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Article

The role of industry-academia collaboration in enhancing educational opportunities and outcomes under the digital driven Industry 4.0

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Abstract: We studied the role of industry-academic collaboration (IAC) in the enhancement of educational opportunities and outcomes under the digital driven Industry 4.0 using research and development, the patenting of products/knowledge, curriculum development, and artificial intelligence as proxies for IAC. Relevant conceptual, theoretical, and empirical literature were reviewed to provide a background for this research. The investigator used mainly principal (primary) data from a sample of 230 respondents. The primary statistics were acquired through a questionnaire. The statistics were evaluated using the structural equation model (SEM) and Stata version 13.0 as the statistical software. The findings indicate that the direct total effect of Artificial intelligence (Aint) on educational opportunities (EduOp) is substantial (Coef. 0.2519916) and statistically significant ($p < 0.05$), implying that changes in Aint have a pronounced influence on EduOp. Additionally, considering the indirect effects through intermediate variables, Research and Development (Res_dev) and Product Patenting (Patenting) play crucial roles, exhibiting significant indirect effects on EduOp. Res_dev exhibits a negative indirect effect (Coef = −0.009969, $p = 0.000$) suggesting that increased research and development may dampen the impact of Aint on EduOp against a priori expectation while Patenting has a positive indirect effect (Coef = 0.146621, $p = 0.000$), indicating that innovation, as reflected by patenting, amplifies the effect of Aint on EduOp. Notably, Curriculum development (Curr_dev) demonstrates a remarkable positive indirect effect (Coef = 0.8079605, $p = 0.000$) underscoring the strong role of current development activities in enhancing the influence of Aint on EduOp. The study contributes to knowledge on the effective deployment of artificial intelligence, which has been shown to enhance educational opportunities and outcomes under the digital driven Industry 4.0 in the study area.

Keywords: Industry 4.0; industry-academia collaboration; artificial intelligence; patent development; curriculum; research and development; SEM

1. Introduction

Collaboration frameworks (Perkmann, Tartari et al., 2012) have been developed in response to modifications of the working environments of different corporate institutions (Cunningham and Link, 2014). Industries have always looked to institutions of higher education as possible sources of new ideas and knowledge in an effort to expand their knowledge base and to improve their ability to provide fresh solutions to the complex problems confronting society (Perkmann, Neely et al., 2011). According to Perkmann, Neely et al. (2011), in order to achieve their goals of knowledge and innovation, a rising number of organizations are collaborating with academic institutions. Academics and policymakers are now more interested than ever in the effect of university study on corporate innovation.

Universities have the potential to collaborate with businesses in a mutually beneficial manner, thereby enhancing educational possibilities and value. This can be achieved through the creation of improved resources for higher and advanced education, facilitating the exchange of innovative ideas and technology transfer, and cultivating an environment conducive to continuous learning. There exists potential for enhanced collaboration between higher education institutions and industries, with the aim of collectively attaining shared objectives and ensuring that graduates possess the necessary skills and knowledge to successfully integrate into the labor market and make meaningful contributions to global economies (Weagle et al., 2019). This is one of the most effective strategies for technological development in developed or industrialized countries and is a useful instrument for the effective and efficient application of science and technology to solve social issues. There are several ways in which these collaborations can take place, including through cooperative research initiatives, joint curriculum creation, and joint product patenting (product collaborations) (Lucietto et al., 2021). Schools and businesses can work together to increase the eminence of education and design training programs by means of collaborating. In an increasingly competitive global market, success requires a workforce that can keep up with and learn from new markets and technologies. Quality educational programs are clearly essential to the sustainability of industrialization. Accordingly, there has been a shift in thinking regarding education and industry partnership,which is now gathering steam (Weagle et al., 2019).

Mukherji and Silberman (2021) posit that the phenomenon of industry-academic collaboration, commonly denoted as industry-academia collaboration (IAC) or university-industry collaboration (UIC), entails a mutually beneficial alliance between academic establishments (such as universities and research institutions) and industrial entities (including companies, businesses, and industries). The establishment of partnerships between universities and industries, frequently facilitated by government action, is widely recognized as a crucial factor in enhancing regional and national innovation systems (O'Dwyer et al., 2023). The purpose of this partnership is to leverage the respective experience, resources, and capacities of the involved parties in order to promote the advancement of research, innovation, and societal improvement in a mutually beneficial manner. Fischer et al. (2019) argue that the establishment of partnerships between industry and academics serves as a means to foster the flow of knowledge and expertise. Academic institutions play a vital role in generating theoretical knowledge and conducting research, whereas industry offer valuable practical insights and present real-world issues. Collaborative endeavors encompass cooperative research initiatives aimed at resolving industry-specific challenges, propelling technological advancements, and nurturing the cultivation of innovative ideas (Alexander et al., 2020). Academic research frequently generates novel technologies that are subsequently commercialized through collaborative efforts, effectively bridging the gap between academia and practical market applications. The partnership aims to synchronize educational curriculum with the requirements of the industry, so augmenting the competencies of graduates and facilitating their seamless integration into the labor market (O'Dwyer et al., 2023). Moreover, the institution provides opportunities for internships, training programs, and workshops, hereby facilitating the exposure of students and staff members to real-world industrial experiences.

The percentage of industry-academia collaboration in China has been increasing in recent years. In 2019, the Chinese government issued a policy document that called for increased collaboration between industry and academia, and set a goal of doubling the number of industry-academia collaboration projects by 2025 (Ministry of Science and Technology China, 2020). According to a report by the Chinese Ministry of Science and Technology, the number of industry-academia collaboration projects in China increased from 180,000 in 2015 to 320,000 in 2020, representing a quantum leap. The total funding for industry-academia collaboration projects in China also increased from 100 billion Yuan in 2015 to 300 billion Yuan in 2020 as shown in **Figure 1**. The Chinese government is expected to continue to promote industry-academia collaboration in the coming years. The government has identified a number of key areas for industry-academia collaboration, including artificial intelligence, big data, and semiconductors.

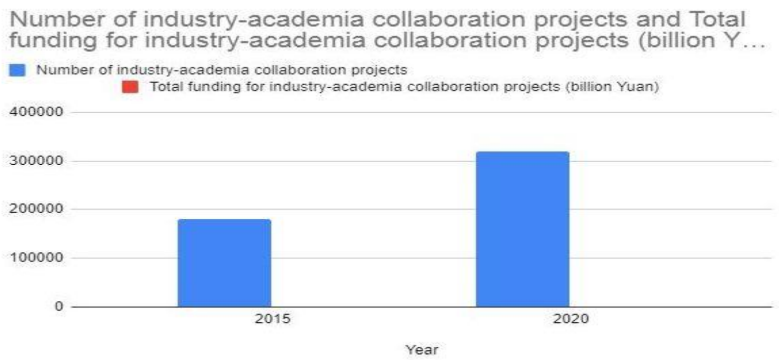

Figure 1. Percentage Increase in industry-academia collaboration.

Industry-academia collaboration in China has been steadily increasing in recent years, fueled by government policies, initiatives, and a growing emphasis on innovation-driven development. China's "Double First Class" initiative, which aims to cultivate world-class universities and disciplines, has encouraged closer ties between academia and industry. The government has encouraged research institutions and universities to work closely with industries to drive innovation and technology transfer (Ministry of Science and Technology China, 2020). Particularly, special economic zones and tech hubs in cities like Beijing, Shanghai, Shenzhen, and Hangzhou have witnessed a surge in collaboration between universities and tech companies. The establishment of innovation centers, research parks, and incubators has created conducive environments for collaboration, allowing academia to contribute theoretical knowledge and research expertise while industries provide practical application and market-driven insights. Moreover, programs like the "Industry-Academia Cooperation Project" by the Ministry of Education and various research grants have further incentivized collaboration between academia and industry (Ministry of Science and Technology China, 2020).

