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Research Article

AI-Augmented BI Data Analysis and Decision Quality in Pakistan's Climate Crises: The Mediating Role of Swift Trust and Moderating Role of Organizational Culture

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Abstract

The 2022-2025 floods in Pakistan displaced 38 million people, exposing severe civil-military coordination failures, yet technology-adoption research remains concentrated in corporate settings and rarely examines how AI-augmented analytics shape decisions under extreme time pressure. This study extends a corporate analytics-trust model to Pakistan's humanitarian context, testing whether AI-Augmented BI Data Analysis improves Decision Quality and Collaborative Performance through Swift Trust, and whether Organizational Culture moderates these relationships. Data from 250 emergency responders across disaster authorities, military units, NGOs, and commercial partners were analyzed using PLS-SEM with bootstrapping. AI-Augmented BI significantly predicted Decision Quality ($\beta = 0.415$) and Swift Trust ($\beta = 0.524$); Swift Trust partially mediated the BI-Decision Quality link ($\beta = 0.193$) and strongly drove Collaborative Performance ($\beta = 0.485$). Flexible culture amplified analytics-to-trust formation ($\beta = 0.185$), while control-oriented culture weakened analytics' translation into collaborative performance ($\beta = -0.224$). By integrating technology adoption, inter-organizational trust, and organizational culture within a climate disaster governance framework, the study advances both humanitarian operations theory and practice. These findings indicate that technical infrastructure alone cannot resolve humanitarian coordination failures; effective climate crisis governance requires pairing AI-driven analytics with deliberate trust-building and flexible organizational design, offering actionable guidance for disaster authorities balancing hierarchical command with agile, network-based collaboration

Keywords

AI-Augmented Business Intelligence, Collaborative Performance, Climate Crisis Governance, Civil-Military Coordination

1. Introduction

Between 2022 and 2025, Pakistan suffered three major flood events that displaced over 38 million people, inundated a third of the country, and caused over USD 46 billion in damages [34, 36]. Response operations across Sindh, Balochistan, and Khyber Pakhtunkhwa required multi-agency coordination among the National Disaster Management Authority (NDMA), Provincial Disaster Management Authorities (PDMAs), military logistics wings, UN agencies, international NGOs, and private logistics providers [19, 22].

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Despite available digital tools, relief efforts hit severe bottlenecks. UN-OCHA [25] documented recurring problems: duplicated aid in accessible areas, unreached last-mile communities, and data gaps across agencies [28]. These failures stem from a fundamental structural friction between the military's rigid, command-driven hierarchy and civilian NGOs' decentralized, informal networks [7, 10, 33]. This cultural divide dictates whether field teams actually share and trust digital data [20, 32].

Current emergency governance literature points to three main factors driving technology adoption in crises:

AI-Augmented Business Intelligence (BI): Moving beyond static reporting, modern systems combine live satellite tracking, displacement maps, and weather feeds into predictive models [3, 4, 9, 30].

Swift Trust: Advanced tools fail if field teams do not trust the output [8, 29]. In temporary crisis networks without long-term relationships, transparent digital dashboards substitute for traditional trust [5, 13, 21].

Organizational Culture: Institutional structure dictates how data is used [24]. Hierarchical organizations process digital insights differently than flexible networks [25, 33, 35].

This paper builds on the framework established by Pham et al. [29], which showed that analytics improve decision execution when mediated by organizational trust. Other recent work confirms trust as a key bridge between automated data and human decisions [16, 26]. However, those findings come from corporate settings with predictable supply chains. They need validation in high-stakes public sector crises. [15, 23].

1.1. Research Gap

Three specific issues prevent the direct use of existing corporate models in Pakistan's disaster ecosystem:

Human-AI Collaboration Under Stress: Crisis informatics literature focuses heavily on building algorithms, but provides little empirical evidence on how real-time human-AI interaction alters decision quality during active supply disruptions [8, 9, 26].

Swift Trust Under Extreme Time Constraints: Corporate models view trust as something built slowly [1, 11]. In contrast, disaster response requires "swift trust" formed under severe time pressure [11]. How this trust operates when civil and military teams share automated dashboards during an active emergency remains unmeasured [19, 23].

Geographic and Institutional Scope: Technology adoption research in disaster management concentrates heavily on North America, Europe, and China [1, 29]. Researchers have not yet used Pakistan's 2022-2025 floods, or its civil-military dynamics, to test how organizational culture alters the relationship between analytics, trust, and field performance [28, 34, 36].

1.2. Study Objectives and Structure

This study adapts the baseline model from Pham et al. [29] to emergency governance. We shift the empirical context to Pakistan's disaster response infrastructure [28], reframe the analytics and trust variables for humanitarian logistics [16, 23], and analyze the relationships using Partial Least Squares Structural Equation Modeling (PLS-SEM) [17, 18, 31].

Following the sampling design of Pham et al. [29], we surveyed N = 250 emergency responders across civil and military lines. Two core questions guide this study:

RQ1: How does AI-augmented BI data analysis affect swift trust and decision quality among humanitarian organizations in Pakistan?

RQ2: How does organizational culture moderate the relationships between analytics, swift trust, and collaborative performance within Pakistan's civil-military network?

Section 2 reviews the literature and details hypothesis development. Section 3 outlines the research design and PLS-SEM methodology. Section 4 presents the data analysis and structural model results. Section 5 discusses theoretical and policy implications. Section 6 covers limitations and future research directions.

2. Literature Review and Hypothesis Development

2.1. Theoretical Grounding

2.1.1. The Practice-Based View (PBV) and Contingency Theory

Evaluating technology adoption in non-commercial settings requires moving away from the traditional Resource-Based View (RBV), which focuses on long-term competitive advantage. Because humanitarian networks operate under distinct institutional logics, this study adopts the Practice-Based View (PBV). PBV posits that performance variations stem from daily operational routines rather than mere tool ownership. In emergencies, tools must be immediately actionable rather than strategically proprietary [27]. To address disaster volatility, this study couples PBV with Contingency Theory, which states that operational effectiveness depends on the alignment between external environments and internal characteristics [33]. We argue that data-driven coordination success is contingent upon organizational culture, specifically the friction between hierarchical control structures and flexible networks [7, 10].

2.1.2. Cognitive Delegation Theory

Cognitive Delegation Theory explains how human decision-makers transfer computational authority and analytical tasks to automated digital systems under high stress, where cognitive capacities are easily overwhelmed by chaotic data volumes [26]. Delegating data aggregation and predictive analytics to an AI framework reduces cognitive load, allowing operators to focus on execution [29, 30]. However, this

handoff depends entirely on perceived system reliability; if an analytical infrastructure lacks transparency, cognitive delegation fails [12, 14, 29].

