Article

Factors Influencing Public Risk Perception of Emerging Technologies: A Meta-Analysis

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Abstract: The development and application of emerging technologies pose many social risks, which raise public concerns. Various factors influence the public risk perception of emerging technologies, and a systematic and accurate understanding of these factors plays a vital role in promoting the sustainable development of emerging technologies. Considerable inconsistency and ambiguity exist in the influence of relevant factors on the public risk perception of emerging technologies in existing studies, which need to be explored systematically and comprehensively through meta-analysis. This study constructs an analytical framework of "technology–psychology–society" and conducts a meta-analysis of 272 papers, including 449 correlations and 191,195 samples. The results show that perceived benefit, knowledge, innovativeness, trust, and social influence have significant negative effects on risk perception. Perceived cost has a significant positive effect on risk perception. Gender and cultural dimensions of power distance, uncertainty avoidance, individualism–collectivism, and masculinity–femininity have moderating effects on the relationship between relevant factors and risk perception; the type of emerging technology, age, and the cultural dimension of long-term/short-term orientation do not have moderating effects. Based on the above findings, this study proposes corresponding suggestions from the perspectives of R&D, application, and management of emerging technologies.

Keywords: emerging technologies; risk perception; meta-analysis; sustainable development

1. Introduction

The rapid development and widespread application of emerging technologies have brought tremendous economic benefits, life convenience, and social well-being. According to the research of PricewaterhouseCoopers (PwC), an international accounting and auditing institution, artificial intelligence is expected to drive global economic growth of 14% by 2030, equivalent to USD 15.7 trillion [1], exceeding China's GDP in 2020. In addition, research by Strategy Analytics, a global market research and advisory firm, found that as of June 2021, about four billion people worldwide had smartphones, accounting for half of the total population [2]. Since the outbreak of COVID-19, mobile Internet technologies such as online offices, cloud-based learning, and health codes have provided intelligent solutions to the epidemic. Furthermore, with the advantages of low cost and high yield and disease and pest resistance, genetically modified technology can improve the ecological environment and help solve the food crisis.

However, emerging technologies have become a source of risk because of their radical novelty, uncertainty, and ambiguity [3]. These risks include the security threat to autonomous vehicles, the invasion of personal privacy by Internet apps, the health controversy over genetically modified technology, etc. Compared with traditional risk, emerging technology risk exhibits a higher degree of gradualness, concealment, coupling, and uncertainty [4], which are more likely to trigger public anxiety and group panic and even lead to mass incidents.

Because of the "double-edged sword" nature, the government must consider the risk governance of emerging technologies while vigorously developing and promoting them. At

the same time, it is crucial to note that factors affecting public risk perception have become essential for decision making in emerging technology risk governance strategies [5–7]. Unlike the objective risk assessment based on precise scientific analysis, risk perception is somewhat subjectively constructed. It comprises psychological processing based on intuition, experience, and the overall judgment of specific behaviors or events [8]. Public risk perception is often inconsistent with and differs from the results of objective risk assessment. For example, although the damage caused by nuclear, biological, and chemical technologies is much less than that caused by natural disasters, traffic accidents, and local conflicts, people are more worried about it. Although scientific evidence has not proven that genetically modified technology is harmful, people believe it may lead to disasters [9]. As with responses to objectively real threats or potential harm, such biased perception can also lead to public concern, panic, and unacceptable behavior. This will hinder the sustainable development of emerging technologies and increase public distrust of professional groups and government agencies, leading to social instability [10]. Therefore, conducting an in-depth and systematic study of the factors influencing public risk perception is necessary.

The existing research on public risk perception of emerging technologies has been relatively fruitful, but there are still deficiencies. First, established research has comprehensively integrated the psychological, social, and cultural factors that shape technological risk perception [7]. However, it mainly uses a systematic overview approach, and quantitative studies based on large samples are scarce. Second, existing research has mainly considered a particular technology as an example, with less discussion on different types of technologies. Third, there is still disagreement and ambiguity about the direction and intensity of factors affecting risk perception in the existing studies. For example, previous studies have found that the correlation coefficient between trust and risk perception is -0.801 to 0.176 [11,12], and the correlation coefficient between knowledge and risk perception is -0.528 to 0.345 [13,14]. Fourth, the established studies are inadequate in explaining the considerable differences in the factors affecting risk perception. Insufficient attention has been paid to the role of moderators such as gender, age, technology type, and culture. In conclusion, there are few holistic, systematic, and integrated empirical studies on the factors influencing the public risk perception of emerging technologies and their mechanisms.

Therefore, this paper used the technology–organization–environment (TOE) framework, a general classification framework that is more systematic, operable, and flexible based on technology application scenarios [15–17]. This comprehensive framework can analyze the impact of technological factors (advantages, costs, and benefits of the technology), organizational factors (size, structural characteristics, and human resources of the organization), and environmental factors (the specific environment in which the organization is located, involving market structure, policies, society, culture, and values) on the application of technology [16,18–22]. Based on the TOE framework, we constructed a theoretical analysis framework of "technology–psychology–society", an integrated theoretical model of influencing factors affecting risk perception from three levels, namely, technological economy, psychological cognition, and social environment, and explored the role of relevant typical factors on the public risk perception of emerging technologies. At the same time, we selected four emerging technologies [23], namely, genetically modified technology, nanotechnology, artificial intelligence, and information communication technology, to conduct a meta-analysis of 272 empirical studies worldwide and verify the proposed theoretical model. This paper has three main focuses: first, to construct an integrated theoretical model of factors influencing risk perception based on the review of existing studies; second, to draw more accurate and more evident conclusions on the direction and strength of influencing factors based on a large sample meta-analysis; and third, to explore and validate the mechanisms of moderating variables.

2. Theory and Hypothesis

2.1. Conceptual Background

The academic research on risk has been fruitful, but there is still no consensus on the definition of risk. One study systematically analyzed dozens of conceptual representations of risk [24]. Referring to this study, we found that risk consists of three core elements. Most of the definitions of risk in previous studies have focused on a combination of the three elements, as shown in Table 1 and Figure 1. Although there are different definitions, the essence of risk is uncertainty. This uncertainty stems not only from the randomness of risk events and behaviors but also from the uncertainty in understanding and perceiving the impact of risk [25], that is, the perception of risk. Risk perception refers to people's subjective awareness, judgment, and feelings about dimensions such as damage extent, duration, probability of occurrence, and acceptability based on information, knowledge, and experience [10,26–28].

Table 1. Definitions of risk and the representative literature.

Elements/Combination of Elements	Definition	Representative Literature
Element 1: Event/Action/Consequence/Outcome	Most studies characterize risk as negative, i.e., "undesirable event", "loss", "damage", "disutility", etc., while some argue that risk contains not only negative consequences but also positive outcomes, such as "opportunity", "utility", etc.	Aven T [24] Cabinet Office [29]
Element 2: Degree	"severity", "intensity", "size", "extension", "scope", "magnitude", etc.	Aven T [24] Aven T and Renn O [30]
Element 3: Uncertainty	"possibility", "probability", "chance", "likelihood", etc.; this element implies the future direction of risk, that is, it has not yet occurred	Aven T [24]
Combination of elements	"Risk is the expected loss", "Risk equals the combination of probability of an event and its consequences", "Risk is uncertainty about events/consequences of an activity, seen in relation to the severity of the events/consequences", "Risk refers to uncertainty about and severity of the consequences (or outcomes) of an activity with respect to something that humans value", "Risk refers to the combination of probability and the extent of consequences", etc.	Verma, M and Verter, V [31] Willis, H.H [32] ISO [33] Aven T and Renn O [30] Ale, B.J.M [34] Aven T [24]

In recent years, emerging technology has gradually become a hot topic in research and practice, but the academic community has also not reached a consensus on its definition. Because of this, Rotolo et al. [3] systematically integrated relevant research and summarized the definition of emerging technologies from the following five core attributes: (a) radical novelty, that is, the revolutionary and evolutionary character of innovation in the process of technology formation, as manifested by revolutionary breakthroughs in previously limiting technologies, or the application of existing technologies from one field in another; (b) relatively fast growth, that is, rapid growth compared to other technologies in the same domain; (c) coherence, that is, the detachment and identity of emerging technologies are always in the process of realization; (d) prominent impact, that is, a potentially considerable impact on specific domains or the entire socioeconomic system (such as bringing significant economic benefits) by changing the knowledge production processes and reshaping the technological institution; (e) uncertainty and ambiguity, that is, emerging technologies are

still in the process of development and in an "unfinished" state; their prominent impact lies somewhere in the future, and their applications are still malleable, fluid, and even contradictory in some cases, with unpredictable consequences, especially unintended or undesirable consequences.
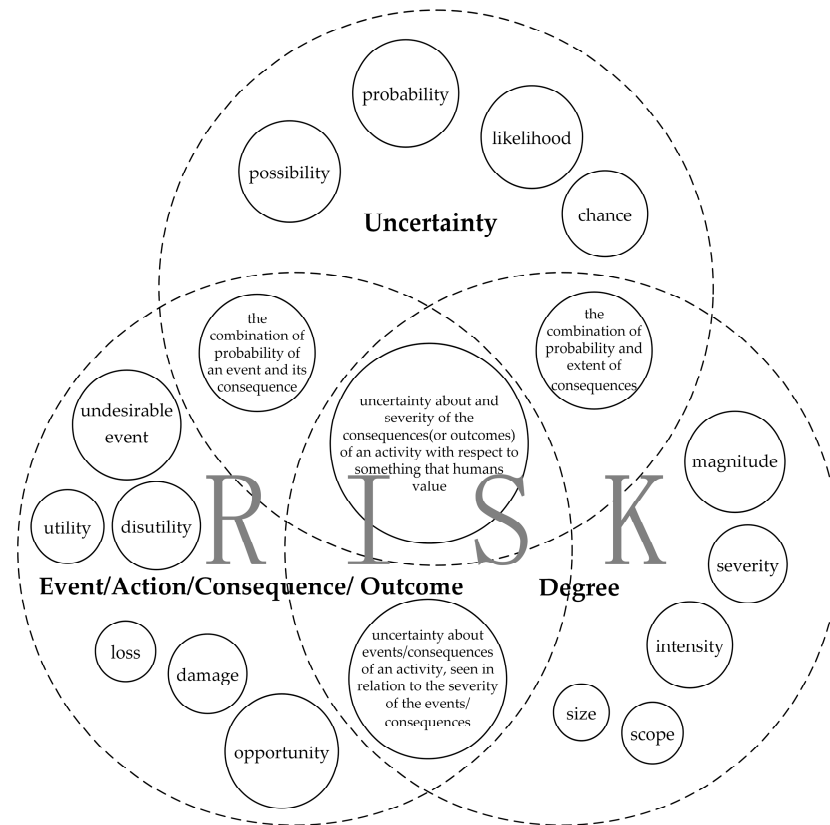
Figure 1. Illustration of risk concept.

