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Research article

Mapping the educational Frontier: Unleashing the Potential of artificial intelligence talents through cooperative planning in the Guangdong-Hong Kong-Macao greater bay area

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ABSTRACT

The Guangdong-Hong Kong-Macao Greater Bay Area (GBA) has become an important hub for technological innovation and economic development in China. With the growing demand for artificial intelligence (AI) and big data technology talents, it is essential to develop educational cooperation within the GBA to develop a talent pool that can meet the changing needs in the region. This paper focuses on the development of dynamic demand for AI talents and proposes a strategic planning framework for educational cooperation in the GBA. We use the research idea of common attributes and key chain clustering-factor association selection-analysis of the driving force and subordination among factors-the key characteristics of AI talents. Using collinear analysis of citations and grounded theory methods, an operational definition of the influencing factors of AI talent literacy characteristics is constructed. Using the Interpretative Structural Modeling(ISM) and MICMAC (Matrice d'Impacts Croises-Multipication Applique A Classement), analyze and identify the driving force and subordination of the influencing factors of key traits of talents, and present the combined effect of multi-level factors of key traits of talents. Combined with the educational differences and complementary advantages in the GBA, five strategies and seven implementation suggestions for the GBA's AI talent education cooperation plan are formulated to establish a collaborative ecosystem that promotes the growth and integration of AI in the GBA.

1. Introduction

The GBA relies on cutting-edge information technologies, including the Internet, big data, and artificial intelligence, as crucial drivers in the new economic normal. These modern technological advancements hold significant strategic and developmental

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importance in steering the growth and progress of the region. The new economic normal benefits from the global informatization brought about by the technological revolution in information technology and the global economic integration that weakens national economic boundaries [1]. AI fully demonstrates the technological change on which the new economy depends and develops, as well as the promotion of global informatization and economic integration. In terms of developmental trajectories, AI is poised to assume a pivotal role in reshaping the global value chain, whether through optimizing and integrating innovation resources or by spearheading and advancing the profound changes associated with the fourth industrial revolution. The transformative impact of AI is anticipated to empower a wide array of sectors, symbolizing its pervasive influence across various domains. The imperative role of AI in driving these changes underscores its significance in shaping and influencing the future landscape [2]. The construction of the 9 + 2 urban agglomeration in the GBA has become another major national development strategy following the "Belt and Road Initiative", the "Beijing-Tianjin-Hebei Economic Belt" and the "Yangtze River Economic Belt". It is the fourth largest bay area in the world. It is also an important spatial carrier for China to build a world-class urban agglomeration and participate in global competition. Focusing on the construction of the Guangdong-Hong Kong-Macao Greater Bay Area, cooperation between Guangdong, Hong Kong, and Macao, and regional cooperation in the Pan-Pearl River Delta, China is comprehensively promoting mutually beneficial cooperation between mainland China, Hong Kong, and Macao. Western values have influenced Hong Kong and Macao for a long time, and there are significant differences in values and ideologies among social groups in the GBA. With the acceleration of the cooperation process in the GBA, its conflicts are becoming increasingly apparent. The resolution of these problems urgently requires the active participation of education. The GBA refers to the urban agglomeration composed of nine prefecture-level cities in Guangdong Province and the two particular administrative regions of Hong Kong and Macau. They have witnessed rapid development in various fields, among which AI and big data technologies are driving innovation, competitiveness, and sustainable growth. As the demand for AI and big data professionals continues to grow, it is crucial to establish a comprehensive framework for educational cooperation in the GBA. This framework should focus on cultivating a talent pool with the key characteristics required in AI technologies. By aligning educational collaboration efforts with the needs of industry, academia, and society, the GBA can enhance its position as the world's leading innovation center for AI.

Currently, in the age of digital intelligence within the context of the new economy, traditional industries and occupational transformation face fresh challenges brought about by AI [3]. The integrated development of AI in the social field has subversively changed the original business model and labor structure. Educators are beginning to think about the interconnected factors between AI and people. Their focus gradually shifted from the initial theory of technological panic to the theory of technological control. Education researchers generally believe that human beings' dependence on AI technology will become the mainstream form of future work scenarios and emphasize AI's new requirements on people's knowledge, skills, and literacy. They began to think about the key characteristics of AI professionals and technical talents. Research on the necessary character, key abilities, and core competencies that talents should possess has always been a hot topic in the international community. Researchers began to study how to use computer science to develop literacy frameworks from the perspective of specific teaching implementation so that learners can be competent in the challenges posed by the intelligent era [4]. They proposed that to face the challenges brought by AI, learners need to possess core competencies such as coding and computational thinking, data awareness, critical thinking, and post-AI humanism. Zheng, Qin and Li (2021) started from the impact of AI on social relations and production, combined with specific characteristics from the five dimensions of knowledge, ability, thinking, application and cultural value, and proposed an AI literacy framework [5]. It can be seen from the existing research accumulation that education researchers know that in the face of new technological challenges, they need to cultivate innovative talents with new abilities and qualities. However, there is no response to the connotative characteristics of innovative talents from the standpoint of a differentiated educational environment in a specific scenario. The GBA, comprising Guangdong, Hong Kong, and Macao, is unique due to the combination of the 'one country, two systems' framework, three customs territories, and four core cities. Scholarly investigations have revealed significant variations in the educational systems, cultural environments, and industrial landscapes of these regions. It is evident that the GBA presents distinctive characteristics that set it apart from other areas [6]. These have resulted in educational differences among the nine urban agglomerations in Guangdong Province and the two special administrative regions of Hong Kong and Macau in four aspects: education system [7,8], academic cooperation [9,10], industrial integration [11–14], and cross-border opportunities [15–17]. These will profoundly impact the five major factors of educational background [18–21], cultural and language [22,23], industry and opportunities [24–26], collaboration and communication [27,28], policies and support [29–31] for cultivating AI talents.

This study is based on the strategic transformation needs of cultivating and promoting innovative talents under AI. It combines domestic and foreign theoretical research and practical experience analysis. Based on sorting out the connotation and characteristics of innovative talents in the context of AI, a theoretical framework and characteristic elements of the quality of innovative talents in the intelligent era were constructed. We pay attention to the relationship between social economy and education development in the GBA based on AI talents' key characteristics and quality cultivation. We focus on the feasibility, strategy, and realization path of the strategic planning of education cooperation in the GBA. We propose a strategic planning framework for educational cooperation in the GBA. Align educational collaboration work with industry needs by leveraging the key characteristics of these talents. We are looking forward to the unique geographical advantages and multicultural resources of the GBA, providing a rich soil for educational cooperation, fostering a thriving ecosystem of innovative thinking, knowledge exchange, and collaborative research, and promoting the growth and integration of AI and big data in the GBA. In this way, we will create a first-class layout of "technology + industry + innovation" in the Bay Area, promote the development of the GBA to an innovative economic stage, and promote the future direction of the GBA to form a robust new ecology of the global value chain of the technology industry. In this work, we aim to address the following research questions.

(1) How do educational differences manifest within the context of "one country, two systems, three customs territories, and four core cities" in the GBA, and what are the key characteristics and disparities in education across its diverse regions?
(2) What are the primary attributes and influencing factors associated with AI professionals and technical talents within the GBA and how do these characteristics vary across different regions?
(3) How do the combined factors affecting the varied educational environments within the GBA impact the development of AI professionals and technical talents? Can these factors provide specific insights and recommendations for enhancing educational cooperation?
(4) Can the strategic planning framework proposed in this study effectively guide and promote cooperation in AI education within the GBA, ultimately contributing to sustainable economic growth and social progress in the region?

The structure of this work is as follows. In Section 2, we provide an overview of the educational disparities in the GBA and the factors influencing the education of AI talent. In Section 3, we introduce an innovative survey method, building upon the operational definitions of population characteristics proposed in axial coding, to conduct selective coding to develop a scale of thematic research questions and assess the reliability and validity of the sample. In Section 4, based on the ISM, we establish the MICMAC classification, which analyzes determinant factors, driving forces, and the hierarchy of dependencies. Section 5 discusses influencing factors of the constructed AI talent capability characteristics, and conclusive strategies, implementation plans. Section 6 provides conclusion, limitations and prospects.

2. Materials and methods

According to the guidance of the grounded theory method, based on the operational definition of the influencing factors of the population traits proposed by the axial coding, we carry out the selective coding to obtain the scale items of the thematic research. We will execute and implement other questionnaires with descriptive statistics.

2.1. Identification and association strategy of common attributes and grouping factors

According to the two steps of "common attribute and key chain clustering-factor association selection," the retrospective literature research of academic genealogy is carried out. We use VOSviewer to conduct citation collinear analysis (CCA) [1], which is used to evaluate the common attributes and correlation degree of the characteristic attributes of AI talents. We combine SPSS hierarchical clustering by open coding, summarize the categories of its research content, and form the facet of the factors associated with the characteristics of AI talents. Selective coding is finally carried out based on the operational definition of the influencing factors of AI talent literacy characteristics proposed by axial coding. The specific steps are described as follows:

The first step is a clustering of common attributes and key chains. Based on the theme of AI technology research and application, we look back at the academic pedigree for citation co-occurrence and use the co-occurrence statistics and category analysis of the characteristics of AI technology talent literacy to represent the common theoretical attributes and association chains at the macro level. Using keyword co-occurrence statistics and cluster analysis to represent prior research common attributes and key chains at the micro level. Use the hierarchical clustering algorithm to conduct cluster analysis on the data of citations or highly cited documents and cooperate with the co-occurrence statistics of VOSviewer. To reflect the cross-research structure and knowledge characteristics of AI technology and talent literacy characteristics, discover co-occurrence association chains to carry out open coding. The second step is the operational definition of the influencing factors of AI talent literacy characteristics. We identified research literature cues aligned with the theme based on thematic clues obtained through the open coding of grounded theory. Through axial coding, find out the influencing factors of talent literacy that fit the characteristics of the theme and have the regional and industrial characteristics of the urban agglomeration planning in the GBA, and put forward operational definitions.

