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Grass is always dark(*er*) on the other side: Exploring the dark side of artificial intelligence humanitarian supply chain operations

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ABSTRACT

Humanitarian supply chains (HSCs) have undergone significant changes over the years, shifting from traditional systems to more intelligent and, eventually, AI-enabled operations. With technological advancements accelerating across sectors, humanitarian organizations have also begun adopting artificial intelligence (AI) to enhance their workflows, improve efficiency, and reduce losses. While much of the existing research has focused on the benefits of AI in business and logistics, there is still limited understanding of its potential downsides—particularly within humanitarian settings. This study addresses that gap by exploring how AI may negatively affect HSC activities, both at the individual (micro) and organizational (macro) levels. To guide our analysis, we draw on the Belief-Action-Outcome (BAO) framework, which helps connect personal and institutional beliefs to actions and resulting outcomes. Humanitarian supply chains operate in complex environments where technology use intersects with human behavior, organizational culture, and social values. To better understand these dynamics, we conducted qualitative interviews with professionals working in humanitarian organizations. These insights allowed us to identify and map various challenges—what we refer to as the "dark side" of AI—onto specific functions within HSC operations. Our findings not only highlight areas of concern but also contribute to the broader application of the BAO model in the humanitarian field.

1. Introduction

The use of Artificial Intelligence (AI) in supply chain management has been a topic of interest for researchers and practitioners in recent years, primarily due to the fact that AI has the potential to influence operational effectiveness as well as organizational competencies (Min, 2010; Samadhiya et al., 2023). AI-powered tools are increasingly being utilized to forecast risk, justify resources, enhance logistics, and create supply chain resilience. But supply chain operations driven by AI present complicated ethical, contextual, and cultural challenges, notably for humanitarian supply chains (HSCs). Unlike traditional supply chains, which operate in structured and predictable environments (Toorajipour et al., 2021), HSCs operate to address timely emergencies and minimize human suffering in events such as pandemics and natural disasters. The very nature of the mission of HSCs is to serve and protect vulnerable groups, making their alignment with AI an issue of opportunity and contention (Dash et al., 2019; Pournader et al., 2021).

Although past research has extensively studied the "bright side" of AI for consumers, more and more research now indicates its "dark side" (Barari et al., 2024). When defining the dark side, AI can acquire in-depth knowledge about customers without them knowing (Modgil et al., 2022; Ivanov and Dolgui, 2020). Consequently, the emotional and psychological expenses of AI can be felt by customers to a large extent, given that AI may not be regarded as trustworthy (Papagiannidis et al., 2023). Additionally, Longoni et al. (2019) posit that customers feel neglected by AI, in that they believe it does not consider their uniqueness, thus influencing their responses. Also, Esmaeilzadeh (2020) studied the impact of factors such as communication and social difficulties

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caused by AI which may negatively affect the customers' intent in utilizing AI-based tools.

For example, AI in humanitarian supply chain operations have been checked via technostress (Gupta et al., 2022), change resistance (Chin et al., 2025; Chin et al., 2024a), and IT illiteracy (Alabed et al., 2022). However, the adoption of advanced technology, employee acceptance, and capability building is uniquely challenging because of the nature of humanitarian operations and the intricacy of its stakeholders (Dubey et al., 2022; Dash et al., 2019; Karuppiah et al., 2025). Brock and Von Wangenheim (2019) and Dubey et al. (2022) provide empirical insights from managers' views of how their companies will shape corporate strategy in the era of AI and big data analytics. Against these challenges, more intricate analysis is necessary to quantify the dark effect of AI in HSCs and develop long-lasting, human-centered AI architectures (Chin et al., 2024b;Mishra et al., 2022; Kwon et al., 2016). We recognize this as an omission and therefore positioned it as a main research gap in our study leading to research question of;

RQ: What are the adverse impacts of AI on HSC activities within organizations, both micro- and macro-level?

