiguity undermines their value. For brands with established standing the dynamic is advantageous, since strong existing social proof is amplified by personalised distribution and increasingly by generative retrieval; for new entrants it constitutes a visibility barrier that product quality alone cannot overcome, which returns the analysis to the broader pattern of authority concentration that recurs throughout the study.

4.5 Governance, Human Oversight and the Limits of Automation

The evidence on governance presents the sharpest contradiction in the entire study, and resolving it clarifies why automation raises rather than lowers the importance of human oversight. The survey identified governance as the gravest weakness in the practitioner sample. Every safeguard recorded a mean at or below the midpoint of the scale, with only approval workflows (3.14) marginally above it, indicating that oversight was at best partially in place, and the safeguards bearing most directly on content integrity were among the weakest: while approval workflows and compliance checks were the most established, human review and fact-checking of AI-generated content (2.89) sat below the midpoint and transparency about AI use (2.71) was the least embedded of all. This is difficult to reconcile with the same respondents' own risk assessment, in which content accuracy, misinformation, and governance were each named among the leading organisational risks and a lack of employee skills was the single most cited concern. The sample recognised the dangers of unsupervised automation with considerable clarity and had, for the most part, not built the machinery to manage them. Documented editorial standards, already shown to be uncommon among the signalling practices of section 3.4, reappeared here as the same systematic deficiency, indicating that the weakness is structural rather than incidental within this sample.

The expert interview describes, almost point for point, the capability whose scarcity the survey documents, and the contrast between the two is one of organisational investment rather than of awareness. The intermediary maintained a governance architecture in which human oversight was constitutive rather than residual: dedicated local-language content teams reviewed submissions, verified authenticity, and validated material against user intent; content passedthrough copywriting, editorial review, proofreading, and multiple reviewers before publication; and material identified as AI-generated was rejected outright. Where the broad practitioner population holds the belief that quality must be controlled without having built the means to control it, the intermediary has institutionalised that control as a core operational function. The juxtaposition is analytically valuable precisely because both populations understand the problem; what separates them is that one has made the standing investment in editorial infrastructure and the other has not.

The theoretical reading of this contrast turns on the economics of information set out in Chapter 1. As the cost of producing content that imitates expertise falls toward zero, the value of credible signals of genuine quality rises rather than falls, because a market saturated with cheap imitation must find means to distinguish substance from its counterfeit (Akerlof, 1970; Google, 2023). The intermediary's rejection of machine-generated content and its insistence on redundant human verification is the organisational expression of this logic: in an environment of abundant automated text, demonstrable human editorial control becomes itself a source of differentiation and trust. Governance, on this account, is not a brake on automation but the infrastructure that allows a firm to automate without forfeiting the authenticity and accountability on which its visibility depends, and it is also the means by which the abstract construct of trust is operationalised inside the organisation, through editorial standards that specify what quality means and policies that define where human authorship or review is required. The organisational-learning perspective sharpens the warning, since an excessive tilt toward the exploitation of cheap automated output at the expense of the exploration and maintenance of genuine quality can, over time, atrophy the very expertise that constitutes the firm's durable asset (March, 1991).

The conclusion for RQ4 is that the relationship between automation and governance is inverse to the one intuition suggests. The more a firm automates content production, the more the scarce and differentiating capability becomes the human judgement that governs it, so that the importance of oversight increases with the degree of automation rather than diminishing as the technology matures. The survey's most troubling result, that the safeguards bearing most directly on content integrity remain the weakest even where the corresponding risk is most clearly perceived, is therefore not a minor operational oversight but a strategic failure in the making: it describes organisations capturing the efficiency dividend of automation while neglecting the governance through which that efficiency is converted into trustworthy visibility. The interview suggests that the alternative is not the abandonment of automation but its disciplined containment within an editorial architecture, and that this architecture is itself a competitive capability of the kind the thesis identifies as durable, because it is built slowly, depends on tacit editorial judgement, and cannot be acquired by purchase.

4.6 Competitive Advantage in the Age of AI-Driven Search

The threads of the preceding sections converge on the question that situates the thesis within the field of business organisation and strategy: what is the source of sustainable competitive advantage when the tools of search optimisation are available to everyone? The resource-based view supplies the organising answer, and the empirical evidence supplies its content. The benefits that practitioners most readily associate with AI are overwhelmingly operational, dominated by efficiency, time savings, and higher output, with the higher-order benefits of better decision quality and strategic scalability reported far less often. This is decisive, because efficiency of this kind is competitively self-neutralising once the underlying tools are widely available: a resource confers sustained advantage only when it is valuable, rare, difficult to imitate, and not readily substitutable, and automation tools, sold as a service to anyone willing to pay, are valuable but neither rare nor inimitable (Barney, 1991). As adoption spreads, the efficiency they provide migrates from a source of advantage to a condition of remaining in the game, which is the strategic meaning of the survey's finding that the sample is realising precisely the benefit the framework identifies as least durable.

The interview locates advantage where the resource-based view predicts it must lie: not in the technology but in the resources that automation cannot reproduce. The intermediary attributed its competitive position to a combination of an extensive publisher network reported to exceed two hundred thousand websites, international reach, long-standing publisher relationships, an automated content-distribution infrastructure, local-market expertise, and the organisational knowledge accumulated over years of operation. These resources map onto the criteria of the resource-based view with notable precision. The publisher network is valuable because it grants clients distribution at a scale and across markets they could not assemble independently; it is rare because few intermediaries command comparable breadth; and it is difficult to imitate because it is the product of relationships, reputation, and local knowledge built over time rather than of capital a competitor could simply deploy. A new entrant could purchase software and hire staff, but could not instantaneously reproduce the trust and the publisher relationships on which the network depends, because these are path-dependent and socially complex, exactly the conditions the resource-based view associates with inimitability. The automated distribution infrastructure, by contrast, is the more replicable element of the offer, and the implicit recognition that the protection against commoditisation lies in the relational and editorial assets surrounding the technology rather than in the technology itself is the strategic crux of the whole account.

This supplies the answer to what resists commoditisation under conditions of ubiquitous automation. If link-building tools are accessible to anyone, the differentiating resource cannot be the capacity to place links but must be the quality, curation, and trustworthiness of the network through which they are placed, which is to say the editorial governance examined in the previous section and the authority-building capability examined in the section before it. The intermediary's advantage is the integration of a hard-to-imitate publisher network with the editorial capability to maintain its quality, a combination that automation commoditises in neither of its parts and that becomes more valuable, not less, in precisely the environment of cheap and ubiquitous content generation that might appear to threaten an intermediary's relevance. The resource-based view thus explains both why the survey's organisations, having adopted the same tools as everyone else, have not thereby gained advantage, and why the intermediary, having built assets that the tools cannot replicate, retains it.

