

THE IMPACT OF EXPLAINABLE AI ON CROWD MANAGEMENT EFFICIENCY: A STAKEHOLDER PERSPECTIVE

Afnan Al Azbah ¹
Khalid Fakeeh
Osama Rabie

Received 25.11.2024.
Revised 28.03.2025.
Accepted 15.05.2025.

Keywords:

Crowd Management, Explainable Artificial Intelligence (XAI), Stakeholder Perspective, Saudi Arabia

ABSTRACT

This study examines how explainable artificial intelligence (XAI) improves Saudi crowd management efficiency and transparency. Large-scale gatherings, especially culturally and religiously significant ones, require intelligent systems that stakeholders can trust and understand. Integration and stakeholder reliance on XAI solutions continue to hinder adoption. This research aims to bridge the gap between technological advancement and real-world crowd management by addressing transparency, reliability, and integration. The results showed that stakeholders valued XAI for real-time data analysis and decision-making, but technical challenges, infrastructure constraints, and a lack of understanding prevented its full integration. Stakeholders emphasized improved decision-making, enhanced operational efficiency, and positive stakeholder engagement as major benefits. However, technical barriers, lack of understanding, and infrastructure limitations were noted. Explainable AI improves risk prediction, and better resource allocation. Different stakeholders expressed varied needs for XAI explanations, requiring customization based on role clarity and transparency. XAI also improved inter-departmental collaboration, data sharing, and decision-making alignment, while concerns about data privacy, security risks, and regulatory compliance were highlighted. The study emphasizes the need for adaptable XAI systems for different user groups, contributing to contingency and stakeholder theory.



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1. INTRODUCTION

Explainable Artificial Intelligence (XAI) improves decision-making and trust in complex systems like crowd management (Laato et al., 2022; Haque et al., 2023), where stakeholders need transparent and understandable insights for efficient operations (Amann et al., 2020; Epstein et al., 2022; de Bruijn et al., 2022). Hybrid

models with textual and visual explanations may improve crowd management stakeholder trust and decision-making (Haque et al., 2023; Kou et al., 2022). Zuheros et al. (2022, 2023) proposed the ECDM-SDAM to explain AI-based decisions. Neural networks were used to extract meaningful insights, and weighted collective evaluation matrices were used to explain the final ranking, which provided both positive and negative justifications. Crowd

¹ Corresponding author: Afnan Al Azbah
Email: aazbah0001@stu.kau.edu.sa

management involves planning and controlling large gatherings for safety, security, and smooth operations, especially at high-density events. Effective crowd management prevents accidents, mitigates risks, and ensures efficient people flow, especially during religious pilgrimages and public festivals (Amann et al., 2020; Epstein et al., 2022). Despite its importance, this field has yet to integrate advanced technologies like XAI, leaving a gap in research and practice. Balance transparency with operational complexity is difficult, especially in real-time systems (de Bruijn et al., 2022). Zuheros et al. (2023) made AI decisions transparent and trustworthy by providing explainable outputs. Laato et al. (2022) list five key effects of XAI: trust, transparency, understandability, usability, and fairness. Laato et al. (2022) stressed the importance of these factors in human-AI interaction and proposed a framework linking XAI representation to human behavior, like AI adoption. Laato et al. (2022) used the information system (IS) success model and the theory of reasoned action (TRA) to support their findings and provide a practical guide for designing AI systems with explainability in mind.

In addition, Haque et al. (2023) examined how XAI affects healthcare and legal user perceptions. de Bruijn et al. (2022) discussed the challenges of using XAI in public decision-making and that while it can increase transparency, it also struggles with social acceptance and understanding. Even with explanations, the public often disputes AI-based decisions, especially in fraud detection and immigration (de Bruijn et al., 2022). Hybrid explanations using text and images improved user understanding and trust in AI systems (Haque et al., 2023). Explainability is key to user acceptance in healthcare and finance (Haque et al., 2023).

Research shows how AI automates and improves public service delivery (Kulal et al., 2024). Another study found that XAI can boost trust in AI systems but also noted the difficulty of balancing transparency and complexity (Epstein et al., 2022). In addition, Kou et al. (2022) showed that AI-based COVID-19 misinformation detection systems with crowdsourcing-based human oversight improve detection accuracy. Epstein et al. (2022) found that explanations for AI-generated fake news labels increased user engagement and discernment, supporting human-AI collaboration. Explainability helps healthcare AI systems meet medical, legal, and ethical standards (Amann et al., 2020). Additionally, Rajabi & Etmnani, (2024) systematically review XAI systems' knowledge graphs (KGs). KGs are mostly used in pre-modelling for feature and relationship extraction, which improves machine learning model interpretability (Rajabi & Etmnani, 2024). Post-model KGs have been used for reasoning and inference, especially in healthcare, where transparency is essential for decision-making (Rajabi & Etmnani, 2024).

Security teams, event organizers, and public safety officials all have different concerns about efficiency,

fairness, and real-time decision-making in crowd management. Hybrid explanation models (Haque et al., 2023) can boost stakeholder confidence. Research on human-AI collaboration in misinformation detection (Kou et al., 2022) shows complex stakeholder dependencies, making it essential to study how they affect XAI adoption in crowd management. Based on the research gaps and problem statement, the study offers the research questions:

- 1) How do stakeholder groups perceive the role of XAI in strengthening crowd management efficiency?
- 2) What challenges and opportunities do stakeholders face in integrating XAI in crowd management?
- 3) How does dependency of stakeholders influence the adoption and implementation of XAI in crowd management?

This section discussed the introduction with background, research gaps, problem statement and research objectives. Second, the study discussed the literature review with pieces of literature evidence. Third, the study introduced the methodology section to describe the sections that carried out the research. Fourth, the study discussed and concluded the findings from interviews. Fifth, the study discussed the findings with literature support. Sixth, the study concludes the findings.

2. LITERATURE REVIEW

2.1 Types of Explanations

XAI is gaining attention as AI systems are integrated into decision-making, especially in healthcare, finance, and governance. Various objectives and target audiences have led researchers to classify XAI. It includes the types of XAI.

