Li, S., & Gu, X. (2023). A Risk Framework for Human-centered Artificial Intelligence in Education: Based on Literature Review and Delphi–AHP Method. *Educational Technology & Society*, *26*(1), 187-202. https://doi.org/10.30191/ETS.202301_26(1).0014

A Risk Framework for Human-centered Artificial Intelligence in Education: Based on Literature Review and Delphi–AHP Method

Shijin Li and Xiaoqing Gu*

Department of Education Information Technology, East China Normal University, China // shijinliEdu@163.com // xqgu@ses.ecnu.edu.cn

*Corresponding author

ABSTRACT: With artificial intelligence (AI) is extensively applied in education, human-centered AI (HCAI) has become an active field. There although has been increasing concern about how to systematically enhance the AI applications effect, AI risk governance in HCAI education has not been discussed yet. This study adopted literature meta-analysis, along with the Delphi and analytic hierarchy process (AHP) methods in order to establish the risk framework and calculate the index weight of HCAI education. The results confirm that the risk framework includes eight indicators, which respectively are misunderstanding of the HCAI concept (MC), misuse of AI resources (MR), mismatching of AI pedagogy (MP), privacy security risk (PSR), transparency risk (TR), accountability risk (AR), bias risk (BR), and perceived risk (PR). Meanwhile, the eight indicators are divided into four categories such as HCAI concept, application process, ethical security, and man-machine interaction. Moreover, the trend of risks types indicates that more than half of the articles consider only three or less risks types, and the evolution results of risks indicators gradually increased between 2010 and 2021. Additionally, the weights of the eight indicators are MP > MR > AR > PSR > TR > PR > BR > MC. Results obtained could provide theoretical evidence and development suggestions for future scientific governance of HCAI education. Furthermore, the risk framework not only systematically considers the risk governance order of HCAI education, but more importantly, it is the key bridge to the collaborative advancement of stakeholders such as managers, teachers, students, and parents, which can contribute to the scientific, healthy, and sustainable HCAI education.

Keywords: Human-centered artificial intelligence (HCAI), Risk framework, Index weight, AHP, Delphi

1. Introduction

With data analysis and autonomous learning, artificial intelligence in education (AIED) applications have been making a wider impact on personalized learning, classroom monitoring, student performance, sentiment analysis and decision evaluation (Hwang et al., 2020). For example, intelligent tutors and virtual learning partners can help students perform communication and cooperative tasks independently and efficiently (Holmes et al., 2019). Adaptive learning systems can provide adaptive feedback and service support (Chin & Tseng, 2021). Automatic question-answering technology can solve students' classroom problems in real time (Lu et al., 2021; Perikos et al., 2017). Emotion detection technology can dynamically perceive students' emotional needs and provide personalized emotional support (Chen et al., 2021; Saneiro et al., 2014). Decision management technology can automatically diagnose students' learning needs and assist them in decision-making (Yang et al., 2021). In summary, AI has become a key point in empowering and transforming education, and AIED applications will be developed at a large scale (Zawacki-Richter et al., 2019; UNESCO, 2019). Similar to the "dual-use" nature of biochemical technologies, AIED applications offer both rewards and potential risks. With proper use of AI, it can improve the human condition for education in many ways, but the misuse of AI due to a range of risks (White & Lidskog, 2022). Therefore, the risk governance framework must be developed to ensure the responsible and sustainable of AIED applications.

Human-centered AI (HCAI) is one effective approach that holds promise for the responsible AIED applications, as well as systematically consider AI algorithms through humanistic situation, thereby enhancing human intelligence rather than replace them with machines. Stanford University, UC Berkeley and MIT have set up HCAI research institutes, aiming to develop humanistic, ethical, and beneficial AI education. Researchers have begun to discuss ethical design approaches, but AI risk governance in HCAI education has not been discussed yet. More importantly, the risks of HCAI education are highly complex, unpredictable, and nonlinear (Renn, 2021), and without an overall framework, it is difficult to systematically identify, understand and manage risks (Schweizer, 2021). Although previous studies have reviewed algorithm bias (Kusner & Loftus, 2020), technology abuse (Jim & Chang, 2018), privacy security (Sivill, 2019), and role ambiguity (Guilherme, 2019), but there is no systematic risk framework for HCAI education. Therefore, it is necessary to put forward the risk framework as well as index weight of HCAI education. In order to advocate the idea of HCAI, implement the method of AI under human-control and avoid potential negative effects, the study adopted literature meta-analysis, along with the Delphi and analytic hierarchy process (AHP) methods, and established the risk framework and calculate the index weight. The main objective of this study is to solve how to systematically govern risks and help stakeholders obtain optimal benefits while adopting forward-looking actions. In addition, we can implement responsible, sustainable, and healthy HCAI education based on the risk framework. In particular, this study offers a reference risk regulatory framework of HCAI education, which can contribute to enhancing the practice effects and application benefits.

2. Literature review

2.1. Responsible AIED: HCAI research and discovery

HCAI is an ideological paradigm that places humans at the center of the man-machine collaboration paradigm, abiding by the ethics, common values, and interests of human beings. Different research teams have also carried out a series of discussions, aiming to introduce the HCAI concept into the design and practice process, so as to promote the sustainable and responsible AIED applications. Shneiderman (2020b) visually described HCAI as the "AI Copernican Revolution," and profoundly expounded on the HCAI concept and widely advocated the use of humanistic algorithms for design, development and application. Schmidt (2020) argued that HCAI was designed with a clear purpose for human benefit, while being transparent about who had control over data and algorithms. Xu (2019) proposed an extended HCAI framework that included ethically aligned design, technology enhancement and human factor design, so as to ensure AI solutions are explainable and comprehensible.