Yet the resource-based view alone is insufficient, because in an environment that changes faster than any fixed endowment can accommodate, even valuable and inimitable resources lose their value if they are not continually reconfigured, and it is here that dynamic-capabilities theory completes the analysis. The intermediary identified the opacity of AI ranking systems, the difficulty of optimising for retrieval mechanisms whose criteria are neither published nor stable, as its single greatest strategic challenge, and described a portfolio of forward investments, in AI-visibility and generative engine optimisation, brand-authority monitoring, AI literacy, and cross-functional collaboration, aimed at extending its established advantage into the emerging domain of AI-mediated search. Framed through the dynamic-capabilities lens, this is sensing under conditions of genuine ambiguity: the organisation has detected the environmental shift toward generative search and begun to assemble the capabilities it judges necessary to meet it, while acknowledging that the precise form of the required response cannot yet be specified (Teece, 2007). The continuity that the interview insisted upon, that content remains the foundation of both conventional search and large language models, is what makes this reconfiguration possible, because the path-dependent capabilities a firm has built around content quality and authority transfer across the transition from conventional to generative search rather than being rendered obsolete by it.

The argument that emerges, and that constitutes the answer to RQ4, is that sustainable competitive advantage in AI-driven search emerges from organisational capabilities rather than from technology adoption alone, and that these capabilities are of two complementary kinds. The first are the resource-based assets, reputation, expertise, relationships, editorial quality, and the networks that embody them, that are valuable, rare, and inimitable because they are accumulated slowly and socially. The second is the dynamic capability to keep reconfiguring those assets as the environment shifts, which is itself developed through organisational learning and the absorptive capacity that allows a firm to recognise and apply new knowledge (Cohen & Levinthal, 1990). The capacity to hold both at once, to exploit an established advantage in authority and distribution while exploring the still-unsettled terrain of generative search, is the organisational ambidexterity that the learning literature identifies as itself a dynamic capability (March, 1991; O'Reilly & Tushman, 2008). Advantage, on this reading, is not a position a firm reaches but a capability it must continuously exercise, and the work of adaptation is consequently continuous rather than terminal.

4.7 Theoretical Contributions

The contributions of this study are modest in scope and analytical rather than statistical in character, consistent with a descriptive survey of twenty-eight respondents and a single expert interview, but within those bounds they extend three bodies of literature in specific ways. The first contribution is to the literature on search engine optimisation. By reading SEO consistently through the resource-based and dynamic-capabilities lenses, the study reframes it from a technical marketing practice into an organisational capability, and it grounds that reframing in empirical evidence from both a practitioner population and a strategically placed intermediary. The most pointed empirical contribution here is the documentation of an adoption-adaptation gap as a practitioner-level phenomenon: the finding that adoption is near-universal while transformation is shallow gives concrete, measured form to the digital-transformation literature's general caution that technology accumulation does not by itself produce organisational change (Verhoef et al., 2021; Vial, 2019), and locates that caution specifically within the domain of AI-driven search.

The second contribution is to the literature on digital trust and the E-E-A-T framework. The study's evidence supports, and renders operational, the argument that E-E-A-T alignment is a capability problem rather than a checklist, by exposing a belief-behaviour gap in which practitioners recognise the importance of authority and expertise but have not built the editorial machinery that would substantiate them. More distinctively, the study extends the treatment of social proof beyond its established role as a behavioural influence by documenting its emerging function as an algorithmic input to generative search, drawn from community and review platforms into the assessments that AI systems form of brands. This dual behavioural-and-algorithmic conception of social proof, evidenced by the convergence of the survey's strongest belief with the interview's account of how AI systems mine user-generated validation, is the study's most novel theoretical extension, though it is offered as an interview-informed development warranting further investigation rather than as a settled result.

The third contribution is to the literature on organisational adaptation and absorptive capacity. The study identifies a specific empirical signature of incomplete adaptation, the decoupling of self-rated preparedness from demonstrated capability, in which the least adapted organisations report themselves as ready as the most adapted. This felt-preparedness illusion operationalises, at the level of practitioner perception, the absorptive-capacity claim that confidence resting on adoption rather than on assimilated capability is confidence without foundation (Cohen & Levinthal, 1990), and it offers a measurable indicator that organisations and researchers might use to distinguish genuine readiness from its appearance. Across all three contributions the appropriate register is analytical generalisation to theory rather than statistical generalisation to a population: the value of the evidence lies in its capacity to illustrate, refine, and ground the conceptual framework, not in its representativeness, and the limitations established in Chapter 2 bound these claims accordingly.

4.8 Managerial Implications

The analysis carries direct and actionable implications for the practitioners whose work it examines, and these follow from the single organising proposition that advantage derives from capability rather than from tools. The first concerns how AI should be integrated. The evidence counsels against the pursuit of automation for its own sake and in favour of selective augmentation: managers should automate the tasks that are routine, scalable, and tolerant of standardisation, while deliberately protecting the judgement-intensive, relational, and creative work that automation performs poorly, and they should treat the capacity freed by automation as something to be reallocated toward higher-value work rather than as a simple cost saving. The strategic gain from efficiency lies in this reallocation, not in producing the same low-value output more cheaply, and the firms that capture it are those that redirect freed expert attention toward the cultivation of authority, expertise, and relationships.

The second implication concerns capability development. Because the binding constraint on adaptation is the organisation's ability to learn rather than its access to tools, managers should invest in absorptive capacity through AI literacy, continuous learning, and the redesign of workflows, rather than confining adaptation to the low-cost forms, cross-functional encouragement and written guidance, that the survey shows organisations reach for first. The interview's identification of resistance to change as a principal challenge is a warning that the deeper adaptations are contested and slow, and that they require active management rather than the issuing of policies. Managers should also be sceptical of their own sense of readiness, since the felt-preparedness illusion suggests that confidence is a poor guide to capability; an honest audit of workflow integration, role design, and governance is more informative than a self-assessment of preparedness.

