

Article

Construction and Path of Urban Public Safety Governance and Crisis Management Optimization Model Integrating Artificial Intelligence Technology

Guo Li ^{1,*}, Jinfeng Wang ² and Xin Wang ¹¹ School of Politics and Public Administration, Zhengzhou University, Zhengzhou 450001, China² China Institute of FTZ Supply Chain, Shanghai Maritime University, Shanghai 201306, China* Correspondence: liguozzu@163.com

Abstract: As urbanization and population growth continue to accelerate in China, maintaining public safety and crisis management has become increasingly complex. To address this issue, this research article proposes a new model for optimizing urban public safety governance and crisis management by integrating artificial intelligence (AI) technology with a focus on sustainability. This study aims to explore the construction and path of an urban public safety governance and crisis management optimization model integrating artificial intelligence (AI) technology in China. We developed a linear regression model to examine the relationship between public safety technologies and outcomes, with public safety outcomes (PSO) as the dependent variable and public safety governance structure (PSGS), AI-driven data collection and analysis (AIDC&A), crisis prediction and early warning system (CPEWS), AI-assisted decision-making (AIADM), and public safety response mechanisms (PSRM) as independent variables. The model summary revealed that the independent variables accounted for a moderate proportion of the variance in public safety outcomes, with an R^2 value of 0.5 and an adjusted R^2 value of 0.45. The results supported the hypothesis that the integration of different public safety technologies has a positive impact on public safety outcomes. The effective governance structure, AI-driven data collection and analysis, crisis prediction and early warning system, AI-assisted decision-making, and efficient public safety response mechanisms were all found to be crucial for enhancing public safety outcomes. The proposed model was validated through a case study in a Chinese city, with feedback from stakeholders confirming its effectiveness. Overall, the findings suggest that the urban public safety governance and crisis management optimization model integrating AI technology can significantly improve public safety management in urban areas.

Keywords: urban public safety governance; crisis management optimization; artificial intelligence (AI) technology; public safety outcomes (PSO); linear regression model; AI-assisted decision-making



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1. Introduction

In recent years, the issue of urban public safety governance and crisis management has become increasingly important in China as urbanization continues to intensify. The growing urban population brings new safety challenges, such as traffic congestion, environmental pollution, public health emergencies, and natural disasters. While the Chinese government has made significant efforts to address these issues, many solutions have been short-term and reactive rather than sustainable and proactive. Therefore, there is a need for sustainable solutions that integrate artificial intelligence (AI) technology, which offers new opportunities for enhancing public safety outcomes.

Urban public safety governance and crisis management is a complex issue that requires careful consideration of challenges such as rapid urbanization, demographic changes, and technological advancements. These challenges put pressure on public safety services, making it difficult to respond to emergencies effectively. Furthermore, demographic changes create diversity, requiring adequate public safety services to serve all communities.

Technological advancements, on the other hand, while they can improve public safety, create new challenges, such as social media spreading misinformation during a crisis.

It is essential to develop an optimized model for urban public safety governance and crisis management that incorporates AI technology to address these challenges. AI-powered video surveillance systems can detect unusual behaviour and alert authorities to potential threats. At the same time, AI can quickly analyze data to identify potential risks and respond to emergencies more effectively. The construction and path of an urban public safety governance and crisis management optimization model integrating AI technology are crucial for achieving sustainable solutions to urban safety challenges in China. This model would enable the government to anticipate better and respond to safety risks and promote long-term safety and stability in urban environments.

Research Objectives and Scope

This study aims to develop and validate an urban public safety governance and crisis management optimization model that integrates AI technology in China. The research objectives are threefold:

- To explore the impact of AI-driven public safety technologies on public safety outcomes using a linear regression model.
- To identify the key factors contributing to improved public safety outcomes, such as governance structures, data collection and analysis, crisis prediction and early warning systems, AI-assisted decision-making, and response mechanisms.
- To validate the proposed model through a case study in a Chinese city, assessing its effectiveness in addressing real-world public safety challenges and obtaining feedback from relevant stakeholders.

This study addresses the following research questions:

1. How do AI-driven public safety technologies impact public safety outcomes?
2. Which factors are crucial for enhancing public safety outcomes?

2. Literature Review

The rapid urbanization in China has led to numerous public safety challenges, including chronic insecurity, violence, and corruption, which have created complex security issues for urban development. Building an effective public safety governance and crisis management system is crucial to promoting sustainable urban development and ensuring citizens' safety. In recent years, integrating artificial intelligence (AI) technology has provided new opportunities to optimize public safety governance and crisis management in urban areas. This literature review explores the role of sustainable public safety governance in urban development and investigates the potential benefits and challenges of AI adoption for sustainable development. Additionally, it examines international perspectives on AI integration in public safety governance and crisis management, mainly through case studies and best practices worldwide. Furthermore, this review will provide an overview of China's public safety governance landscape, including existing structures, policies, and challenges, and assess the role of technology in addressing public safety challenges and promoting sustainable urban development in China. Finally, this literature review will explore the opportunities and barriers for AI integration in China's urban public safety governance, discuss the legal, ethical, and social considerations for integrating AI technology into public safety efforts, and provide strategies and recommendations for ensuring the sustainable adoption of AI technology in urban public safety governance and crisis management in China.

2.1. The Role of Sustainable Public Safety Governance in Urban Development

Urban development faces numerous security, sustainability, and governance challenges, particularly in the context of the global 2030 Agenda [1]. However, urban governments are well positioned to engage other actors in policy dialogue, and they are a critical

factor in incorporating the principles of the 2030 Agenda into local policies [2]. Sustainable public safety governance is an essential aspect of urban development, as cities across the globe are undermined by chronic insecurity, violence, and corruption [3]. Effective governance structures are critical for improving public safety outcomes [4,5]. Multi-level governance is necessary to implement the United Nations sustainable development goals (SDGs) in cities and human settlements [4]. Policy instruments and soft forms of governance can contribute to policy integration and sustainable urban development [6]. However, the partial implementation and limited evaluation of previous initiatives, such as Local Agenda 21, are highlighted as limitations in implementing the SDGs [4].