To respond to this question, we employ the Belief-Action-Outcome (BAO) framework (Melville, 2010). The BAO framework suggests that organizational and social structures impact individual beliefs and attitudes toward AI-based HSCs (Mishra et al., 2022; Kwon et al., 2016). Organizational and humanitarian outcomes, however, are impacted by individual actions. Our qualitative research explores relief agencies and their stakeholders to discuss how AI affects HSCs at various levels. Micro-level insights are obtained from personal responses toward the adoption of AI, whereas macro-level findings are established from organizational policies and strategies (Behl and Dutta, 2019). By correlating these perceptions, we discuss an integrated understanding of the effects of AI on humanitarian decision-making and operations.

The originality of this study lies in its critical exploration of the intersection between Artificial Intelligence (AI) and Humanitarian Supply Chain operations, emphasizing the often-overlooked human and social dimensions. Throughout this study, an interpretivist approach is taken, which views reality as a product of human experiences, as well as interactions with other people (Schwandt, 1994). It is important to keep in mind that in the complex and emotionally charged setting of humanitarian supply chains - especially in an age when artificial intelligence is becoming more involved - this perspective helps us understand how people make sense of and react to new technologies. This view is well supported by the Belief-Action-Outcome (BAO) framework, as it focuses on how behaviors within organizations are shaped by personal beliefs and actions.

2. Theoretical framework

Though previous research accounts for the potential of HSC in remaking sustainability efforts, empirical studies on the key motivators for adopting AI into HSC frameworks are limited. In a study of managers' perspectives on AI adoption for enhancing HSC, this study presents new empirical insights into decision-making processes and its consequences (Shrivastav and Sareen, 2025; Singh, 2025). Through shedding light on the dynamic inter-play between AI into HSC strategies, this study enables more informed decision-making and the design of context-specific approaches to incorporating AI into HSC practices, with the aim of promoting the advancement of dark side dimensions and map them with one or more functions of HSC efforts in real-life settings (Kreutzer et al., 2025; Aryatwijuka et al., 2024). To address this research question, we employ the Belief-Action-Outcome (BAO) framework (Melville, 2010), which provides a structured lens to examine how individual beliefs about AI influence actions within humanitarian supply chains (HSCs) and, ultimately, shape organizational and humanitarian outcomes. The outcome is a result of such actions, and it can be positive or negative. In this study, it can be the functional and human outcomes, e.g., improved efficiency or unforeseen negative impacts on vulnerable populations (Aryatwijuka et al., 2024; Chukwuebuka et al., 2025).

2.1. Application of Belief-Action-Outcome (BAO) framework for AI-based HSCs

In BAO models, macro and micro level variables influence an organization's performance (Behl and Dutta, 2019). Organizational and societal systems influence individual attitudes, and they influence their psychic states. A person's psychic state helps them think and analyze situations before taking action (Matli and Phurutsi, 2023). An organization's actions are a direct result of its beliefs. Achieving desirable results requires consistency between individual and organizational beliefs (Damoah et al., 2021; Kwon et al., 2016). Individual behavior has an impact on organizational outcomes (Damoah et al., 2021; Kwon et al., 2016). An organization can't achieve its goals if there's a deviation or inconsistency.

In humanitarian supply chain systems, the BAO model indicates that environmental sustainability concerns will be important in the future, especially when implementing AI (Behl and Dutta, 2019). Therefore, in selecting the theoretical backdrop to this study, we selected a BAO model that illustrates the congruence of humanitarian and IS aspects to environmental sustainability (Melville, 2010; Behl and Dutta, 2019). In this study, the BAO model was utilized since it was congruent with other studies that employed the same model (Anthony Jr, 2019; Gupta et al., 2020). In HSC, the key player is the individual players, so any negative impact of AI would result in lack of coordination and wastage of resources (Kreutzer et al., 2025; Aryatwijuka et al., 2024). Therefore, we assume that individual adverse AI impacts will have adverse effects on HSC. Using AI in HSC can result in environmental sustainability when individuals' beliefs and behaviors are aligned (Damoah et al., 2021; Kwon et al., 2016). Individual behavior can therefore be controlled by their psychic state and social structure. According to the BAO theory, the study focused on belief and action determining outcomes.