The third implication concerns governance, which the evidence identifies as the most neglected dimension of practice relative to its recognised importance. Managers should close the gap between the risks they perceive and the safeguards they implement, beginning with the most basic and most neglected of all, the human review and fact-checking of machine-generated content, and extending to documented editorial standards, clear accountability for accuracy, transparency about the use of AI, and compliance with the regulatory obligations that the European context imposes. Governance should be understood not as a constraint on speed but as the infrastructure that allows automation to be pursued without forfeiting trust, and as a competitive capability in its own right, since demonstrable editorial control is increasingly a source of differentiation in a market saturated with automated content.

The fourth implication concerns the building of trust and authority, which the analysis treats as a long-term organisational investment rather than a technical adjustment. Managers should associate content with identifiable and genuinely expert authors, invest in original evidence and editorial depth rather than volume, and cultivate authentic social proof across the review and community platforms that both consumers and AI systems now consult, managing brand sentiment as an algorithmic input as well as a reputational one. For smaller organisations the realistic strategy is rarely to imitate the signal profile of large publishers but to build defensible authority within a narrower domain, concentrating on a specific topic or audience where genuine experience can be demonstrated convincingly. The final implication concerns future readiness. The expectation, near-unanimous among practitioners, that AI will grow in strategic importance implies that the organisational pressures documented here will intensify, and managers should prepare for visibility within generative and AI-mediated retrieval by diversifying discovery across platforms, monitoring how their brands are represented in AI-generated outputs, and treating the capabilities built around content quality and authority as the assets that will carry their visibility across the transition to generative search.

4.9 Discussion Summary

Read together, the literature, the survey, and the expert interview tell a single and consistent story. The integration of machine learning and large language models into search has transformed the criteria of visibility, displacing technical optimisation from the centre of competition and replacing it with demonstrated trust, authority, expertise, and social validation, signals that are evaluated by algorithms and human audiences alike and that increasingly determine which sources are surfaced, cited, and believed. In this environment the adoption of AI tools has become a condition of mere participation: it is near-universal, it delivers a genuine but self-neutralising efficiency dividend, and it confers no durable advantage on its own, because anything available to everyone advantages no one. Durable advantage derives instead from organisational capabilities, the capacity to adapt routines and not merely acquire tools, to govern automation through human oversight, to build trust and authority through sustained editorial and reputational investment, and to keep learning and reconfiguring as the environment shifts.

The empirical evidence shows both how widely this logic is recognised and how unevenly it is enacted. Within this sample, the survey indicates a practitioner group that has adopted AI almost universally but adapted to it shallowly, that believes in the importance of trust and authority but has not built the editorial machinery to substantiate them, that perceives the risks of automation clearly but has not constructed the governance to manage them, and that systematically mistakes the possession of tools for readiness to use them well. The interview reveals, in a single strategically placed intermediary, what the deeper capability looks like in practice: a deliberate boundary between augmentation and human judgement, an editorial governance architecture that treats human oversight as constitutive, an authority and social-proof strategy attuned to both human and algorithmic audiences, and a stock of relational and reputational assets, integrated with the capacity to reconfigure them under uncertainty, that automation cannot reproduce. The distance between the two is the distance between adoption and adaptation, and it is the central finding of the thesis.

The argument that the study sustains, across its theoretical framework and its empirical evidence, is therefore that competitive advantage in AI-driven search is an organisational and not a technological achievement: it belongs to firms that treat automation as an occasion to build capability rather than as a substitute for it, that earn visibility through demonstrated quality rather than configure it through technical means, and that govern, learn, and reconfigure continuously in an environment whose rules are still being written. The conclusion that follows draws these threads together, returns them to the research questions, and considers their implications for theory, practice, and the further research that the study's limitations invite.

CHAPTER 5: CONCLUSION

5.1 Summary of Research Findings

This thesis set out to examine how the integration of artificial intelligence into search is reshaping the determinants of digital visibility, the formation of trust and authority, the operation of social proof, and the organisational conditions under which firms compete. Drawing upon a narrative synthesis of literature spanning information retrieval, digital marketing, consumer behaviour, and strategic management, and complemented by an empirical investigation combining a practitioner survey with an expert interview, the study explored how these developments are being interpreted and addressed by professionals operating within the field. Interpreted through the lenses of the resource-based view, dynamic capabilities theory, and organisational learning theory, the findings point towards a pattern that appears consistently across both the theoretical and empirical components of the research. Within this sample, artificial intelligence has been widely adopted across digital-marketing and SEO activities, yet the organisational adaptations required to translate adoption into sustained strategic advantage remain unevenly developed. The contribution of the research therefore lies not in establishing the importance of AI itself, which is already widely recognised in both academic and professional discourse, but in identifying where its competitive significance appears to reside. The evidence gathered throughout the study suggests that advantage is less closely associated with access to AI tools, which are increasingly available to all market participants, and more closely associated with the organisational capabilities, governance mechanisms, expertise, and learning processes developed around those tools.

The first research question examined how the integration of machine learning and large language models into search has transformed the criteria through which content achieves visibility and what implications this transformation may hold for firms. The findings suggest that the change represents more than a simple extension of previous ranking practices and reflects a broader shift in the foundations of visibility itself. As search systems have evolved from lexical matching towards semantic interpretation and, more recently, generative synthesis, visibility appears increasingly tied to signals of quality, credibility, expertise, and authority rather than solely to technical optimisation. Both the literature and the empirical findings indicate that search systems are becoming more capable of approximating forms of human evaluation when assessing content relevance and usefulness. Within the survey sample, AI adoption was most evident in activities associated with efficiency gains and content production, while the expert interview suggested that organisations with stronger capabilities increasingly view AI as a tool for augmentation rather than complete automation. The evidence therefore points towards a strategic environment in which visibility is influenced less by the ability to produce content at scale and more by the capacity to consistently create content that demonstrates expertise, trustworthiness, and value for users.

The second research question examined how the E-E-A-T framework operationalises digital trust within AI-driven ranking systems and what meaningful alignment with it may require from organisational strategy and capability. The findings suggest that E-E-A-T functions less as a technical specification and more as a representation of the characteristics associated with credible and trustworthy sources. Alignment with these principles therefore appears to be primarily an organisational challenge rather than a purely technical one. The survey revealed a notable distinction between recognition and implementation. While respondents generally acknowledged the importance of authority, expertise, and trustworthiness in determining visibility, the organisational mechanisms that substantiate these qualities, including documented expertise, original evidence, and editorial governance, appeared to be less consistently developed. The expert interview offered a complementary perspective, describing a business model in which authority is built gradually through reputation, accumulated knowledge, and long-term relationships with publishers and clients. Taken together, the findings suggest that meaningful alignment with E-E-A-T depends upon organisational routines related to authorship, editorial review, quality assurance, and reputation management. These capabilities closely resemble the forms of path-dependent and difficult-to-imitate resources emphasised within the resource-based view of the firm.