With the five attributes mentioned above, emerging technologies promote economic development and the efficiency of social operation. However, they also create problems such as the limited social understanding of them, the insufficient capacity to govern them, and difficulty in detecting their potential negativity. These problems lead to potential physical, economic, and social losses from the accumulation and development of technologies during their life cycle [7]. The risk of emerging technologies has gradually become a major social risk category, raising public concern [35–37]. The risk perception of emerging technologies refers to people's processing of the physical signals and information about potential hazards and risks associated with emerging technologies and their judgment of the severity, possibility, and acceptability of emerging technologies based on their knowledge and experience [7]. The five core attributes of emerging technologies are intertwined with the complexity and uncertainty characteristics of risk, resulting in various factors affecting public risk perception [38,39]. Thus, this study summarized six typical influencing factors at three levels based on the analysis framework of "technology–psychology–society" by combing the relevant literature. They are technical–economic factors, including perceived benefit and perceived cost; psychological–cognitive factors, including knowledge and innovativeness; and social–environmental factors, including trust and social influence. In addition, we explored the moderating effects of relevant variables.

2.2. Technical–Economic Factors

2.2.1. The Relationship between Perceived Benefit and Public Risk Perception of Emerging Technologies

　　An innovation without additional benefits is almost a paradox [40]. In most cases, emerging technologies offer benefits or advantages that exceed those existing in general technologies because of their attributes, such as long-term economic benefits, functional advantages, environmental protection, and nutritional health. However, emerging technologies often carry more significant risks and pose severe dilemmas for social development. The rational decision analysis approach treats risks and benefits as isolated concepts and conducts risk–benefit analysis to weigh the benefits and losses to solve this dilemma [41]. Thus, risk and benefit tend to have an objective positive correlation [42]. At the same time, high risk–high benefit and low risk–low benefit are almost psychological common sense. However, like risk perception, perceived benefit is somewhat subjective, and its meaning refers to the public judgment and perception of the benefits or advantages that emerging technologies can bring. Research has shown a negative correlation between perceived benefit and perceived risk. For example, Gardner et al. [43] found that the perceived benefit of nuclear power technology was negatively correlated with the perceived risk. The public who believed that nuclear power technology was beneficial to society felt less risk than those who did not hold this view.

　　In most cases, the public does not judge risk and benefit independently using a scientific risk–benefit evaluation approach but rather closely correlates their perceptions of both [44]. People perceive less risk because they perceive more benefit [41,44]. In addition, the public does not have the knowledge and ability to assess risk to a large extent. Because benefits are more tangible and more closely related to individuals, people have more experience in this area. Hence, it is much easier for the public to perceive the benefit of technology than the risk. From this perspective, it is more reasonable for a perceived benefit to influence risk perception than the opposite [45–47]. In addition, the theory of cognitive consistency holds that people must maintain consistent beliefs in their work and life [48,49]. Therefore, to avoid cognitive dissonance, people tend to agree that an activity or technology is low-risk when they perceive it as beneficial [41]. Based on the above analysis, this study proposes the following hypothesis:

Hypothesis 1 (H1). *There is a negative relationship between perceived benefit and risk perception.*

2.2.2. The Relationship between Perceived Cost and Public Risk Perception of Emerging Technologies

　　Prospect theory suggests that individuals tend to be more sensitive to losses than gains [50]. Additionally, Arrow and Pratt's theory assumes that individuals are generally risk averse [51–53]. Given the novelty, complexity, ambiguity, and other characteristics of emerging technology, people will not only consume more time, money, and other explicit costs but also incur implicit costs such as psychological hindrance, burden, or emotional unpleasantness in the process of selecting, using, and converting from the previous technology or service to a new one [54,55]. Perceived cost refers to the public's perception and cognition of these costs. There is a lack of detailed discussion on the relationship between the perceived cost and risk perception of emerging technology. Mustapa et al. [56] found that the perceived cost of adopting genetically modified crops strongly affects farmers' risk perception; the higher the perceived cost, the higher the perceived risk. The transaction cost theory explains this result. It suggests that the limited rationality of traders, information asymmetry, uncertainty in the exchange environment, and other factors during the transaction process lead to transaction costs, which are manifested in the time, information, expenses, and psychological costs incurred in searching, consulting, and defending rights [57,58]. The more complex the transaction, the higher the transaction cost, and the more uncertainty the traders will feel or the more inclined they will be to perceive the outcome as unfavorable. Therefore, they will perceive a higher risk [59,60].

Studies have found that transaction cost or perceived transaction cost positively affects risk perception [61,62]. Similarly, the public may bear more explicit or implicit costs in selecting and using emerging technologies because of their lack of experience, information asymmetry, and habituation to prior technologies. The higher the cost perceived by the public, the worse their experience with the emerging technologies and the higher the risk perception. Therefore, this study proposes the following hypothesis:

Hypothesis 2 (H2). *There is a positive relationship between perceived cost and risk perception.*

2.3. Psychological–Cognitive Factors

2.3.1. The Relationship between Knowledge and Public Risk Perception of Emerging Technologies

Knowledge represents the public's awareness, understanding, and familiarity with the characteristics, functions, and usage of emerging technologies. When faced with something new, everyone perceives, identifies, and evaluates its risk under a specific predetermined knowledge structure. A person's knowledge structure constitutes the premise and psychological foundation of risk perception. The public usually perceives and judges the risks of emerging technologies based on specific knowledge. Generally speaking, the more knowledge the public has about a specific thing's characteristics, functions, and usage, the lower the degree of risk perception. Emerging technologies form an insurmountable knowledge barrier before the public because of their complexity, uncertainty, and ambiguity. There is a large gap between the "knowledge demand" of the public to comprehensively and thoroughly understand emerging technologies and their limited "knowledge reserve" [63]. This knowledge gap is an essential factor that leads to fear, uncertainty, and doubt among the public. Some scholars believe that if a person's knowledge structure is complete, there is no uncertainty [64]. Related studies have found that knowledge can negatively predict the public risk perception of emerging technologies [65,66]. A proper understanding of emerging technologies can help the public to dispel doubts and confusion and reduce fear and anxiety. However, some studies have come to the opposite conclusion [14,67]. This may be because with the improvement of knowledge level, the public may pay more attention to the principles, functions, quality, and potential hazards of emerging technologies, resulting in more doubts and negative perceptions. Although the findings of existing studies are divergent, in general, a complete body of knowledge and adequate understanding facilitate a more positive public attitude toward emerging technologies. Accordingly, this study proposes the following hypothesis:

Hypothesis 3 (H3). *There is a negative relationship between knowledge and risk perception.*

2.3.2. The Relationship between Innovativeness and Public Risk Perception of Emerging Technologies

Innovativeness is derived from the diffusion of innovation theory, also known as personal innovativeness. It reflects the individual's distinctive attitude toward emerging things and is an essential factor affecting their intention to accept innovative ideas and things. Rogers et al. [68] defined innovativeness as the degree to which individuals adopt new technologies, products, or services earlier than others from the perspective of time. Midgley and Dowling [69] considered innovativeness from the perspective of individual psychology as a higher-order potential personality trait in a broad sense—the degree to which individuals tend to accept new ideas, products, or services. In practice, people with innovative traits are more open and risk-taking, have an intense curiosity about new things, and enjoy experiencing new technologies or services. Bommer and Jalajas [70] suggested that innovativeness reflects an individual's ability and willingness to take and tolerate risks. Rogers et al. [68] pointed out that innovative individuals can cope with high levels of uncertainty and form more positive attitudinal intentions. Some studies have found a significant negative effect of innovativeness on the risk perceptions of emerging technologies [71,72]. However, other studies found this effect to be insignificant [73],

suggesting that the role of innovativeness needs further exploration. Nevertheless, a high level of innovativeness is more likely to weaken the perception of uncertainty and risk on the whole. Therefore, this study proposes the following hypothesis:

Hypothesis 4 (H4). *There is a negative relationship between innovativeness and risk perception.*

2.4. Social–Environmental Factors

2.4.1. The Relationship between Trust and Public Risk Perception of Emerging Technologies

The extent to which society embraces emerging things is closely related to the level of overall social trust. The famous "Tacitus trap" posits that once government power loses trust, society will give a negative evaluation no matter how it communicates or acts [74]. Theoretically, trust is a complex and multidimensional concept defined differently by different disciplines. Mayer et al. [75] defined trust as the willingness of one party to be vulnerable to the actions of another party because of its expectation that the other party will take a particular action that is important to the trustor, regardless of the ability to monitor or control that other party. In other words, trust is an interactive relationship between the trustor and trustee that depends on the attributes or elements that trust possesses. Established research suggests that trust contains three core elements: Ability, benevolence, and integrity [75]. Ability refers to the trustor's belief that the trustee has sufficient expertise, skills, and competencies to meet reasonable expectations. Benevolence is the degree to which a trustee is perceived to want to do good for the trustor, excluding consideration of self-interest. Integrity means that the trustor perceives that the trustee adheres to a set of principles that the trustor deems acceptable.