3. Literature review

3.1. Humanitarian supply chain

Organizations have been adopting humanitarian approaches to manage risk and disruption because of the constantly changing business environment. In times of crisis, humanitarian supply chains (HSCs) play a key role in getting aid to people (Fosso Wamba, 2020).

The disruptions and logistical challenges of COVID-19 have been extensively studied (Dubey et al., 2022). Despite this, AI's role in supporting HSC operations during such crises remains underexplored (Singh, 2025; Kreutzer et al., 2025). AI could improve HSC functions like demand forecasting, resource allocation, and real-time tracking, but it's not integrated yet. Barriers like data silos, outdated systems, and inconsistent standards make it hard. Despite these challenges, organizations are investing in AI to improve operational efficiency (Behl and Dutta, 2019; Datta, 2017). Due to the fact that HSC aims to minimize human suffering and save lives, it's different from traditional supply chain operations (Dohale et al., 2024). It's important to streamline the HSC operation by forecasting the epicenter of disasters and the extent of damage (Dohale et al., 2024). AI-based solutions are helping organizations manage HSC and reduce barriers to aid provision. As a result of the need to channel resources and maintain operational efficiency, companies are investing heavily in AI-enabled HSC (Behl and Dutta, 2019). AI has facilitated smart solutions for forecasting, planning, and deciding (Taghipour et al., 2021). The integration of artificial intelligence into supply chain operations is still in its infancy. As a result of data silos, inconsistent standards, and legacy systems, AI adoption requires seamless data sharing and integration across these disparate entities. As a result, AI-based HSC systems are getting better. Many industries such agriculture (Nayal et al., 2022), healthcare (Damoah et al., 2021; Kwon et al., 2016) and hospitals (Samadhiya et al., 2023) has reported positive

impact of AI in HSC.

3.2. AI in humanitarian supply chain

In order to mitigate HSC risks during disruptions, artificial intelligence-based techniques include robots, deep learning, big data, machine learning, and experience systems. As Dohale et al. (2024) highlighted that how inappropriate and inadequate information confuses the responder and subsequently lead to causalities. Therefore, advanced AI techniques in supply chain facilitate better quality and service (Nayal et al., 2022). In contrast, Castillo et al. (2021) suggest that AI-powered interaction may lead to co-destruction of services too. The study discusses the negative impact of AI-powered services on the people who use them.

Integration of AI with existing systems is essential for the successful implementation of HSC. In addition, AI coordination in HSC is highly dependent on humanitarian actors in the process (Dubey et al., 2022). AI-driven information integration is challenged by many studies due to organization structure, lack of communication within groups (Rao and Jarvenpaa, 1991), mistrust among actors, and a lack of appropriate relief guidance and culture (Davenport, 2014; Altay and Labonte, 2014). Furthermore, the efficiency of coordination among HSC players depends on their ability to analyze the data (Mishra et al., 2022).

4. Methodology

This study employs a qualitative case study methodology, with convenience sampling used to recruit participants. As a result of convenience sampling, we were able to reach professionals in humanitarian logistics, while snowball sampling enabled us to reach additional respondents with relevant experience, thereby broadening the perspectives (Behl and Dutta, 2019; Jayawardena et al., 2024). There were 35 participants in this study, mostly Asian (84 % of men, 52 % of women) and European. Although the sample is heavily Asian, this aligns with the study's objectives for two reasons. First, Asia remains a critical hub for humanitarian supply chain (HSC) activities, particularly in disaster-prone regions where AI is actively being explored for logistics and crisis management (Behl and Dutta, 2019). Second, qualitative research emphasizes depth over breadth, and sample sizes of 20–40 participants are considered sufficient to generate meaningful insights in exploratory contexts (Creswell, 2013; Mishra et al., 2022; Dubey et al., 2022).