The third research question examined how personalised algorithms and social proof together influence consumer behaviour and visibility across platforms governed by different relevance logics. The findings suggest that social proof increasingly functions as a dual signal operating simultaneously at the behavioural and algorithmic levels. Personalisation influences which forms of social evidence users encounter, meaning that reviews, ratings, and community discussions are themselves filtered through algorithmic processes before reaching consumers. At the same time, those same signals increasingly appear to inform the ranking and generative systems responsible for determining which content, brands, and sources are surfaced in search environments. Within the survey, social proof represented one of the strongest areas of agreement among respondents and one of the clearest examples of belief translating into practice. The expert interview reinforced this observation by indicating that AI systems increasingly draw upon reviews, community platforms, and brand mentions when forming assessments of credibility and relevance. The evidence therefore suggests that social proof should no longer be viewed solely as a mechanism influencing consumer choice, but also as an increasingly important signal informing algorithmic visibility across both traditional and AI-mediated search environments.

The fourth research question examined which organisational capabilities and structural adaptations may be required to achieve and sustain competitive visibility in a search landscape characterised by AI-generated answers, trust-based quality standards, and increasing platform fragmentation. This question brings together the central themes of the study and provides the basis for its broader interpretation. The findings suggest that because the efficiency benefits associated with automation are becoming widely accessible, their competitive value may diminish over time as adoption becomes commonplace. As a result, durable advantage appears increasingly dependent upon resources and capabilities that are more difficult to replicate, including reputation, expertise, relationships, editorial quality, accumulated knowledge, and the organisational capacity to continuously adapt those resources to changing environmental conditions. The survey findings indicated a gap between perceived preparedness and demonstrated organisational capability, suggesting that access to tools alone is not necessarily equivalent to readiness to compete effectively within AI-mediated environments. The expert interview provided a practical illustration of this distinction through the example of a publisher network and editorial governance system that have been developed over time and are not easily reproduced by competitors. Taken together, the findings suggest that sustained competitive visibility is best understood not as a technological achievement secured through adoption alone, but as an organisational achievement grounded in capability development, governance, learning, and continuous adaptation.

5.2 Theoretical Contributions

The theoretical contributions of this thesis are necessarily proportionate to its scope as a Master's study and should therefore be understood as analytical rather than statistical in character. Rather than seeking to establish new theory, the study contributes to existing debates by bringing together insights from search engine optimisation, digital trust, consumer behaviour, and strategic management within the emerging context of AI-mediated search. Its primary contribution lies in the integration of these perspectives into a single conceptual framework and in the use of empirical evidence to explore how these relationships are experienced and interpreted by practitioners.

To the literature on search engine optimisation, the thesis contributes a reframing of SEO from a predominantly technical marketing practice towards a broader organisational capability. Viewed through the resource-based view and dynamic capabilities perspective, the findings indicate that competitive visibility increasingly depends not only on technical optimisation but also on the organisational resources, routines, and learning processes that support the effective use of AI technologies. One of the more notable observations emerging from the empirical investigation is the apparent gap between AI adoption and organisational adaptation. Within the sample, AI tools were widely adopted, yet the capabilities required to integrate them into broader strategic and organisational processes appeared to be less consistently developed. Although exploratory in nature, this observation is consistent with wider discussions in the digital-transformation literature which argue that technological adoption alone does not necessarily produce meaningful organisational change.

To the literature on digital trust and E-E-A-T, the thesis contributes an operational perspective on why alignment with quality standards appears to be a capability issue rather than a purely technical one. The survey findings revealed a distinction between recognising the importance of authority, expertise, and trustworthiness and developing the organisational practices needed to support them. The study also extends the discussion of social proof beyond its traditional role as a behavioural influence. The evidence collected suggests that reviews, ratings, community discussions, and other forms of user-generated validation increasingly function not only as signals influencing consumer decisions but also as inputs used by search and generative systems when assessing relevance and credibility. The convergence between the survey findings and the expert interview provides preliminary support for viewing social proof as both a behavioural and an algorithmic phenomenon, although further research would be required to examine this relationship more systematically.

To the literature on organisational adaptation and absorptive capacity, the thesis contributes an illustration of how perceptions of readiness may diverge from demonstrated organisational capability. Within the sample, respondents who expressed confidence in their preparedness for AI-driven change did not always report the organisational practices commonly associated with effective adaptation. While the limited scope of the study does not permit broader generalisation, this pattern is consistent with absorptive-capacity arguments that distinguish the acquisition of technology from the ability to assimilate, apply, and derive value from it. In this respect, the findings suggest that perceived preparedness may not always provide a reliable indication of actual organisational readiness and may therefore represent a useful area for future research.

Across these contributions, the appropriate level of inference is analytical rather than statistical. The value of the evidence lies less in its ability to support broad generalisations and more in its capacity to refine, illustrate, and provide empirical grounding for the conceptual relationships identified throughout the thesis. The contributions should therefore be interpreted as exploratory insights that help extend existing discussions while also pointing towards directions for future research.

5.3 Managerial Implications

For the professionals and organisations operating within digital marketing, SEO, and content-driven environments, the findings point towards a relatively coherent strategic direction. Across both the literature and the empirical evidence, a recurring theme emerges: competitive advantage appears to depend less on the acquisition of AI tools themselves and more on the organisational capabilities developed around their use. In this respect, the findings suggest that the most effective responses to AI-driven change are likely to involve not only technological adoption but also organisational adaptation.

The first implication concerns the integration of AI into everyday workflows. The evidence collected in this study suggests that organisations may derive greater value from selective rather than indiscriminate automation. Routine, scalable, and repetitive activities appear particularly well suited to automation, whereas tasks requiring judgement, creativity, contextual understanding, and relationship management continue to benefit from human involvement. From this perspective, the strategic value of AI lies not solely in reducing costs or increasing output, but in freeing organisational resources that can be redirected towards activities associated with expertise, authority, innovation, and customer value. The findings therefore suggest that automation may be most effective when treated as a complement to human capability rather than as a substitute for it.