The relationship between trust and risk is close. There is considerable inconsistency in the degree of the relationship between trust and risk perception in existing studies [11,12]. Mayer et al. [75] explained trust as the willingness to take risks, and it can also be said that trust is essentially a response to risk, that is, the belief that the trustee cannot take advantage of the trustor's vulnerability to act in an opportunistic manner [76]. For example, in using information technology, customers allow network operators to access their personal information because they believe that the operators can do an excellent job in security protection and will not abuse this information by taking advantage of the customers' weaknesses. Establishing this trust leads to the reduction of the customers' risk perception levels [77,78]. Some studies have identified trust as an effective mechanism for simplifying complexity. When facing the complexity of society, individuals have difficulties obtaining sufficient information about a specific cognitive object because of the limited rationality of the cognitive world. Trust can effectively compensate for the lack of rationality, deal with information omissions, simplify the cognitive process, and establish a sense of security [79–81]. Because of the radical novelty and high uncertainty of emerging technologies, public trust in technology and technology stakeholders (including government agencies, industry organizations, and scientific communities) can serve as a means to bridge the gap between their own "knowledge reserve" and the "knowledge demand" required for a comprehensive understanding of emerging technologies", thereby offsetting some of the worries about emerging technologies caused by the lack of knowledge [82,83]. For example, studies have shown that one way for people to cope with their lack of experience is to use social trust mechanisms when judging technical risk [84]. Studies in gene technology have also found that trust in institutions or persons involved in researching, developing, and using technologies causes people to perceive a lower technical risk [82,85]. Furthermore, some studies have found that trust can also be used as a heuristic to conserve individual's cognitive resources, enable them to process complex technical information and social controversies quickly, overcome uncertainty and anxiety about behavior and its outcomes, and reduce the level of risk perception [86,87]. Accordingly, this study proposes the following hypothesis:

Hypothesis 5 (H5). *There is a negative relationship between trust and risk perception.*

2.4.2. The Relationship between Social Influence and Public Risk Perception of Emerging Technologies

The concept of social influence is derived from the unified theory of acceptance and use of technology [88]. As the name implies, social influence mainly reflects the influence of the social environment on individual behavior, which can be defined as the pressure individuals perceive from the social network on their decisions to adopt a specific behavior or accept a particular idea [88,89]. It consists of three constructs [88]: subjective norm, that is, the degree to which individuals perceive that significant others or organizations think they should adopt a specific behavior, reflecting an individual's motivation to comply; social factors, that is, the influence of cultural and social norms on an individual's behavior, reflecting their belief in social norms and group will; and image, that is, the extent to which individuals perceive that the use of innovation contributes to improving their social image and enhancing their social status. Existing in-depth exploration of the relationship between social influence and risk perception is relatively lacking. Karahanna et al. [90] found that information and support from significant others impact the formation of beliefs and choices about new technologies among potential adopters. Specifically, on the one hand, individuals internalize information from experts and others into their cognitive system; on the other hand, they will conform to social norms and obtain social recognition through image and identity confirmation. Social influences play an essential role in the cognition of emerging technologies, and people usually adjust their attitudes, beliefs, and behaviors toward technologies based on their social networks [89]. The novelty and ambiguity of emerging technologies make people feel uncertain and anxious. Thus, the information, opinions, and behaviors of their surrounding relatives and friends, professional groups, public figures, and related institutions can play a vital reference role in their perceptions and judgments. Studies have found that the use of new technologies in social circles will often indicate to individuals the rationality and appropriateness of the technology. This support and influence from significant others may reduce people's feelings of uncertainty about new technologies [91,92]. At the same time, compliance with social influences helps individuals feel an enhanced self-identity and social image, thereby reducing the risk perception of emerging technologies. Therefore, this study proposes the following hypothesis:

Hypothesis 6 (H6). *There is a negative relationship between social influence and risk perception.*

2.5. The Influence of Moderating Variables

The moderator analysis in meta-analysis helps explain the heterogeneity among studies. The analysis of the included literature may reveal that the relationship between relevant factors and risk perceptions varies, indicating the possible existence of moderating variables. This study summarized the following possible moderating variables.

2.5.1. The Moderating Effect of Type of Emerging Technology

This study selected genetically modified technology, nanotechnology, artificial intelligence, and information and communication technology with reference to the relevant literature [23]. These four technologies have characteristics typical of emerging technologies. However, there are undeniable differences in the types of hazards that these technologies may generate. For example, genetically modified technology and nanotechnology may cause more health hazards. Artificial intelligence and information and communication technology may cause information leakage and property loss. The public sensitivity to the hazards of these technologies may be different, affecting their risk perception. Hence, this study proposes the following hypothesis:

Hypothesis 7 (H7). *The type of emerging technology has a moderating effect on the relationship between relevant factors and risk perception.*

2.5.2. The Moderating Effect of Demographic Variables

Demographic variables include gender and age. Elder et al. [93] found that women are more skeptical of genetically modified foods. Kalinić et al. [94] found that men are less affected by potential risks than women when it comes to mobile payment use. Thus, gender may moderate the impact of relevant factors on risk perception. In terms of age, it is generally believed that younger generations encounter fewer barriers and hold more open attitudes in their acceptance and use of emerging technologies [95]. Therefore, age may also be a moderating factor. Hence, this study proposes the following hypotheses:

Hypothesis 8a (H8a). *Gender has a moderating effect on the relationship between relevant factors and risk perception.*

Hypothesis 8b (H8b). *Age has a moderating effect on the relationship between relevant factors and risk perception.*

2.5.3. The Moderating Effect of Culture

Culture is the collective programming of the mind that distinguishes members of one group or society from another [96]; it includes a set of artifacts, symbols, values, norms, and assumptions that people share and shapes people's beliefs, attitudes, and behaviors at different levels of society [97,98]. Hofstede identified five dimensions of cultural values: power distance, uncertainty avoidance, individualism–collectivism, masculinity–femininity, and long-term/short-term orientation [99]. Specifically, power distance refers to the extent to which the members of organizations and institutions accept that power is distributed unequally. Uncertainty avoidance refers to the degree to which a culture makes its members feel uncomfortable in unstructured situations. Individualism–collectivism refers to the extent to which individuals should care for themselves or remain integrated with the groups. Masculinity–femininity is the distribution of emotional roles between the genders. Long-term/short-term orientation is the extent to which a culture enables its members to accept delays in meeting their material, social, and emotional needs.

First, in a high power distance cultural context, pressure from the government and superiors plays an important role in how people view and adopt emerging technologies [99], which may influence people's risk perception. Second, people usually accept conventional risks but fear ambiguous situations and uncommon risks in strong uncertainty avoidance societies. In contrast, people generally accept ambiguous situations and unusual risks in weak uncertainty avoidance societies [100]. The risk of emerging technologies is highly uncertain and ambiguous. There may be differences in people's risk perceptions of emerging technologies in different degrees of uncertainty avoidance cultural contexts. Third, people in collectivistic cultures are more influenced by group membership and decisions [97]. However, people in individualistic cultures are more focused on their own needs, have more freedom, and prefer challenging work [100]. Fourth, masculinity implies that men are dominant in society or the power structure and that women are less self-assured and competitive than men [101]. Moreover, in a society dominated by masculinity, people enjoy challenges more [100]. Thus, masculinity–femininity may influence people's attitudes toward emerging technologies and their risks. Fifth, a long-term-oriented culture may be more focused on resource conservation, environmental protection, and the sustainable development of the economy and society. The development and use of emerging technologies can help achieve this goal. Thus, long-term/short-term orientation may also affect people's recognition of emerging technologies and their risks. In summary, culture dimensions are considered potential moderating variables. Hence, this study proposes the following hypotheses:

Hypothesis 9a (H9a). *Power distance has a moderating effect on the relationship between relevant factors and risk perception.*

Hypothesis 9b (H9b). *Uncertainty avoidance has a moderating effect on the relationship between relevant factors and risk perception.*

Hypothesis 9c (H9c). *Individualism–collectivism has a moderating effect on the relationship between relevant factors and risk perception.*

Hypothesis 9d (H9d). *Masculinity–femininity has a moderating effect on the relationship between relevant factors and risk perception.*

Hypothesis 9e (H9e). *Long-term/short-term orientation has a moderating effect on the relationship between relevant factors and risk perception.*