HCAI emphasizes the integration of human role into the human-machine system, and develops human-machine hybrid enhanced intelligence through the complementation of human-machine intelligence. Nowadays, the research progresses of HCAI domain mainly focus on human intelligence enhancement, human-machine hybrid enhanced intelligence, human-AI cooperation, explicable AI, human-controllable autonomy, intelligent human-machine interaction, and ethical AI design (Xu et al., 2021). In particular, ethical AI design is an important issue in HCAI education, and it is also the basis for achieving the HCAI goals. Moreover, without an ethical AI design framework, the HCAI concept cannot be realized, and safe, reliable, and trustworthy AI systems cannot be developed. Therefore, an important task of HCAI research is to develop AI risk governance framework.

2.2. AIED risk governance as a scientific way to realize HCAI education

In 2015, google image software labeled a black African-American couple as "gorilla," which not only showed the poor performance of the model in face recognition, but more importantly the lack of basic respect for colored race (Benjamin, 2019). A Princeton university study emphasize that the biased AI algorithm link women with "family" and "art," men with "career" and "ambition," and link colored race with unpleasant words (Caliskan et al., 2017). Angwin et al. (2016) and Kay et al. (2015) exposed gender and racial biases in career development and predictive education systems. According to Ahn et al. (2021), intelligent agents can automatically obtain students' learning styles, habits, and abilities. However, if the AI systems predict that students will fail in the next exam according to student behavior data during a certain period, will it affect students' self-confidence? In addition, questions such as who can own data or whether the data are real and valid are common risks in AIED applications (Ketamo, 2018).

Whenever a new technology appears, we are always eager to put it into use for fear of missing its educational benefits, which often leads to a series of risks. The AIED risk governance has become a social consensus (Floridi et al., 2018). Different research teams also conducted a series of systematic reviews and pointed out practical problems (Deeva et al., 2021; Winters et al., 2020; Scherer, 2015; Jim & Chang, 2018), which are (1) How to define and dispose of the new roles of teachers and their relationship with intelligent systems? (2) How can students' privacy safety be protected when collecting behavioral data? (3) What kind of ethical knowledge should stakeholders possess and what ethical criteria should they follow? (4) Whose interests should AI give priority to conflicting stakeholders? (5) If AI learning fails, who should be held accountable? In fact, an accountability system accompanies the entire life cycle of the AI systems, and responsible AI systems can be constructed through access regulations, timely supervision, and decision-making evaluation. In this process, it is difficult to identify the party responsible. This might because the responsibility is based on free will, but machines do not have free will, in this way, social structural barriers and personal cognitive barriers lead to design, data, and algorithm biases in AIED applications. Furthermore, the responsibility for defects in intelligent products cannot be completely transferred to manufacturers, nor can designers and programmers be absolved in the AI systems development process.

AIED risk governance is the scientific way to realize HCAI education. However, there are three deficiencies at present, first, the research perspectives are mostly theoretical exploration of risks characterization, and there is no research to systematically consider the risk framework in HCAI education. Moreover, research method is mainly the literature or the survey method, and there is no method for calculating the risk weight. Additionally, the guidance, operability and extensibility of research conclusions need to be improved urgently.

2.3. Purpose of the current study

Since AIED risks are not only AI technical issues, but also involve the relationship between education and society, so it is necessary to integrate the characteristics of "Technology-Education-Society," and systematically consider the risk framework and index weight. Delphi-AHP is a qualitative and quantitative decision-making method (Turón et al., 2019), by collecting, summarizing and analyzing the relative importance of experts to each index, using the AHP method to determine the index weight, and combining qualitative and quantitative evidence feedback, an operable theory framework and index weight are finally formed. Based on this, we used Delphi-AHP to develop the risk framework and index weight of HCAI education. Through the analysis of index meaning and weight level, which not only provide theoretical evidence for risks governance, but also enhance practical guidance for the design of risks intervention programs and the development of risks assessment tools.

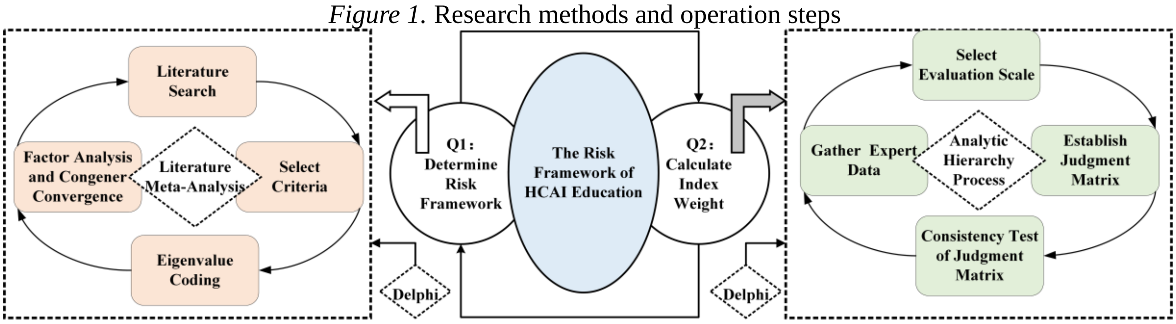
This study aims to answer the following four problems:

- What indicators are included in the risk framework of HCAI education? And what are characteristics of each risk?
- What is the trend of risks types in HCAI education?
- What are the evolution results of risks indicators in HCAI education?
- What are the weights of these indicators?

3. Methodology

The purpose of this study is to develop the risk framework and establish index weight of HCAI education. To achieve the aims, the following research methods and operation steps are designed based on systematic principles (see Figure 1).