At the heart of this collaboration is the infusion of artificial intelligence in IAC. Artificial intelligence (AI) is the ability of a machine to simulate human intelligence. AI systems can learn from data, identify patterns, and make decisions in order to solve problems. AI is used in a wide range of applications. Artificial intelligence (AI) has emerged as a transformative force within the realm of education Murphy (2020), finding widespread applications primarily within educational institutions in a multitude of forms (L Chen et al., 2020). The inception of AI in education can be traced back to its initial manifestations through computer and computer-related technologies. Over time, its presence expanded into web-based and online intelligent education systems (Murphy, 2020). Subsequently, AI further evolved to encompass embedded computer systems, humanoid robots, and web-based chatbots, enabling diverse modalities for executing the responsibilities and functions of instructors. The integration of AI platforms has significantly streamlined administrative tasks for educators, leading to enhanced effectiveness and efficiency in their roles. Moreover, AI has proven instrumental in curriculum development and research activities (Estevez et al., 2019). By leveraging machine learning and adaptability, educational systems can tailor curriculum and content to suit the unique needs of individual students. A distinctive feature of AI-enabled education is its capacity for customization and personalization. AI algorithms analyze data and patterns, allowing for the creation of personalized learning paths for students. This tailored approach contributes to heightened engagement and retention rates among students, thereby enriching the overall learning experience and augmenting the quality of education provided (L Chen et al., 2020). In essence, AI has evolved to become a vital enabler within the educational landscape, profoundly impacting teaching methodologies, administrative processes, and student outcomes. As technology continues to advance and AI capabilities become increasingly sophisticated, the educational sector stands to benefit even more, with the potential to revolutionize the way knowledge is imparted, acquired, and applied in the pursuit of academic excellence Global Development of AI-Based Education.

A successful university–industry collaboration is led by academic management (Rahm et al., 2000; Edmondson et al., 2012); an emphasis on long-term calculated relationships (Calder, 2007); and a mutual vision and approach to the accomplishment of a goal. All of these elements are crucial to the success of a relationship with industry. In China, science and technology (S&T) now accounts for 56.4 percent of economic growth, up from 56.4 percent in 2016 and 59.5 percent in 2019; this represents an increase from 39.7 percent in 2003. Theratio of enterprise R&D spending to national R&D spending increased from 62.37 percent to 77.46 percent over the same time period (Zheng and Wang, 2021). In China, company innovation has become a driving force for national innovation. China's global competitiveness may be increased (J Hong et al., 2015), and the "average-earning trap" can be avoided (Liu et al., 2017) by enhancing the innovative capacity of Chinese businesses.

Collaboration is common in many different fields, as evidenced by several authors. China is a massive economic powerhouse in Asia, and its influence on global infrastructural development and technological innovation is immense. A constructive industry-academic partnership is vital for this to be achievable (Agrawal, 2001). Industry–university collaboration is required for research and development (Scandura, 2016), product patenting and licensing (Luan et al., 2010; Leydesdorff, 2004; Rosell and Agrawal, 2009; Dill, 1995; Balconi and Laboranti, 2006), curriculum development, and delivery and evaluation (Guimón, 2013; Deborah, 2011). In line with Shewakena Tessema (2017), we believe that collaboration in curriculum development and delivery would ensure that what is taught in universities is pertinent to the goals of the industry. Numerous Chinese research institutes have engaged in significant market-oriented operations since the late 1990s. Research institutes have regularly worked with businesses on a wide range of innovative projects due to their excellent R&D skills and increased market sensitivity (Liu et al., 2017). In contrast, since 2005, as a result of the most recent wave of science and technology (S&T) reforms, in addition to teaching and research as a "third mission", Chinese universities are starting to collaborate with businesses (W Hong, 2008).

To improve educational prospects for students, there has been a tremendous push for collaboration between academia and industry over the past decade (Ziegler, 1983). The importance of providing students with suitable education, particularly at the undergraduate level, by universities has long been recognized (Eli, 1986). The "industry/academic gap" has been the subject of a slew of sessions at conferences, frequently characterized by a lack of comprehension of the goals and approaches of each side (Judy, 1986). Successful relationships are driven by individuals who have a thorough understanding of both the academic and corporate worlds (Edmondson et al., 2012). When industry and academics collaborate, qualified workers who are prepared with the latest technologies to answer society's concerns are offered to industry. One of the numerous educational benefits of industry-academia partnerships is the opportunity to learn about the process of innovation. It is challenging to establish and use sets of indicators to evaluate industry-academia collaborations, given the goal of these collaborations is to produce new results. Traditional measures cannot capture the intricacies and complexities of innovation. A wide range of indications must be used instead (Smith, 2006).

Through a computational process, artificial intelligence aims to explain all characteristics associated with human intelligence. It is able to interact with its surroundings through the use of sensors and can make decisions autonomously (Aishath et al., 2019). Simply said, AI is a type of manufactured intelligence. Intelligence is a distinguishable individual attribute or quality that can be distinguished from all other individual properties. The behaviors of artificial intelligence are also observable in the performance of specific tasks. The fourth industrial revolution, or "Industry 4.0", is propelled by innovative technology, particularly improved information and communication technologies.

ICT stands for Information and Communication Technology. It represents a broad term that encompasses all technologies used to manage, process, transmit, and exchange information in various forms including data, text, sound, images, and video (UNESCO, 2019). The core objective of ICT is to enhance communication and facilitate efficient storage, retrieval, processing, and usage of information. Almost every level of industrial operation is affected by advanced ICT. ICT is a significant factor that enhances the responsiveness and effectiveness of production and supply chains (Apiyo and Kiarie, 2018). The urge to delegate human duties and tasks in various settings to machines has led to the rise of smart environments as the world continues to enter the digital era. The educational context is one of these environments. We hypothesize that the adoption of artificial intelligence will be a prerequisite for achieving the desired level of educational opportunities.

China is one of the world's leading centers of artificial intelligence (AI) development, with its largest technology companies driving R&D. Its large populace and varied industrial composition can generate enormous amounts of data and create a vast market (Manyika et al., 2017). China's future economic growth could be contingent on the extensive adoption of artificial intelligence (AI) technologies in R&D, product patenting, and curriculum development. The application of AI in industry-academia collaborations has enormous economic potential for China due to its rapidly evolving nature. The country will need to pay close attention to developing its potential for innovation. For instance, despite the fact that Chinese scholars have written and published more research articles on AI than American researchers, their works have not had the same influence as those authored by American or British authors. Furthermore, a comparable AI environment to that of the United States, which has generated a lot more AI startup businesses than China, is also lacking in China (Manyika et al., 2017). The American environment is vast, creative, and diverse (including study institutions and further education colleges as well as private corporations). It incorporates all of Silicon Valley's well-known strengths and has numerous advantages that are uncommon elsewhere (Biba, 2016). In addition, current expansion of quantitative research is occurring (for example, Kim et al., 2019; Belitski et al., 2019). It is still necessary to do quantitative research, particularly in China, to determine the role of intermediaries (such as artificial intelligence) in the connection between academic-industrial collaboration and industrial innovation.

As an outcome of the rapid transformation of the technical growth of industrialized nations, China, which is unquestionably the Asian superpower in every field, must find a more efficient and expedient means of improving educational prospects. To reach the current level of industry-academia collaboration in the USA, a more effective method of enhancing educational outcomes is required in China. The adoption of artificial intelligence enables the university and industry to make great decisions, hence improving the speed and accuracy of strategic decision-making processes, which will improve basic business operations and enhance the product and services quality.

The research problem addressed in this study revolves around investigating the transformative potential of industry–academia collaboration in the context of enhancing educational opportunities and outcomes amidst the pervasive digital landscape of Industry 4.0. The study recognizes the fundamental shift brought about by Industry 4.0, driven by advanced digital technologies and artificial intelligence (AI), and aims to comprehend how the synergy between academia and industry can be harnessed to optimize educational prospects. It seeks to elucidate the mediating role of AI, acting as a catalyst, in mediating the relationship between industry–academia collaboration and educational outcomes. This research problem encapsulates the pressing need to explore innovative strategies that align educational systems with the rapidly evolving demands of the digital era, ultimately fostering a symbiotic relationship between academia and industry to nurture a skilled and adaptable workforce for the future. The investigation is grounded in the urgency to bridge the existing knowledge gap and identify effective pathways to leverage this collaboration, shaping a dynamic educational landscape within the ambit of Industry 4.0. The broad objective of the study is to examine the role of industry–academia collaboration in enhancing educational opportunities and outcomes under the digitally driven Industry 4.0. The study was guided by the following research questions:

1) What is the effect of research and development on educational opportunities and outcomes under the digital driven Industry 4.0 in China.
2) What is the effect of patenting of products/knowledge on educational opportunities and outcomes under the digital driven Industry 4.0 in China.
3) What is the effect of curriculum development on educational opportunities and outcomes under the digital driven Industry 4.0 in China.
4) What is the mediating role played of artificial intelligence on the relationship between industry–academia collaboration and educational opportunities and outcomes under the digital driven Industry 4.0 in China.

