Cognitive Cross-Pollination among AI Developers, Industry Application Integrators, and Beneficiaries in a Future AGI & ASI Society

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ABSTRACT

Purpose: *This study aims to conceptualise a Three-Level Cognitive Cross-Pollination Model involving AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries in a hypothetical future Artificial General Intelligence (AGI) and Artificial Superintelligence (ASI) society. It seeks to explore multidirectional knowledge exchange, stakeholder collaboration, and governance mechanisms to promote responsible AI innovation, equitable benefit distribution, and sustainable human-centred societal development.*

Methodology: *This study adopts an exploratory, qualitative, literature-based conceptual research approach, drawing upon secondary sources to examine cognitive cross-pollination among three stakeholder groups in a hypothetical future AGI and ASI society. It employs SWOC, ABCD, PESTLE, qualitative predictive scenario analysis, and impact analysis to evaluate the proposed model's technological, organisational, ethical, economic, and societal implications.*

Analysis/Result: *The integrated SWOC, ABCD, PESTLE, predictive scenario, and impact analyses highlight the potential strengths, opportunities, benefits, constraints, and challenges of cognitive cross-pollination among the three stakeholder groups in a future AGI and ASI society. The findings suggest that multidirectional knowledge exchange, stakeholder collaboration, continuous feedback, and responsible governance could promote technological innovation, industrial integration, equitable benefit distribution, and sustainable human-centred societal development.*

Originality/Value: *This study proposes a novel Three-Level Cognitive Cross-Pollination Model that integrates AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries into a unified conceptual framework for a hypothetical future AGI and ASI society. Its originality lies in examining multidirectional knowledge exchange and stakeholder interdependence through integrated SWOC, ABCD, PESTLE, predictive scenario, and impact analyses, offering valuable insights into responsible AI governance, collaborative innovation, and sustainable human-centred development.*

Type of Paper: *Exploratory Research Analysis*,

Keywords: Cognitive cross-pollination; Artificial General Intelligence; Artificial Super Intelligence; AI developers and controllers; Industry application integrators; AI beneficiaries; future society; SWOC, ABCD, PESTLE analysis; Predictive analysis; Impact analysis

1. INTRODUCTION :

Artificial Intelligence (AI) has evolved from early rule-based and symbolic computing systems into increasingly sophisticated technologies capable of learning, reasoning, pattern recognition, natural language processing, and supporting complex decision-making. The development of machine learning, deep neural networks, and generative AI has significantly expanded the applicability of intelligent systems across industries, education, healthcare, governance, scientific research, and business management. LeCun et al. (2015) [1] explain how deep learning enables computational systems to discover hierarchical representations from large datasets, thereby improving their performance in complex recognition and analytical tasks. Haenlein and Kaplan (2019) [2] trace the historical progression of AI and emphasise its growing technological, organisational, and societal significance.

This evolution reflects a transition from task-specific automation towards increasingly adaptable intelligent systems that can assist human cognitive activities. As AI technologies become more capable and interconnected, their development raises important questions concerning the distribution of technological expertise, the integration of intelligent applications into industry, and the participation of individuals and communities in an increasingly AI-enabled society.

The continuing advancement of AI has stimulated scholarly interest in the possible emergence of Artificial General Intelligence (AGI) and Artificial Superintelligence (ASI). AGI generally refers to artificial systems possessing broad, adaptable intellectual capabilities across diverse domains, whereas ASI represents the hypothetical possibility of intelligence substantially exceeding human cognitive performance across a wide range of activities. Goertzel (2014) [3] discusses alternative conceptual foundations and technological approaches to AGI, highlighting both the ambition of developing generally intelligent systems and the difficulties involved in evaluating progress towards such capabilities. Grace et al. (2018) [4] demonstrate that expert expectations regarding future AI capabilities and development timelines vary considerably, indicating substantial uncertainty surrounding technological progress. Bostrom (2012) [11] examines the potential motivations and goal-directed behaviour of hypothetical superintelligent agents, drawing attention to problems of alignment, control, and unintended consequences. Although the emergence, capabilities, and timelines of AGI and ASI remain uncertain, their possible development provides an important conceptual basis for exploring future relationships among technological creators, application developers, institutions, and society.

A future society characterised by increasingly capable AI could experience substantial transformations in employment patterns, professional responsibilities, industrial structures, educational systems, public administration, economic productivity, and human decision-making. Advanced intelligent systems may automate selected activities, augment professional expertise, create new occupational categories, and alter the distribution of economic opportunities and technological influence. Frank et al. (2019) [5] emphasise that understanding AI's influence on employment requires consideration of changing occupational tasks, skills, and the relationships between technological capabilities and labour-market structures. Simultaneously, the widespread deployment of intelligent technologies raises concerns involving accountability, transparency, fairness, privacy, unequal access, and human autonomy. Jobin et al. (2019) [6] identify important common principles across international AI ethics guidelines while demonstrating differences in their interpretation and implementation. Shneiderman (2020) [7] advocates human-centred AI approaches that combine high levels of automation with meaningful human control and institutional responsibility. Against this background, the present study proposes three interconnected societal roles: **AI Developers and Controllers**, who create and oversee advanced systems; **Industry Application Integrators**, who translate AI capabilities into domain-specific applications; and **AI Beneficiaries**, comprising individuals, organisations, and communities that use or are affected by intelligent technologies. These levels represent conceptual and potentially overlapping roles rather than rigid or predetermined societal classes.

Within this proposed societal structure, **cognitive cross-pollination** refers to the continuous, multidirectional exchange of knowledge, experiences, technological capabilities, practical requirements, feedback, and ethical perspectives among the three stakeholder groups. AI Developers and Controllers contribute technical expertise, system architectures, and safety mechanisms; Industry Application Integrators transform these capabilities into practical solutions while communicating industry-specific requirements; and AI Beneficiaries contribute user experiences, contextual knowledge, societal expectations, and feedback concerning the consequences of AI adoption. Jarrahi (2018) [8] demonstrates the importance of combining human judgement with computational capabilities in organisational decision-making, while Dellermann et al. (2019) [9] conceptualise hybrid intelligence as a means of combining complementary human and artificial capabilities. Shneiderman (2020) [7] further establishes the importance of human participation, reliable system design, and responsible oversight in the development and deployment of intelligent technologies. Building on these scholarly perspectives, this exploratory study develops a three-level cognitive cross-pollination model for a hypothetical future AGI and ASI society and examines its potential strengths, weaknesses, opportunities, challenges, advantages, benefits, constraints, and disadvantages through SWOC, ABCD, and PESTLE analyses, supplemented by qualitative predictive-scenario and impact analyses. The investigation seeks to identify conditions supporting collaborative innovation, responsible

technological governance, equitable benefit distribution, and sustainable human-centred societal development.

2. REVIEW OF LITERATURE :

2.1 Existing Research on Artificial General Intelligence (AGI):

Artificial General Intelligence (AGI) has emerged as an important research direction aimed at developing artificial systems capable of performing diverse intellectual tasks, adapting knowledge across domains, and responding effectively to unfamiliar situations. Unlike conventional Artificial Intelligence (AI), which has historically focused on specific applications, AGI research investigates the possibility of developing more general cognitive capabilities. Legg and Hutter (2007) [10] examined the theoretical foundations of machine intelligence and proposed a formal approach to evaluating intelligence across different environments. Their work emphasises the importance of learning, adaptation, and goal achievement in assessing intelligent systems. Goertzel (2014) [3] reviewed major approaches to AGI development, including symbolic, emergentist, hybrid, and universalist architectures, and discussed the conceptual difficulties associated with defining and measuring general intelligence. These studies establish AGI as a multidisciplinary research objective involving computer science, cognitive science, mathematical modelling, and theories of intelligence.

The possible emergence of AGI raises questions about the relationships among technological developers, industrial organisations, and human society. Grace et al. (2018), [4] through a survey of AI researchers, examined expectations regarding the future development of advanced AI capabilities and highlighted substantial variation in expert predictions. Their findings demonstrate the uncertainty surrounding the achievement of human-level or broadly general artificial intelligence. Although such projections cannot establish when AGI will emerge, they provide a basis for examining possible organisational and societal adaptations. From the perspective of the present study, AGI research suggests that increasingly capable intelligent systems could require new arrangements for technological development, application integration, professional collaboration, and human oversight. Consequently, understanding future AI society requires attention not only to machine intelligence but also to the relationships among the individuals and institutions responsible for developing, deploying, and using advanced systems.

2.2 Existing Research on Artificial Superintelligence (ASI):

Artificial Superintelligence (ASI) represents a hypothetical stage of artificial intelligence in which computational systems substantially exceed human cognitive performance across a broad range of intellectual activities. Scholarly discussions of ASI generally address its possible capabilities, autonomous behaviour, goal-directed decision-making, and implications for human control. Bostrom (2012) [11] examined the relationship between intelligence and motivation in advanced artificial agents, proposing that an intelligent system's goals need not necessarily correspond with human ethical expectations. The study also discussed instrumental convergence, suggesting that sufficiently capable agents pursuing different objectives might adopt similar intermediate strategies. These arguments highlight the importance of designing appropriate control mechanisms, aligning technological objectives with human interests, and anticipating the consequences of increasingly autonomous systems.

The prospect of ASI also raises fundamental questions concerning responsibility, institutional authority, and the distribution of decision-making power in technologically advanced societies. Floridi et al. (2018) [12] proposed an ethical framework for a good AI society, highlighting the importance of beneficence, non-maleficence, autonomy, justice, and explicability. Although their framework addresses AI governance broadly rather than an observed ASI society, its principles are relevant to evaluating possible future developments. Shneiderman (2020) [7] similarly emphasised the importance of reliable, safe, and trustworthy AI through a human-centred approach that maintains meaningful human control alongside advanced automation. Together, these studies suggest that any future movement towards highly autonomous intelligence should be accompanied by appropriate institutional safeguards and opportunities for human participation. However, ASI remains hypothetical, and its emergence, capabilities, and societal consequences cannot presently be treated as established empirical facts.

2.3 Human–AI Collaboration and Hybrid Intelligence:

Human–AI collaboration has received growing scholarly attention as intelligent systems increasingly support organisational decision-making, professional activities, and knowledge-intensive work. Jarrahi (2018) examined the complementary roles of human judgement and AI-based analytical capabilities, arguing that human intuition, contextual understanding, and creativity can complement the computational strengths of intelligent systems. This perspective challenges the assumption that AI adoption necessarily requires complete replacement of human decision-makers. Dellermann et al. (2019) [9] developed the concept of hybrid intelligence, highlighting the potential of combining human and artificial capabilities in problem-solving and organisational activities. Their work provides a foundation for examining collaborative arrangements in which human participants contribute contextual understanding, values, and judgement while AI systems provide computational assistance and analytical capabilities.

The relationship between human expertise and AI technologies is nevertheless complex. Raisch and Krakowski (2021) [13] examined the automation–augmentation paradox, demonstrating that the replacement and enhancement of human activities cannot always be treated as separate organisational processes. Shrestha et al. (2019) [14] proposed alternative organisational decision-making structures involving AI-supported decisions, human–AI sequential arrangements, and aggregated decision-making. Empirical evidence also demonstrates the potential value of human–AI collaboration in specific tasks. Noy and Zhang (2023) [15] found that generative AI assistance improved productivity and output quality in controlled professional writing tasks, although the findings concern a particular technology and activity rather than general intelligence. Collectively, these studies suggest that productive collaboration depends on appropriate task allocation, human expertise, organisational design, feedback mechanisms, and responsibility structures. In the proposed three-level model, such collaboration provides a foundation for relationships among AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries.

2.4 Knowledge Exchange and Cognitive Cross-Pollination:

Knowledge exchange constitutes a fundamental process through which individuals, organisations, and technological communities develop new capabilities, improve decisions, and generate innovation. Nonaka (1994) proposed a dynamic theory of organisational knowledge creation, emphasising interactions between tacit and explicit knowledge. The study explains how knowledge creation emerges through continuous interactions among individuals and organisational environments. Cohen and Levinthal (1990) [16] introduced the concept of absorptive capacity, demonstrating that organisations require appropriate prior knowledge to recognise the value of external information, assimilate it, and apply it productively. These contributions indicate that effective knowledge exchange involves more than information transmission; participants must possess the capabilities necessary to understand and use the knowledge received.

Carlile (2004) [17] extended the discussion by examining knowledge transfer across organisational and professional boundaries. The study identified syntactic, semantic, and pragmatic knowledge boundaries and described processes of transferring, translating, and transforming knowledge to support innovation. This perspective is especially relevant when participants possess different technical backgrounds, professional priorities, institutional responsibilities, and practical experiences. In advanced AI ecosystems, technological developers may understand system architecture and computational limitations, while industry integrators possess domain-specific implementation knowledge and beneficiaries possess contextual information about usability, accessibility, and societal consequences. The present study conceptualises **cognitive cross-pollination** as the continuous, multidirectional exchange and transformation of these complementary forms of knowledge. Drawing on Nonaka (1994) [18], Cohen and Levinthal (1990) [16], and Carlile (2004) [17], the proposed model interprets cognitive cross-pollination as a process through which technical knowledge, application requirements, user experiences, ethical considerations, and operational feedback may circulate among three stakeholder groups. This proposed extension of knowledge-management theory to a hypothetical AGI/ASI society remains conceptual and requires subsequent empirical investigation.

2.5 Industrial Integration and Organisational Adoption of AI:

The industrial integration of AI involves transforming computational capabilities into practical applications within manufacturing, healthcare, finance, education, logistics, agriculture, public administration, and other sectors. Duan et al. (2019) [19] examined the opportunities and challenges associated with AI-supported decision-making in data-intensive organisational environments. Their research highlighted the importance of technological capabilities, human–AI interaction, organisational integration, and decision-making structures. Wuest et al. (2016) [20] reviewed machine learning applications in manufacturing and identified opportunities for improving industrial processes while recognising challenges involving data availability, implementation complexity, and technical expertise. These studies demonstrate that the value of AI depends not merely on the availability of algorithms but also on the ability of organisations to integrate them into appropriate operational environments.

Organisational readiness is another critical condition influencing the successful adoption of intelligent technologies. Jöhnk et al. (2021) [21], based on interviews with AI experts and a review of relevant literature, identified organisational readiness factors affecting AI implementation. Their findings emphasise the importance of appropriate resources, capabilities, and institutional commitment. More recent empirical evidence provides insight into the effects of current generative AI adoption. Brynjolfsson et al. (2025) [22] examined AI assistance among customer-support workers and reported productivity improvements, with particularly important gains among less-experienced employees. These findings illustrate how AI capabilities may be translated into economic and professional value through industry-specific integration. However, they do not establish corresponding effects for hypothetical AGI or ASI technologies. The proposed three-level model therefore assigns **Industry Application Integrators** an important intermediary role: interpreting technological capabilities, adapting systems to industrial requirements, establishing deployment procedures, and transferring operational experiences and user feedback to AI developers. Their effectiveness may influence how widely, safely, and equitably AI-enabled benefits are realised.

2.6 Governance, Ethical Responsibility, and Societal Implications:

The rapid development and widespread deployment of AI have generated substantial scholarly interest in governance, ethical responsibility, institutional accountability, and public participation. Jobin et al. (2019) [6] systematically examined international AI ethics guidelines and identified broad convergence around transparency, justice and fairness, non-maleficence, responsibility, and privacy. However, the study also revealed differences in how these principles are interpreted and implemented. Floridi et al. (2018) [12] proposed a comprehensive ethical framework for promoting beneficial AI while addressing technological risks and institutional responsibilities. Their contributions establish the importance of ethical principles and coordinated governance arrangements involving developers, organisations, governments, and civil society.

The governance of advanced AI also requires attention to organisational decision rights and the distribution of responsibility between humans and automated systems. Shneiderman (2020) [7] advocated human-centred AI design that combines sophisticated automation with human oversight and accountability. Shrestha et al. (2019) [14] showed that organisational decision-making structures can vary according to the degree of human involvement and AI delegation. The societal implications extend beyond technical reliability and include employment, skill development, economic inequality, and institutional adaptation. Frank et al. (2019) [5] examined the challenges of understanding AI's potential effects on labour markets and emphasised the importance of analysing occupational tasks, workforce capabilities, and technological change. These studies indicate that AI governance is not exclusively a responsibility of technological developers. Industry integrators, professional organisations, policymakers, and beneficiaries also contribute to identifying risks, defining acceptable practices, and evaluating social consequences. Accordingly, governance in the proposed three-level model is conceived as a cross-cutting responsibility supported by continuous communication, stakeholder participation, human oversight, and feedback across the AI ecosystem.

2.7 Synthesis of Literature and Identification of Research Gap:

The reviewed literature establishes several complementary foundations for understanding the possible emergence and societal integration of advanced AI. Research on AGI and ASI examines the conceptual foundations, capabilities, uncertainties, and risks associated with increasingly intelligent systems (Goertzel, 2014 [3]; Bostrom, 2012 [11]; Grace et al., 2018 [4]). Studies of human–AI collaboration

demonstrate the importance of combining computational capabilities with human expertise and judgement (Jarrahi, 2018 [8]; Dellermann et al., 2019 [9]; Raisch & Krakowski, 2021 [13]). Knowledge-management research explains how information and expertise can be transferred, assimilated, translated, and transformed across disciplinary and organisational boundaries (Nonaka, 1994 [18]; Cohen & Levinthal, 1990 [16]; Carlile, 2004 [17]). Industrial integration studies identify organisational readiness, implementation capabilities, and practical applications as important factors influencing AI adoption (Duan et al., 2019 [19]; Jöhnk et al., 2021 [21]; Brynjolfsson et al., 2025 [22]). Finally, governance literature emphasises ethical responsibility, institutional oversight, accountability, and societal participation in the development and use of intelligent systems (Floridi et al., 2018 [12]; Jobin et al., 2019 [6]; Shneiderman, 2020 [7]).

Despite these contributions, the reviewed studies do not collectively establish an integrated societal model explicitly examining the reciprocal relationships among AI technology developers, industry-specific application integrators, and beneficiaries within a hypothetical future AGI/ASI environment. Existing scholarship addresses technological capability, human–AI collaboration, knowledge transfer, industrial adoption, and governance through substantially different analytical perspectives. The conceptual gap identified in this review therefore concerns the need to examine how these dimensions may interact through continuous, multidirectional cognitive exchange. In response, the present exploratory study proposes a **Three-Level Cognitive Cross-Pollination Model** comprising **(1) AI Developers and Controllers, (2) Industry Application Integrators, and (3) AI Beneficiaries**. It investigates possible mechanisms of technical knowledge transfer, domain-specific adaptation, user participation, feedback exchange, responsibility allocation, and value creation. The proposed model is subsequently examined using SWOC, ABCD, and PESTLE frameworks, supported by qualitative scenario-based predictive analysis and impact analysis. The intended scholarly contribution is an integrated conceptual framework for examining collaboration, governance, and equitable participation in a possible future AGI/ASI society, rather than an empirically validated prediction of that society's structure.

3. RESEARCH GAP AND PROBLEM STATEMENT :

3.1 Research Gap:

Existing scholarly research on Artificial Intelligence (AI) has made substantial contributions to understanding the technological development, potential capabilities, organisational applications, human collaboration, and governance implications of increasingly intelligent systems. Studies concerning Artificial General Intelligence (AGI) explore the possibility of developing broadly adaptable computational intelligence, while research on Artificial Superintelligence (ASI) examines hypothetical systems possessing capabilities beyond human cognitive performance (Goertzel, 2014 [3]; Bostrom, 2012 [11]). Grace et al. (2018) [4] demonstrate considerable uncertainty surrounding predictions of advanced AI development. Although these contributions provide important technological and theoretical foundations, they offer limited explanations of how different societal stakeholders might interact, collaborate, exchange knowledge, and distribute responsibilities in a future society influenced by AGI or ASI. The principal gap identified in the selected literature is therefore not the absence of research on advanced intelligence itself, but the limited integration of technological, industrial, organisational, and societal perspectives into a unified stakeholder-interaction framework.

Research on human–AI collaboration provides valuable insights into complementary intelligence, organisational decision-making, and the potential benefits of combining human expertise with machine capabilities. Jarrahi (2018) [8] examines human–AI symbiosis in organisational decision-making, while Dellermann et al. (2019) [9] conceptualise hybrid intelligence as a collaborative arrangement involving complementary human and artificial capabilities. Shrestha et al. (2019) [14] further investigate organisational structures in which humans and AI systems participate in decision-making. However, these studies primarily examine relationships between humans and intelligent systems within organisational settings. They do not directly establish how three distinct but interconnected societal roles—AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries—might exchange technical, industrial, experiential, and ethical knowledge across multiple organisational and institutional boundaries. Consequently, the potential mechanisms of multidirectional cognitive exchange among these groups remain insufficiently explained within the reviewed literature.

Knowledge-management research offers an additional foundation for understanding the proposed interactions. Nonaka (1994) [18] explains organisational knowledge creation through interactions between tacit and explicit knowledge, while Cohen and Levinthal (1990) [16] emphasise the importance of absorptive capacity in recognising, assimilating, and applying external knowledge. Carlile (2004) [17] examines knowledge transfer, translation, and transformation across organisational boundaries, highlighting difficulties arising from differences in expertise, interpretation, and interests. Although these theories establish the importance of knowledge exchange for innovation and organisational learning, their application to a hypothetical AGI/ASI society remains conceptually underdeveloped. In particular, limited attention has been given to how AI developers might transfer technological capabilities to industry integrators, how integrators might translate those capabilities into usable applications, and how beneficiaries' experiences, expectations, and concerns might influence subsequent technological development. The mechanisms through which such feedback could generate continuous cognitive cross-pollination across all three levels require further conceptual investigation.

The industrial integration and governance literature identifies additional challenges. Jöhnk et al. (2021) [21] demonstrate the significance of organisational readiness in AI adoption, while Floridi et al. (2018) [12] and Jobin et al. (2019) [6] emphasise ethical principles, accountability, transparency, and responsible AI governance. Selbst et al. (2019) [23] further argue that AI-related interventions must be understood within their broader sociotechnical contexts. These studies highlight important organisational and institutional requirements, but they do not jointly specify how responsibilities, decision-making authority, risk information, and accountability might circulate among the proposed three stakeholder groups in an AGI/ASI environment. Questions concerning the effectiveness of beneficiary participation, the management of unequal technological capabilities, the prevention of knowledge asymmetries, and the equitable distribution of benefits therefore require further examination. These gaps are particularly significant because technological development, industrial deployment, and societal consequences may be governed by different institutions with potentially conflicting interests.

The foregoing synthesis identifies a need for an integrated conceptual framework that examines **cognitive cross-pollination as a continuous, multidirectional process of knowledge exchange, collaborative learning, technological adaptation, feedback integration, and shared responsibility**. The reviewed literature provides theoretical foundations for particular components of this process but does not establish a comprehensive framework explicitly connecting the three proposed societal roles within a hypothetical AGI/ASI environment. The present research addresses this conceptual gap by developing a Three-Level Cognitive Cross-Pollination Model and exploring its potential organisational, technological, economic, ethical, and societal implications. The model is intended as an exploratory framework rather than a prediction that future society will necessarily develop into three fixed or mutually exclusive groups.

3.2 Problem Statement:

The potential emergence of Artificial General Intelligence and Artificial Superintelligence may significantly transform the ways intelligent technologies are developed, integrated into industries, governed, and utilised by individuals and communities. However, the uncertain nature of AGI and ASI development creates fundamental difficulties in anticipating future stakeholder relationships, knowledge-sharing arrangements, and institutional responsibilities. Existing research provides important insights into advanced intelligence, human–AI collaboration, organisational readiness, and ethical governance, but limited integrated understanding exists concerning how AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries might interact as interconnected participants in a hypothetical future AGI/ASI society. Without a suitable conceptual framework, it becomes difficult to systematically examine how technological knowledge could be translated into practical applications, how beneficiaries' needs and experiences could influence technological decisions, and how responsibility and accountability could be distributed across the AI development and application ecosystem.