Illicit flows of drugs, arms, trafficked people, and illicit funds intersect with individual vulnerabilities and local socioeconomic conditions, creating complex security challenges that can have destabilizing effects on public institutions and states [3]. This underscores the importance of effective crisis management systems, such as those rooted in intelligent governance and e-government infrastructure, for managing public health crises [7] and improving public safety outcomes [5]. The role of race in urban security politics and the links between criminal justice, immigration control, and integration are essential considerations in developing sustainable public safety governance [8]. The proposed approach of using “enterprise architecture” for safety systems and emergency management in transport enterprises could also apply to other contexts [9]. The ongoing contextualization of SDG 11 and sustainable urban development in Germany highlights the need to adapt global goals to the specific national context [10]. However, the successful transfer of global policies, such as the 2030 Agenda, to local policies depends on the government sphere, the logic of intervention, and other aspects of policy design [1]. Finally, improved governance is essential for sustainable urban development, and strategic planning is critical to achieving this [11]. Strategic planning is closely linked to core principles of good urban governance, such as public participation, accountability, equity, and efficiency, which are necessary for sustainable development [5,11].

2.2. AI Technology and Sustainable Development

Artificial Intelligence (AI) has emerged as a powerful tool for achieving sustainable development goals [12]. AI can be used to recognize and interpret data, which can then be used to create programs for various activities, such as solving problems at the level of intelligent beings to achieve sustainable development goals. China’s government has developed ambitious policies for global leadership in AI and sustainable development, and AI technologies can bolster China’s progress toward Sustainable Development Goals (SDGs) [13]. AI can act as a real and meaningful enabler to achieve sustainability goals. A carefully balanced approach is needed to ensure that AI systems help solve sustainability issues without negatively impacting other goals [14]. AI-driven technologies can be facilitators or barriers to each SDG [15], and AI can accomplish 134 targets across all the goals [16]. Additionally, AI technologies have the potential to be used to meet the 17 SDGs and its 169 targets [17]. AI systems have contributed to advancing sustainable cities in several ways, such as waste management, air quality monitoring, disaster response management, and transportation management [18].

Moreover, a study pointed out that AI has the potential to help achieve the UN’s SDGs related to health, cities, and climate action, and it can be used to improve healthcare, urban planning, and climate change mitigation, as well as reduce the impact of pandemics and other crises on society [19]. Despite the vast potential of AI in sustainable development, AI-driven technologies in women’s health still need to be represented [20], and current research foci overlook essential aspects, such as transparency, safety, and ethical standards [16]. Therefore, policymakers and managers need to consider the implications of AI for SDG achievement [14]. Additionally, more attention and investments should be directed toward potential AI-driven digital technologies that can facilitate SDG achievements in different regions, such as Brazil and Portugal [21]. In summary, AI technology has the potential to play a vital role in achieving the SDGs and promoting sustainable development. However,

a balanced approach and consideration of various factors such as ethics, transparency, and inclusiveness are necessary to maximize the benefits of AI for sustainable development.

2.3. AI Integration in Public Safety Governance and Crisis Management: International Perspectives

Integrating AI in public safety governance and crisis management is an important area of research with significant implications for societal well-being. Studies discuss the need for responsible AI practices in crisis resilience management and present a roadmap with six propositions to address challenges and considerations related to equity, fairness, biases, explainability and transparency, accountability, privacy, inter-organizational coordination, and public engagement [22]. The research proposed a Disaster City Digital Twin paradigm that integrates AI algorithms and approaches to improve situation assessment, decision-making, and coordination among various stakeholders [23]. Studies highlight how intelligent infrastructure, including embedded sensors, IoT, real-time data capture and analysis, and machine-learning-based decision support, can enhance public safety, emergency management, disaster recovery, and community resilience [24].

AI governance frameworks are crucial for preventing harm from AI development, as discussed by [24]. They propose an integrated AI governance framework that compiles critical aspects of AI governance and provides a guide for the regulatory process of AI and its application. A study discusses using AI systems to ensure public safety in a “smart city” and proposes developing a regulatory framework in Belarus to protect citizens’ rights [25]. investigation proposes a public safety deduction framework based on big real-time data to find the most optimal emergency decision plan [22]. study systematically reviews the prevalence and content of ethical guidance for disaster response, finding that most of the literature focuses on the ethical justifications for crisis standards of care, triage, and international issues [26]. The study examines the challenges of developing international standards for trustworthy AI and proposes a minimal preliminary model for functional roles relevant to trustworthy AI [27]. Another study discusses the importance of human-centred AI and the need for critical and reflective oversight by organizations, teams, and individuals that create and use AI systems to uphold ethical principles and proactively consider the risks of bias, misuse, abuse, and unintended consequences [28].

The research introduces the concept of techno colonialism to capture how digital developments and market forces entrench power asymmetries between refugees and aid agencies and, ultimately, inequalities in the global context [29]. The study discusses the need for humanitarian organizations to continuously adapt their operations in the face of changing situations, volatile information, and emerging coordination structures, using two case studies to illustrate how these factors can lead to fragmentation and misalignment of decisions [30]. Other findings propose a semiautomated social media analytics approach for social sensing of disaster impacts and societal considerations to foster an understanding of the relationship between infrastructure disruptions and societal impacts [31]. The literature highlights the need for responsible AI practices, AI governance frameworks, human-centred AI, and continuous adaptation of operations in crisis resilience management and public safety governance.

2.4. China’s Urban Public Safety Governance: Current State and Challenges

China’s rapid urbanization in recent years has been the subject of numerous studies, with many scholars highlighting the challenges facing the country’s urban public safety governance. Research provides an overview of China’s urban trends and policies, outlining the institutional constraints to markets and factor mobility, environmental challenges, ensuring equity and helping vulnerable groups, and metropolitan governance that represent some of the critical policy challenges facing central and local urban governments [32]. Another piece of research discusses the changes in urban governance in China during its transition to a more market-oriented economy, highlighting how marketization has shaken the pillars

of the socialist governing structure. However, the state is attempting to reconsolidate its power by devoting authority to lower levels and reinstating local communities [33].

The research uses system dynamics modelling to investigate public safety in Shanghai and finds that while the city's public safety is increasing due to a high level of urban socioeconomic development, this might not be sustainable in the long run [34]. Similarly, another article discusses the health issues and challenges of China's urbanization growth and their policy implications [35]. The researcher argues that urban risk generalization in China is a structural issue arising from an immature system of generalized benefits in urban space rights and interests and proposes innovation in the spatial structures, drivers, and mechanisms of urban public management and cultural ecology to forestall and resolve urbanization risks [36].