Based on the above analysis of relevant theories and existing studies, a "technology–psychology–society" integrated theoretical model of the factors influencing the public risk perception of emerging technologies was constructed, as shown in Figure 2.
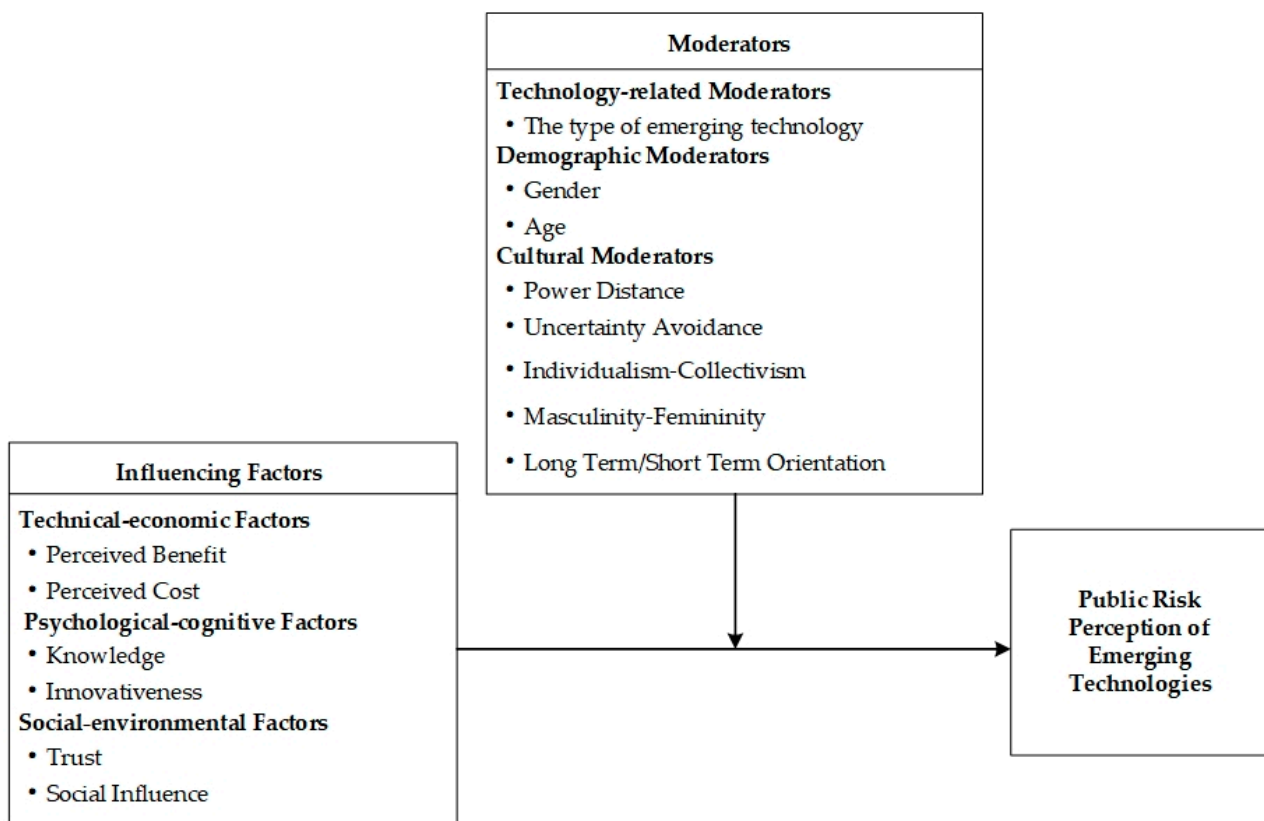

Figure 2. Research model.

3. Methods and Data

3.1. Meta-Analysis Method

Meta-analysis is an empirical method for the comprehensive quantitative analysis and evaluation of existing research results [102]. This method has the following advantages. First, it can combine and analyze the results of several existing quantitative studies on a specific topic, thus effectively reducing the sampling error and measurement error in a single study and improving the validity of research results [103]. Second, it can systematically evaluate and explain the inconsistencies among research results and obtain a more comprehensive and accurate understanding of a specific problem [104]. Third, it can conduct a more precise analysis and comparison of differences in the relationships between research variables and explore the potential factors causing differences by setting

moderating variables [102,105]. In conclusion, meta-analysis helps reduce the research bias caused by the sample limitations, research situations, and subjective bias of researchers in a single study to obtain more objective and valid research results [106]. A meta-analysis combines quantitative and qualitative research techniques, and its main steps include identifying research topics, searching and screening the literature, data coding, literature quality evaluation, and statistical processing. For this paper, we conducted the research and reported the results strictly following the process.

3.2. Literature Search and Inclusion Criteria

From May to October 2021, we accessed a total of 15 databases, including 10 English databases and 5 Chinese databases. Specifically, the English databases included the core collection of Web of Science, Scopus, EBSCOhost (APA PsycInfo), EBSCOhost (Academic Source Complete), EBSCOhost (Business Source Complete), ScienceDirect, the Wiley Online Library, PubMed, ProQuest, and Springer Link; the Chinese databases included CNKI (China National Knowledge Infrastructure), Wanfang Data (a Chinese database), VIP (VIP Chinese database), Airiti Academic Literature Database, and the Digital Library of Theses and Dissertations in Taiwan. In order to ensure the quality of the included literature, the Chinese journal databases were limited to retrieving the literature included in the CSSCI (Chinese Social Science Citation Index), CSCD (Chinese Science Citation Database), Peking University Chinese core journals list, TSSCI (Taiwan Social Science Citation Index), THCI (Taiwan Humanities Citation Index), and ACI (Taiwan Academic Citation Literature Database). The literature collected in these five Chinese journal databases was recognized to be of high quality. The retrieval words included "risk perception, perceived risk, perception of risk, biotech*, genetically modif*, transge*, synthetic biology, nanotech*, artificial intelligence, AI, face recognition, robot*, big data, drone, information and communication tech*, ICT, mobile payment, emerging tech*". We used both English and Chinese for retrieval. Specifically, we matched the retrieval words of emerging technologies with the retrieval words of risk perception to search the titles, keywords, and abstracts in the database. In the later research process, we supplemented the eligible literature that was missed at any time in the literature search stage. Considering the meta-analysis requirement of complete and comprehensive literature categories, the literature retrieved in this study included journal papers, dissertations, and conference papers.

After retrieval, we screened the literature according to the following inclusion criteria: (a) it must be empirical research, excluding purely theoretical research, qualitative research, and reviews; (b) it contains the impact of relevant factors on the public risk perception of emerging technologies or the relationship between the two; (c) it explicitly reports the Pearson correlation coefficient (r), excluding the regression coefficient in regression analysis and the path coefficient in the structural equation model; (d) it explicitly reports the sample size. Moreover, we retained only the journal paper if it and a dissertation were the same studies.

3.3. Data Coding and Literature Quality Assessment

Data coding is the process of extracting data from the screened literature. In this study, coding was performed according to the procedure recommended by Lipsey and Wilson [107]. We developed a coding manual and instructions. Then, we extracted study characteristics and effect values, including authors, year of publication, type of literature, sample size, gender characteristics of the sample (proportion of males), age characteristics of the sample (average number of years), types of emerging technologies, country of the sample, cultural dimension score, and the correlation coefficient (r). Two researchers coded independently according to the coding manual and instructions. After coding, the two researchers cross-checked, and the inconsistent information was reviewed and discussed until an agreement was reached. Finally, a random literature sample was selected for verification to check the consistency of the coding results and ensure the coding accuracy.

The quality of the literature is a critical factor affecting the accuracy of the meta-analysis results. We developed the following evaluation criteria with reference to the quality evaluation methods of observational research [108,109]: (a) Selection of subjects. Random sampling was scored 2 points, non-random sampling was scored 1, and unreported was scored 0. (b) Data validity. A data validity rate of 0.8 and above was scored 2 points, between 0.7–0.8 was scored 1, and below 0.7 or not reported was scored 0. (c) Completeness of sample information and outcome indicator reporting. We scored 2 points for complete reporting, 1 for incomplete reporting, and 0 for non-reporting. (d) Reliability of measurement instruments. A reliability coefficient of 0.8 and above was scored 2 points, between 0.7–0.8 was scored 1, and below 0.7 or not reported was scored 0. The total score of the literature quality was calculated based on this criterion, and higher scores indicated a higher quality of literature.

3.4. Data Analysis

3.4.1. Heterogeneity Test

The heterogeneity test aims to analyze the degree of differences in the included studies. The Q test is widely used for heterogeneity tests, and a Q value at the significance level $p < 0.05$ indicates that the heterogeneity is statistically significant [110]. At the same time, the size of heterogeneity is evaluated using I^2, with a larger I^2 indicating greater heterogeneity ($I^2 < 25\%$ and $I^2 \geq 75\%$ indicating low and high heterogeneity, respectively) [110]. A random effects model is used for analysis when heterogeneity is significant; otherwise, a fixed effects model is used [111]. Tau^2 is used in the random effects model to assign the study weights to explain the degree of heterogeneity caused by differences between subgroups [112].

3.4.2. Main Effect Test

In this study, the Pearson correlation coefficient (r) was selected as an effect size indicator of the corresponding variable on risk perception. The mean value of r was used when only the r of the sub-dimension of the variable was reported in the literature. Furthermore, Fisher Z-Transformation was adopted to calculate the combined effect size. First, the original correlation coefficient was converted to Fisher Z; then, the Z value was weighted to convert back to the correlation coefficient; finally, the overall effect size was derived [112]. Comprehensive Meta-Analysis (CMA) version 3.0 software was used to calculate the effect size and 95% CI (95% confidence intervals).

3.4.3. Moderating Effect Test

When the heterogeneity test was significant, a moderating effect test was performed to determine the source of heterogeneity. Subgroup analysis was used when the moderator was a categorical variable, and a significant between-group heterogeneity test statistic, Q_B, indicated that the moderator had a moderating effect. Meta-regression analysis based on the Knapp and Hartung method was used when the moderator was a continuous variable, and a significant model test statistic, F, indicated that the moderator had a moderating effect [113]. In this study, the moderators of emerging technology type and cultural dimensions were categorical variables. Data on the five cultural dimensions were obtained through the "Hofstede Insights" website [114]. Specifically, the culture dimension scores were between 0 and 100, with more than or equal to 50 indicating a high score, and less than 50 indicating a low score. For example, in the case of individualism–collectivism, a score of 50 or above indicated individualism, while a score below 50 indicated collectivism. In addition, the moderators of gender and age were continuous variables in this study. Specifically, gender was represented by the percentage of males, and age was represented by the average number of years. It is necessary to note that this study also analyzed the interaction effect of gender and age to test robustness, which was performed using R software (version 4.2.2).