The central research problem is therefore the limited conceptual understanding of the mechanisms, relationships, opportunities, constraints, and governance requirements associated with cognitive cross-pollination among the three stakeholder groups in a possible future AGI/ASI society**.** This problem involves identifying how technical knowledge, domain-specific expertise, user experiences, ethical

expectations, operational feedback, and institutional decisions might circulate among the groups to support responsible innovation and societal benefit. It also requires examining potential barriers arising from unequal access to advanced AI capabilities, differences in professional expertise, conflicting stakeholder interests, inadequate communication, technological dependence, and uncertain accountability arrangements. Accordingly, the present study proposes a Three-Level Cognitive Cross-Pollination Model and evaluates its potential characteristics through Strengths, Weaknesses, Opportunities, and Challenges (SWOC) Analysis; Advantages, Benefits, Constraints, and Disadvantages (ABCD) Analysis; and Political, Economic, Social, Technological, Legal, and Environmental (PESTLE) Analysis. Qualitative scenario-based predictive analysis and impact analysis are additionally employed to explore alternative societal developments and possible stakeholder consequences. The research seeks to develop an integrated conceptual foundation for understanding collaboration, knowledge exchange, governance, and equitable participation in a hypothetical future AGI/ASI society, while recognising that its proposed relationships require subsequent empirical validation.

4. RESEARCH OBJECTIVES AND QUESTIONS :

The following five objectives are considered in the article:

(1) To conceptualise a three-level future AGI and ASI society comprising AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries, and identify their potential functions and responsibilities.
(2) To explore the mechanisms of cognitive cross-pollination, knowledge exchange, collaboration, and feedback among the three groups.
(3) To evaluate the proposed societal model through SWOC, ABCD, and PESTLE analyses, considering technological, organisational, ethical, and societal dimensions.
(4) To develop qualitative future scenarios and examine the potential impacts of advanced AI on employment, industry, education, governance, and human well-being.
(5) To propose an integrated framework and evidence-informed recommendations for responsible collaboration, equitable benefit distribution, human oversight, and sustainable development in a possible AGI/ASI society.

5. RESEARCH METHODOLOGY :

The present study adopts an **exploratory, qualitative, literature-based conceptual research methodology** to examine the potential relationships and cognitive cross-pollination among AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries in a hypothetical future Artificial General Intelligence (AGI) and Artificial Superintelligence (ASI) society. The study relies on secondary information obtained from peer-reviewed scholarly articles, research reviews, conference publications, institutional reports, and relevant policy and governance literature. Relevant publications are identified through keyword-based searches using Google Scholar, other academic search engines, and AI-driven GPT tools to assist preliminary information discovery and thematic organisation. The principal search terms include *Artificial General Intelligence, Artificial Superintelligence, Human–AI Collaboration, Hybrid Intelligence, Knowledge Exchange, AI Industrial Integration, AI Governance, Cognitive Cross-Pollination,* and *Future AI Society*. Sources are selected purposively according to their relevance to the research objectives, conceptual contributions, and applicability to the proposed societal model. The literature is examined through thematic interpretation and integrative synthesis to identify relationships, theoretical foundations, emerging opportunities, and potential challenges. Snyder (2019) [24] emphasises the importance of methodological transparency in literature-based research, while Torraco (2005) [25] explains how integrative literature reviews can generate conceptual insights by synthesising existing knowledge. Accordingly, the present investigation focuses on developing an explanatory conceptual framework rather than testing predetermined hypotheses through primary empirical data.

The analytical methodology integrates five complementary approaches: SWOC Analysis, ABCD Analysis, PESTLE Analysis, Qualitative Predictive Scenario Analysis, and Impact Analysis**.** These approaches are selected to evaluate the proposed three-level societal structure from technological, organisational, stakeholder, and socioeconomic perspectives. SWOC Analysis examines the Strengths, Weaknesses, Opportunities, and Challenges associated with cognitive cross-pollination, adapting the

strategic assessment principles discussed by Helms and Nixon (2010) [26]. ABCD Analysis evaluates the Advantages, Benefits, Constraints, and Disadvantages of the proposed model separately for AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries, following the analytical framework developed by Aithal et al. (2015) [27] and Aithal (2016) [28]. PESTLE Analysis examines Political, Economic, Social, Technological, Legal, and Environmental factors influencing the possible development and governance of advanced AI society, drawing upon the macro-environmental assessment approach discussed by Yüksel (2012) [29]. Qualitative Predictive Scenario Analysis explores alternative future conditions involving responsible AI integration, unequal technological development, and disruptive or inadequately governed advanced intelligence, consistent with the scenario-planning principles reviewed by Amer et al. (2013) [30]. Impact Analysis identifies potential positive and negative consequences for employment, education, productivity, governance, human autonomy, social inclusion, and economic welfare without independently estimating causal effects. The findings from these five approaches are integrated to develop the proposed Cognitive Cross-Pollination Model, identify multidirectional knowledge-exchange mechanisms, and formulate recommendations for collaborative innovation and responsible governance. This integration is consistent with Jaakkola (2020) [31], who emphasises the importance of clearly justified conceptual research designs and theoretical synthesis.

The study is subject to several **methodological limitations** arising from its exploratory and conceptual orientation. First, AGI and ASI remain uncertain technological possibilities, and their eventual capabilities, development trajectories, institutional arrangements, and societal consequences cannot be predicted reliably from existing evidence. Second, the investigation depends on secondary information, which may contain differences in terminology, theoretical assumptions, publication quality, and interpretations of advanced AI development. Third, keyword-based searching and purposive source selection may introduce selection bias, while AI-driven GPT tools may generate inaccurate summaries or unverifiable references; consequently, scholarly claims and bibliographic details require independent verification against original publications, as highlighted by Adel and Alani (2025) [32]. Fourth, SWOC, ABCD, PESTLE, scenario-based, and impact analyses involve qualitative interpretation and do not independently establish statistically significant relationships, numerical forecasts, or causal effects. The proposed three-level societal structure is therefore treated as a conceptual representation of potentially overlapping stakeholder roles rather than an empirically established or inevitable future social hierarchy. Despite these limitations, the integrated methodology provides a structured basis for exploring knowledge exchange, stakeholder collaboration, governance responsibilities, and potential societal implications, while establishing propositions for future empirical investigation and validation.

6. PROPOSED THREE-LEVEL MODEL OF FUTURE AGI & ASI SOCIETY :

6.1 Conceptual Foundation of the Three-Level Model:

The potential development of Artificial General Intelligence (AGI) and Artificial Superintelligence (ASI) raises important questions concerning the future organisation of technological capabilities, industrial activities, human participation, and institutional governance. AGI refers to the proposed development of artificial systems capable of demonstrating broadly adaptable intelligence across different domains, while ASI represents the hypothetical possibility of artificial intelligence substantially exceeding human cognitive capabilities. Goertzel (2014) [3] discusses the technological and conceptual foundations of AGI, whereas Bostrom (2012) examines the possible behaviour and goal-directed characteristics of superintelligent agents. Although the emergence and eventual capabilities of AGI and ASI remain uncertain, these perspectives provide a foundation for exploring alternative models of future AI-enabled society.

The present study proposes a **Three-Level Cognitive Cross-Pollination Model** consisting of **(1) AI Developers and Controllers, (2) Industry Application Integrators, and (3) AI Beneficiaries**. These levels represent three interconnected functional roles through which advanced AI capabilities may be developed, translated into practical applications, and utilised or experienced by society. The model assumes that technological progress and societal value creation require more than the development of sophisticated AI systems; they also depend on effective communication, knowledge exchange, institutional accountability, and the integration of human requirements. Dellermann et al. (2019) [9] emphasise the complementary potential of human and artificial intelligence, while Shneiderman (2020)

[7] highlights the importance of maintaining human control, safety, and responsibility in increasingly automated environments.
The image illustrates a **layered AI ecosystem and collaboration framework** that connects technical development, industry integration, and end-user adoption through continuous feedback loops.

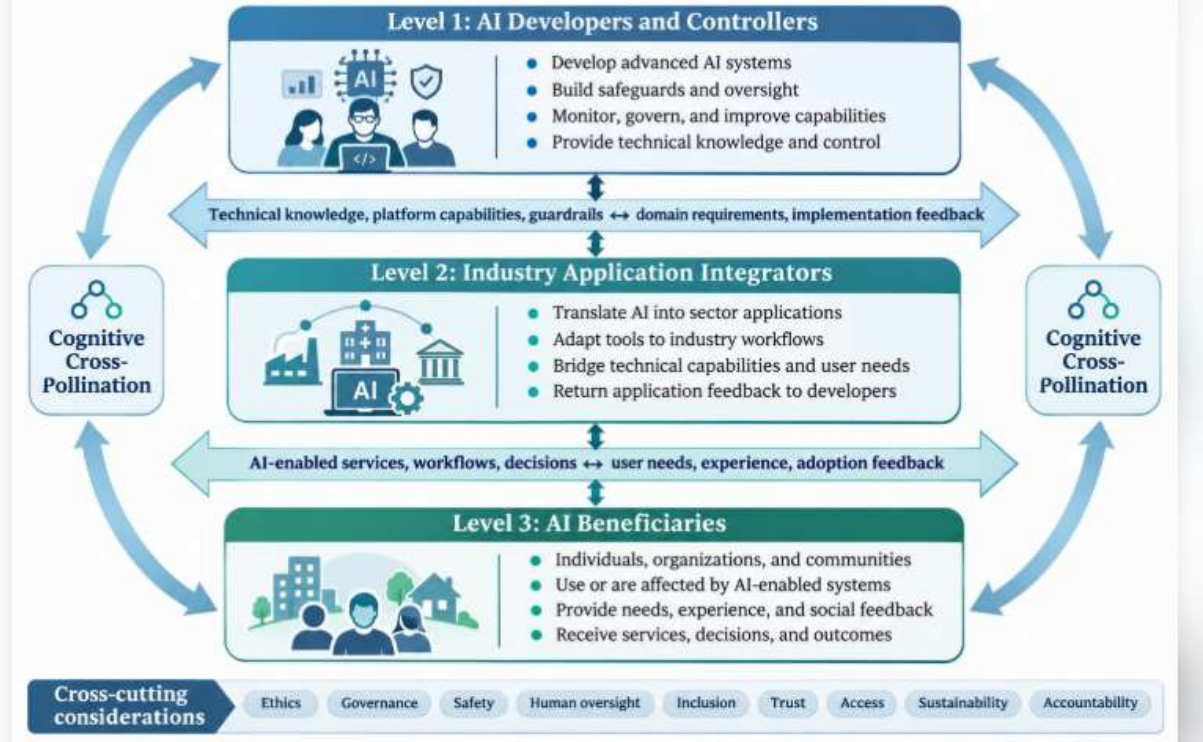

Fig. 1: Proposed Three-Level Cognitive Cross-Pollination Model of a Future AGI and ASI Society

As illustrated in **Figure 1**, the three levels are interconnected through continuous, bidirectional cognitive cross-pollination involving technical knowledge, application requirements, operational experiences, user feedback, and societal expectations. The proposed structure represents functional interdependence rather than a rigid social hierarchy. Individuals, organisations, and institutions may participate in more than one level, while governance responsibilities extend across the entire system.

6.2 Level 1: AI Developers and Controllers:

Definition: AI Developers and Controllers represent the individuals, research institutions, technology enterprises, engineering teams, and authorised oversight bodies involved in designing, developing, evaluating, maintaining, and governing increasingly advanced AI systems. In a hypothetical AGI/ASI society, this level would encompass specialised technological capabilities and oversight functions necessary for creating advanced intelligent systems and managing their risks.
Characteristics: This level is characterised by expertise in machine learning, advanced computational architectures, algorithm design, data engineering, system safety, cybersecurity, model evaluation, and technological governance. Its defining feature is the capacity to develop and evaluate AI systems while establishing technical and institutional mechanisms for their responsible use. Goertzel (2014) [3] highlights the complexity of developing generally intelligent architectures, while Bostrom (2012) [11] identifies important risks associated with the possible goals and behaviour of highly capable artificial agents.
Roles and Responsibilities: The principal responsibilities of this level include developing advanced AI capabilities, evaluating system performance, identifying technological limitations, implementing safety safeguards, maintaining technical documentation, and supporting meaningful human oversight. Developers are expected to communicate system capabilities and limitations to application integrators, while oversight institutions establish appropriate accountability and governance requirements. Raji et al. (2020) [33] propose an end-to-end internal algorithmic auditing framework that illustrates the importance of systematic documentation, evaluation, and accountability throughout the AI development

lifecycle. Shneiderman (2020) [7] further emphasises reliable system design and human-centred control as important foundations for trustworthy AI.

Relationships with Other Levels: AI Developers and Controllers provide technological capabilities, development tools, technical documentation, safety requirements, and system updates to Industry Application Integrators. In return, they receive domain-specific requirements, implementation experiences, performance observations, and information concerning emerging risks. They may also interact directly with beneficiaries, researchers, public institutions, and affected communities to understand societal expectations and potential harms. These relationships establish a continuous feedback process through which technological development may become more responsive to practical and societal needs.

6.3 Level 2: Industry Application Integrators:

Definition: Industry Application Integrators represent the organisations, professionals, technology service providers, consultants, systems engineers, and domain specialists responsible for adapting advanced AI capabilities into practical applications across different economic and social sectors. This level functions as an intermediary between the technical development of intelligent systems and their operational implementation in areas such as healthcare, education, manufacturing, agriculture, finance, logistics, governance, and public services.

Characteristics: The distinguishing characteristic of this level is the combination of technological understanding with industry-specific knowledge. Application integrators possess expertise concerning business processes, professional workflows, operational requirements, regulatory environments, organisational behaviour, and the practical limitations of technology adoption. Duan et al. (2019) [19] discuss the opportunities and challenges associated with integrating AI into organisational decision-making, while Jöhnk et al. (2021) [21] identify organisational readiness factors influencing AI adoption. These studies demonstrate that successful technological integration depends on appropriate organisational resources, capabilities, and implementation conditions.

Roles and Responsibilities: Industry Application Integrators translate general-purpose AI capabilities into sector-specific solutions, redesign organisational processes, connect AI applications with existing information systems, establish operational safeguards, and support workforce adaptation. They are also responsible for evaluating the suitability of AI applications for particular tasks, monitoring implementation outcomes, documenting failures, and ensuring that users understand relevant system limitations. Shrestha et al. (2019) [14] demonstrate that human and AI decision-making can be organised through different structures involving delegation, sequential interaction, and combined decision-making. Accordingly, application integrators may contribute to determining when AI should support, inform, or execute decisions and when human review is required.

Relationships with Other Levels: Application integrators receive technical capabilities, system specifications, development support, and governance requirements from AI Developers and Controllers. They translate these resources into practical applications and communicate implementation-related challenges back to technical developers. Simultaneously, they interact with AI Beneficiaries to understand requirements, assess application usefulness, provide training, collect feedback, and identify unintended consequences. Their central role involves transferring, translating, and transforming knowledge across technological and organisational boundaries, consistent with the framework proposed by Carlile (2004) [17].

6.4 Level 3: AI Beneficiaries:

Definition: AI Beneficiaries represent individuals, employees, consumers, students, professionals, organisations, communities, and public institutions that use, receive services from, or are otherwise affected by AI-enabled systems. This level includes both direct users of intelligent applications and individuals who may experience their consequences without directly interacting with the technologies. The term *beneficiaries* therefore identifies an intended role in the proposed framework rather than assuming that every AI-related outcome will necessarily be favourable.

Characteristics: This level is characterised by diverse needs, professional capabilities, educational backgrounds, socioeconomic circumstances, technological access, digital literacy, cultural expectations, and degrees of participation in AI-enabled activities. Beneficiaries may contribute specialised professional knowledge, contextual understanding, user experiences, practical judgements,

and ethical perspectives that cannot be adequately inferred from technical performance indicators alone. Jarrahi (2018) [8] emphasises the complementary contributions of human judgement and AI capabilities in organisational decision-making. Similarly, Dellermann et al. (2019) [9] highlight the importance of combining human and machine capabilities in hybrid intelligence systems.

Roles and Responsibilities: The principal roles of AI Beneficiaries involve using AI-enabled services where appropriate, communicating practical requirements, providing informed feedback, participating in evaluation processes, and identifying issues concerning accessibility, fairness, reliability, privacy, and human well-being. Where beneficiaries act in professional or institutional capacities, they may also have responsibilities concerning appropriate use, data protection, and compliance with applicable regulations. However, responsibility for technological safety and accountability should not be transferred disproportionately from developers and deploying organisations to individual users. Selbst et al. (2019) [23] demonstrate the importance of considering the broader sociotechnical environment when evaluating algorithmic systems.

Relationships with Other Levels: AI Beneficiaries interact primarily with Industry Application Integrators through applications, services, professional workflows, training systems, and feedback channels. Their experiences may influence the improvement of applications, the redesign of organisational processes, and the identification of previously unrecognised risks. Beneficiaries may also communicate directly with AI developers, regulators, researchers, and public institutions through consultation, participation, complaints, and independent assessment mechanisms. Such relationships are essential for ensuring that societal expectations and affected communities receive appropriate consideration in technological development and governance.

6.5 Relationships and Cognitive Cross-Pollination among the Three Levels:

The proposed model considers **cognitive cross-pollination** to be a continuous, multidirectional process through which knowledge, technical capabilities, operational requirements, professional expertise, ethical expectations, and practical experiences are exchanged among the three stakeholder groups. It involves not merely transferring information but also interpreting, adapting, and transforming knowledge into improved technological and organisational outcomes. Cohen and Levinthal (1990) [16] emphasise the importance of absorptive capacity in recognising, assimilating, and applying external knowledge, while Carlile (2004) [17] explains how knowledge transfer, translation, and transformation facilitate collaboration across organisational boundaries.

The first relationship operates between **AI Developers and Controllers and Industry Application Integrators**. AI developers provide technical capabilities, system architectures, implementation tools, safety requirements, and information about technological limitations. Application integrators provide domain knowledge, operational requirements, deployment experiences, and feedback concerning system performance. This exchange may support the refinement of AI capabilities and the development of applications better suited to particular industrial contexts.

The second relationship operates between **Industry Application Integrators and AI Beneficiaries**. Integrators provide practical AI-enabled applications, training, operational assistance, and relevant information concerning system decisions and limitations. Beneficiaries contribute user requirements, experiences, feedback, professional knowledge, and information about social consequences. This exchange may support application improvement, more effective adoption, accessibility, and the identification of unintended consequences.

The third relationship involves **direct communication between AI Developers and Controllers and AI Beneficiaries**, supplementing the intermediary role of application integrators. Such engagement may involve participatory system design, consultations, independent evaluations, complaints, incident reporting, and public-interest assessments. This direct relationship helps prevent important societal concerns from being filtered out through purely commercial or technical communication channels. Selbst et al. (2019) [23] emphasise that technical interventions must account for the wider social systems within which AI technologies operate.

Table 1: Definitions, Roles, Responsibilities, and Cognitive Cross-Pollination Relationships in the Proposed Three-Level Model

Dimension	Level 1: AI Developers and Controllers	Level 2: Industry Application Integrators	Level 3: AI Beneficiaries
Primary function	AI development, technical evaluation, and oversight	Industry-specific adaptation and deployment	Use of, participation in, or experience of AI-enabled services
Core characteristics	Advanced technical expertise, system design, safety and governance capabilities	Domain expertise, technological integration, operational knowledge	Diverse needs, contextual knowledge, practical experience, and societal perspectives
Principal responsibilities	Develop, evaluate, document, safeguard, and monitor AI systems	Integrate, validate, deploy, maintain, and evaluate AI applications	Communicate requirements, participate in feedback, and use systems responsibly where applicable
Knowledge contributed	Algorithms, technical capabilities, architecture, limitations, and safeguards	Industry knowledge, workflows, implementation experience, and sector requirements	User experience, professional judgement, social expectations, and information about consequences
Knowledge received	Application feedback, domain requirements, user concerns, and risk information	Technical documentation, system capabilities, beneficiary requirements, and implementation feedback	AI-enabled services, guidance, explanations, training, and opportunities for participation
Expected contribution	Technological capability and accountable development	Practical implementation and operational value creation	Human-centred application improvement and societal relevance
Major challenges	Alignment, safety, concentration of capabilities, and accountability	Integration complexity, interoperability, regulatory compliance, and workforce readiness	Unequal access, digital literacy, privacy, autonomy, and exposure to potential harms
Cognitive cross-pollination mechanism	Technical knowledge sharing and incorporation of external feedback	Translation and exchange of technical, industrial, and user knowledge	Communication of experiential, contextual, ethical, and social knowledge

Source: Conceptual synthesis developed for the present study, informed by Cohen and Levinthal (1990) [16], Carlile (2004) [17], Jarrahi (2018) [8], Dellermann et al. (2019) [9], Jöhnk et al. (2021) [21], and Shneiderman (2020) [7].

6.6 Cross-Cutting Governance and Societal Responsibilities:

As represented in Figure 1, the proposed three-level model is supported by cross-cutting considerations involving **ethics, governance, safety, human oversight, inclusion, trust, access, sustainability, and accountability**. These considerations apply to all three levels rather than constituting the exclusive responsibility of AI Developers and Controllers. Floridi et al. (2018) [12] propose an ethical framework for beneficial AI development and use, while Jobin et al. (2019) [6] identify important principles concerning transparency, fairness, non-maleficence, responsibility, and privacy in international AI governance guidelines. Raji et al. (2020) [33] further demonstrate the importance of incorporating accountability procedures throughout the system-development lifecycle. These contributions suggest

that responsible future AI integration may require cooperation among technical developers, application organisations, regulators, independent oversight institutions, and affected communities.

The model also recognises that access to technological capabilities, economic resources, specialised knowledge, and institutional influence may be unevenly distributed. Consequently, effective cognitive cross-pollination should involve transparent communication, appropriate feedback mechanisms, meaningful stakeholder participation, clearly allocated responsibilities, and safeguards against the concentration or misuse of technological power. The proposed three levels should not be interpreted as predetermined social classes or as implying that technological development necessarily produces equitable outcomes. Their relationships are better understood as adaptable functional arrangements through which knowledge and responsibilities may be coordinated in alternative future AI environments.

6.7 Conceptual Significance of the Proposed Model:

The proposed Three-Level Cognitive Cross-Pollination Model contributes an integrated perspective on the possible organisation of technological development, industrial application, and societal participation in a hypothetical AGI/ASI society. Its central proposition is that the potential value of advanced AI depends not only on technological sophistication but also on the quality of relationships connecting technical expertise, industry knowledge, and human experiences. Through multidirectional exchanges, the three levels may collectively support technological improvement, application relevance, organisational learning, responsible governance, and societal participation.

The model extends existing discussions of human–AI collaboration, knowledge transfer, industrial AI integration, and responsible governance by examining these dimensions within a common stakeholder-oriented conceptual framework. It provides a foundation for subsequent SWOC, ABCD, PESTLE, qualitative scenario-based predictive, and impact analyses. However, the model remains exploratory, and its proposed relationships, governance arrangements, and expected outcomes require future empirical investigation. Its value lies in offering a structured framework for examining how interconnected stakeholder roles might contribute to responsible and human-centred development in possible future AGI/ASI environments.