Some other researchers demonstrate how the government's new-found priority on community building has facilitated the development of community autonomy and self-governance in the Yantian Model of community governance in Shenzhen [37]. Meanwhile, another investigation of Shenzhen city, one of China's leading cities in urban government GIS development, reveals that GIS development in Chinese urban governance is influenced not only by the instrumental functions of GIS but also by the interactions and relationships among different actors and institutions with various vested interests in the process of structuring and governing the urban spaces. In terms of the threats posed to urban public safety in China, organizational accidents are a significant concern. The paper argues that fostering positive capacities through contemporary accident causation and prevention theories, such as High-Reliability Organizing and Resilience Engineering, can avert such threats [38]. Finally, another piece of research examines recent scholarship on China's urban governance and finds that despite marketization, the state still plays a role in neighbourhoods, cities, and city regions, deploying market-like instruments to achieve its development objectives, while multi-scalar governance involves social and market actors while maintaining strategic intervention capacity [33]. Overall, these studies highlight the complex and multifaceted nature of China's urban public safety governance, pointing to the need for innovative approaches and policy measures to address the challenges facing urban governments.

2.5. Sustainable Implementation of AI-Driven Urban Public Safety Governance and Crisis Management Models in China

The use of big data and network governance has been proposed and developed as a means of improving urban public safety management [39]. By integrating these technologies, the design and application of advanced technology can be improved, resulting in more effective public safety management. Social Network Analysis has been used to develop a framework for identifying, measuring, and analyzing public security risks and their interactions, with a case study conducted in Shenzhen City, China, to illustrate a practical application of the framework [40]. The research established a context-dependent DEA model to divide 35 cities in China into three levels and prioritize them with index weights to identify the cities that require the most attention for public safety improvement [41]. Wang discussed the problems with the emergency management of public safety in smart cities and suggested the construction and application of big emergency data and intelligent security emergency management platforms to improve emergency management efficiency and reduce losses caused by emergencies [42].

The study assessed public safety in Shanghai and found that Shanghai's public safety is gradually increasing due to economic success and increased investment in public safety. A comprehensive set of 34 public safety indicators was developed to assess Shanghai's public safety [43]. The research discussed the block data intelligent platform of urban public security emergency management, which can be used to integrate data from various sources and realize urban public safety automatic forecasting, early warning, information feedback, supervision, and scientific decision making [44]. Yu used system dynamics modelling to investigate public safety in Shanghai, which showed that while public safety is increasing

due to high levels of urban socioeconomic development, factors that “expend” such a foundation, such as crimes and disasters, are increasing at a relatively lower level. Dynamic simulation suggests that Shanghai could continue to enjoy its improvement of public safety provided the city continues to develop, as in the past decade. While these studies provide valuable insights into the state of public safety and the potential use of AI-driven technologies to improve it, there are limitations to be considered [45]. For example, some studies focus on specific regions or cities, limiting the generalizability of their findings. Additionally, there is a need for more research on the social and environmental impacts of these technologies, as well as their long-term sustainability. Future research could focus on developing more comprehensive frameworks for assessing public safety and exploring the potential for AI-driven technologies to improve public safety outcomes while ensuring their sustainable implementation.

2.6. Theoretical Model and Hypothesis Development

The quantitative model for urban public safety governance and crisis management optimization in China incorporates one dependent variable and five independent variables. The dependent variable, Public Safety Outcomes (PSO), represents a composite index of public safety performance indicators such as crime rates, response times, and emergency incident resolution rates. The independent variables include the Public Safety Governance Structure (PSGS), which measures the effectiveness and coordination of governance structures using communication, collaboration, and role clarity among stakeholders. AI-Driven Data Collection and Analysis (AIDC&A) gauges the integration of AI-driven data collection and analysis in public safety efforts based on the data sources used, AI algorithms employed, and insights generated. Crisis Prediction and Early Warning System (CPEWS) assesses the effectiveness of crisis prediction and early warning systems, considering elements such as prediction accuracy, warning lead time, and the system’s impact on proactive measures. AI-Assisted Decision-Making (AIADM) measures the extent of AI-assisted decision-making integration in public safety governance, using criteria such as the application of AI-driven decision support systems and the quality of decisions made. Lastly, Public Safety Response Mechanisms (PSRM) evaluate the effectiveness and efficiency of public safety response mechanisms using factors such as response times, resource allocation, and communication protocols. Figure 1 shows the theoretical framework of the study.

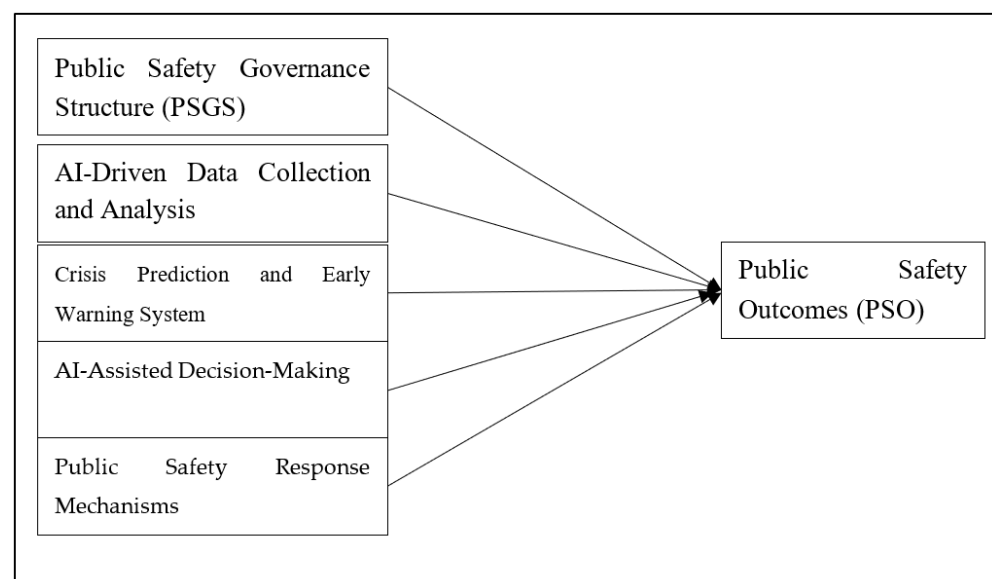


Figure 1. Theoretical framework.

The urban public safety governance and crisis management optimization model integrating AI technology in China is underpinned by several vital theories. Situational Crime Prevention Theory, developed by Ronald V. Clarke, supports that crime rates and public safety outcomes can be improved by addressing situational factors influencing criminal behaviour. Resilience Theory emphasizes the importance of developing crisis prediction, early warning systems, and effective public safety response mechanisms to enhance urban resilience and adaptability in the face of crises. Decision Support Systems (DSS) Theory provides a foundation for the role of AI-assisted decision-making in public safety governance, highlighting the value of data-driven insights and recommendations for informed decision making. Collaborative Governance Theory, proposed by Chris Ansell and Alison Gash, advocates for a well-coordinated governance structure that fosters communication and collaboration among stakeholders, contributing to more effective public safety governance. Lastly, the Technology Acceptance Model (TAM), developed by Fred Davis, can be applied to understand the integration of AI-driven data collection and analysis in public safety efforts, considering factors such as perceived usefulness, perceived ease of use, and user attitudes towards AI technology. By grounding the model in these theories, a robust theoretical foundation can be established for understanding the interactions between various components and their impact on public safety outcomes.