- Intrinsic Explainability
- Post-hoc Explainability
- Feature Attribution Methods
- Counterfactual Explanations
- Model-specific Explanations
- Model-agnostic Explanations
- Interactive Explanations
- Visual Explanations

A key difference between XAI types is intrinsic and post-hoc explainability. AI models with intrinsic explainability, such as decision trees or linear regressions, make decisions transparent by design (Rai, 2020; Gregor & Benbasat, 1999). Post-hoc explainability uses external methods to explain predictions from opaque models like deep neural networks (Guidotti et al., 2018; Adadi, & Berrada, 2018). To understand AI decisions in opaque models, feature attribution, rule extraction, and counterfactual reasoning were developed (Biran et al., 2017).

Post-hoc feature attribution methods like LIME and SHAP are popular for explaining how input features affect AI model decisions. These methods suit end-users and data scientists because they analyze model output based on feature changes (Adadi, & Berrada, 2018). They have limitations, particularly scalability and non-technical stakeholder comprehensibility (Kim et al., 2024). Counterfactual explanations, which show how changing inputs could change the outcome, are another type of post-hoc explainability that is intuitive and useful (Wang et al., 2019). Counterfactuals can help managers and regulators get actionable insights from AI models by focusing on hypothetical scenarios (Miller, 2019).

Another important XAI classification is model-specific vs. model-agnostic explanations. Model-specific explanations are optimized for specific algorithms, such as decision trees or neural networks (Saeed & Omlin, 2023). Model-agnostic explanations work across AI models, giving them more flexibility but possibly less precision (Liao et al., 2020). Stakeholder needs and AI system complexity determine whether to use model-specific or model-agnostic explanations. Governance and healthcare decision-makers may prefer model-agnostic methods for their broad applicability and generalizability, while technical users may prefer model-specific methods for more precise insights (de Bruijn et al., 2022; Mehdiyev & Fettke, 2021).

Social and contextual factors have led to interactive and visual explanations as another type of XAI, especially for end-users who need more intuitive interfaces. Interactive XAI lets users directly query the AI system, changing inputs and seeing results, which builds trust and engagement (de Bruijn et al., 2022; Eiband et al., 2018). Visual explanations show the decision-making process through charts, graphs, and heatmaps (Zuheros et al., 2023). These methods are popular in healthcare and air traffic management, where transparency and usability are essential (Degas et al., 2022; Cirqueira et al., 2020). Interactive and visual explanations improve user engagement but struggle with scalability and accessibility across user groups (Arrieta et al., 2020; Hoffman & Klein, 2017). These explanations will likely become more important as XAI evolves to make AI systems transparent and understandable to stakeholders.

2.2 Crowd Management Challenges

Crowd management is challenging, especially in high-stakes environments like public events, crisis response, and urban transportation systems. AI systems have made it more visible (Samarajeewa et al., 2024). One of the biggest challenges is coordinating large groups safely and efficiently. Traditional crowd management systems use human operators to make quick decisions based on real-time data, but the volume and complexity of this information make human error likely. AI systems that provide real-time analysis and crowd management recommendations, especially those incorporating

explainability and human-AI collaboration, are promising solutions (Samarajeewa et al., 2024; Surowiecki, 2005). AI-driven crowd management must balance decision-making autonomy with transparency to maintain operator and public trust. Epstein et al. (2022) emphasize the importance of transparent AI systems, especially in environments where machine-generated decisions must be trusted, such as fake news detection. Kou et al. (2022) noted that crowd input could improve AI decisions in misinformation detection.

The Surowiecki (2005) "wisdom of crowds" theory underpins crowd management. The theory suggests that diverse, independent large groups can make better decisions than individuals or small groups. This principle applies to modern AI systems that use crowd-sourced data and opinions to make decisions. Zuheros et al. (2022) used sentiment analysis to improve AI decision-making accuracy by leveraging the "wisdom of crowds" in sentiment-based systems. AI complicates crowd management, especially when dealing with conflicting crowd behaviors and dynamic public gatherings. AI systems must analyze real-time environmental and movement data to predict crowd flow and risks. Zuheros et al. (2023) proposed Explainable Crowd Decision Making (ECDM) using sentiment analysis and deep learning models to explain AI system decisions.

AI has great potential in crowd management, but ethical issues with explainable AI remain. Human operators struggle to interpret opaque "black-box" models in AI-driven crowd management systems. This opacity raises accountability concerns, especially in high-risk AI environments. Explainable AI systems ensure human operators can trust and validate the system's predictions (Samarajeewa, et al., 2024). Additionally, these systems must be flexible enough for real-time human intervention, mainly when unexpected crowd behaviors occur. Stakeholder needs vary, making AI-based crowd management difficult. Public safety officials, event organizers, and the public may need different levels of AI system decision-making explanations. Zuheros et al. (2023) found that stakeholder-specific explanations improve trust and AI system adoption.

Hybrid AI models that combine human expertise and machine-generated insights can help solve these problems. In their COVID-19 misinformation detection study, Kou et al. (2022) used crowd-sourced and expert input to improve AI performance. In crowd management, hybrid models can use human operators to validate and interpret AI predictions, while AI systems can process large amounts of data faster and more efficiently. AI in crowd management solves many problems associated with managing large, dynamic groups. However, crowd behavior complexity, ethical concerns about AI transparency, and stakeholder needs present significant challenges. By using explainable AI models, crowd wisdom, and hybrid human-AI systems, researchers and practitioners can create more effective, transparent, and

trustworthy crowd management systems (Epstein et al., 2022; Kou et al., 2022; Zuheros et al., 2022). AI potential to improve crowd management safety and efficiency is clear, but these systems still need improvement.

2.3 Stakeholder Perceptions

Desires and Possibilities

The earlier studies discuss the requirements for explanations; however, they do not provide any engineering guidance that can be immediately applied to the system's design. In this article, we refer to these requirements as "*desirements*" (Hoffman, R. R., & Elm, W. C. (2006; Hoffman, & McCloskey, 2013). This concept was not the same as the idea of "*interpretability desiderata*," which Lipton, (2018), Sokol & Flach, (2020), and Langer et al. (2021) investigated. The term "*desires*" refers to the wishes that users, operators, or other stakeholders have expressed for particular functionalities or capabilities that they believe would improve the tasks that they are performing. As opposed to immediate design solutions, decrements bring attention to the problems that already exist and point out potential paths that could be taken to solve them in the future.