Figure 1. Research methods and operation steps



3.1. Literature meta-analysis method

To solve the first research question, the literature meta-analysis method was used to determine the risk framework, which followed the process of "literature search → select criteria → eigenvalue coding → factor analysis and congener convergence." The literature search terms were conducted with reference to previous studies (e.g., "HCAI" in Shneiderman (2020a) and "ethical framework" in Floridi et al. (2018)) by considering both HCAI and risk fields.

The processes of literature meta-analysis are as follows:

- The academic databases used to collect articles are Web of Science, Scopus, Science Direct, EBSCO, Wiley Online Library, ProQuest, ACM, IEEE and Google Scholar.
- The keywords used for literature search are ("artificial intelligence" OR "AI" OR "Human-centered artificial intelligence" OR "HCAI" OR "AIED" OR "AIEd") AND ("risk" OR "risk framework").
- The time range of articles published from January 2010 to December 2021, as AIED applications have become widely popular since 2010.

- The selected articles are used to develop the risk framework of HCAI education, and the selection criteria mainly consider the following two points, one is the research context is AI education, another is the research topic includes risk types. When one of the selection criteria was not met, the article was excluded. According to the above selection criteria, 50 valid samples were finally obtained.
- In the process of eigenvalue coding, we focus on what types of risks are included in the literature? And what are the significant or potential features of risks? Through factor analysis and congener convergence, and after two rounds of expert consultation, we finally developed the risk framework of HCAI education.

3.2. Delphi-AHP method

To solve the second research question, the Delphi and AHP methods were used to calculate index weight. Expert groups directly determine the content of consultation and the validity of data results (Goodman, 1987). In order to ensure the scientificity and validity of the research samples, the study adopted a combination of cluster sampling and convenience sampling to determine the expert groups (Etikan & Bala, 2017; Cohen et al., 2017). First, we used the cluster sampling method, and took 147 double-first-class universities in China as the first-level sampling units. Then, the convenience sampling method was used to select expert groups that could meet the research needs. Additionally, three selection criteria were set throughout the sampling process: (1) Very familiar or relatively familiar with the research topics of "HCAI education" and "AIED risk." (2) The work unit is a double first-class university. (3) Both domestic and foreign multicultural background. Based on this, we finally identified 37 experts who traversed 10 universities in eastern, central and western China (see Table 1).

Table 1. Basic information statistics of 37 experts

Basic information of experts		Number	Proportion
Gender	Male	29	78.4%
	Female	8	21.6%
Multicultural background	Study abroad experience	25	67.6%
	International exchange program	12	32.4%
Work units	Tsinghua University	2	5.4%
	Beijing University	2	5.4%
	Beijing Normal University	4	10.8%
	East China Normal University	6	16.2%
	Zhejiang University	2	5.4%
	Central China Normal University	5	13.6%
	Shaanxi Normal University	6	16.2%
	Southwest University	3	8.1%
	South China Normal University	3	8.1%
	Nanjing Normal University	4	10.8%

Meanwhile, in order to ensure the objectivity of data samples, the level judgment of expert authority (Cr)is added, that is from the judgment basis (Ca) and familiarity (Cs) comprehensively consider the data results of experts (see Table 2). According to the calculation formula, Cr= (Ca + Cs)/2, 37 experts' judgment basis (Ca) is (35*0.5+2*0.4+32*0.3+5*0.2+34*0.1+3*0.1+25*0.1+5*0.1+7*0.1)/37 = 0.98. The degree of familiarity (Cs) is (30*1.0+7*0.8)/37 = 0.96. Thus, expert authority (Cr) is (0.98 + 0.96)/2 = 0.97. Since the degree of expert authority (Cr) ≥ 0.7, the results of expert consultation are reliable.

Table 2. Expert authority and weight coefficient

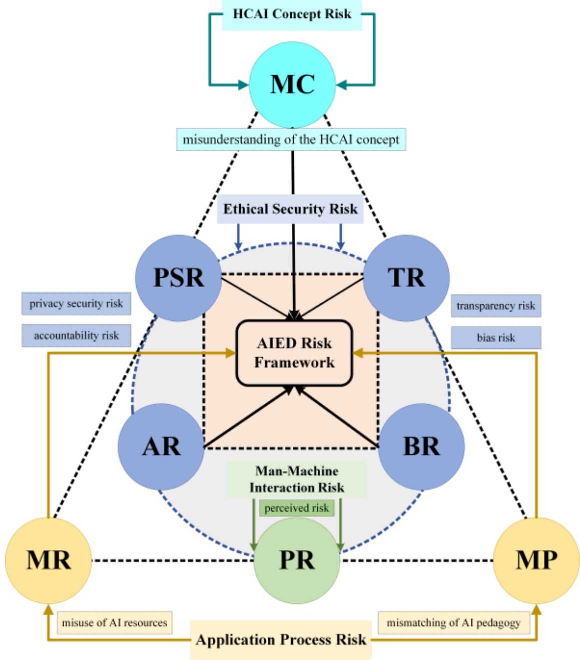
Judgment basis and weight coefficient					
Judgment basis	Large		Medium		Small
Practical experience	0.5		0.4		0.3
Theoretical analysis	0.3		0.2		0.1
Peer understanding	0.1		0.1		0.1
Intuitive feeling	0.1		0.1		0.1
Familiarity and weight coefficient					
Familiarity	Very familiar	Familiar	General Familiar	Not very familiar	Unfamiliar
Weight coefficient	1.0	0.8	0.6	0.4	0.2

4. Results

4.1. Analysis of the risk framework structure of HCAI education

Through literature meta-analysis and two rounds of Delphi, we finally determined the risk framework of HCAI education (See Figure 2), which includes misunderstanding of the HCAI concept (MC), misuse of AI resources (MR), mismatching of AI pedagogy (MP), privacy security risk (PSR), transparency risk (TR), accountability risk (AR), bias risk (BR), and perceived risk (PR). Meanwhile, these eight indicators are divided into four categories such as HCAI concept, application process, ethical security, and man-machine interaction.