2. Literature review and theory

2.1. Industry academia collaboration (IAC)

Many researchers have examined the role of academic–industry collaboration in various contexts, for example, in the United Kingdom (D'Este and Patel, 2007), the United States (Ponomariov, 2013), Japan (Motohashi and Muramatsu, 2012), and others (D'Este and Patel, 2007). IAC articles, in spite of the apparent diversity of the study contexts, can be divided into three groups: IAC drivers, IAC patterns, and IAC outputs. This study focused on the output dimension of academic–industry collaboration. Alliances, joint ventures, networks, and consortia are the most common types of industry-academia cooperation (Ankrah and Al-Tabbaa, 2015). There are a variety of ways in which the participating organizations are linked. Organizations can often jointly develop initiatives that focus on certain scientific or technological topics through various kinds of partnership. It is also possible that, under some circumstances, long-term collaborations are developed rather than being a requirement to solve a technical challenge or produce commercial items rapidly.

Companies are looking for ways to increase their social capital as well as their capacity for the generation of new ideas through long-term collaborations. University-industry partnerships and collaborations may be widespread; however there may be variations between industries, according to Perkmann and Walsh (2007). Open and networked innovation activities have demonstrated that real partnerships and collaborations—rather than merely abstract connections—play a stronger role in fostering innovative activities and the potential of participating organizations. It has been pointed out that corporations involved in these relationships are looking for enhanced innovative capabilities, rather than rapid, commercialized, tangible results. Large corporations are no longer the only ones interested in collaborating with universities. Collaboration networks are being formed by large and small organizations in order to further their creative efforts aimed at benefiting both markets and customers. The Triple Helix model is a common way for public institutions to support university and industry collaborations. It has been found to be a critical component in the development of regions and countries around the world (Cai and Etzkowitz, 2020; Guimón, 2013; Dooley and Kirk, 2007).

2.2. Collaboration in the Chinese context

The China growth model is based on the switch from massive industrial investment to development encouraged by a creative society (Naughton and Tsai, 2015). One important strategy for generating this kind of inventive growth has been suggested: science and technology. The enthusiasm of prominent Chinese universities for university-industry collaboration (UIC) appears to be much lower than that of their European and American counterparts, according to a similar analysis conducted by Li et al. (2020). On average, each of the top US colleges publishes twice as many UIC publications as China's equivalent top-ranked institutions. Tsinghua University, a Chinese university, produced 1581 papers between 2013 and 2016, which is comparable to the University of Minnesota Twin Cities, which was ranked 15th among 175 American universities in the 2018 Leiden Ranking. Tsinghua University, ranked number one in China, is about on par with Freie Universität Berlin, ranked 10th in the European Union. According to Argyropoulou et al. (2019), there is no evidence to support this conclusion. They claim that there a paradox of innovation is occurring in China. These authors argue that while China's scientific outputs and inputs are of the highest quality, productivity gains are not as strong. As a result, China ranks low in terms of its industry–academic collaboration when compared to other countries due to the lack of collaboration and publication in scholarly publications.

Collaboration between industry and academics is capital-intensive. When government funding is insufficient, participation in industry-academia partnerships is poor. For instance, the UK government's Higher Education Innovation Fund will invest two hundred and thirteen million Euros to facilitate contact between universities and industries. It has been observed in China that collaborations with institutions of higher education are predominantly created with big corporations, notably state-owned industries, leaving SMEs, which constitute a significant share of the Chinese industrial base, with less assistance for their R&D operations (Liu et al., 2017). In addition, the customary technological vision of creativity and the importance placed on formal collaboration channels have restricted Uniform Industrial Corporations (UICs) to influential colleges and the fields of science, technology, engineering, and mathematics (STEM). First-tier and regional universities are the two categories used to categorize universities in China. Regional institutions are less research-focused and are run by their individual provincial governments, but first-tier universities are generally thought to produce higher-quality research and are directly governed by the Ministry of Education. In contrast to the eight programs operated by regional universities, each top-tier university engages in an average of 61 industry collaboration programs, according to a national research project conducted by the Chinese Ministry of Education in 2019 (Ministry of Education, 2019). According to a survey conducted by Hughes and Kitson (2012), in the UK, nearly half of the 4452 collaborative projects recorded involved STEM fields and the health sciences, with around 30% involving the arts and humanities, and about 20% involving the social sciences. Although the importance of top-tier academic institutions and the natural sciences has been acknowledged, more research should be done to ascertain how regional institutions with lower rankings and the social sciences may aid in industrial innovation.

2.3. The Helix models

The framework focuses on academia, universities, and industry as innovation agents. In this study, academia and industry form the unit of analysis as an agent of the incubation of innovations (universities) and the utilization of innovation (industry). Their fruitful interactions and collaborative efforts promote economic growth and innovation in the region. The Triple Helix hypothesis suggests that the purpose of universities should go beyond social instruction and investigation to also include the contribution to provincial advancement through the creation, dissemination, and utilization of industry-driven knowledge. The Triple Helix model is an "innovation-push" approach, in which innovation is pushed from the academic world into industry, where it is then refined and put to use. According to this model, the government is able to fulfill its responsibility to the public by funding research at universities and outlining the path forward for regional or national innovation systems through public policy. The conventional concept of a "triple helix" has been developed further (Miller et al., 2016) in order to encourage interactions between all of the various social sectors to jointly produce new knowledge and innovations. **Figure 2** is a path diagram that describes the pathways between the variables included in the study and the covariance between the exogenous variables together with the recursive nexus between the endogenous variable and the control variable (artificial intelligence).

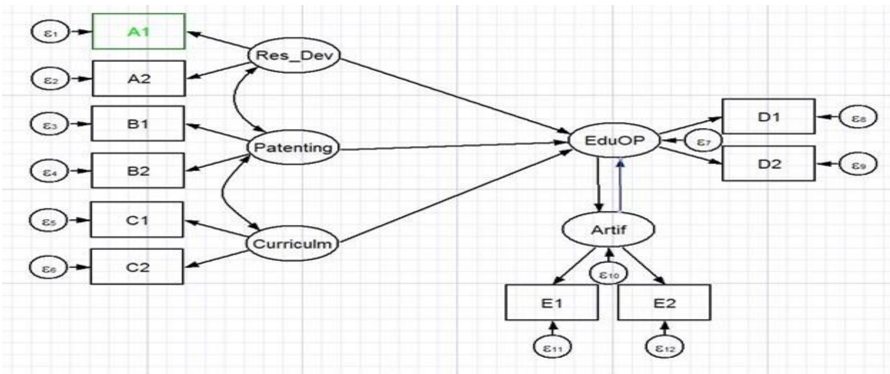

Figure 2. Path diagram (source: research model).

H1: Industry-academia collaboration through joint R&D does not significantly enhance educational opportunities.

Firms' level of R&D has been noted as a key determinant (Laursen and Salter, 2004) in industry–academia collaboration (Fernández López et al., 2014; Aiello et al., 2019). Investment in internal R&D increases a company's capacity for learning and absorbing external knowledge, because university knowledge may be difficult to transfer to businesses (Cohen and Levinthal, 1989). It is via the use of artificial intelligence (e.g., artificial intelligence, automation technologies, and others) that corporations and academia are able to work together. The Chinese government has made a huge investment in R&D, reaching up to 301.32 billion Yuan, which represents a significant increase. According to Albahari (2017), academic institutions and private enterprises enter into R&D partnership agreements to work together on research projects, regardless of who is providing the funding. Such projects can include anything from industry-funded cooperative research programs to research pacts, experimentation, compliance and accreditation testing for organizations, and joint publications with experts from the company. It also includes co-funding for PhD students as well as industrial PhDs (Khachoo et al., 2018). When the worlds of academia and industry come together, there is an assumption that both will benefit (Payne, 2007; Breese, 2012).

H2: The development and patenting of products does not improve educational opportunities.

Mazzocchi (2004) measured the industry–academia partnership by submitted and granted patents, the patent utilization ratio, the percentage of supported ideas, and the revenue from external licenses. Patenting uses these metrics. These metrics show industry-academia collaboration. Relevant literature examined the roles of intermediaries in university-industry collaboration (Kim, 2019; Belitski, 2019). We hypothesize that using AI to patent manufactured goods will improve Chinese education. Research promotes industrial innovation through product creation, patenting, and human capital transfer (Perkmann, Tartari et al., 2012; Motohashi, 2006). Universities produce patentable goods when they support local and regional economic development, commercialize research, and improve faculty contact with industry scientists. Increased Chinese university patenting is driven by the "Chinese Bayh-Dole Act" and a research assessment system that supports patenting by researchers. Due to flaws in the evaluation system and the sequential structure of university-industry ties, rapid growth in academic patents results in low patent quality and low university patent utilization.

H3: Curriculum development and delivery does not significantly enhance educational opportunities.