Stakeholder roles

Stakeholders were a primary antecedent in XAI. XAI system development has traditionally focused on explaining to "end-users," raising whether other stakeholders need different explanations (Hoffman et al., 2023). However, many stakeholder group classifications are speculative. Do different stakeholder groups need different explanations? The difference between stakeholder categories and roles is significant because people can play multiple roles (McDermid et al., 2021). Developers may train others. Individual roles may involve multiple stakeholder groups. End-users may be skilled and interested in software development. Due to this complexity, assigning a single explanation to a stakeholder group may not be feasible (Hepenstal et al., 2020).

Stakeholder Dependency

Many XAI researchers have stressed the importance of stakeholder or domain dependence in machine-generated explanations (Langer et al., (2021; Eiband et al., 2018; Sheh & Monteath, 2018; Mittelstadt et al., 2019). Many stakeholder relativity discussions only distinguish between end-users, system developers, and generalized groups. Developers want "scientific" explanations, while end-users want "everyday" ones (Langer et al., 2021). Based on Tomsett et al. (2018), Hind et al. (2019), and Naiseh et al. (2020) identify creators, AI researchers, lay users, operators, domain experts, decision-makers, affected individuals, ethicists, theorists, regulatory bodies, and oversight organizations as stakeholders. Stakeholder explanation needs have been speculated (Hind et al., 2019; Goodman & Flaxman, 2017; Kaur et al., 2020; Tjoa & Guan, 2020). Arya et al. (2019)

proposed a taxonomy of explanation types and methods and examined their relevance for loan officers, applicants, and bank executives. Langer et al. (2021) listed 28 explanation requirements, including trust, fairness, performance, and acceptance. The four main stakeholders were users, developers, regulators, and affected parties. Langer et al. (2021) argued that XAI-related research and findings are necessary for various explanations, demonstrating the growing interest in this topic.

Hind et al. (2019) speculated on stakeholder explanation needs. However, affected parties need explanations to determine fairness. Developers need information to test the AI and diagnose issues, while regulators want fairness and safety explanations. Hind et al. (2019) also stressed that AI explanations should justify system decisions, build user trust, be verifiable, and use domain-specific terminology. In addition, Weller (2019) linked stakeholder groups to "transparency" or explanation types. Developers must understand the AI system's functionality to improve, debug, and evaluate its performance. Users need explanations that help them trust the AI decisions and act on its output. Thus, this study develops the stakeholder perception-based framework. Figure 1 shows a three-stage framework emphasizing stakeholder needs in AI system design and validation. Stage 1, "Stakeholder Dependency," addresses stakeholder groups' specific explanation needs by understanding and identifying their needs. Stage 2, "Contingency-Based Design," uses contingency theory to create flexible interfaces that meet diverse user needs. Stage 3, "Validate," tests the designed system to meet stakeholder expectations and makes adjustments based on feedback to improve functionality and stakeholder role alignment. This structured approach ensures that AI systems are technically sound and meet stakeholders' diverse needs, improving trust and usability.

2.4 Explainable AI: How and Where?

AI explanations were first used in rule-based expert systems to produce detailed, drill-down outputs (Gregor & Benbasat, 1999; Biran et al., 2017). Data analytics and machine learning are becoming more common across industries (Beydoun et al., 2019; Abedin et al., 2020), increasing the need for standardized methods to analyze and verify AI systems' structure and intent. AI research is usually interdisciplinary, even though no single framework exists for explainability or interpretability (Arrieta et al., 2020). There is consensus that XAI involves showing humans how the system makes decisions, generates outputs, and performs its functions (Rai, 2020).

Though distinct, AI discourse often uses explainability, interpretability, and transparency interchangeably (Ntoutsis et al., 2020). As research across fields has increased, terms like XAI (Adadi & Berrada, 2018), explicable AI, Robbins (2019), and black box

explanations Guidotti et al. (2018) have emerged, adding to the confusion. Although scholars like Arrieta et al. (2020) and Rai, (2020) have distinguished these concepts, they remain interconnected and aim to address critical AI systems issues like ethics, bias, fairness, and privacy (Bertino et al., 2019). The concepts include prospective (knowledge of data collection before it happens) and retrospective (knowledge of decision-making aspects (Felzmann et al., 2019).

According to Adadi and Berrada (2018), AI explainability serves four purposes: justify the system's outputs and recommendations, enable control by

identifying vulnerabilities and addressing unknowns, improve the system by clarifying how specific outcomes are generated, and support discovery by revealing new insights. Stakeholders also need different explanations. Five main groups are identified by Arrieta et al. (2020): Managers and executives concerned with regulatory compliance, regulatory entities ensuring legal adherence, expert users who apply AI models in their fields (e.g., medical or insurance professionals), affected individuals who need to understand the model's effects, and data scientists and developers responsible for model creation. AI algorithm type affects explanation ease (Rai, 2020).