2.1.1. Data retrieval

We maintain consistency with the literature review methodology, utilizing the Web of Science core collection as the data retrieval source and employing 'AI' as the precise keyword for retrieval. The literature search encompasses fields such as title, abstract, author and affiliation, journal name, and year of publication. We categorize the retrieved information based on the publication year (PY), researcher's address (AD), and research direction (SC). The data accumulation period spans from 1975 to 2022, with the last update on March 21, 2023. Our retrieval yielded 439,170 citations and literature information, including 2823 highly cited papers and 152 hot papers in the field. An analysis of the existing literature on AI reveals a notable increase in the number of research fields covered over the years. Starting from less than two subject areas in 1999, the literature has expanded to cover more than 253 research areas and directions by 2022, illustrating the evolving interdisciplinary nature of AI. Notably, Computer Science AI (N = 226,830), Engineering Electrical Electronics (N = 87,105), Computer Science Theory Methods (N = 78,899), and Computer Science Information Systems (N = 58,236) emerge as the top four disciplines and directions with the highest cumulative number of research literature, highlighting their significant contribution to the field. Furthermore, the stock literature within the specific focus of Education Scientific Disciplines stands at 5,168, accounting for 1.177 % of the total literature.

2.1.2. Hierarchical cluster

Initially, we conducted a co-occurrence context analysis using VOSviewer, extracting 233 research subject keywords, including the researcher keyword 'DE' and the research content supplement keyword 'ID' from cited literature records. The exported Links resulted

Table 1
Citation topics Meso.

(1) Technical Knowledge. The first group of keyword co-occurrence matrices obtained from hierarchical clustering corresponds to the total link strength' weight and co-occurrences' weight of the output keyword analysis. We found the characteristic attributes of crowds in 93 nodes, such as machine learning, algorithm, language, statistical analysis, modeling technology, and big data technology. Highlights the technical knowledge association chain content and common attribute knowledge characteristics, keyword extraction content and citation research topics have information overlap, total link strength' weight and co-occurrences weight both express the adaptability of mainstream research keywords.
(2) Analytical Thinking. The second set of keyword co-occurrence matrices obtained from hierarchical clustering corresponds to the output keyword analysis's total link strength and co-occurrences' weight. We found 102 node trait attributes of complex problem decomposition, identifying data sets, spotting trend skills, analyzing and interpreting data, insight ability, critical thinking, and logical reasoning ability. Highlights the knowledge characteristics of Analytical Thinking related to chain content and common attributes, the coincidence of keyword extraction content and citation research topics, total link strength' weight, and co-occurrences weight both express the adaptation of mainstream research fields and directions and keywords sex.
(3) Problem Solving. The third group of keyword co-occurrence matrices obtained from hierarchical clustering corresponds to the total link strength' weight and co-occurrences' weight of the output keyword analysis. We found the characteristics of the population of 71 nodes, such as AI challenges, big data problems, creative methods, innovative solutions, scalable optimization algorithms, and debugging technical capabilities. The coincidence of content and citation research topics, total link strength weight, and co-occurrences weight all express the adaptability of mainstream research fields, directions, and keywords.
(4) Communication. The fourth group of keyword co-occurrence matrices obtained from hierarchical clustering corresponds to the total link strength' weight and co-occurrences' weight of the output keyword analysis. We found the characteristics of crowd traits in 29 nodes, such as conveying technical concepts, complex information presentation, multidisciplinary collaboration, discovery methods, and explanations, highlighting the knowledge characteristics of communication association chain content and common attributes, and the overlap between keyword extraction content and citation research topics, total link strength' weight and co-occurrences weight both express the adaptability of mainstream research fields and directions and keywords.
(5) Adaptability. The fifth group of keyword co-occurrence matrices obtained from hierarchical clustering corresponds to the total link strength' weight and co-occurrences' weight of the output keyword analysis. We found 37 attributes of crowd traits, including technological trend follow-up, ability to adapt to change, ability to adapt to the dynamic environment, new ideas and methods, and open attitude. It highlights the knowledge characteristics of association chain content and common attributes in the two aspects of psychology and sociology of crowd characteristics, the coincidence of keyword extraction content and citation research topics, and the total link strength' weight and co-occurrences weight both express the mainstream The suitability of research fields and directions and keywords.
(6) Ethical Awareness. The sixth group of keyword co-occurrence matrices obtained from hierarchical clustering corresponds to the total link strength' weight and co-occurrences' weight of the output keyword analysis. We found crowd-specific attributes of 69 nodes, including ethical considerations, data privacy, security concerns, fairness and bias, commitment, and zero-proof technology. It highlights the knowledge characteristics of Ethical Awareness of crowd traits, the coincidence of keyword extraction content and citation research topics, and the total link strength' weight and co-occurrences' weight all express the adaptability of mainstream research fields and directions to keywords.
(7) Leadership and Teamwork. The seventh group of keyword co-occurrence matrices obtained from hierarchical clustering corresponds to the total link strength' weight and co-occurrences' weight of the output keyword analysis. We found 26 nodes of crowd trait attributes such as management project ability, coordination team skills, guidance ability, collaboration ability, inclusiveness, etc. Highlights the characteristics of the leadership and teamwork association chain content and common attribute knowledge characteristics of the crowd characteristics, the coincidence of the keyword extraction content and the citation research theme, the total link strength' weight, and co-occurrences weight all express the mainstream research field and direction and keyword fit.
(8) Business Acumen. The eighth group of keyword co-occurrence matrix obtained from hierarchical clustering corresponds to the total link strength' weight and co-occurrences' weight of the output keyword analysis. We found 44 attributes of crowd traits, including understanding goals, technical insights, operability suggestions, ability to identify opportunities, and technical feasibility. The Business Acumen association chain content and common attribute knowledge characteristics that highlight the characteristics of the crowd, the coincidence of keyword extraction content and citation research topics, total link strength' weight, and co-occurrences' weight all express the mainstream research fields and directions and keywords adaptability.

	Citation Topics Meso	Record Count	% of 439,170
1	4.47.463 Answer Set Programming	14,310	3.26 %
2	4.61.145 Feature Selection	10,309	2.35 %
3	4.48.672 Natural Language Processing	9744	2.22 %
4	4.116.862 Reinforcement Learning	7844	1.79 %
5	4.84.169 Particle Swarm Optimization	7348	1.67 %
6	4.48.322 Semantic Web	6120	1.39 %
7	4.116.1415 Human-robot Interaction	6102	1.39 %
8	4.17.118 Face Recognition	5328	1.21 %
9	4.29.435 Multi Agent Systems	4682	1.07 %
10	4.61.56 Fuzzy Sets	4086	0.93 %
11	4.61.493 Load Forecasting	3854	0.88 %
12	4.47.1360 Boolean Satisfiability	3784	0.86 %
13	4.48.817 Collaborative Filtering	3766	0.86 %
14	4.116.133 Simultaneous Localization And Mapping	3630	0.83 %
15	4.48.120 Complex Networks	3508	0.80 %
16	4.17.630 Action Recognition	3411	0.78 %
17	4.61.869 Clustering	3278	0.75 %
18	4.61.1124 Rough Sets	3229	0.74 %
19	4.17.953 Object Tracking	3200	0.73 %
20	4.29.104 Adaptive Control	3094	0.71 %
21	4.61.1460 Bayesian Networks	2882	0.66 %
22	4.47.281 Abstract Interpretation	2880	0.66 %
23	4.174.152 Speech Recognition	2623	0.60 %
24	4.29.30 Linear Matrix Inequalities	2607	0.59 %
25	4.61.1302 Intrusion Detection	2594	0.59 %
26	4.13.807 Internet of Things	2561	0.58 %
27	1.54.79 Gene Expression Data	2463	0.56 %
28	6.11.31 Self-regulated Learning	2329	0.53 %

(*continued on next page*)

Table 1 (*continued*)

	Citation Topics Meso	Record Count	% of 439,170
29	4.61.1336 Association Rules	2313	0.53 %
30	4.17.942Optical Character Recognition，OCR	2274	0.52 %
31	4.47.410 Software Metrics	2172	0.50 %
32	4.17.282 Image Segmentation	2050	0.47 %

in a weight of 17,668, with a Total link strength weight of 24,316. The occurrence's weight amounted to 3143, with an Avg. Citations' score of 0.275, and an Avg. norm. Citations' score of 3.168. Applying Chen's (2021) hierarchical aggregation analysis method, we utilized a co-occurrence weight of subject keywords $\geq$1 % to form the co-occurrence matrix for hierarchical clustering analysis. SPSS was then employed for hierarchical clustering, classifying 233 research subject keywords into eight distinct categories (Items). Subsequently, we employed the 'AI Co-occurrence keyword Total link strength' weight as the distance between clustering groups. Merge clustering was performed through hierarchical clustering using SPSS22.0 for MAC. Clusters were merged with another similarity category until all were consolidated into one category. Finally, a tree diagram visually represents the categorical relationships among the research field groups, using the total link strength to aggregate the associated chain. The degree of association, determined by the total link strength, indicates the similarity of attributes. A higher degree suggests more significant similarity, while a lower degree reflects dissimilarity.

2.1.3. *Operation definition*

According to the guidelines of the grounded theory of open coding, we are based on the induction of the content of the association chain and the characteristics of common attribute knowledge. According to the eight categories output by the merged clustering, through the Co-occurrence keyword, the highly cited documents affected by the dual factors of the relevance of the research content and the number of citations are retrieved. Combined with the Citation Topics Meso>0.50 % of the label in the category (as shown in Table 1), the final output of the hierarchical clustering is to perform open coding.

2.2. *Scale development*

The determinants shaping essential characteristics in AI talents involve innovative concepts. The operational definition of observed variables adheres to the principles of approximation and reference. The influencing factors behind key talent traits are operationally defined using a methodology inspired by the grounded theory coding approach. The development process of scale items involves several steps: (1) Expressing scale items based on content from prior research literature. (2) Employing the expert interview method to assess the content validity revision of the scale items. (3) Using the Q-Sort classification method developed it to analyze the developed scale items statistically by Chen et al.(2021) [1]. (4) Conducting a pre-test with key industry insiders in AI, considering practical experience, evaluating the reliability and validity of the scale items, and assessing their applicability to real-world scenarios. This step aims to refine and establish the scale items.

Table 2
Demographic information.