3.4.4. Publication Bias Test

Publication bias is the deviation of the meta-analysis results caused by the researchers' inability to fully obtain research data on relevant issues and fields, also known as the "file drawer problem" [115]. Generally, research with significant results is easier to publish; therefore, the published literature did not fully represent the overall state of research in a certain field [116]. In order to avoid publication bias, this study included various types of literature, such as dissertations and conference papers, in the process of collecting literature. In addition, the following methods are commonly used in statistics to test publication bias: (a) Fail-safe numbers (N_{fs}), which indicate that N_{fs} studies with insignificant results need to be added to the meta-analysis in order to make the overall effect size insignificant; if $N_{fs} > 5k + 10$ (k is the number of studies), there is no publication bias [115–117]. (b) Begg and Mazumdar's rank correlation test, where a non-significant test result indicates the non-existence of publication bias [118]. (c) Egger's regression test, where there is no publication bias if the linear regression result is not statistically significant [119]. (d) The trim-and-fill method, which is based on the assumption of asymmetry in the funnel plot caused by publication bias. After trimming and filling some studies using an iterative method, the corrected effect size is recalculated. If the effect size does not change significantly after trimming and filling, publication bias is less likely to exist [120,121]. (e) Funnel plot, in which scattered points that are evenly and symmetrically distributed on both sides of the reference line and concentrated at the middle and upper ends indicate a low probability of publication bias [112].

4. Results

4.1. Description of Data

A total of 272 eligible papers was collected in this study, including 209 journal papers, 18 conference papers, and 45 dissertations; 199 were in English and 73 were in Chinese, published from 2002 to 2022 (see Figure 3). The average score of the literature quality assessment was 5.614, higher than the median value of 4.50. Most studies (224 papers) had a quality assessment score of 5 or higher. This indicated that the overall quality of the included literature was excellent. Since some articles contained several independent effect sizes, this study included 449 effect sizes. The total sample size was 191,195, with samples from more than 40 countries. It should be noted that there was duplication in the total sample size because some of the literature included in the meta-analysis contained more than one influencing factor.

4.2. Heterogeneity

The results of the heterogeneity test are shown in Table 2. Q_w was 67.995 to 3445.787, and I^2 was 73.527% to 97.031%, with all p-values less than 0.001. This indicated significant and high levels of heterogeneity, with 73.527% to 97.031% of the variation in effect on risk perception of emerging technologies caused by the real variance of effect size. The variance between studies was affected not only by sampling error but also by between-group differences. Therefore, the main effect test should use a random effects model, and the moderator analysis must be conducted.
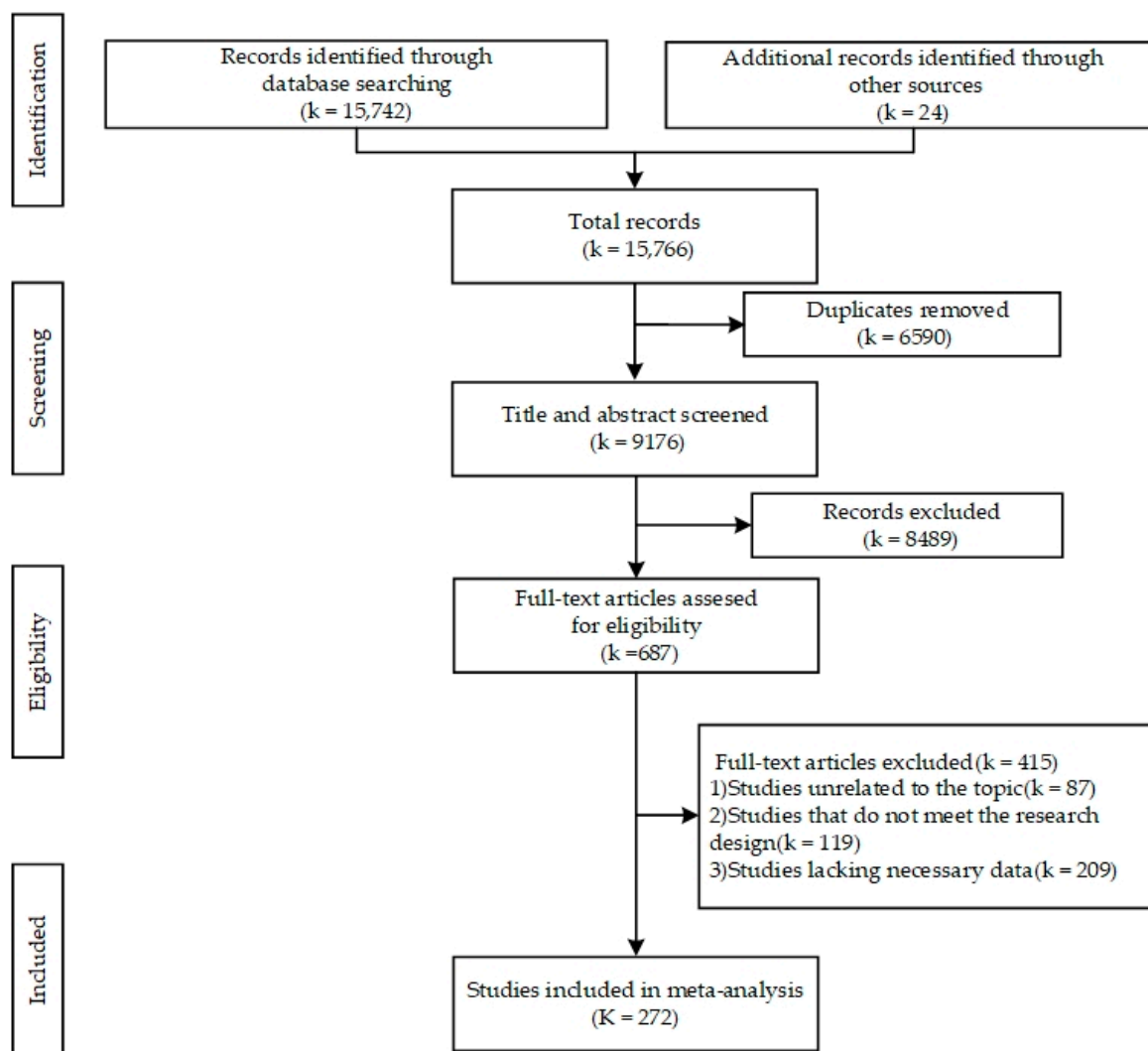
Figure 3. Flowchart of the literature selection.

Table 2. Results of heterogeneity.

Factors	m	Heterogeneity				Tau-Squared			
		Q_w	df	I^2 (%)	p	Tau^2	SE	Variance	Tau
Perceived benefit	38	1246.233	37	97.031	<0.001	0.066	0.018	0.000	0.256
Perceived cost	19	67.995	18	73.527	<0.001	0.009	0.004	0.000	0.097
Knowledge	27	349.447	26	92.560	<0.001	0.025	0.009	0.000	0.158
Innovativeness	78	1138.669	77	93.238	<0.001	0.035	0.007	0.000	0.186
Trust	154	3445.787	153	95.560	<0.001	0.048	0.007	0.000	0.219
Social influence	133	3169.092	132	95.835	<0.001	0.060	0.010	0.000	0.246

Note: m, the number of effect sizes; Q_w, within-group heterogeneity test statistic; df, degree of freedom; I^2 reflects the proportion of the heterogeneity in the total variation of the effect sizes; p, significance level; Tau^2 reflects the proportion of variation between studies that can be used to calculate weights; SE, standard error.

4.3. Main Effects

A random effects model was used to analyze the correlations between the various influencing factors and the risk perception of emerging technologies. Details are presented in Table 3. The results indicated that the relationships between the six factors and risk perception were statistically significant. There was a positive correlation between perceived cost and risk perception (ES = 0.399; $p < 0.001$; 95% CI excluding 0). There were negative correlations between perceived benefit, knowledge, innovativeness, trust, social influence, and risk perception (ES = −0.291, −0.128, −0.163, −0.302, −0.123, respectively; all p-values < 0.001; 95% CI all excluding 0). Hypotheses H1–H6 were verified. Cohen [122] suggested that the absolute value of correlation coefficient (r) = 0.1 is a low correlation, r = 0.3 is a moderate correlation, and r = 0.5 is a high correlation. However, this criterion is based on qualitative analysis and is subjective. Therefore, Gignac and Szodorai [123] suggested r = 0.1 as a low correlation, r = 0.2 as a moderate correlation, and r = 0.3 as a high correlation after quantitative analysis of 708 meta-analytically derived correlations. According to this criterion, correlations between perceived cost, trust, and risk perception were high; the correlation between perceived benefit and risk perception was moderate; and correlations between knowledge, innovativeness, social influence, and risk perception were relatively low.

Table 3. Results of the main effects.

Factors	m	n	Effect Size and 95% CI			Test of Null (2-Tail)	
			ES	LL	UL	Z	p
Perceived benefit	38	19,235	−0.291	−0.365	−0.213	−7.052	<0.001
Perceived cost	19	5750	0.399	0.354	0.442	15.894	<0.001
Knowledge	27	13,840	−0.128	−0.189	−0.065	−3.986	<0.001
Innovativeness	78	31,550	−0.163	−0.205	−0.121	−7.487	<0.001
Trust	154	69,620	−0.302	−0.334	−0.269	−17.091	<0.001
Social influence	133	51,200	−0.123	−0.165	−0.080	−5.624	<0.001

Note: m, the number of effect sizes; n, the sample size; ES, the combined effect size; 95% CI, 95% confidence interval; LL, lower limit; UL, upper limit; Z, the standard score; *p*, significance level.