7. COGNITIVE CROSS-POLLINATION AMONG THE THREE LEVELS :

7.1 Concept and Significance of Cognitive Cross-Pollination:

Cognitive cross-pollination, in the context of the proposed Three-Level Model of a future Artificial General Intelligence (AGI) and Artificial Superintelligence (ASI) society, refers to the continuous, multidirectional exchange of knowledge, expertise, experiences, ideas, technological capabilities, and feedback among **AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries**. The concept assumes that technological innovation and societal value creation can be strengthened when participants possessing different forms of knowledge interact collaboratively rather than functioning as isolated groups. Nonaka (1994) [18] explains organisational knowledge creation through interactions between tacit and explicit knowledge, while Cohen and Levinthal (1990) [16] emphasise the importance of absorptive capacity in recognising, assimilating, and applying external knowledge. Carlile (2004) [17] further demonstrates that effective innovation requires knowledge transfer, translation, and transformation across professional and organisational boundaries. Drawing upon these theoretical foundations, the present study proposes cognitive cross-pollination as an integrative mechanism linking advanced AI development, industry-specific technological applications, and human-centred societal participation.

As represented in Figure 1, the proposed model recognises that the three levels possess complementary knowledge and responsibilities. AI Developers and Controllers primarily contribute technical knowledge, computational expertise, system architectures, and safety mechanisms. Industry Application Integrators contribute domain-specific knowledge, organisational experience, application design, and operational expertise. AI Beneficiaries contribute contextual understanding, practical experiences, societal expectations, user feedback, and knowledge of real-world consequences. The integration of these contributions may facilitate continuous organisational learning, technological refinement, application improvement, and more responsive governance. Dellermann et al. (2019) [9] discuss the potential of hybrid intelligence through the combination of human and artificial capabilities, while Jarrahi (2018) [8] emphasises the complementary contributions of computational intelligence and

human judgement. These perspectives support the conceptual importance of collaboration, although they do not establish the effectiveness of the proposed three-level structure in a future AGI/ASI society.

7.2 Mechanisms of Knowledge Exchange among the Three Levels:

Knowledge exchange constitutes the foundational mechanism of cognitive cross-pollination. The proposed model identifies three principal channels of exchange: developer–integrator interactions, integrator–beneficiary interactions, and direct developer–beneficiary interactions. In the first channel, AI Developers and Controllers communicate system architectures, technical capabilities, performance limitations, safety requirements, and implementation guidelines to Industry Application Integrators. Integrators reciprocate by sharing domain-specific requirements, application performance data, implementation difficulties, and emerging technological needs. Such interactions enable technical knowledge to be interpreted in relation to practical industrial contexts. Carlile (2004) [17] explains that knowledge exchange across professional boundaries requires mechanisms for transferring common information, translating differences in understanding, and transforming knowledge to accommodate competing interests.

The second channel involves Industry Application Integrators and AI Beneficiaries. Integrators provide AI-enabled applications, professional assistance, user training, operational information, and support services. Beneficiaries communicate requirements, experiences, usability problems, accessibility concerns, and expectations concerning technological performance and societal consequences. This interaction allows application developers to understand whether technological solutions adequately address actual user requirements. Payne et al. (2008) [34] highlight the significance of customer participation, interaction, and organisational processes in value co-creation. Their framework offers an analytical basis for examining how beneficiary participation may contribute to the development and improvement of AI-enabled services.

The third channel facilitates direct knowledge exchange between AI Developers and Controllers and AI Beneficiaries through participatory design, public consultation, feedback platforms, independent evaluations, research collaborations, and incident-reporting mechanisms. Such interactions may prevent important societal concerns from being filtered exclusively through industrial intermediaries. Smith et al. (2025) [35] investigated AI co-design with nontechnical participants and demonstrated how AI literacy tools can improve the quality of user feedback and support collaboration between practitioners and end users. Accordingly, the present model suggests that meaningful knowledge exchange should combine formal technical communication with accessible participation mechanisms, while recognising differences in expertise, technological literacy, and institutional influence.

7.3 Collaborative Mechanisms and Interdisciplinary Integration:

Collaboration among the three societal levels involves the coordinated application of complementary capabilities towards shared technological, industrial, and social objectives. AI Developers and Controllers possess specialised expertise in intelligent systems, algorithms, computational architectures, safety evaluation, and model development. Industry Application Integrators possess professional knowledge concerning sector-specific processes, organisational requirements, regulatory compliance, and technological implementation. AI Beneficiaries contribute practical experience, local knowledge, human judgement, ethical expectations, and assessments of application usefulness. The proposed framework assumes that collaborative arrangements linking these capabilities may generate more contextually appropriate outcomes than decisions made within a single stakeholder group.

Jarrahi (2018) [8] argues that human intuition and contextual judgement can complement the analytical capabilities of intelligent systems, particularly when organisational decisions involve complexity and uncertainty. Dellermann et al. (2019) [9] similarly discuss hybrid intelligence as an arrangement involving complementary human and machine capabilities. However, collaboration requires appropriate organisational conditions. Jöhnk et al. (2021) [21] identify organisational readiness factors influencing AI adoption, including the availability of suitable resources, capabilities, and strategic alignment. These studies suggest that cognitive cross-pollination may depend on technical competence, communication infrastructure, institutional support, and the willingness of participants to exchange knowledge.

In the proposed three-level model, collaborative mechanisms may include interdisciplinary research teams, joint innovation programmes, industry–academia partnerships, participatory application design,

professional training, shared knowledge repositories, and stakeholder consultation platforms. Such mechanisms may facilitate the development of common objectives while accommodating differences in technical understanding, operational priorities, and societal expectations. Nevertheless, collaboration should not imply equal technical expertise or identical responsibilities among stakeholder groups. Rather, it requires appropriate role differentiation, transparent decision-making, recognition of stakeholder contributions, and clearly defined accountability arrangements.

7.4 Feedback Mechanisms and Continuous Improvement:

Feedback represents a critical mechanism through which cognitive cross-pollination may become a continuous process rather than a one-time transfer of technological knowledge. In the proposed framework, feedback originates from interactions between intelligent systems, industrial applications, and human users or affected communities. Industry Application Integrators may communicate implementation outcomes, system failures, performance limitations, and changing application requirements to AI Developers and Controllers. AI Beneficiaries may contribute information concerning usability, service quality, accessibility, fairness, professional requirements, and unexpected consequences. Developers and integrators may subsequently use relevant feedback to evaluate systems, redesign applications, improve safeguards, and communicate changes to the affected participants.

This process can be conceptualised as a recurring sequence of **knowledge generation, application integration, beneficiary experience, feedback collection, evaluation, and technological or organisational refinement**. Nonaka (1994) [18] provides a theoretical foundation for understanding continuous knowledge creation, while Payne et al. (2008) [34] emphasise interaction and relationship processes in collaborative value creation. However, the effectiveness of feedback depends upon its relevance, representativeness, reliability, and appropriate interpretation. Feedback from beneficiaries should not automatically be treated as technically correct, nor should technical performance indicators be considered sufficient to represent all societal consequences.

Feedback mechanisms may also generate undesirable outcomes if poorly designed. Glickman and Sharot (2025) [36] experimentally demonstrated that interactions with biased AI systems can reinforce and amplify biases in human judgements. Their findings highlight the possibility that feedback relationships between humans and intelligent systems may produce harmful reinforcing cycles rather than continuous improvement. Consequently, the proposed model incorporates human oversight, independent evaluation, bias monitoring, incident reporting, and transparent corrective procedures as essential safeguards. Raji et al. (2020) [33] propose an end-to-end algorithmic auditing framework that supports organisational accountability across the AI system lifecycle. In a hypothetical AGI/ASI environment, such safeguards could become particularly important because the consequences of errors, misplaced trust, or poorly governed automated decisions may be difficult to anticipate.

7.5 Knowledge Transfer, Translation, and Organisational Learning:

Knowledge transfer among the three societal levels involves communicating technical, professional, contextual, and experiential knowledge in forms that other stakeholders can understand and apply. However, effective transfer requires more than making information available. Participants must be capable of interpreting unfamiliar concepts, recognising their relevance, and adapting them to different organisational or social contexts. Cohen and Levinthal (1990) [16] describe this capability through the concept of absorptive capacity, arguing that prior related knowledge influences an organisation's ability to recognise and utilise external information.

Carlile (2004) [17] distinguishes between three increasingly complex knowledge boundaries: syntactic boundaries involving differences in information representation, semantic boundaries involving differences in interpretation, and pragmatic boundaries involving differences in interests and practical consequences. These distinctions are especially relevant to the proposed model because AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries may approach technological problems from fundamentally different perspectives. Developers may focus on computational performance and technical reliability, integrators on operational feasibility and organisational efficiency, and beneficiaries on accessibility, usefulness, fairness, and personal or societal consequences.

Accordingly, knowledge transfer in the proposed model is expected to operate through three interrelated activities: **transfer**, involving communication of relevant information; **translation**, involving

adaptation of specialised knowledge into forms understandable to other groups; and **transformation**, involving modification of existing knowledge, practices, and technologies through collaborative problem-solving. AI literacy programmes, technical documentation, interdisciplinary workshops, application demonstrations, professional training, and participatory evaluation may support these activities. Smith et al. (2025) [35] provide empirical evidence that structured AI literacy support can strengthen nontechnical participants' engagement in AI co-design. The proposed framework therefore treats knowledge transfer as a two-way learning process in which technological developers may learn from users and application specialists, while integrators and beneficiaries develop improved understanding of intelligent systems.

7.6 Joint Value Creation through Cognitive Cross-Pollination:

Joint value creation refers to the potential generation of beneficial technological, organisational, economic, and societal outcomes through coordinated contributions from the three stakeholder groups. In contrast to a linear model in which technological developers create value and beneficiaries merely receive it, the proposed cognitive cross-pollination framework considers value creation an interactive process involving technical innovation, application adaptation, beneficiary participation, and continuous improvement. Prahalad and Ramaswamy (2004) [37] emphasise the changing role of consumers as active participants in value creation, while Payne et al. (2008) [34] propose a process-based framework for understanding interactions between organisations and customers.

Grönroos and Voima (2013) [38] distinguish value creation from value co-creation and emphasise the importance of direct interaction between service providers and customers. Vargo and Lusch (2016) [39] further explain the role of institutions and institutional arrangements in coordinating value co-creation across wider service ecosystems. These perspectives provide a basis for examining value creation within the proposed three-level AI society, although the economic and institutional arrangements of a hypothetical AGI/ASI society remain uncertain.

At Level 1, potential value may arise through advances in technological capability, reliability, safety, interoperability, and responsible innovation. At Level 2, value may emerge through improved industrial applications, organisational efficiency, service innovation, workforce augmentation, and domain-specific problem-solving. At Level 3, value may be experienced through accessible services, improved professional support, educational opportunities, better-informed decisions, and enhanced quality of life. However, these outcomes are possibilities rather than demonstrated consequences of future AGI or ASI technologies. The distribution of benefits may also be unequal, particularly where technological capabilities, institutional influence, financial resources, and digital access are concentrated among particular groups.

Consequently, successful joint value creation should be assessed not only through technological performance and economic productivity but also through fairness, accessibility, human agency, accountability, social inclusion, and long-term sustainability. Shneiderman (2020) [7] emphasises the importance of designing AI systems that combine high levels of automation with meaningful human control. Selbst et al. (2019) [23] similarly demonstrate that algorithmic systems must be evaluated within their broader sociotechnical environments. The proposed framework therefore conceptualises joint value creation as a conditional outcome of effective collaboration, knowledge exchange, responsible governance, and meaningful beneficiary participation.

7.7 Integrated Cognitive Cross-Pollination Mechanism:

Based on the preceding discussion, the proposed model identifies five interrelated mechanisms through which cognitive cross-pollination may operate: knowledge exchange, collaborative integration, feedback, knowledge transfer and transformation, and joint value creation. These mechanisms are mutually reinforcing but may also be constrained by technological uncertainty, institutional barriers, unequal access, conflicting interests, or inadequate governance arrangements.

Table 2: Proposed Cognitive Cross-Pollination Mechanisms among the Three Levels of a Future AGI/ASI Society

Mechanism	Principal interactions	Potential outcomes
Knowledge exchange	Developers, integrators, and beneficiaries communicate technical	Improved mutual understanding and identification of application needs

	capabilities, domain requirements, and user experiences	
Collaborative integration	Stakeholders combine technical expertise, sector-specific knowledge, and human contextual understanding	More appropriate application design and interdisciplinary problem-solving
Continuous feedback	Integrators and beneficiaries communicate performance observations, user experiences, emerging risks, and changing requirements	Identification of system limitations and opportunities for improvement
Knowledge transfer and transformation	Technical and experiential knowledge is translated, assimilated, adapted, and incorporated into new practices	Organisational learning, professional capability development, and improved implementation
Joint value creation	Stakeholders contribute complementary resources and participate in application development, adoption, evaluation, and governance	Potential technological innovation, organisational benefits, societal usefulness, and more responsive governance

Source: Proposed conceptual synthesis informed by Nonaka (1994) [18], Cohen and Levinthal (1990) [16], Carlile (2004) [17], Prahalad and Ramaswamy (2004) [37], Payne et al. (2008) [34], Dellermann et al. (2019) [9], and Vargo and Lusch (2016) [39].

The conceptual relationships presented in Table 3 indicate that cognitive cross-pollination may operate through direct and mediated interactions rather than through a strictly sequential or hierarchical flow of technological capabilities. The effectiveness of these relationships would depend on the ability of stakeholders to exchange meaningful information, overcome knowledge boundaries, participate in decisions, and establish appropriate safeguards.

The following exploratory propositions emerge from the conceptual analysis:

- **Proposition 1:** Greater opportunities for multidirectional knowledge exchange among the three stakeholder groups may improve mutual understanding of technological capabilities, application requirements, and beneficiary needs.
- **Proposition 2:** Collaborative integration of technical, industrial, and contextual knowledge may support the development of more relevant and usable AI applications.
- **Proposition 3:** Structured feedback mechanisms, supported by independent evaluation and accountability arrangements, may strengthen the identification and correction of technological and organisational problems.
- **Proposition 4:** Effective knowledge translation and absorptive capacity may influence how successfully technical knowledge and user experiences are converted into organisational learning.
- **Proposition 5:** Joint value creation is more likely to support broad societal benefits when stakeholder participation is accompanied by responsible governance, equitable access, and appropriate protection of human interests.

These propositions are conceptual and have not been empirically tested within a future AGI/ASI society. They are intended to guide subsequent research using interviews, stakeholder surveys, organisational case studies, comparative assessments, and other empirical methods.

7.8 Summary and Implications:

The proposed Three-Level Cognitive Cross-Pollination Model presents knowledge exchange, collaboration, feedback, knowledge transfer, and joint value creation as interconnected processes that may influence the development and societal integration of advanced intelligent technologies. The model emphasises that technological expertise, industrial knowledge, and beneficiary experiences are complementary rather than mutually exclusive sources of innovation and learning. Its principal contribution lies in conceptualising how knowledge and responsibilities may circulate among AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries within a common stakeholder-oriented framework.

Nevertheless, cognitive cross-pollination should not be assumed to produce beneficial outcomes automatically. Its effectiveness may be influenced by differences in knowledge, technological access, organisational capabilities, institutional authority, trust, governance arrangements, and the potential for harmful feedback cycles. Furthermore, AGI and ASI remain uncertain technological possibilities, making the proposed societal relationships exploratory rather than predictive findings. The framework therefore provides a foundation for subsequent SWOC, ABCD, PESTLE, qualitative predictive-scenario, and impact analyses examining the opportunities, limitations, stakeholder consequences, and governance requirements of a possible future AGI/ASI society.

8. SWOC ANALYSIS OF THE PROPOSED THREE-LEVEL COGNITIVE CROSS-POLLINATION MODEL :

8.1 Introduction to SWOC Analysis:

Strengths, Weaknesses, Opportunities, and Challenges (SWOC) Analysis is a strategic assessment technique used to examine the internal capabilities, limitations, external possibilities, and challenges associated with a proposed system, organisation, or conceptual framework. It is adapted from the established SWOT approach, which has been extensively applied in strategic management and organisational planning. Helms and Nixon (2010) [26] demonstrate the usefulness of SWOT analysis for evaluating organisational capabilities, identifying strategic alternatives, and supporting managerial decisions, while recognising its dependence on context and qualitative judgement. In the present study, the term *Challenges* replaces *Threats* to accommodate the technological uncertainties, institutional complexities, and evolving socioeconomic conditions associated with a hypothetical Artificial General Intelligence (AGI) and Artificial Superintelligence (ASI) society.

The proposed Three-Level Cognitive Cross-Pollination Model comprises **AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries**. These interconnected stakeholder groups are expected to contribute different forms of knowledge, technological expertise, operational capabilities, and societal perspectives. As explained in Sections 6 and 7, the model conceptualises cognitive cross-pollination as a continuous, multidirectional exchange of technical knowledge, industry-specific requirements, practical experiences, user feedback, and governance considerations. The present SWOC Analysis examines the potential internal strengths and weaknesses of these relationships and the external opportunities and challenges that might influence their development. Since the model represents a hypothetical future societal arrangement, the analysis is interpretative and exploratory rather than an empirical assessment of an existing AGI/ASI society.

8.2 Strengths of the Proposed Three-Level Model:

(1) Complementary Knowledge and Expertise: A principal strength of the proposed model is its capacity to conceptually integrate three complementary forms of expertise: technological knowledge from AI Developers and Controllers, domain-specific expertise from Industry Application Integrators, and practical and contextual knowledge from AI Beneficiaries. Cohen and Levinthal (1990) [16] explain that the capacity to recognise, assimilate, and utilise external knowledge contributes to organisational innovation. Carlile (2004) [17] further demonstrates the importance of transferring, translating, and transforming knowledge across professional boundaries. These perspectives support the proposition that collaboration among technically and socially diverse stakeholders may improve problem identification, application development, and technological adaptation.

(2) Continuous Knowledge Exchange and Organisational Learning: The bidirectional relationships represented in Figure 1 provide opportunities for continuous learning among the three societal levels. Developers may obtain application-specific requirements from integrators, while integrators may acquire practical feedback from beneficiaries. The resulting information may support improvements in technological design, operational processes, and application relevance. Dellermann et al. (2019) [9] highlight the potential of hybrid intelligence, in which human and artificial capabilities complement one another in solving problems. Accordingly, cognitive cross-pollination may strengthen the capacity of stakeholders to learn collectively and respond to changing technological and societal requirements.

(3) Improved Contextual Relevance of AI Applications: The presence of a distinct Industry Application Integrator level may help translate advanced AI capabilities into applications suited to particular professional, industrial, and organisational environments. Jarrahi (2018) [8] emphasises the complementary contributions of human judgement and computational intelligence in organisational

decision-making. Similarly, Jöhnk et al. (2021) [21] identify organisational readiness as an important condition for successful AI adoption. Within the proposed model, integrators may reduce the gap between general technological capabilities and the requirements of particular industries, thereby improving the contextual suitability of AI-enabled solutions.

(4) Potential for Human-Centred Development and Shared Accountability: Incorporating beneficiaries as active participants rather than passive recipients represents another conceptual strength. Beneficiary participation may help developers and integrators identify accessibility requirements, user expectations, potential harms, and ethical concerns. Shneiderman (2020) [7] argues that effective human-centred AI systems should combine sophisticated automation with meaningful human control. Floridi et al. (2018) [12] further emphasise beneficence, non-maleficence, autonomy, justice, and explicability as foundations for responsible AI. These principles suggest that multidirectional stakeholder involvement could improve the responsiveness and accountability of future AI development.

8.3 Weaknesses of the Proposed Three-Level Model:

(1) Differences in Technical Knowledge and Cognitive Capabilities: A significant weakness concerns the unequal distribution of specialised knowledge among the three stakeholder groups. AI Developers and Controllers may possess advanced computational expertise, whereas integrators may emphasise operational applications and beneficiaries may have varying levels of technological literacy. Such differences can create misunderstandings, communication difficulties, and unequal influence over decisions. Cohen and Levinthal (1990) [16] demonstrate that absorptive capacity depends partly on existing knowledge, while Carlile (2004) [17] identifies syntactic, semantic, and pragmatic barriers that complicate knowledge exchange. These limitations may restrict the effectiveness of cognitive cross-pollination unless appropriate knowledge-translation mechanisms are established.

(2) Dependence on Effective Intermediary Institutions: The model assigns Industry Application Integrators a central role in translating technological capabilities into practical applications. This intermediary function creates potential dependence on the competence, transparency, financial resources, and ethical practices of integrating organisations. Jöhnk et al. (2021) [21] highlight organisational readiness challenges involving resources, capabilities, and commitment. In the proposed model, inadequate integration capabilities may interrupt communication between developers and beneficiaries, resulting in unsuitable applications, delayed feedback, and inefficient knowledge transfer.

(3) Unequal Stakeholder Participation and Representation: Although the model proposes bidirectional communication, it does not automatically guarantee meaningful beneficiary participation. Developers and integrating organisations may possess greater access to technological infrastructure, specialist expertise, financial resources, and decision-making authority. Consequently, beneficiary perspectives may receive insufficient consideration, particularly among socially or economically disadvantaged groups. Selbst et al. (2019) [23] demonstrate that fairness-related technological interventions can fail when designers inadequately account for broader sociotechnical contexts. The model therefore contains a potential structural weakness if beneficiary participation is limited to formal consultation without genuine influence over system design and governance.

(4) Complexity of Feedback Processing and Responsibility Allocation: Continuous information exchange among three interconnected levels may generate large volumes of feedback involving technical performance, operational efficiency, professional expectations, ethical concerns, and social consequences. Processing potentially inconsistent feedback and determining responsibility for corrective actions may be difficult. Glickman and Sharot (2025) [36] demonstrate that feedback loops involving humans and AI can amplify biases in human judgements. Furthermore, Raji et al. (2020) [33] emphasise the need for systematic auditing and clearly established accountability mechanisms throughout AI development. Without effective evaluation procedures and responsibility allocation, continuous feedback may increase organisational complexity without necessarily producing beneficial improvements.

8.4 Opportunities Associated with the Proposed Three-Level Model:

(1) Development of Interdisciplinary Innovation Ecosystems: The model offers opportunities for collaboration among AI researchers, technology enterprises, professional organisations, educational institutions, public authorities, and beneficiaries. Knowledge exchange across these groups may support

interdisciplinary innovation and encourage technological applications addressing complex organisational and societal problems. Carlile (2004) [17] establishes the importance of knowledge transformation across professional boundaries, while Dellermann et al. (2019) [9] identify opportunities for combining complementary human and artificial capabilities. Such interactions could support collaborative research, joint application development, professional training, and new forms of knowledge-intensive activity.

(2) Expansion of AI-Enabled Industrial Productivity and Services: Increasingly capable AI technologies may provide opportunities to improve selected industrial processes, professional services, decision-support activities, and organisational productivity. Brynjolfsson et al. (2025) [22] report productivity improvements associated with generative AI assistance in a customer-support setting, illustrating how contemporary AI can generate measurable benefits when integrated into specific organisational tasks. Although such findings cannot be generalised directly to hypothetical AGI or ASI systems, they provide a basis for exploring possible future industrial applications. The proposed model positions Industry Application Integrators as potential facilitators of context-sensitive adoption and practical value creation.

(3) Workforce Development and Cognitive Augmentation: Cognitive cross-pollination may encourage the development of new educational programmes, professional competencies, and collaborative arrangements between humans and intelligent technologies. AI Developers and Controllers may provide technological knowledge, integrators may identify emerging industry skills, and beneficiaries may communicate practical learning needs. Jarrahi (2018) [8] highlights the complementary capabilities of humans and AI in decision-making, while Frank et al. (2019) [5] emphasise the importance of examining changing occupational tasks and workforce skills when assessing the labour-market implications of AI. These findings indicate opportunities for reskilling, lifelong learning, and human-centred augmentation, although employment outcomes will depend on organisational and economic conditions.