Item	Statistical category	Frequency	%
Sex	Male (M)	367	70.85 %
	Female (F)	151	29.15 %
Age	21–30 years old	172	33.20 %
	31–40 years old	117	22.59 %
	41–50 years old	94	18.15 %
	Over 51 years old	135	26.06 %
Educationl	High school education	49	9.46 %
	Bachelor or College degree	294	56.76 %
	Master or above degree	175	33.78 %

Table 3
Position statistics.

	Position	Frequency	%
1	Senior Engineer	76	14.67 %
2	Staff Engineer，Mts	133	25.68 %
3	Manager/Senior Staff Engineer/Smts	94	18.15 %
4	Senior Manager/Principal Engineer/Pmts	71	13.71 %
5	Director	66	12.74 %
6	Senior Director	48	9.27 %
7	Vice President/Vp	19	3.67 %
8	Ceo/President/General Manager(Gm)	11	2.12 %
Total		518	1

Table 4
The factor structure in the AI talent literacy characteristics set (A).

Factors	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17	S18	S19	S20	S21	S22	S23	S24	S25	S26	S27	S28	S29	S30	S31	S32
S1 Understanding of machine learning algorithms.	–	1	0	0	0	0	0	0	0	0	1	0	1	1	1	0	1	0	0	1	0	0	0	1	0	1	1	0	1	1	0	0
S2 Proficiency in programming languages (e.g., Python, R, Java).	1	–	1	0	0	0	0	1	1	0	0	1	1	0	0	1	0	0	1	0	0	0	0	1	1	0	1	1	1	0	1	0
S3 Knowledge of statistical analysis and data modeling techniques.	0	1	–	0	0	0	0	1	0	1	1	1	1	1	0	1	1	0	0	1	1	0	1	0	0	1	0	1	0	0	1	0
S4 Familiarity with big data technologies (e.g., Hadoop, Spark).	0	1	1	–	1	0	1	0	0	1	0	1	0	0	1	0	1	1	1	1	1	0	0	0	1	1	1	0	1	0	1	1
S5 Ability to break down complex problems into manageable components.	0	0	0	1	–	1	0	1	0	1	1	0	0	0	0	0	1	0	1	0	0	1	0	0	0	1	1	1	0	1	1	1
S6 Skill in identifying patterns and trends within datasets.	0	0	1	0	1	–	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	0	0	0	1	0	0	0	1
S7 Capacity to analyze and interpret data to derive meaningful insights.	1	0	0	0	1	0	–	0	1	0	0	1	1	0	1	0	0	1	1	1	1	0	1	0	1	1	1	1	0	0	0	0
S8 Aptitude for critical thinking and logical reasoning.	0	1	0	1	1	1	1	–	0	0	0	0	1	1	0	1	0	0	1	1	1	0	1	0	0	0	1	1	1	0	0	0
S9 Creative approach to tackling challenging AI and big data problems.	1	0	1	1	0	0	1	1	–	1	0	1	1	0	0	1	0	1	0	1	1	1	1	0	1	1	0	1	0	1	1	1
S10 Skill in developing innovative solutions and algorithms.	0	0	1	0	0	0	0	0	0	–	1	0	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	0	1	1	1	0
S11 Ability to optimize algorithms for performance and scalability.	0	0	1	0	0	0	0	1	0	1	–	0	1	0	1	1	0	1	1	0	1	0	1	1	0	1	0	0	0	1	0	0
S12 Capacity to troubleshoot and debug technical issues effectively.	0	1	1	0	1	0	1	1	0	0	0	–	1	0	0	0	1	1	0	1	0	1	1	0	1	0	1	1	1	1	0	1
S13 Proficient in conveying technical concepts to non-technical stakeholders.	1	1	1	1	0	1	1	1	0	0	0	1	–	0	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	0	0	1
S14 Skill in presenting complex information in a clear and concise manner.	0	1	1	0	1	0	0	1	1	0	1	0	1	–	0	1	0	0	1	1	0	0	0	1	1	1	0	1	0	0	1	0
S15 Capacity to collaborate effectively within multidisciplinary teams.	1	1	0	0	0	0	1	0	1	1	1	0	1	0	–	0	0	1	1	1	0	1	0	0	0	0	0	0	0	1	0	1
S16 Ability to document and explain methodologies and findings.	1	1	0	0	0	0	0	1	1	1	1	0	0	0	0	–	1	0	1	0	0	1	1	0	0	1	0	0	1	1	1	1
S17 Willingness to learn and keep up with the latest advancements in AI and big data.	1	1	1	1	1	1	0	0	0	1	0	1	0	1	1	0	–	0	0	0	1	1	0	1	1	0	1	1	1	0	1	0
S18 Ability to adapt to changing project requirements and technologies.	1	0	1	1	0	0	0	1	1	1	0	1	0	1	1	0	0	–	0	1	1	0	0	1	1	1	1	1	0	1	0	0
S19 Capacity to work in fast-paced and dynamic environments.	0	0	1	0	1	0	1	0	0	1	1	1	0	1	0	0	1	1	–	0	1	0	1	0	1	1	1	0	0	0	0	0
S20 Openness to new ideas and approaches.	0	1	0	0	1	1	0	1	1	0	0	1	0	1	0	1	0	0	1	–	1	0	0	1	0	1	1	0	0	0	0	1
S21 Knowledge of ethical considerations in AI and big data technologies.	1	0	1	1	1	1	1	0	0	0	0	1	0	1	0	0	0	0	1	1	–	1	0	0	1	0	0	1	0	0	0	0
S22 Understanding of privacy and security issues in data handling.	0	0	1	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	1	1	1	–	1	0	0	1	1	1	1	0	1	0
S23 Ability to incorporate fairness and bias mitigation techniques.	1	0	0	0	0	0	0	0	0	0	0	1	1	1	0	1	0	1	0	1	1	1	–	1	0	0	1	1	1	0	1	0
S24 Commitment to responsible and transparent use of data.	0	1	0	1	1	0	1	0	0	0	0	0	0	1	1	0	0	0	0	1	0	1	0	–	0	1	1	1	1	1	1	1
S25 Capability to lead and manage AI and big data projects.	0	1	0	1	0	0	1	0	1	1	0	1	1	1	0	0	1	1	1	0	1	0	0	0	–	0	1	0	0	1	0	1

(continued on next page)

Table 4 (*continued*)

Factors	*S1*	*S2*	*S3*	*S4*	*S5*	*S6*	*S7*	*S8*	*S9*	*S10*	*S11*	*S12*	*S13*	*S14*	*S15*	*S16*	*S17*	*S18*	*S19*	*S20*	*S21*	*S22*	*S23*	*S24*	*S25*	*S26*	*S27*	*S28*	*S29*	*S30*	*S31*	*S32*
S26 Skill in delegating tasks and coordinating team efforts.	0	0	1	0	1	0	0	1	1	0	0	1	0	0	0	0	1	0	0	1	1	0	0	0	0	–	0	1	0	0	0	0
S27 Ability to mentor and guide junior team members.	1	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	–	1	1	1	0	1
S28 Aptitude for fostering a collaborative and inclusive work environment.	1	1	0	0	1	0	1	1	0	1	0	1	1	0	1	1	0	1	0	0	0	1	0	1	0	0	1	–	0	0	0	0
S29 Understanding of business objectives and how AI and big data can contribute.	0	1	1	0	0	0	1	1	1	1	1	1	1	1	0	0	1	1	0	0	1	1	1	1	0	1	1	0	–	1	0	0
S30 Skill in translating technical insights into actionable business recommendations.	1	0	1	1	0	1	1	0	0	0	0	1	0	0	1	1	1	1	0	0	1	0	0	1	1	1	0	0	0	–	0	1
S31 Capacity to identify and prioritize high-impact opportunities.	1	1	0	1	0	0	1	0	1	1	0	1	1	1	1	0	1	0	1	0	1	0	0	1	0	0	0	0	1	0	–	1
S32 Ability to balance technical feasibility with business constraints.	0	1	0	1	0	0	1	1	0	1	1	0	0	1	0	1	0	0	1	0	1	1	1	0	1	0	1	0	1	0	0	–

The pre-test samples involve subjects selected based on the principle of matching geographical attributes and ensuring cognitive equivalence. We selected key informants for practical experience in the AI industry from prominent organizations, including the Guangdong AI Industry Association (the most prominent civil society organization for AI industry clusters in Guangdong Province), the Hong Kong Society of AI and Robotics (the most prominent civil society organization for AI industry clusters in Hong Kong), and the Macao Productivity and Technology Transfer Center and Macao Smart City Alliance Association (Macao's largest AI industry cluster civil society organization). These informants, operating primarily in the Guangdong-Hong Kong-Macao GBA, are involved in administrative management and technical engineering roles, making them essential insiders in the functioning of the AI industry. The Q-Sort process involved two scale measurement items based on the aforementioned steps. The classification random consistency probability was employed to ascertain and validate the scale test items' degree of aggregation and discriminant validity. Following the definition by Landis & Koch (1977) [31], the probability of random agreement in classification aligns with the basic agreement level, with statistical values k of 0.633 and 0.731 in the two rounds, respectively. These results indicate that the interviewees could promptly identify the measurement items' fundamental dimensions and construct properties, thereby establishing item construct validity. Developed and structured using the three-level coding method of grounded theory, the scale comprises eight dimensions: Technical Knowledge, Analytical Thinking, Problem Solving, Communication, Adaptability, Ethical Awareness, Leadership and Teamwork, and Business Acumen. In total, there are 32 variable measurement items. Operational items for the observation variables of the scale of influencing factors of key characteristics of AI talents are outlined in the Appendix.