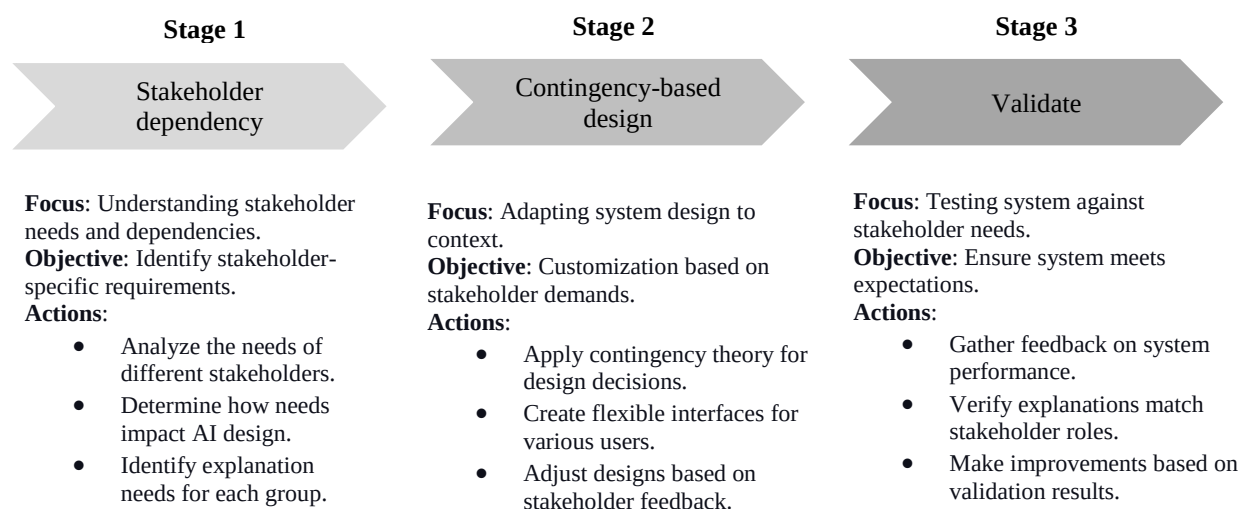


Figure 1. Stages of stakeholder dependency

2.5 Underpinning concept: Contingency theory and explainable AI

Contingency theory, first introduced in organizational theory to study leadership effectiveness (Epstein et al., 2022; Kulal et al., 2024), has become popular because it challenges the idea that there is a single best management approach (Csaszar, & Ostler, 2020). The theory states that there is no single solution for managing organizations and that tasks vary across organizations depending on environmental and contextual factors (Galbraith, 1973). Despite contributions from philosophy, psychology, and cognitive science on human decision-making, most XAI research relies on researchers' intuitive sense of a "good" explanation (Miller, 2019). Social science theories must be used to make XAI systems more user-friendly (Miller, 2017). Technical research in AI and data analytics often lacks these social and psychological foundations (Felzmann et al., 2019).

Philosophical and psychological insights help Wang et al., (2019) design user-centric, theory-driven XAI systems. Hoffman and Klein (2017) examine causation, causal reasoning, and abductive inference in explanations. Their research does not thoroughly examine how XAI outcomes affect stakeholders and their

decision-making goals. Guzman & Lewis, (2020) address the gap between traditional communication theories and AI technologies. Mohamed et al. (2020) applies postcolonial and decolonial theories to AI, suggesting they can promote ethical AI development and protect marginalized communities. Business and information systems scholars have studied AI theoretical foundations since the 1990s (Gregor & Benbasat, 1999), but most of their attention has focused on its technical development. Contingency theory is ideal for addressing XAI challenges because it recognizes that no solution fits all problems (Gregor & Benbasat, 1999; Tjoa, E., & Guan, 2020). Contingency theory empowers researchers to find flexible, situation-dependent solutions by considering each problem context, which improves AI explainability.

2.6 Explainable AI and Crowd Management

According to the "wisdom of crowds" theory, groups can outperform their smartest members (Surowiecki, 2005). Even with limited knowledge, a group can make a good decision. Independence, diversity, and decentralization are essential for a wise crowd. XAI provides an accurate model reflection and an easily understandable format to connect human understanding with decision-making systems (Arrieta et al., 2020). In the digital age, natural language processing can analyze social media opinions

to harness crowd wisdom. The opinions feed decision-making (DM) systems, tapping crowd intelligence. Herrera-Viedma et al. (2020) and Sano et al (2022) investigated how social media data could be used in DM frameworks and tourism chatbots to capture collective judgments. The novel Crowd Decision Making (CDM) method uses large-scale, unfiltered evaluations from individuals to tap crowd wisdom. This method processes natural language input without consensus-building using sentiment analysis (SA). Due to its global, decentralized, and independent reviews, social media is ideal for CDM (Zuheros et al., 2022). But there is no study in the literature review that focus on the impacts of XAI in crowd management. Therefore, this study explores the factors to enhance XAI in crowd management.

3. RESEARCH METHODOLOGY

3.1 Research design

This study used a qualitative research design with semi-structured interviews. Qualitative research provides rich, detailed insights into human behaviors, needs, and experiences, making it helpful in understanding complex phenomena (Creswell & Poth, 2016). Stakeholder interactions were used to gather nuanced views on XAI and its effects in crowd management. Firsthand accounts from interviews and focus groups were likely used to understand better how stakeholders view and interact with AI systems (Creswell & Poth, 2016). Qualitative research is also ideal for studying the social and organizational contexts of AI systems.

3.2 Data collection procedures

This study collected data through semi-structured interviews with 9 Saudi crowd management stakeholders from various industries, including the Ministry of Interior, General Directorate of Civil Defense, Saudi Red Crescent Authority, Ministry of Hajj and Umrah, and private security companies specializing in crowd control at religious pilgrimages. Crowd management is handled differently in public safety, healthcare, transportation logistics, and event organization. Semi-structured interviews provided detailed information about each stakeholder's experiences and perceptions of AI-based crowd-management solutions. The study used quota sampling to represent all relevant crowd management ecosystem stakeholders. Quota sampling was used to select participants and provide diverse crowd management perspectives. Quota sampling was justified because it allowed all major stakeholder groups to be represented without over representing any group and capturing diverse viewpoints (Etikan, & Bala, 2017). This sampling method is ideal for qualitative research because it includes critical stakeholder perspectives while focusing on data saturation rather than random selection (Moser & Korstjens, 2018).

9 stakeholders were interviewed using semi-structured questions with guided and open-ended responses, allowing them to express their opinions while keeping the discussion on the topic. Semi-structured interviews are recommended for exploratory research because they allow the researcher to probe deeper into participants' responses while exploring unexpected insights (Gill et al., 2008). The study collected rich qualitative data from semi-structured interviews to identify patterns and themes in crowd management, AI integration, and departmental challenges.

The study conducted Zoom interviews with departmental heads' permission due to the sensitive topics. Twenty-two potential participants received consent letters, but only 9 agreed to be interviewed due to privacy and security concerns. Online interviews in qualitative research are becoming more popular due to their convenience and accessibility, especially for remote participants (Archibald et al., 2019). As well-educated professionals, all interviews were conducted in English on Zoom for security. After transcription, the interviews were analyzed thematically, using a qualitative research method to identify, organize, and reveal key meaning patterns (Braun & Clarke, 2006). Twelve interview questions were prepared:

- 1) How does XAI improve crowd management in your department or sector?
- 2) Experience with current crowd management systems? Have you used AI-driven systems? How have they affected operations?
- 3) How can XAI improve crowd management and decision-making during large events like Hajj or Umrah?
- 4) What challenges do you expect when integrating explainable AI into crowd management systems?
- 5) What advantages can XAI offer your department, especially in handling unpredictable crowd behavior?
- 6) Do security, healthcare, and transportation stakeholders have different AI-generated explanation needs? If so, how?
- 7) How can explainable AI improve coordination between public safety, healthcare, and transportation departments?
- 8) How does stakeholder dependence affect the adoption and implementation of the crowd management system XAI?
- 9) Do you think XAI can build stakeholder trust (e.g., public safety, event organizers)? If so, how? No? Why not?
- 10) What are your concerns about AI and XAI in crowd management, especially data privacy and security?
- 11) How important is staff training on XAI in crowd management systems? What kind of training is needed?
- 12) What factors will drive the adoption of Saudi crowd management systems' XAI?