(4) Development of Participatory and Responsible AI Governance: The proposed framework offers opportunities to integrate ethical considerations and societal feedback into technological development and deployment. Beneficiary participation, independent evaluation, and communication between developers and implementing institutions may help identify risks earlier and improve organisational responses. Floridi et al. (2018) [12] propose ethical principles and institutional recommendations for beneficial AI, while Jobin et al. (2019) [6] identify substantial international convergence around transparency, fairness, responsibility, privacy, and non-maleficence. The three-level model may provide a conceptual basis for incorporating these principles into collaborative governance processes.

(5) Greater Accessibility and Societal Value Creation: The interaction among developers, integrators, and beneficiaries may facilitate the development of AI-enabled applications responsive to different socioeconomic, educational, cultural, and accessibility requirements. Application integrators could adapt general-purpose technologies to underserved contexts, while beneficiary feedback could inform improvements in usability and service delivery. Shneiderman (2020) [7] supports the importance of human-centred technology design, and Floridi et al. (2018) [12] emphasise the role of justice and human welfare in responsible AI development. Accordingly, the model presents opportunities for broader participation and potentially more equitable benefits, provided that appropriate institutional safeguards and access mechanisms exist.

8.5 Challenges Associated with the Proposed Three-Level Model:

(1) Uncertainty Surrounding AGI and ASI Development: The most fundamental challenge concerns uncertainty about whether, when, and in what forms AGI or ASI might emerge. Existing research does not establish a reliable trajectory towards superintelligent systems or their eventual organisational characteristics. Bostrom (2012) [11] examines possible motivational and instrumental properties of hypothetical superintelligent agents, highlighting potential concerns about goal alignment and human control. Consequently, the proposed three-level model must remain adaptable to alternative technological developments rather than assuming a predetermined progression towards AGI or ASI.

(2) Ethical Risks, Algorithmic Bias, and Unintended Consequences: AI systems may generate inaccurate, unfair, discriminatory, or otherwise harmful outcomes when deployed in complex social environments. Selbst et al. (2019) [23] show that technical approaches to fairness can be insufficient when broader institutional and social relationships are overlooked. Glickman and Sharot (2025) [36]

further demonstrate that human–AI feedback interactions can reinforce biases. In a hypothetical AGI/ASI society, such concerns may become particularly important if increasingly capable systems influence consequential decisions across multiple sectors. The challenge involves establishing appropriate evaluation, human oversight, corrective mechanisms, and opportunities for affected individuals to contest harmful outcomes.

(3) Concentration of Technological and Economic Power: Advanced AI development may depend on substantial computational infrastructure, specialised personnel, financial investment, and access to relevant information resources. These requirements may concentrate technological capabilities and institutional influence among comparatively few organisations. Bender et al. (2021) [40] discuss the financial, environmental, and social concerns associated with increasingly large language models, including the consequences of resource-intensive development. Such concentration could weaken the proposed model's assumption of balanced knowledge exchange by increasing the dependence of integrators and beneficiaries on powerful technology providers. Maintaining meaningful stakeholder participation and avoiding excessive technological dependence therefore constitute important challenges.

(4) Employment Disruption and Socioeconomic Inequality: The industrial adoption of increasingly capable AI may transform occupational tasks, professional responsibilities, workforce requirements, and economic opportunities. Frank et al. (2019) [5] emphasise the complexity of predicting employment consequences because technological change interacts with workforce skills, task structures, and economic conditions. Brynjolfsson et al. (2025) [22] demonstrate that contemporary AI assistance can produce heterogeneous productivity effects across workers. These findings indicate that future AI-enabled benefits and disadvantages may not be distributed uniformly. In the proposed model, ensuring opportunities for workforce adaptation and equitable access to technological benefits represents an important societal challenge.

(5) Regulatory Fragmentation and Accountability: Different jurisdictions and industries may adopt varying approaches to AI regulation, safety, privacy, intellectual property, transparency, and liability. Jobin et al. (2019) [6] identify differences in the interpretation and implementation of AI ethics principles despite broad international agreement on certain values. Raji et al. (2020) [33] further highlight organisational accountability gaps and the importance of systematic auditing procedures. In the proposed three-level structure, determining responsibility for technological failures may be especially difficult when AI systems are developed by one organisation, adapted by another, and deployed in settings affecting numerous beneficiaries. Effective governance would therefore require clear allocation of responsibilities without assuming that each level possesses equal authority or identical obligations.

(6) Environmental Sustainability and Resource Consumption: The expansion of computationally intensive AI may increase demand for electricity, specialised hardware, data-centre infrastructure, and associated natural resources. Strubell et al. (2019) examine the financial and environmental implications of training deep-learning models and emphasise the importance of considering computational resource requirements in AI research. Bender et al. (2021) similarly highlight environmental and financial concerns associated with very large language models. Although the environmental footprint of hypothetical AGI and ASI systems cannot presently be established, future technological development may require careful consideration of energy efficiency, resource availability, environmental accountability, and sustainable infrastructure.

8.6 Integrated SWOC Matrix:

The preceding analysis identifies several interconnected factors that may influence the proposed Three-Level Cognitive Cross-Pollination Model. **Table 3** summarises the principal Strengths, Weaknesses, Opportunities, and Challenges from the perspectives of the three stakeholder levels and the overall cognitive cross-pollination system.

Table 3: SWOC Analysis of the Proposed Three-Level Cognitive Cross-Pollination Model of a Future AGI/ASI Society

Stakeholder level	Strengths	Weaknesses	Opportunities	Challenges

Level 1: AI Developers and Controllers	Specialised technical expertise; AI system development; safety evaluation capabilities; technological innovation	Limited direct knowledge of all industry contexts; dependence on external feedback; potential concentration of technical authority	Advanced research; interdisciplinary innovation; safer system architectures; collaborative technological development	Alignment and control uncertainties; accountability; safety failures; financial and environmental resource requirements
Level 2: Industry Application Integrators	Domain-specific expertise; application adaptation; operational knowledge; translation between developers and users	Dependence on technology providers; integration complexity; variable organisational readiness; intermediary communication gaps	New industrial applications; productivity improvement; service innovation; professional capability development	Interoperability; implementation failures; regulatory compliance; workforce adaptation; competing stakeholder interests
Level 3: AI Beneficiaries	Contextual knowledge; practical experience; identification of real-world needs; user and societal feedback	Unequal technological literacy; limited decision-making influence; dependence on accessible and reliable applications	Improved services; education; workforce augmentation; inclusive innovation; greater participation in technological development	Privacy concerns; unfair outcomes; employment disruption; unequal access; reduced autonomy and technological dependence
Integrated Cognitive Cross-Pollination System	Complementary expertise; bidirectional knowledge exchange; collaborative learning; potential shared accountability	Coordination complexity; knowledge asymmetry; inconsistent feedback; uncertain allocation of responsibilities	Joint value creation; continuous improvement; participatory governance; socially responsive technological innovation	Conflicting interests; biased feedback loops; institutional fragmentation; concentration of power; uncertain AGI/ASI development

Source: Conceptual SWOC synthesis developed for the present study, informed by Helms and Nixon (2010) [26], Cohen and Levinthal (1990) [16], Carlile (2004) [17], Dellermann et al. (2019) [9], Jöhnk et al. (2021) [21], Floridi et al. (2018) [12], Selbst et al. (2019) [23], and other studies cited in this section.

The integrated matrix indicates that the proposed model's potential strengths arise primarily from complementary expertise and multidirectional knowledge exchange, whereas its weaknesses concern coordination difficulties, unequal capabilities, and dependence on effective communication and institutional arrangements. Opportunities are associated with technological innovation, industrial application, education, responsible governance, and societal participation. Challenges arise from technological uncertainty, ethical risks, economic inequalities, institutional fragmentation, and sustainability considerations.

8.7 Interpretation and Implications of the SWOC Analysis:

The SWOC Analysis suggests that the proposed Three-Level Cognitive Cross-Pollination Model possesses several potentially valuable structural characteristics, particularly the integration of technological knowledge, industrial expertise, and beneficiary perspectives within a common framework. The model's central strength lies in treating knowledge exchange as reciprocal rather than assuming a one-directional transfer of technology from developers to users. However, the analysis also indicates that effective cognitive cross-pollination requires more than the existence of communication

channels. It depends upon participants' ability to understand and apply exchanged knowledge, the willingness of institutions to incorporate external feedback, and the availability of appropriate organisational and governance mechanisms.

The findings further suggest that strengths and weaknesses may interact with external opportunities and challenges. For example, complementary expertise could support interdisciplinary innovation, but differences in technical capabilities may create barriers to meaningful collaboration. Similarly, continuous feedback could support technological improvement, but poorly designed feedback mechanisms may reinforce errors or biases. Expanded industrial integration may create productivity opportunities while simultaneously introducing workforce adjustment requirements and new accountability concerns. Therefore, the practical value of the proposed model would depend on how stakeholders manage such competing effects.

From a strategic perspective, the analysis supports the development of transparent knowledge-sharing arrangements, interdisciplinary collaboration, beneficiary participation, organisational readiness assessments, independent evaluation procedures, and appropriate governance mechanisms. Nevertheless, the findings are not empirical evidence that these arrangements will necessarily emerge or produce favourable outcomes in a future AGI/ASI society. They represent reasoned conceptual propositions derived from the existing literature on current AI systems, organisational learning, knowledge transfer, and technological governance.

In conclusion, the SWOC Analysis establishes that cognitive cross-pollination among AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries may provide a useful conceptual foundation for examining future AI-enabled societal relationships. Its potential effectiveness will depend on balancing technological innovation with organisational capabilities, ethical responsibility, equitable participation, human oversight, and environmental sustainability. The findings provide a basis for the subsequent ABCD Analysis, which examines the proposed model in greater detail through its Advantages, Benefits, Constraints, and Disadvantages from the perspectives of the three stakeholder groups.

9. ABCD ANALYSIS OF THE PROPOSED THREE-LEVEL COGNITIVE CROSS-POLLINATION MODEL :

9.1 Introduction to ABCD Analysis:

The Advantages, Benefits, Constraints, and Disadvantages (ABCD) Analysis Framework is a systematic qualitative evaluation technique used to examine the favourable and unfavourable characteristics of business models, strategies, operational concepts, organisational systems, and proposed conceptual frameworks. Aithal (2016) [28] introduced the ABCD analytical approach to identify and evaluate the critical factors influencing the effectiveness, feasibility, and potential consequences of a given model. The framework distinguishes between Advantages, representing favourable structural characteristics; Benefits, representing potential positive outcomes; Constraints, representing conditions that may restrict effective implementation; and Disadvantages, representing possible negative consequences arising from the model's adoption or functioning.

The present study applies ABCD Analysis to the proposed Three-Level Cognitive Cross-Pollination Model of a hypothetical Artificial General Intelligence (AGI) and Artificial Superintelligence (ASI) society. As illustrated in Figure 1, the model comprises three interconnected stakeholder groups: (1) AI Developers and Controllers, (2) Industry Application Integrators, and (3) AI Beneficiaries. These groups perform complementary functions involving technological development, industry-specific implementation, and the utilisation or experience of AI-enabled applications. Continuous knowledge exchange, collaborative learning, feedback, and shared value creation are considered the principal mechanisms connecting the three levels. Carlile (2004) demonstrates the importance of transferring, translating, and transforming knowledge across organisational boundaries, while Dellermann et al. (2019) [9] highlight the complementary potential of human and artificial intelligence.

Unlike the preceding SWOC Analysis, which examines strategic strengths, weaknesses, opportunities, and challenges at an overall system level, the present ABCD Analysis focuses specifically on **stakeholder-wise value propositions, expected outcomes, implementation barriers, and potential adverse consequences**. The analysis is qualitative, literature-informed, and exploratory. Since AGI and ASI remain hypothetical technological possibilities, the identified factors represent conceptual

assessments rather than empirically measured outcomes or established characteristics of a future society.

9.2 ABCD Analysis from the Perspective of AI Developers and Controllers:

9.2.1 Advantages:

(1) Access to Diverse Knowledge and Practical Requirements: AI Developers and Controllers may benefit from systematic access to industry-specific knowledge and beneficiary experiences through the proposed cross-pollination network. Such information can help technical teams identify practical requirements, evaluate system limitations, and improve the contextual relevance of future AI applications. Cohen and Levinthal (1990) [16] demonstrate that an organisation's ability to recognise and assimilate external knowledge is important for innovation. The proposed model provides a conceptual mechanism through which developers may obtain relevant knowledge from multiple organisational and societal environments.

(2) Opportunities for Collaborative Technological Development: Interactions with Industry Application Integrators and AI Beneficiaries may allow developers to collaborate with professionals possessing complementary expertise. Carlile (2004) [17] explains how knowledge translation and transformation across specialised domains can support innovation. Consequently, the three-level structure may strengthen problem identification, interdisciplinary research, and the development of application-oriented AI capabilities.

(3) Improved Access to System Evaluation and Feedback: The model creates opportunities for collecting information concerning application performance, usability, reliability, accessibility, and potential adverse consequences. Feedback from real-world deployment contexts may assist developers in identifying issues that are not apparent during laboratory evaluations. Raji et al. (2020) [33] emphasise systematic evaluation and accountability throughout the AI development lifecycle, supporting the importance of structured feedback and auditing mechanisms.

9.2.2 Benefits

(1) Potential Improvement in Technological Reliability: Continuous interaction with industry integrators and beneficiaries may support improvements in AI system evaluation, error identification, and application suitability. Such benefits would depend on reliable feedback, appropriate testing procedures, and the capacity to incorporate external knowledge into technical development processes (Raji et al., 2020 [33]).

(2) Enhanced Innovation and Application Relevance: Exposure to diverse industrial requirements may encourage developers to identify new applications, refine technological architectures, and respond more effectively to practical problems. Duan et al. (2019) [19] discuss the opportunities and challenges associated with integrating AI into organisational decision-making, illustrating the importance of connecting technological development with application requirements.

(3) Potential Improvement in Trust and Institutional Legitimacy: Transparent engagement with users, application organisations, and oversight institutions may support more accountable technological development. Floridi et al. (2018) [12] establish ethical principles for beneficial AI, while Shneiderman (2020) emphasises reliable, safe, and trustworthy human-centred systems. Accordingly, participatory evaluation and appropriate safeguards may strengthen confidence in AI development processes.

9.2.3 Constraints

(1) High Requirements for Technical and Organisational Resources: Developing, evaluating, and maintaining increasingly capable AI systems may require substantial computational infrastructure, specialised expertise, financial resources, and technical coordination. Bender et al. (2021) [40] identify the financial and environmental costs associated with large-scale language-model development, highlighting resource-related limitations relevant to advanced AI research.

(2) Difficulties in Interpreting Diverse Stakeholder Feedback: Developers may receive inconsistent or conflicting requirements from industries, users, and governance institutions. Differences in technical knowledge, terminology, expectations, and organisational priorities can restrict the effective utilisation of external information. Carlile (2004) [17] identifies knowledge boundaries that must be addressed through transfer, translation, and transformation.

(3) Safety, Governance, and Accountability Requirements: Increasingly capable systems may require extensive testing, monitoring, documentation, human oversight, and independent evaluation. These activities can impose significant development and operational demands. Raji et al. (2020) [33] demonstrate the organisational complexity associated with establishing comprehensive algorithmic accountability procedures.

9.2.4 Disadvantages:

(1) Increased Exposure to Accountability and Reputational Risks: AI Developers and Controllers may face legal, institutional, and reputational consequences when systems generate harmful or unreliable outcomes. In a complex development-and-deployment ecosystem, responsibility may be distributed across several organisations, creating uncertainty regarding accountability (Jobin et al., 2019 [6]; Raji et al., 2020 [33]).

(2) Risk of Inappropriate Feedback-Based System Modification: Continuous feedback does not necessarily lead to technological improvement. Glickman and Sharot (2025) [36] demonstrate that human–AI feedback loops may amplify existing biases under certain conditions. If feedback data are inaccurate, unrepresentative, or insufficiently evaluated, technical modifications could reinforce undesirable system behaviour.

(3) Potential Concentration of Technological Power: Resource-intensive development may strengthen the influence of a limited number of technology providers and reduce the diversity of participating organisations. Bender et al. (2021) [40] highlight concerns about resource demands and the broader consequences of large-scale AI development. Such concentration may weaken meaningful stakeholder participation and create unequal relationships between technological developers and other societal groups.

9.3 ABCD Analysis from the Perspective of Industry Application Integrators:

9.3.1 Advantages:

(1) Access to Advanced Technological Capabilities: Industry Application Integrators may obtain specialised AI capabilities, development platforms, technical documentation, and implementation support from AI Developers and Controllers. This access can enable organisations to develop sector-specific applications without independently creating every underlying technology. Duan et al. (2019) [19] highlight the growing importance of integrating AI capabilities into organisational decision-making.

(2) Strategic Intermediary Position: Integrators occupy an important position between technological developers and application beneficiaries. They can interpret technical capabilities, communicate industry-specific requirements, and translate user experiences into actionable implementation feedback. Carlile (2004) [17] provides a theoretical explanation of how such knowledge translation can facilitate collaboration across specialised organisational boundaries.

(3) Opportunities for Human–AI Capability Integration: Integrators can combine computational capabilities with professional expertise, organisational processes, and contextual judgement. Jarrahi (2018) [8] examines the complementary contributions of humans and AI to organisational decision-making, while Dellermann et al. (2019) [9] discuss hybrid intelligence as a means of combining human and artificial capabilities.

9.3.2 Benefits:

(1) Potential Improvements in Productivity and Operational Efficiency: Appropriate AI integration may support selected improvements in task performance, professional assistance, and service delivery. Brynjolfsson et al. (2025) [22] report productivity gains following the introduction of generative AI assistance in a customer-support environment. Although these results concern existing AI technology rather than AGI or ASI, they provide empirical evidence of possible benefits from carefully designed AI integration.

(2) Development of New Applications and Business Opportunities: Integration capabilities may enable organisations to develop specialised products, services, decision-support systems, and innovative operational processes. The complementary roles of human expertise and intelligent systems discussed by Jarrahi (2018) [8] provide a foundation for exploring such opportunities.

(3) Improved Responsiveness to Customer and Stakeholder Requirements: By communicating directly with beneficiaries, integrators may identify unmet needs, usability problems, and changing application requirements. The resulting information can support application adaptation and more contextually appropriate technological solutions (Carlile, 2004 [17]; Jöhnk et al., 2021 [21]).

9.3.3 Constraints:

(1) Organisational Readiness and Implementation Capabilities: Successful integration depends on appropriate infrastructure, technical expertise, employee preparedness, managerial commitment, and organisational resources. Jöhnk et al. (2021) [21] identify organisational readiness factors influencing AI adoption and emphasise the importance of aligning resources and capabilities with implementation objectives.

(2) Dependence on External Technology Providers: Integrators may depend on developers for access to underlying models, system updates, technical support, and essential infrastructure. Such dependence can restrict independent decision-making, increase switching costs, and reduce operational flexibility. These consequences are plausible strategic risks inferred from the proposed model rather than directly measured AGI/ASI outcomes.

(3) Regulatory and Interoperability Requirements: Integrating advanced AI into established organisational systems may require attention to data protection, security, technical compatibility, professional standards, and accountability. Jobin et al. (2019) [6] demonstrate differences in the interpretation and implementation of AI ethics requirements, indicating potential difficulties in maintaining consistent governance across sectors.

9.3.4 Disadvantages:

(1) Financial and Operational Exposure: AI integration may require expenditure on infrastructure, software adaptation, workforce training, maintenance, security, and compliance. Unsuccessful implementation could generate financial losses, operational interruptions, or limited returns on investment. Jöhnk et al. (2021) [21] identify organisational readiness as a significant consideration in reducing implementation difficulties.

(2) Responsibility for Inappropriate or Harmful Applications: Integrators may face accountability challenges when deployed AI systems produce inaccurate, discriminatory, or otherwise undesirable outcomes. Selbst et al. (2019) [23] explain that technological interventions can become ineffective or harmful when wider sociotechnical relationships are inadequately considered.

(3) Workforce Disruption and Organisational Resistance: AI deployment may alter existing occupational roles, professional responsibilities, and established workflows. Frank et al. (2019) [5] emphasise the complexity of anticipating AI-related employment changes, demonstrating the need to evaluate occupational tasks, workforce skills, and broader economic conditions.

9.4 ABCD Analysis from the Perspective of AI Beneficiaries:

9.4.1 Advantages:

(1) Access to AI-Enabled Knowledge and Decision Support: AI Beneficiaries may gain access to intelligent systems supporting learning, professional activities, problem-solving, information retrieval, and decision-making. Jarrahi (2018) [8] demonstrates the complementary potential of computational analysis and human judgement, suggesting that AI may provide valuable assistance in complex organisational contexts.

(2) Opportunities for Personalised and Context-Specific Services: Industry integrators may adapt general AI capabilities to particular user requirements, professional contexts, educational needs, and service environments. This may enable beneficiaries to access applications that are more responsive to their circumstances, provided that accessibility, reliability, and appropriate human oversight are maintained (Shneiderman, 2020) [7].

(3) Participation in Technological Development: The proposed model recognises beneficiaries as contributors of contextual knowledge, experiences, feedback, and ethical perspectives rather than passive recipients of technology. This role offers opportunities to communicate needs and participate in application evaluation. Floridi et al. (2018) [12] establish the importance of human welfare, autonomy, and justice in responsible AI development.

9.4.2 Benefits:

(1) Potential Improvements in Individual and Professional Productivity: AI-enabled assistance may improve the efficiency and quality of certain activities. Noy and Zhang (2023) [15] found improvements in task completion time and output quality when participants used generative AI for professional writing tasks. However, these results are task-specific and cannot be treated as evidence of equivalent benefits from hypothetical AGI or ASI systems.

(2) Enhanced Learning and Skill Development: Intelligent applications may assist beneficiaries in acquiring knowledge, developing professional competencies, and adapting to changing workplace requirements. Brynjolfsson et al. (2025) [22] report evidence of learning-related benefits among workers using AI assistance, particularly for less-experienced employees.

(3) Potential Improvements in Accessibility and Quality of Life: Appropriately designed AI applications may support education, healthcare-related services, communication, administrative assistance, and other activities. Shneiderman (2020) [7] advocates systems that combine automation with human control, providing a conceptual foundation for developing applications responsive to individual and societal needs.

(4) Increased Opportunities for Participation in Knowledge Creation: Beneficiaries may contribute observations, practical knowledge, and local experiences that influence application improvement and technological refinement. Cohen and Levinthal (1990) [16] and Carlile (2004) [17] provide theoretical foundations for understanding how externally generated knowledge can contribute to innovation when relevant knowledge-transfer mechanisms exist.

9.4.3 Constraints:

(1) Unequal Digital Literacy and Technological Access: Beneficiaries may differ substantially in technical understanding, educational background, financial resources, language proficiency, and access to digital infrastructure. Such inequalities may restrict their ability to utilise advanced AI applications or participate meaningfully in development processes.

(2) Dependence on Application Availability and Reliability: Beneficiaries generally rely on developers and integrating organisations for system functionality, service continuity, technical support, and appropriate safeguards. Limited transparency or inadequate technical assistance may reduce their ability to evaluate system recommendations independently.

(3) Privacy, Security, and Consent Requirements: Effective AI-enabled services may depend on the collection, processing, or exchange of personal and organisational information. Jobin et al. (2019) [6] identify privacy, transparency, and responsibility as central concerns in AI governance, indicating the importance of safeguarding beneficiary interests.