Figure 2. The risk framework for HCAI in education



Based on our results, HCAI concept risk includes MC, application process risks include MR and MP, ethical security risks include PSR, TR, AR and BR, and man-machine interaction risk includes PR. In particular, intelligent concept risk stems from the ontological risk of ignoring AI technology to restore education world, application process risk originates from the cognitive risk of masking AI technology to characterize education ecology, ethical security risk stems from the value risk that neglecting AI technology goes against the original intention of education, man-machine interaction risk stems from the ethical risk of education governance caused by the misuse of AI technology.

4.2. Analysis of the trend of risks types in HCAI education

Table 3 shows the trend of risks types. The eight indicators are distributed in 50 articles. The top one risk index accounted for 64% of the total articles. The top three articles ranked by number of indicators are included seven indicators, the first article focuses on the risks in AIED applications process, and the last two specialize in the risks and challenges of AIED. Among the articles listed, BR (28), AR (26) and TR (24) are almost equally numerous. Meanwhile, more than half of the articles consider only three or less risks types.

Table 3. The trend of risks types in HCAI education

Indicators	Citation	Brief description of the research	MC	MR	MP	PSR	TR	AR	BR	PR
			8	14	13	32	24	26	28	13
7	Zhang, 2021	The reform and innovation of AI technology for information service		Yes	Yes	Yes	Yes	Yes	Yes	Yes
7	Hwang et al., 2020	Vision, challenges, roles and research issues of AIED		Yes	Yes	Yes	Yes	Yes	Yes	Yes
7	UNESCO, 2019	Challenges and opportunities for sustainable		Yes	Yes	Yes	Yes	Yes	Yes	Yes

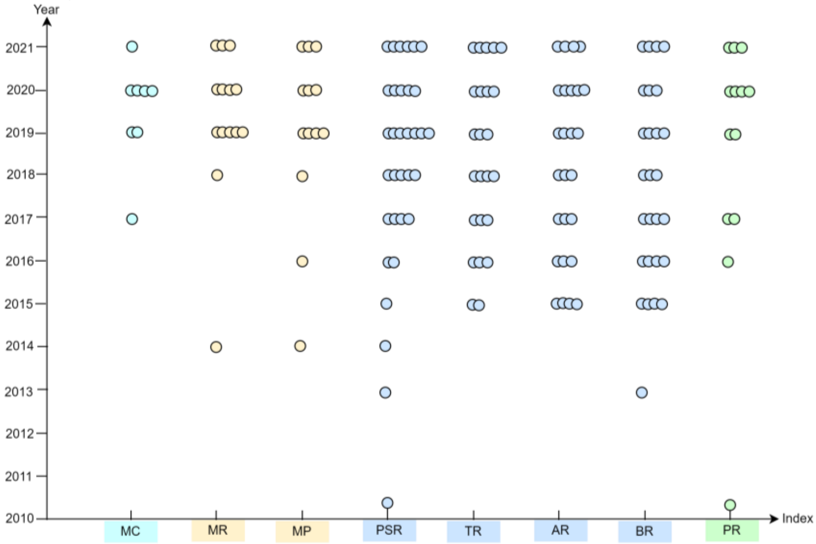
		development of AIED								
6	Renz & Vladova, 2021	HCAI in educational technologies	Yes			Yes	Yes	Yes	Yes	Yes
5	Xu, 2019	HCAI from interaction aspect	Yes	Yes	Yes	Yes				Yes
5	Floridi et al.,2018	An ethical framework (AI4People) for a good AI society		Yes		Yes	Yes	Yes	Yes	
5	Caliskan et al., 2017	Bias in humans and machines				Yes	Yes	Yes	Yes	Yes
4	White & Lidskog, 2022	Ignorance and the regulation of AI technology				Yes	Yes	Yes	Yes	
4	Ahn et al., 2021	Privacy, transparency and trust in K-12 learning analytics				Yes	Yes	Yes	Yes	
4	Deeva et al., 2021	Automated feedback systems for learners		Yes	Yes	Yes	Yes			
4	Wu et al., 2020	Ethical principles and governance process of AI technology				Yes	Yes	Yes	Yes	
4	Sivill, 2019	Ethical and statistical considerations in models of moral judgments				Yes	Yes	Yes	Yes	
4	Intel Corporation, 2018	Individuals' privacy and data in the AI world				Yes	Yes	Yes	Yes	
4	Jim & Chang, 2018	Data governance in higher education				Yes	Yes	Yes	Yes	
4	Boddington, 2017	Ethics for artificial intelligence				Yes	Yes	Yes	Yes	
4	Wessels, 2015	Authentication, status, and power in a digitally organized society				Yes	Yes	Yes	Yes	
3	Winters et al., 2020	Digital structural violence in future learning systems					Yes	Yes	Yes	
3	Chen et al., 2020	Application and theory gaps in AIED	Yes	Yes	Yes					
3	Auernhammer, 2020	HCAI design framework	Yes			Yes				Yes
3	Kusner & Loftus, 2020	Conceptual paper on the fairer algorithms					Yes	Yes	Yes	
3	Zawacki-Richter et al., 2019	AI applications in higher education		Yes	Yes	Yes				
3	Friedman et al., 2017	A survey of value sensitive design methods	Yes			Yes				Yes
3	Kitchin, 2017	Thinking critically about and researching algorithms					Yes	Yes	Yes	
3	OECD, 2016	The impact of digital technologies on teaching and learning			Yes	Yes				Yes
3	Mittelstadt et al., 2016	The ethics of algorithms					Yes	Yes	Yes	
3	Ozga, 2016	Digital data use in education					Yes	Yes	Yes	
3	Burrell, 2016	The opacity in machine learning algorithms					Yes	Yes	Yes	
3	Pasquale, 2015	The black box society					Yes	Yes	Yes	
3	Chang et al., 2014	Augmented reality versus interactive simulation technology		Yes	Yes	Yes				