The Belief-Action-Outcome (BAO) framework guided both the structure of inquiry and the interpretation of data. Both micro (individual beliefs and experiences) and macro (organizational strategy and policies) perspectives were taken into account in the study. In multiple countries, semi-structured interviews were conducted with male and female professionals aged 26 to 46 (Aryatwijuka et al., 2024; Chukwuebuka et al., 2025). The analysis was conducted in three phases: evaluation of participant demographics, qualitative content analysis and word similarity analysis using NVivo. Each interviewee got 30 to 45 min of time, and the interview mode was English (Behl and Dutta, 2019). While both snowball sampling and convenience sampling are non-probabilistic and commonly used in qualitative research, convenience sampling was chosen since it was likely that our research would not be able to reach geographically dispersed or hard-to-reach participants, particularly within humanitarian networks. Convenience sampling enabled faster access to participants. Participants were interviewed online and in person between October and December 2024. With informed consent, each interview lasted 45–60 min (Behl and Dutta, 2019). To keep things confidential, all the data was anonymized during transcription. Interview questions were guided by the Belief-Action-Outcome (BAO) framework, allowing us to probe individual attitudes toward AI (belief), observed behaviors (action), and perceived outcomes (organizational or humanitarian). The transcripts were returned to participants for member verification, which made the study more credible. In this field where there's little literature on AI's “dark side,” we wanted to gather rich, contextualized insights from 35 participants. In humanitarian and technology adoption contexts, this range has been found to be adequate (Mishra et al., 2022; Dubey et al., 2022). Additionally, data saturation was monitored: no new themes emerged by the 30th interview. Five more interviews were conducted to make sure thematic saturation was reached. By iterating, we made sure the themes represented a mature, stable understanding.

4.1. Manual coding and thematic analysis

Using Braun and Clarke's (2006) six-phase thematic analysis, the interview data were analyzed manually without any software. Researchers were able to engage more deeply with the material and better understand participants' perspectives because of this direct approach. The interviews were recorded, transcribed, and reviewed multiple times. By coding the transcripts line by line, we looked for repeating patterns and organized them into broader themes. The themes were developed inductively from the data and then aligned with the Belief-Action-Outcome (BAO) framework (Melville, 2010) for theoretical grounding. Two researchers independently coded a subset of the transcripts and compared the results. The level of agreement, measured using Cohen's Kappa, was above 0.75, showing a high degree of consistency (Landis and Koch, 1977). Any differences in coding were discussed and resolved together to ensure accuracy. Through this process, we identified five main themes: (1) the use of cognitive computing tools for analysing unstructured data; (2) limitations in human judgment; (3) tension between humanitarian goals and supply chain efficiency; (4) difficulties in partnerships and inter-agency collaboration; and (5) organizational knowledge and capabilities at a broader level.

Each theme was interpreted in light of both the study's research focus and the BAO model. This transparent, theory-informed process added methodological strength by clearly outlining how the data were handled, involving multiple coders, and grounding the analysis in an interpretivist perspective. Our focus on meaning-making through participants' own narratives aligns with the goals of qualitative research rooted in a constructivist worldview.

4.2. Brief overview on manual coding

The data collected from the semi-structured interviews was analyzed using Braun and Clarke's (2006) thematic analysis, a method well-suited for exploring social processes and gaining a deeper understanding of participants' perspectives. The analysis followed a step-by-step approach. All interviews were audio-recorded and transcribed, and the transcripts were reviewed multiple times to ensure familiarity with the content and to begin identifying emerging patterns. The researcher then conducted line-by-line coding to highlight key points across the data. These codes expressed important information related to the research question. Following the initial coding, the comparable codes were integrated into broader themes. Themes were developed in an iterative coding process and ongoing comparison between transcripts, which improved their consistency and relevance. Finally, the themes uncovered were carefully mapped onto the Belief-Action-Outcome (BAO) framework (Melville, 2010) so that each was conceptually linked to the theoretical foundation of the study. This gave coherence to the findings and enabled a better understanding of how individual beliefs and organizational actions influence outcomes in AI implementation in humanitarian supply chains.