The second implication concerns capability development and organisational governance.

One of the clearest patterns emerging from the research is that access to technology alone does not necessarily translate into effective adaptation. The findings indicate that organisations may benefit from investing in AI literacy, continuous learning, workflow redesign, and the development of internal capabilities that allow employees to use AI tools critically and effectively. Equally important is the establishment of governance mechanisms capable of maintaining quality and accountability. Within the survey, concerns relating to misinformation, quality control, and factual accuracy were widely recognised, yet some of the practices most closely associated with mitigating these risks appeared to be less consistently implemented. This suggests that governance should not be viewed simply as a constraint on speed or efficiency, but as part of the organisational infrastructure required to sustain trust and credibility in increasingly automated environments.

The third implication concerns the development of trust, authority, and long-term visibility. The findings suggest that organisations seeking to remain visible within AI-mediated search environments may benefit from treating authority as a strategic asset developed over time rather than as a short-term optimisation objective. This includes investing in expert authorship, original evidence, editorial quality, and transparent communication practices that strengthen credibility. The evidence also indicates that social proof is becoming increasingly important not only because it influences consumer behaviour but also because it may contribute to the signals used by search and generative systems when evaluating relevance and trustworthiness. For many organisations, particularly smaller firms, the most realistic path may therefore lie not in attempting to replicate the scale of larger competitors, but in developing recognised expertise and credibility within clearly defined domains where genuine experience and authority can be demonstrated. More broadly, the findings suggest that organisations should prepare for a search environment in which visibility is distributed across multiple platforms and increasingly shaped by AI-generated retrieval systems. In such a context, investments in expertise, reputation, content quality, and organisational learning appear likely to remain among the most durable sources of competitive differentiation.

5.4 Research Limitations

The conclusions of this study should be interpreted within the boundaries of its research design. These limitations do not invalidate the findings, but they do influence the level of inference that can reasonably be drawn from the evidence collected. Acknowledging these limitations is therefore important to ensure that the conclusions remain proportionate to the empirical basis on which they rest.

The most evident limitation is the size of the survey sample. While twenty-eight responses provide sufficient material to identify patterns and support exploratory interpretation, they do not allow for statistical generalisation to the wider population of SEO and digital-marketing professionals. Similarly, the sample size does not support inferential statistical analysis. For this reason, the quantitative findings have been presented throughout the thesis as descriptive and indicative rather than as confirmatory evidence of broader industry trends.

A second limitation concerns the composition of the sample itself. Participants were recruited primarily through professional networks and self-selected into the study, which may have increased the likelihood of participation from individuals already interested in or engaged with AI-related developments. In addition, the sample was intentionally focused on professionals working within or closely connected to SEO and content-marketing activities. While this strengthens the relevance of the findings to the research questions, it also limits their applicability beyond these professional contexts. The sample is also weighted towards junior practitioners, with more than half of respondents reporting fewer than two years of professional experience. Furthermore, a small proportion of respondents occupied roles only indirectly related to SEO or content marketing. These characteristics reinforce the exploratory nature of the findings and suggest caution when considering their broader applicability.

A third limitation is the reliance on a single expert interview. The interviewee was selected because of their strategic position within the industry and their ability to provide insights into organisational responses to AI-driven search. Nevertheless, a single interview inevitably reflects the perspective of one organisation and cannot capture the full diversity of practices across agencies, intermediaries, and in-house teams. This limitation was partially mitigated through the triangulation of interview findings with both the survey results and the academic literature. Even so, the interview should be understood primarily as an interpretive source of insight rather than as representative evidence of industry-wide practice.

Two further limitations arise from the nature of both the analytical approach and the phenomenon under investigation. The study adopts a descriptive and exploratory approach that is appropriate to the available data and research objectives. While this approach allows for the identification of patterns and the development of theoretically informed interpretations, it does not establish causal relationships or measure them with statistical precision. In addition, AI-driven search remains a rapidly evolving field. Several developments examined in this thesis, particularly those related to generative search, AI Overviews, and zero-click search behaviour, continued to evolve while the research was being conducted. The findings should therefore be understood as a time-specific snapshot of practitioner perceptions and organisational responses during a period of significant technological change.

Taken together, these limitations define the scope within which the findings should be interpreted. The purpose of the study was not to provide statistically generalisable measurement of industry behaviour, but rather to offer theoretically informed and empirically grounded insight into how organisations are adapting to AI-driven search environments. In this respect, the limitations help clarify the boundaries of the study's claims while also identifying several avenues for future research.

5.5 Directions for Future Research

The limitations of the present study, taken together with the developments it has only begun to chart, mark out a clear agenda for further investigation. The most immediate opportunity lies in the domain of generative search itself. The emergence of Generative Engine Optimisation and the spread of AI Overviews are reshaping the contest for visibility faster than settled practice can form, and dedicated research into how organisations optimise for citation within generative responses, and into how the opacity of these retrieval systems can be navigated, would extend the thesis's analysis onto terrain that remains, at present, only partially mapped. Closely related is the question of AI-mediated trust formation: the finding that social proof has become an algorithmic as well as a behavioural signal invites systematic study of how large language models actually weigh community validation, reviews, and brand sentiment when assembling their assessments, and of how evolving E-E-A-T practices are interpreted and rewarded as the underlying models continue to improve.

A second cluster of opportunities concerns scale and time. The descriptive, cross-sectional design of this study could be productively extended through larger-scale quantitative work capable of testing, rather than merely characterising, the relationships it identifies, most notably the adoption-adaptation gap and the decoupling of preparedness from capability. Longitudinal research would be especially valuable, since organisational adaptation is by nature a process that unfolds over time, and tracking how firms move, or fail to move, from shallow adoption toward genuine reconfiguration would illuminate the mechanisms that this study could observe only at a single moment. Cross-industry and comparative research would complement this temporal extension by establishing how far the patterns found within an AI-adjacent, marketing-centred population hold in sectors with different competitive and regulatory conditions, and comparative studies of the AI-visibility strategies pursued by different organisations would test whether the capability-based account of advantage developed here generalises beyond the intermediary case through which it was most clearly observed. Each of these directions follows naturally from the thesis, and together they indicate that the questionsit has raised are more durable than the particular answers any single study, conducted at one moment in a fast-moving field, can provide.