2	Zhang et al., 2021	Interactive smart education framework		Yes	Yes					
2	Cui & Wu, 2021	The influence of media use on public perceptions of AI technology				Yes				Yes
2	Shneiderman, 2020a	HCAI: Reliable, safe & trustworthy	Yes	Yes						
2	Schmidt, 2020	The definition and research challenges of interactive HCAI	Yes							Yes
2	Cao et al., 2020	Aided teaching system and teaching pattern		Yes	Yes					
2	Orr & Davis, 2020	Attributions of ethical responsibility by AI practitioners				Yes		Yes		
2	Benjamin, 2019	The race after technology				Yes			Yes	
2	Dignum, 2019	How to develop and use AI in a responsible way	Yes	Yes						
2	Reddy et al., 2019	A commentary on algorithmic accountability						Yes	Yes	
2	Sharples, 2019	News on education pedagogy		Yes	Yes					
2	Gunning & Aha, 2019	DARPA's XAI program				Yes	Yes			
2	Elish, 2019	Cautionary tales in human-robot interaction				Yes		Yes		
2	Ketamo, 2018	How AI will change education			Yes	Yes				
2	Guidotti et al., 2018	Methods for explaining black box models				Yes	Yes			
2	Capatosto, 2017	The use of predictive analytics				Yes			Yes	
2	Angwin et al., 2016	News case on machine Bias				Yes			Yes	
2	Scherer, 2015	Risks, challenges and strategies of regulating AI systems						Yes	Yes	
2	Kay et al., 2015	Unequal representation and gender stereotypes in image search results						Yes	Yes	
2	Nathanson et al., 2013	The school choices and placements of low-achieving students				Yes			Yes	
2	Connor & Siegrist, 2010	Factors influencing people's acceptance of gene technology				Yes				Yes
1	Chatterjee & Bhattacharjee, 2020	The adoption factors of AI in higher education								Yes

4.3. Results of the evolution of risks indicators in HCAI education

Figure 3 shows evolution results of the risks indicators. From the time dimension, very limited risks indicators (e.g., PSR, TR, AR, BR) are considered before 2015. However, with the widespread increase of AIED applications, both the quantities and types of risks indicators (e.g., MC, MR, MP, PR) have increased in the last five years. For example, the risk like MC appeared since 2017, the risks types of MR, MP, PR increased during 2019—2021, and there was also a growth trend in the PSR, TR, AR, BR between 2018 and 2021. From the content dimension, AIED risks types gradually increased between 2010 and 2021. Particularly, in 2019, the eight risks indicators were appeared simultaneously. Additionally, ethical security risks like PSR, TR, AR, BR are always the focus of AIED applications.

Figure 3. Evolution results of the risks indicators in HCAI education



4.4. Results of index weight

According to the analysis process of "establish judgment matrix → consistency test of judgment matrix → gather expert data," we used the AHP method and Yaahp software to calculate the weights of eight risks indicators.

The first is the establish judgment matrix, in this process, the key is to select evaluation scale. AHP method usually uses the nine-level evaluation to judge index factors in pairs (Saaty, 1987). This is because the limit of the difference between the two objects is 7±2. Therefore, in order to eliminate errors as much as possible, we selected the classic nine-level evaluation method to compare the importance of indicators in pairs (see Table 4). In the specific operation process, 37 experts used a nine-level evaluation method to judge the relative importance of eight indicators, and eight judgment matrices were established in Yaahp software for eight risks indicators.

Table 4. Evaluation method of judgment matrix

Scale	Definition	Connotation
1	Equally important	The two elements are of equal importance
3	Slightly important	Compared with the two elements, the former is slightly more important than the latter
5	Quite important	Compared with the two elements, the former is quite important than the latter
7	Obviously important	Compared with the two elements, the former is obviously more important than the latter
9	Absolutely important	Compared with the two elements, the former is absolutely more important than the latter
2,4,6,8	—	Indicates an intermediate value between the above criteria
Reciprocal of 1~9	—	Indicates the importance of the comparison of the corresponding two-factor exchange order

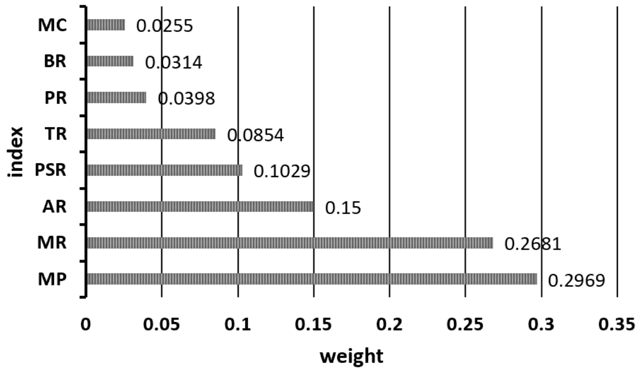
The second is the consistency test of judgment matrix. In this process, the minimum algorithm was used for automatic correction. After correction, the judgment matrices of 37 experts all met the statistical standard of consistency ratio CR < 0.1. Then, 37 judgment matrices corresponding to each expert's information were formed in Yaahp software, based on which an aggregated judgment matrix was formed (see Table 5).