5. Qualitative thematic analysis

As part of the analysis, the researchers used NVivo-generated word clouds along with a manual coding process. During manual coding, they carefully read through the data, assigned specific codes and themes, and then reviewed the results to ensure that they were accurate (Basit, 2003; Bogdan and Biklen, 2003). Smaller sample sizes work well with this

method. Scholars like Basit (2003) and Bogdan and Biklen (2003) have described manual coding techniques like cut-and-paste and note cards. In order to make sure the codes were reliable, a panel of qualitative researchers with expertise in wearable technology reviewed them (Wicks, 2017). The analysis is broken down into two parts: first, the manual coding process, and second, the justification using NVivo word clouds.

The research design, interview questions, and interpretation of the findings were guided by the Belief-Action-Outcome (BAO) framework (Melville, 2010). By emphasizing perception and meaning, the BAO framework helps explain how beliefs and social contexts influence behaviors and outcomes. Instead of unstructured reflection, the researchers used BAO constructs to frame participant responses, develop themes, and interpret data. Using the belief-action-outcome structure promoted consistency throughout the coding and reduced researcher bias (e.g., Kwon et al., 2016; Mishra et al., 2022). By iteratively coding, validating between researchers, and directly linking participant answers to BAO framework, the research team minimized interpretive bias. The method served as a form of structured reflexivity, ensuring that the findings reflected participants' views, not the researchers'.

5.1. *A cognitive computing tool for analysing unstructured data obtained from tweets and images*

The initial themes emerged from node cluster diagrams, manual coding techniques, and note cards, including Basit (2003) and Bogdan and Biklen (2003). It has been found that participants explained the need for a cognitive computing tool to analyze unstructured data obtained from tweets and images based on the results of their query (Table 1).

The codes of extraction; biased algorithms and trending are the words that are aligned with the main theme of cognitive computing tool usage (Barari et al., 2024). For example, cognitive computing allows humanitarians to use a more customized strategy for humanitarian aid. Unlike traditional systems with normalized protocols, cognitive tools can tailor their recommendations according to specific situations and requirements of a given crisis or geography (Karuppiah et al., 2025). Furthermore, when linking this point of cognitive computing tools for analysing unstructured data obtained from tweets and images eventually supports in forecasting climate trends and by predicting future disaster patterns (Papagiannidis et al., 2023; Longoni et al., 2019).

Cognitive computing software personalization features are AI systems' capabilities to tailor services, communications and products based on specific needs and preferences (Shrivastav and Sareen, 2025). Personalization is done through data analysis, machine learning and predictive analytics, which allow cognitive computing tools to develop an understanding of user behavior and preferences over time (Longoni et al., 2019). These personalization features in HSC can significantly enhance the efficacy and efficiency of assistance provision, resulting in improved beneficiary outcomes (Beduschi, 2022). The cognitive computing tool's role in HSC is particularly helpful in facilitating the transition from reactive to anticipatory practice (Srivastava and Bag, 2025; Bicrel and Delagoutte, 2024). Through the use of AI for analysis, humanitarian agencies can forecast needs and better distribute resources (Beta et al., 2025) in advance before the situation spirals out of control (Mishra et al., 2022; Dubey et al., 2022). For instance, AI can analyze historical information and real-time information to discover patterns that indicate impending shortages or crises, facilitating anticipatory action that can limit the impact of disasters (Shrivastav and Sareen, 2025). Anticipatory action is particularly critical in humanitarian logistics, where timely intervention can save lives and less pain.

The NVivo word cloud map was used to further justify the manual

Table 1
Manual coding findings.