Courses, modules, programs, majors or minors, planned experiments, and course delivery by outside organizations may be jointly produced and supplied. This includes joint PhD supervision, the creation and organization of new study programs, guest lectures by business representatives, curriculum evaluation, and student business experiences. University–industry collaboration is important, especially for curriculum development and implementation. Few curriculum development models are specific enough to be used in practice or generalized outside their area of origin. In recent years, many examples of curriculum design collaboration have been published to adapt higher education to technical and social realities. Literature examples include design in Portugal (Motohashi, 2006), renewable energy in Latin America and Europe (Comodi et al., 2019), tourism (Dopson and Tas, 2004), the automotive industry in the USA (Mears, 2009), industrial engineering in Thailand

(Koomsap et al., 2019), and the development of Industry 4.0 competences in Estonia and Tanzania (Kusmin et al., 2018; Mgaiwa, 2021).

H4: There is no recursive nexus between artificial intelligence and educational opportunities.

The recursive nexus between artificial intelligence and educational opportunities that exist through artificial intelligence offers limitless opportunities to students in school and industry experts (Jing, 2018; S Chen, 2018; He and Bowser, 2017). AI can assist school students in obtaining solutions to their most frequently asked questions within seconds. This not only saves teachers a significant amount of time but also reduces the time spent by students looking for answers or awaiting a response to their inquiries. Artificial intelligence is a flourishing field of technology that has the potential to change peoples' experiences. In education, the role of AI has been attributed to its ability to provide answers to the problems of society. This development is currently being evaluated as a variety of scenarios (S Chen, 2018). AI requires sophisticated infrastructure and a strong community of innovators. The goal of the experimental artificial intelligence course conducted under the aegis of the industry/academic partnership was to strengthen the partnership, as there is a Granger causality effect of artificial intelligence on educational opportunities. We believe that artificial intelligence (AI) has the power to moderate, reshape, and transform the global technological landscape by improving educational opportunities. AI is being broadly used across all major fields of human endeavor as well as for national defense and security (Zhang et al., 2018). Consequently, its usage as a moderating variable to expedite educational outcomes in industry–academia collaboration is a positive factor in the continuing discussion over industry–academia collaboration.

2.4. Gaps in literature

Despite the work and progress in the study of university-industry collaboration, there are at least two knowledge gaps. First, most of the prior research on the outcomes of collaboration has been primarily concentrated on technological advancement without taking into account the opportunities that this has presented to the educational sector as a spillover effect. This suggests that debates on the effects of R&D collaboration on educational opportunities have been conspicuously absent from most industry–academia collaboration studies, especially in the study area. There is still a lack of consensus regarding the manner in which the industry-academia collaboration enhances educational outcomes in the study area. Second, this research contributes to the literature as well as practices that are currently in use by building on past academic conversations and published works of literature. Specific to China, the investigation of the function that a recursive nexus in artificial intelligence plays in facilitating industry–academia collaboration to expand educational opportunities is novel. It adds to the diminutive body of research on how the influence of artificial intelligence is able to mediate this nexus. Even though the Chinese use of artificial intelligence is not new, its application in research and development, product patenting, and curriculum development has been low compared to other developed countries (He and Bowser, 2017; Ryan, 2021). The study equally highlights the directions of the movement of the exogenous variables as they interact to affect educational opportunities.

3. Research methodology

3.1. Research design

A survey research methodology was used for this study in which structured questionnaires were distributed to the target population by researcher assistants. The study protocols were approved by the Chang'an University research committee. For research of this nature, data can be collected from a variety of secondary databases. Due to a paucity of crucial information required to answer our research questions, secondary databases of industry–university collaboration in China do not contain information on specific activities associated with industry–university collaboration in the study area. To address study objectives 1–3, a dataset at the firm level that combines industry and academic collaboration data is necessary which necessitate the use of survey in obtaining the relevant data.

3.2. Study area

China has a vast geographic area with a wide range in terms of the degree of regional development. These seven regions were chosen because they have similar institutional contexts, which made it easier to control the sample selection bias. The National Bureau of Statistics ranks them as the top seven provinces for GDP (National Bureau of statistics of China, 2010). Comparatively to businesses in other locations, these businesses tend to be more contemporary, aggressive, and innovative. The general managers, CEOs, and R&D managers of these firms were targeted because they understand their companies' progress. This indicates that the information gathered for scholarly research is accurate and trustworthy.

3.3. Sample and sampling technique

To gather data for the academic part of the project, seven (7) universities from the seven regions were sampled evenly. A total of 327 participants were included in the sample for this investigation. Knowledge of the topic area, experience, position, and specialization were used as the criteria for selecting respondents. Also, the proportion of samples selected by each partner was contingent on the availability of employee-related R&D projects in any of these businesses. A total of 223 firms and 7 universities agreed to participate in the survey, making a total of 230 research units. The study sample was not large due to limits on time and availability of willing respondents to provide information on the research questions of the study. The questionnaire was divided into two sections: the first collected demographic information about the respondents, and the second referred to the study objectives. Out of the 327 respondents included in the study, only 230 completed the survey, leading to a response rate of 70.34%. Purposive sampling was used to identify the suitable respondents for the study as earlier stated.

3.4. Data collection techniques

All participants were adequately informed about the purpose and procedure of the study and their informed consent were obtained before participation. Random individuals from Guangdong, Jiangsu, Zhejiang, Shandong, Henan, Beijing, and Shanghai received questionnaires. IT, communication, business and economics, electronics, construction, service firms, and manufacturing firms were the major respondent industries. Data were collected from 13 August to 24 October 2022. The study's objectives were captured in a structured questionnaire that was developed by the area's firms and universities. Two professors and 5 PhD holders trained to conduct online and face-to-face surveys collected the data. The questionnaire was designed using google forms (Esangbedo, Zhang, Esangbedo, Kone and Xu, (2023)), which is a popular online survey tool for gathering data from respondents, especially from those located far away. Top managers of the firms and the selected universities were contacted by the researchers and research assistants by phone and email to inform them about the purpose of the survey and to solicit for their participation.

3.5. Validity and reliability of the instrument

A pilot study was carried out with one third of the total sample to ensure representativeness. The pilot study was necessary as it provided the means to obtain a first information by the researcher. The questionnaire was validated using content validity which take into account the expert contributions from my supervisor and statistician (Hair, 2011). Since construct validity statistics require a large dataset(Ong, 2014), the content validity was assessed. This required the supervisors to validate the wording of the instrument to ensure it was consistent with the objectives of the study. Cronbach Alpha statistics were used to determine the instrument's internal consistency. The result of the reliability test is as shown in **Table 1**:

Table 1. Cronbach alpha reliability coefficients.

Code	Constructs	Cronbach-α
A	Research and Development (R&D)	
A1	We are engaged in inventive and methodical efforts to expand the body of human knowledge.	0.9794
A2	The results of research and development are freely transferred or traded on the market.	0.98
B	Development and patenting of products	
B1	Most patent investment strategies are contingent on the investment's potential market returns.	0.9791
B2	In terms of product development, there has been a rise in patenting due to increased interaction between the university and industry.	0.9799
C	Curriculum development and delivery	
C1	The course description accurately describes the types of responsibilities a graduate can anticipate performing in the workplace.	0.9774
C2	The length of the program is sufficient to provide graduates with the knowledge and/or skills required to enter the field.	0.9781
D	Educational opportunities	
D1	When industry and academia collaborate, educational opportunities are plentiful.	0.9789
D2	Collaboration increases the industry's access to qualified workers.	0.9776
E	Artificial intelligence utilization	
Aint	There is substantial investment in artificial intelligence research.	0.9803

Table 1 shows the Cronbach reliability of the instrument. From **Table 1**, the statistics for the study's individual variables show index values of 0.9794 for A1, 0.9800 for A2, 0.9791 for B1, 0.9799 for B2, 0.9774 for C1, 0.9781 for C2, 0.9789 for D1, and 0.9776 for D2. The Artificial Intelligence construct (Aint) index is 0.9803. The overall index of reliability is 0.9813, as shown in **Table 1**. According to George and Mallery (2021), a Cronbach Alpha value of 0.70 is reliable for social science research. In early research, a reliability of 0.70 or higher was sufficient (Thorndike, 1995). Even with a reliability of 0.90, the standard error of measurement is almost one-third as large as the standard deviation of the test scores, so 0.90 is the minimum acceptable reliability, and 0.95 is the desired standard. Thus, this study's data collection instrument is reliable.

Table 2 shows the results of an item correlation test that was conducted to determine whether any test item was inconsistent with the averaged behavior of the others and could therefore be discarded. The 9-item study value scale reliability was analyzed. The questionnaire's Cronbach's Alpha was 0.9813, which is acceptable. Most items were shown to be worth keeping; deleting them would lower the alpha value. No item's Cronbach value was higher than the overall Cronbach Alpha value. Deleted items would not improve the overall Cronbach Alpha statistics for any of the study's variables.

Table 2. Detailed cronbach alpha statistics.