3.3 Data analysis

Following qualitative interviews, the study used thematic analysis to identify stakeholder response patterns and themes. This method lets researchers analyze and interpret the qualitative data to understand the role of AI in decision-making (Braun & Clarke, 2006). Qualitative research is ideal for identifying how developers, operators, end-users, and regulatory bodies have different AI explanation needs due to the nature of AI systems and the diversity of stakeholder groups involved (Miles et al., 2014). The transcription and thematic analysis allowed researchers to rigorously interpret data and ensure the findings were based on participants' experiences and met the study's objectives.

The coding was done with 9 semi-structured interviews. Manual coding was performed in the excel sheet then converted into themes, sub-themes, codes, sources and quotations. Sources include the number of semi-structured interviews. References include the total number of coding repeat in 9 semi-structured interviews.

4. RESEARCH METHODOLOGY

4.1 Demographic analysis

The study targeted 9 stakeholders from different departments. Table 1 shows that 9 stakeholders in Saudi Arabia have a wide range of crowd management expertise, experiences, and educational backgrounds. Most participants are 37–52 years old and have over a decade of experience. This extensive experience,

particularly in fields that directly manage large-scale crowds and public safety, suggests that these interviews were conducted by highly knowledgeable individuals with a deep understanding of crowd management operational challenges and solutions. The stakeholders' education proves their expertise. 6 of the 9 participants have master's degrees in criminal justice, logistics, event management, or operations management. 2 participants have doctorates in healthcare management and management, demonstrating academic proficiency in leadership and decision-making. Their diverse educational backgrounds—from security studies to public administration—indicate a multidisciplinary approach to crowd management, combining safety, logistics, and strategic operations skills.

4.2 Thematic analysis

The study identified the themes and sub-themes from 9 semi-structured interviews (see Table 2). The study found diverse views of XAI in crowd management, focusing on its potential to improve decision-making and operational efficiency. According to stakeholders, XAI improves decision-making (15 references from interviews 1, 4, 5, and 9), operational efficiency (12 references from interviews 2, 7, and 9), and stakeholder engagement (10 references from interviews 1, 6, and 8). This suggests stakeholders value XAI for streamlining operations, improving real-time decision-making, and engaging stakeholders with AI-driven solutions. The widespread recognition of XAI ability to manage large crowds emphasizes its importance in crowd control.

Table 1. Demographics

ID	Department/Industry	Role/Position	Age	Years of Experience	Education Level	Nationality	Gender
S1	Ministry of Interior (Public Security)	Senior Officer	45	14	Master in Criminal Justice	Saudi	Male
S2	General Directorate of Civil Defense	Operations Manager	50	19	Master's in Operations Management	Saudi	Male
S3	Saudi Red Crescent Authority	Emergency Coordinator	41	15	PhD in Management	Saudi	Male
S4	Ministry of Hajj and Umrah	Logistics Manager	42	18	Master's in Logistics	Saudi	Male
S5	Private Security Company (Event Control)	Security Consultant	52	17	Bachelor's in Security Studies	Saudi	Male
S6	Transportation Department (Public Transit)	Transit Coordinator	39	12	Bachelor's in Transportation Engineering	Saudi	Male
S7	Healthcare Emergency Services	Medical Director	37	22	Doctorate in Healthcare Management	Saudi	Male
S8	Event Management Company	Event Planner	49	14	Master's in Event Management	Saudi	Male
S9	Public Safety (Local Police)	Public Safety Officer	44	19	Master in Public Administration	Saudi	Male

However, the challenges in integrating XAI show that adopting these systems is difficult. Lack of stakeholder understanding (10 references from interviews 4, 6, and

9), technical barriers (12 references from interviews 3 and 7), and infrastructure limitations (8 references from interviews 1 and 6) were common XAI implementation

barriers. These challenges highlight the need for improved infrastructure and stakeholder education to integrate XAI into crowd management. To overcome these barriers, departments and industries must work together to equip stakeholders with XAI tools and knowledge. The results also suggest that XAI could improve real-time data analysis (10 references from

interviews 5 and 6), risk prediction (9 references from interviews 3, 5, and 6), and resource allocation (8 references from interviews 3 and 5). XAI, say stakeholders, can predict risks and optimize resource use during large-scale events. Stakeholders stressed the importance of transparency in building trust in AI systems (13 references from interviews 3, 4, and 7).