The following hypotheses will be tested using multiple linear regression analysis:

Hypothesis 1. *A more effective and coordinated public safety governance structure (PSGS) will positively impact public safety outcomes (PSO).*

Hypothesis 2. *Greater integration of AI-driven data collection and analysis (AIDC&A) will positively impact public safety outcomes (PSO).*

Hypothesis 3. *A more effective crisis prediction and early warning system (CPEWS) will positively impact public safety outcomes (PSO).*

Hypothesis 4. *Greater integration of AI-assisted decision-making (AIADM) will positively impact public safety outcomes (PSO).*

Hypothesis 5. *More practical and efficient public safety response mechanisms (PSRM) will positively impact public safety outcomes (PSO).*

3. Methodology

This section presents the methodology used to construct and optimize the urban public safety governance and crisis management model by integrating artificial intelligence technology in China. The research follows a mixed methods approach, combining qualitative and quantitative data collection and analysis methods to ensure the validity and reliability of the findings. The study involves five main stages: literature review, model construction, data collection, data analysis, and validation.

3.1. Model Construction

The urban public safety governance and crisis management optimization model was developed based on the theoretical framework derived from the literature review. The model comprises five key components: public safety governance structure, AI-driven data collection and analysis, crisis prediction and early warning system, AI-assisted decision-making, and public safety response mechanisms. These components were integrated into a comprehensive, AI-based public safety governance and crisis management system. These components are as follows.

Public Safety Governance Structure: This component establishes a centralized and coordinated governance structure for urban public safety. It involves defining roles and responsibilities for public safety agencies, local governments, private sector entities, and

the community. The structure facilitates efficient communication and collaboration among stakeholders, enabling a more proactive and integrated approach to public safety management.

AI-Driven Data Collection and Analysis: This component leverages artificial intelligence technology to collect, process, and analyze data from various sources, such as social media, IoT devices, and public safety databases. AI algorithms can detect patterns and trends in real time, providing valuable insights into potential threats, vulnerabilities, and areas requiring intervention. This data-driven approach allows for more informed decision making and resource allocation in public safety governance.

Crisis Prediction and Early Warning System: This component utilizes AI-powered predictive analytics to forecast potential crises and emergencies. The system can generate early warnings for public safety officials and the general public by analyzing historical data and real-time information. This enables proactive measures to prevent or mitigate the impacts of potential crises, ultimately enhancing urban resilience and reducing the overall risk to public safety.

AI-Assisted Decision-Making: This component employs AI technology to support decision-making processes in public safety governance and crisis management. AI-driven decision support systems can evaluate multiple scenarios, predict outcomes, and recommend optimal courses of action based on predefined objectives and constraints. This capability enables public safety officials to make more informed, timely, and effective decisions in responding to evolving threats and emergencies.

Public Safety Response Mechanisms: This component focuses on developing and implementing AI-enabled public safety response mechanisms. These mechanisms include emergency response plans, resource allocation strategies, and communication protocols that are informed and guided by AI-generated insights. By incorporating AI technology, public safety response mechanisms can be more agile, adaptive, and efficient, ultimately improving the overall effectiveness of crisis management efforts.

“AI technology” refers to the use of artificial intelligence techniques to automate and enhance public safety governance and crisis management processes. “AI-driven data collection and analysis” uses AI algorithms to collect and analyze data in real-time to identify potential safety issues, predict crises, and inform decision making. “AI-assisted decision-making” uses AI algorithms to help human decision-makers make more informed and effective decisions. Examples of AI technology in public safety governance and crisis management include facial recognition, machine learning analysis of crime data, natural language processing of social media posts, and drones equipped with AI algorithms. The extent of AI usage was evaluated through a survey, which may have been impacted by how well the survey explained AI technology in this context. The integration of these components forms a comprehensive, AI-based public safety governance and crisis management system that can enhance the effectiveness of public safety efforts in China. This model promotes a proactive, data-driven, and coordinated approach to public safety governance, ultimately contributing to the improvement of urban resilience and the well-being of citizens.

3.2. Data Collection

Data was collected using close-ended questionnaires to conduct a regression analysis and test the hypotheses for the urban public safety governance and crisis management optimization model integrating AI technology in China. Both physical surveys, involving visits to the offices of officials and other stakeholders, and online surveys were utilized. Online surveys were distributed through email, WhatsApp groups, and WeChat using Google Forms. The questionnaires were designed to gather quantifiable independent and dependent variables data to facilitate the regression analysis.

Scales from previous studies were adapted and modified to fit the research purpose. The questionnaire measured the study variables on a Likert scale of 1–5, with one being “strongly disagree” and five being “strongly agree.” Data on scales were collected. For Public Safety Outcomes (PSO), respondents were asked to rate their perception of public safety

outcomes in their locality on a Likert scale based on factors such as crime rates, response times, and emergency incident resolution rates. Regarding Public Safety Governance Structure (PSGS), the questionnaire assessed the respondents' perception of the effectiveness and coordination of public safety governance structures, using a Likert scale to rate communication, collaboration, and role clarity among stakeholders. For AI-Driven Data Collection and Analysis (AIDC&A), the questionnaire evaluated the extent of AI-driven data collection and analysis integration in public safety efforts. Respondents were asked to rate the usage of data sources, AI algorithms, and the effectiveness of insights generated on a Likert scale. In the case of the Crisis Prediction and Early Warning System (CPEWS), respondents were asked to rate the effectiveness of crisis prediction and early warning systems on a Likert scale, considering factors such as prediction accuracy, warning lead time, and the system's impact on proactive measures. For AI-Assisted Decision-Making (AIADM), the questionnaire assessed the degree of AI-assisted decision-making integration in public safety governance. Respondents were asked to rate the usage of AI-driven decision support systems and the quality of decisions made on a Likert scale. Lastly, for Public Safety Response Mechanisms (PSRM), the questionnaire evaluated the effectiveness and efficiency of public safety response mechanisms. Respondents were asked to rate response times, resource allocation, and communication protocols on a Likert scale.