Item	Obs	Sign	Item-test correlation	Item-rest correlation	Average inter-item covariance	alpha
A1	230	+	0.926	0.9078	0.32478	0.9794
A2	230	+	0.9158	0.8914	0.31477	0.98
B1	230	+	0.9302	0.9119	0.32061	0.9791
B2	230	+	0.9139	0.8902	0.31835	0.9799
C1	230	+	0.9674	0.9569	0.30475	0.9774
C2	230	+	0.9523	0.938	0.31022	0.9781
D1	230	+	0.9373	0.922	0.32448	0.9789
D2	230	+	0.9595	0.9483	0.31478	0.9776
Aint	230	+	0.9038	0.8792	0.32369	0.9803
Test scale					0.31738	0.9813

Test scale = mean (unstandardized items).

3.6. Variable specification

Definition of constructs: This study used hypothetical constructs. Hypothetical constructs are not directly observed but are assumed to explain observable phenomena, according to Colman (2015).

Research and development: Research and development is the process by which a company generates new knowledge to create new technologies, products, services, or systems to solve societal challenges.

Product patenting and development: A patent grants investors and others derivation rights and the right to exclude others from manufacturing, using, or selling patented products or methods or processes for a limited period of time (Vedaraman, 1971).

Curriculum development and delivery: Curriculum development is a planned, thoughtful, and deliberate process that improves student learning. It involves the development and organization of learning activities to meet learning outcomes using the best methods.

Educational opportunities: Educational opportunity is defined as anything that adds value to the educational experience and better prepares you for meeting academic challenges and challenges posed by the larger society**.**

Artificial intelligence utilization: Artificial intelligence was used as the control variable in this study. It was included to establish how artificial intelligence mediates between IAC and educational opportunities. The simulation of human intelligence processes by machines, primarily computer systems, is known as artificial intelligence. In this study, it was measured as the level of spending by firms on the use of artificial intelligence for business operations.

3.7. Measurement of variables

The measurement items were adapted from Hou, Hong, Chen et al. (2019), who studied whether academia-industry R&D collaboration promotes industrial innovation in China with a focus on technology transfer institutions. The constructs were modified for this study. The questionnaire was based on prior research and interviews. The study have three independent variables of research and development, patenting and curriculum development. It also has one moderating variable of artificial intelligence and one dependent variable of educational opportunities. The independent variables have six (6) measurement variables. Artificial intelligence and educational opportunities have two measurement variables respectively. Twelve error terms are associated with the structural equation model arising from all the variables of the study.

3.8. Model specification

STATA version 13.0 for windows was used to create a structural equation model (SEM) to determine the study's variable relationships.

As shown in **Figure 2**, there are three independent variables of research and development, patenting and curriculum development being moderated by artificial intelligence leading to their impact on the dependent variable of educational opportunities. The relationships and hypothesized pathways is indicated using arrows between latent variables and observed variable. These relationships represent the theoretical connections between the constructs in the model.

Two measurement variables items are associated with each of the construct, leading to ten measurement items for all the variables used in the study. Twelve error terms are associated with each variable, accounting for unexplained variance in the model. Artificial intelligence mediates the relationship between the independent variables and the dependent variable. The model specifies a and tests the hypothesis that there is no recursive nexus between artificial intelligence and educational opportunities.

3.9. Method of data analysis

Data obtained from this study was analyzed using descriptive statistics such as frequencies and percentages. The relationship between the variables of the study were modeled using structural equation model.

Fit indices and model evaluation criteria:

Several SEM model fit indices were used to evaluate the goodness of fit and appropriateness of the model in modeling the relationship between the study variables. These indices are:

Comparative Fit Index (CFI): The Comparative Fit Index (CFI) is a statistical measure in Structural Equation Modeling (SEM) to assess the goodness of fit of a hypothesized model. It is a comparative index, comparing the fit of the specified model to a baseline or null model, often a model where the variables are assumed to be uncorrelated. The CFI ranges from 0 to 1, with higher values indicating a better fit of the specified model to the observed data. A CFI close to 1 (typically above 0.90 or 0.95) suggests that the hypothesized model fits the observed data well, indicating a good fit.

Root Mean Square Error of Approximation (RMSEA): The Root Mean Square Error of Approximation (RMSEA) was used in the study to assess the goodness of fit of a hypothesized model by evaluating the discrepancy between the observed data and the model's implied covariance matrix. RMSEA is important because it accounts for the model’s complexity by adjusting for the degrees of freedom. It is especially valuable for evaluating how well the model reproduces the observed covariance matrix, providing insights into the discrepancies between the model and the data.

Tucker–Lewisindex (TLI): The Tucker-Lewis Index (TLI), also known as the Non-Normed Fit Index (NNFI), is a goodness-of-fit index used in Structural Equation Modeling (SEM) to evaluate the fit of a statistical model to the observed data. It is one of the several fit indices used to assess the adequacy of the model in explaining the relationships between observed and latent variables.

LR test of model fitness (LR): The Likelihood Ratio (LR) test, also known as the chi-square difference test, is a statistical test used to assess the goodness of fit of a structural equation model (SEM) by comparing the fit of a specified model with a more restricted or nested model. It helps in evaluating whether adding or removing parameters significantly improves or worsens the model fit.

4. Result and discussion

4.1. Demographic characteristics of the respondents

Figures 3–5 on the sectoral distribution of respondents, show that 144 (62.61%) of respondents were from the academic sector, while 86 (37.39%) were from industry, thus giving academia a greater representation in the results of the survey. **Figure 3** shows that the majority of the sampled respondents (209; 90.87%) were undergraduates, while 21 (9.13%) of the respondents were postgraduate students. This shows a high level of participation of university students in collaborations between the university and industry. This proves that forging a partnership at the early stages of university education provides a key advantage for enhancing the educational opportunities of Chinese citizens. More males participated in the survey than their female counterparts. Males constituted 56.52% of the sample (130 respondents), while female respondents represented 43.48% of the sample (100 respondents).

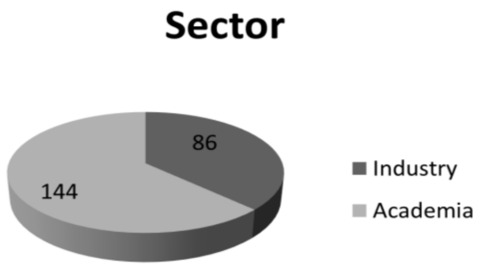

Figure 3. Sectoral distribution.

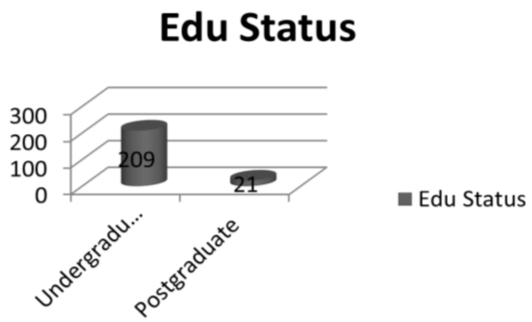

Figure 4. Educational distribution.

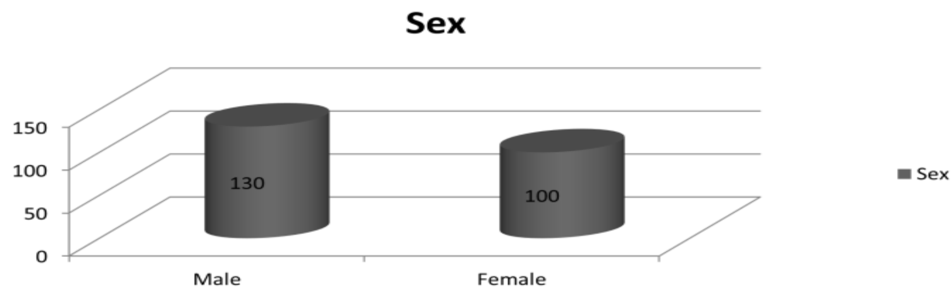

Figure 5. Gender distribution.

4.2. Summary statistics

Table 3 summarizes all study variables. The study variables have a standard deviation of less than 1, indicating that their values are close to the population mean. Our study results are reliable because a high standard deviation indicates that values are spread out and less reliable (Kollo et al., 2005). The maximum response value was 4, representing strongly agree, and the minimum value was 1, representing strongly disagree.

Table 3. Summary of the statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
A1	230	3.4	0.5575993	2	4
A2	230	3.15217	0.6463668	1	4

Table 3. (*Continued*).