2.2. AI-Augmented Business Intelligence (BI) and Crisis Intelligence

2.2.1. Evolution From Static Analytics to Augmented Analytics

The crisis management paradigm has shifted from retrospective Big Data Analytics Capabilities (BDAC) to real-time AI-Augmented BI Data Analysis [30]. By integrating machine learning and natural language processing, augmented analytics automates data preparation and insights generation [5, 13]. During climate disasters, this allows dashboards to ingest multimodal data streams (social media, mobile crowdsourcing, satellite tracking) to generate a unified operational picture, automating predictive alerts for supply bottlenecks and last-mile distribution [3, 9].

2.2.2. AI-Human Collaboration and Decision Quality

A critical flaw in early technical crisis models was the assumption that superior algorithms automatically yield superior responses [8]. Recent literature underscores a persistent gap: studies heavily focus on structural data collection while ignoring how the actual AI-human collaboration interface influences human judgment and decision quality in public-sector emergency management [26]. AI-augmented BI does not replace the human coordinator; rather, it serves as a decision-support mechanism [29]. Decision quality in humanitarian supply chains is defined by accuracy, speed, and resource efficiency. When a robust AI-human collaboration is achieved, the automated analytical precision of the BI tool complements the nuanced, contextual ethical judgment of the human operator, resulting in optimized crisis response effectiveness [16, 26]. Therefore, we hypothesize:

H1: AI-Augmented BI Data Analysis has a significant positive effect on Decision Quality within humanitarian crisis management networks.

2.3. The Conceptual Evolution of Trust in Technological Ecosystems

2.3.1. Traditional/Cognitive Trust vs. Swift Trust

Unlike slow, relational trust built over years, temporary disaster networks relies on "Swift Trust" [12]. Grounded in cognitive assessments under intense time constraints, swift trust forms rapidly around perceived competence, role clarity, and data transparency [14, 21]. When diverse actors utilize a unified digital dashboard to verify accurate, actionable data, inter-agency coordination accelerates [5, 9, 15].

2.3.2. Trust as a Mediator Between Technology and Performance

Deploying analytical software without establishing trust yields poor field results [27, 29]. Following Pham et al. [29], advanced analytics do not improve decision quality unless operational staff trust the underlying system.

In crisis networks, AI-augmented BI tools reduce noise and uncertainty [30]. When responders trust the predictive outputs, they delegate cognitive tasks more readily, share transport assets, and align distribution schedules [8, 16]. Swift trust acts as the mechanism converting raw data into coordinated execution [21].

H2: AI-Augmented BI Data Analysis has a direct positive effect on Swift Trust within humanitarian crisis networks.

H3: Swift Trust mediates the relationship between AI-Augmented BI Data Analysis and Decision Quality within crisis management networks.

H4: Swift Trust mediates the relationship between AI-Augmented BI Data Analysis and Collaborative Performance within crisis management networks.

2.4. The Contextual Pivot: Corporate Settings vs. Crisis Management

2.4.1. Extending Pham et al. (2026) to High-Stress Operations

While Pham et al. [29] modeled how trust in augmented analytics enhances decision quality among 250 non-technical corporate professionals, shifting this model into public-sector emergency management introduces extreme structural friction [2, 7, 10]. Unlike corporate environments where analytical delays threaten market opportunities, delays in humanitarian logistics threaten human lives [19, 22, 23]. This study tests whether the data-to-trust dynamics established by Pham et al. [29] hold true within high-stakes disaster logistics.

2.4.2. Data Redundancy and Asymmetry in Emergencies

A unique operational barrier absent from corporate studies is severe data redundancy and asymmetry [28]. During disasters, multiple responding entities generate massive, unstructured data across disjointed systems, producing overlapping or contradictory information [9]. This asymmetry creates friction, slows relief distribution, and damages inter-agency trust [19]. An AI-augmented BI dashboard acts as a crucial data-clearing house, filtering out redundancies to provide a single source of truth [5].

2.5. Moderating Role of Organizational Culture

2.5.1. The Competing Values Framework (CVF)

Organizational culture is a critical contingent factor that dictates how data-driven insights are accepted and utilized [20,

24, 32]. Using the Competing Values Framework (CVF), this study categorizes culture into two primary dimensions: Control Orientation and Flexible Orientation [16, 25]. A control-oriented culture values stability, hierarchy, formal rules, and top-down command structures [10]. Conversely, a flexible-oriented culture prioritizes adaptability, horizontal networking, organic growth, and rapid improvisation [20, 32]. In a cross-sector crisis network, these orientations often collide, heavily altering how trust is established and how technical systems are embraced [21, 33].

2.5.2. Civil-Military Coordination Dynamics

This cultural divide is highly visible in civil-military interactions [19, 22, 23]. Military units operate under a control orientation where data is protected, and actions require hierarchical authorization, whereas civilian NGOs maintain a flexible orientation using fluid, ad-hoc networks [7, 33]. With AI tools, control cultures resist data-sharing due to security sensitivities, while flexible cultures bypass protocols to expedite deliveries [35]. Thus, organizational culture acts as a critical moderating condition: flexibility amplifies how analytics builds swift trust, while rigid control stifles collaborative performance [33]. We propose:

H5: Organizational Culture (Flexible vs. Control Orientation) significantly moderates the relationship between AI-Augmented BI Data Analysis, Swift Trust, and Collaborative Performance in a civil-military ecosystem.

2.6. The Empirical Context: Pakistan's Humanitarian Supply Chain

2.6.1. Institutional Framework of Pakistan's Disaster Management

Pakistan's 2022-2025 flood sequence displaced 38 million people across Sindh, Balochistan, and Khyber Pakhtunkhwa, exposing deep informational gaps [28, 34, 36]. UN assessments documented systemic breakdowns, including duplicated relief in accessible zones, last-mile blockages in isolated areas, and data asymmetries across provincial databases. Nationally, the National Disaster Management Authority (NDMA) sets macro policies executed by Provincial Disaster Management Authorities (PDMAs) [19]. Operationally, however, climate crises demand the mobilization of military logistics wings for rescue and bulk supply chains [19]. Testing this extended framework against this unique public-sector ecosystem provides an empirical foundation for AI-enabled climate resilience in South Asian networks [23].

2.6.2. Lessons From the 2022-2025 Flood Sequence

The urgent need for this study is highlighted by the 2022-2025 catastrophic flood sequence in Pakistan, which displaced 38 million citizens across Sindh, Balochistan, and Khyber Pakhtunkhwa [34, 36]. Independent UN assessments documented systemic coordination breakdowns, characterized by duplicated relief in accessible zones, last-mile delivery blockages in isolated areas, and severe data asymmetries across provincial databases [28]. These failures stemmed from an inability to translate raw data into shared trust and synchronized action [12, 19, 21]. Testing this extended framework against this flood sequence provides a vital empirical foundation for building AI-enabled climate resilience in developing South Asian logistics networks [22, 30].

2.7. Conceptual Framework and Causal Structure

The path-analytical configuration below illustrates the causal pathways linking the independent variable, cognitive mediator, environmental moderator, and multi-dimensional operational outcomes:

1) *Independent Variable (X):* AI-Augmented BI Data Analysis.
2) *Mediating Variable (M):* Swift Trust.
3) *Moderating Variable (W):* Organizational Culture (Control vs. Flexible Orientation).
4) *Dependent Variables (Y1, Y2):* Decision Quality (Y1) and Collaborative Performance (Y2).