2.3. Survey

Utilizing the Peer Esteem Snowballing Technique (PEST), we employed data from registrations within the 9 + 2 urban agglomeration of the GBA up to December 30, 2022. They are the key informants of the unit or group members of the AI industry. We conducted non-probabilistic questionnaire sampling. We refer to the definition of the non-random sampling sample size to determine the sample size and set $p(1\text{-}p)$ as the maximum value when $p = 0.5$. Take the confidence level $1\text{-}\alpha = 95$ %, $d = 0.05$, and calculate according to the design effect of 1–1.1. The final sample size is $N = 422$, estimated to be 528 questionnaires based on the 80 % questionnaire recovery rate. We distributed the questionnaire to 528 respondents via WeChat, sending a questionnaire to each participant within 1 h of receiving the first response. Of the 500 respondents, 173 actively participated in the survey research and extended the interview invitation to individuals within their social relations sample frame. To mitigate isomorphism, the invitations were carefully validated through guidelines and settings. Additionally, the invitations encouraged extensive forwarding to other populations within the sample frame to avoid homogeneity. 561 questionnaires were distributed within 30 days (January 1, 2023–January 31, 2023). We examine the validity and authenticity of the questionnaire formally and pre-process the data by eliminating omissions, multiple choices, and regular questionnaires. We eliminated 43 samples, accounting for 7.7 % of the sample volume, and effectively recovered 518 samples, with an effective recovery rate of 92.34 %, $N = 518 > 422$. Sample Statistics Description.

(1) Concerning the geographical distribution of enterprises within the 9 + 2 urban agglomerations of the GBA, the majority of the samples, 67.33 %, were from the nine urban agglomerations of Guangdong Province. The Hong Kong region contributed 26.41 % of the samples, and the Macao region comprised 6.26 %.
(2) The demographic information presented in Tables 2 and 3 aligns with the predetermined target interviewee population for the study.

2.4. Descriptive statistics

(1) Following the Kaiser (1960) [32] criterion, we eliminated factors by discarding index variables with eigenvalue roots more significant than one due to multi-factor cross-load or first-order load factor. Factors with eigenvalues greater than one were retained. The results indicate that all item loadings ($p < 0.05$) collectively explained 76.281 % of the variance. Standardized factor loads for items ranged from 0.721 to 0.912, surpassing the critical standard of 0.50, suggesting no substantial cross-loading of multiple factors on a single item. The significance verification using the critical ratio revealed $p < 0.001$ for all 32 items (8-dimensional hierarchical test) of the developed observation variables, confirming their discriminative capacity.
(2) Cronbach coefficients for the items, calculated across the four dimensions, range from 0.810 to 0.911, all surpassing the 0.70 threshold. Notably, the coefficients do not increase by eliminating any item, indicating that the items exhibit strong reliability. Analysis of the statistical summary table, including standardized loading and AVE, reveals that correlation coefficients among the factors of latent variables are all below the square root of AVE. This demonstrates high discriminant validity, as these factors are less susceptible to the influence of multiple commonalities. In summary, the operationally defined items exhibit robust discriminant validity.
(3) To assess the significance of the scale items, we employed a 5-level Likert scale to investigate the perceived importance of factors influencing the characteristics of AI talent literacy among respondents. Respondents rated these factors on a scale of 1–5, ranging from 'very unimportant' to 'very important.' The results indicated that the mean values (μ) for the importance of the 32 measured variables varied from 3.652 to 4.130, with standard deviations (σ) ranging from 0.712 to 0.894. This suggests that respondents rated each influencing factor as either 'important' or 'very important.' The developed scale for AI talent literacy characteristics has been widely recognized.

3. Results

The application of the ISM helps mitigate subjective opinions within the sample frame groups during the statistical analysis of Q-Sort classifications, promoting objectivity and mitigating human subjective bias and cognitive homology bias (Wang et al., 2023). Utilizing the ISM, we established a classification based on MICMAC to analyze and determine the driving forces and subordination levels of influencing factors. This approach aligns more closely with the objectivity of the factors influencing the characteristics of AI talents, thereby enhancing accuracy. The specific methodology is outlined below.

3.1. Analysis of the Interpretative structural model

We followed the calculation steps outlined by Wang et al.(2023) [26] to establish the structural model. Initially, we determined the affiliation relationship between the influencing factors of AI talent literacy characteristics and pairwise factors. By interpreting direct influence, mutual influence, and mutual non-influence, we constructed the Structural Self-Interaction Matrix (SSIM) and formed a binary relationship matrix (A) to represent the pairwise relationships. Second, 'AND' operations were performed on the SSIM and the identity matrix (I), transforming into a reachability matrix (R). The transitivity of the matrix was then checked, and the reachability set (RS) and antecedent set (AS) were calculated. Third, the intersection of the reachable set ($R(Pi)$) and the initial set (AS, $A(Pi)$) was transformed into a level matrix. Factors at the same level were identified through the factor relationships in the reachability matrix. Finally, we established the ISM level partition with the hierarchical matrix, drew the ISM hierarchical correlation graph, and presented the hierarchical relationships among influencing factors of AI talent characteristics. This process resulted in a multi-level hierarchical structure illustrating the set and correlation of factors influencing AI talent literacy characteristics.

3.2. Factor structure interaction matrix

Given the uncertainty of the threshold of factor affiliation, we conducted the empirical analysis with four thresholds of 50 %, 60 %, 70 %, and 80 % to identify the subordination of factors. If 70 % is determined as the threshold value for identifying factor relationships, the affiliation between factors can be divided into 3–6 levels. Therefore, we agree to use 70 % to determine the relationship between factors. The binary relationship of the characteristic factor set of AI talent literacy is the precondition for constructing SSIM. We establish the pairwise relationship between factors in a binary matrix (Formula1).

$$A = \begin{array}{c} \\ s_1 \\ s_2 \\ \cdots \\ s_n \end{array} \begin{bmatrix} s_1 & s_2 & \cdots & s_n \\ & & \cdots & \\ & & \cdots & \\ & & \cdots & \\ & & \cdots & \end{bmatrix} \tag{1}$$

For example: whether the evaluation factor s_i affects the evaluation factor s_j, the binary relationship matrix A of SSIM can be expressed as s_1 is the first evaluation factor, s_2 is the second evaluation factor, and so on, sn is the nth evaluation factor. In matrix A, "1″ indicates a direct impact relationship between the assessment factors. That is, the assessment factor s_1 affects s_2, and "0″ indicates that the assessment factor s_1 does not directly affect s_2. Based on the above description, we use SSIM identified in this step and express it as a binary relationship matrix. The calculation results are shown in Table 4.

As an illustration, we determine the impact of evaluation factor s_i on evaluation factor s_j using a binary relationship matrix A derived from the Structural Self-Interaction Matrix (SSIM). The matrix A is represented with s_1 as the first evaluation factor, s_2 as the second, and so forth, with sn denoting the nth evaluation factor. In matrix A, '1′ signifies a direct impact relationship between evaluation factors, indicating that assessment factor s_1 directly affects s_2, while '0′ signifies no direct impact from s_1 to s_2. Utilizing the SSIM identified in this step, we express it as a binary relationship matrix, and the calculation results are presented in Table 4.

3.3. Reachability set and hierarchical structure

In the initial step, following the construction of the binary relationship matrix, the reachability matrix (R) can be calculated using the following Formula 2:

$$R = A + I \tag{2}$$

Here, we represented the identity matrix I (refer to Formula 3):

$$I = \begin{array}{c} \\ s_1 \\ s_2 \\ \cdots \\ s_n \end{array} \begin{bmatrix} s_1 & s_2 & \cdots & s_n \\ 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 1 \end{bmatrix} \tag{3}$$

The reachability matrix R in Formula 3, also known as the element connection matrix, is derived by summing the matrix A and matrix I. The second step involves obtaining a reachability set through Boolean operations, as specified in Formula 4:

$$R \neq R^2 \neq R^3 \neq R^4 = R^r \neq R^{r+1} \neq RS \tag{4}$$

When the rth power of the matrix N equals the $(r+1)$th power of N, the reachable set (RS) can be determined. The third step involves establishing the intersection between the reachable set (RS) and the antecedent set (AS) in the reachability matrix. The reachable set comprises the columns corresponding to elements in the reachability matrix—sets of elements corresponding to matrix elements containing '1'. Similarly, the antecedent set comprises the rows corresponding to elements in the reachability matrix sets of elements corresponding to matrix elements containing '1'. Different hierarchical levels can be identified by comparing the consistency of factor elements in reachable sets and intersection sets. Additional levels can be determined through the same process (as shown in Table 5).

3.4. Hierarchical structure association directed graph based on ISM

The final step in the ISM development process involves creating the ISM's hierarchical structure association graph and directed graph. Solid lines are utilized between levels to depict the reachable associations among influencing factor levels. For influencing factors between levels, we represent the pre-correlation with dotted lines. This representation is shown in Fig. 1. The directed graph visually illustrates the hierarchical relationship of characteristic factors in AI talent literacy, showcasing a 6-level hierarchical structure of the 32-factor sets and their correlation relationships.

(1) The first highest level (Level 1) of the AI talent literacy characteristic factor structure, there is a singular factor, the capability to lead and manage AI and big data projects (S25), which falls under the leadership and teamwork (G) dimension. Leadership and teamwork, representing essential values and wisdom in human society, are reflected in their connection (Linkage) to lower levels within the ISM hierarchy model. This factor has the most significant driving ability from top to bottom. It is at the top of the structure of characteristic factors of AI talent literacy and is the core factor. Demonstrate the importance of leadership and teamwork in the quality of AI talents, including the ability to teamwork, resource management, decision making, and goal realization. Factors at this level emphasize the capabilities of AI talent in leading and managing AI projects. It directly affects the factor of proficiency in programming languages at the next level. Therefore, the core factor of AI talent literacy is the ability to lead and manage AI and big data projects. This factor reflects the emphasis on leadership and teamwork capabilities to ensure that AI projects can effectively advance and achieve their goals.

(2) The second highest level (Level 2) of the characteristic factor structure of AI talent literacy has only one factor. It is proficiency in programming languages (S2), which belongs to the dimension of technical knowledge (A), and is the link to the requirements of leadership and teamwork on technical knowledge. Proficiency in programming languages is a key factor in the ability to lead and manage AI and big data projects and has a direct correlation. Proficiency in a programming language is one of the key factors in realizing an AI project. Programming language is the foundation of AI technology and is crucial for developing and implementing AI algorithms and models. Therefore, the most directly related element of leadership and teamwork that needs to be considered systematically lies in technical knowledge. Possessing good programming skills can help AI talents better understand and apply AI technology and provide technical support for the successful implementation of projects.