Theme	Codes	Query results
Cognitive computing tool usage	Extraction	* It is possible to extract meaningful insights and patterns from large volumes of unstructured data by using these tools.. (Male, 2) * Classify tweets into positives, negatives, or neutrals based on their sentiment. (Female, 20)
	Biased algorithms	* Using biased algorithms might unfairly prioritize certain regions or groups in the allocation of aid, leading to inequitable distribution (Female, 20) * AI systems are only as good as the data they are fed. Decision-making processes can perpetuate or even amplify biases in training data. …. (Male, 14) * I don't honestly have much idea but I think… cognitive computing tool usage is something prominent now within the AI field (Female, 27)
	Trending	* yes, using biased algorithms could result in inequitable distribution of aid among specific regions or groups. (Female, 28) * AI systems can be opaque, making it difficult to understand how decisions are made but it is a trend now (Female, 20)

Fig. 1. Word cloud map analysis for cognitive computing tool for analysing unstructured data obtained from tweets and images.
Source: Developed by authors.

coding process (Fig. 1). (See Tables 1–5.)

5.2. Deficiency in human judgment

The initial themes emerged from node cluster diagrams, manual coding techniques, and note cards, including Basit (2003) and Bogdan and Biklen (2003). It has been found that participants explained the need for a loss of human judgment within the artificial intelligence based humanitarian supply chain operations considering the results of their query (Table 2).

The codes of empathy; ethical reasoning and overuse of artificial intelligence are the words that are aligned with the main theme of deficiency in human judgment. The interrelationship of these codes can be explained as follows. The lack of human judgment in AI-HSC operations is the second negative side of AI. As much as AI is quick and accurate in reading enormous amounts of data, it lacks understanding the subtleties of human dynamics, society, and morality within a humanitarian setup (Ivanov and Dolgui, 2020). Decision-makers must examine AI-based recommendations within the broader humanitarian context instead of uncritically adopting them (Hurwitz et al., 2015; Parlangeli et al., 2024). This is because AI can, for instance, rationalize resource allocation and call for greater tact in determining who to provide it to first (Modgil et al., 2022; Ivanov and Dolgui, 2020). If the dataset is progressively more important, getting rid of non-relevant data may accelerate the training regardless of the increase in testing and training times. As lost information will decrease classification performance, review containing missing values is detected and not included in step one

Table 2
Manual coding findings.

Theme	Codes	Query results
Cognitive computing tool usage	Empathy	* In situations that require empathy, ethical considerations, or a deep understanding of local contexts, the over-reliance on artificial intelligence could undermine the role of human judgment…(Male, 12) * Many AI systems are more accurate and faster than humans at processing large amounts of data. In situations that require empathy, ethical considerations, and nuanced understanding of context, AI can reduce the application of human judgment. (Female, 21)
	Ethical reasoning	* Algorithms and data don't inherently include ethical reasoning in AI (Female, 20) * Data-driven decisions can't be used to decide who should get a limited supply of humanitarian aid, for example…. (Male, 17) * I don't honestly have much idea, but I think… cognitive computing tool usage is something prominent now within the AI field (Female, 27)
	The overuse of artificial intelligence	* yes, using biased algorithms could result in inequitable distribution of aid among specific regions or groups. (Female, 28) *Many AI systems are more accurate and faster than humans at processing large amounts of data. In situations that require empathy, ethical considerations, and nuanced understanding of context, AI can reduce the application of human judgment. (Female, 21) * Data-driven decisions can't be used to decide who should get a limited supply of humanitarian aid, for example…. (Male, 17)

Table 3
Manual coding findings.

Theme	Codes	Query results
Humanitarian goals	Timely	* Aid must be delivered in a timely and cost-effective manner by maintaining a balance between humanitarian ideals and operational efficiency.... (Male, 11) * Many AI systems are more accurate and faster than humans at processing large amounts of data… (Female, 21)
	Cost-effective	* To ensure that humanitarian aid reaches the most vulnerable populations as soon as possible, humanitarian operations must ensure that aid is distributed fairly and equitably (Female, 22)
Humanitarian efficiency	Flexible	* Being flexible in supply chain operations means addressing unforeseen circumstances, like natural disasters or sudden outbreaks of violence.. (Female, 21) * Data-driven decisions can't be used to decide who should get a limited supply of humanitarian aid, for example…. (Male, 17)
	Alleviating Suffering	* In order to be successful, it is crucial to be able to adapt to the changing needs on the ground. In any humanitarian supply chain, the primary objective is to save lives and reduce the suffering of humans as much as possible (Female, 30)

Table 4
Manual coding findings.