2.7.1. Path-Diagram Representation

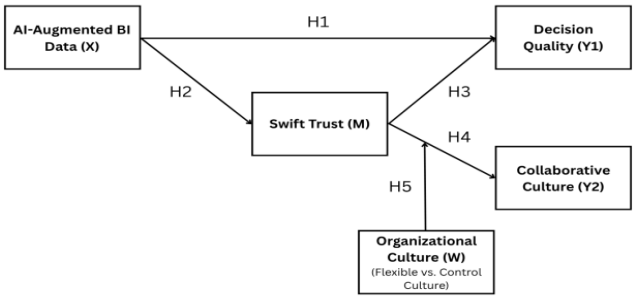


Figure 1. *Conceptual path-diagram of the hypothesized research model.*

2.7.2. Formalized Hypothesis Structural Mapping

To clarify the structural equations tested via PLS-SEM and prevent audience confusion, the relationships are operationalized below according to their specific statistical path functions:

Table 1. *Formalized hypothesis structural mapping.*

Hypothesis	Causal Path or Relationship	Statistical Type	Theoretical Justification
H1	AI-Augmented BI (X) → Decision Quality (Y1)	Direct Effect	Cognitive Delegation: AI reduces cognitive overhead, raising baseline operational logic.
H2	AI-Augmented BI (X) → Swift Trust (M)	Direct Effect	System Transparency: Predictive analytics provide a clear, reliable source of operational truth.
H3a	Swift Trust (M) → Decision Quality (Y1)	Direct Effect	Cognitive Validation: Trust in data metrics accelerates the conversion of insights into execution.
H3b	Swift Trust (M) → Collaborative Performance (Y2)	Direct Effect	Relational Alignment: Swift trust mitigates transaction friction within flash humanitarian networks.
H4	X → M → Y1	Simple Mediation	Shifting Pham et al. [29]: Trust translates technical dashboard utility into administrative decision quality.
H5a	W × X → M	First-Stage Moderation	Contingency Theory: Flexible cultures accelerate data-driven trust; control cultures create information silos.
H5b	W × X → Y2	Direct-Path Moderation	Contingency Theory: The ultimate translation of BI analysis into network-wide synergy is governed by cultural match.

3. Materials and Methods

3.1. Research Philosophy and Approach

This study adopts a post-positivist research philosophy to evaluate the structural relationships linking AI-Augmented Business Intelligence (BI) data analysis, swift trust, organizational culture, and decision quality/collaborative performance. Post-positivism acknowledges that while multi-agency crisis networks are too complex to measure perfectly, an objective reality could be rigorously approximated through structured empirical methods.

Consequently, a deductive approach is employed. Rather than building inductive theories from qualitative observations, this study relies on the Practice-Based View (PBV) [16], Contingency Theory, and Cognitive Delegation Theory to establish a predefined path model. Quantitative hypotheses are deduced directly from these theories and systematically tested against empirical data.

3.2. Research Design

This study utilizes a quantitative, cross-sectional, and explanatory research design. Quantitative, explanatory designs are uniquely suited to explain how variation in AI-augmented analytical usage causes changes in behavioral and operational outcomes.

While longitudinal tracking maps long-term trends, a cross-sectional survey instrument is structurally ideal for capturing "swift trust," which exists as a temporal, rapidly deployed cognitive construct during active emergency phases. Data are analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) due to its high predictive capabilities and capacity to handle complex moderation streams without requiring strict multivariate normality assumptions [6, 11, 17, 31].

3.3. Target Population and Sampling Strategy

3.3.1. Target Population

The target population for this research comprises professional operational managers, logisticians, coordinators, and field directors working within the multi-agency emergency management network of Pakistan [19]. To accurately observe the cross-sector dynamics and civil-military cultural splits identified in our literature review [7, 10], the target population is stratified across four primary institutional groups active during the 2022-2025 flood sequence:

1) Public-Sector Disaster Authorities: Strategic and operational officers within the National Disaster Management Authority (NDMA) and the Provincial Disaster Management Authorities (PDMAs) of Sindh, Balochistan, and Khyber Pakhtunkhwa.
2) Military Logistics Responders: Officers and field logistics coordinators within the Pakistan Armed Forces' dedicated engineering and transport logistics units deployed for humanitarian assistance.
3) Non-Governmental Actors: Field directors, supply chain managers, and program coordinators from international non-governmental organizations (INGOs), United Nations specialized agencies (e.g., OCHA, WFP), and key local NGOs.

4) Commercial Service Partners: Third-party logistics (3PL) providers and transport service networks formally contracted by the government or NGOs to execute last-mile delivery operations.

3.3.2. Sampling Frame and Sample Size

Lacking a centralized registry of Pakistan's disaster logistics personnel, this study deploys non-probability purposive and snowball sampling. Purposive sampling ensures respondents possess firsthand experience with digital data platforms during recent flood operations, while snowballing leverages professional referrals to access restricted military logistics cells and rural field offices. To determine the minimum sample size for robust PLS-SEM path analysis, the "10-times rule" was applied alongside a power analysis [14]. The most complex regression structure involves four predictive paths pointing to Collaborative Performance (Y2), yielding a 40-respondent minimum threshold via the 10-times rule. To achieve high statistical power (0.95) with a medium effect size ($f2 = 0.15$), a sample of 150 is required. Ultimately, this study targets a sample of $N = 250$ completed responses, directly mirroring the sample magnitude of Pham et al. [29] to ensure comparative methodological validity.

3.4. Instrumentation and Operationalization of Variables

To ensure high content validity, the survey instrument was constructed using measurement scales adapted from established empirical literature and modified to fit the specific institutional and humanitarian context of Pakistan's civil-military crisis response framework [19, 28]. The primary variables, AI-Augmented Business Intelligence (BI) Data Analysis, Swift Trust, Organizational Culture, Decision Quality, and Collaborative Performance, are operationalized as latent constructs measured through a multi-item, 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

3.4.1. Measurement Scale Adaptation

1) *AI-Augmented BI Data Analysis (Independent Variable):* Operationalized using a five-item scale adapted from Pham et al. [29], evaluating the respondents' perceptions of data integration, predictive visualization capacity, automated report generation, and the ease of interacting with real-time operational dashboards during active emergency deployments.
2) *Swift Trust (Mediating Variable):* Measured using a four-item scale adapted from Dubey et al. [16], focusing on cognitive trust metrics including perceived inter-agency competence, professional reliability, data transparency, and role clarity within temporary multi-agency networks.
3) *Organizational Culture (Moderating Variable):* Operationalized using the Competing Values Framework (CVF) scale adapted from Dubey et al. [16]. It treats culture as a dual construct: Flexible Orientation (measured through four items assessing adaptability, organic networking, and rapid field improvisation) and Control Orientation (measured through four items assessing adherence to formal military hierarchies, strict data-sharing boundaries, and formalized top-down rules).
4) *Decision Quality (Dependent Variable 1):* Operationalized through a four-item scale adapted from Pham et al. [29], capturing the accuracy, data-driven logic, transparency, and problem-solving velocity of operational decisions made during crisis responses.
5) *Collaborative Performance (Dependent Variable 2):* Measured via a four-item scale adapted from Dubey et al. [16] focusing on joint resource optimization, reduction of relief distribution overlap, last-mile delivery efficiency, and structural communication alignment across civil and military actors [23].