4.4. Moderating Effects

The results of the moderating effects test are shown in Table 4. The type of emerging technology, age, and long-term/short-term orientation had no significant moderating effects on the relationships between the various factors and risk perception (all p-values > 0.05), so hypotheses H7, H8b, and H9e were not valid. Gender had a significant moderating effect on the relationship between perceived benefit and risk perception (F = 5.105, $p < 0.05$). Power distance had a significant moderating effect on the relationships between perceived benefit, trust, and risk perception (Q_B = 5.737, $p < 0.05$; Q_B = 6.183, $p < 0.05$). Uncertainty avoidance had a significant moderating effect on the relationship between knowledge and risk perception (Q_B = 5.283, $p < 0.05$). Individualism–collectivism had a significant moderating effect on the relationships between perceived benefit, trust, and risk perception (Q_B = 7.521, $p < 0.01$; Q_B = 4.322, $p < 0.05$). Masculinity–femininity had a significant moderating effect on the relationship between knowledge and risk perception (Q_B = 5.677, $p < 0.05$). In conclusion, hypotheses H8a, H9a, H9b, H9c, and H9d were valid.

The specific results of the moderating effects test of gender are shown in Table 5 and Figure 4. With increases in the male proportion, the negative correlation between perceived benefit and risk perception gradually weakened ($\beta1$ = 0.892, t = 2.259, $p < 0.05$).

Table 4. Results of the moderating effects.

Moderators	Factors	Perceived Benefit	Perceived Cost	Knowledge	Innovativeness	Trust	Social Influence
TYPE	Q_B	3.816	/	2.038	0.114	1.673	0.920
	p	0.282	/	0.361	0.736	0.643	0.337
Gender	F	5.105	0.316	1.381	0.006	0.012	0.035
	p	0.031	0.582	0.252	0.936	0.911	0.852
Age	F	0.476	/	/	0.605	2.107	1.521
	p	0.561	/	/	0.472	0.169	0.246
POW DIS	Q_B	5.737	/	0.001	3.200	6.183	0.435
	p	0.017	/	0.974	0.074	0.013	0.509
UNC AVO	Q_B	0.902	0.461	5.283	0.029	1.115	0.115
	p	0.342	0.497	0.022	0.865	0.291	0.735
IND-COL	Q_B	7.521	/	0.482	3.765	4.322	0.648
	p	0.006	/	0.488	0.052	0.038	0.421
MAS-FEM	Q_B	0.277	0.128	5.677	0.436	0.958	1.478
	p	0.599	0.720	0.017	0.509	0.328	0.224
LON/SHO	Q_B	0.121	2.537	2.220	0.101	1.446	2.304
	p	0.728	0.111	0.136	0.751	0.229	0.129

Note: TYPE, the type of emerging technology; POW DIS, power distance; UNC AVO, uncertainty avoidance; IND-COL, individualism–collectivism; MAS-FEM, masculinity–femininity; LON/SHO, long-term/short-term orientation; Q_B, the between-group heterogeneity test statistic; F, test statistic for the model; *p*, significance level; "/" indicates that the number of effect size for the subgroup or the number of data corresponding to the moderating variable is less than three, and estimates are not provided.

Table 5. Meta-regression analysis of gender.

Factor	Test of the Model		Moderator	Covariate	Coefficient	SE	95% CI		*t*	*p*
	F	*p*					LL	UL		
Perceived benefit	5.105	0.031	gender	β0 (intercept)	−0.722	0.194	−1.118	−0.327	−3.728	<0.001
				β1 (male proportion)	0.892	0.395	0.086	1.699	2.259	0.031

Note: F, test statistic for the model; *p*, significance level; SE, standard error; 95% CI, 95% confidence interval; LL, lower limit; UL, upper limit; *t*, statistic for *t*-test.
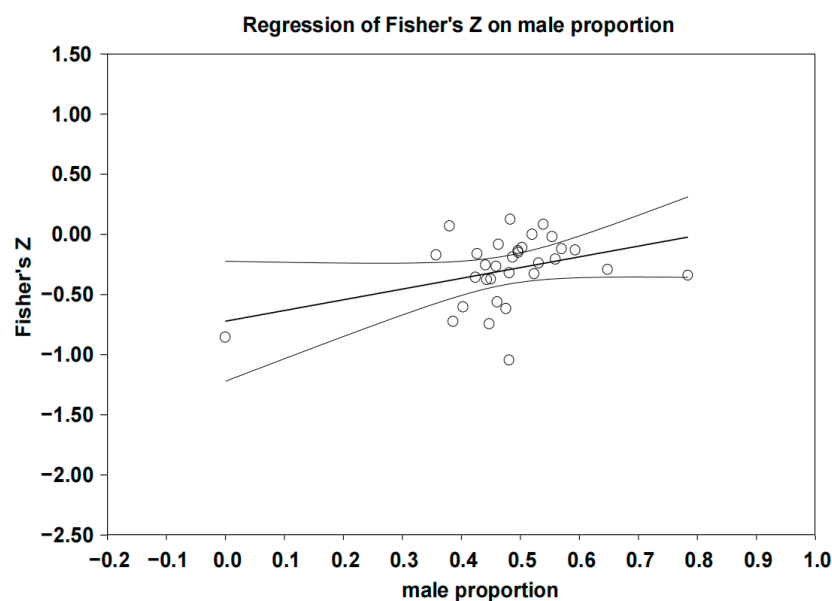
Figure 4. Meta-regression analysis of gender.

The results of the interaction tests for gender and age are shown in Table 6. The age indicators corresponding to perceived benefit, perceived cost, and knowledge lacked sufficient data for interaction analysis. Therefore, we only tested for innovativeness, trust, and social impact. Specifically, the model test results were all non-significant (F = 1.170, 2.261, 0.783; all *p*-values > 0.05). In addition, the results of regression coefficient tests for gender, age, and interaction terms were all insignificant (all *p*-values > 0.05). This indicated that the change in gender ratio did not have a significant effect on the relationships between three factors and risk perception at a specific age. Additionally, the increase in age did not have a significant effect on the relationships at a specific gender ratio. In addition, with the increase in age, the change in gender ratio did not have a significant effect on the relationships. Furthermore, with the change in gender ratio, the increase in age did not have a significant effect on the relationships. Overall, this proves to some extent that the above tests for the moderating effect of gender and age are robust.

Table 6. The interaction of gender and age.

Factors	Test of the Model		Covariate	Estimate	SE	95% CI		*t*	*p*
	F	*p*				LL	UL		
Innovativeness	1.170	0.450	β0 (intercept)	−0.054	0.061	−0.248	0.140	−0.885	0.442
			β1 (gender)	−0.959	0.582	−2.812	0.893	−1.648	0.198
			β2 (age)	0.001	0.006	−0.018	0.019	0.138	0.899
			β3 (gender × age)	−0.011	0.048	−0.165	0.143	−0.228	0.835
Trust	2.261	0.134	β0 (intercept)	−0.221	0.028	−0.282	−0.160	−7.869	<0.001
			β1 (gender)	0.022	0.193	−0.399	0.444	0.114	0.911
			β2 (age)	−0.004	0.003	−0.009	0.002	−1.497	0.160
			β3 (gender × age)	0.029	0.015	−0.004	0.062	1.936	0.077
Social influence	0.783	0.536	β0 (intercept)	−0.149	0.074	−0.320	0.023	−2.002	0.080
			β1 (gender)	0.259	1.097	−2.270	2.789	0.236	0.819
			β2 (age)	−0.010	0.008	−0.028	0.008	−1.304	0.229
			β3 (gender × age)	−0.069	0.128	−0.365	0.227	−0.537	0.606

Note: F, test statistic for the model; *p*, significance level; SE, standard error; 95% CI, 95% confidence interval; LL, lower limit; UL, upper limit; *t*, statistic for *t*-test.

The specific results of the moderating effect test of culture dimensions are shown in Table 7. The intensity of the relationship between perceived benefit, trust, and risk perception was greater in cultures with low power distance (ES = −0.480/−0.233; −0.390/−0.287; all *p*-values < 0.001). The negative relationship between knowledge and risk perception was non-significant in high uncertainty avoidance cultures but significant in low uncertainty avoidance cultures (ES = −0.047, *p* > 0.05; ES = −0.196, *p* < 0.001). The intensity of the relationship between perceived benefit, trust, and risk perception was stronger in cultures with individualism (ES = −0.457/−0.222; −0.365/−0.289; all *p*-values < 0.001). The relationship between knowledge and risk perception was non-significant in cultures with femininity but significant in cultures with masculinity (ES = 0.032, *p* > 0.05; ES = −0.187, *p* < 0.001).

Table 7. Subgroup analysis of moderators.

Factors	Heterogeneity		Moderators	m	Effect Size and 95% CI			Test of Null (2-Tail)	
	Q_B	*p*			ES	LL	UL	Z	*p*
Perceived benefit	5.737	0.017	High POW DIS	31	−0.233	−0.310	−0.153	−5.620	<0.001
			Low POW DIS	6	−0.480	−0.630	−0.296	−4.694	<0.001
Perceived benefit	4.426	0.035	IND	8	−0.457	−0.583	−0.309	−5.578	<0.001
			COL	29	−0.222	−0.297	−0.143	−5.441	<0.001
Knowledge	5.283	0.022	High UNC AVO	12	−0.047	−0.156	0.064	−0.823	0.411
			Low UNC AVO	14	−0.196	−0.260	−0.131	−5.799	<0.001
Knowledge	5.677	0.017	MAS	19	−0.187	−0.242	−0.130	−6.318	<0.001
			FEM	7	0.032	−0.139	0.202	0.368	0.713
Trust	6.183	0.013	High POW DIS	116	−0.287	−0.324	−0.250	−14.227	<0.001
			Low POW DIS	29	−0.390	−0.457	−0.318	−9.841	<0.001
Trust	4.322	0.038	IND	37	−0.365	−0.422	−0.305	−11.099	<0.001
			COL	108	−0.289	−0.328	−0.248	−13.284	<0.001

Note: Q_B, the between-group heterogeneity test statistic; *p*, significance level; POW DIS, power distance; IND-COL, individualism–collectivism; UNC AVO, uncertainty avoidance; MAS-FEM, masculinity–femininity; m, the number of effect sizes; ES, the combined effect size; 95% CI, 95% confidence interval; LL, lower limit; UL, upper limit; Z, the standard score.