(3) The third level (Level 3) of the characteristic factor structure of AI talent literacy falls on the factor of Skill in delegating tasks and coordinating team efforts (S26). It also belongs to the leadership and teamwork (G) dimension. It expresses the importance of the leadership and teamwork dimension in the characteristic factor structure of AI talent literacy. The two-level (level 1 and level 3) factor structure of the leadership and teamwork (G) dimension directly correlates with vertical interactions. Therefore, the third level of the characteristic factor structure of AI talent literacy still shows the driving force and subordination of the leadership and teamwork dimensions. This factor underscores the need for leaders to have good task assignment and team coordination skills in AI projects. By assigning tasks reasonably and effectively coordinating the work of team members, the efficient operation and smooth progress of AI projects can be achieved.

(4) The fourth level (Level 4) of the characteristic factor structure of AI talent literacy, consisting of openness to new ideas and approaches (S20), knowledge of ethical considerations in AI and big data technologies (S21), ability to incorporate fairness and bias mitigation techniques (S23), a collection of 3 impact factors. They cover the two dimensions of adaptability (E) and ethical Awareness (F), and the subjective cognitive attributes have significant characteristics of talent literacy, showing a subordinate relationship with the dimension of leadership and teamwork (G). Therefore, we need to consider the synergy between the above-influencing factors. These three factors reflect the importance of the ethical and moral aspects of AI talent literacy. The application of AI technology faces numerous ethical and moral challenges, including fairness, privacy protection, and bias handling. These factors indicate that AI talents need to have the knowledge and ability to consider ethical considerations, effectively apply fairness and bias mitigation techniques in AI projects, and always uphold ethical and moral principles.

(5) The fifth level (Level 5) of the characteristic factor structure of AI talent literacy consists of proficient in conveying technical concepts to non-technical stakeholders (S13), capacity to collaborate effectively within multidisciplinary teams (S15), ability to document and explain A collection of five impact factors: methodologies and findings (S16), ability to adapt to changing project requirements and technologies (S18), and skill in translating technical insights into actionable business recommendations (S30). They are subordinate to the three dimensions of communication (D), adaptability (E), and business acumen (H), reflecting the characteristics of talent accomplishment of autonomous skills and expressive ability and reflecting the subordinate relationship with the dimension of leadership and teamwork (G). They emphasize that AI talents should be able to communicate technical concepts to non-technical stakeholders, collaborate effectively in interdisciplinary teams, document and explain methods and findings, adapt to project needs and technological changes, and turn insights into technology trends into

Table 5
Hierarchical structure of characteristic factors of AI talent literacy.

Element P(i)	Reachability Set R(Pi)	Antecedent Set A(Pi)	Intersection R(Pi) & A(Pi)	Level
S1	*S2, S11, S13, S14, S15, S17, S20, S24, S25, S26, S27, S29, S30*	*S2, S7, S9, S13, S15, S16, S17, S18, S21, S23, S27, S28, S30, S31*	S2, S13, S15, S17, S27, S30	6
S2	*S1, S3, S8, S9, S12, S13, S16, S19, S24, S25, S27, S28, S29, S31*	*S1, S3, S4, S8, S12, S13, S14, S15, S16, S17, S20, S24, S25, S28, S29, S31,S32*	S1, S3, S8, S12, S13, S16, S24, S25, S28, S29, S31	2
S3	*S2, S8, S10, S11, S12, S13, S14, S16, S17, S20, S21, S23, S25, S26, S28, S31*	*S2, S4, S6, S9, S10, S11, S12, S13, S14, S17, S18, S19, S21, S22, S26, S29, S30*	S2, S10, S11, S12, S13, S14, S17, S21, S26	6
S4	*S2, S3, S5, S7, S10, S12, S15, S17, S18, S19, S20, S21, S26, S27, S29, S31, S32*	*S5, S8, S9, S13, S17, S18, S21, S24, S25, S30, S31, S32*	S5, S17, S18, S21, S31, S32	6
S5	*S4, S6, S8, S10, S11, S17, S19, S22, S26, S27, S28, S30, S31, S32*	*S4, S6, S7, S8, S12, S14, S17, S19, S20, S21, S22, S24, S26, S28*	S4, S6, S8, S17, S19, S22, S26, S28	6
S6	*S3, S5, S7, S8, S9, S10, S11, S12, S14, S15, S17, S18, S19, S20, S21, S22, S23, S24, S28, S32*	*S5, S8, S13, S17, S20, S21, S30*	S5, S8, S17, S20, S21	6
S7	*S1, S5, S9, S12, S13, S15, S18, S19, S20, S21, S23, S25, S26, S27, S28*	*S4, S6, S8, S9, S12, S13, S15, S19, S21, S24, S25, S28, S29, S30, S31, S32*	S9, S12, S13, S15, S19, S21, S25, S28	6
S8	*S2, S4, S5, S6, S7, S13, S14, S16, S19, S20, S21, S23, S27, S28, S29*	*S2, S3, S5, S6, S9, S11, S12, S13, S14, S16, S18, S20, S26, S27, S28, S29, S32*	S2, S5, S6, S13, S14, S16, S20, S27, S28, S29	6
S9	*S1, S3, S4, S7, S8, S10, S12, S13, S16, S18, S20, S21, S22, S23, S26, S28, S30, S31, S32*	*S2, S6, S7, S14, S15, S16, S18, S20, S25, S26, S29, S31*	S7, S16, S18, S20, S26, S31	6
S10	*S3, S11, S13, S14, S15, S16, S17, S18, S20, S21, S22, S23, S24, S26, S29, S30, S31*	*S3, S4, S5, S6, S9, S11, S15, S16, S17, S18, S19, S25, S27, S28, S29, S31, S32*	S3, S11, S15, S16, S17, S18, S29, S31	6
S11	*S3, S8, S10, S13, S15, S16, S18, S19, S21, S23, S24, S25, S26, S30*	*S1, S3, S5, S6, S10, S14, S15, S16, S19, S22, S27, S29, S32*	S3, S10, S15, S16, S19	6
S12	*S2, S3, S5, S7, S8, S13, S17, S18, S20, S22, S23, S27, S28, S29, S30, S32*	*S2, S3, S4, S6, S7, S9, S13, S17, S18, S19, S20, S21, S23, S25, S26, S27, S28, S29, S30, S31*	S2, S3, S7, S13, S17, S18, S20, S23, S27, S28, S29, S30	6
S13	*S1, S2, S3, S4, S6, S7, S8, S12, S15, S16, S17, S18, S21, S22, S23, S24, S25, S26, S27, S28, S29, S32*	*S1, S2, S3, S7, S8, S9, S10, S11, S12, S14, S15, S23, S25, S27, S28, S29, S31*	S1, S2, S3, S7, S8, S12, S15, S23, S25, S27, S28, S29	5
S14	*S2, S3, S5, S8, S9, S11, S13, S16, S19, S20, S24, S26, S28, S31*	*S1, S3, S6, S8, S10, S17, S18, S19, S20, S21, S23, S24, S25, S27, S29, S31, S32*	S3, S8, S19, S20, S24, S31	6
S15	*S1, S2, S7, S9, S10, S11, S13, S18, S19, S20, S22, S25, S30, S32*	*S1, S4, S6, S7, S10, S11, S13, S17, S18, S24, S27, S28, S30, S31*	S1, S7, S10, S11, S13, S18, S30	5
S16	*S1, S2, S8, S9, S10, S11, S17, S19, S22, S23, S26, S29, S30, S31, S32*	*S2, S3, S8, S9, S10, S11, S13, S14, S20, S22, S23, S27, S28, S30, S32*	S2, S8, S9, S10, S11, S22, S23, S30, S32	5
S17	*S1, S2, S3, S4, S5, S6, S10, S12, S14, S15, S21, S22, S24, S25, S27, S28, S29, S31*	*S1, S3, S4, S5, S6, S10, S12, S13, S16, S19, S25, S26, S27, S29, S30, S31*	S1, S3, S4, S5, S6, S10, S12, S25, S27, S29, S31	6
S18	*S1, S3, S4, S8, S9, S10, S12, S14, S15, S20, S21, S24, S25, S26, S27, S28, S30*	*S4, S6, S7, S9, S10, S11, S12, S13, S15, S19, S23, S25, S28, S29, S30*	S4, S9, S10, S12, S15, S25, S28, S30	5
S19	*S3, S5, S7, S10, S11, S12, S14, S17, S18, S21, S23, S26, S27*	*S2, S4, S5, S6, S7, S8, S11, S14, S15, S16, S20, S21, S22, S25, S31, S32*	S5, S7, S11, S14, S21	6
S20	*S2, S5, S6, S8, S9, S12, S14, S16, S19, S21, S24, S26, S27, S32*	*S1, S3, S4, S6, S7, S8, S9, S10, S12, S14, S15, S18, S21, S22, S23, S24, S26, S27*	S6, S8, S9, S12, S14, S21, S24, S26, S27	4
S21	*S1, S3, S4, S5, S6, S7, S12, S14, S19, S20, S22, S25, S28*	*S3, S4, S6, S7, S8, S9, S10, S11, S13, S17, S18, S19, S20, S22, S23, S25, S26, S27, S29, S30, S31, S32*	S3, S4, S6, S7, S19, S20, S22, S25	4
S22	*S3, S5, S11, S16, S19, S20, S21, S23, S25, S26, S27, S28, S29, S31*	*S5, S6, S9, S10, S12, S13, S15, S16, S17, S21, S23, S24, S27, S28, S29, S32*	S5, S16, S21, S23, S27, S28, S29	6
S23	*S1, S12, S13, S14, S16, S18, S20, S21, S22, S24, S27, S28, S29, S31*	*S3, S6, S7, S8, S9, S10, S11, S12, S13, S16, S19, S22, S27, S29, S32*	S12, S13, S16, S22, S27, S29	4
S24	*S2, S4, S5, S7, S14, S15, S20, S22, S26, S27, S28, S29, S30, S31, S32*	*S1, S2, S6, S10, S11, S13, S14, S17, S18, S20, S23, S27, S28, S29, S30, S31*	S2, S14, S20, S27, S28, S29, S30, S31	6
S25	*S2, S4, S7, S9, S10, S12, S13, S14, S17, S18, S19, S21, S27, S30, S32*	*S2, S4, S7, S9, S10, S12, S13, S14, S17, S18, S19, S21, S27, S30, S32*	*S2, S4, S7, S9, S10, S12, S13, S14, S17, S18, S19, S21, S27, S30, S32*	1
S26	*S3, S5, S8, S9, S12, S17, S20, S21, S28*	*S1, S3, S4, S5, S7, S9, S10, S11, S13, S14, S16, S18, S19, S20, S22, S24, S27, S29, S30*	S3, S5, S9, S20	3
S27	*S1, S8, S10, S11, S12, S13, S14, S15, S16, S17, S20, S21, S22, S23, S24, S25, S26, S28, S29, S30, S32*	*S1, S2, S4, S5, S7, S8, S12, S13, S17, S18, S19, S20, S22, S23, S24, S25, S28, S29, S32*	S1, S8, S12, S13, S17, S20, S22, S23, S24, S25, S28, S29, S32	6
S28	*S1, S2, S5, S7, S8, S10, S12, S13, S15, S16, S18, S22, S24, S25, S27*	*S2, S3, S5, S6, S7, S8, S9, S12, S13, S14, S17, S18, S21, S22, S23, S24, S26, S27*	S2, S5, S7, S8, S12, S13, S18, S22, S24, S27	6
S29	*S2, S3, S7, S8, S9, S10, S11, S12, S13, S14, S17, S18, S21, S22, S23, S24, S25, S26, S27, S30*	*S1, S2, S4, S8, S10, S12, S13, S16, S17, S22, S23, S24, S27, S31, S32*	*S2, S8, S10, S12, S13, S17, S22, S23, S24, S27*	6
S30	*S1, S3, S4, S6, S7, S12, S15, S16, S17, S18, S21, S24, S25, S26, S32*	*S1, S5, S9, S10, S11, S12, S15, S16, S18, S24, S25, S27, S29*	*S1, S12, S15, S16, S18, S24, S25*	5
S31	*S1, S2, S4, S7, S9, S10, S12, S13, S14, S15, S17, S19, S21, S24, S29, S32*	*S2, S3, S4, S5, S9, S10, S14, S16, S17, S22, S23, S24*	*S2, S4, S9, S10, S14, S17, S24*	6
S32	*S2, S4, S7, S8, S10, S11, S14, S16, S19, S21, S22, S23, S25, S27, S29*	*S4, S5, S6, S9, S12, S13, S15, S16, S20, S24, S25, S27, S30, S31*	*S4, S16, S25, S27*	6