Table 2. Themes and sub-themes

Themes	Sub-Themes	References	Sources
Perception of XAI in Crowd Management	Improved decision-making	15	Laato et al. (2022); Epstein et al. (2022); de Bruijn et al. (2022); Kulal et al. (2024)
	Enhanced operational efficiency	12	Haque et al. (2023); Zuheros et al. (2022); Kulal et al. (2024)
	Positive stakeholder engagement	10	Laato et al. (2022) Kou et al. (2022); Zuheros et al. (2023)
Challenges in Integrating XAI	Technical barriers	12	Amann et al. (2020); Zuheros et al. (2022)
	Lack of stakeholder understanding	10	Epstein et al. (2022); Kou et al. (2022); Kulal et al. (2024)
	Infrastructure limitations	8	Laato et al. (2022); Kou et al. (2022)
Opportunities with XAI	Real-time data analysis	10	de Bruijn et al. (2022); Kou et al. (2022)
	Improved risk prediction	9	Amann et al. (2020); de Bruijn et al. (2022); Kou et al. (2022)
	Better resource allocation	8	Amann et al. (2020); de Bruijn et al. (2022)
Stakeholder Needs for XAI Explanations	Varied explanation requirements	8	Laato et al. (2022); Amann et al. (2020)
	Customization based on role	7	Epstein et al. (2022); de Bruijn et al. (2022); Zuheros et al. (2022)
	Clarity and transparency	9	Haque et al. (2023); de Bruijn et al. (2022); Kou et al. (2022)
Coordination Between Stakeholders	Inter-departmental collaboration	14	Laato et al. (2022); de Bruijn et al. (2022); Zuheros et al. (2023)
	Data sharing and integration	12	Haque et al. (2023); Kou et al. (2022); Zuheros et al. (2022)
	Communication and decision-making alignment	10	Laato et al. (2022); Haque et al. (2023)
Trust in AI Systems	Building trust through transparency	13	Amann et al. (2020); Epstein et al. (2022); Zuheros et al. (2022)
	Confidence in AI recommendations	9	(Laato et al. 2022); Haque et al. (2023); Amann et al. (2020)
	Clear understanding of AI outputs	8	Laato et al. (2022); Haque et al. (2023); Epstein et al., (2022); de Bruijn et al. (2022); Kou et al. (2022)
Privacy and Security Concerns	Data privacy and ethical concerns	9	Laato et al., 2022, Haque et al. (2023); Amann et al. (2020); Epstein et al. (2022); Kou et al. (2022); Zuheros et al. (2022)
	Risk of data breaches	7	Amann et al. (2020); Epstein et al. (2022); de Bruijn et al. (2022); Zuheros et al. (2022); Zuheros et al. (2023)
	Compliance with regulations	6	Laato et al. (2022); Amann et al. (2020), Epstein et al. (2022); de Bruijn et al. (2022)
Training for XAI Usage	Skill development	11	Laato et al. (2022); Haque et al. (2023); Kou et al. (2022); Zuheros et al. (2023); Kulal et al. (2024)
	Need for ongoing training	9	Laato et al. (2022); Epstein et al. (2022) de Bruijn et al. (2022)
	Understanding XAI functionality	8	Laato et al. (2022); Amann et al. 2(020); Zuheros et al. (2022); Zuheros et al, (2023)

The study answered the research questions by following the findings of the interviews.

4.3 Research Question 1: How do different stakeholder groups perceive the role of XAI in enhancing crowd management efficiency?

First, the study answers the 1st research question (Table 3). The findings show a strong consensus among stakeholders about the transformative impact of XAI on crowd management efficiency in Saudi Arabia. All stakeholders recognized XAI ability to speed up decision-making, increase operational efficiency, and boost stakeholder engagement. These findings are consistent with previous research that has highlighted XAI's role in enabling real-time data analysis and predictive capabilities for more informed decision-making in complex environments (Liao et al., 2020; Mehdiyev & Fettke, 2021). Stakeholders emphasized XAI's importance in high-stress situations such as the Hajj pilgrimage, where prompt and accurate decisions are critical. This is consistent with previous research demonstrating XAI capability to improve operational outcomes and streamline decision-making in high-risk scenarios (Degas et al., 2022; Cirqueira et al., 2020). Furthermore, the study's findings on improved stakeholder collaboration and engagement are consistent with previous research demonstrating XAI potential to promote transparency and trust among users, resulting in better inter-departmental coordination (Arrieta et al., 2020; Hoffman & Klein, 2017). For example, Participant 1 and 5 claimed that.

"XAI provides the insights needed for faster, better event decision-making. XAI provides real-time, data-driven intelligence that helps us respond quickly and effectively to large events like the Hajj pilgrimage, where managing millions of people is a daily challenge. We can anticipate risks, streamline operations, and ensure public safety and security more accurately than ever with XAI guiding our strategies."

This sentiment was reiterated by other stakeholders, especially those engaged in public safety and emergency response, who emphasized the importance of XAI in delivering actionable information to avert hazardous situations, such as overcrowding or bottlenecks, from worsening. The capacity to make data-driven decisions is deemed essential, especially when human intuition or conventional decision-making methods fail to address the intricacies and magnitude of crowd dynamics. The second sub-theme, improved operational efficiency, was extensively addressed. Stakeholders from diverse departments acknowledged that XAI facilitates more efficient operations by enhancing communication, alleviating decision-making bottlenecks, and automating routine tasks that generally impede response times. Participant 9, representing the Ministry of Hajj and

Umrah, remarked on the efficacy of XAI in optimizing operations.

"It significantly enhances the efficiency of our operations, particularly during Hajj."

In the realm of crowd management, where time is of the essence, XAI capacity to automate routine decisions and deliver prompt alerts was regarded as a substantial enhancement compared to conventional approaches. Participants said XAI systems improved their ability to quickly and accurately address potential issues, which is crucial at large events like the Grand Mosque. Previous studies have shown that explainable AI can help facilitate rapid responses in high-pressure situations, where timely interventions are crucial (Guidotti et al., 2018; Biran & Cotton, 2017). Centralization of operations and improved inter-departmental coordination through XAI were also important, supporting earlier research that shows explainable AI improves operational integration and communication across sectors like public safety and healthcare (Adadi & Berrada, 2018; Kim et al., 2024). Through transparent and accessible information, XAI improves stakeholder collaboration, as shown by its ability to build trust and coordinate diverse groups (Gregor & Benbasat, 1999; Wang et al., 2017). Participant 6 emphasized this aspect, observing that.

"As a member of the Saudi security department, I've witnessed how the utilization of XAI fosters increased positive interactions among various departments. Providing clear, transparent data enhances collaboration, ensuring everyone works together seamlessly to manage large events more efficiently."

This engagement is crucial in crowd management scenarios, where inter-agency collaboration is vital for effective responses. The capacity of XAI to enable communication among stakeholders, deliver pertinent information customized for various roles, and improve overall coordination was regarded as a significant benefit. XAI establishes a unified platform for information exchange and decision-making, promoting a more integrated crowd management strategy, thereby aligning all stakeholders' actions and objectives.

4.4 Research Question 2: What challenges and opportunities do stakeholders identify in integrating XAI in crowd management systems?

The study also illuminated stakeholders' XAI integration challenges and opportunities in crowd management systems. XAI has many benefits, but stakeholders identified technical barriers, stakeholder understanding, and infrastructure limitations. Previous research has shown the difficulty of integrating XAI systems into

existing frameworks, where infrastructure and technical readiness often lag behind XAI advanced capabilities (McDermid et al., 2021; Sheh & Monteath, 2018). XAI complex data processing requirements were too much for participants' systems, which is consistent with findings that legacy systems struggle with modern AI (Hepenstal & McNeish, 2020). However, stakeholders recognized XAI potential to address these issues by providing real-time data analysis, improved risk prediction, and efficient resource allocation, echoing prior studies affirming XAI

capability to improve decision-making in dynamic environments (Hoffman et al., 2023; Eiband et al., 2018). As Participant 7 said,

"In the Saudi security sector, our biggest issue is that our systems are not ready for XAI integration. We need major infrastructure upgrades to fully implement and benefit from this advanced technology."