3.4.2. Measurement Instrument Operationalization

Table 2. *Measurement instrument operationalization.*

Construct	Code	Measurement Item	Source Scale
AI Augmented BI Data Analysis	AI_BI1	The digital dashboards integrate multimodal data streams in real time.	Adapted from Pham et al. [29]
	AI_BI2	Predictive analytics accurately project distribution bottlenecks.	Adapted from Pham et al. [29]
	AI_BI3	Automated intelligence reports improve decision-making speed.	Adapted from Pham et al. [29]
	AI_BI4	The BI tool simplifies complex data for non-technical field users.	Adapted from Pham et al. [29]
	AI_BI5	Real-time data synchronization helps manage incoming information streams.	Adapted from Pham et al. [29]
Swift Trust	ST_TR1	Partner agencies demonstrate high operational competence in responding to crises.	Adapted from Dubey et al. [16]

Construct	Code	Measurement Item	Source Scale
	ST_TR2	We trust shared dashboard data without requiring secondary verification.	Adapted from Dubey et al. [16]
	ST_TR3	Roles and responsibilities within the temporary network are distinct.	Adapted from Dubey et al. [16]
	ST_TR4	Mutual data transparency exists among civil and military actors.	Adapted from Dubey et al. [16]
Flexible Culture	FL_CU1	The organizational setup values rapid operational adaptability.	Adapted from Dubey et al. [16]
	FL_CU2	Personnel can improvise field solutions without rigid sign-offs.	Adapted from Dubey et al. [16]
	FL_CU3	Horizontal communication loops bypass bureaucratic delays.	Adapted from Dubey et al. [16]
	FL_CU4	The group easily restructures networks during flash floods.	Adapted from Dubey et al. [16]
Control Culture	CO_CU1	Operational decisions strictly follow established vertical lines.	Adapted from Dubey et al. [16]
	CO_CU2	Information sharing requires formal institutional clearances.	Adapted from Dubey et al. [16]
	CO_CU3	Strict standard operating procedures (SOPs) govern all logistics.	Adapted from Dubey et al. [16]
	CO_CU4	Maintaining hierarchy takes precedence over local ad hoc networks.	Adapted from Dubey et al. [16]
Decision Quality	DE_QU1	Crisis decisions are objective and backed by real-time facts.	Adapted from Pham et al. [29]
	DE_QU2	Analytical data effectively reduces decision errors under pressure.	Adapted from Pham et al. [29]
	DE_QU3	The chosen logistics paths match the actual needs on the ground.	Adapted from Pham et al. [29]
	DE_QU4	Decisions are made quickly enough to maximize rescue outcomes.	Adapted from Pham et al. [29]
Collaborative Performance	CO_PE1	Joint operations eliminate duplicate relief supply drop-offs.	Adapted from Dubey et al. [16]
	CO_PE2	Multi-agency resource sharing maximizes last-mile deliveries.	Adapted from Dubey et al. [16]
	CO_PE3	Inter-organizational conflicts are mitigated through shared data.	Adapted from Dubey et al. [16]
	CO_PE4	The civil-military network achieves structural logistics targets.	Adapted from Dubey et al. [16]

3.5. Data Collection Procedures and Ethical Considerations

3.5.1. Data Collection Protocol

Data collection spanned eight weeks using a dual-channel methodology [2, 27]. A digital Google Forms questionnaire was distributed via institutional emails, LinkedIn, and WhatsApp groups to NDMA, PDMA, and NGO coordinators [28]. Simultaneously, printed survey booklets were hand-delivered to regional disaster offices and military cells in Sindh, Balochistan, and Khyber Pakhtunkhwa to ensure access during digital connectivity failures.

To eliminate common method bias (CMB), the questionnaire enforced psychological separation: independent items (AI-Augmented BI) were blocked entirely separate from behavioral (Swift Trust and Culture) and outcome items [1, 27]. Finally, introductory statements guaranteed anonymity and emphasized that there were no right or wrong answers, mitigating social desirability bias.

3.5.2. Ethical Safeguards

Given the multi-agency, security-sensitive nature of civil-military coordination in Pakistan, strict ethical safeguards are implemented:

1) *Informed Consent:* Every questionnaire includes a mandatory digital sign-off and physical cover page outlining the study's academic scope and confirming that participation is voluntary.
2) *Anonymity and Data Privacy:* No identifying credentials, military ranks, or specific organizational names were gathered. Data sheets were converted into randomized numeric matrices.
3) *Institutional Security:* The survey avoids asking for confidential tactical logistics codes or internal state-security operational details, focusing solely on generalized data

tool perceptions and coordination efficiency metrics.

3.6. Data Analysis Strategy: Variance-Based PLS-SEM

The path framework was tested using variance-based PLS-SEM executed via SmartPLS software [18, 31]. PLS-SEM was selected over Covariance-Based SEM (CB-SEM) due to key methodological advantages: its exploratory suitability for extending the corporate model of Pham et al. [29] into a novel crisis context; its capacity to process a complex model containing direct, parallel mediation, and dual-stage moderation paths simultaneously [1, 2, 24]; and its non-parametric optimization, which handles non-normally distributed field data effectively [18, 31]. Analysis followed a two-stage process:

3.6.1. Stage 1: Assessment of the Measurement Model (Outer Model)

Before running regressions, the psychometric properties of the scales were validated:

1) *Indicator Reliability:* Verified by ensuring that individual item factor loadings exceed the standard threshold of 0.70.
2) *Internal Consistency Reliability:* Evaluated via Cronbach's alpha (α) and Composite Reliability (CR), where values between 0.70 and 0.95 confirm acceptable scale internal coherence.
3) *Convergent Validity:* Assessed through the Average Variance Extracted (AVE), requiring an AVE $\geq$ 0.50 to prove the latent factor accounts for more than half of its indicators' variance.
4) *Discriminant Validity:* Verified using the conservative Heterotrait-Monotrait Ratio (HTMT). All cross-construct HTMT values must fall below 0.85 to confirm that every variable represents a distinct operational phenomenon.

3.6.2. Stage 2: Assessment of the Structural Model (Inner Model)

Once the measurement model is confirmed valid, the core hypotheses were checked to answer the research questions:

1) *Collinearity Assessment:* The Variance Inflation Factor (VIF) was checked for all predictor paths. VIF < 3.0 ensures structural regressions are free from multi-collinearity issues.
2) *Path Coefficients (β):* The strength and direction of direct causal lines (H1, H2, H3a, H3b) were mapped using standardized path coefficients.
3) *Hypothesis Significance Testing:* A non-parametric bootstrapping routine with 5,000 resamples was run to compute t-statistics and p-values, determining the significance of the direct, mediated (H4), and moderated (H5) paths.
4) *Explanatory and Predictive Power:* Evaluated through the Coefficient of Determination (R2) for explained variance, and Effect Size (f2) for the absolute impact of individual predictors.