Theme	Codes	Query results
Partnerships	Local communities	* Building local capacity and partnering with local organizations can help humanitarians be more effective.... (Male, 3) * To ensure that humanitarian aid reaches the most vulnerable populations as soon as possible, humanitarian operations must ensure that aid is distributed fairly and equitably (Female, 22)
	Local organizations	* Many local organizations have a better understanding of the context and can assist in navigating logistical challenges more effectively. Additionally, investing in local capacity means the community can handle future crises on its own. (Female, 4)
Networking	Decision making	* Data-driven decisions can't be used to decide who should get a limited supply of humanitarian aid, for example…. (Male, 17)

(Hurwitz et al., 2015). This is mainly because this factor will not help the learning of the classifier and there is a possibility for numerical values to be discarded from the text (Parlangeli et al., 2024; Zellner et al., 2021).

The NVivo word cloud map was used to further justify the manual coding process (Fig. 2).

5.3. Humanitarian goals and efficiency in supply chain

The initial themes emerged from node cluster diagrams, manual coding techniques, and note cards, including Basit (2003) and Bogdan and Biklen (2003). It has been found that participants explained the need for a loss of human judgment within the artificial intelligence based humanitarian goals and efficiency in supply chain operations considering the results of their query (Table 3).

The codes of timely; cost-effective, flexible, and alleviating suffering of artificial intelligence are the words that are aligned with the main themes of Humanitarian goals and efficiency in supply chain. While the BAO model establishes a connection between macro and micro level variables that influence the performance of an organization (Behl and Dutta, 2019). Attitudes of individuals are influenced by organizational

Table 5
Manual coding findings.

Theme	Codes	Query results
Data management	Data handling	* I personally believe that data management as a skill similarly to the data analysis (Female, 4) * Many AI systems are more accurate and faster than humans at processing large amounts of data… For example the data from various sources (e.g., weather reports, social media images or posts and even the product reviews) can be processed in real-time with AI. (Female, 21)
	Skills	* To ensure that humanitarian aid reaches the most vulnerable populations as soon as possible, humanitarian operations must ensure that aid is distributed fairly and equitably. For example, a natural disaster can be predicted using AI tools based on historical data (Female, 22) * Being flexible and having data management skills with data handling is important right as they are handling humanitarian supply chains though AI. (Female, 17)
Training and development	Job Knowledge	* Being flexible in supply chain operations means addressing unforeseen circumstances, like natural disasters or sudden outbreaks of violence. Having the right job knowledge when it comes to doing a job is important… (Female, 21) * In order to be successful, it is crucial to be able to adapt to the changing needs on the ground. In any humanitarian supply chain, the primary objective is to save lives and reduce the suffering of humans as much as possible (Female, 30)

and societal systems, which in turn influence their psychological well-being. In order to take effective action, an individual's psychic state allows them to perform cognitive processes and analyze the situation (Parlangeli et al., 2024). Only 20 % of humanitarian organizations consistently measure performance (Blecken, 2010). It is challenging because of data inaccuracy, limited IT capabilities, chaotic conditions, and organizational resistance (Queiroz et al., 2020). Measurement of performance refers to the collection and analysis of metrics to manage and provide feedback on an organization's actions (Queiroz et al., 2020). Although many frameworks use a balanced scorecard approach, its rigidity is considered unsuitable for humanitarian situations (Davidson, 2006). A large number of studies focus on efficiency-in particular cost, time, and volume metrics like lead-time and fill rate-while ignoring societal or environmental impacts (Haavisto and Goentzel, 2015; Hurwitz et al., 2015; Ivanov and Dolgui, 2020).

The NVivo word cloud map was used to further justify the manual coding process (Fig. 3).