Variable	Obs	Mean	Std. Dev.	Min	Max
B1	230	3.3913	0.5865397	1	4
B2	230	3.17826	0.6188146	1	4
C1	230	3.24783	0.6767309	1	4
C2	230	3.22609	0.6482879	1	4
D1	230	3.33913	0.5510919	1	4
D2	230	3.3	0.6067308	2	4
Aint	230	3.42609	0.5845294	2	4

4.3. Test for multicollinearity

In **Table 4**, all items show positive covariance between one construct and another. This implies that these variables move in the same direction in their relationship (Kollo et al., 2005). For the covariance results, the values are low, less than 0.5, which implies that they are not highly correlated. A high correlation, for example, 0.9, could indicate the presence of multicollinearity in the dataset. The consequence of multicollinearity is that it makes the standard errors much larger than they would otherwise be, thereby decreasing the *t*-statistics and increasing the probability. The consequence of this is that the study variables will not be significant. The values are low, less than 0.5, which is suggestive of moderate correlation and low multicollinearity.

Table 4. Correlation matrix.

	A1	A2	B1	B2	C1	C2	D1	D2	Aint
A1	0.3109								
A2	0.2707	0.4178							
B1	0.3188	0.2895	0.344						
B2	0.2603	0.3789	0.2749	0.3829					
C1	0.3197	0.3944	0.3393	0.3705	0.458				
C2	0.2934	0.3847	0.3129	0.3613	0.4153	0.4203			
D1	0.2742	0.2844	0.2816	0.2755	0.3392	0.3116	0.3037		
D2	0.2943	0.3297	0.31	0.3218	0.3882	0.3598	0.3083	0.3681	
Aint	0.3004	0.2799	0.3216	0.2687	0.3263	0.3006	0.2654	0.2996	0.3417

4.4. Model fitness

The criteria for determining whether or not a model is a good fit are listed in **Table 5**. The model's accuracy can be assessed with four different metrics: the root-mean-squared error of approximation (RMSEA), the comparative fit index (CFI), the Tucker–Lewis index (TLI), and the LR test of model fitness (TLI). Browne and Cudeck (1993) suggested that the LR should be greater than 0.05. A small RMSEA (0.05) indicates a good fit between the hypothesized model and the observed data, while a moderate RMSEA (0.05–0.10) indicates a fair fit, and a large RMSEA (> 0.10) indicates a poor fit. However, an RMSEA of 0.06 may indicate a good fit, as suggested by Hu and Bentler (1999) in the root-mean-squared error of approximation (RMSEA) formula. Higher values of CFI, a fit index with a range from 0 to 1, indicate a better fit. Thus, CFI is the most popular measure of compatibility at 0.95 (Hu and Bentler, 1999; West et al., 2012). The TLI (Tucker and Lewis, 1973) assesses the degree to which there has been a reduction in misfitting. As shown by the data, the model fitness hypothesis cannot be supported (RMSEA = 0.048). This means the model was fitted according to this measure of appropriateness. The CFI and TLI values should be close to 1 to be considered acceptable; these values can be used as criteria for model fitness (West et al., 2012). The study results show values of CFI = 0.756 and TLI = 0.582. Evidence from these statistics suggests that the study's model is appropriate, and that the study's estimates can be used to confidently advise policymakers. Standardized root-mean-squared residual coefficient of determination.

Table 5. Model fitness.

Fit statistic		Value	Description
Likelihood ratio	chi2_ms (121) *p* > chi2 chi2_bs (36)	1020.060 4136.97	model vs. saturated baseline vs. saturated
	p > chi2	0.357	
Population error	RMSEA 90% CI, lower bound upper bound	0.048 0.037	Root mean squared error of approximation
	p-close	−0.000	Probability RMSEA ≤ 0.05
Information criteria	AIC BIC	767.822 881.279	Akaike's information criterion Bayesian information criterion
Baseline comparison	CFI TLI	0.756 0.582	Comparative fit index Tucker-Lewis index
Size of residuals	SRMR CD	0.54 0.998	Standardized root mean squared residual Coefficient of determination

4.5. Model stability test

As shown in **Table 6**, all eigenvalues lie inside the unit circle (SI = 0.593987), thus satisfying the structural equation model stability condition. Model stability is a condition for accepting the results of the model for policy recommendations.

Table 6. Stability test.

Eigenvalue		Modulus
0+	0.5939587i	0.59396
0−	0.5939587i	0.59396
0		0
0		0

Table 6. (*Continued*).

Eigenvalue	Modulus
0	0
0	0
0	0
0	0
0	0
0	0

All eigenvalues lie inside the unit circle. SEM satisfies the stability conditions.

4.6. Path analysis

Figure 6 depicts a pathway analysis, a method for determining the effects of multiple variables on a specified outcome. The model shows that research and development, patenting, and curriculum development are exogenous variables, while educational opportunities and artificial intelligence usage are endogenous variables.

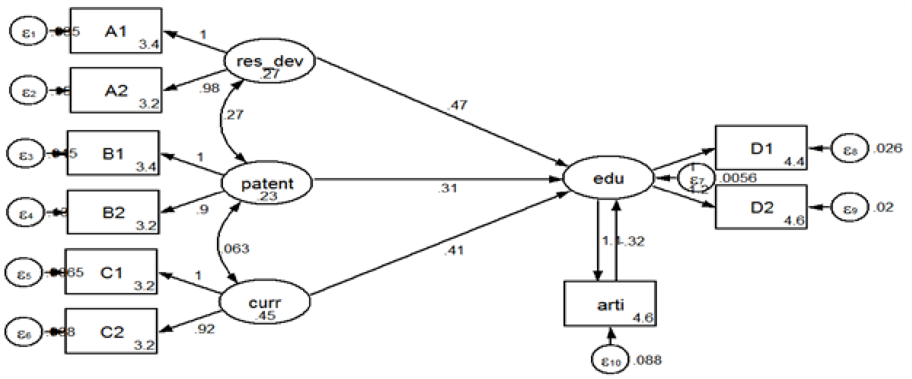

Figure 6. Path analysis.

The path for the covariance between the exogenous variables in the model is represented by res-dev, patent, and curr. The recursive nexus between educational opportunities and artificial intelligence is established. The path shows that all the exogenous variables are positive and significant predictors of the dependent variables.

Table 7 shows the conceptual model's SEM results. SEM models the relationships between latent variables, not their means, to control for measurement errors(Preacher and Hayes, 2004). In the first system of the equation, the recursive nexus between artificial intelligence and educational opportunities [aint & edu] indicates that educational opportunities is a positive and significant predictor of artificial intelligence (β = 1.099941, p < 0.05). This result supports the hypothesis that the deployment of artificial intelligence positively and significantly improves educational opportunities. The second system of the equation presents the nexus between the endogenous variable of educational opportunities (eduop) and a set of three other predictor variables: research and development (res_dev), product patenting (patent), and curriculum development (curr). Res_dev positively and significantly impacts educational opportunities (β = 1.099941, $p < 0.05$).

Table 7. Structural equation model result.

		Coef.	OIM Std. Err.	*z*	*p* > |*z*|	[95% Conf.	Interval]
Structural	eduop_cons	1.099941	0.0462845	23.76	0.000	1.009224	1.190657
Aint<−		4.628884	0.2671965	17.32	0.000	4.105188	5.152579
eduop<−	Aint	−0.3207327	0.066768	−4.80	0.000	−0.4515956	−0.1898699
	Res_dev	0.4691786	0.0705133	6.65	0.000	0.3309751	0.6073822
	Patent	0.3128488	0.0661369	4.73	0.000	0.1832229	0.4424746
	Cur	0.4053915	0.0445172	9.11	0.000	0.3181393	0.4926437
var (e.A1)		0.0345934	0.007506			0.02261	0.0529279
var (e.A2)		0.1517086	0.0155744			0.1240584	0.1855216
var (e.B1)		0.044637	0.006473			0.0335938	0.0593103
var (e.B2)		0.1261177	0.0124299			0.1039641	0.1529919
var (e.C1)		0.0064627	0.0060898			0.0010194	0.0409731
var (e.C2)		0.0380115	0.0062344			0.0275617	0.0524233
var (e.D1)		0.0260292	0.0032946			0.0203105	0.033358
var (e.D2)		0.0197908	0.0036084			0.0138441	0.0282918
var (e. Aint)		0.0876614	0.0094441			0.0709749	0.1082708
var (e. eduop)		0.0055586	0.0031074			0.0018583	0.0166269
var (Res_dev)		0.2749718	0.0294761			0.2228652	0.3392612
var (patent)		0.2314285	0.0314248			0.1773518	0.3019939
var (cur)		0.4495108	0.0429452			0.3727507	0.5420782
cov (Res_dev, patent)		0.2720847	0.0290304	9.37	0.000	0.2151863	0.3289832
cov (patent, cur)		0.0630601	0.0190935	3.30	0.000	0.0256374	0.1004827

LR test of model vs. saturated: chi2(21) = 1020.06, Prob > chi2 = 0.0846.