5.6 Final Concluding Remarks

The central argument developed throughout this thesis is ultimately straightforward. As artificial intelligence becomes increasingly embedded within search systems, the adoption of AI technologies is rapidly becoming a basic requirement for participation rather than a source of competitive advantage in itself. What appears to distinguish organisations is not whether they use AI, but how effectively they integrate it into their broader organisational capabilities, decision-making processes, and strategic priorities. Across the literature reviewed, the practitioner survey, the expert interview, and the subsequent discussion, a common theme emerged: technology alone is rarely sufficient to create advantage. The organisations that appear best positioned to succeed are those that combine technological adoption with learning, governance, expertise, and continuous adaptation.

This conclusion places trust, authority, and human judgement at the centre of competitive visibility in AI-mediated environments. As search systems become increasingly capable of generating content, summarising information, and evaluating relevance, the value of producing content alone is likely to diminish. At the same time, the importance of demonstrating genuine expertise, maintaining credibility, and building trusted relationships appears to become even greater. The findings of this study suggest that many of the capabilities most closely associated with long-term visibility are also those least susceptible to automation: the ability to earn trust, exercise editorial judgement, develop meaningful expertise, and adapt to changing conditions over time. These capabilities are accumulated gradually through organisational learning and experience, and they closely reflect the forms of advantage described within the strategic-management theories that informed this research.

More broadly, the findings challenge the idea that AI-driven transformation reduces the importance of human contribution within digital environments. If anything, the evidence points towards a redistribution of where human value is created. As automation lowers the cost of execution and content production, greater importance is placed on judgement, governance, creativity, credibility, and the ability to make informed strategic decisions. In this sense, the challenge facing organisations is not simply technological but organisational. The question is no longer whether AI should be adopted, but how organisations can develop the capabilities required to use it effectively and responsibly.

Viewed from this perspective, the future of digital visibility is unlikely to be determined solely by advances in technology. It will also be shaped by the capacity of organisations to learn, adapt, build trust, and maintain authority in an environment where information is increasingly abundant and easily generated. The technologies examined in this thesis will continue to evolve, and many of the practices associated with AI-driven search will undoubtedly change with them. Yet the broader lesson emerging from this research is likely to remain relevant: in a landscape where access to technology becomes increasingly widespread, sustainable advantage appears less dependent on the tools organisations possess and more dependent on the capabilities they develop around them. Ultimately, it is this combination of technology, expertise, governance, and organisational learning that is most likely to shape visibility and competitiveness in the evolving search environment.

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APPENDICES

Appendix A – Survey Questionnaire

The practitioner questionnaire was administered online via Google Forms and distributed through the WhitePress professional network. It comprised twenty-five items across six thematic sections: closed items (Q1–Q21) provided the quantitative data reported in Chapter 3, and four optional open-ended items (Q22–Q25) were coded thematically. The instrument is reproduced below as administered.

Section 1 – Respondent Profile

Q1. Which best describes your current role? (single answer) - SEO / search specialist; Content strategist or content manager; Marketing manager or director; Digital marketing specialist; Agency consultant / account manager; Business owner or founder; Other (please specify).

Q2. How many years of professional experience do you have in digital marketing, SEO or content? - Less than 2 years; 2–5 years; 6–10 years; 11–15 years; More than 15 years.

Q3. In which sector does your organisation primarily operate? - Marketing / SEO agency; B2B services; B2C / e-commerce; Media / publishing; Technology / SaaS; Other (please specify).

Q4. Approximately how many people work in your organisation? - 1–9 (micro); 10–49 (small); 50–249 (medium); 250 or more (large).

Q5. How directly are you involved in decisions about your organisation's search visibility and content strategy? - Not involved; Occasionally consulted; Regularly involved; I lead these decisions.

Q6. How would you describe your own use of AI tools in your work? - I do not use AI tools; Occasional / experimental use; Regular use for specific tasks; Daily, integral to my work.

Section 2 – AI Adoption and AI Maturity

Q7. Which statement best describes your organisation's use of AI today? (principal cross-cutting variable) - We do not currently use AI tools; AI use is experimental and individual; AI is used within selected teams; AI is integrated across multiple departments; AI is strategically embedded across the organisation.

Q8. How frequently does your organisation use AI tools in search, content or marketing activities? - Never; Rarely; Monthly; Weekly; Daily.

Q9. In which activities does your organisation currently apply AI? (select all that apply) - Content creation / drafting; Keyword and topic research; Analytics and performance reporting; Workflow / task automation; Customer or audience insights; Translation / localisation; Technical SEO; We do not currently use AI.

Q10. To what extent is AI integrated into your organisation's standard workflows, rather than used ad hoc? (linear scale 1–5; 1 = not at all integrated, 5 = fully integrated).

Section 3 – Digital Trust, E-E-A-T and Visibility

Q11. To what extent do you agree with the following statements? (five-point Likert; 1 = strongly disagree, 5 = strongly agree):

- Search visibility increasingly depends on demonstrated expertise and experience, not just technical optimisation.
- Content credibility and author authority materially affect where content ranks.
- An organisation's perceived trustworthiness affects its business performance online.
- Social proof (reviews, ratings, engagement) influences both rankings and customer decisions.
- Building trust and authority is a long-term organisational investment, not a quick technical fix.

Q12. How does your organisation primarily try to signal expertise and trustworthiness in its content? (select all that apply) - Named expert authors / stated credentials; Original research or proprietary data; Citations and reputable sources; Customer reviews and testimonials; Case studies and demonstrated results; Editorial or fact-checking standards; We do not actively do this.

Section 4 – Organisational Adaptation and Capability

Q13. How prepared is your organisation for the growing role of AI in search, content production and digital visibility? (linear scale 1–5; second cross-cutting variable).

Q14. In response to AI-driven search, to what extent has your organisation done the following? (five-point Likert):

- Invested in training or upskilling staff.
- Built AI literacy and understanding across the team.

- Redesigned workflows or processes.
- Created new roles or reassigned responsibilities.
- Increased collaboration across functions (e.g., marketing, content, data, IT).
- Established internal guidelines or oversight for AI use.

Q15. Which concrete changes has your organisation actually made? (select all that apply) - New roles or hires; A dedicated AI / SEO team or task force; Formal training programmes; Revised performance metrics or KPIs; Written AI-use guidelines or policy; Cross-functional working groups; None yet.