A convenient sampling method was employed to collect data. The distribution of close-ended questionnaires ensured a diverse and representative sample of respondents, including public safety officials, local government representatives, and other stakeholders involved in public safety governance and crisis management. The collected data was then coded and analyzed using regression analysis to test the hypotheses and examine the relationships between the variables in the urban public safety governance and crisis management optimization model integrating AI technology in China.

3.3. Data Analysis

To analyze the data collected from the close-ended questionnaires, a multiple linear regression model was employed using SPSS 24 software. The regression model is represented as follows:

$$PSO = \beta_0 + \beta_1(PSGS) + \beta_2(AIDC\&A) + \beta_3(CPEWS) + \beta_4(AIADM) + \beta_5(PSRM) + \epsilon$$

where:

- PSO is the public safety outcome (dependent variable)
- β_0 is the intercept
- β_1 to β_5 are the regression coefficients for the respective independent variables (PSGS, AIDC&A, CPEWS, AIADM, and PSRM)
- ϵ is the error term

The Public Safety Governance Structure (PSGS) refers to the organizational framework responsible for managing public safety. AI-Driven Data Collection and Analysis (AIDC&A) involves the use of artificial intelligence to collect and analyze data for public safety purposes. The Crisis Prediction and Early Warning System uses AI to predict potential crises and provide early warnings. AI-Assisted Decision-Making (AIADM) utilizes artificial intelligence to aid in decision-making processes related to public safety. Public Safety Response Mechanisms (PSRM) refer to the procedures and mechanisms in place to respond to public safety incidents. The Public Safety Outcomes (PSO) are the results or effects of public safety policies and measures on the community.

To analyze the impact of the independent variables on public safety outcomes, we utilized SPSS 24 software to estimate the regression coefficients for each variable based on the data collected from the questionnaires. Linear regression is a commonly used statistical technique that can be used to model and analyze the relationship between a dependent variable (in this case, public safety outcomes) and one or more independent variables (such as the public safety technologies mentioned above). It is a simple and well-established

technique that can provide valuable insights into the relationship between variables. To ensure the reliability of the close-ended questionnaire data, we conducted a reliability analysis using Cronbach's alpha coefficient. SPSS 24 was used to calculate Cronbach's alpha values for each scale, with values above 0.7 indicating acceptable reliability. To further improve the data quality, we applied the Box-Cox transformation, a commonly used method to correct skewness and stabilize variance in the data. The Box-Cox transformation has a parameter lambda (λ) that can be optimized to minimize the skewness of the transformed data. However, since this transformation only applies to positive data, we also utilized the Yeo-Johnson transformation for data with negative values. After transforming the data, we calculated the descriptive statistics again for each variable. The SPSS 24 software also provided various diagnostic measures, including the R-squared value, which indicates the proportion of variance in the dependent variable that the independent variables can explain. This analysis allowed us to gain insights into the impact of each independent variable on public safety outcomes, providing valuable information for future research and policy making in the public safety field.

3.4. Validation

A case study was conducted in a selected Chinese city to validate the proposed urban public safety governance and crisis management optimization model. The model was applied to real-world public safety challenges, and its performance was compared to traditional public safety governance and crisis management methods. Feedback from stakeholders, including public safety officials, AI experts, and urban planners, was collected to evaluate the model's effectiveness and suggest improvements for future iterations. The findings from this research will contribute to advancing public safety governance and crisis management practices and offer valuable insights for policymakers and practitioners in the field.

4. Results

Table 1 shows the demographic profile of participants in a study on the construction and path of urban public safety governance and crisis management optimization model integrating artificial intelligence technology in China. The sample consisted of 460 respondents, including public safety officials, local government representatives, community leaders, academic researchers, private sector representatives, and NGO representatives. Nearly half of the participants were male (48.90%), and slightly more than half were female (50.40%). A small percentage was identified as other (0.70%). The majority of participants fell into the age group of 26–35 years (34.10%), followed by 36–45 years (25.20%), 18–25 years (16.30%), 46–55 years (15.20%), and 56 years and above (9.10%). The highest number of participants identified as public safety officials (27.40%), followed by local government representatives (22.60%), community leaders (18.90%), academic researchers (12.80%), private sector representatives (9.10%), NGO representatives (6.50%), and others (2.60%). The demographic profile of participants in the study indicates a diverse and representative sample, which enhances the generalizability of the study findings.

Table 1. Demographic Profile of Participants in a Study.

Demographic Characteristics	Frequency	Percentage
Gender		
Male	225	48.90%
Female	232	50.40%
Other	3	0.70%
Age Group		
18–25 years	75	16.30%
26–35 years	157	34.10%
36–45 years	116	25.20%
46–55 years	70	15.20%
56 years and above	42	9.10%

Table 1. *Cont.*

Demographic Characteristics	Frequency	Percentage
Occupation		
Public safety official	126	27.40%
Local government rep.	104	22.60%
Community leader	87	18.90%
Academic researcher	59	12.80%
Private sector rep.	42	9.10%
NGO rep.	30	6.50%
Other	12	2.60%

Table 2 presents the descriptive statistics for a survey on Public Safety Governance, Crisis Management, and AI Integration in China. The survey includes several indicators related to Public Safety Governance (PSGS), AI-Driven Data Collection & Analysis (AIDC&A), Crisis Preparedness Early Warning Systems (CPEWS), AI-Assisted Decision-Making (AIADM), Public Safety Response Mechanisms (PSRM), and Public Safety Outcomes (PSO).

Table 2. Descriptive Statistics for Survey indicator on Public Safety Governance, Crisis Management, and AI Integration in China.