In accordance with the hypothesis, artificial intelligence is a significant predictor of educational opportunities (β= −0.3207327, $p < 0.05$). This result demonstrates a negative correlation between artificial intelligence and educational opportunities. This may be the case due to a number of factors, including low investment in science and technology and the absence of national strategies (Abrahams et al., 2010). The patent was signed in accordance with a priori expectations (β= 0.3128488, $p < 0.05$). Curriculum development (cur) was shown to have a positive impact on educational opportunities in the study area (β = 0.405391, $p < 0.05$), and this effect was statistically significant and consistent with a priori expectations. This indicates that an increase of one unit in [cur] will result in a 0.4053915.

The research and development construct is significantly predicted by item A2 (β = 0.9803375, $p < 0.05$), which indicates that the outcomes of R&D are freely transferred or traded in the market. B2 is a significant predictor of product patenting (β = 0.9009662, $p < 0.05$). This indicates that there is an increase in patenting due to greater interaction between the university and industry in product development. Curriculum development is positively and significantly affected by C2 (β = 0.9299666, $p < 0.05$). The D2 measure of how collaboration increases the supply of quality workers to the industry is a strong indicator of future academic success.

Cov (res dev, patent) and Cov (patent, curr) are positively and significantly correlated (cov1 = 0.2720847, p = 0.000 and cov2 = 0.0630601, p = 0.001). Positive covariance indicates that the two variables are positively related and have similar trends over time. However, because the variables all trend in the same direction, there is not much of a correlation between them. The sign of the covariance between two variables specifies the direction of their linear dependence. Coefficients are positive if there is a general trend toward an increase or decrease in both variables (Xie and Bentler, 2003).

Specific mechanisms through which AI contributes to educational opportunities (direct and indirect effect).

This structural equation model (SEM) **Table 8** focuses on the direct effects in the context of how artificial intelligence (Aint) mediates the relationship between the role of industry-academia collaboration and educational opportunities (EduOp) within the digital-driven Industry 4.0 landscape. The coefficient (Coef.) of 0.2262638 indicates a statistically significant positive direct effect of artificial intelligence (Aint) on educational opportunities (EduOp). Aint plays a crucial role in enhancing educational opportunities, particularly in the context of Industry 4.0. The statistical significance (p-value < 0.001) and a 95% confidence interval ([0.1764826, 0.2760449]) suggest a robust and reliable effect. The coefficient (Coef.) of −0.009969 suggests a statistically significant negative direct effect of educational opportunities (EduOp) on itself. This negative effect may imply a regulatory mechanism where an increase in educational opportunities could lead to a slight decrease in further opportunities, possibly due to saturation or other contextual factors. The statistical significance (p-value < 0.001) and a narrow 95% confidence interval ([−0.010293, −0.0096451]) indicate a highly reliable effect.

Table 8. Direct effects.

	Coef.	**OIM Std. Err.**	***z***	***p* > |*z*|**	**[95% Conf.**	**Interval]**
Structural EduOp<-						
Aint	0.2262638	0.025399	8.91	0.000	0.1764826	0.2760449
EduOp	−0.009969	0.0001653	−60.32	0.000	−0.010293	−0.0096451
Res_dev	−0.0089512	0.0116673	−9.75	0.000	−0.0908396	−0.1365746
Patenting	0.1316513	0.0024307	−6.16	0.000	−0.0102057	−0.0197337
Curr_dev	0.7254695	0.026716	27.12	0.000	0.6730372	0.7779017

The coefficient (Coef.) of −0.0089512 suggests a statistically significant negative direct effect of research and development (Res_dev) on educational opportunities (EduOp). Increased research and development may have a dampening effect on educational opportunities, potentially due to resource allocation or other factors. The coefficient (Coef.) of 0.1316513 suggests a statistically significant positive direct effect of product patenting (Patenting) on educational opportunities (EduOp). This implies that product patenting positively influences educational opportunities, likely through innovation and knowledge dissemination. The coefficient (Coef.) of 0.7254695 indicates a statistically significant strong positive direct effect of curriculum development (Curr_dev) on educational opportunities (EduOp). Enhancements in the curriculum development significantly boost educational opportunities, underscoring the critical role of educational structures in the context of Industry 4.0.

The direct effect of Aint on EduOp in the SEM model suggests that artificial intelligence (AI) has a positive and statistically significant effect on educational opportunities, even after controlling for other factors such as research and development (Res_dev), product patenting (Patenting), and curriculum development (Curr_dev). Overall, these direct effects illuminate how artificial intelligence and other key variables directly influence educational opportunities, shedding light on the dynamics of the relationship within the context of Industry 4.0.

This SEM **Table 9** presents the result of the indirect effects in the context of how artificial intelligence (Aint) mediates the relationship between the role of industry-academia collaboration and educational opportunities (EduOp) within the digital-driven Industry 4.0 landscape. The coefficient (Coef.) of 0.0257278 indicates a statistically significant positive indirect effect of artificial intelligence (Aint) on educational opportunities (EduOp). This indirect effect suggests that Aint has a positive influence on EduOp through other pathways or mediating variables. The statistical significance (p-value < 0.001) and a 95% confidence interval ([0.0200673, 0.0313883]) suggest a robust and reliable indirect effect. The coefficient (Coef.) of 0.1137071 suggests a statistically significant positive indirect effect of educational opportunities (EduOp) on itself. This indirect effect implies that the level of educational opportunities positively affects itself through various pathways or mediated by other variables.

Table 9. Indirect effects.

	Coef.	**OIM Std. Err.**	***z***	***p* > |*z*|**	**[95% Conf.**	**Interval]**
Structural EduOp<-						
Aint	0.0257278	0.002888	8.91	0.000	0.0200673	0.0313883
EduOp	0.1137071	0.0116673	9.75	0.000	0.0908396	0.1365746
Res_dev	−0.0010178	0.0001653	−6.16	0.000	−0.0013417	−0.0006939
Patenting	0.0149697	0.0024307	6.16	0.000	0.0102057	0.0197337
Curr_dev	0.082491	0.0115652	7.13	0.000	0.0598236	0.1051584

As shown in **Table 10**, the statistical significance (p-value < 0.001) and a 95% confidence interval ([0.0908396, 0.1365746]) indicate a highly reliable indirect effect. For Res_dev, the coefficient (Coef.) of −0.0010178 suggests a statistically significant negative indirect effect of research and development (Res_dev) on educational opportunities (EduOp). This implies that the impact of Res_dev on EduOp is partially mediated through other variables. However, for the variable Patenting, the coefficient (Coef.) of 0.0149697 suggests a statistically significant positive indirect effect of product patenting (Patenting) on educational opportunities (EduOp). This implies that the impact of Patenting on EduOp is partially mediated through other variables. For, Curr_dev, the coefficient (Coef.) of 0.082491 suggests a statistically significant positive indirect effect of curriculum development (Curr_dev) on educational opportunities (EduOp). This indicates that the impact of Curr_dev on EduOp is partially mediated through other variables.Overall, these indirect effects shed light on the complex interplay of variables, particularly the mediating role of artificial intelligence (Aint) and the impact of research and development, product patenting, and curriculum development on educational opportunities (EduOp) within the context of Industry 4.0. The significant indirect effects underscore the importance of considering these mediators when exploring the relationship between industry-academia collaboration and educational outcomes.

Table 10. Total effects.

	Coef.	**OIM Std. Err.**	***z***	***p* > |*z*|**	**[95% Conf.**	**Interval]**
Structural EduOp<-						
Aint	0.2519916	0.0282871	8.91	0.000	0.1965499	0.3074332
EduOp	0.1137071	0.0116673	9.75	0.000	0.0908396	0.1365746
Res_dev	−0.009969	0.0001653	−60.32	0.000	−0.010293	−0.0096451
Patenting	0.146621	0.0024307	60.32	0.000	0.141857	0.151385
Curr_dev	0.8079605	0.023006	35.12	0.000	0.7628695	0.8530515

The structural equation model (SEM) total summary table provides crucial insights into the relationship between the independent variables “Res_dev”, “Patenting”, and “Curr_dev”, and the dependent variable “EduOp”, while considering the mediating influence of “Aint”. The analysis reveals a multifaceted picture of how “Aint” impacts “EduOp”. Firstly, the direct total effect of “Aint” on “EduOp” is substantial (Coef. 0.2519916) and statistically significant, implying that changes in “Aint” have a pronounced influence on “EduOp” without any mediation. Additionally, considering the indirect effects through intermediate variables, “Res_dev” and “Patenting” play crucial roles, exhibiting significant indirect effects on “EduOp”. “Res_dev” exhibits a negative indirect effect, suggesting that increased research and development may dampen the impact of “Aint” on “EduOp”, while “Patenting” has a positive indirect effect, indicating that innovation, as reflected by patenting, amplifies the effect of “Aint” on “EduOp”. Notably, “Curr_dev” demonstrates a remarkable positive indirect effect, underscoring the strong role of current development activities in enhancing the influence of “Aint” on “EduOp”.