Q16. Where does primary responsibility for AI-in-search decisions sit in your organisation? - Individual employees; The marketing / SEO team; A cross-functional group; Senior leadership / strategy; An external agency; No clear owner.

Section 5 – Opportunities and Challenges

Q17. Which benefits has your organisation realised, or does it expect, from AI in search and content? (select all that apply) - Efficiency / time savings; Higher output and productivity; Scalability of content or campaigns; Faster responsiveness to change; Better quality of decisions; Cost reduction; No clear benefits yet.

Q18. Which challenge represents the greatest organisational risk when using AI in SEO and content-related activities? - Content accuracy; Misinformation; Lack of employee skills; Governance issues; Compliance concerns; Data privacy concerns; Brand reputation risks; Over-reliance on automation.

Q19. To what extent are the following safeguards in place in your organisation? (five-point Likert):

- Human review and fact-checking of AI-generated content.
- Documented quality or editorial standards.
- Approval workflows before publishing.
- Transparency or disclosure about AI use.
- Compliance checks (e.g., data protection, regulatory).

Section 6 – Future Outlook

Q20. Rank the following factors by their expected importance for future digital visibility (1 = most important): AI adoption; Content quality; Human expertise; E-E-A-T; Brand authority; Customer reviews; Technical SEO.

Q21. Over the next two to three years, how do you expect AI's strategic role in your organisation's digital visibility to change? - Decline; Stay about the same; Grow moderately; Grow significantly; Become central to strategy.

Open-Ended Questions (Q22–Q25, optional)

Q22. What is the most significant change your organisation has made in how it works because of AI in search and content?

Q23. How does your organisation try to maintain content quality and trust when using AI tools?

Q24. What is the biggest organisational challenge you face in integrating AI into your digital-visibility work?

Q25. Looking ahead, which capabilities or skills do you think organisations will most need to build to stay visible?

Appendix B – Interview Protocol

The expert interview was conducted as a single semi-structured remote conversation of approximately 45–60 minutes with a senior WhitePress informant whose responsibilities span content-quality governance, publisher-network management, and strategic adaptation. The guide comprised a warm-up question and twelve core questions organised across five analytical themes, weighted toward RQ2 (digital trust and E-E-A-T) and RQ4 (organisational capability and adaptation). The full guide is reproduced below.

Warm-up (W). Could you describe your role at WhitePress and the parts of the platform's operation you are most directly responsible for?

Theme 1 – AI Adoption and Organisational Consequences

Q1. Where has AI genuinely changed how WhitePress works - and, just as importantly, where have you deliberately kept humans in the loop rather than automating?

Q2. As AI moved into your operations, how did roles and responsibilities actually change - did new roles appear, did existing ones shift, and what skills suddenly mattered more?

Theme 2 – Content-Quality Governance and E-E-A-T

Q3. Walk me through how a piece of content is judged 'good enough' to publish across your network - what does the governance process look like in practice, and where does AI-generated material get reviewed?

Q4. Of the four E-E-A-T dimensions - Experience, Expertise, Authoritativeness, Trustworthiness - which is hardest for clients to demonstrate convincingly, and how do you help a client that lacks the editorial resources to signal it on their own?

Theme 3 – Digital Trust and Publisher-Network Management

Q5. When you assess whether a publisher belongs in the network, what are you really looking at - and how do you weigh authority, topical fit and trust signals against each other?

Q6. How do you draw the line between a link that genuinely signals authority and one that is merely technically present - and how do you explain that distinction to clients who don't see it?

Theme 4 – Social Proof, Client Outcomes and Competitive Positioning

Q7. What part do social-proof signals - reviews, engagement, community validation - play in the placement strategies you support, and have client requests shifted as TikTok and Instagram became search environments?

Q8. With automated link-building tools available to anyone, what actually makes WhitePress's offer distinctive - and how do you guard against your services being commoditised?

Theme 5 – Future Outlook and Strategic Adaptation

Q9. How is WhitePress adapting to AI-generated answers - AI Overviews, Perplexity, Copilot citations - that satisfy users without sending them to a linked page?

Q10. What is the single biggest strategic challenge you see for WhitePress and for the content-marketing ecosystem over the next few years, and how are you building the capability to meet it?

Q11. Thinking organisationally rather than tactically: which capability do you believe separates firms that will stay visible in AI-driven search from those that won't?

Closing

Q12. Is there anything important about the relationship between AI-driven search, content quality and organisational adaptation that we haven't touched on but that you think I should understand?

Appendix C – Interview Transcript / Findings Summary

The interview was audio-recorded with the informant's consent and analysed using the six-phase thematic procedure of Braun and Clarke (2006). To preserve the commercial confidentiality agreed with the informant, a thematic findings summary is provided here in place of a verbatim transcript; the full interpretive analysis is reported in Section 3.8. The seven themes that emerged are summarised below.

1. AI Adoption and Workflow Automation

AI is located in the operational layer - content drafting, translation and localisation, categorisation, data processing, and the optimisation of repetitive tasks - while strategic decisions, client relationships, and high-level content planning remain under human control. AI is treated as an efficiency-enhancing technology that augments rather than replaces professional expertise.

2. Organisational Adaptation and Capability Development

The formal job architecture has not changed substantially, but workflows, required skills, and training have been reconfigured beneath it. AI literacy and continuous learning have become conditions of competence, new AI-related services have emerged, and resistance to change has become a principal internal challenge; the premium has shifted toward creativity and strategic thinking.

3. Human Oversight and Content Governance

Dedicated local-language content teams review submissions, verify authenticity, and validate material against user intent; content is copywritten, edited, proofread, and checked, and material identified as AI-generated is rejected. Every piece passes through multiple reviewers, so oversight is distributed and redundant rather than vested in a single gatekeeper.

4. Digital Trust, E-E-A-T and Authority

Visibility depends less on backlinks considered in isolation and more on a composite of brand perception, demonstrated expertise, niche experience, trustworthiness, and positive brand sentiment. Authority is increasingly constructed through reputation and demonstrated knowledge accumulated over time rather than through technical signals.

5. Social Proof and AI Visibility

Platforms carrying user-generated validation - Reddit, Trustpilot, LinkedIn, Google Reviews, and X - are increasingly drawn upon by AI systems when assessing brands. Social proof now performs a dual function: a behavioural influence on customers and an algorithmic input that AI-driven retrieval treats as evidence of standing.