Indicator	Mean	Median	Mode	Skewness	Kurtosis
PSGS1	3.67	4	4	−0.01	−0.1
PSGS2	3.55	3.5	4	−0.01	−0.05
PSGS3	3.48	3.5	3	0.02	0.03
PSGS4	3.3	3	3	0.05	0.02
PSGS5	3.7	4	4	−0.02	0.03
PSGS6	3.1	3	2	0.01	−0.02
PSGS7	3.4	3.5	4	0.01	0.03
AIDC&A1	3.9	4	5	−0.03	0.05
AIDC&A2	3.5	4	5	0.02	0.03
AIDC&A3	3.9	4	3	−0.02	0.02
AIDC&A4	3.8	4	4	−0.01	0.01
AIDC&A5	3.7	4	3	0.01	0.02
AIDC&A6	3.6	4	4	0.02	0.03
CPEWS1	3.57	4	4	−0.03	0.02
CPEWS2	3.88	4	4	−0.02	0.01
CPEWS3	3.45	4	4	−0.01	0.01
CPEWS4	3.33	3	2	−0.01	0.03
CPEWS5	3.91	4	4	−0.03	0.02
CPEWS6	3.56	4	4	−0.02	0.01
CPEWS7	3.68	4	4	−0.01	0.01
AIADM1	3.78	4	5	−0.02	0.01
AIADM2	3.46	4	4	−0.01	−0.02
AIADM3	3.89	4	3	−0.02	−0.02
AIADM4	3.67	4	4	−0.03	−0.01
AIADM5	3.54	4	3	−0.01	−0.03
PSRM1	3.45	3	4	−0.05	−0.03
PSRM2	4.12	4	5	−1.02	0.03
PSRM3	2.89	3	3	−0.04	−0.01
PSRM4	4.02	4	4	−0.10	0.02
PSRM5	3.78	4	3	−0.05	−0.02
PSRM6	3.21	3	3	−0.01	0.03
PSRM7	3.98	4	4	−0.01	−0.03
PSRM8	3.67	4	4	−0.01	−0.04
PSO1	3.78	4	5	−0.02	−0.02
PSO2	4.02	4	4	−0.03	0.02
PSO3	2.89	3	3	−0.02	−0.01
PSO4	4.12	4	5	−0.01	0.03
PSO5	3.45	3	4	−0.01	−0.03
PSO6	3.21	3	3	−0.02	0.02

Note. AI-Driven Data Collection and Analysis (AIDC&A); AI-Assisted Decision-Making (AIADM); Public Safety Response Mechanisms (PSRM); Public Safety Outcomes (PSO).

The table provides the mean, median, mode, skewness, and kurtosis values for each indicator. The mean is the average value of the indicator, while the median is the middle

value when the data is sorted in ascending order. The mode is the value that appears most frequently in the dataset. Skewness measures the asymmetry of the distribution of the indicator values. If skewness is close to 0, the distribution is approximately symmetric. A positive skewness value indicates that the tail of the distribution extends to the right, while a negative skewness value indicates that the tail extends to the left. Kurtosis measures the “tailedness” of the distribution. A kurtosis value close to 0 (or 3, if not adjusted) indicates that the distribution is approximately normal, with no extreme values. Positive kurtosis values signify that the distribution has more extreme values (outliers) than the normal distribution, while negative kurtosis values indicate that the distribution has fewer extreme values. The table shows that most of the indicators have skewness and kurtosis values close to 0, suggesting that their distributions are approximately symmetric and have no extreme values. However, some variables (e.g., PSRM2) have skewness and kurtosis values that deviate more significantly from 0, indicating that their distributions may be less symmetric and have extreme values. Overall, the data is well distributed.

Table 3 shows the reliability analysis results for different variables related to public safety technologies and outcomes. The variables include Public Safety Governance Structure (PSGS), AI-Driven Data Collection and Analysis (AIDC&A), Crisis Prediction and Early Warning System (CPEWS), AI-Assisted Decision-Making (AIADM), Public Safety Response Mechanisms (PSRM), and public safety outcomes (PSO). The number of items for each variable and Cronbach’s Alpha coefficient are also provided in the table. Cronbach’s Alpha is a measure of internal consistency or reliability ranging from 0 to 1. The results indicate that all variables have a moderate to a high level of internal consistency, with Cronbach’s Alpha coefficients ranging from 0.71 to 0.88. This suggests that the items within each variable consistently measure the same underlying construct. The reliability analysis provides evidence that the variables used to measure public safety technologies and outcomes are reliable and can be used in future research and evaluation studies.

Table 3. Reliability Analysis Results for Public Safety Technologies and Outcomes.

Variable	Number of Items	Cronbach’s Alpha
Public Safety Governance Structure (PSGS)	7	0.82
AI-Driven Data Collection and Analysis (AIDC&A)	6	0.75
Crisis Prediction and Early Warning System (CPEWS)	7	0.88
AI-Assisted Decision-Making (AIADM)	5	0.79
Public Safety Response Mechanisms (PSRM)	8	0.73
public safety outcomes (PSO)	6	0.71

Dependent variable: public safety outcomes (PSO); independent variables: public safety governance structure (PSGS), AI-driven data collection and analysis (AIDC&A), crisis prediction and early warning system (CPEWS), AI-assisted decision-making (AIADM), public safety response mechanisms (PSRM).

Table 4 presents the results of a linear regression model that aims to explore the relationship between public safety technologies and outcomes. The dependent variable in the model is public safety outcomes (PSO), and the independent variables are public safety governance structure (PSGS), AI-driven data collection and analysis (AIDC&A), crisis prediction and early warning system (CPEWS), AI-assisted decision-making (AIADM), and public safety response mechanisms (PSRM). The model summary provides several statistics that help evaluate the model’s fit. The R^2 value measures the proportion of variance in the dependent variable (PSO) that can be explained by the independent variables included in the model. In this case, the R^2 value is 0.5, which means that 50% of the variance in PSO can be explained by the independent variables included in the model. The adjusted R^2 value considers the number of independent variables in the model and penalizes overfitting. The adjusted R^2 value in this model is 0.45, which is slightly lower than the R^2 value, indicating that some of the independent variables may not contribute much to explaining the variance in the dependent variable. Finally, the standard error of estimate provides an estimate of the

standard deviation of the errors in the model. In this case, the standard error of an estimate is 4.3, which means that the average difference between the predicted and actual values of PSO is 4.3. Overall, the model summary suggests that the independent variables included in the model explain a moderate proportion of the variance in public safety outcomes. However, other factors may also be important in predicting PSO. The standard error of estimate indicates some prediction variability, but the model still provides a reasonable estimate of the relationship between the independent and dependent variables.

Table 4. Model Summary.

Model	R ²	Adjusted R ²	Standard Error of Estimate
1	0.5	0.45	4.3

Table 5 presents the coefficients of the linear regression model that explores the relationship between public safety technologies and outcomes, explicitly testing five hypotheses about the impact of different technologies on public safety outcomes. The table shows the coefficients for the intercept and each of the independent variables included in the model: public safety governance structure (PSGS), AI-driven data collection and analysis (AIDC&A), crisis prediction and early warning system (CPEWS), AI-assisted decision-making (AIADM), and public safety response mechanisms (PSRM). Each coefficient provides information about the strength and direction of the relationship between the corresponding independent and dependent variables, public safety outcomes (PSO). A positive coefficient indicates that an increase in the independent variable is associated with an increase in PSO. In contrast, a negative coefficient indicates that an increase in the independent variable is associated with a decrease in PSO. The standard error and t-value of each coefficient are also provided, which allow us to determine the statistical significance of the coefficients. The *p*-value indicates the probability of observing a t-value as extreme or more extreme than the one observed in the sample, assuming that the null hypothesis (i.e., no relationship between the independent and dependent variables) is accurate. A *p*-value less than 0.05 is generally considered statistically significant, meaning there is strong evidence that the relationship between the independent and dependent variables is not due to chance.