4.7. Discussion

This study answers crucial research questions about how R&D, product development, patenting, and curriculum development bring about educational opportunities, contributing to previous research on industry–academia collaboration.

Further, it shows the influences of causal variables and their respective directions. The first set of equations revealed a positive and statistically significant relationship ($\beta = 1.099941$, $p < 0.05$) between AI and educational possibilities. This indicates that access to education can increase the application of AI in teamwork, and vice versa.

In the first set of equations, AI is a significant predictor of educational opportunities, despite its negative sign ($\beta = -0.3207327$, $p < 0.05$). This is in contrast to the views of Polt et al. (2001), who credited industry-academia collaboration with increasing productivity in the workplace. The researchers found that higher levels of innovation, productivity, competitiveness, and growth (educational opportunities) are the desired outcomes when university–industry cooperation is used in innovation processes (such as AI) (Argyropoulou et al., 2019). One of the biggest obstacles to the implementation of AI in the classroom is the current state of funding and investment in the field. Several things could be at play here. While artificial intelligence has the potential to greatly enhance educational opportunities in China, the country's low investment in science and technology (such as AI) and lack of national strategies in these areas make this goal extremely challenging to achieve, as stated by Abrahams et al. (2010). The "innovation paradox" is not unique to Europe; it is also present in China. This paradox describes a scenario in which high-quality scientific outputs or inputs (like AI) have low conversion to productivity (Argyropoulou et al., 2019; Dosi et al., 2006; Wang and Wang, 2016). The findings indicate that while China has made some investments in AI, putting those resources to use to improve educational opportunities has not been a top priority.

There is a connection between the exogenous variable "educational opportunities" (eduop) and three explanatory variables: "research and development", "product patenting" and "curriculum development" (curr). [$\beta > 1$ $p < 0.05$)] . This finding is consistent with the opinions of Hommaet et al. (2008) and Munyoki et al. (2011), who argued that one common way that universities link up with industry to carry out research and development collaborations is by providing opportunities for student attachments and co-op placements in the productive sector. Student research projects may also have input from industries if they address problems and issues that are of immediate relevance to those sectors (Boersma et al., 2008). Similarly, Hou, Hong, Wang et al. (2018) discovered that R&D collaboration between academic institutions and commercial businesses boosts innovation productivity. Universities are the key to science and technology innovation. Patents are an important indicator of scientific and technological innovation. Positive patent signing is expected ($\beta = 0.3128488$, $p < 0.05$). When product patent and development increases by 1, the endogenous variable increases by 0.3128488. In the study of Hou, Hong, Wang et al. (2018), it was found that Chinese universities lack experience in successful industry collaboration and market understanding, which may lead to inefficient collaborative outcomes. Positive patenting figures indicate technological knowledge creation, which benefits education (Griliches, 1990; Nagaoka et al., 2010). Incentives for patenting in China have been successful (Prud'homme, 2017). This positive effect could be due to political pressure in China via state-set patent targets tied to the performance evaluations of managers at State Owned Enterprises and university and government officials (Liefner et al., 2016; Cheng and Drahos, 2017).

In China, the incentivization of patenting has shown considerable success, a phenomenon attributed to various factors, including a unique blend of government policies and institutional mechanisms that encourage and reward patenting activities. This positive effect can be linked to the exertion of political pressure within China's governance structure, where state-set patent targets play a pivotal role. One crucial factor driving this success is the alignment of patenting goals with the performance evaluations of key stakeholders, such as managers at State Owned Enterprises (SOEs), university faculties, and government officials. The Chinese government has set specific patent targets that individuals and organizations are expected to achieve within a defined timeframe. These targets are tied to performance assessments, promotions, and other professional advancements. This effectively integrates the pursuit of patents into the core objectives and career advancement pathways of professionals within these sectors. As expected, curriculum development (cur) was found to improve educational opportunities in the study area (β = 0.4053915, p < 0.05). A unit increase in [cur] will increase educational opportunities by 0.4053915. This may be why instruction has shifted from a teacher-centered input model to one that emphasizes student–teacher communication.

Cov (res dev, patent), Cov (patent, curr) are positive and significant (cov = 0.2720847, p = 0.000 & covβ = 0.0630601, p = 0.001). Positive covariance means the two variables are related and move in the same direction. The study's variables move in the same direction, but the variance is low, so their relationship is weak. Covariance determines the direction of the linear relationship. There is a positive coefficient if both variables increase or decrease together (Xie and Bentler, 2003). This shows that the study's exogenous variables move in the same direction regarding the explanation of educational opportunities.

For the direct and the indirect effect, the SEM results illuminate key dynamics in educational opportunities (EduOp) within Industry 4.0. Artificial intelligence (Aint) positively impacts EduOp, while EduOp's negative direct effect on itself hints at potential regulatory mechanisms. Research and development (Res_dev) negatively affect EduOp, emphasizing the need for a balanced research approach. Conversely, product patenting (Patenting) and curriculum development (Curr_dev) exhibit positive direct effects on EduOp, highlighting the role of innovation and structured curricula in enhancing educational prospects. These insights emphasize leveraging AI, managing research effectively, and innovating product strategies and curricula to boost educational outcomes in the evolving digital era. For the indirect effect result, the SEM results underscore the significant indirect impact of artificial intelligence (Aint) on educational opportunities (EduOp) within the context of Industry 4.0. This indirect effect emphasizes the pivotal role of AI as a mediator, influencing EduOp through various pathways. Additionally, the positive indirect effect of EduOp on itself implies a self-enhancing relationship, suggesting that educational opportunities contribute to their own augmentation. Conversely, research and development (Res_dev) exhibit a negative indirect effect on EduOp, signifying a need for careful management to ensure a positive impact. Furthermore, product patenting (Patenting) and curriculum development (Curr_dev) demonstrate positive indirect effects on EduOp, underlining the importance of innovation and structured curriculum in shaping educational prospects within the Industry 4.0 landscape. These insights emphasize the intricate interplay of factors and the critical mediating role of AI, providing valuable guidance for optimizing educational opportunities amidst the evolving digital landscape.

5. Conclusion and recommendations

The study examined the role of industry–academia collaboration in enhancing educational opportunities and outcomes under the digital driven Industry 4.0 using the proxies of research and development, patenting and development, curriculum development mediated by artificial intelligence.The study was anchored on double helix theory and relevant conceptual and empirical studies were reviewed to provide the empirical background to the study. Purposive sampling was used while data was collected using questionnaire. Validity and reliability of the instrument was done using content validity and reliability of the instrument was accessed Cronbach Alpha statistics. The study was estimated using descriptive and inferential statistics. The inferential statistics deals with frequencies and percentages. Other results were presented using graph. The results of the descriptive statistics showed the distributions of the respondents in the study area. The specific objectives of the study were estimated using structural equation model.

This study significantly contributes to the Triple Helix hypothesis by investigating the pivotal role of industry–academia collaboration in augmenting educational opportunities and outcomes within the digitally driven Industry 4.0 paradigm. Grounded in the Double Helix theory, the research employs proxies such as research and development (R&D), patenting, and curriculum development, mediated by artificial intelligence (AI), to delineate the intricate relationship between academia and industry. Drawing on empirical evidence and conceptual frameworks, the study underscores universities as not only conduits for disseminating knowledge and nurturing innovative talent but also as crucibles for knowledge and technology innovation. The findings illuminate that collaborative efforts between academia and industry, fortified by AI, engender a virtuous cycle, positively influencing educational opportunities. Notably, the results underscore the burgeoning advancements in China, positioning the nation to stride alongside Western economies in the digital economy of the 21st century, fueled by robust R&D, patenting, and curriculum development. Furthermore, the research emphasizes the imperative for increased investment and attention directed towards integrating AI into educational pursuits within the studied domain. The study advocates for resource allocation from governmental bodies and stakeholders to harness the potential of AI in amplifying educational opportunities through industry–academic collaboration. The insights gleaned from this study are paramount for businesses, governments, and policymakers, urging a paradigm shift towards prioritizing Industry–Academia Collaboration (IAC) to enrich educational prospects, thus propelling socioeconomic development and sustainability, particularly in the era of Industry 4.0.

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