(4) Limited Influence over Technological Decisions: Beneficiaries may not possess sufficient institutional authority or technical expertise to influence important development, deployment, or governance decisions. Selbst et al. (2019) [23] highlight the risks of technological approaches that inadequately incorporate broader social perspectives.

9.4.4 Disadvantages:

(1) Potential Employment Displacement and Skill Obsolescence: Increased AI capabilities may automate or substantially transform selected tasks and professional responsibilities. Frank et al. (2019) [5] demonstrate that understanding AI-related labour-market changes requires consideration of occupational structures, skills, and economic conditions. Consequently, some beneficiaries may experience employment insecurity or increased pressure to acquire new competencies.

(2) Technological Dependence and Reduced Human Autonomy: Excessive reliance on intelligent systems may weaken independent judgement or encourage inappropriate delegation of important decisions. Shneiderman (2020) [7] emphasises the need to maintain meaningful human control, particularly in applications involving consequential outcomes.

(3) Exposure to Bias and Inaccurate Recommendations: AI beneficiaries may experience unfair treatment, misleading information, or distorted decision-making outcomes. Glickman and Sharot (2025) [36] provide experimental evidence that interactions with biased AI systems can amplify certain human judgement biases. Such findings highlight the importance of independent evaluation and responsible use.

(4) Unequal Distribution of Economic and Societal Benefits: AI-enabled productivity gains may not be shared equally among individuals, occupations, organisations, and communities. Brynjolfsson et al. (2025) [22] document heterogeneous productivity effects across workers, while Frank et al. (2019) [5] emphasise the importance of examining differences in occupational exposure to technological change. The proposed model must therefore consider how benefits, costs, and risks could be distributed across society.

9.5 Integrated Stakeholder-Wise ABCD Matrix:

The preceding analysis demonstrates that the proposed Three-Level Cognitive Cross-Pollination Model may generate different advantages, benefits, constraints, and disadvantages for each stakeholder group. Table 4 consolidates the principal factors identified through the qualitative assessment.

Table 4: Stakeholder-Wise ABCD Analysis of the Proposed Three-Level Cognitive Cross-Pollination Model

Stakeholder group	Advantages	Benefits	Constraints	Disadvantages
Level 1: AI Developers and Controllers	Access to diverse knowledge; interdisciplinary collaboration; application feedback; technical expertise	Improved system evaluation; context-relevant innovation; potential gains in reliability and institutional trust	High computational costs; conflicting stakeholder requirements; safety obligations; complex accountability procedures	Reputational and liability exposure; biased feedback; possible concentration of technological influence
Level 2: Industry Application Integrators	Access to advanced AI capabilities; intermediary knowledge-translation role; domain expertise; human–AI integration opportunities	Potential productivity improvements; innovative applications; improved service delivery; greater responsiveness to user needs	Organisational readiness; interoperability; dependence on technology providers; training and compliance requirements	Financial exposure; implementation failures; workforce disruption; accountability for harmful applications
Level 3: AI Beneficiaries	Access to AI-enabled services; decision support; personalised applications; opportunities for feedback and participation	Potential productivity improvements; learning support; improved accessibility; enhanced service experiences	Digital literacy gaps; unequal access; limited technical understanding; privacy requirements; restricted decision influence	Employment insecurity; technological dependence; biased or inaccurate outputs; unequal benefit distribution
Integrated Three-Level System	Complementary expertise; multidirectional knowledge exchange; collaborative learning; broader stakeholder participation	Potential joint value creation; continuous application improvement; more responsive governance; socially relevant innovation	Coordination complexity; knowledge asymmetry; institutional fragmentation; unequal participation; uncertain AGI/ASI development	Diffused accountability; power imbalances; feedback amplification of errors; uneven distribution of costs and benefits

Source: Conceptual ABCD synthesis developed for the present study, based on Aithal (2016) [28], Cohen and Levinthal (1990) [16], Carlile (2004) [17], Jarrahi (2018) [8], Dellermann et al. (2019) [9], Jöhnk et al. (2021) [21], Floridi et al. (2018) [12], Raji et al. (2020) [33], and other literature cited in this section.

The integrated matrix indicates that the proposed model's major advantages arise from complementary expertise, access to technological capabilities, and opportunities for multidirectional knowledge exchange. Potential benefits include technological improvements, industrial productivity, professional assistance, and more responsive applications. Constraints primarily concern resources, organisational readiness, unequal technological knowledge, institutional coordination, and governance requirements. Disadvantages include possible financial losses, employment disruption, bias amplification, excessive technological dependence, and unequal distribution of benefits.

9.6 Comparative Interpretation and Strategic Implications:

The stakeholder-wise ABCD Analysis suggests that the proposed Three-Level Cognitive Cross-Pollination Model may create different forms of value for participants occupying different positions within the AI development and application ecosystem. AI Developers and Controllers may obtain technical and application-related knowledge that supports innovation and system refinement. Industry Application Integrators may benefit from the ability to transform advanced technological capabilities into practical applications and services. AI Beneficiaries may gain access to knowledge, professional assistance, and improved services while contributing information about actual societal requirements. However, these potential advantages depend upon the availability of effective knowledge-transfer processes, appropriate organisational capabilities, reliable evaluation, and responsible governance arrangements.

The analysis also indicates that **advantages and benefits should not be treated as identical**. Access to advanced AI technology represents an advantage for an integrating organisation, but improved productivity constitutes a benefit only when that technology is implemented effectively and produces favourable outcomes. Similarly, beneficiary participation represents a structural advantage of the proposed model, but improved fairness, accessibility, or service quality cannot be assumed merely because feedback mechanisms exist. These distinctions are consistent with the evaluative purpose of the ABCD framework proposed by Aithal (2016) [28].

The constraints and disadvantages also differ in their implications. Limited technological literacy represents a constraint that may hinder participation, whereas an inaccurate or discriminatory AI-generated decision constitutes a possible disadvantage experienced through the system's operation. Likewise, high implementation costs are constraints for integrating organisations, while financial losses resulting from unsuccessful deployment are potential disadvantages. Recognising these distinctions enables a clearer evaluation of the model's practical feasibility and possible stakeholder consequences.

From a strategic management perspective, the findings suggest four important conditions for improving the proposed model's potential effectiveness. First, **knowledge-sharing and knowledge-translation mechanisms** should be designed to accommodate differences in technical expertise and professional understanding. Second, **organisational readiness and implementation capabilities** should be assessed before introducing advanced AI applications. Third, **beneficiary participation and feedback processes** should be supported by meaningful opportunities to identify problems and influence corrective decisions. Fourth, **governance and accountability arrangements** should establish responsibilities for system development, deployment, monitoring, incident response, and protection of affected stakeholders. These implications are consistent with the broader scholarly emphasis on organisational readiness, human-centred design, and responsible AI governance (Jöhnk et al., 2021 [21]; Floridi et al. 2018 [21]; Shneiderman, 2020 [7]).

The analysis further suggests that technological benefits and societal disadvantages may emerge simultaneously. Improvements in productivity could coexist with employment displacement; increased technological accessibility could be accompanied by greater dependence on platform providers; and continuous feedback could support innovation while also creating opportunities for bias amplification. Consequently, the proposed model should not be evaluated solely through technological performance or economic efficiency. Its potential value should also be examined in terms of human autonomy, fairness, accountability, inclusive participation, and the distribution of benefits and risks.

9.7 Findings and Implications for Future Research:

The ABCD Analysis produces four principal conceptual findings. First, **AI Developers and Controllers** may gain advantages from access to diverse knowledge and application feedback, but face substantial technical, financial, safety, and accountability requirements. Second, **Industry Application**

Integrators may occupy an important position in translating AI capabilities into industrial value, but their effectiveness depends on organisational readiness, integration capabilities, and access to reliable technologies. Third, **AI Beneficiaries** may experience improvements in knowledge access, professional assistance, and service quality, but also face challenges involving digital inequality, privacy, technological dependence, and workforce adaptation. Fourth, the overall success of the proposed system depends on the effectiveness of multidirectional knowledge exchange and the institutional arrangements governing technological responsibilities and societal participation.

These findings support the conceptual proposition that cognitive cross-pollination could contribute to joint value creation when technical innovation, industrial adaptation, and beneficiary knowledge are integrated through effective collaboration. However, the magnitude, distribution, and durability of such benefits cannot be established through the present exploratory methodology. The study does not employ stakeholder surveys, field experiments, operational performance measurements, or empirical observations of an existing AGI/ASI society. Accordingly, the identified ABCD factors should be regarded as literature-informed conceptual possibilities rather than empirically validated results.

Future research may extend the proposed analysis by developing measurable indicators of cross-level knowledge exchange, stakeholder participation, organisational readiness, feedback effectiveness, accountability, and perceived benefits. Surveys involving AI developers, industrial application specialists, organisational decision-makers, and AI users could be employed to evaluate the relevance of the identified factors in existing AI ecosystems. Comparative case studies and longitudinal investigations could further examine how knowledge-sharing relationships influence application quality, institutional accountability, and value distribution as AI capabilities evolve.

In conclusion, the ABCD Analysis provides a multidimensional assessment of the proposed Three-Level Cognitive Cross-Pollination Model from the perspectives of its three stakeholder groups. It highlights the importance of balancing technological development and industrial innovation with practical implementation requirements, human participation, ethical responsibility, and equitable distribution of outcomes. The findings provide a foundation for the subsequent PESTLE Analysis, which examines the external political, economic, social, technological, legal, and environmental conditions that may influence the development and operation of the proposed model in a hypothetical future AGI/ASI society.

10. PESTLE ANALYSIS OF THE PROPOSED THREE-LEVEL COGNITIVE CROSS-POLLINATION MODEL :

10.1 Introduction to PESTLE Analysis:

Political, Economic, Social, Technological, Legal, and Environmental (PESTLE) Analysis is a strategic assessment framework used to examine the macro-environmental factors influencing the development, operation, and sustainability of organisations, technological systems, and proposed societal structures. The framework provides a systematic approach to understanding external conditions that may create opportunities, impose constraints, or generate risks. Yüksel (2012) [29] emphasises the importance of examining relationships among macro-environmental factors rather than treating them as entirely independent variables. In the context of emerging Artificial General Intelligence (AGI) and Artificial Superintelligence (ASI), PESTLE Analysis offers a useful conceptual approach for assessing the broader institutional, economic, social, technological, regulatory, and environmental conditions that could influence the development and application of advanced intelligent systems.

The present study applies PESTLE Analysis to the proposed Three-Level Cognitive Cross-Pollination Model**,** comprising (1) AI Developers and Controllers, (2) Industry Application Integrators, and (3) AI Beneficiaries. As presented in Figure 1, these stakeholder groups are interconnected through multidirectional exchanges of technological knowledge, industry-specific expertise, operational feedback, user experiences, and governance considerations. Their relationships may be influenced by national AI policies, economic restructuring, societal expectations, technological capabilities, regulatory obligations, and environmental sustainability requirements. Taeihagh (2021) [41] demonstrates that AI governance involves complex relationships among technological developments, public policy, institutions, and society. Accordingly, the present analysis examines how the six macro-environmental dimensions may affect the three stakeholder groups individually and collectively. Since AGI and ASI remain uncertain technological possibilities, the identified influences represent literature-informed conceptual assessments rather than empirically established characteristics of a future society.

10.2 Political Influences:

Political factors involve government policies, national technology strategies, international cooperation, geopolitical relationships, public-sector investment, institutional governance, and the distribution of authority over advanced AI development. Governments and international organisations may significantly influence the development and deployment of increasingly capable AI systems through research funding, infrastructure investment, public procurement, strategic priorities, and regulatory coordination. Taeihagh (2021) [41] examines emerging AI governance approaches and emphasises the challenges governments face in responding to rapid technological change. Radu (2021) [42] further analyses national AI strategies, demonstrating how political priorities and institutional perspectives influence approaches to AI development and governance.

For **AI Developers and Controllers**, political conditions may affect access to research funding, computational resources, advanced technologies, international collaboration, and institutional oversight. Government-supported research programmes could encourage innovation and safety evaluation, whereas geopolitical tensions or restrictions on technological cooperation could limit cross-border knowledge exchange. For **Industry Application Integrators**, national digital-transformation policies, public infrastructure initiatives, and sector-specific technology programmes may influence the adoption and commercialisation of advanced AI applications. For **AI Beneficiaries**, political decisions may affect access to publicly supported AI services, opportunities for digital participation, and mechanisms for representing societal concerns in technological policymaking.

Political influences may also create challenges concerning the concentration of technological power and the relationship between public institutions and private AI developers. Gasser and Almeida (2017) [43] propose a layered approach to AI governance, highlighting information asymmetries between technology developers, users, and policymakers. These asymmetries may complicate informed political oversight and public participation. Within the proposed three-level model, effective cognitive cross-pollination would therefore benefit from transparent public consultation, multidisciplinary policy development, international research cooperation, and institutional arrangements that allow technical specialists, industry organisations, and affected communities to contribute to governance decisions. Political governance is understood here as the setting of public priorities and institutional arrangements, while specific enforceable obligations are considered separately under the Legal dimension.

10.3 Economic Influences:

Economic factors include productivity, employment, income distribution, investment, technological adoption costs, industrial competitiveness, market concentration, and the creation of new products and services. Increasingly capable AI may influence economic activity by automating selected tasks, augmenting professional capabilities, reducing certain operational costs, and creating opportunities for new industries. However, technological change may also alter labour demand, create adjustment costs, and distribute economic benefits unevenly. Acemoglu and Restrepo (2019) [44] explain that automation can displace labour from existing tasks while the creation of new tasks may generate countervailing employment opportunities. Their task-based framework highlights the importance of examining both displacement and reinstatement effects when evaluating the economic consequences of technological development.

Empirical research on current AI technologies provides additional evidence concerning potential economic opportunities. Brynjolfsson et al. (2025) [22] examined generative AI assistance in customer-support operations and identified productivity improvements, with substantial variation across employees. These findings suggest that appropriate technological integration can generate economic benefits, although they do not demonstrate equivalent effects for hypothetical AGI or ASI systems. For **AI Developers and Controllers**, economic opportunities may include technological innovation, research investment, licensing arrangements, and the creation of advanced intelligent systems. Simultaneously, substantial development costs and infrastructure requirements may restrict participation and contribute to concentration among financially powerful organisations. Bender et al. (2021) [40] discuss the financial and resource-related challenges associated with increasingly large language models.

For **Industry Application Integrators**, economic opportunities may arise through process automation, new business models, improved service delivery, specialised applications, and enhanced decision support. However, implementation costs, organisational restructuring, workforce training, and

dependence on external technology providers may restrict the realisation of benefits. For **AI Beneficiaries**, advanced AI applications could improve access to services, professional productivity, education, and economic opportunities. Nevertheless, some individuals may experience task displacement, skill obsolescence, employment insecurity, or unequal access to technological benefits. Accordingly, cognitive cross-pollination may support economic value creation by connecting technological capabilities with industrial requirements and beneficiary needs, but its broader effectiveness would depend on appropriate investment, workforce adaptation, competition, and mechanisms for distributing benefits and costs.

10.4 Social Influences:

Social factors include demographic characteristics, education, technological literacy, cultural values, public trust, social inclusion, professional identity, human autonomy, and attitudes towards intelligent technologies. The introduction of increasingly capable AI systems may influence how individuals learn, work, communicate, make decisions, and participate in society. Social acceptance may depend not only on technological performance but also on perceptions of reliability, fairness, transparency, accessibility, and human control. Floridi et al. (2018) [12] emphasise the importance of beneficence, non-maleficence, autonomy, justice, and explicability in developing socially beneficial AI systems. Similarly, Jobin et al. (2019) [6] identify transparency, fairness, responsibility, privacy, and non-maleficence as recurring principles in international AI ethics guidelines, while recognising differences in their interpretation and implementation.

The three stakeholder groups may experience these influences differently. **AI Developers and Controllers** must consider the social consequences of system design, training data, evaluation methods, and deployment decisions. **Industry Application Integrators** must adapt technologies to different professional practices, cultural contexts, educational backgrounds, and user requirements. **AI Beneficiaries** may contribute practical experiences, social expectations, accessibility requirements, and information concerning unintended consequences. However, unequal digital literacy, differences in socioeconomic conditions, and limited opportunities for participation may restrict the effectiveness of knowledge exchange.

The social dimension also requires attention to the possibility of harmful feedback relationships. Selbst et al. (2019) [23] demonstrate that algorithmic fairness problems cannot be adequately understood without considering the broader sociotechnical environment. Glickman and Sharot (2025) [36] provide experimental evidence that interactions with biased AI systems can amplify certain biases in human judgements. These findings suggest that continuous interaction between humans and intelligent systems does not necessarily produce favourable cognitive outcomes. In the proposed model, responsible cognitive cross-pollination would therefore require inclusive participation, accessible communication, AI literacy, independent evaluation, and mechanisms for identifying and correcting harmful social effects. Particular attention should be given to ensuring that beneficiaries can communicate concerns meaningfully rather than serving only as passive sources of application data.

10.5 Technological Influences:

Technological factors concern the capabilities, reliability, scalability, interoperability, security, adaptability, and accessibility of advanced AI systems. The proposed AGI/ASI society depends conceptually on continued developments in machine learning, intelligent system architectures, computational infrastructure, data processing, automated reasoning, and human–AI interaction. However, future technological progress cannot be assumed to follow a predetermined pathway. Bender et al. (2021) [40] highlight important limitations and risks associated with large language models, including data quality, representational bias, resource consumption, and insufficient consideration of development objectives. These concerns demonstrate that increasing technological scale does not automatically guarantee reliability, general intelligence, or societal usefulness.

For **AI Developers and Controllers**, technological influences include advances in system architectures, model evaluation, cybersecurity, safety testing, computational efficiency, and monitoring capabilities. The ability to develop systems that are reliable, adaptable, and appropriately governed would be important for transferring advanced capabilities to application integrators. For **Industry Application Integrators**, technical interoperability, system compatibility, data quality, organisational infrastructure, and application-specific validation may determine whether advanced AI capabilities can

be translated effectively into operational environments. Jöhnk et al. (2021) [21] identify organisational readiness factors influencing AI adoption, indicating that successful implementation depends on more than access to intelligent technologies.

For **AI Beneficiaries**, technological influences involve usability, reliability, affordability, accessibility, service continuity, and the capacity to understand relevant system limitations. The three-level model assumes that knowledge exchange can help align technological development with practical requirements and user experiences. Carlile (2004) [17] explains that collaboration across specialised domains requires knowledge transfer, translation, and transformation. This principle is relevant to the proposed relationship between technical developers, industry integrators, and beneficiaries.

However, technological interdependence may also create systemic vulnerabilities. Shared models, cloud platforms, or application infrastructures could transmit errors or failures across numerous organisations. Raji et al. (2020) [33] emphasise the importance of systematic auditing and accountability throughout the AI development lifecycle. Consequently, technological cross-pollination should incorporate documented evaluation procedures, independent testing, secure information exchange, interoperability standards, and mechanisms for communicating system limitations and emerging risks.

10.6 Legal Influences:

Legal factors include data protection, privacy, intellectual property rights, contractual responsibility, product and service liability, consumer protection, discrimination, cybersecurity obligations, and the regulation of automated decision-making. As AI technologies become integrated into increasingly consequential organisational and societal activities, legal systems may need to clarify the rights and responsibilities of developers, deploying organisations, professional users, and affected individuals. Wachter et al. (2017) [45] examine the interpretation of automated decision-making provisions under the European Union's General Data Protection Regulation, demonstrating that the relationship between transparency, explanation, and legally enforceable rights requires careful analysis. Their work cautions against treating broad ethical expectations as identical to specific statutory obligations.

For **AI Developers and Controllers**, legal considerations may concern intellectual property, data acquisition, model documentation, contractual obligations, system safety, and responsibility for technical defects or foreseeable misuse. For **Industry Application Integrators**, legal responsibilities may involve sector-specific compliance, appropriate deployment, data protection, cybersecurity, consumer safeguards, and the management of contractual relationships with technology providers. For **AI Beneficiaries**, relevant legal considerations include privacy, protection from unlawful discrimination, access to appropriate remedies, contractual rights, and opportunities to challenge certain consequential decisions where applicable law provides such protections.

A central legal challenge arises from the distribution of responsibility across the development and deployment ecosystem. When an AI system is designed by one organisation, integrated by another, and used in a context affecting numerous individuals, determining responsibility for harmful outcomes may involve complex factual and legal questions. Raji et al. (2020) [33] identify accountability gaps within AI development processes and propose organisational auditing mechanisms to improve traceability and responsibility. Jobin et al. (2019) [6] further demonstrate that international AI ethics principles vary in their interpretation and implementation. Within the proposed model, effective legal governance may therefore require clear contractual arrangements, documented responsibilities, appropriate oversight, transparent incident-reporting procedures, and accessible mechanisms for redress.

However, the three-level conceptual model cannot itself determine legal liability. Legal duties would depend on the jurisdiction, applicable legislation, industry, contractual relationships, and nature of the particular AI application. Moreover, the potential development of AGI or ASI may create legal questions that existing frameworks do not fully anticipate. The present analysis therefore identifies possible areas of legal influence without assuming that hypothetical AGI/ASI systems possess a particular legal status or that uniform international rules will emerge.

10.7 Environmental Influences:

Environmental factors involve energy consumption, greenhouse-gas emissions, computational infrastructure, water use, electronic waste, hardware production, resource efficiency, and the broader ecological consequences of technological development and application. Advanced AI systems may

require extensive computational resources for model development, training, deployment, and continuous operation. Strubell et al. (2019) [46] examine the energy consumption and financial and environmental costs associated with training deep-learning models. Similarly, de Vries (2023) [47] highlights concerns regarding the growing electricity requirements of AI-related computational infrastructure. These studies indicate that technological progress should be evaluated not only through computational performance but also through resource consumption and environmental consequences.

For **AI Developers and Controllers**, environmental influences may include the energy efficiency of computational architectures, the carbon intensity of electricity supplies, hardware requirements, and the environmental implications of model development. For **Industry Application Integrators**, sustainability considerations may involve selecting computationally appropriate systems, improving operational efficiency, reducing unnecessary processing, and incorporating environmental indicators into technology procurement and deployment decisions. For **AI Beneficiaries**, relevant influences may include the environmental consequences of widespread AI service consumption, changes in resource availability, and the potential use of intelligent applications to support energy management, environmental monitoring, and sustainability-related decisions.

However, the environmental effects of AI are not necessarily negative. Kaack et al. (2022) [48] propose a framework for examining the relationship between AI and climate-change mitigation, distinguishing computing-related emissions, the immediate consequences of AI applications, and broader system-level effects. Their analysis demonstrates that AI may support emissions reductions in some contexts while increasing energy consumption or enabling environmentally harmful activities in others. Consequently, the overall environmental implications of advanced AI depend on technological design, application selection, energy systems, institutional policies, and the indirect effects of deployment.

Within the proposed three-level model, environmental cognitive cross-pollination may involve developers communicating energy and resource requirements, integrators identifying opportunities for efficiency improvements, and beneficiaries providing feedback concerning environmental priorities and application outcomes. Joint sustainability assessments could help stakeholders evaluate environmental trade-offs rather than assuming that greater computational intelligence necessarily produces sustainable development. Since future AGI and ASI architectures remain uncertain, their specific environmental footprints cannot presently be established.

10.8 Integrated PESTLE Matrix:

The preceding analysis indicates that Political, Economic, Social, Technological, Legal, and Environmental factors may influence the three stakeholder groups differently while simultaneously shaping the relationships connecting them. Table 5 consolidates the principal macro-environmental influences and their implications for cognitive cross-pollination.