4.5. Publication Bias

We used five methods to comprehensively evaluate publication bias: fail-safe number (N_{fs}), Begg and Mazumdar's rank correlation test, Egger's regression test, the trim-and-fill method, and the funnel plot. The results are shown in Table 8 and Figure 5. Specifically, Egger's regression test for the factor of social influence was significant (*p*-value < 0.05), but the remaining four tests indicated that publication bias was less likely to exist. Except for the factor of social influence, the results obtained from all five tests for the other factors indicated that publication bias was unlikely to exist. As shown in Figure 5, the funnel plot illustrated that the scatter points of all factors were evenly and symmetrically concentrated in the upper middle of the reference line. In summary, there was no significant publication bias, and the results of this study were stable and reliable.

Table 8. Publication bias test.

Factors	m	Nfs and Criterion		Begg and Mazumdar's Test		Egger's Regression Test		Confidence Interval after Trimming and Filling	
		N_{fs}	Criterion	Z	*p*	Intercept	*p*	LL	UL
Perceived benefit	38	14,941	200	0.440	0.660	−1.732	0.601	−0.435	−0.281
Perceived cost	19	4645	105	0.350	0.726	2.124	0.254	0.354	0.442
Knowledge	27	1677	145	0.667	0.505	3.050	0.148	−0.189	−0.065
Innovativeness	78	15,818	400	0.617	0.537	0.688	0.662	−0.237	−0.154
Trust	154	36,642	780	1.754	0.079	−0.297	0.805	−0.386	−0.321
Social influence	133	29,931	675	0.096	0.100	4.294	0.002	−0.244	−0.161

Note: m, the number of effect sizes; N_{fs}, fail-safe numbers; Z, the standard score; *p*, significance level; LL, lower limit; UL, upper limit.
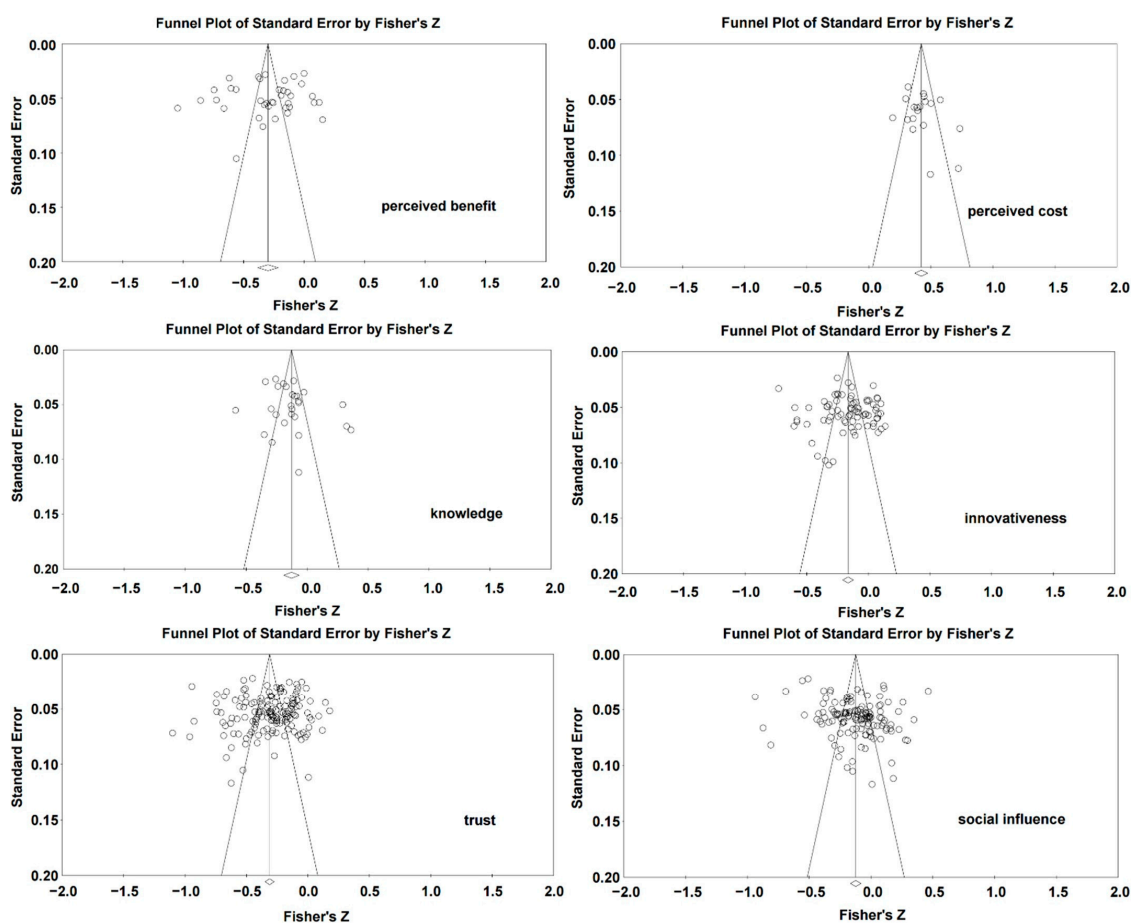
Figure 5. Funnel plot.

5. Discussion

5.1. Key Findings

This study constructed a "technology–psychology–society" analysis framework with reference to TOE theory. A meta-analysis of 272 papers, including 449 effect sizes and 191,195 samples, was conducted to systematically and comprehensively explore the essential factors and specific mechanisms affecting the public risk perception of emerging technologies. The following key findings were derived from this study.

5.1.1. The Influence of Technical–Economic Factors

This study found that perceived benefit negatively influenced public risk perception of emerging technologies, which was generally consistent with the findings of the meta-analysis of innovative food technology and nuclear energy technology [44,124], as well as further confirming the reliability and robustness of the findings by examining a large sample. Specifically, unlike the general common perception that high benefits bring high risks, the public perceived benefit will offset the perceived negative consequences of emerging technologies to a certain extent and cause a more positive judgment and evaluation of risk. Additionally, perceived cost had a positive effect on risk perception. This study further explored the relationship between the two when related research studies were relatively lacking and not in-depth. Specifically, because of characteristics such as radical novelty and the uncertainty of emerging technologies, the public perceived more adverse experiences and higher risk if they perceived higher costs in the process of selection and switching.

5.1.2. The Influence of Psychological–Cognitive Factors

This study found that knowledge and innovativeness had a negative influence on the public risk perception of emerging technologies. Specifically, a meta-analysis of nuclear energy technology yielded a minimal negative correlation coefficient between knowledge and risk perception (effect size = −0.04), and this correlation was not significant [124]. However, this study demonstrated a significant negative correlation between the two by analyzing a large sample of typical emerging technologies. A comprehensive understanding of relevant knowledge helps the public to objectively view the possibility and severity of emerging technology hazards, enhances their sense of control, reduces concerns about uncertainty, and weakens the perception of risk. Furthermore, meta-analysis explicitly addressing the relationship between innovativeness and risk perception was rare. Our study yielded a negative correlation between the two. Generally, people with high innovativeness hold a more open attitude, are willing to accept emerging technologies, and are more capable of dealing with high uncertainty and issues that arise during the use of technologies, which helps reduce their risk perception.

5.1.3. The Influence of Social–Environmental Factors

This study found that trust and social influence had negative effects on public risk perception of emerging technologies. Specifically, the negative relationship between trust and risk perception was consistent with the results of the existing meta-analyses on e-services and nuclear energy technology [124,125]. Trust in the technology stakeholders is essential to simplify complexity, dissolve uncertainty, build security, and avoid excessive worry. Additionally, a meta-analysis of e-shopping reported a negative correlation coefficient between social influence and risk perception (effect size = −0.20), and this correlation was not significant [126]. However, this study revealed a significant negative correlation between the two. The public tends to interact with social networks, follow social norms, and adjust their beliefs and attitudes based on the information and opinions of influential people and organizations when choosing and using emerging technologies. This social influence mechanism reduces their risk perception to a certain extent.

5.1.4. The Comparison of the Degree of Impact

This study found differences in the intensity of the effects of various factors on the public risk perception of emerging technologies. Specifically, perceived cost and trust had a strong impact on risk perception; perceived benefit had a moderate impact on risk perception; and knowledge, innovativeness, and social influence had relatively weak impacts on risk perception. This suggests that the public may be more sensitive to technical–economic factors, such as costs consumed and benefits derived from emerging technologies. Furthermore, social–environmental factors such as trust are essential in reducing public risk perception. Technology-related R&D and management bodies should make this a concern when formulating relevant strategies, policies, and initiatives.

5.1.5. The Effect of Moderators

Regarding technology-related moderating variables, this study found no moderating effect of emerging technology type on the relationship between related factors and risk perception. This may be because the common characteristics of emerging technologies have a masking effect on the differences in effects.