The third is the gather expert data, which includes two methods of calculation result aggregation and judgment matrix aggregation. The former calculates the average of the ranking weights obtained by each expert judgment matrix as the aggregation result, and the latter takes the average of the expert judgment matrix results and calculates the ranking index weight. Even if 37 experts' judgment matrices meet the consistency requirements, the final results obtained after the combined judgment matrices are also likely to have some problems, like the individual and the group judgment matrix have inconsistent meanings, and lack of data semantics. Therefore, we used the calculation result aggregation to output weights of eight risks indicators (see Figure 4).

Table 5. Aggregated judgment matrix of 37 experts

AIED risk	MC	MR	MP	PSR	TK	AR	BR	PR
MC	1	0.0953	0.0861	0.2482	0.2992	0.1704	0.8142	0.6422
MR	10.4946	1	0.9032	2.6053	3.1404	1.7878	8.5452	6.7396
MP	11.6198	1.1072	1	2.8846	3.4771	1.9794	9.4614	7.4623
PSR	4.0282	0.3838	0.3467	1	1.2054	0.6862	3.2800	2.5869
TK	3.3418	0.3184	0.2876	0.8296	1	0.5693	2.7211	2.1461
AR	5.8703	0.5594	0.5052	1.4573	1.7566	1	4.7799	3.7699
BR	1.2281	0.1170	0.1057	0.3049	0.3675	0.2092	1	0.7887
PR	1.5571	0.1484	0.1340	0.3866	0.4660	0.2653	1.2679	1

Figure 4. Weights of eight risks indicators



5. Discussion

In this study, we used the literature meta-analysis method to systematically develop eight risk indicators in HCAI education, which were divided into four categories of risks such as HCAI concept (MC), application process (MR, MP), ethical security (PSR, TR, AR, BR) and man-machine interaction (PR). Meanwhile, we used the Delphi and AHP methods to calculate the weights of eight indicators, which were MP > MR > AR > PSR > TR > PR > BR > MC. Furthermore, such a framework provides theoretical reference standard for the risk governance in HCAI education. Findings regarding risk framework and weights analyses provide profound insight for future HCAI education research, as described in the following subsections from large to small weights.

5.1. The MP and weight analysis

Innovative pedagogy is the key of the AIED application process. That would mean if AI pedagogy is not innovated in time and not adequately prepared for the potential of AI technology, the AIED practice effect may be more harmful than beneficial. Harri Ketamo, an AI researcher who held the same view, pointed out that "learning is hard work, but we can make learning more enjoyable, easier and effective through good pedagogy" (Ketamo, 2018). Moreover, Sharples (2019) argued that the key to innovative teaching lies in how to construct a pedagogy-technology fit. To solve this, Lu et al. (2021) proposed that the school management level should form AI interschool alliances and explore pedagogy-technology fit through expert support or case studies. Furthermore, according to Chen et al. (2021), we can use innovative pedagogies such as chat robots and remote collaborative learning to strengthen learners' knowledge about constructive, social, and contextual understanding, also promote the continuous excitation of inquiry motivation and intelligent emotion.

Our research found that MP is the biggest risk in HCAI education. Therefore, in order to prevent AIED applications from falling into the dilemma of "wearing new shoes and walking the old road," it is important to pay attention to pedagogy-technology fit. However, as AI courses are mostly used as an elective or school-based curriculum, the curriculum coherence of each semester is also insufficient. In addition, the teaching materials, teaching concepts, and intelligent tools of different schools are quite different, which generally leads to unsystematic AIED pedagogy design (Zhang et al., 2021). Thus, future research may consider exploring HCAI teaching practice based on innovative pedagogy-AI technology fit.

5.2. The MR and weight analysis

School-based resources are the foundation of the AIED application process, and if the intelligent resources are unreliable or invalid, which will lead to poor AI learning effects. Our results showed that MR is the second risk in HCAI education. This might include the following three reasons: First, AI resources are complex and cluttered, because AI resources are not specifically targeted at education activities, so they are not directly meet the AIED applications. Second, AI resources generally lack systematic course design and resource construction, which also lead to the incoherence of intelligent resources between each learning section. Third, the contents of AI resources are differentiated, and a large number of AI resources in the exploratory stage or esoteric have entered the classroom. If schools fail to transform intelligent resources in time, the AIED practice will fall into the misunderstanding of blindly "seeking innovation" or "seeking perfection." Therefore, K-12 schools need to tailor, adjust, arrange, and even re-develop existing AI resources, so that AI resources can adapt to different teaching scenarios.

According to Holmes et al. (2019), from the perspective of intelligent resource design, the primary task is to build school-based intelligent resources, and use AI technologies such as big data, deep learning and knowledge graph to open up AI resource-sharing platforms in different regions and schools. From the perspective of intelligent resource linkage, we can establish collaborative mechanisms and scientifically adjust the allocation plan of AI resources based on regional structure, investment level, dynamic mechanism, power, and responsibility. Meanwhile, the whole process should also provide corresponding regulatory measures and institutional guarantees. Furthermore, we recommend that future research should focus on the three forms of risks: The first are source risks, such as the convergence, sharing, and circulation mechanisms of social AI resources; the second are process risks, such as identifiable, traceable, decentralized, and transparent; and the third are port risks, such as certification standards and evaluation indicators of school-based AI social resources.