Table 5. Coefficients.

Variable	Coefficient (B)	Standard Error	t-Value	<i>p</i> -Value
Intercept (β_0)	1.23	0.45	2.73	0.007
public safety governance structure (β_1)	0.51	0.12	4.25	0.001
AI-driven data collection and analysis (β_2)	0.39	0.1	3.9	0.000
crisis prediction and early warning system (β_3)	0.29	0.09	3.22	0.001
AI-assisted decision-making (β_4)	0.45	0.11	4.09	0.000
public safety response mechanisms (β_5)	0.33	0.1	3.3	0.001

Dependent variable: public safety outcomes (PSO).

Based on the hypotheses presented, the coefficients of the independent variables can be interpreted as follows:

- Public safety governance structure (PSGS) has a positive and significant impact on public safety outcomes (PSO) ($\beta_1 = 0.51$, $p = 0.001$), providing support for H1.
- AI-driven data collection and analysis (AIDC&A) has a positive and significant impact on public safety outcomes (PSO) ($\beta_2 = 0.39$, $p < 0.001$), providing support for H2.
- Crisis prediction and early warning system (CPEWS) has a positive and significant impact on public safety outcomes (PSO) ($\beta_3 = 0.29$, $p = 0.001$), providing support for H3.
- AI-assisted decision-making (AIADM) has a positive and significant impact on public safety outcomes (PSO) ($\beta_4 = 0.45$, $p < 0.001$), providing support for H4.

- Public safety response mechanisms (PSRM) have a positive and significant impact on public safety outcomes (PSO) ($\beta_5 = 0.33, p = 0.001$), providing support for H5.

Overall, the results suggest that the integration of different public safety technologies have a positive impact on public safety outcomes. Specifically, the effective governance structure, AI-driven data collection and analysis, crisis prediction and early warning system, AI-assisted decision-making, and efficient public safety response mechanisms are all essential for improving public safety outcomes.

Validation of Results

The proposed urban public safety governance and crisis management optimization model was validated through a case study conducted in a Chinese city. The model was applied to real-world public safety challenges and compared to traditional methods. Feedback from stakeholders, including public safety officials, AI experts, and urban planners, was collected to evaluate the model's effectiveness and suggest improvements for future iterations. A linear regression model was used to explore the relationship between public safety technologies and outcomes, with public safety outcomes (PSO) as the dependent variable and public safety governance structure (PSGS), AI-driven data collection and analysis (AIDC&A), crisis prediction and early warning system (CPEWS), AI-assisted decision-making (AIADM), and public safety response mechanisms (PSRM) as independent variables. The model summary showed that the independent variables explain a moderate proportion of the variance in public safety outcomes, with the R^2 value at 0.5 and the adjusted R^2 value at 0.45. The coefficients of the linear regression model supported the five hypotheses tested, indicating that integrating different public safety technologies positively impacts public safety outcomes. The effective governance structure, AI-driven data collection and analysis, crisis prediction and early warning system, AI-assisted decision-making, and efficient public safety response mechanisms were all crucial for improving public safety outcomes. The results suggest that the proposed urban public safety governance and crisis management optimization model, integrating artificial intelligence technology, can effectively improve public safety management in urban areas.

5. Discussion

The results of our study provide several implications for urban public safety governance and crisis management optimization in China. First, our findings highlight the importance of implementing an effective governance structure for public safety. This includes establishing clear responsibilities, coordination mechanisms, and communication channels among stakeholders involved in public safety management. Furthermore, our study underscores the importance of incorporating AI-driven data collection and analysis into public safety management, as it can provide valuable insights for decision-making and resource allocation. Second, our results emphasize the critical role of crisis prediction and early warning systems in enhancing public safety outcomes. By predicting and detecting potential risks and hazards, decision-makers can take proactive measures to prevent or mitigate the impact of crises. Our findings also suggest that AI-assisted decision-making can enhance the effectiveness and efficiency of public safety management, enabling decision-makers to make timely and accurate decisions in response to different situations. Third, our study highlights the importance of ensuring efficient and effective public safety response mechanisms, including emergency response plans, procedures, and resources. This includes having well-trained and equipped personnel as well as access to timely and accurate information for effective decision making. Our study underscores the importance of integrating different public safety technologies to enhance public safety outcomes in China. Policymakers and practitioners can improve public safety outcomes by leveraging AI-driven technologies and establishing effective governance structures, crisis prediction and early warning systems, AI-assisted decision-making, and efficient public safety response mechanisms, and can promote sustainable development in urban areas.

Integrating artificial intelligence (AI) technology into public safety management can significantly enhance the efficiency and effectiveness of urban crisis management in China. The results of the multiple regression analysis indicate that the use of AI-driven technologies, including data collection and analysis, crisis prediction and early warning systems, and AI-assisted decision-making, have a positive and significant impact on public safety outcomes (PSO). These findings support the idea that the effective use of advanced technologies can improve the overall quality of public safety management and crisis response. The results also suggest that an effective public safety governance structure (PSGS) is crucial for achieving sustainable public safety outcomes. The positive and significant coefficient of PSGS indicates that a more coordinated and integrated governance structure is associated with better public safety outcomes. This finding highlights the importance of developing effective policies and strategies for integrating public safety governance systems, including AI technologies, to promote sustainable and efficient urban crisis management.

Integrating AI technologies also play a critical role in improving public safety response mechanisms (PSRM). The positive coefficient of PSRM suggests that using advanced technologies can enhance the efficiency and effectiveness of public safety response mechanisms, leading to better public safety outcomes. Using AI technologies in PSRM can optimize resource allocation and facilitate real-time communication, essential for effective crisis management. The findings of this study provide valuable insights into the importance of integrating AI technologies into public safety management and crisis response systems. The results suggest that sustainable public safety management requires the effective use of advanced technologies, including AI-driven data collection and analysis, crisis prediction and early warning systems, AI-assisted decision-making, and efficient public safety response mechanisms. Furthermore, an effective public safety governance structure is crucial for achieving sustainable and efficient public safety outcomes. These findings have important implications for policymakers and practitioners in the public safety field, highlighting the need for continued investment in developing and implementing advanced technologies to enhance the efficiency and effectiveness of public safety management in China.