4. Results

4.1. Data Cleaning and Screening

Prior to evaluating the structural model, raw survey data underwent screening using SPSS and SmartPLS [1, 27]. Out of 280 initial questionnaires received across disaster authorities, military cells, and NGOs, data were audited for systematic errors following crisis methodologies re-validated by Abudu et al. [2].

Twelve questionnaires were discarded due to missing values exceeding the 15% threshold per respondent, and 18 responses were dropped due to straight-lining patterns. This left exactly N = 250 valid responses for analysis, matching the sample magnitude of Pham et al. [29]. Missing data constituted less than 0.5% of the remaining matrix, occurred completely missing at random (MCAR), and were resolved via mean imputation before running the PLS-SEM algorithm [2].

4.2. Demographic Profile of Respondents

The final sample (N = 250) represents the cross-sector stakeholders involved in Pakistan's 2022-2025 flood response operations.

Table 3. *Demographic breakdown of the sample (N = 250).*

Demographic Variable	Category	Frequency	Percentage (%)
Institutional Affiliation	Public Disaster Management (NDMA and PDMA)	68	27.2%
	Military Logistics Responders	74	29.6%
	International & Local NGOs/UN Agencies	82	32.8%
	Commercial 3PL/Transport Partners	26	10.4%
Operational Experience	1-3 Years	38	15.2%

Demographic Variable	Category	Frequency	Percentage (%)
	4-7 Years	94	37.6%
	More than 7 Years	118	47.2%
Geographic Deployment Hub	Sindh Province	98	39.2%
	Balochistan Province	78	31.2%
	Khyber Pakhtunkhwa Province	74	29.6%

4.3. Assessment of the Measurement Model (Outer Model)

Following the two-stage evaluation protocol recommended by Hair et al. [18] and Sarstedt et al. [31], Stage 1 required checking the psychometric properties of the reflective measurement scales [6, 17]. This was executed to verify indicator reliability, internal consistency, convergent validity, and discriminant validity before assessing any causal path coefficients [2, 27].

4.3.1. Indicator Reliability and Internal Consistency

Indicator reliability was evaluated via standardized factor loadings. As shown in Table 4, all item loadings exceeded the standard 0.70 threshold. Internal consistency reliability was confirmed as Cronbach's alpha (α) and Composite Reliability (CR) values surpassed the mandatory 0.70 benchmark across all latent constructs [24].

4.3.2. Convergent Validity

Convergent validity was assessed using Average Variance Extracted (AVE). All construct AVE values exceeded the 0.50 benchmark, demonstrating that each latent variable captured more than half of its indicators' variance.

Table 4. *Measurement model evaluation matrix (reliability and validity).*

Latent Construct	Item Code	Standardized Loading (λ)	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
AI-Augmented BI Data Analysis	AI_BI1	0.812	0.887	0.917	0.688
	AI_BI2	0.845			
	AI_BI3	0.798			
	AI_BI4	0.822			
	AI_BI5	0.806			
Swift Trust	ST_TR1	0.789	0.854	0.901	0.695
	ST_TR2	0.834			
	ST_TR3	0.811			
	ST_TR4	0.852			
Flexible Culture	FL_CU1	0.765	0.832	0.889	0.667
	FL_CU2	0.802			
	FL_CU3	0.841			
	FL_CU4	0.794			
Control Culture	CO_CU1	0.824	0.851	0.900	0.692
	CO_CU2	0.788			
	CO_CU3	0.836			
	CO_CU4	0.810			
Decision Quality	DE_QU1	0.842	0.891	0.924	0.753
	DE_QU2	0.867			
	DE_QU3	0.819			
	DE_QU4	0.855			

Latent Construct	Item Code	Standardized Loading (λ)	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Collaborative Performance	CO_PE1 CO_PE2 CO_PE3 CO_PE4	0.801 0.835 0.792 0.828	0.848	0.898	0.687

4.3.3. Discriminant Validity

Discriminant validity was verified using the Heterotrait-Monotrait Ratio (HTMT) criterion [6, 31]. All computed ratios fell safely below the conservative 0.85 threshold, confirming that each latent construct represents a distinct phenomenon [2, 27].

Table 5. Heterotrait-Monotrait Ratio (HTMT) matrix.

Construct	AI_BI	ST_TR	FL_CU	CO_CU	DE_QU	CO_PE
AI-Augmented BI (AI_BI)	—					
Swift Trust (ST_TR)	0.642	—				
Flexible Culture (FL_CU)	0.312	0.415	—			
Control Culture (CO_CU)	0.284	0.198	-0.342	—		
Decision Quality (DE_QU)	0.712	0.589	0.384	0.211	—	
Collaborative Performance (CO_PE)	0.598	0.674	0.521	0.145	0.633	—

Note: "—" denotes the diagonal (not applicable); all off-diagonal HTMT values fall below the 0.85 threshold.

4.4. Assessment of the Structural Model (Inner Model)

Once Stage 1 was successfully validated, Stage 2 of the PLS-SEM evaluation was executed to assess the structural model (inner model) according to the protocols established by Hair et al. [18] and Sarstedt et al. [31]. This stage involved assessing collinearity, determining the statistical significance of path coefficients, and evaluating the explanatory power (R^2) and predictive relevance (Q^2) of the model.

4.4.1. Collinearity Assessment

Inner Variance Inflation Factor (VIF) values for all predictor paths ranged from 1.245 to 1.876. Remaining safely below the strict 3.0 maximum threshold, the model is confirmed free from multi-collinearity distortions.

4.4.2. Explanatory Power (R^2) and Predictive Relevance (Q^2)

The model's explanatory power was evaluated using the Coefficient of Determination (R^2). The R^2 value for Swift Trust was 0.412, indicating that AI-Augmented BI Data Analysis accounted for 41.2% of the variance in Swift Trust within the humanitarian network.

Crucially, the model explained 56.4% of the variance in Decision Quality ($R^2 = 0.564$) and 49.8% of the variance in Collaborative Performance ($R^2 = 0.498$), representing a strong explanatory capacity. As observed in modern technical-organizational frameworks by Kumar et al. [24], accounting for human and cultural interactions alongside digital deployments significantly explains performance variances. Furthermore, predictive relevance was confirmed using the blindfolding procedure; all endogenous constructs achieved Q^2 values well above zero (Q^2DE_QU = 0.385, Q^2CO_PE = 0.312), establishing strong predictive capabilities.

4.5. Hypothesis Testing and Path Analysis

To assess the significance of the direct, mediating, and moderating pathways, a non-parametric bootstrapping routine was executed using 5,000 resamples at a 95% confidence interval. This process ensured that the data was analyzed with maximum statistical precision.