Table 3. Answers to questions

Research Questions	Themes	Sub-Themes	Description	Quotations
1. How do different stakeholder groups perceive the role of XAI in enhancing crowd management efficiency?	Perception of XAI in Crowd Management	Improved decision-making	XAI improves decision-making in dynamic crowd environments.	"XAI gives us the insights needed to make faster, better decisions during events." (Participant 1)
		Enhanced operational efficiency	XAI enhances the operational efficiency of managing large crowds.	"It definitely helps streamline our operations, especially during Hajj." (Participant 9)
		Positive stakeholder engagement	XAI fosters better engagement from all stakeholders involved in crowd management.	"We see more positive interactions between departments when XAI is used." (Participant 6)
2. What challenges and opportunities do stakeholders identify in integrating XAI in crowd management systems?	Challenges in Integrating XAI	Technical barriers	There are significant technical challenges in integrating XAI into existing systems.	"The biggest issue is that our systems are not ready for XAI integration." (Participant 7)
		Lack of stakeholder understanding	Many stakeholders don't fully understand how XAI works.	"Not all departments understand what XAI can really do for us." (Participant 9)
		Infrastructure limitations	Existing infrastructure lacks the capacity to support XAI.	"The infrastructure just isn't there yet to implement XAI effectively." (Participant 1)
	Opportunities with XAI	Real-time data analysis	XAI offers real-time data analysis for better crowd management.	"It's the real-time data analysis that makes all the difference." (Participant 5)
		Improved risk prediction	XAI improves risk prediction during large events.	"With XAI, we can predict and prevent issues before they happen." (Participant 6)
		Better resource allocation	XAI helps allocate resources more efficiently.	"We're able to use our resources where they're needed the most, thanks to XAI." (Participant 3)
3. How does the dependency between stakeholders influence the adoption and implementation of XAI in crowd management?	Stakeholder Needs for XAI Explanations	Varied explanation requirements	Different stakeholders need varied levels of explanation from XAI.	"Everyone has different needs when it comes to understanding XAI." (Participant 1)
		Customization based on role	XAI explanations must be customized according to the role of the stakeholder.	"The explanations have to be tailored, especially for technical vs. non-technical users." (Participant 5)
		Clarity and transparency	Clear and transparent explanations build trust among stakeholders.	"Clarity is key if we are to trust these systems." (Participant 6)
	Coordination Between Stakeholders	Inter-departmental collaboration	XAI promotes better collaboration between departments in crowd management.	"XAI helps us coordinate much better across departments." (Participant 8)

		Data sharing and integration	XAI encourages seamless data sharing and integration across departments.	"It makes it easier to share data, which is crucial during large events." (Participant 7)
		Communication and decision-making alignment	XAI aligns communication and decision-making across stakeholders.	"It helps ensure we're all on the same page when making decisions." (Participant 1)
	Trust in AI Systems	Building trust through transparency	Trust is built when XAI provides transparent outputs that can be verified.	"We trust the system when we understand why it's making those decisions." (Participant 4)
		Confidence in AI recommendations	Confidence in AI recommendations increases with clear explanations.	"When the AI explains its decisions, we have more confidence in following them." (Participant 3)
		Clear understanding of AI outputs	Stakeholders need a clear understanding of AI outputs to act on them.	"We need to fully understand the outputs if we're going to trust the system." (Participant 2)
	Privacy and Security Concerns	Data privacy and ethical concerns	There are significant concerns about data privacy and ethical issues when using XAI.	"We have to ensure the data used is secure and ethical." (Participant 6)
		Risk of data breaches	The risk of data breaches is a major concern for stakeholders.	"With so much data being processed, security is always a concern." (Participant 4)
		Compliance with regulations	Ensuring XAI complies with local and international regulations is vital.	"Regulatory compliance is essential if we're to use AI effectively." (Participant 3)
	Training for XAI Usage	Skill development	Training is needed to develop skills for using XAI effectively in crowd management.	"We need training to fully understand how to use XAI." (Participant 1)
		Need for ongoing training	Ongoing training is required to keep up with evolving XAI systems.	"Regular training is necessary to stay updated with AI systems." (Participant 4)
		Understanding XAI functionality	Stakeholders need to understand how XAI functions to implement it properly.	"A deep understanding of the system's functionality is critical." (Participant 3)

The challenge was greatest in departments with legacy systems or limited technical expertise. Stakeholders worried that XAI's potential would be limited without significant infrastructure investment. Many participants said they lacked the technical expertise to integrate XAI into existing systems. Lack of stakeholder understanding was another issue. Despite their optimism about XAI, many stakeholders admitted they did not fully understand how it works or how it could be used in their context. Participant 9 said,

"Not all departments know what XAI can do for us."

Stakeholders unfamiliar with XAI capabilities and limitations may hesitate to invest in the technology or use it ineffectively. A lack of understanding of XAI may make stakeholders less likely to trust its recommendations, hindering departmental collaboration. Infrastructure constraints were the stakeholders' third biggest issue. Several participants noted that their data storage and processing infrastructure could not support

XAI systems' large data volumes. On this topic, Participant 1 said,

"The infrastructure just is not there yet to implement XAI effectively."

Real-time data processing is crucial for crowd management decision-making, so these limitations were problematic. Stakeholders worried that XAI would not be able to process data quickly enough to make decisions without the proper infrastructure. Despite these challenges, stakeholders saw several strong XAI crowd management opportunities. Data analysis in real time was the first opportunity. So the findings are consistent with the previous studies (de Bruijn et al., 2022; Gregor & Benbasat, 1999; Wang et al., 2019; Liao et al., 2020). According to several participants, XAI's real-time crowd behavior insights allow participants to address potential issues before they escalate. Participant 5 said,

"Real-time data analysis makes all the difference."