In terms of demographic moderating variables, this study indicated that gender had a significant moderating effect on the relationship between perceived benefit and risk perception. The negative effect of perceived benefit on risk perception diminished as the proportion of males increased. In other words, the negative effect of perceived benefit on risk perception was more pronounced in the female group. The reason may be that women's perceptions of emerging technologies have more emotional components, and their perceptions of specific benefits or advantages play a stronger role in reducing risk perception. In contrast, men often consider factors other than benefits, resulting in the

weaker influence of perceived benefit than women. It should be noted that there are fewer studies on the moderating effect of gender on the relationship between perceived benefit and risk perception. The social cognitive theory holds that men and women differ in their decision-making processes. Men are often more outcome-oriented and concerned more with usefulness, while women are more process-oriented and concerned more with security and privacy when participating in new activities [127]. Moreover, it has been shown that the positive effect of perceived benefit on online repurchase intention is higher for male consumers than female ones [128]. These findings are somewhat different from the results of this study. Therefore, the moderating effect of gender must be further explored.

Moreover, there was no moderating effect of age, indicating that the effect of relevant factors on risk perception is not influenced by the age of the public. This may be due to the limited data collected, as many studies do not report the mean age of the sample. In addition, the majority of the sample was under the age of 40, and young people were more consistent in their perception of emerging technologies, mostly holding a more tolerant and accepting attitude [95].

This study found that culture played an important moderating role. Specifically, the negative effect of perceived benefit and trust on risk perception was stronger in societies with low power distance cultures. It may be that in societies with low power distance cultures, the public risk perception of emerging technologies is less disturbed by pressure factors such as the government and superiors [99,129], allowing the role of perceived benefit and trust to be exploited to a greater extent. Moreover, the reduction effect of knowledge on risk perception is more evident in societies with low uncertainty avoidance cultures, especially in societies with high uncertainty avoidance cultures, where the reduction effect of knowledge on risk perception becomes insignificant. Specifically, people in low uncertainty avoidance contexts have more positive and tolerant attitudes toward the uncertainty and ambiguity of emerging technologies [100]. Their technology-related knowledge plays a more pronounced role in reducing risk perception. However, by and large, people in high uncertainty avoidance cultures are reluctant to take risks and more cautious about innovation. In other words, they are more cautious about emerging technologies and more fearful of possible risks. This resulted in a less significant effect of knowledge. Moreover, the mitigating effect of perceived benefit and trust on the risk perception of emerging technologies was stronger in societies with individualistic cultures. The possible reason is that in a more individualistic society, users are less concerned with group norms that refuse to abide by emerging technologies; therefore, they generally ignore the spillover effects of their use on other members of the group. In addition, in societies with individualistic cultures, people prefer challenges and may be more willing to take and tolerate the risks associated with emerging technologies [97,100]. This leads to a more pronounced reduction effect of perceived benefit and trust on risk perception. Finally, the role of knowledge in reducing the risk perception of emerging technologies was more robust in societies with strong masculinity. However, the effect of knowledge on risk perception becomes insignificant in societies with femininity cultures. This may be because in male-dominated cultures, men are considered audacious and assertive, and women are considered modest and tender, with more pronounced gender differences [101]. However, in female-dominated cultures, both males and females are considered to be modest and tender. Thus, audacity and assertiveness in masculine societies help alleviate public worries about the risk of emerging technologies, leading to a more pronounced role of knowledge.

In addition, long-term/short-term orientation did not have a moderating effect on the relationship between relevant factors and risk perception. Specifically, long-term/short-term orientation is closely related to the country's economic growth, policy making, sustainable development, etc. Long-term orientation usually means persistence, thrift, resource-saving, environmental protection, etc., and short-term orientation implies a propensity to consume, respect for traditions, fulfillment of social responsibilities and obligations, etc. [100,130]. Similarly, this study found that the moderating effect of long-term/short-term orientation was insignificant. It may be that the development and utilization of

emerging technologies can stimulate short-term consumption while also bringing about long-term economic and social benefits, which may lead to a less prominent moderating role of long-term and short-term orientation. Last but not least, the moderating effects of uncertainty avoidance and short-term orientation must be explored more deeply in the future.

5.2. Theoretical Contributions

To the best of our knowledge, this is the first meta-analysis to provide a comprehensive, systematic, and integrated discussion of the factors influencing the public risk perception of emerging technologies. First, this study constructed a "technology–psychology–society" analytical framework with reference to TOE theory. Moreover, we used a combination of theoretical analysis and quantitative tests to more comprehensively summarize the factors affecting risk perception, which to some extent compensated for the lack of empirical studies. Second, this study selected four typical emerging technologies and included 272 papers, 449 effect sizes, and 191,195 samples to ensure the objectivity and accuracy of the study results. Third, this study drew more consistent and robust conclusions about the direction and intensity of the influence of relevant factors on the risk perception of emerging technologies, addressing the inconsistencies and ambiguities of established studies. Fourth, this study tested for the moderating effects of moderators such as the type of emerging technology, gender, age, and culture, which helped explain the differences in the effects of influencing factors on risk perception.

5.3. Managerial Implications

This study provides management implications to facilitate the public's scientific knowledge, rational understanding, and proper treatment of the technical risks and to promote the sustainable research, development, diffusion, and use of emerging technologies and their products. First, the cost of application must be reduced while appropriately publicizing the benefits of emerging technology products. It is crucial to find ways to reduce the costs of investment, information searches, and time consumption for the public during the development and diffusion of emerging technologies. In addition, management should emphasize the economic, social, health, and environmental benefits of emerging technologies and express the direct and tangible benefits for the public through financial incentives such as rebates, coupons, and discount activities. Second, full play must be given to the influence of social networks on improving the public's level of scientific knowledge. Expert groups should strengthen the popularization of science, enhance the interaction with the public, and address the public's technical knowledge deficiency. At the same time, full play should be given to the driving effect of innovative groups, and appropriate use should be made of celebrity influence in publicity. This will cultivate the public's scientific knowledge and rational literacy while alleviating their doubts and worries about emerging technologies. Third, the credibility of technology stakeholders should be improved and risk governance enhanced. The government should adhere to the idea of pluralistic governance, establish a sound technology open decision-making system, risk-monitoring mechanism, and unobstructed risk communication channels, and guarantee the public's right to know and participate. The scientific community should enhance the transparency of technology risk assessment and promote dialogue with the public. R&D and promotion organizations should continuously improve the safety and reliability of technologies, enhance warranty measures, and establish good reputations.

5.4. Limitations and Future Research

The main limitations of this study are as follows. First, although we collected the relevant literature as comprehensively as possible, we could not ensure that all relevant literature was included because of a lack of database access, unavailability of full text articles, and language barriers. Second, although we summarized the typical techno-economic, psycho-cognitive, and social environment aspects that influence the public risk perception

of emerging technologies based on the theoretical framework, the factors influencing risk perception in practice are complex and diverse, and other essential factors, such as information media and the individual's emotions, were not examined. In addition, possible mediating factors between influencing factors and risk perception were not explored. Third, we examined the effects of the following moderating variables: The type of emerging technology, gender, age, and culture. However, other moderators, such as measurement instruments of the variables, were not examined. Furthermore, there were fewer data for certain moderating variables. Fourth, this meta-analysis mainly included cross-sectional studies, which could not reveal the causal relationship between influencing factors and risk perception. These deficiencies may have some impact on the precision of the study results.

Future research can be conducted in the following directions. The first is to explore other factors influencing the risk perception of emerging technologies and the moderating effects of other variables. Second, a meta-analysis of intervention studies related to the risk perception of emerging technologies can be performed. Third, further research on the causal relationships and specific mechanisms of action between relevant factors and risk perception can be carried out using longitudinal studies, meta-analytic structural equation modeling, and qualitative comparative analysis.

6. Conclusions

As far as we know, this study is the first to use meta-analysis to systematically and comprehensively explore the factors influencing the public risk perception of emerging technologies. First, we constructed a theoretical analysis framework of "technology–psychology–society" with reference to TOE theory. A theoretical analysis and literature review were conducted according to the analytical framework, and various influencing factors were summarized. Furthermore, this meta-analysis selected four typical emerging technologies and included 272 pieces of literature, with a total sample size of 191,195, to test the proposed hypotheses. The results showed a high positive relationship between perceived cost and risk perception; a high negative relationship between trust and risk perception; a moderate negative relationship between perceived benefit and risk perception; and a relatively low negative relationship between knowledge, innovativeness, social influence, and risk perception. In addition, gender and cultural dimensions such as power distance, uncertainty avoidance, individualism–collectivism, and masculinity–femininity moderated the relationship between the relevant factors and risk perception. In summary, this study addressed the inconsistency and lack of clarity and depth in the relationships between the related factors and public risk perception of emerging technologies that exist in established studies through large-sample empirical analysis.

According to the study results, first, the public is sensitive to economic factors, which should prompt the relevant R&D and sales departments to reduce the application costs as much as possible and convince the public of the benefits of emerging technologies and their products. Second, trust in the technology stakeholders also plays a vital role in the public risk perception of emerging technologies. This suggests that technology stakeholders should strive to improve their credibility, and technology management departments should improve their ability to deal with the risks of emerging technologies. Specifically, these include a full range of warranty measures and enhanced hazard identification, monitoring, and regulation to help hedge risk wherever possible. In addition, there are differences in the influence of relevant factors on risk perception among different gender groups or cultural backgrounds, suggesting that differences in gender and cultural contexts should be considered in the design and promotion of emerging technologies and their products. It should be clarified that these recommendations aim to raise proper public understanding and promote the sustainable development and use of emerging technologies rather than ignoring and avoiding the technical risks. The joint efforts of various stakeholders to reduce risks are equally crucial for the sustainable development of emerging technologies. Finally, some limitations of this study must be acknowledged, such as the insufficient exploration of other moderators such as the measurement instruments of variables and the inability to

reveal the causal relationships between variables, which also should direct further research in the future.

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