6. The Evolution of SEO and Search Visibility

SEO is evolving rather than disappearing: traditional signals retain relevance, but visibility increasingly depends on the satisfaction of user intent, content authenticity, brand mentions, authority signals, and emerging practices of Generative Engine Optimisation and AI-Overview visibility. Content remains the foundation of both conventional search engines and large language models. -

7. Competitive Advantage and Future Capabilities

Competitive position rests on a combination of resources - an extensive publisher network (reported to exceed 200,000 websites), international reach, long-standing publisher relationships, automated content distribution, local-market expertise, and accumulated organisational knowledge - whose relational and editorial elements resist commoditisation. Future priorities centre on AI-visibility and Generative Engine Optimisation, brand-authority monitoring, AI literacy and data analytics, and cross-functional collaboration; the single greatest challenge identified was the opacity of AI ranking systems.

Appendix D – Additional Survey Tables

This appendix consolidates the full set of descriptive results from the practitioner survey (N = 28). Percentages are rounded and may not sum to 100; for multiple-response items the percentages denote the share of respondents selecting each option. These tables correspond to the results discussed in Sections 3.1–3.6.

Table D.1. Respondent profile (N = 28)

Characteristic	Category	n	%
Current role (Q1)	SEO / search specialist	3	11
	Content strategist or content manager	5	18
	Marketing manager or director	6	21
	Digital marketing specialist	5	18
	Agency consultant / account manager	1	4
	Business owner or founder	1	4
	Other (content creator, IT, finance, banking)	7	25
Experience (Q2)	Less than 2 years	14	50
	2–5 years	10	36
	6–10 years	3	11
	11–15 years	1	4
Sector (Q3)	Marketing / SEO agency	6	21
	B2B services	9	32
	Technology / SaaS	4	14
	Media / publishing	4	14
	B2C / e-commerce	1	4
	Other / unspecified (finance, banking, healthcare)	4	14
Organisation size (Q4)	1–9 (micro)	7	25
	10–49 (small)	7	25

	50–249 (medium)	5	18
	250 or more (large)	9	32
Decision involvement (Q5)	Not involved	6	21
	Occasionally consulted	11	39
	Regularly involved	10	36
	I lead these decisions	1	4
Personal AI use (Q6)	Occasional / experimental	4	14
	Regular use for specific tasks	11	39
	Daily, integral to work	12	43

No respondent reported "more than 15 years" experience or "I do not use AI tools."

Table D.2. AI maturity, frequency of use, and workflow integration (N = 28)

Item	Category	n	%
AI maturity (Q7)	Experimental / individual use	6	21
	Used within selected teams	7	25
	Integrated across multiple departments	10	36
	Strategically embedded	5	18
Frequency of use (Q8)	Daily	16	57
	Weekly	7	25
	Monthly	5	18
Workflow integration (Q10)	1 – Not at all integrated	2	7
	2	9	32
	3	7	25
	4	6	21
	5 – Fully integrated	4	14

Q10 mean = 3.04 on a five-point scale. No respondent selected "We do not currently use AI tools" or "Never / Rarely."

Table D.3. Activities to which AI is applied (Q9; multiple responses, N = 28)

Activity	n	%
Content creation / drafting	15	54
Keyword and topic research	12	43
Analytics and performance reporting	13	46
Workflow / task automation	9	32
Translation / localisation	10	36
Customer or audience insights	8	29
Technical SEO	6	21

Table D.4. Beliefs about trust and visibility (Q11; five-point scale, N = 28)

Statement	Mean	% agree (4–5)
Visibility depends on demonstrated expertise, not just technical optimisation	3.57	61
Content credibility and author authority materially affect ranking	3.96	75
Perceived trustworthiness affects business performance online	3.71	68
Social proof influences both rankings and customer decisions	4.00	79
Building trust and authority is a long-term investment, not a quick fix	4.04	79

Table D.5. Trust and expertise signalling practices (Q12; multiple responses, N = 28)

Signalling practice	n	%
Customer reviews and testimonials	16	57
Named expert authors / stated credentials	10	36
Citations and reputable sources	10	36
Case studies and demonstrated results	11	39
Original research or proprietary data	9	32

Editorial or fact-checking standards	5	18
Does not actively signal expertise / trustworthiness	3	11

Table D.6. Extent of capability-building actions (Q14; five-point scale, mean)

Adaptation action	Mean
Increased cross-functional collaboration	3.36
Established internal guidelines or oversight for AI use	3.22
Built AI literacy and understanding across the team	3.07
Redesigned workflows or processes	3.19
Invested in training or upskilling staff	3.11
Created new roles or reassigned responsibilities	3.00

Means computed over valid responses; between 24 and 25 respondents answered each row.

Table D.7. Adaptation, governance, and preparedness by AI maturity stage (Q7)

Maturity stage	n	Preparedness (Q13)	Adaptation (Q14)	Governance (Q19)
Experimental / individual	6	3.17	2.36	2.03
Within selected teams	7	3.14	3.11	2.83
Multiple departments / embedded	15	3.53	3.47	3.31

Group means on five-point scales; the two higher maturity stages are combined for legibility.

Table D.8. Realised or expected benefits of AI (Q17; multiple responses, N = 28)

Benefit	n	%
Efficiency / time savings	20	71
Higher output and productivity	16	57
Faster responsiveness to change	8	29
Better quality of decisions	6	21
Cost reduction	6	21
Scalability of content or campaigns	5	18

No clear benefits yet	3	11

Table D.9. Greatest perceived organisational risk (Q18; N = 28)

Risk	n	%
Lack of employee skills	12	43
Compliance concerns	10	36
Content accuracy	8	29
Misinformation	7	25
Governance issues	7	25
Brand reputation risks	7	25
Data privacy concerns	6	21
Over-reliance on automation	6	21

Q18 was rendered as a multiple-selection field; several respondents recorded more than one risk, so percentages denote the share of respondents flagging each risk.

Table D.10. Governance safeguards in place (Q19; five-point scale, mean)

Safeguard	Mean
Approval workflows before publishing	3.14
Compliance checks (data protection, regulatory)	2.93
Documented quality or editorial standards	2.89
Transparency or disclosure about AI use	2.71
Human review and fact-checking of AI-generated content	2.89

Table D.11. Expected strategic trajectory of AI over the next two to three years (Q21, N = 28)

Expected trajectory	n	%
Become central to strategy	10	36
Grow significantly	11	39
Grow moderately	5	18
Stay about the same	1	4
Decline	1	4