Table 5: PESTLE Analysis of the Proposed Three-Level Cognitive Cross-Pollination Model of a Future AGI/ASI Society

PESTLE Dimension	AI Developers and Controllers	Industry Application Integrators	AI Beneficiaries	Implications for Cognitive Cross-Pollination
Political	Research funding, national AI strategies, international cooperation, and public oversight	Digital-transformation policies, industrial incentives, and government-supported adoption	Public access, participation, inclusion, and representation in technology policy	Requires transparent communication, institutional coordination, and participation in governance
Economic	Development costs, innovation investment, infrastructure concentration, and commercial opportunities	Productivity, implementation costs, competition, operational efficiency, and workforce restructuring	Employment, income, affordability, professional opportunities, and distribution of benefits	Requires knowledge sharing, economic adaptation, and attention to equitable benefit distribution

Social	Ethical system design, public trust, social responsibility, and responsiveness to affected communities	User-centred integration, professional adaptation, accessibility, and workforce readiness	Digital literacy, human autonomy, privacy expectations, inclusion, and social well-being	Requires meaningful feedback, accessible participation, trust, and responsiveness to diverse needs
Technological	System development, reliability, safety, scalability, and computational capabilities	Interoperability, application adaptation, technical infrastructure, and implementation quality	Usability, reliability, access, service continuity, and understanding of system limitations	Requires technical knowledge transfer, application feedback, system evaluation, and continuous improvement
Legal	Intellectual property, data protection, documentation, safety obligations, and potential liability	Sector-specific compliance, contractual responsibilities, security, and deployment accountability	Privacy, consumer safeguards, applicable rights, and access to remedies	Requires clear allocation of responsibilities, traceability, documentation, and appropriate redress mechanisms
Environmental	Computing resources, hardware requirements, energy consumption, and emissions	Sustainable deployment, efficiency, procurement choices, and environmental monitoring	Resource impacts, environmental awareness, and access to sustainability-supporting services	Requires shared environmental information, life-cycle assessment, and coordinated sustainability initiatives

Source: Conceptual PESTLE synthesis developed for the present exploratory study, informed by Yüksel (2012) [29], Taeihagh (2021) [41], Acemoglu and Restrepo (2019) [44], Floridi et al. (2018) [12], Jöhnk et al. (2021) [21], Wachter et al. (2017) [45], Strubell et al. (2019) [46], and Kaack et al. (2022) [48].

The integrated matrix indicates that the proposed cognitive cross-pollination system would be influenced by interconnected macro-environmental conditions rather than by technological capabilities alone. Political priorities may shape funding and governance, economic conditions may determine investment and adoption, social factors may influence participation and acceptance, technological capabilities may affect operational feasibility, legal requirements may define responsibilities, and environmental considerations may influence the sustainability of continued technological expansion.

10.9 Interpretation and Strategic Implications:

The PESTLE Analysis suggests that the potential effectiveness of the proposed Three-Level Cognitive Cross-Pollination Model would depend on the interaction of several external conditions. Technological progress may create new opportunities for intelligent applications, but these opportunities could be restricted by economic inequalities, inadequate organisational capabilities, regulatory uncertainty, insufficient public trust, or environmental resource constraints. Similarly, favourable public policies and industrial investment might encourage technological adoption, while unequal access to knowledge and decision-making authority could restrict beneficiary participation.

The analysis also highlights the interdependence of the six PESTLE dimensions. For example, government investment in AI infrastructure represents a political decision with economic and technological consequences. Increased automation may produce economic benefits while generating social concerns about employment and professional identity. Legal requirements concerning accountability and data protection may influence technological design, implementation costs, and user confidence. Environmental policies may encourage computational efficiency while altering the economics of AI development. Yüksel (2012) [29] emphasises the importance of examining

relationships among macro-environmental factors, supporting the integrated interpretation adopted in this study.

From the perspective of cognitive cross-pollination, five strategic implications emerge. First, **adaptive and participatory governance** may support coordination among public institutions, AI developers, integrators, and affected communities. Second, **economic and educational preparedness** may improve the ability of organisations and individuals to adapt to technological changes. Third, **inclusive stakeholder participation** may strengthen the identification of social needs, fairness concerns, and unintended consequences. Fourth, **technical interoperability, evaluation, and accountability** may improve the reliability of knowledge exchange and practical integration. Fifth, **environmentally responsible development and deployment** may support the long-term sustainability of advanced AI applications.

However, the relative importance of these influences cannot be quantified through the present exploratory methodology. The study does not assign empirical weights to PESTLE factors, estimate the probability of AGI or ASI emergence, or measure the causal effects of particular policy or technological interventions. The identified relationships are conceptual interpretations informed by existing research on contemporary AI systems and their societal environments. Future investigations may employ stakeholder surveys, expert assessments, scenario planning, comparative case studies, or multicriteria decision-making techniques to examine the relevance and relative importance of the proposed factors.

The PESTLE Analysis provides a comprehensive macro-environmental assessment of the proposed Three-Level Cognitive Cross-Pollination Model of a hypothetical future AGI/ASI society. It demonstrates that the potential relationships among AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries must be considered within broader political, economic, social, technological, legal, and environmental contexts. These dimensions may simultaneously create opportunities for collaborative innovation, organisational development, improved services, and societal participation while introducing challenges involving governance, economic inequality, technological dependence, accountability, and sustainability.

The principal conceptual finding is that **effective cognitive cross-pollination would require coordination between technological capabilities and the institutional, economic, social, regulatory, and environmental conditions governing their development and application**. The proposed model therefore provides a structured basis for examining how stakeholder relationships might evolve under alternative future technological and societal circumstances. The findings support the subsequent qualitative Predictive Scenario Analysis and Impact Analysis, where the possible consequences of different AGI/ASI development pathways can be explored without presuming that any particular future outcome is inevitable.

11. PREDICTIVE ANALYSIS OF FUTURE AGI & ASI SOCIETY :

11.1 Conceptual Basis of Qualitative Predictive Analysis:

Predictive analysis of a hypothetical future Artificial General Intelligence (AGI) and Artificial Superintelligence (ASI) society requires an exploratory approach because the emergence, capabilities, developmental trajectories, and societal consequences of such technologies remain uncertain. Unlike quantitative forecasting, which estimates future outcomes through statistical relationships and measurable historical patterns, qualitative scenario analysis examines alternative futures by considering different combinations of technological, institutional, economic, and social conditions. Amer et al. (2013) [30] explain that scenario planning provides a systematic method for examining uncertainty, evaluating alternative developments, and supporting strategic decisions. Grace et al. (2018) [4] demonstrate considerable variation in AI researchers' expectations concerning future technological capabilities, reinforcing the difficulty of establishing reliable long-term predictions. Accordingly, the present study employs qualitative scenario-based predictive analysis to explore how the proposed Three-Level Cognitive Cross-Pollination Model—comprising AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries—might evolve under different technological and societal conditions. The analysis does not predict specific dates for the emergence of AGI or ASI; instead, it identifies plausible relationships, opportunities, uncertainties, and potential consequences associated with alternative future developments.

11.2 Critical Drivers and Uncertainties Influencing Future AI Society:

The possible development of an AGI/ASI society may be influenced by several interdependent factors, including the capabilities and reliability of intelligent systems, availability of computational resources, distribution of technological expertise, industrial adoption, governance effectiveness, workforce readiness, and societal acceptance. The relationships among these variables may determine whether advanced AI capabilities support inclusive development or contribute to economic and institutional inequalities. Raisch and Krakowski (2021) [13] identify the interdependence of automation and human augmentation, demonstrating that the organisational consequences of AI cannot be understood through a simple replacement-versus-collaboration distinction. Bostrom (2012) [11] further examines the possibility that highly capable artificial agents may pursue objectives that do not necessarily correspond with human values, highlighting important questions concerning alignment and control. Within the proposed three-level model, two critical uncertainties are particularly relevant: **the distribution of advanced AI capabilities and benefits among stakeholder groups, and the effectiveness of cross-level collaboration, accountability, and governance mechanisms**. Different combinations of these conditions provide a conceptual foundation for developing alternative societal scenarios. The following three scenarios are illustrative possibilities rather than exhaustive predictions or mutually exclusive future outcomes.

11.3 Scenario I—Collaborative and Human-Centred AGI/ASI Society:

Under an optimistic but conditional scenario, increasingly capable AI systems may be developed and deployed through coordinated relationships among technological developers, industrial integrators, governments, and beneficiary communities. AI Developers and Controllers would prioritise reliable system architectures, transparent evaluation, appropriate safeguards, and responsiveness to stakeholder feedback. Industry Application Integrators would translate advanced technological capabilities into context-specific applications supporting healthcare, education, manufacturing, finance, agriculture, scientific research, and public services. AI Beneficiaries would actively participate in identifying needs, evaluating applications, and communicating their experiences, thereby contributing to continuous technological and organisational improvement. Jarrahi (2018) [8] emphasises the complementary contributions of human judgement and AI-based analytical capabilities, while Dellermann et al. (2019) [9] discuss hybrid intelligence as a framework for combining human and artificial capabilities. Brynjolfsson et al. (2025) [22] provide empirical evidence that contemporary generative AI assistance can improve productivity in specific occupational settings, although such findings cannot establish equivalent outcomes for future AGI or ASI systems. Floridi et al. (2018) [12] further establish ethical principles supporting human-centred technological development. In this scenario, effective cognitive cross-pollination could contribute to shared knowledge creation, responsible innovation, workforce augmentation, improved accessibility, and wider societal participation, provided that appropriate institutional and governance conditions are maintained.

11.4 Scenario II—Uneven and Concentrated AGI/ASI Development:

A second possible scenario involves substantial technological progress accompanied by unequal access to advanced AI capabilities, economic resources, specialised expertise, and institutional influence. Under these conditions, a comparatively small number of well-resourced AI Developers and Controllers might control important computational infrastructure, proprietary technologies, and advanced system capabilities. Industry Application Integrators could become increasingly dependent on these providers for access to intelligent systems, implementation support, and technological updates. Meanwhile, AI Beneficiaries might experience different levels of access depending on their economic circumstances, geographic locations, educational backgrounds, professional skills, and organisational affiliations. Acemoglu and Restrepo (2019) [44] explain how automation can alter labour demand and income distribution through the displacement of existing tasks and the creation of new activities. Brynjolfsson et al. (2025) [22] demonstrate that the productivity effects of contemporary generative AI can differ across workers, indicating that benefits need not be uniformly distributed. Carlile (2004) [17] further identifies differences in knowledge and professional interests as important barriers to effective knowledge exchange. Consequently, cognitive cross-pollination in this scenario may become asymmetrical, with technological knowledge flowing primarily from developers to integrators and beneficiaries, while beneficiary feedback and societal concerns exert relatively limited influence over

strategic decisions. This development could create significant opportunities for innovation while simultaneously intensifying technological dependence, digital inequality, and differences in economic and institutional power.

11.5 Scenario III—Disruptive or Poorly Governed AGI/ASI Society:

A third scenario considers the possibility that increasingly capable AI systems may develop or become widely deployed faster than institutions can establish effective evaluation, oversight, accountability, and societal adaptation mechanisms. Under such circumstances, technical limitations, misaligned objectives, organisational incentives, and inadequate governance could contribute to unreliable applications, harmful decisions, security vulnerabilities, or disruptions to professional and institutional activities. Bostrom (2012) [11] examines potential risks associated with the motivations and instrumental behaviour of hypothetical superintelligent agents, providing a conceptual basis for considering advanced AI control challenges. Selbst et al. (2019) [23] demonstrate that AI-related interventions may produce inappropriate or harmful outcomes when wider sociotechnical relationships are inadequately considered. Glickman and Sharot (2025) [36] provide experimental evidence that interactions with biased AI systems can amplify biases in human judgements, highlighting the possibility of harmful feedback cycles. In the proposed three-level structure, developers might struggle to evaluate complex technological behaviour, integrators might face difficulties identifying and controlling deployment risks, and beneficiaries could experience reduced autonomy, unfair outcomes, employment insecurity, or loss of confidence in AI-enabled services. Importantly, this scenario does not imply that such consequences are inevitable or that present AI systems demonstrate superintelligence. Rather, it illustrates the potential significance of inadequate oversight, insufficient knowledge exchange, concentrated decision-making authority, and delayed institutional responses in a hypothetical advanced-AI environment.

11.6 Comparative Implications for the Three Stakeholder Groups:

The three scenarios indicate that the future roles and relationships of AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries may vary substantially according to technological capabilities, organisational arrangements, governance quality, and the distribution of resources. In a collaborative scenario, developers may receive meaningful feedback from integrators and beneficiaries, integrators may translate technological capabilities into socially relevant applications, and beneficiaries may contribute actively to technological improvement and shared value creation. In an uneven-development scenario, technological and financial concentration may restrict knowledge exchange and reduce the influence of comparatively less powerful stakeholders. In a disruptive scenario, inadequate evaluation, poorly defined responsibilities, and weak institutional coordination may undermine confidence and increase the risks associated with AI deployment. Carlile (2004) [17] demonstrates the importance of transferring, translating, and transforming knowledge across organisational boundaries, while Raisch and Krakowski (2021) [13] emphasise the complex interdependence of automation and human augmentation. These theoretical perspectives suggest that the relationships among the three stakeholder groups should not be interpreted as fixed or universally beneficial. Instead, the effectiveness of cognitive cross-pollination may depend on institutional arrangements that facilitate meaningful participation, transparent communication, appropriate role allocation, and responsible responses to emerging technological and societal challenges.

11.7 Strategic Interventions and Indicators of Alternative Futures:

Although the scenarios cannot establish the probability of particular AGI/ASI outcomes, they can help identify strategic interventions and observable indicators relevant to responsible AI development. Potential interventions include strengthening independent safety evaluations, establishing transparent knowledge-sharing arrangements, improving organisational readiness, supporting workforce reskilling, increasing beneficiary participation, and clarifying governance responsibilities. Raji et al. (2020) [33] propose an end-to-end framework for internal algorithmic auditing, demonstrating the importance of documentation, accountability, and systematic evaluation throughout the AI development lifecycle. Jobin et al. (2019) [6] identify substantial convergence among international AI ethics guidelines concerning transparency, justice, fairness, responsibility, privacy, and non-maleficence, while noting important implementation differences. Accordingly, indicators that may help distinguish emerging

societal pathways include the accessibility of AI capabilities, concentration of technological infrastructure, frequency and effectiveness of independent evaluations, participation of beneficiaries in governance, workforce adaptation opportunities, distribution of productivity gains, and the responsiveness of institutions to reported harms. Within the proposed model, these indicators could support ongoing qualitative monitoring of cognitive cross-pollination and facilitate adjustments to organisational strategies and governance arrangements. However, their empirical usefulness would require clearly defined measurements, reliable data, and subsequent validation.

11.8 Interpretation, Limitations, and Implications for Future Research:

The qualitative predictive analysis suggests that the potential development of an AGI/ASI society should be understood as a set of alternative technological and institutional possibilities rather than a single predetermined future. The three scenarios illustrate how different combinations of technological capability, knowledge exchange, economic distribution, social participation, and governance effectiveness might shape relationships among AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries. Amer et al. (2013) [30] emphasise that scenario planning supports the exploration of uncertainty and alternative strategic developments, while Grace et al. (2018) [4] demonstrate the limitations of relying on expert expectations as definitive forecasts of AI progress. The present analysis is therefore subject to important limitations, including dependence on secondary literature, uncertainty surrounding AGI and ASI, subjective scenario selection, and the absence of empirical evidence concerning the proposed future societal structure. No numerical probabilities, development timelines, or statistically validated causal relationships are claimed. Nevertheless, the analysis contributes to the article by identifying possible future configurations of the Three-Level Cognitive Cross-Pollination Model and the conditions under which knowledge exchange might support or undermine beneficial outcomes. Future research may develop more detailed scenarios through expert elicitation, stakeholder interviews, comparative case studies, longitudinal monitoring, and empirical assessment of existing AI development and deployment ecosystems. These investigations could help refine the model and evaluate the conditions supporting collaborative innovation, responsible governance, and equitable societal participation.

12. IMPACT ANALYSIS OF THE PROPOSED THREE-LEVEL COGNITIVE CROSS-POLLINATION MODEL :

12.1 Conceptual Foundation of Impact Analysis:

Impact Analysis provides a systematic approach to examining the potential positive and negative consequences of the proposed Three-Level Cognitive Cross-Pollination Model in a hypothetical future Artificial General Intelligence (AGI) and Artificial Superintelligence (ASI) society. The model identifies three interconnected stakeholder groups: (1) AI Developers and Controllers, responsible for technological development, safety, and oversight; (2) Industry Application Integrators, responsible for translating AI capabilities into sector-specific applications; and (3) AI Beneficiaries, comprising individuals, organisations, and communities using or affected by intelligent systems. As discussed in the preceding sections, cognitive cross-pollination involves multidirectional exchanges of technological knowledge, professional expertise, operational feedback, and societal expectations. The consequences of these relationships may extend across employment, education, industrial productivity, institutional governance, economic inequality, human autonomy, and social welfare. Jarrahi (2018) [8] emphasises the complementary roles of human judgement and AI in organisational decision-making, while Raisch and Krakowski (2021) [13] explain the complex interdependence between automation and human augmentation. These studies suggest that the societal consequences of advanced AI cannot be understood exclusively through technological capabilities. Accordingly, the present analysis evaluates plausible direct, indirect, beneficial, and adverse consequences of the proposed model, recognising that AGI and ASI remain uncertain technological possibilities and that the analysis does not establish causal relationships or numerical forecasts.

12.2 Potential Impact on Employment and Workforce Transformation:

The development and widespread integration of increasingly capable AI systems may significantly alter occupational structures, employment opportunities, professional responsibilities, and workforce skill requirements. AI-enabled automation may replace selected routine and knowledge-intensive tasks,

while human–AI collaboration could generate new professional activities involving technology development, application integration, specialised supervision, evaluation, and governance. Acemoglu and Restrepo (2019) [44] explain that automation can displace labour from existing tasks while the creation of new tasks may generate countervailing employment opportunities. Frank et al. (2019) [5] further emphasise the difficulty of forecasting AI-related employment changes because technological capabilities interact with occupational tasks, workforce competencies, and economic structures. Empirical research by Brynjolfsson et al. (2025) [22] demonstrates that contemporary generative AI assistance can improve productivity in particular customer-support activities, with heterogeneous effects across workers. Within the proposed model, AI Developers and Controllers may create demand for specialised technical and safety-related expertise, Industry Application Integrators may facilitate workforce adaptation and the development of new occupational roles, and AI Beneficiaries may experience productivity improvements, employment restructuring, or job insecurity. Cognitive cross-pollination could support workforce transition by connecting technological knowledge with industry skill requirements and beneficiary experiences. However, the extent to which new employment opportunities would compensate for displaced tasks remains uncertain, highlighting the importance of reskilling, lifelong learning, labour-market adjustment policies, and equitable access to emerging professional opportunities.

12.3 Potential Impact on Education and Human Capital Development:

Education and human capital development may undergo substantial transformation as increasingly capable AI systems become integrated into teaching, learning, assessment, research, and professional development. Intelligent educational applications could potentially support personalised instruction, adaptive learning, automated feedback, multilingual educational resources, and assistance with complex knowledge-intensive activities. Roll and Wylie (2016) [49] examine the evolution of AI in education and emphasise opportunities for developing technologies that support diverse learning environments, educational practices, and learner needs. Holmes and Tuomi (2022) [50] provide a critical review of AI applications in education, highlighting the importance of pedagogical assumptions, educational purposes, and the limitations of technologically driven approaches. Within the proposed model, AI Developers and Controllers may design learning technologies and evaluation mechanisms; Industry Application Integrators, including educational institutions and educational technology providers, may adapt these capabilities to curricula, assessment systems, and professional training; and AI Beneficiaries, including students, teachers, researchers, and lifelong learners, may contribute educational requirements, learning experiences, and feedback. Cognitive cross-pollination may therefore support more responsive educational innovation and continuous development of human capabilities. Nevertheless, excessive dependence on automated assistance could weaken independent learning, critical thinking, and academic integrity if educational applications are poorly designed. Unequal access to advanced technologies could also widen educational disparities. Consequently, the potential educational benefits of future AGI/ASI systems should be assessed alongside pedagogical quality, human participation, affordability, accessibility, data protection, and the preservation of meaningful teacher–student relationships.

12.4 Potential Impact on Industrial Development and Economic Productivity:

The industrial integration of increasingly capable AI may influence manufacturing, healthcare, finance, agriculture, transportation, logistics, communication, scientific research, and professional services through automation, improved analytical capabilities, application innovation, and organisational restructuring. Industry Application Integrators occupy a central position within the proposed three-level model because they translate technological capabilities developed at Level 1 into operational systems and services used or experienced at Level 3. Jöhnk et al. (2021) [21] identify organisational readiness, strategic alignment, resources, and implementation capabilities as important conditions influencing AI adoption. Raisch and Krakowski (2021) [13] further demonstrate that automation and human augmentation are interdependent organisational processes rather than mutually exclusive strategic alternatives. Empirical research by Noy and Zhang (2023) [15] shows that generative AI assistance can improve performance in specified professional writing tasks, while Brynjolfsson et al. (2025) [22] identify productivity improvements in customer-support operations. Although these findings concern contemporary AI applications rather than AGI or ASI, they illustrate how technological capabilities

may generate practical economic value through effective organisational integration. In the proposed model, cognitive cross-pollination may improve communication between developers, industrial specialists, and beneficiaries, thereby supporting application relevance, operational learning, and technological refinement. However, industrial outcomes may also include implementation costs, cybersecurity concerns, technological dependence, organisational disruption, and the concentration of capabilities among financially powerful enterprises. The net impact would therefore depend on application suitability, institutional readiness, human oversight, competition, and the distribution of resulting economic benefits.

12.5 Potential Impact on Governance, Accountability, and Institutional Responsibility:

A future society increasingly dependent on advanced intelligent systems may require substantial development of governance mechanisms, ethical standards, accountability arrangements, and institutional oversight. The proposed model distributes technological development, application integration, and beneficiary participation across three interconnected functional levels, thereby creating opportunities for collaborative governance while introducing difficulties in assigning responsibility for technological outcomes. Floridi et al. (2018) [12] propose an ethical framework for beneficial AI development based on principles including beneficence, non-maleficence, autonomy, justice, and explicability. Jobin et al. (2019) [6] identify broad international convergence around transparency, fairness, responsibility, privacy, and non-maleficence, while noting differences in interpretation and implementation. Raji et al. (2020) [33] further propose an end-to-end framework for algorithmic auditing that emphasises documentation, organisational accountability, and continuous evaluation. Within the proposed three-level framework, AI Developers and Controllers may contribute system documentation, technical safeguards, and performance evaluations; Industry Application Integrators may establish application-level compliance, monitoring, and operational accountability; and AI Beneficiaries may contribute practical concerns, incident reports, and assessments of societal consequences. Cognitive cross-pollination could support governance by enabling the continuous communication of risks, responsibilities, and corrective requirements. Nevertheless, knowledge exchange alone cannot guarantee accountability, particularly when institutional authority, technological expertise, and economic influence are distributed unequally. Effective governance would therefore require enforceable responsibilities, independent oversight, transparent evaluation, accessible remedies, and meaningful opportunities for participation by affected communities.