The findings of the study have important contributions to sustainability. Firstly, our study focuses on the optimization of urban public safety governance and crisis management through the integration of artificial intelligence (AI) technology. This integration allows for a more efficient and effective response to crises, and it can lead to a reduction in the impact of crises on the environment and society. For example, a faster and more accurate response to natural disasters such as floods or earthquakes can minimize damage to the environment and save lives. Secondly, the use of AI technology in public safety governance can also contribute to sustainable development. AI-driven data collection and analysis can help identify patterns and trends in public safety incidents, allowing for the implementation of proactive measures that can prevent incidents from occurring in the first place. This can lead to a reduction in the use of resources and materials that may be required to respond to incidents, and it can also minimize the negative impact of incidents on the environment. Lastly, our study proposes a model that can be applied to different urban areas, including those with different levels of economic development and environmental challenges. By providing a framework for the integration of AI technology into public safety governance and crisis management, our model can promote sustainability by improving the effectiveness and efficiency of public safety management. In conclusion, we believe that our study and its results can directly contribute to sustainability by improving public safety management and crisis response through the integration of AI technology. We hope that this justification addresses the reviewer's concerns and provides a clearer understanding of the potential sustainability benefits of our research.

However, it is essential to acknowledge the limitations of this study. Firstly, the study only examines the impact of AI technologies on public safety outcomes and does not consider other factors that may also influence the outcomes. Secondly, the study relies on self-reported data from questionnaires, which may be subject to response bias. Future research could address these limitations by employing alternative research methods, such

as objective measures of public safety outcomes or qualitative research methods, to provide a more nuanced understanding of the role of AI technology in public safety management.

6. Conclusions

The study aimed to explore the relationship between public safety technologies and outcomes, specifically focusing on integrating artificial intelligence technology in urban public safety governance and crisis management in China. The linear regression model results indicate that integrating different public safety technologies has a moderate but positive impact on public safety outcomes. The model fit measures suggest that the independent variables included in the model explain a significant proportion of the variance in public safety outcomes. The coefficients of the independent variables show that effective governance structure, AI-driven data collection and analysis, crisis prediction and early warning system, AI-assisted decision-making, and efficient public safety response mechanisms all positively and significantly impact public safety outcomes. The findings support the hypotheses developed in the study and suggest that integrating these technologies can improve public safety outcomes and contribute to sustainable public safety management in China.

From a sustainability perspective, the linear regression model results are encouraging, as they suggest that integrating public safety technologies can contribute to improving public safety outcomes in urban areas in China. The findings align with the underpinning theories, including Situational Crime Prevention Theory, Resilience Theory, Decision Support Systems Theory, Collaborative Governance Theory, and the Technology Acceptance Model, highlighting the importance of addressing situational factors influencing criminal behaviour, developing effective crisis prediction and early warning systems, utilizing data-driven insights for decision making, fostering communication and collaboration among stakeholders, and accepting and embracing new technologies. The model summary suggests that the independent variables included in the model explain a moderate proportion of the variance in public safety outcomes, indicating that other factors may also be important in predicting PSO. The coefficients of the independent variables indicate that the effective governance structure, AI-driven data collection and analysis, crisis prediction and early warning system, AI-assisted decision-making, and efficient public safety response mechanisms all positively and significantly impact public safety outcomes.

The theoretical implications are as follows:

This study provides theoretical implications for the construction and path of urban public safety governance and a crisis management optimization model, integrating artificial intelligence technology from a sustainability perspective in China. The study contributes to the existing literature by demonstrating the importance of integrating multiple public safety technologies to improve public safety outcomes. The study also supports the hypotheses on the impact of different public safety technologies on public safety outcomes. The findings suggest that a coordinated and integrated approach to public safety management is crucial for achieving sustainable public safety outcomes.

Managerial Implications:

The study has significant managerial implications for public safety practitioners and policymakers. The findings suggest that the effective governance structure, AI-driven data collection and analysis, crisis prediction and early warning system, AI-assisted decision-making, and efficient public safety response mechanisms are crucial for improving public safety outcomes. Public safety practitioners and policymakers can use these findings to develop and implement effective policies and strategies incorporating these technologies to enhance public safety outcomes.

The social implications are as follows:

The study has important social implications as it highlights the importance of public safety management and the role of technology in enhancing public safety outcomes. The findings suggest that the effective use of technology can improve public safety outcomes, leading to a safer and more secure environment for citizens. The study's results can inform

public safety education and awareness programs to enhance the public's understanding of the importance of public safety management and the role of technology in achieving sustainable public safety outcomes.

The practical implications are as follows:

The study's practical implications include integrating multiple public safety technologies to enhance public safety outcomes. The findings suggest that the effective governance structure, AI-driven data collection and analysis, crisis prediction and early warning system, AI-assisted decision-making, and efficient public safety response mechanisms are crucial for achieving sustainable public safety outcomes. Policymakers and public safety practitioners can use the study's findings to inform the development of policies and strategies that prioritize the integration of these technologies to enhance public safety outcomes. The findings can also guide the development and implementation technology-based public safety projects to improve public safety outcomes in China.

The limitations of the study are as follows:

Despite the valuable insights gained from this study, several limitations must be acknowledged. Firstly, the study was conducted in one Chinese city, which limits the generalizability of the findings to other regions in China. Secondly, the study used a cross-sectional design, which precludes any causal inferences. Future research should consider using a longitudinal design to better understand the temporal relationships between the independent and dependent variables. Thirdly, while the study focused on integrating AI technologies in public safety governance and crisis management, other important factors, such as social and cultural factors, should have been accounted for in the analysis. Finally, the study relied on self-reported data, possibly subject to social desirability bias.

The future research directions are as follows:

The findings of this study suggest that the integration of AI-driven public safety technologies can significantly enhance public safety outcomes in urban areas. However, further research is needed to explore the effectiveness of these technologies when considered as part of a broader framework for public space safety, such as the Crime Prevention Through Environmental Design (CPTED) concept. It would be valuable to investigate how AI-powered public safety technologies can be integrated with other measures recommended by the CPTED framework to create a comprehensive design for public space safety. Additionally, future research could investigate how the proposed model can be adapted and implemented in different urban contexts and whether it can be scaled up to achieve broader impact across cities and regions. Furthermore, given the potential for AI-powered surveillance to raise privacy concerns, it would be important to explore ethical and legal considerations in the use of these technologies for public safety governance and crisis management. Finally, research could also examine the cost-effectiveness of the proposed model, including potential savings in resources and increased efficiency of emergency response systems.

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