5.3. The AR and weight analysis

AR is one of ethical security risks in AIED applications. In Boddington (2017), since intelligent algorithms failed to understand the real cause of risks, and this also led to the ambiguity of responsibility. Orr and Davis (2020) also emphasized that AR determination with AI technology is not easy. Specifically, AI systems do not have the ability to bear legal responsibility independently, so the accountability mechanism is meaningless to some degree. Moreover, AI products have the ability of autonomous and independent learning, judgment, and decision-making, product designers and program developers cannot fully govern the evolutionary behavior of AI products, so it is difficult to plan the possible adverse consequences in advance. In addition, there is a lack of effective accountable design methodologies or technical details to guide design specification about the AR in AIED applications.

Our research found that AR is the third risk in HCAI education. However, little considerations are given to how to effectively clarify responsibilities and normative criterion, and most developers even consider responsibility design at a later stage rather than during the development process of AI systems. Therefore, future research may focus on establishing accountability mechanism from the key links such as technical design and institutional guarantee. Also, we recommend that more studies consider implementing accountability in AI systems design based on HCAI approach, and taking systematic and effective measures in design, testing and professional training.

5.4. The PSR and weight analysis

PSR is that may expose personal privacy and personalized needs in AI applications, which belongs to one of the ethical security risks. Zhang (2021) argued that the breach of data privacy is eroding the well-being of learners. For example, the information leakage caused by the head ring, the labeling of learning evidence or the hybridization of heterogeneous data. In this way, AIED applications are releasing a lot of privacy security through procedures and rules, as the Foucault-style "panoramic prison." Moreover, when learners use AI technology for a long time, it is easy to develop the bad habit of "technical flow." That is to say, once learners are out of the technical cage, they will avoid the cooperation and communication between peers, and then produce undesirable symptoms such as withdrawn temperament and emotional alienation.

Based on the results, PSR is the fourth risk in HCAI education. Nevertheless, privacy security runs through the whole process of AIED applications. Thus, more studies may comprehensively consider the PSR combined with different scenarios. For example, at the individual level, AI systems must fully focus on the privacy protection of independent personal data, mobile data, names and so on (Zhang et al., 2021). At the collective level, since AI systems are likely to collect and utilize group information illegally by stealing, tampering, and leaking, so future research should focus on data flow and interaction specification. In addition, it is also necessary to establish blockchain trust mechanisms and data regulatory agencies to supervise data collection, legal use and privacy security.

5.5. The TR and weight analysis

TR represents AI technology cannot provide sufficient explanatory information. In Mittelstadt et al. (2016), most explainable AI projects are carried out only within the AI discipline. Also, some AI personnel adopted an "algorithm-centric" approach, and even built explainable AI for themselves rather than users, which exacerbated the opacity of algorithms. In this way, AI technology process and implementation details are often hidden, the packaging characteristics of the "black box" create a near "perfect illusion" for AIED applications, making it difficult for stakeholders to grasp the actual differences between data and entities (Burrell, 2016; Kitchin, 2017; Ozga, 2016). Subsequently, explainable AI (XAI) has become a research hotspot. For example, develop or improve ML technology to obtain interpretable algorithmic models. Also, develop XAI of user models with the help of advanced human-machine interaction technology. Furthermore, evaluate specific psychological explanation theories to assist in the development of XAI.

In our research, TR is the fifth risk in HCAI education. This might because the lack of transparent design of AI systems, which affects the credibility of AIED applications. Thus, we should not only regard AI technology as an education tool, focusing on specific categories such as "why to teach" "who to teach" "what to teach" and "how to teach," but should "apply to... no longer used for... ," breaking through the shackles of "technology black box." Moreover, if education information is transmitted in an understandable way, which can also enhance the fluidity, interactivity, and openness of XAI. Thus, future research may focus on developing XAI solutions based on HCAI concepts to meet AIED need.

5.6. The PR and weight analysis

PR is a combination of behavioral and environmental insecurity. In the era of AI, benefit trust and risk perception are interactive. In other words, the public's subjective perception at the cognitive level can easily lead to panic or concern about privacy infringement. Specifically, Chatterjee and Bhattacharjee (2020) argued that when risk perception is high, individuals are less willing to adopt AI technology. Moreover, several findings also revealed that the lower the human–machine interaction risk, the more willing schools are to carry out AIED (Wang et al., 2021; Chai et al., 2020). In addition, if the effective communication in man-machine interaction can be enhanced, people's perceived risks can be reduced in AIED applications. According to Xu (2019), man-machine interaction should pay attention to artificial stupidity (AS), because even a perfect computer program is nothing but a cold mechanism. This also shows that AS can stimulate the enthusiasm of human participation to some degree.

The man–machine interaction risk is ranked sixth. This might because when AI technology is integrated into education ecology, the multiple stakeholders of "home-school-society-enterprise" are prone to worry and panic that "intelligent tutors will replace human teachers" due to their lack of technical experience. In this situation, we should obtain systematic experience through literature meta-analysis to provide a basis for the human-machine interaction practice. Based on our results, there is still a lack of innovative human-machine collaborative teaching models, thus, we should set boundaries for man-machine interaction based on AS, and fully explore innovative models of balanced cooperation between machine intelligence and human intelligence. Meanwhile, future more studies may focus on reasonable and appropriate human-machine collaborative teaching process and evaluation technology, so as to build a new human-machine interaction ecology.

5.7. The BR and weight analysis

BR is the unfair attitude and biased judgment of a certain social group in advance. Knox et al. (2019) found that AI products intentionally excluded specific groups from the target audience, making it difficult for some learners to obtain equivalent education services. According to Nathanson et al. (2013), AI recommendation system did not achieve the goals of debiasing, which resulted in most of the low-achieving students being recommended to poor high schools. In particular, the algorithm is actually a "human concept embedded in mathematics," the process follows the rule of "prejudice goes in, then prejudice goes out." In this way, "filter bubble" can mislead teachers' decisions, narrow students' minds and ideologies, and cause "echo chamber bias," "Matthew effect," "halo effect" and even "digital structural violence" in education (Wu et al., 2020).