actionable business recommendations. Therefore, we must pay attention to the combined characteristics of the above-influencing factors. To cultivate talents' thinking, communication, and cooperation literacy combined ability. These capabilities help AI talents communicate effectively with non-technical stakeholders and promote effective collaboration between teams of different disciplines.

(6) The sixth level (Level 6) of the characteristic factor structure of AI talent literacy consists of understanding of machine learning algorithms(S1) , knowledge of statistical analysis and data modeling techniques(S3) , familiarity with big data technologies (S4) , ability to break down complex problems into manageable components(S5) , skill in identifying patterns and trends within datasets(S6) , capacity to analyze and interpret data to derive meaningful insights(S7) , aptitude for critical thinking and logical reasoning(S8) , creative approach to tackling challenging AI and big data problems(S9) , skill in developing innovative solutions and algorithms(S10) , ability to optimize algorithms for performance and scalability(S11) , capacity to troubleshoot and debug technical issues effectively(S12) , skill in presenting complex information in a clear and concise manner(S14) , willingness to learn and keep up with the latest advancements in AI and big data(S17) , capacity to work in fast-paced and dynamic environments(S19) , understanding of privacy and security issues in data handling(S22) , commitment to responsible and transparent use of data(S24) , ability to mentor and guide junior team members(S27) , aptitude for fostering a collaborative and inclusive work environment(S28) , understanding of business objectives and how AI and big data can contribute(S29) , capacity to identify and prioritize high-impact opportunities(S31) , and ability to balance technical feasibility with business constraints(S32) constitute a collection of 21 impact factors. They cover all eight dimensions and release the necessary technical skills, analytical thinking, problem-solving ability, and ethical awareness that AI talents should possess. These factors together constitute the most basic comprehensive quality of AI talents, reflecting the importance of technical skills, analytical thinking, problem-solving ability, and ethical awareness in the field of AI. These factors emphasize technical competence and problem-solving skills in AI talent literacy. These factors cover a broad range of technical knowledge required for AI talent, including machine learning algorithms, statistical analysis, data modeling, and more. These technical capabilities are critical to the development, implementation, and problem solving of AI projects. At the same time, these factors also emphasize that AI talents need critical thinking, logical reasoning, innovative thinking, and other abilities to deal with complex AI problems and provide innovative solutions. Therefore, we need to pay attention to the future utility of the new ecology of the value chain existing among the above influencing factors.

3.5. MICMAC analysis

MICMAC offers a comprehensive understanding of the systematic structure governing their interactions by delving into the indirect connections and feedback loops between factors. In the MICMAC framework, the driving force is quantified as the cumulative impact on other factors, measuring the number and intensity of these effects. On the other hand, dependence power reflects the total influence exerted on a specific factor by all other factors. These calculations provide nuanced insights into the dynamics within the network of influencing factors. Applying this methodology to our study, we analyzed the driving and dependence power of each of the 32 influencing factors constituting the characteristic factor set of AI talent literacy. The results of this analysis are meticulously presented in Table 6, shedding light on the intricate relationships and hierarchical structure among these influential factors.

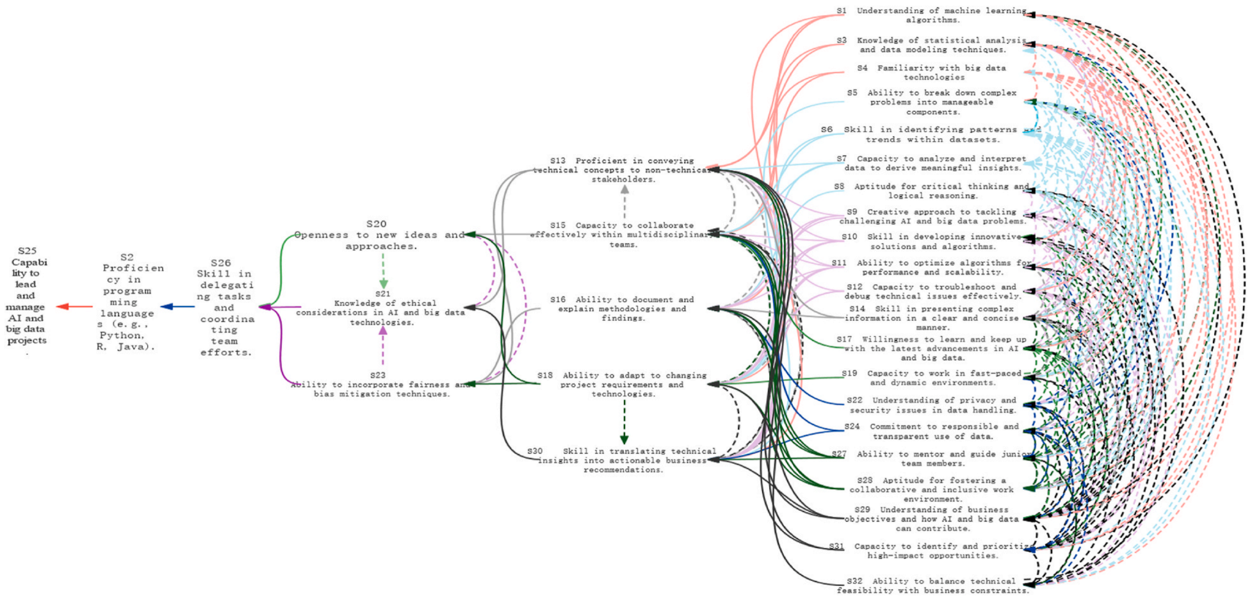


Fig. 1. Hierarchical structure directed graph of characteristic factors of AI talent literacy.

Utilizing the driving power and dependence power values presented in the table above, we classify the four quadrants of the coordinate axes, and the 32 influencing factors of the characteristic factor set of AI talent literacy can be divided into four types of factors (as shown in Fig. 2).

4. Discussion

4.1. Educational differences and influential factors

4.1.1. Educational differences

(1) In terms of the education system. The education system of the nine urban agglomerations in Guangdong Provinceusually adopts a centralized teaching method based on the credit system. AI education usually forms part of the systematic content of professional courses in universities and technical institutions. Courses focus on theoretical knowledge, technical skills, and practical application [7]. Hong Kong and Macau have their education systems that place more emphasis on liberal arts education [8]. Universities in these regions offer AI programs in computer science and engineering, emphasizing interdisciplinary learning and critical thinking.

(2) In terms of academic cooperation. Universities and research institutes in the nine urban agglomerations in Guangdong Provinceare working extensively with industry and government agencies to promote AI research and development. These collaborations involve joint research projects, technology transfer, and industry partnerships [9]. Hong Kong and Macau universities are closely linked with international academic institutions and collaborate on AI-related research projects. They also participate in knowledge exchange events, conferences, and symposiums to foster collaboration and learn about the latest developments [10].

(3) In terms of industrial integration. the nine urban agglomerations in Guangdong Provincehave a robust industrial ecosystem within the GBA, with numerous technology companies, start-ups, and innovation hubs. AI talents are often exposed to real-world industry projects and internships, promoting hands-on learning and industry integration [11]. Hong Kong and Macau have mature financial and service industries increasingly adopting AI technology. AI talent education teaching in these regions often involves collaboration with industry partners, internships, and hands-on training to address industry-specific needs [12–14].

(4) In terms of cross-border opportunities, the nine urban agglomerations in Guangdong Province are strategically positioned adjacent to Hong Kong and Macau. This geographical proximity creates favorable conditions for fostering cross-border cooperation in AI education. The spatial alignment of these regions presents an opportunity-rich environment for collaborative initiatives and knowledge exchange in AI education [15]. Universities and research institutions in Guangdong can collaborate with their counterparts in Hong Kong and Macau for knowledge exchange, joint projects, and student mobility. Hong Kong and Macau's international vision and multicultural environment provide unique advantages for AI education [16]. Collaborative programs with mainland China, such as joint research projects and academic exchange programs, allow students to develop a deep understanding of local and global perspectives [17].