12.6 Potential Impact on Economic Inequality and Digital Inclusion:

The societal integration of increasingly capable AI may influence income distribution, occupational opportunities, educational access, institutional power, and the broader digital divide. Technological development may generate significant economic value, but the distribution of resulting benefits could favour organisations and individuals possessing advanced technical expertise, substantial investment resources, computational infrastructure, and privileged access to intelligent systems. Acemoglu and Restrepo (2019) [44] explain how automation and the introduction of new tasks can influence labour demand and the distribution of economic opportunities. Brynjolfsson et al. (2025) [22] demonstrate that contemporary AI assistance can produce different productivity effects across workers, while Noy and Zhang (2023) [15] provide evidence of reduced performance disparities in a specific experimental setting. These findings indicate that AI may either narrow or widen selected inequalities depending on task characteristics, deployment arrangements, and institutional conditions. Within the proposed model, AI Developers and Controllers could benefit from ownership of specialised technological capabilities, Industry Application Integrators could obtain commercial advantages through application expertise, and AI Beneficiaries could experience unequal access to services and economic opportunities. Cognitive cross-pollination may support inclusion by facilitating the development of accessible applications, targeted training, and feedback mechanisms representing underserved populations. However, Selbst et al. (2019) [23] demonstrate that technological interventions may fail to achieve fairness when broader sociotechnical contexts are inadequately considered. Consequently, reducing inequality would require deliberate policies concerning access, education, market competition, affordability, representation, and the equitable distribution of technological benefits rather than relying on innovation alone.

12.7 Potential Impact on Human Agency, Autonomy, and Decision-Making:

The increasing involvement of intelligent systems in professional, organisational, and personal decisions may transform the relationship between human judgement and technological authority. Advanced AI applications could support information processing, decision evaluation, creative activities, and problem-solving, potentially enhancing human cognitive capabilities. However, excessive reliance on automated recommendations may weaken independent judgement, increase technological dependence, or reduce meaningful human participation in consequential decisions. Jarrahi (2018) [8] emphasises the complementary roles of human intuition and computational intelligence in decision-making under complexity and uncertainty. Shneiderman (2020) [7] advocates human-centred AI systems that combine high levels of automation with meaningful human control, highlighting the importance of preserving human responsibility and oversight. Experimental research by Glickman and Sharot (2025) [36] further demonstrates that interactions with biased AI systems can amplify biases in human perceptual, emotional, and social judgements. These findings indicate that continuous human–AI interaction does not necessarily produce improved cognition or more reliable decisions. Within the proposed three-level model, AI Developers and Controllers may influence human agency through system architecture, transparency, and control mechanisms; Industry Application Integrators may determine how automated recommendations are embedded within organisational processes; and AI Beneficiaries may experience the resulting effects on independence, choice, confidence, and responsibility. Cognitive cross-pollination could strengthen human agency if beneficiary feedback influences system design, explanations, and oversight arrangements. Conversely, unequal technical knowledge and concentrated decision-making authority could reduce opportunities for meaningful human control. The proposed model therefore requires explicit safeguards supporting informed consent, contestability, explainability where appropriate, independent judgement, and proportional human oversight.

12.8 Potential Impact on Social Welfare and Sustainable Human Development:

The long-term societal significance of a hypothetical AGI/ASI society would depend not only on technological sophistication or economic productivity but also on its consequences for human well-being, social justice, accessibility, public services, environmental sustainability, and quality of life. Increasingly capable AI applications could potentially support healthcare delivery, education, scientific discovery, public administration, environmental monitoring, and the allocation of organisational resources. However, technological benefits may coexist with privacy risks, employment disruption, unequal access, institutional dependence, social exclusion, and environmental costs. Floridi et al. (2018) [12] emphasise that beneficial AI development should be evaluated through ethical principles concerning human welfare, autonomy, justice, and the prevention of harm. Kaack et al. (2022) [48] demonstrate that AI technologies may influence environmental outcomes through computing-related resource consumption, direct application effects, and broader system-level consequences, thereby highlighting the importance of evaluating sustainability impacts comprehensively. Within the proposed model, AI Developers and Controllers may contribute responsible technological capabilities, Industry Application Integrators may translate those capabilities into socially relevant services, and AI Beneficiaries may identify practical needs and evaluate resulting improvements or harms. Cognitive cross-pollination could therefore contribute to social welfare when technical expertise, institutional responsibilities, and beneficiary experiences are integrated through meaningful participation and accountable governance. Nevertheless, no particular welfare improvement can be assumed from the hypothetical emergence of AGI or ASI. The integrated impact analysis suggests that the potential value of the proposed Three-Level Cognitive Cross-Pollination Model lies in its capacity to facilitate responsible knowledge exchange, inclusive technological development, human-centred applications, and collaborative governance. Future empirical research should examine these relationships through measurable indicators of employment, educational outcomes, organisational performance, accountability, inequality, human autonomy, and social welfare before drawing conclusions about the model's effectiveness.

13. INTEGRATED DISCUSSION AND MAJOR FINDINGS :

13.1 Integration of the Five Analytical Approaches:

The integrated analysis of the proposed Three-Level Cognitive Cross-Pollination Model provides a multidimensional understanding of how AI Developers and Controllers, Industry Application

Integrators, and AI Beneficiaries might interact in a hypothetical future Artificial General Intelligence (AGI) and Artificial Superintelligence (ASI) society. The five analytical approaches offer complementary perspectives: SWOC Analysis identifies internal strengths, weaknesses, external opportunities, and challenges; ABCD Analysis examines stakeholder-specific advantages, benefits, constraints, and disadvantages; PESTLE Analysis evaluates macro-environmental influences; Qualitative Predictive Scenario Analysis explores alternative future developments; and Impact Analysis considers possible consequences for individuals, organisations, and society. These approaches draw upon established strategic and conceptual analytical traditions (Helms & Nixon, 2010 [26]; Aithal, 2016 [28]; Yüksel, 2012 [29]; Amer et al., 2013 [30]). Their synthesis suggests that the potential effectiveness of the proposed model depends not merely on advancements in artificial intelligence but also on the coordination of technological capabilities, industry expertise, knowledge exchange, institutional governance, and beneficiary participation. The central conceptual finding is that future AI-enabled societal development may be better understood as an interconnected system of technological creation, practical integration, and human participation than as a unidirectional process of technological innovation and consumption**.** However, the proposed framework represents a theoretical interpretation of possible future relationships rather than an empirically established structure of an AGI/ASI society.

13.2 Synthesis of SWOC and ABCD Findings:

The combined SWOC and ABCD analyses indicate that complementary expertise and multidirectional knowledge exchange constitute the principal potential strengths and advantages of the three-level model. AI Developers and Controllers contribute computational knowledge, technological innovation, and system evaluation capabilities; Industry Application Integrators provide domain-specific expertise, implementation knowledge, and organisational adaptation; and AI Beneficiaries contribute contextual understanding, practical experiences, societal requirements, and feedback. Carlile (2004) [17] explains that effective collaboration across knowledge boundaries requires processes of transfer, translation, and transformation, while Dellermann et al. (2019) [9] highlight the importance of combining complementary human and artificial capabilities. The integrated findings further suggest that the principal expected benefits include improved application relevance, collaborative innovation, organisational learning, and potentially more responsive technological governance. Conversely, the analyses identify knowledge asymmetry, organisational dependence, unequal stakeholder participation, implementation complexity, and ambiguous accountability as important weaknesses and constraints. Jöhnk et al. (2021) [21] demonstrate that organisational readiness influences the adoption of AI technologies, reinforcing the importance of implementation capabilities. Thus, the first major conceptual insight is that cognitive cross-pollination is potentially beneficial only when appropriate knowledge-translation mechanisms, organisational capabilities, communication channels, and accountability arrangements support interactions among the three levels**.**

13.3 Synthesis of PESTLE Findings and Governance Implications:

The PESTLE Analysis reveals that the proposed three-level structure would operate within an interconnected political, economic, social, technological, legal, and environmental context. Political priorities and governmental policies may influence technological investment, research cooperation, public participation, and institutional oversight. Economic conditions may shape AI adoption, organisational productivity, employment opportunities, and the distribution of technological benefits. Social factors, including education, trust, cultural expectations, digital literacy, and inclusion, may influence beneficiary participation. Technological developments determine available capabilities and implementation requirements, while legal frameworks influence accountability, privacy, intellectual property, and the allocation of responsibilities. Environmental conditions introduce additional considerations concerning computational infrastructure, energy consumption, and sustainable technological development. Yüksel (2012) [29] emphasises the interdependence of macro-environmental factors, while Floridi et al. (2018) propose ethical principles for beneficial AI development and Jobin et al. (2019) [6] identify important similarities and differences among international AI governance guidelines. Kaack et al. (2022) [48] further demonstrate the importance of evaluating the environmental consequences of AI systems beyond their immediate applications. The second major conceptual insight is that effective cognitive cross-pollination requires supportive institutional and macro-environmental conditions, with governance, accountability, inclusion, and

sustainability functioning as cross-cutting responsibilities across all three stakeholder groups rather than as isolated technical concerns**.**

13.4 Synthesis of Qualitative Predictive Scenario Findings:

The scenario-based predictive analysis identifies three illustrative pathways through which the proposed AGI/ASI societal model might evolve: a collaborative and human-centred society, an uneven and technologically concentrated society, and a disruptive or inadequately governed society. These scenarios demonstrate that the consequences of increasingly capable AI may depend on the distribution of technological resources, the quality of stakeholder relationships, and the effectiveness of institutional safeguards. In the collaborative scenario, continuous knowledge exchange and meaningful beneficiary participation could support responsible innovation, accessible applications, and shared value creation. In the uneven-development scenario, concentrated technological resources and knowledge asymmetries could weaken reciprocal exchange and increase dependence on dominant technology providers. In the disruptive scenario, inadequate evaluation, weak governance, and harmful feedback mechanisms could undermine trust, accountability, and human autonomy. Amer et al. (2013) [30] establish the usefulness of scenario planning for exploring uncertain future conditions, while Glickman and Sharot (2025) [36] provide empirical evidence that some human–AI feedback loops can amplify biased judgements. Raji et al. (2020) [33] highlight the importance of systematic auditing and accountability in reducing risks associated with AI deployment. Consequently, the third major conceptual insight is that cognitive cross-pollination may operate as either a mechanism supporting collaborative improvement or a channel through which technological dependence, misinformation, errors, and undesirable feedback effects are amplified, depending on the governance and institutional conditions under which it occurs**.**

13.5 Synthesis of Impact Analysis Findings:

The integrated Impact Analysis indicates that the proposed model could have far-reaching implications for employment, education, industrial development, governance, economic inequality, human agency, and social welfare. Increasingly capable AI may support the automation of selected activities, the augmentation of professional capabilities, personalised educational services, organisational innovation, and improved access to knowledge-intensive applications. However, potential adverse consequences include occupational displacement, skill obsolescence, digital exclusion, concentration of economic benefits, reduced human autonomy, and unequal access to technological opportunities. Acemoglu and Restrepo (2019) [44] demonstrate that automation and the creation of new tasks may generate competing labour-market effects, while Brynjolfsson et al. (2025) [22] provide empirical evidence of productivity improvements associated with contemporary generative AI, with differences across workers. Shneiderman (2020) [7] emphasises that human-centred AI development should maintain meaningful human control alongside sophisticated automation. The integration of these perspectives suggests that technological progress and societal welfare should not be treated as equivalent outcomes**.** The fourth major conceptual insight is that the societal value of cognitive cross-pollination depends on how technological benefits and responsibilities are distributed, how effectively individuals and organisations adapt, and whether human autonomy, fairness, accessibility, and well-being remain central to AI development and deployment. Consequently, the proposed model requires evaluation through social and institutional indicators in addition to technical performance and economic productivity.

13.6 Major Conceptual Findings and Scholarly Contribution:

The synthesis of the five analytical approaches yields five interrelated conceptual findings: **(1)** the proposed three-level framework identifies complementary and potentially overlapping stakeholder roles connecting AI development, industry-specific integration, and societal participation; **(2)** multidirectional knowledge exchange, translation, collaboration, and feedback constitute the principal proposed mechanisms of cognitive cross-pollination; **(3)** the effectiveness of these mechanisms may depend on organisational readiness, institutional coordination, technological accessibility, and meaningful stakeholder participation; **(4)** governance, accountability, ethical responsibility, and equitable benefit distribution are essential conditions for evaluating the model's potential societal value; and **(5)** alternative technological and institutional developments may produce substantially different outcomes, making adaptive governance and continuous evaluation preferable to deterministic

assumptions about the future. These findings are consistent with knowledge-boundary theory (Carlile, 2004) [17], hybrid intelligence research (Dellermann et al., 2019) [9], organisational AI-readiness studies (Jöhnk et al., 2021) [21], and human-centred AI principles (Shneiderman, 2020) [7]. The principal originality of the present study lies in integrating these perspectives into a **Three-Level Cognitive Cross-Pollination Model** and systematically examining it through five complementary analytical approaches. Nevertheless, the findings remain conceptual because the investigation relies on secondary literature and qualitative interpretation without primary stakeholder data or empirical validation of a future AGI/ASI society. The proposed model therefore provides a foundation for subsequent research examining knowledge-exchange effectiveness, stakeholder relationships, organisational readiness, governance responsibilities, human participation, and the distribution of technological benefits and risks.

14. RECOMMENDATIONS AND IMPLICATIONS :

14.1 Introduction:

The integrated findings of the SWOC, ABCD, PESTLE, Qualitative Predictive Scenario, and Impact analyses indicate that the potential effectiveness of the proposed Three-Level Cognitive Cross-Pollination Model depends on the coordinated development of technological capabilities, industry-specific applications, human participation, and institutional governance. In a hypothetical future Artificial General Intelligence (AGI) and Artificial Superintelligence (ASI) society, AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries may perform complementary functions while facing different technological, organisational, economic, ethical, and societal challenges. Consequently, effective cognitive cross-pollination would require deliberate strategies supporting multidirectional knowledge exchange, responsible technological innovation, workforce development, transparent governance, and equitable participation. Floridi et al. (2018) [12] emphasise that beneficial AI development should be guided by ethical principles concerning human welfare, autonomy, justice, and accountability, while Shneiderman (2020) [7] advocates human-centred technological systems that combine advanced automation with meaningful human control. Drawing upon these perspectives, the present section proposes an integrated set of recommendations intended to improve the potential effectiveness, inclusiveness, accountability, and sustainability of the three-level model. These recommendations are literature-informed conceptual proposals rather than empirically validated interventions for an existing AGI/ASI society.

14.2 Strategies for Responsible AI Innovation:

Responsible technological innovation should constitute a foundational requirement of the proposed three-level model. AI Developers and Controllers should integrate safety evaluation, transparency, technical reliability, privacy protection, security, and human oversight into the design, development, testing, and maintenance of advanced intelligent systems. Floridi et al. (2018) [12] identify ethical principles for the development of socially beneficial AI, while Jobin et al. (2019) [6] demonstrate substantial international agreement on transparency, fairness, responsibility, privacy, and non-maleficence, alongside differences in their implementation. These studies suggest that ethical principles must be translated into operational procedures rather than remaining abstract commitments. Accordingly, the proposed model recommends that AI developers adopt structured risk identification, documented evaluation procedures, independent testing where appropriate, and continuous monitoring of deployed systems.

Responsible innovation should also incorporate feedback from Industry Application Integrators and AI Beneficiaries throughout the technological development lifecycle. Application integrators can provide domain-specific requirements, implementation difficulties, operational observations, and information concerning emerging risks. Beneficiaries can contribute contextual knowledge, practical experiences, accessibility concerns, and feedback regarding unintended consequences. Raji et al. (2020) [33] propose an end-to-end algorithmic auditing framework that emphasises accountability and evaluation across the AI development process. Building upon this perspective, the present study recommends establishing formal mechanisms for reporting system failures, evaluating corrective actions, communicating technological limitations, and incorporating stakeholder feedback into subsequent design decisions. In a possible future AGI/ASI environment, these procedures may require further adaptation to address the capabilities and risks of increasingly autonomous systems. However, the adequacy of any specific

control mechanism would need to be demonstrated through appropriate technical and institutional evaluation.

14.3 Strategies for Strengthening Cognitive Collaboration and Knowledge Exchange:

Effective collaboration among the three stakeholder groups requires institutional arrangements that facilitate continuous communication, knowledge transfer, interdisciplinary learning, and joint problem-solving. Carlile (2004) [17] explains that knowledge exchange across professional boundaries involves transferring information, translating different interpretations, and transforming knowledge to accommodate practical requirements and competing interests. Consequently, the proposed model recommends establishing collaborative research networks, joint innovation platforms, interdisciplinary working groups, shared technical documentation, and structured stakeholder consultation mechanisms. AI Developers and Controllers should communicate technological capabilities and limitations in accessible forms, while Industry Application Integrators should translate these capabilities into industry-specific requirements and applications. AI Beneficiaries should be provided with meaningful opportunities to communicate their experiences and participate in application evaluation.

Collaboration should operate through both vertical and horizontal knowledge relationships. Vertical collaboration involves interactions between developers and integrators, integrators and beneficiaries, and direct communication between developers and beneficiaries. Horizontal collaboration involves knowledge exchange among organisations and professional communities operating within the same societal level. Dellermann et al. (2019) [9] discuss hybrid intelligence as a framework for combining complementary human and artificial capabilities, while Jarrahi (2018) [8] highlights the importance of integrating computational analysis with human judgement and contextual understanding. These perspectives support the proposition that effective cognitive cross-pollination may depend on combining specialised technical knowledge with professional experience and human perspectives. The present study therefore recommends developing stakeholder-specific communication protocols, knowledge-sharing repositories, collaborative training programmes, and feedback mechanisms that can accommodate differences in technological expertise, institutional authority, and practical requirements. Particular attention should be given to reducing knowledge asymmetries and ensuring that beneficiary participation influences relevant decisions rather than functioning merely as a symbolic consultation process.

14.4 Strategies for Workforce Readiness and Human Capital Development:

The possible expansion of increasingly capable AI technologies may transform occupational structures, professional responsibilities, educational requirements, and the demand for specialised competencies. Consequently, workforce readiness should be considered a central responsibility shared by technology developers, industry integrators, educational institutions, employers, policymakers, and professional organisations. Acemoglu and Restrepo (2019) [44] explain that automation may displace labour from existing tasks while technological development can also create new activities in which human capabilities remain important. Frank et al. (2019) [5] emphasise that understanding AI-related labour-market changes requires examining occupational tasks, workforce skills, and the broader economic conditions influencing technological adoption. These findings suggest that workforce preparation should move beyond narrow technical training towards continuous capability development and adaptation.

The proposed model recommends a three-level workforce development strategy. At **Level 1**, AI Developers and Controllers should strengthen expertise in advanced AI engineering, system evaluation, cybersecurity, safety research, ethical governance, and technical accountability. At **Level 2**, Industry Application Integrators should develop competencies in AI implementation, systems integration, industry-specific applications, workflow redesign, data governance, and human–AI collaboration. At **Level 3**, AI Beneficiaries should have opportunities to develop AI literacy, digital skills, critical thinking, problem-solving abilities, and informed decision-making competencies. Raisch and Krakowski (2021) [13] explain the complex interdependence of automation and human augmentation, suggesting that workforce strategies should address both technological substitution and complementary human–AI activities. Brynjolfsson et al. (2025) [22] provide empirical evidence that contemporary generative AI assistance can improve productivity and facilitate learning in particular occupational settings, although such findings do not establish equivalent effects for hypothetical AGI or ASI.

Accordingly, the proposed framework recommends periodic skill assessments, accessible professional development programmes, industry–academia collaboration, lifelong learning opportunities, and institutional support for workers affected by technological change.

14.5 Strategies for Governance, Accountability, and Ethical Oversight:

The development and integration of increasingly capable AI technologies may require governance arrangements capable of addressing technical reliability, institutional accountability, privacy, fairness, security, and the potential concentration of technological power. Governance within the proposed three-level model should be understood as a shared but differentiated responsibility rather than an activity controlled exclusively by technological developers. AI Developers and Controllers should be responsible for appropriate system-level evaluation, technical safeguards, and documentation. Industry Application Integrators should establish deployment-specific controls, operational monitoring, regulatory compliance, and procedures for responding to application failures. AI Beneficiaries should have accessible mechanisms for communicating concerns, reporting harmful outcomes, and participating in relevant consultation processes. Public authorities and independent oversight institutions should exercise their own responsibilities according to applicable legal and institutional frameworks.

Floridi et al. (2018) [12] provide an ethical foundation for beneficial AI governance, while Jobin et al. (2019) [6] identify the importance of translating widely recognised ethical principles into consistent implementation practices. Raji et al. (2020) [33] further highlight the importance of internal auditing, documented accountability, and continuous evaluation. Based on these contributions, the present study recommends adopting **risk-proportionate governance arrangements**, including clearly defined responsibilities, independent evaluation for consequential applications, transparent incident-reporting mechanisms, documented decision processes, and appropriate procedures for corrective action and redress. Governance structures should distinguish ethical recommendations from legally enforceable obligations and should account for differences in jurisdiction, sector, and application context. In a hypothetical AGI/ASI society, additional governance concerns may arise from increasingly autonomous systems and the possibility of capabilities exceeding existing oversight arrangements. Therefore, governance mechanisms should remain adaptable, evidence-informed, and subject to independent scrutiny rather than assuming that existing institutional controls will necessarily be sufficient.

14.6 Strategies for Human-Centred AI Deployment:

Human-centred deployment should ensure that technological applications are designed and implemented with appropriate attention to human needs, capabilities, limitations, dignity, autonomy, and well-being. Shneiderman (2020) [7] argues that reliable and trustworthy AI systems should support meaningful human control while making effective use of computational automation. Amershi et al. (2019) [51] propose human–AI interaction guidelines addressing user expectations, communication of system capabilities, feedback, correction, and the management of interactions over time. These studies suggest that successful deployment requires not only technically functional systems but also interfaces, organisational processes, and accountability mechanisms that support appropriate human understanding and participation.

Accordingly, the proposed model recommends that Industry Application Integrators conduct user-needs assessments, context-specific evaluations, accessibility reviews, and appropriate human–AI interaction testing before introducing intelligent applications into consequential settings. Applications should communicate relevant limitations and uncertainty, support meaningful user feedback, provide suitable mechanisms for correcting errors, and enable human review or escalation where appropriate. AI Developers and Controllers should assist by making system capabilities, restrictions, and known limitations sufficiently understandable to integrating organisations. AI Beneficiaries should be involved in evaluating usability, practical relevance, accessibility, and the effects of applications on professional and personal decision-making.

The importance of human-centred deployment extends beyond interface design. Selbst et al. (2019) [23] demonstrate that technical approaches to fairness may be ineffective when broader social and institutional conditions are inadequately considered. Therefore, the proposed model recommends evaluating AI applications within their actual sociotechnical contexts, including organisational

incentives, institutional responsibilities, user capabilities, and the potential consequences of automated decisions. Human oversight should be proportionate to the risks associated with particular applications, and the introduction of AI should not automatically eliminate opportunities for human judgement, explanation, or accountability. These recommendations are especially relevant to hypothetical AGI/ASI environments, although their practical effectiveness would require evaluation as technological capabilities develop.

14.7 Strategies for Equitable Participation, Inclusive Development, and Sustainability:

The potential benefits of advanced AI may be distributed unevenly because stakeholders differ in financial resources, technical expertise, infrastructure access, education, and institutional influence. Consequently, the proposed three-level model should incorporate deliberate measures supporting inclusive participation and equitable access to technological opportunities. Acemoglu and Restrepo (2019) [44] demonstrate that automation and the creation of new tasks can have competing implications for labour demand and income distribution, while Frank et al. (2019) [5] emphasise the importance of understanding differences in occupational exposure to technological change. These findings indicate that technological innovation does not automatically produce equitable economic outcomes. The present study therefore recommends accessible AI education, targeted workforce support, inclusive application design, affordable service provision where feasible, and meaningful representation of underserved communities in technological evaluation and governance.