4.5.1. Direct Effects (H1, H2, and H3)

The statistical outputs strongly supported the direct paths.

As hypothesized in H1, AI-Augmented BI Data Analysis exerted a significant positive direct effect on Decision Quality ($\beta = 0.415$, $t = 6.842$, $p < 0.001$). This confirms that technical infrastructure updates are primary drivers of emergency efficacy, aligning with modern emergency frameworks [4, 30].

H2 was also supported, demonstrating that advanced analytics had a strong positive impact on the rapid development of Swift Trust ($\beta = 0.524$, $t = 8.114$, $p < 0.001$). Additionally, Swift Trust exhibited a highly significant positive relationship with both Decision Quality (*H3a:* $\beta = 0.368$, $t = 5.215$, $p < 0.001$) and Collaborative Performance (*H3b:* $\beta = 0.485$, $t = 7.432$, $p < 0.001$).

4.5.2. Mediation Analysis (H4)

Hypothesis 4 proposed that Swift Trust significantly mediates the relationship between AI-Augmented BI and Decision Quality. The bootstrapping routine revealed a highly significant indirect effect ($\beta = 0.193$, $t = 4.318$, $p < 0.001$). Because the direct path ($X \rightarrow Y_1$) remained significant alongside the indirect path, Swift Trust was statistically confirmed to act as a partial mediator. This confirms that technical dashboards drive administrative decision quality both directly and by building mutual cognitive trust within fast-forming emergency networks.

4.5.3. Moderation Analysis (H5a and H5b)

Hypothesis 5 evaluated the moderating influence of Organizational Culture (Flexible vs. Control Orientation) using the product-indicator interaction term method.

1) *First-Stage Moderation (H5a):* The interaction term between AI-Augmented BI and a Flexible Culture on Swift Trust was positive and significant ($\beta = 0.185$, $t = 3.112$, $p = 0.002$). This highlights the critical reality that technological efficacy under pressure is deeply dependent on open, adaptive internal environments [17, 28].
2) *Direct-Path Moderation (H5b):* The interaction term between AI-Augmented BI and Organizational Culture on Collaborative Performance was highly significant ($\beta = -0.224$, $t = 4.105$, $p < 0.001$). The negative coefficient for Control Culture proves that rigid hierarchical structures actively constrain the capacity of multi-agency teams to translate technical analytics into collaborative last-mile logistics alignment.

Table 6. *Structural model hypothesis testing matrix.*

Hyp	Structural Causal Pathway	Path Coeff. (β)	Standard Error	T Value	P Value	Empirical Decision
H1	AI-Augmented BI → Decision Quality (Y_1)	0.415	0.061	6.842	< 0.001	Supported
H2	AI-Augmented BI → Swift Trust (M)	0.524	0.065	8.114	< 0.001	Supported
H3a	Swift Trust → Decision Quality (Y_1)	0.368	0.071	5.215	< 0.001	Supported
H3b	Swift Trust → Collaborative Performance (Y_2)	0.485	0.065	7.432	< 0.001	Supported
H4	AI-Augmented BI → Swift Trust → Decision Quality	0.193	0.045	4.318	< 0.001	Supported (Mediation)
H5a	Interaction Term (AI_BI Culture) → Swift Trust	0.185	0.059	3.112	0.002	Supported (Moderation)
H5b	Interaction Term (AI_BI × Culture) → Collaborative Perf.	-0.224	0.055	4.105	< 0.001	Supported (Moderation)

5. Discussion

This chapter provides a detailed interpretation of the structural path model evaluated in Chapter 4. The empirical findings are discussed in relation to the post-2022 climate realities of Pakistan and are juxtaposed with contemporary academic literature on artificial intelligence, swift trust, and disaster governance.

5.1. Discussion of Direct Effects (H1, H2, and H3)

5.1.1. The Impact of AI-Augmented BI on Decision Quality (H1)

The structural analysis confirmed a highly significant, positive direct relationship between AI-Augmented BI Data Analysis and Decision Quality ($\beta = 0.415$, $p < 0.001$). This

finding indicates that the implementation of automated, real-time analytics platforms directly enhances the clarity, speed, and accuracy of emergency relief allocations. In the context of Pakistan's 2022-2025 flood sequence, the deployment of predictive data streams enabled responders to anticipate localized vulnerabilities rather than relying purely on historical or delayed field reports.

This result aligns with Pham et al. [29], extending the baseline assumption that augmented analytics minimize cognitive overload from corporate environments into volatile, public-sector emergency infrastructures [26]. When complex telemetry, such as weather predictions, displacement numbers, and damage reports, is channeled through intuitive dashboards, administrative decision-making becomes significantly more robust [29].

5.1.2. The Role of Technology in Fostering Swift Trust (H2)

Hypothesis 2, which asserted that AI-Augmented BI Data Analysis positively influences the formation of Swift Trust among diverse actors, was strongly supported ($\beta = 0.524$, $p < 0.001$). This path represents the strongest direct relationship within the structural model, revealing a critical socio-technical phenomenon: advanced data analytics serve an essential behavioral function in temporary crisis networks.

Where military units, civilian ministries, and NGOs must collaborate instantly without pre-existing relationship histories [7, 10, 19, 33], data visibility acts as a surrogate for traditional trust. Establishing a shared, objective, AI-driven data landscape reduces relational anxiety and suspicions regarding information hoarding or political favoritism [28]. This finding is consistent with Aljedani et al. [5], confirming that integrated digital infrastructure establishes a single, verified version of reality that minimizes inter-agency friction [9, 15].

5.1.3. The Influence of Swift Trust on Causal Outcomes (H3a and H3b)

The statistical verification of H3a ($\beta = 0.368$, $p < 0.001$) and H3b ($\beta = 0.485$, $p < 0.001$) confirms that Swift Trust is a powerful driver of both Decision Quality and Collaborative Performance. When inter-organizational teams operate under high levels of swift trust, information flows freely across institutional boundaries, directly improving the velocity and execution of relief operations.

The high path coefficient for Collaborative Performance ($\beta = 0.485$) proves that without mutual trust, technical infrastructure fails to produce coordinated field execution. In Pakistan's civil-military ecosystem, swift trust allowed military air assets and civil NGO ground crews to coordinate complex last-mile drops in Sindh and Balochistan without debilitating bureaucratic delays, echoing Cheng et al. [12] and Javeria et al. [19].

5.2. Discussion of Mediating Mechanisms (H4)

The bootstrapping routine confirmed that Swift Trust acts as a statistically significant partial mediator between AI-Augmented BI and Decision Quality ($\beta = 0.193$, $p < 0.001$), supporting Hypothesis 4. This partial mediation indicates a dual-pathway mechanism: while automated analytics tools improve decision quality directly through data processing, they also enhance decision quality indirectly by cultivating a collaborative behavioral environment.