Our research found that although BR is ranked second to last, we still need to widely expand educators' action awareness about BR in HCAI education. We thus suggest that stakeholders such as managers, researchers, and educational practitioners need to adopt collaborative innovation approach to maintain the dynamic balance and positive interaction in AIED applications. Meanwhile, scholars should keep up with the latest trends and components framework of PR, and comprehensively explore its dynamic mechanisms and avoidance strategies. In addition, future studies may consider exploring the PR models based on HCAI concept, so as to develop AI systems that are useful, usable, and in which humans have final control.

5.8. The MC and weight analysis

HCAI concept is the goal foundation of AIED applications. If the HCAI concept is widely integrated into AIED applications, moral values will become part of the AI systems design, so as to ensure the healthy, controllable and reliable AIED ecology. This might because the HCAI concept advocates the development of responsible AI education, which is crucial for establishing "high-quality and warm" AIED ecology. Also, this is consistent with the concept of human-in-the-loop (Honeycutt et al., 2020). According to Yang et al. (2021), human beings have features that are incomparable to AI in terms of cognition, emotion, attitude, and values. Verkijika et al. (2015) argued that it is possible to further explore enabling conditions for innovative learning and create effective intervention scaffolds from the perspective of human beings. For example, Dignum (2019) proposed that human value design and value-sensitive design (VSD), which put human rights, dignity, and freedom at the center of AI systems design, could identify, consider, and determine the adaptive path of man-machine collaboration.

Based on the results, although HCAI risk accounts for the smallest proportion in the risk framework, it is the primary index. Since it is consistent with the essential pursuit of HCAI education, which can also guarantee the integration of goals, processes, and results. In particular, the three forms of HCAI governance structure of reliable design, safe management, and credible certification can enhance public trust and confidence in AIED applications. Overall, the fundamental way to break through the AIED risk is to adhere to the HCAI concept and its endogenous laws. We thus suggest that more studies may consider designing, developing and applying HCAI-oriented practice paradigm.

6. Conclusions

Our study was the first-in-depth to explore the risk framework and establish index weight of HCAI education. To achieve the first aim, we used the literature meta-analysis method to determine the risk framework, and to achieve the second aim, we used the Delphi and AHP methods to calculate index weight. In sum, our study indicates that (1) the risk framework includes eight indicators, which are MC, MR, MP, PSR, TR, AR, BR, and PR; (2) eight indicators are divided into four categories such as HCAI concept, application process, ethical security, and man-machine interaction; (3) the trend of risks types confirms that more than half of the articles consider only three or less risks types; (4) the evolution results show that very limited risks indicators (e.g., PSR, TR, AR, BR) are considered before 2015, however, with the widespread increase of AIED applications, both the quantities and types of risks indicators (e.g., MC, MR, MP, PR) have increased in the last five years; (5) the weights of the eight indicators are MP > MR > AR > PSR > TR > PR > BR > MC.

Our findings provide theoretical evidence and development suggestions for future scientific governance of HCAI education. Also, the ranking of MP > MR > AR > PSR > TR > PR > BR > MC reflects the key risk factors that need to be paid attention to at the present stage. Moreover, the risk framework not only systematically considers the risk governance order of HCAI education, but more importantly, it is the key bridge to the collaborative advancement of stakeholders such as managers, teachers, students, and parents in AIED applications. For example, at the procurement stage, it can provide managers with judgmental evidence on the access regulations and application safety of AIED products. At the design stage, it can provide key scaffolding and intervention directions for teachers to carry out AIED activities. In the application stage, it can provide guidance and support for students' scientific cognition and rational use of AIED tools. For parents in the promotion stage, it can help them further rationally accept AIED applications and enhance the value effect of intelligent efficiency.

7. Limitations and future works

Although this study does propose some valuable risk governance factors and potential intervention directions in HCAI education, there are still some limitations. First, our research sample used only English language articles. However, as AIED applications are being promoted and explored worldwide, publications in other languages should also be considered in future research. Moreover, the initial keywords search is limited to the two domains of HCAI and risk, which may lead to the latest AI technology reports are not being included in this study, future more studies may consider optimizing the search strategy, such as extending keywords like HCAI challenges and HCAI governance. Additionally, although the study provides a systematic risk governance framework, the current research results still lack inclusiveness, thus future analysis could go back further in time to explore the phased trends in risk governance.

In the future, if the AIED applications early warning systems can be developed according to the risk framework and index weight, it will promote the scientific, healthy and sustainable HCAI education. However, the research on effect size of each risk is lacking, especially how to provide corresponding intervention scaffolds based on the effect size. A possible future direction could be to conduct a series of meta-analyses on the specific effect sizes of each risk, so as to explore the dynamic trends and key dilemmas of risk governance in HCAI education. Another potential direction is to implement the risk framework, for example, we can carry out intervention experiments for learners in different regions, learning segments, and queues, so as to generate different types and different characteristics of avoidance strategies and promotion measures. Furthermore, attention should reach beyond AIED applications to the latest trends of HCAI education, future more studies may consider comparing the characteristics of different regions and carrying out innovative practices in HACI education, for example, developing an index framework of the HCAI education, promoting HCAI education based on social experiments, and using multi-agent simulation experiments to simulate the trend of HCAI education.

Acknowledgement

This study is supported by the Major Projects of the National Social Science Foundation of China (grant number 19ZDA364).

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