4.1.2. Influencing factors

(1) Education background factors. The education systems of the nine cities of Guangdong Province and Hong Kong, and Macao have their characteristics in terms of curriculum, teaching methods, and academic requirements [18,19]. That will lead to differences in the educational background of AI talents [20]. Education in the nine urban agglomerations in Guangdong Provincemay emphasize technical skills and knowledge, while Hong Kong and Macau may focus on interdisciplinary learning and critical thinking [19,21].

(2) Cultural and language factors. Hong Kong and Macau have a more international and diverse cultural environment than the nine urban agglomerations in Guangdong Province [22]. This exposure to different cultures and languages can shape the characteristics of AI talent, developing adaptability, intercultural communication skills, and a global mindset [23].

(3) Industry and opportunity factors. The industrial landscape of each region in the GBA may vary in terms of key industries and opportunities [24]. The nine cities in Guangdong Province, as important manufacturing centers, may emphasize the application of AI in manufacturing and supply chain management. Hong Kong and Macau have strong financial and service industries and may focus more on applications in finance, banking, and innovative city development [25]. These differences will affect AI talent's characteristics and skill requirements in each region [26].

(4) Collaboration and communication factors. The level of collaboration and networking opportunities within the GBA may vary [27]. The nine urban agglomerations in Guangdong Provincehave an extensive network of technology companies and research institutions, which may provide more opportunities for cooperation and industry participation. With their international connections, Hong Kong and Macau can offer unique opportunities to network with global companies and academic institutions [28].

(5) Policies and supporting factors. Government policies and support for the development of AI in the GBA vary, and there are fundamental differences in "one country, two systems, and three customs territories." Each region may have its own initiatives, incentives, and funding programs to promote talent development and innovation in these areas [29,30]. These differences can shape the characteristics and motivations of AI talent in the GBA.

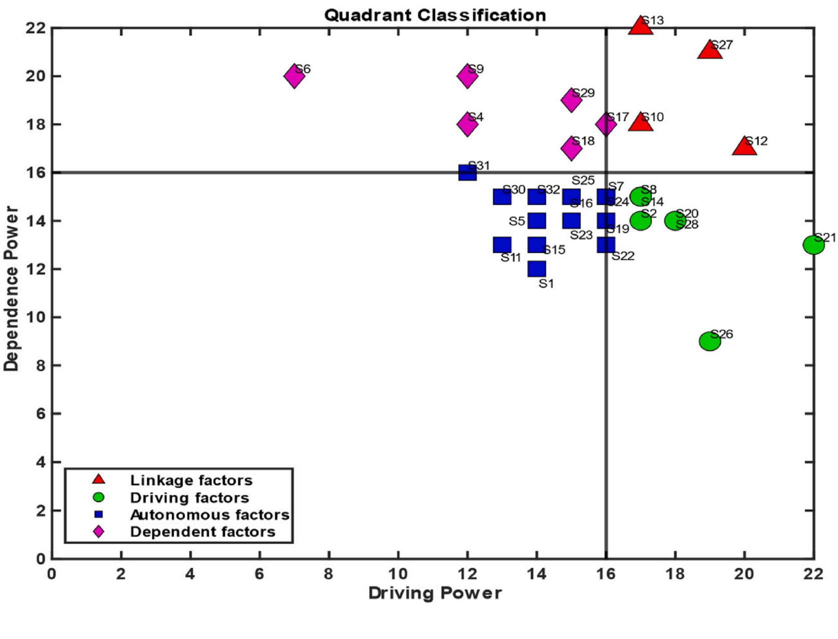
Table 6
Driving power and dependence power of factors set.

Element	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17	S18	S19	S20	S21	S22	S23	S24	S25	S26	S27	S28	S29	S30	S31	S32
Driving-Power	14	17	17	12	14	7	16	17	12	17	13	20	17	17	14	15	16	15	16	18	22	16	15	16	15	19	19	18	15	13	12	14
Dependence-Power	12	14	15	18	14	20	15	15	20	18	13	17	22	15	13	15	18	17	14	14	13	13	14	15	15	9	21	14	19	15	16	15

4.2. Cultivation direction

We explored the individual characteristics of talent in AI technology, and the research identified critical traits for AI technology professionals. The findings emphasize the importance of theoretical knowledge, technical foundation, data processing and analysis skills, machine learning and deep learning expertise, problem-solving and innovation skills, interdisciplinary collaboration and communication skills, ethical and legal awareness, and continuous learning and adaptability. According to the above empirical results, we found that: First, the linkage factors of AI talent literacy have strong driving power and dependence power, and there is a relationship between them and mutual influence. In educational cooperation planning, we should focus on these factors and give full play to their driving force and influence to improve the quality of AI talents. Second, the driving factors of AI talent literacy have strong driving power and can impact other factors. In education cooperation planning, we should focus on cultivating and strengthening these driving factors to provide AI talents with the necessary knowledge and skills to cope with challenges and changing needs. Third, the autonomous factors of AI talent literacy show weak driving power and dependence power but have autonomy and independence. In educational cooperation planning, the independent ability and thinking of AI talents should be encouraged and cultivated to work independently and innovate in a rapidly changing and dynamic environment. Fourth, the dependent factors of AI talent literacy are weaker in driving power but more substantial independence. Other factors influence them and play an important role in educational cooperation planning. In particular, factors related to ethical considerations and teamwork should be given attention to ensure AI talents' comprehensive development and continuous cooperation. In the strategic plan for education cooperation in the Guangdong-Hong Kong-Macao Greater Bay Area, the exploration of the characteristics of AI talents is of strategic importance because the development of this field is crucial to the economy and innovation capabilities in the region, and people are the primary productive forces. The following is the direction for cultivating the characteristics of AI talent literacy.

(1) Basic technical knowledge: The basic knowledge that AI talents should possess, including theories and methods in mathematics, statistics, computer science, machine learning, and data mining.
(2) Interdisciplinary ability: the ability of AI talents in interdisciplinary fields, such as communication and cooperation with domain experts, understanding and application of multidisciplinary knowledge.
(3) Data analysis and processing: the literacy of AI talents in data analysis and processing, including data cleaning, feature extraction, data visualization, and other skills.
(4) Algorithm and model development: the ability of AI talents in algorithm design and model development, including deep learning, neural network, machine learning algorithms, etc.
(5) Ethical and legal awareness: AI talents can recognize and respond to ethical and legal issues, including data privacy protection, algorithmic fairness, and moral hazard.
(6) Ability to solve practical problems: The ability of AI talents to solve practical problems, including the understanding of industry needs, innovative thinking, problem modeling, and solution design.



(caption on next page)

Fig. 2. Four-quadrant classification of Characteristic factors.

(1) Linkage factors: In the first quadrant, skill in developing innovative solutions and algorithms (S10), capacity to troubleshoot and debug technical issues effectively (S12), proficient in conveying technical concepts to non-technical stakeholders (S13), ability to mentor and guide junior team members (S27), a total of 4 impact factors fall in this quadrant, they are significant correlation factors, these factors have strong driving power and dependence power. Their sensitive qualities suggest that any force acting on these factors will have opposing forces on other factors as well as on themselves， and willingness to learn and keep up with the latest advancements in AI and big data (S17) is an impact factor, which shows the commonality of associated factors and subordinate factors.
(2) Driving factors: In the second quadrant, knowledge of statistical analysis and data modeling techniques (S3), familiarity with big data technologies (S4), skill in identifying patterns and trends within datasets (S6), creative approach to tackling challenging AI and big data problems (S9), ability to adapt to changing project requirements and technologies (S18), understanding of business objectives and how AI and big data can contribute (S29), willingness to learn and keep up with the latest advancements in AI and big data (S17), a total of 7 impact factors fall in this quadrant. As a prominent driving factor, an influential element exhibits strong driving power and weak dependency power. This indicates its significant capability to influence other factors, underscoring the importance of highlighting such driving factors. In alignment with the earlier discussion, an illustrative example is the willingness to learn and keep up with the latest advancements in AI and big data (S17), which is a prime impact factor. This particular factor demonstrates commonality with subordinate factors and a distinct driving force. The manifestation of strong driving power emphasizes this factor's specific force on related elements within the AI talent literacy landscape. Understanding such relationships contributes to a more nuanced comprehension of the factors' roles and their hierarchical significance in influencing the overall landscape of AI talent characteristics.
(3) Autonomous factors: In the third quadrant, understanding of machine learning algorithms (S1), ability to break down complex problems into manageable components (S5), capacity to analyze and interpret data to derive meaningful insights (S7), ability to optimize algorithms for performance and scalability (S11), capacity to collaborate effectively within multidisciplinary teams (S15), ability to document and explain methodologies and findings (S16), capacity to work in fast-paced and dynamic environment ments (S19), understanding of privacy and security issues in data handling (S22), ability to incorporate fairness and bias mitigation techniques (S23), commitment to responsible and transparent use of data (S24), Capability to lead and manage AI and big data projects (S25)), skill in translating technical insights into actionable business recommendations (S30), capacity to identify and prioritize high-impact opportunities (S31), ability to balance technical feasibility with business constraints (S32), a total of 14 impact factors fall in this quadrant. As a substantial autonomous factor, this element exhibits weak driving and dependency power, suggesting limited connections to sensitive traits of AI talent literacy. This implies that the factor neither easily influences nor is significantly influenced by other elements within the landscape of AI talent literacy. A noteworthy observation is the parallel characteristics shared between autonomous and subordinate factors, exemplified by the capacity to identify and prioritize high-impact opportunities (S31). This shared trait highlights these factors' commonalities, emphasizing their distinctive position within the broader context of AI talent literacy. Despite being autonomous, such factors may hold unique importance or contribute in specific ways to the overall landscape, further enriching our understanding of their role within the system. This also shows that this factor depends on the associated factors. Similarly, as mentioned above, the capacity to analyze and interpret data to derive meaningful insights (S7), the capacity to work in fast-paced and dynamic environments (S19), Understanding of privacy and security issues in data handling (S22), Commitment to responsible and transparent use of data (S24), the commonality of autonomous factors and driving factors shown by the four impact factors. They show a specific autonomous driving power to other autonomous factors under the action of driving power.
(4) Dependent factors: In the fourth quadrant, proficiency in programming languages (S2), aptitude for critical thinking and logical reasoning (S8), skill in presenting complex information in a clear and concise manner (S14), openness to new ideas and approaches (S20), knowledge of ethical considerations in AI and big data technologies (S21), skill in delegating tasks and coordinating team efforts (S26), aptitude for fostering a collaborative and inclusive work environment (S28), a total of 7 impact factors fall in this quadrant, which are significant subordinate factors. These factors are weak in terms of driving power but substantial in terms of dependence. Dependent factors are positively affected by associated factors and drivers while less likely to affect other factors. In addition, knowledge of ethical considerations in AI and big data technologies (S21) shows the most robust driving power feature.