Environmental responsibility should also be integrated into the proposed model. Kaack et al. (2022) [48] explain that AI technologies may influence environmental outcomes through computational resource consumption, direct application effects, and broader changes in economic and social systems. Consequently, AI Developers and Controllers should consider computational efficiency and resource requirements, Industry Application Integrators should evaluate the environmental implications of deployment choices, and AI Beneficiaries should have opportunities to communicate sustainability priorities and concerns. The model recommends incorporating appropriate environmental indicators into application assessments, encouraging responsible infrastructure use, and evaluating possible trade-offs between technological benefits and resource consumption. These considerations should be treated as conditional strategic requirements rather than assumptions about the environmental footprint of hypothetical AGI or ASI systems, whose future technological architectures remain uncertain.

14.8 Integrated Stakeholder-Wise Implementation Framework:

The preceding recommendations suggest that responsible cognitive cross-pollination requires coordinated action across the three stakeholder groups. However, the responsibilities of each group should remain differentiated according to its technical capabilities, institutional authority, practical involvement, and relationship to AI-enabled applications. Table 6 presents a proposed stakeholder-wise implementation framework connecting the major recommendations with illustrative actions and evaluation indicators.

Table 6: Recommended Strategies and Implementation Responsibilities for the Three-Level Cognitive Cross-Pollination Model

Strategic dimension	AI Developers and Controllers	Industry Application Integrators	AI Beneficiaries	Illustrative evaluation indicators
Responsible innovation	Conduct system evaluation, document limitations, implement safeguards, and support technical accountability	Validate applications in relevant operational contexts and report implementation risks	Provide practical feedback and report adverse experiences	Evaluation coverage, documented limitations, identified risks, and corrective actions
Collaboration and knowledge exchange	Share technical information and incorporate relevant	Translate technical knowledge, coordinate stakeholder	Communicate experiences, needs, and	Participation levels, feedback quality, knowledge-sharing activities, and

	external requirements	interaction, and communicate domain requirements	contextual knowledge	documented application improvements
Workforce readiness	Develop advanced technical, safety, and governance competencies	Provide implementation training, professional development, and workflow adaptation	Participate in accessible AI literacy, reskilling, and lifelong learning opportunities	Training participation, assessed competencies, workforce adaptation, and access to learning opportunities
Governance and accountability	Maintain development documentation, safety evaluations, and technical responsibility	Establish deployment controls, compliance procedures, monitoring, and incident response	Use available reporting, consultation, and redress mechanisms	Accountability assignments, audit completion, incident resolution, and stakeholder participation
Human-centred deployment	Support interpretable system information, evaluation tools, and appropriate control mechanisms	Conduct user testing, usability assessment, and context-sensitive implementation	Evaluate usefulness, accessibility, reliability, and effects on autonomy	User feedback, accessibility findings, reported errors, and effectiveness of human oversight
Equitable development	Consider accessibility and the potential distributional effects of technical design	Adapt applications to diverse institutional and user requirements	Communicate barriers to access and participate in inclusive evaluation	Accessibility coverage, representation of affected groups, and identified distributional disparities
Environmental sustainability	Assess computational efficiency and technical resource requirements	Evaluate deployment-related energy and infrastructure implications	Communicate sustainability concerns and application-level experiences	Energy and resource-use indicators, environmental assessments, and improvement actions

Source: Proposed conceptual framework developed for the present exploratory study, informed by Carlile (2004) [17], Floridi et al. (2018) [12], Amershi et al. (2019) [51], Jöhnk et al. (2021) [21], Raji et al. (2020) [33], Shneiderman (2020) [7], and Kaack et al. (2022) [48].

The indicators presented in Table 7 are illustrative suggestions for future operationalisation rather than measurements undertaken in the present study. Their validity, relevance, and appropriate thresholds would need to be established through stakeholder consultation, empirical research, and application-specific evaluation.

14.9 Theoretical, Managerial, Policy, and Societal Implications:

Theoretical Implications: The proposed recommendations extend existing discussions of organisational knowledge exchange, human–AI collaboration, and responsible technological governance by integrating these perspectives within a common three-level stakeholder framework. Carlile (2004) [17] establishes the importance of knowledge transfer, translation, and transformation across organisational boundaries, while Dellermann et al. (2019) [9] emphasise the complementary potential of human and artificial capabilities. The present study builds upon these foundations by proposing cognitive cross-pollination as a multidirectional process connecting technological development, industrial application, and societal participation. Its principal theoretical implication is

that the potential value of advanced AI may depend on relationships among stakeholders rather than technological capabilities alone.

Managerial Implications: For managers, technological professionals, and industry application specialists, the findings suggest that successful AI integration requires organisational readiness, cross-functional collaboration, appropriate human–AI task allocation, and continuous evaluation. Jöhnk et al. (2021) [21] identify important organisational readiness factors, while Raisch and Krakowski (2021) [13] explain the interdependence of automation and augmentation in organisational settings. Consequently, managers should evaluate technological opportunities alongside workforce capabilities, operational requirements, implementation risks, and stakeholder expectations. The proposed framework encourages organisations to treat AI deployment as a continuing process of adaptation and learning rather than a single technological acquisition decision.

Policy Implications: For governments, regulators, professional bodies, and public institutions, the findings emphasise the importance of supporting responsible innovation, appropriate regulatory oversight, public participation, workforce development, and accessible mechanisms for accountability. Floridi et al. (2018) [12] and Jobin et al. (2019) [6] provide foundations for understanding the ethical considerations influencing AI governance, while Raji et al. (2020) [33] demonstrate the importance of translating accountability principles into operational evaluation procedures. The proposed model suggests that policymaking should consider the distinct roles and responsibilities of developers, integrators, and beneficiaries while maintaining appropriate independent oversight and legal safeguards.

Societal Implications: For individuals and communities, the proposed framework highlights the importance of meaningful technological participation, digital literacy, protection of human autonomy, equitable access, and the responsible distribution of technological benefits and risks. Shneiderman (2020) [7] establishes the importance of meaningful human control, while Acemoglu and Restrepo (2019) [44] demonstrate that technological changes can influence the distribution of economic opportunities. These perspectives indicate that future AI-enabled societal development should be evaluated through broader indicators of human welfare, inclusion, accountability, and sustainability rather than technological performance alone.

14.10 Concluding Recommendations:

The recommendations emerging from the integrated analysis suggest that the proposed Three-Level Cognitive Cross-Pollination Model may provide a useful conceptual foundation for examining responsible technological development and societal participation in a possible future AGI/ASI environment. The principal strategic priorities involve responsible innovation, multidirectional knowledge exchange, workforce preparedness, differentiated governance responsibilities, human-centred deployment, inclusive participation, and environmental sustainability. These priorities are interconnected: responsible technological innovation requires appropriate governance; successful industrial integration requires knowledge transfer and organisational readiness; meaningful beneficiary participation depends on accessibility and human agency; and equitable societal development requires attention to the distribution of benefits, responsibilities, and risks.

The central recommendation is therefore to approach future advanced-AI development as a **collaborative, adaptive, and accountable sociotechnical process** rather than as a purely technological progression. Nevertheless, the proposed model and its recommended interventions remain exploratory. Their effectiveness cannot be established without empirical evaluation, and no assumption is made that AGI or ASI will emerge in a particular form or within a predictable timeframe. Future research should investigate the proposed relationships through stakeholder surveys, comparative organisational studies, expert assessments, longitudinal evaluations, and appropriate measures of knowledge exchange, implementation effectiveness, governance, and societal outcomes.

15. LIMITATIONS AND FUTURE RESEARCH :

The present study is subject to several limitations arising from the uncertain development and potential characteristics of Artificial General Intelligence (AGI) and Artificial Superintelligence (ASI). Their emergence, capabilities, developmental trajectories, and societal consequences cannot presently be predicted with confidence. Grace et al. (2018) [4] demonstrate considerable uncertainty in expert expectations concerning future AI capabilities, while Amer et al. (2013) [30] emphasise the importance of exploring alternative futures under uncertain conditions. Accordingly, the proposed Three-Level

Cognitive Cross-Pollination Model represents a hypothetical societal framework rather than an empirically established or inevitable future structure.

A second limitation concerns the conceptual classification of society into AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries. Although this classification provides analytical clarity, actual individuals and organisations may simultaneously perform multiple roles, making the boundaries between stakeholder groups flexible and overlapping. Furthermore, the model does not fully capture differences in institutional power, technological access, cultural contexts, or governance arrangements. Jaakkola (2020) [31] emphasises the importance of clearly specifying conceptual constructs and their relationships, while Carlile (2004) [17] demonstrates the complexity of knowledge exchange across organisational boundaries. Future research should therefore examine alternative stakeholder classifications and the conditions influencing their interactions.

A third limitation arises from the study's **exploratory, secondary literature-based methodology**. The SWOC, ABCD, PESTLE, qualitative predictive scenario, and impact analyses depend on theoretical interpretation rather than primary empirical observations. Consequently, their findings may be influenced by source selection, differences in scholarly perspectives, and subjective analytical judgements. Snyder (2019) [24] highlights the importance of transparency and methodological rigour in literature-based research, while Amer et al. (2013) [30] discuss methodological challenges associated with scenario development. The present analyses do not establish statistically significant relationships, causal effects, or numerical predictions concerning a future AGI/ASI society.

Future studies may undertake **empirical validation of the proposed three-level model** through stakeholder surveys, structured interviews, focus-group discussions, and comparative organisational case studies involving AI developers, industry application specialists, and beneficiaries. Potential variables include the frequency and quality of knowledge exchange, collaboration effectiveness, feedback utilisation, organisational readiness, stakeholder trust, and perceived value creation. Carlile (2004) [17] provides a theoretical foundation for examining knowledge-transfer mechanisms, while Jöhnk et al. (2021) [21] identify organisational factors relevant to AI adoption. Such investigations could test the proposed relationships within existing AI ecosystems without assuming that AGI or ASI has already emerged.

Further research may **employ** longitudinal studies, field experiments, and comparative sectoral investigations to examine how cognitive cross-pollination influences technological adoption, application effectiveness, workforce adaptation, human autonomy, and governance outcomes over time. Particular attention should be given to the possibility that feedback mechanisms may produce both beneficial and harmful effects. Raji et al. (2020) [33] demonstrate the importance of systematic evaluation and organisational accountability in AI development, while Selbst et al. (2019) [23] emphasise the need to examine technological systems within their broader sociotechnical environments. These approaches could help identify causal mechanisms, contextual differences, and unintended consequences associated with stakeholder collaboration.

Finally, future research should explore alternative AGI/ASI scenarios, interdisciplinary governance arrangements, equitable benefit distribution, and human-centred technological development through expert consultations, participatory scenario workshops, and comparative international studies. The proposed framework may be refined by incorporating additional stakeholders, institutional variables, measurable performance indicators, and emerging evidence concerning advanced AI capabilities. Jaakkola (2020) [31] highlights the importance of refining conceptual models through theoretically justified relationships, while Amer et al. (2013) [30] establish the value of scenario-based exploration under uncertainty. Such investigations would strengthen the model's explanatory usefulness and support its gradual empirical assessment as AI technologies and their societal applications evolve.

16. CONCLUSION :

The present exploratory study proposes a **Three-Level Cognitive Cross-Pollination Model** for a hypothetical future Artificial General Intelligence (AGI) and Artificial Superintelligence (ASI) society, comprising AI Developers and Controllers, Industry Application Integrators, and AI Beneficiaries. The integrated SWOC, ABCD, PESTLE, Qualitative Predictive Scenario, and Impact analyses indicate that effective knowledge exchange, interdisciplinary collaboration, continuous feedback, and shared responsibility may influence how advanced AI capabilities are developed, integrated, and utilised. The findings identify potential opportunities for technological innovation, industrial productivity, workforce

augmentation, educational development, and improved societal services, alongside challenges involving knowledge asymmetry, technological dependence, unequal benefit distribution, accountability, human autonomy, and sustainability. The study establishes that the potential societal value of advanced AI depends not merely on technological capabilities but also on the quality of stakeholder relationships and the institutional conditions governing their interactions.

The **originality of the study** lies in conceptualising cognitive cross-pollination as a continuous, multidirectional process connecting three complementary and potentially overlapping societal roles within an integrated analytical framework. Unlike conventional perspectives that primarily emphasise technological development or human–AI interaction, the proposed model connects technological creators, industry-specific application integrators, and beneficiaries through reciprocal knowledge transfer, collaborative learning, application feedback, and joint value creation. The application of five complementary analytical approaches provides a broader understanding of the opportunities, constraints, external influences, alternative scenarios, and potential consequences associated with this conceptual structure. The model thereby contributes a stakeholder-oriented perspective to discussions of future AI-enabled society, highlighting the importance of transforming technical expertise, industrial knowledge, and human experiences into socially responsive technological development.

The implications for future society emphasise the need for responsible innovation, adaptive governance, workforce readiness, equitable technological access, meaningful human oversight, and sustainable development**.** Effective cognitive cross-pollination could support a more collaborative, inclusive, and human-centred AI ecosystem when developers, integrators, beneficiaries, and oversight institutions participate through transparent communication and clearly defined responsibilities. However, the emergence, capabilities, and societal consequences of AGI and ASI remain uncertain, and the proposed three-level structure represents an exploratory conceptual framework rather than an empirically validated prediction. Future research should therefore examine its relationships through stakeholder studies, organisational investigations, longitudinal assessments, and comparative analyses of existing AI ecosystems. Ultimately, the study concludes that the desirable direction of a future AGI/ASI society should be determined not by technological advancement alone, but by the collective capacity of its stakeholders to exchange knowledge responsibly, preserve human agency, distribute benefits equitably, and promote long-term societal well-being.

REFERENCES :

[1] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444. https://doi.org/10.1038/nature14539

[2] Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review, 61*(4), 5–14. https://doi.org/10.1177/0008125619864925

[3] Goertzel, B. (2014). Artificial general intelligence: Concept, state of the art, and future prospects. *Journal of Artificial General Intelligence, 5*(1), 1–48. https://doi.org/10.2478/jagi-2014-0001

[4] Grace, K., Salvatier, J., Dafoe, A., Zhang, B., & Evans, O. (2018). Viewpoint: When will AI exceed human performance? Evidence from AI experts. *Journal of Artificial Intelligence Research, 62*, 729–754. https://doi.org/10.1613/jair.1.11222

[5] Frank, M. R., Autor, D., Bessen, J. E., Brynjolfsson, E., Cebrian, M., Deming, D. J., Feldman, M., Groh, M., Lobo, J., Moro, E., Wang, D., Youn, H., & Rahwan, I. (2019). Toward understanding the impact of artificial intelligence on labor. *Proceedings of the National Academy of Sciences, 116*(14), 6531–6539. https://doi.org/10.1073/pnas.1900949116

[6] Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence, 1*(9), 389–399. https://doi.org/10.1038/s42256-019-0088-2

[7] Shneiderman, B. (2020). Human-centered artificial intelligence: Reliable, safe & trustworthy. *International Journal of Human–Computer Interaction, 36*(6), 495–504. https://doi.org/10.1080/10447318.2020.1741118

[8] Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human–AI symbiosis in organizational decision making. *Business Horizons*, *61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

[9] Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. M. (2019). Hybrid intelligence. *Business & Information Systems Engineering*, *61*(5), 637–643. https://doi.org/10.1007/s12599-019-00595-2

[10] Legg, S., & Hutter, M. (2007). Universal intelligence: A definition of machine intelligence. *Minds and Machines*, *17*(4), 391–444. https://doi.org/10.1007/s11023-007-9079-x

[11] Bostrom, N. (2012). The superintelligent will: Motivation and instrumental rationality in advanced artificial agents. *Minds and Machines, 22*(2), 71–85. https://doi.org/10.1007/s11023-012-9281-3

[12] Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B., Valcke, P., & Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines, 28*(4), 689–707. https://doi.org/10.1007/s11023-018-9482-5

[13] Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, *46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

[14] Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review*, *61*(4), 66–83. https://doi.org/10.1177/0008125619862257

[15] Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, *381*(6654), 187–192. https://doi.org/10.1126/science.adh2586

[16] Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, *35*(1), 128–152. https://doi.org/10.2307/2393553

[17] Carlile, P. R. (2004). Transferring, translating, and transforming: An integrative framework for managing knowledge across boundaries. *Organization Science*, *15*(5), 555–568. https://doi.org/10.1287/orsc.1040.0094

[18] Nonaka, I. (1994). A dynamic theory of organizational knowledge creation. *Organization Science, 5*(1), 14–37. https://doi.org/10.1287/orsc.5.1.14

[19] Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of big data—Evolution, challenges and research agenda. *International Journal of Information Management, 48*, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

[20] Wuest, T., Weimer, D., Irgens, C., & Thoben, K.-D. (2016). Machine learning in manufacturing: Advantages, challenges, and applications. *Production & Manufacturing Research*, *4*(1), 23–45. https://doi.org/10.1080/21693277.2016.1192517

[21] Jöhnk, J., Weißert, M., & Wyrtki, K. (2021). Ready or not, AI comes—An interview study of organizational AI readiness factors. *Business & Information Systems Engineering*, *63*(1), 5–20. https://doi.org/10.1007/s12599-020-00676-7

[22] Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at work. *The Quarterly Journal of Economics*, *140*(2), 889–942. https://doi.org/10.1093/qje/qjae044

[23] Selbst, A. D., boyd, d., Friedler, S. A., Venkatasubramanian, S., & Vertesi, J. (2019). Fairness and abstraction in sociotechnical systems. In *Proceedings of the Conference on Fairness, Accountability, and Transparency* (pp. 59–68). Association for Computing Machinery. https://doi.org/10.1145/3287560.3287598

[24] Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research, 104*, 333–339. https://doi.org/10.1016/j.jbusres.2019.07.039

[25] Torraco, R. J. (2005). Writing integrative literature reviews: Guidelines and examples. *Human Resource Development Review*, *4*(3), 356–367. https://doi.org/10.1177/1534484305278283

[26] Helms, M. M., & Nixon, J. (2010). Exploring SWOT analysis—Where are we now? A review of academic research from the last decade. *Journal of Strategy and Management, 3*(3), 215–251. https://doi.org/10.1108/17554251011064837

[27] Aithal, P. S., Shailashree, V. T., & Suresh Kumar, P. M. (2015). A new ABCD technique to analyze business models & concepts. International Journal of Management, IT and Engineering, 5(4), 409–423. https://ssrn.com/abstract=2778659

[28] Aithal, P. S. (2016). Study on ABCD analysis technique for business models, business strategies, operating concepts & business systems. *International Journal in Management and Social Science, 4*(1), 98–115. https://doi.org/10.5281/zenodo.161137

[29] Yüksel, İ. (2012). Developing a multi-criteria decision making model for PESTEL analysis. *International Journal of Business and Management, 7*(24), 52–66. https://doi.org/10.5539/ijbm.v7n24p52

[30] Amer, M., Daim, T. U., & Jetter, A. (2013). A review of scenario planning. *Futures, 46*, 23–40. https://doi.org/10.1016/j.futures.2012.10.003

[31] Jaakkola, E. (2020). Designing conceptual articles: Four approaches. *AMS Review, 10*(1–2), 18–26. https://doi.org/10.1007/s13162-020-00161-0

[32] Adel, A., & Alani, N. (2025). Can generative AI reliably synthesise literature? Exploring hallucination issues in ChatGPT. *AI & Society, 40*, 6799–6812. https://doi.org/10.1007/s00146-025-02406-7

[33] Raji, I. D., Smart, A., White, R. N., Mitchell, M., Gebru, T., Hutchinson, B., Smith-Loud, J., Theron, D., & Barnes, P. (2020). Closing the AI accountability gap: Defining an end-to-end framework for internal algorithmic auditing. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (pp. 33–44). Association for Computing Machinery. https://doi.org/10.1145/3351095.3372873

[34] Payne, A. F., Storbacka, K., & Frow, P. (2008). Managing the co-creation of value. *Journal of the Academy of Marketing Science, 36*(1), 83–96. https://doi.org/10.1007/s11747-007-0070-0

[35] Smith, F., Sadek, M., Wan, E., Ito, A., & Mougenot, C. (2025). Codesigning AI with end-users: An AI literacy toolkit for nontechnical audiences. *Interacting with Computers, 37*(5), 444–456. https://doi.org/10.1093/iwc/iwae029

[36] Glickman, M., & Sharot, T. (2025). How human–AI feedback loops alter human perceptual, emotional and social judgements. *Nature Human Behaviour, 9*(2), 345–359. https://doi.org/10.1038/s41562-024-02077-2

[37] Prahalad, C. K., & Ramaswamy, V. (2004). Co-creation experiences: The next practice in value creation. *Journal of Interactive Marketing, 18*(3), 5–14. https://doi.org/10.1002/dir.20015

[38] Grönroos, C., & Voima, P. (2013). Critical service logic: Making sense of value creation and co-creation. *Journal of the Academy of Marketing Science, 41*(2), 133–150. https://doi.org/10.1007/s11747-012-0308-3

[39] Vargo, S. L., & Lusch, R. F. (2016). Institutions and axioms: An extension and update of service-dominant logic. *Journal of the Academy of Marketing Science, 44*(1), 5–23. https://doi.org/10.1007/s11747-015-0456-3

[40] Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (pp. 610–623). Association for Computing Machinery. https://doi.org/10.1145/3442188.3445922

[41] Taeihagh, A. (2021). Governance of artificial intelligence. *Policy and Society, 40*(2), 137–157. https://doi.org/10.1080/14494035.2021.1928377

[42] Radu, R. (2021). Steering the governance of artificial intelligence: National strategies in perspective. *Policy and Society, 40*(2), 178–193. https://doi.org/10.1080/14494035.2021.1929728

[43] Gasser, U., & Almeida, V. A. F. (2017). A layered model for AI governance. *IEEE Internet Computing, 21*(6), 58–62. https://doi.org/10.1109/mic.2017.4180835

[44] Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives, 33*(2), 3–30. https://doi.org/10.1257/jep.33.2.3

[45] Wachter, S., Mittelstadt, B., & Floridi, L. (2017). Why a right to explanation of automated decision-making does not exist in the General Data Protection Regulation. *International Data Privacy Law, 7*(2), 76–99. https://doi.org/10.1093/idpl/ipx005

[46] Strubell, E., Ganesh, A., & McCallum, A. (2019). Energy and policy considerations for deep learning in NLP. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics* (pp. 3645–3650). Association for Computational Linguistics. https://doi.org/10.18653/v1/p19-1355

[47] de Vries, A. (2023). The growing energy footprint of artificial intelligence. *Joule, 7*(10), 2191–2194. https://doi.org/10.1016/j.joule.2023.09.004

[48] Kaack, L. H., Donti, P. L., Strubell, E., Kamiya, G., Creutzig, F., & Rolnick, D. (2022). Aligning artificial intelligence with climate change mitigation. *Nature Climate Change, 12*(6), 518–527. https://doi.org/10.1038/s41558-022-01377-7

[49] Roll, I., & Wylie, R. (2016). Evolution and revolution in artificial intelligence in education. *International Journal of Artificial Intelligence in Education, 26*(2), 582–599. https://doi.org/10.1007/s40593-016-0110-3

[50] Holmes, W., & Tuomi, I. (2022). State of the art and practice in AI in education. *European Journal of Education, 57*(4), 542–570. https://doi.org/10.1111/ejed.12533

[51] Amershi, S., Weld, D., Vorvoreanu, M., Fourney, A., Nushi, B., Collisson, P., Suh, J., Iqbal, S., Bennett, P. N., Inkpen, K., Teevan, J., Kikin-Gil, R., & Horvitz, E. (2019). Guidelines for human-AI interaction. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Article 3, pp. 1–13). Association for Computing Machinery. https://doi.org/10.1145/3290605.3300233

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