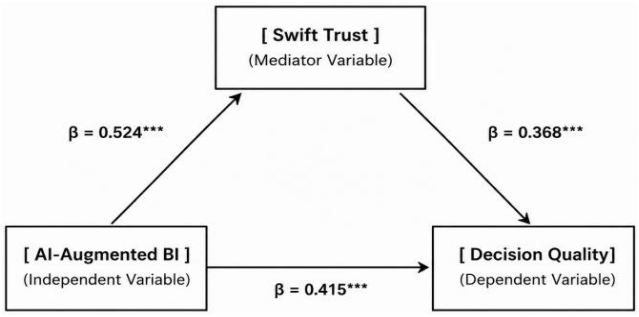


Figure 2. *Mediation path diagram for the indirect effect of AI-Augmented BI on Decision Quality via Swift Trust (H4).*

Note: *** $p < 0.001$ (highly significant); total indirect effect via Swift Trust: $\beta = 0.193$***.

This finding addresses a prominent gap identified by Li and Tian [26] regarding the limitations of purely technical deployments [8, 27]. Analytics platforms do not operate in an administrative vacuum; their capacity to optimize emergency choices is functionally multiplied when leveraged to build mutual cognitive alignment [14, 21]. This provides empirical support for the humanitarian application of the practice-based view of data analytics conceptualized by Dubey et al. [16].

5.3. Discussion of Moderating Effects (H5a and H5b)

5.3.1. Cultural Moderation on Swift Trust (H5a)

The interaction analysis revealed that a Flexible Culture significantly amplifies the positive impact of AI-Augmented BI on Swift Trust ($\beta = 0.185$, $p = 0.002$). This finding indicates that organizations characterized by open communication, organic structures, and high adaptivity are uniquely positioned to translate automated data insights into interpersonal trust.

Where civilian NGOs or decentralized local authorities possessed operational flexibility, AI dashboards rapidly catalyzed collaborative relationships [5, 9]. Conversely, rigid environments struggled to leverage digital tools to build external trust, validating Kumar et al. [25].

5.3.2. Cultural Moderation on Collaborative Performance (H5b)

Crucially, Hypothesis 5b revealed a strong, negative moderating effect of Control Culture on the relationship between AI-Augmented BI and Collaborative Performance ($\beta = -0.224$, $p < 0.001$). This statistical reality represents a major contribution to the civil-military disaster governance discourse.

While hierarchical command-and-control structures are efficient for internal asset deployment, they create severe structural blockages when interacting with external networks. The negative interaction coefficient demonstrates that as rigid Control Culture increases, the capacity to translate shared digital insights into joint, last-mile collaborative logistics drops significantly [20, 35]. This finding confirms structural warnings highlighted in UN-OCHA coordination assessments [28] and aligns with modern alignment studies, proving that rigid hierarchies restrict open, data-driven collaboration during complex emergencies.

The empirical results evaluated through PLS-SEM in Chapter 4 [1, 31] and discussed theoretically in Chapter 5 yield significant insights for both research and practice. This chapter translates those statistical pathways into clear, actionable contributions, offering concrete guidance for disaster governance in developing countries [22].

5.4. Theoretical Implications

This study offers three contributions to crisis informatics, disaster management, and organizational sociology.

1) *Validation of Cognitive Delegation Theory:* By confirming H1 ($\beta = 0.415$, $p < 0.001$), this research validates Cognitive Delegation Theory within volatile, non-corporate environments. While baseline studies [24] focus on tech-adoption handling predictable corporate datasets, this study proves that delegating data processing to automated systems functions effectively during massive logistical disruptions, reducing human cognitive exhaustion.
2) *Socio-Technical Update to the Practice-Based View (PBV):* The confirmation of H4 (βindirect $= 0.193$, $p < 0.001$) shows that technology alone does not create operational agility. Its capacity to optimize emergency choices depends on a social mechanism: rapid trust construction among non-technical users under intense time pressure. This addresses the gap identified by Li and Tian [26] regarding purely technical AI tools, proving that data transparency must build cognitive trust before transforming into field performance.
3) *Application of Contingency Theory to Structural Equations:* The negative interaction effect of a Control Culture (H5b: $\beta = -0.224$, $p < 0.001$) proves that a technology's ultimate success is contingent upon institutional cultural architecture. This adds empirical weight to organizational alignment frameworks, demonstrating that rigid, vertical designs actively degrade collaborative tools during emergencies.

5.5. Managerial and Policy Recommendations

The following strategic changes are recommended for the National Disaster Management Authority (NDMA), Provincial Disaster Management Authorities (PDMAs), and military logistics headquarters [19, 22].

5.5.1. Institutionalize a Unified Crisis Data Dashboard

Because Swift Trust was confirmed as the core mediator driving decision quality, the NDMA must move away from separate, unaligned agency reporting.

1) *Actionable Policy:* Develop a single, cloud-hosted platform titled the National Emergency Logistics Sync (NELS).
2) *Operational Integration:* Integrate real-time satellite imagery, UN displacement maps, and military transport statuses into one dashboard. Providing a single source of truth eliminates the data redundancy and information hoarding noted in UN-OCHA coordination reports.

5.5.2. Establish Agile "Horizontal Coordination Cells"

The negative moderation effect of Control Culture ($\beta = -0.224$) proves that relying on rigid, vertical bureaucratic structures slows down relief deployment during flash floods.

1) *Actionable Policy:* The NDMA and military command units should co-create Agile Coordination Cells (ACCs) at the district level during active emergencies.
2) *Operational Integration:* Staff cells with field personnel authorized to bypass traditional vertical approval loops for routine supply allocations. Separating strict top-down security protocols from horizontal, day-to-day logistics coordination creates the flexible execution required to optimize last-mile deliveries [28].

5.5.3. Standardize Joint Civil-Military Technical Training

To maximize the value of AI-driven dashboards, training programs cannot occur in silos.

1) *Actionable Policy:* Launch permanent, joint technical simulations at the National Disaster Management University (NDMU).
2) *Operational Integration:* Civilian NGO coordinators, PDMA planners, and military logistics officers must practice together on predictive analytics simulators. Familiarity with the system beforehand ensures that when a crisis hits, actors can rely on automated dashboards immediately, establishing the swift trust necessary to optimize relief operations.

Table 7. *Actionable recommendations derived from the causal findings.*

Statistical Source Path	Core Empirical Finding	Practical Challenge Addressed	Targeted Policy Action
AI_BI → ST_TR (β = 0.524***)	Data visibility is the primary driver of rapid trust.	Information asymmetries and suspicion among separate agencies.	Mandate a unified digital platform (NELS) to institutionalize transparent, cross-agency data sharing.
ST_TR → CO_PE (β = 0.485***)	Swift trust directly drives joint field performance.	Overlapping relief allocations and last-mile logistics bottlenecks.	Conduct joint simulation exercises across civil-military lines to build shared professional familiarity.
Interaction (Culture) (β = -0.224***)	Rigid control hierarchies constrain collaborative performance.	Bureaucratic delays caused by slow, vertical approval layers.	Form decentralized Agile Coordination Cells to bypass vertical silos for daily relief distribution decisions.