(7) Continuous learning and adaptability: the ability of AI talents to learn and adapt to the ever-changing technical environment, including attention to new technologies, learning ability, independent learning, and self-improvement.

4.3. Strategy recommendations

Based on the above empirical research and discussion, we finally put forward strategic suggestions for educational cooperation planning in the GBA.

(1) Course exchange and joint projects: Establish course exchange projects between the nine urban in Guangdong Province and universities in Hong Kong and Macau. This enables students to benefit from a broader range of AI courses and expertise. Develop joint projects that leverage the strengths of each region. For example, the nine urban agglomerations in Guangdong Provincecan contribute their technical expertise, while Hong Kong and Macau can provide interdisciplinary approaches and global perspectives.
(2) Industry cooperation and internships: To promote cooperation between universities in the GBA and industry partners. This enables students to gain practical experience through internships, industry projects, and mentoring programs. To promote cross-border internships, students from 9 cities in Guangdong Province, Hong Kong, and Macau have the opportunity to work in companies or research institutions located in different regions. This exposes them to different industry practices and encourages cross-cultural collaboration.

(3) Research and Innovation Cooperation: Encourage joint research projects and bring together researchers and experts from different regions. This fosters collaboration in cutting-edge research areas and facilitates knowledge exchange. Establish innovation or research centers to facilitate collaboration among academia, industry, and government in the GBA. These centers can provide resources, funding, and support for joint research programs.
(4) Knowledge sharing and networking: organizing conferences, seminars, and workshops to bring together students, researchers, and professionals from different parts of the GBA. This allows for knowledge sharing, networking, and the exchange of AI best practices. Facilitate academic and student exchanges between the GBA universities. This provides opportunities for cross-cultural learning and broadens students' horizons.
(5) Coordination of policies and regulations: Promote dialogue and cooperation among relevant government agencies in the GBA to coordinate policies and regulations related to AI education. This ensures a consistent and supportive environment for educational collaboration.

4.4. Implementation plan

(1) Joint degree program: Establish a joint degree program between mainland China, Hong Kong, and Macau universities. These programs can offer integrated programs that combine technical expertise from mainland China with interdisciplinary approaches and international perspectives from Hong Kong and Macau. Students can gain a degree recognized by all participating institutions, enhancing their employability in the GBA.
(2) Cross-border research center: Set up a cross-border research center to bring together researchers, experts and industry professionals from different regions. These hubs can focus on specific areas of AI, fostering collaboration, sharing resources, and conducting joint research projects. They can also provide opportunities for industry collaboration and technology transfer.
(3) Student exchange and internship: to promote student exchanges and internships between universities in the Mainland, Hong Kong and Macao. This enables students to experience different educational settings, be exposed to different perspectives, and develop intercultural competence. Universities could establish credit transfer mechanisms to facilitate industry internships across the GBA.
(4) Cooperative research funding: Establish a funding mechanism to support collaborative research projects between institutions in different regions. This may involve joint grant applications, industry sponsorship, and government funding. The purpose is to promote cross-regional research cooperation and promote the transformation of research results into practical applications.
(5) Teacher exchange and training: Encourage teacher exchange and training opportunities among universities in the GBA. This allows staff to share their expertise, collaborate on research projects, and be exposed to different teaching methods. Workshops and seminars can be organized to enhance teaching skills and facilitate knowledge sharing among educators.
(6) Industry-university cooperation platforms: develop platforms or initiatives to bridge the gap between academia and industry in the GBA. These platforms can facilitate industry collaborations, internships, and joint projects. They can also provide mentorship programs, entrepreneurship support, and access to industry resources and expertise.
(7) Policy docking and regulatory cooperation: Promote dialogue and cooperation between relevant government departments in mainland China, Hong Kong, and Macau, and connect policies and regulations related to AI education. This includes harmonizing certification standards, intellectual property protection, and data privacy regulations. Regular communication channels can be established to address emerging issues and ensure an environment conducive to educational collaboration.

5. Conclusion and limitations

5.1. Conclusion

The rapid development of AI and its widespread application in various fields of society have brought about new changes and challenges that far exceeded human imagination when it first appeared. As a key link in the intelligent social innovation chain, talents must possess new abilities and qualities to face current difficulties and future challenges. We explore a differentiated educational environment with Chinese local characteristics and respond to the connotative characteristics of innovative talents in specific scenarios. We analyze the feasibility, development strategies, and implementation paths of the GBA education cooperation strategic plan and propose a strategic planning framework for the GBA education cooperation. In this way, a framework model of AI innovation talent quality was expanded and established, clarified the characteristic elements of innovative talents in the digital intelligence era, and provided theoretical guidance for cultivating AI innovative talents in the GBA. Based on the above discussion, we suggest that the following aspects should be emphasized in the education cooperation planning of the GBA.

(1) Design a comprehensive training plan, combine relevant and driving factors, and provide comprehensive AI talent training content, including training in technical knowledge, innovation ability, teamwork, and communication skills.
(2) Emphasize the cultivation of autonomous ability and independent thinking of AI talents, encourage students to actively learn and explore, cultivate the ability to solve complex problems, and provide training and support to adapt to the rapidly changing environment.
(3) Strengthen ethical awareness and teamwork ability, cultivate AI talents who can pay attention to ethical issues, cooperate and share, and build a harmonious working environment in technological development.

(4) Strengthen cooperation with enterprises, industries, and society, provide valuable opportunities and project cooperation so that AI talents can apply the knowledge and skills they have learned to solve practical problems and communicate and cooperate with professionals in related fields.

5.2. Limitations and future

Although we developed a questionnaire that was validated correctly and applied to a sample that can be considered representative. However, one of the prerequisites for the research work lies in the research field's complexity and the implementation of educational cooperation measures. The GBA's unique geographical advantages and multicultural resources, with its many socioeconomic and political implications, require the cultivation of an ecosystem where innovative thinking, knowledge exchange, and collaborative research thrive. Therefore, we need to conduct more research to formulate a solid and feasible cooperation framework to promote the future direction of the GBA to form a new solid ecology of the global value chain of the technology industry. In addition, evaluating AI innovation talent quality is a complex systematic project that requires a scientific evaluation index system and practical evaluation tools. In the next stage, we will form a dynamic assessment capability for innovative talents based on the characteristic elements of AI innovative talents in the GBA and the multi-dimensional and complex characteristics of AI innovative talents. Provide comprehensive, objective, and scientific theoretical and technical support to test the effectiveness of innovative talent cultivation in the GBA.

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Data availability statement

Data will be made available on request.

Ethics Statement

This study was conducted following ethical guidelines and principles. The research protocol was approved by the Ethics Committee of Guangdong Provincial Department of Education, with ethics approval reference 2022KCXTD042. All participants involved in this study, including those under the age of 18, provided informed consent. In the case of participants under the age of 18, parental consent was obtained.

CRediT authorship contribution statement

Zhuo Zhang: Writing – review & editing, Validation, Methodology, Investigation, Funding acquisition, Formal analysis. **Jie Li:** Writing – review & editing, Writing – original draft, Resources, Investigation, Funding acquisition, Data curation. **Yansheng Chen:** Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Formal analysis, Conceptualization. **Fajun Chen:** Validation, Methodology, Funding acquisition, Formal analysis, Data curation. **Zhonghao Liu:** Visualization, Validation, Software, Methodology, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Trait Assessment Scale for AI Technology Talents.

Dimension	Item
Technical Knowledge(A)	S1 Understanding of machine learning algorithms. S2 Proficiency in programming languages (e.g., Python, R, Java). S3 Knowledge of statistical analysis and data modeling techniques. S4 Familiarity with big data technologies (e.g., Hadoop, Spark).

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(*continued*)

Dimension	Item
Analytical Thinking(B)	S5 Ability to break down complex problems into manageable components. S6 Skill in identifying patterns and trends within datasets. S7 Capacity to analyze and interpret data to derive meaningful insights. S8 Aptitude for critical thinking and logical reasoning.
Problem Solving(C)	S9 Creative approach to tackling challenging AI and big data problems. S10 Skill in developing innovative solutions and algorithms. S11 Ability to optimize algorithms for performance and scalability. S12 Capacity to troubleshoot and debug technical issues effectively.
Communication(D)	S13 Proficient in conveying technical concepts to non-technical stakeholders. S14 Skill in presenting complex information in a clear and concise manner. S15 Capacity to collaborate effectively within multidisciplinary teams. S16 Ability to document and explain methodologies and findings.
Adaptability(E)	S17 Willingness to learn and keep up with the latest advancements in AI and big data. S18 Ability to adapt to changing project requirements and technologies. S19 Capacity to work in fast-paced and dynamic environments. S20 Openness to new ideas and approaches.
Ethical Awareness(F)	S21 Knowledge of ethical considerations in AI and big data technologies. S22 Understanding of privacy and security issues in data handling. S23 Ability to incorporate fairness and bias mitigation techniques. S24 Commitment to responsible and transparent use of data.
Leadership and Teamwork(G)	S25 Capability to lead and manage AI and big data projects. S26 Skill in delegating tasks and coordinating team efforts. S27 Ability to mentor and guide junior team members. S28 Aptitude for fostering a collaborative and inclusive work environment.
Business Acumen(H)	S29 Understanding of business objectives and how AI and big data can contribute. S30 Skill in translating technical insights into actionable business recommendations. S31 Capacity to identify and prioritize high-impact opportunities. S32 Ability to balance technical feasibility with business constraints.

Scoring: For each trait, evaluate the individual on a scale of 1–5, with 1 being the lowest and 5 being the highest.

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