XAI provides real-time data analysis to help stakeholders track crowds, identify risks, and better allocate resources. In large-scale events like the Hajj, the ability to react quickly to changing conditions is crucial to the safety of millions of people. Improvements in risk prediction were stakeholders' second opportunity. Several participants said XAI's predictive capabilities allow them to anticipate and mitigate risks. Participant 6 said,

"As a Saudi security stakeholder, I've seen XAI predict and prevent issues. Real-time data analysis lets us anticipate risks and improve crowd management at large events."

Predicting and preventing bottlenecks and overcrowding in large crowds can greatly improve crowd management efficiency. XAI helps stakeholders identify risks and make better decisions to avoid dangerous situations. The third opportunity, better resource allocation, was widely discussed. Many participants said XAI helps them allocate resources more efficiently by providing real-time information about resource needs. Participant 3 noted this benefit:

"XAI lets us use our resources where they are needed most."

Effective resource allocation is essential in crowd management, where personnel and equipment are scarce. XAI's real-time data on crowd movements and risks helps stakeholders allocate resources where they are most needed.

4.5 Research Question 3: How does the dependency between stakeholders influence the adoption and implementation of XAI in crowd management?

The third research question examined how stakeholder dependency affects the adoption and implementation of the crowd management system XAI. The findings show that stakeholders' roles and responsibilities affect XAI perception and use. Explanation requirements, role-based customization, and clarity and transparency showed this. According to the first sub-theme, technical experts need detailed XAI process explanations, while decision-makers want actionable summaries. According to previous research, stakeholders have different needs depending on their role, and XAI must accommodate these differences for effective use (Robbins, S. (2019; Felzmann et al., 2019). Role-based customization ensures that each stakeholder receives the necessary detail, building trust and encouraging adoption (Csaszar, & Ostler, 2020; Miller, 2017). Studies also show the importance of tailoring AI explanations to different users. Participant 1 said,

"As a Saudi security official, I've noticed that XAI understanding needs vary. Some want technical explanations, while others want high-level insights to apply it."

This variation in explanation needs emphasizes the need to tailor XAI explanations to each stakeholder group. Without clear explanations, stakeholders may mistrust or misuse XAI systems. Role-based customization was the second sub-theme. Several participants said XAI explanations must be tailored to the stakeholder group and each stakeholder's role. Participant 5 said,

"Explanations must be tailored, especially for technical and non-technical users."

Senior public safety officers may need more details than healthcare coordinators or logistics managers. This role-based customization ensures stakeholders receive the information they need for their roles, boosting system trust. These findings support previous research that emphasizes tailoring explainability to user roles to ensure each stakeholder can use and understand the AI system (Langer et al., 2021; Hoffman et al., 2023). Participants also stressed that stakeholder trust in XAI systems requires clarity and transparency. According to previous research, transparent explanations of how AI systems make decisions are crucial for stakeholder engagement and adoption (McDermid et al., 2021; Hepenstal & McNeish, 2020). Participant 6 stressed this:

"Clarity is key if we are to trust these systems."

When stakeholders must make critical XAI-based decisions, clarity and transparency are essential. Without understanding how these recommendations are made, stakeholders may be hesitant to use XAI for crowd management, limiting its effectiveness. Previous studies have stressed the importance of transparency in AI decision-making, especially in high-stakes environments (Laato et al., 2022; de Bruijn et al., 2022). XAI improves departmental collaboration by improving information sharing and decision-making. Prior research found that XAI can unify decision-makers, improving coordination and informed responses (Haque et al., 2023; Kulal et al., 2024). Participant 8 said,

"I work in Saudi security and can attest that XAI improves departmental coordination. It provides a unified data sharing platform to align teams and improve collaboration during large events."

This coordination was instrumental in crowd management, where public safety, healthcare, and transportation must collaborate to keep people safe. XAI

centralizes operations and provides real-time data to stakeholders to ensure decision-making alignment. This theme also encompassed data sharing and integration. According to several participants, XAI systems promote departmental data sharing and integration, which is crucial for crowd management. Participant 7 said,

"It makes it easier to share data, which is crucial during large events."

XAI helps stakeholders make better decisions and adapt to changing conditions by sharing information. Data integration also ensures all stakeholders have the same information, reducing miscommunication and conflicting decisions. Decision-making and communication XAI improved crowd management by aligning. Several participants said XAI aligns departmental communication and decision-making to ensure everyone works toward the same goals.

4. CONCLUSION

The research conducted through semi-structured interviews with 9 Saudi crowd management stakeholders reveals several key insights into how different groups perceive the role of XAI in enhancing crowd management efficiency. Stakeholders from various sectors agreed that XAI could improve large-scale event decision-making, operational efficiency, and stakeholder engagement. XAI ability to analyze data and predict crowd behavior in dynamic environments, such as the Hajj pilgrimage, was a game-changer for faster and more informed decision-making. XAI improved operations

and interdepartmental collaboration, enabling a more coordinated response to critical crowd management situations.

Although XAI has many benefits, stakeholders found it difficult to integrate it into crowd management systems. Participants cited outdated infrastructure and a lack of preparedness for advanced technology as major technical barriers. Many stakeholders worried about their systems' ability to handle XAI complexity, which could limit its real-time insights. Stakeholder confusion about XAI and infrastructure concerns hampered adoption. To maximize XAI capabilities, technical training and infrastructure upgrades are needed.

XAI in crowd management presents significant opportunities and challenges, according to the research. Stakeholders recognized XAI data analysis, which helps identify risks and make proactive crowd-safety decisions. Stakeholders also noted improved risk prediction and resource allocation due to XAI crowd dynamics-based resource optimization. Preventing bottlenecks improves crowd safety and operational efficiency at large events. In crowd management, stakeholder dependency was crucial to XAI adoption and implementation. Technical experts wanted detailed XAI explanations, while decision-makers wanted high-level summaries. XAI explanations must be customized to build trust and ensure all stakeholders understand and use the technology. The research also found that XAI centralizes data-sharing and aligns decision-making, which improves departmental coordination and communication during complex events involving multiple agencies.

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Afnan Alazbah

King Abdul-Aziz University,
Jeddah,
Saudi Arabia
aazbah0001@stu.kau.edu.sa

Khalid Fakeeh

King Abdul-Aziz University,
Jeddah,
Saudi Arabia
kfakeeh@kau.edu.sa
ORCID 0009-0001-8744-1006

Osama Rabie

King Abdul-Aziz University,
Jeddah,
Saudi Arabia
orabie@kau.edu.sa
ORCID 0000-0001-8680-7080