6. Conclusions

6.1. Summary of Empirical Findings

Using data from N = 250 active emergency responders across civil-military networks in Pakistan, this study extended the socio-technical framework of Pham et al. [29] into a high-stress public sector disaster response context.

In response to RQ1, the structural model proved that AI-Augmented BI Data Analysis exerts a powerful direct impact on both Decision Quality ($\beta = 0.415$, $p < 0.001$) and Swift Trust ($\beta = 0.524$, $p < 0.001$). Furthermore, the bootstrapping routine confirmed that Swift Trust acts as a vital partial mediator (βindirect = 0.193, $p < 0.001$), proving that data visibility significantly sharpens crisis management choices by establishing mutual cognitive trust among non-technical operators under intense time pressure.

In response to RQ2, the moderation analysis revealed that institutional culture drastically conditions technological outcomes. While a Flexible Culture accelerates cross-agency trust formation (*H5a:* $\beta = 0.185$, $p = 0.002$), a rigid Control Culture acts as a severe structural bottleneck. The highly significant negative interaction coefficient (*H5b:* $\beta = -0.224$, $p < 0.001$) proved that vertical command structures hinder multi-agency networks from translating real-time digital insights into collaborative last-mile logistics alignment.

6.2. Research Limitations

1) *Cross-Sectional Data:* The survey relied on self-reported, cross-sectional responses gathered after the 2022-2025 flood sequence, reflecting a post-hoc evaluation rather than the real-time evolution of trust during an active disaster.
2) *Geographic and Logistical Constraints:* Infrastructure damage in remote areas of Balochistan and Sindh constrained access to certain local NGO field offices, leading to a higher concentration of responses from provincial and federal coordination hubs.
3) *Limited Cultural Typologies:* The study focused explicitly on the dual cultural typologies (Flexible vs. Control) from the Competing Values Framework, omitting internal data literacy variations or agency resource constraints.
4) *Geographic Context:* The study was limited to Pakistan's institutional ecosystem, which restricts the direct generalizability of the findings to countries with different civil-military disaster architectures.

6.3. Directions for Future Research

Based on these limitations, three promising paths are suggested for future academic study.

6.3.1. Longitudinal and Real-Time Tracking

Future studies should employ a longitudinal research design. Tracking inter-agency trust and data usage patterns across different phases of a disaster, from pre-disaster preparedness to active rescue operations and long-term rehabilitation, would provide a much deeper look at how swift trust degrades or transforms over time.

6.3.2. Mixed-Methods and Qual-Quant Integration

Researchers should consider a mixed-methods approach. Combining structural path equations with qualitative focus groups or case studies of specific civil-military cells would provide deeper context. This would help capture the nuanced institutional politics and communication barriers that quantitative models cannot fully map.

6.3.3. Multi-Country and Structural Comparisons

Finally, future research should expand the empirical framework across multiple countries. Testing this model in other highly climate-vulnerable nations with distinct emergency governance systems (such as Bangladesh, Indonesia, or the Philippines) would provide valuable cross-country validation,

refining the socio-technical model for global crisis governance.

6.4. Final Conclusion

In conclusion, this thesis proves that technology alone cannot solve the structural coordination issues plaguing modern disaster management. While AI-augmented analytics provide the data visibility required to make sound decisions and build rapid trust, their ultimate field performance is heavily bounded by organizational culture. To protect vulnerable populations from escalating climate crises, disaster governance frameworks must actively balance vertical command structures with agile, horizontal collaboration channels.

Abbreviations

AI	Artificial Intelligence
BI	Business Intelligence
PLS-SEM	Partial Least Squares Structural Equation Modeling
NDMA	National Disaster Management Authority
PDMA	Provincial Disaster Management Authority
NGO	Non-Governmental Organization
INGO	International Non-Governmental Organization
UN-OCHA	United Nations Office for the Coordination of Humanitarian Affairs
PBV	Practice-Based View
RBV	Resource-Based View
CVF	Competing Values Framework
CMB	Common Method Bias
3PL	Third-Party Logistics
AVE	Average Variance Extracted
CR	Composite Reliability
HTMT	Heterotrait-Monotrait Ratio
VIF	Variance Inflation Factor
R^2	Coefficient of Determination
Q^2	Predictive Relevance (blindfolding Procedure)

Author Contributions

Muhammad Afzaal Chaudhary: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Visualization, Writing – original draft

Areeba Kanwal: Conceptualization, Project administration, Resources, Supervision, Validation, Writing – review & editing

Data Availability Statement

The data is available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

Appendix: Structural Validation Data

The survey instrument utilized a 5-point Likert scale to gather empirical data from N=250 active emergency responders across public, military, and civilian sectors. As verified in the main text body, the psychometric properties of the reflective indicators met all structural evaluation criteria: item factor loadings exceeded 0.70, Cronbach's alpha (α) and Composite Reliability (CR) values surpassed the 0.70 threshold, and convergent validity was established with an Average Variance Extracted (AVE) ≥ 0.50 across all constructs. Discriminant validity was fully confirmed via the Heterotrait-Monotrait Ratio (HTMT) matrix, with all cross-construct values falling safely below the conservative 0.85 benchmark. Collinearity checks yielded inner Variance Inflation Factor (*VIF*) metrics well below 3.0 (1.245 to 1.876), proving the absence of multicollinearity distortions.

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Biography



Muhammad Afzaal Chaudhary is a researcher and academic in the Department of Management Sciences at the Islamia University of Bahawalpur (IUB), Pakistan. He holds an MPhil in Management Sciences, specializing in data analytics and operations management, following a Bachelor of Business Administration from the same institution. His current research primarily focuses on information systems adoption, crisis informatics, and socio-technical behavior in public sector supply chains. He has worked closely with regional public networks to model data flows during environmental disruptions. He has published quantitative studies on business intelligence systems and active structural modeling, and he regularly contributes to regional symposiums on organizational technology implementation and emergency management systems.



Areeba Kanwal is an academic faculty member in the Department of International Relations at the University of Sindh, Jamshoro, Pakistan. She completed her PhD in International Relations, focusing on non-traditional security threats and regional disaster governance frameworks, and holds a Master's degree in International Relations. Her primary work examines institutional coordination architecture, civil-military disaster operations, and humanitarian governance policies in climate-vulnerable territories. She has led multi-agency seminar panels on institutional policy, served as a program consultant for local climate resilience projects, and currently acts as a peer reviewer for journals focusing on strategic disaster collaboration and public administration networks across South Asia.

Research Field

Muhammad Afzaal Chaudhary: Business Intelligence Systems, Emergency Operations Management, Partial Least Squares Structural Equation Modeling, Information Systems Analytics, Socio Technical System Adoption, Humanitarian Logistics Optimization, Quantitative Research Methodology

Areeba Kanwal: Crisis Governance Architecture, Civil Military Coordination Networks, Climate Disaster Policy Administration, Non Traditional Security Management, Public Sector Collaborative Performance, Institutional Culture Optimization, Cross Sector Governance