5.4. Partnerships and networking

The initial themes emerged from node cluster diagrams, manual coding techniques, and note cards, including Basit (2003) and Bogdan and Biklen (2003). It has been found that participants explained the need for partnerships and networking within the artificial intelligence based humanitarian supply chain operations considering the results of their query (Table 4).

The codes local communities, local organizations and decision making are the words that are aligned with the main themes of partnerships and networking. Due to the scope of humanitarian missions and the multifaceted nature of its stakeholders, the adoption of advanced technology, workforce adoption, and capability building are unique challenges (Sandvik et al., 2014; Behl and Dutta, 2019). Based on leaders' perceptions of how AI and big data analytics will shape corporate strategy, Brock and Von Wangenheim (2019) and Behl and Dutta (2019) provides empirical insights. While the BAO models discuss about the macro and micro level variables that influence the performance of an organization (Behl and Dutta, 2019), partnerships and networking which plays a major role in external organizational environment can be used to manage unexpected events like disasters, organizations need to be agile and resilient. But after some recent scholarly debates, we feel that organizational theories like the resource-based view or dynamic capability view cannot adequately explain humanitarian supply chain performance. Because assumptions in the underlying commercial supply chain do not apply to the humanitarian supply chain. We state that as a potential gap in the literature. Also, humanitarian agencies remain skeptical regarding the deployment of artificial intelligence-based big data analytics capacity (AI-BDAC) in decision-making.

The NVivo word cloud map was used to further justify the manual coding process (Fig. 4).

5.5. Knowledge capabilities at macro level within the organizations

The initial themes emerged from node cluster diagrams, manual coding techniques, and note cards, including Basit (2003) and Bogdan and Biklen (2003). It has been found that participants explained the need for knowledge capabilities at macro level within the organizations within the artificial intelligence based humanitarian supply chain operations considering the results of their query (Table 5).

Fig. 2. Word cloud map analysis for deficiency in human judgment.

Fig. 3. Word cloud map analysis for humanitarian goals and efficiency in supply chain.

Fig. 4. Word cloud map analysis for partnerships and networking.

The codes data handling, skills and job knowledge aligns with the main themes of knowledge capabilities at macro level within the organizations (Dubey et al., 2022). Omitting the multi-level precursors and their interplay in absorptive capacity studies is detrimental on at least three grounds (Srivastava and Bag, 2025; Bicrel and Delagoutte, 2024). First, from a pragmatic viewpoint, it is firm employees who look, find and select valuable knowledge, internalize and utilize new knowledge in products and services (Esmaeilzadeh, 2020; Papagiannidis et al., 2023). However, they do that by executing some organizational roles, in a particular organizational and strategic context (Longoni et al., 2019). Firm managers are always on their minds thinking about how to offer the best "fit" for every absorptive capacity and for the firm's external environment with respect to new knowledge (Lewin et al., 2011). Organizational design and control mechanisms influence employees'

Fig. 5. Word cloud map analysis for knowledge capabilities at macro level within the organizations.

engagement with the external environment, the way they communicate and embed new knowledge between and within subunits, and what innovations they bring to the market (Bicrel and Delagoutte, 2024; Lewin et al., 2011).

The NVivo word cloud map was used to further justify the manual coding process (Fig. 5).

6. Discussion of the findings in line with the Belief-Action-Outcome (BAO) framework

To answer the research question—"What are the adverse impacts of AI on HSC activities within organizations, both micro- and macro-level?"—the study adopted the Belief-Action-Outcome (BAO) framework as a guiding theoretical lens. This framework enabled us to categorize our findings meaningfully: participants' **beliefs** about AI's limitations, their **actions** (or organizational decisions shaped by those beliefs), and the **outcomes** experienced at both the individual and system level. Accordingly, the five emergent themes are explicitly mapped to the BAO model as follows:

6.1. Theme 1: cognitive computing tool for analysing unstructured data obtained from tweets and images (belief)

Participants described a growing reliance on AI-driven tools for processing unstructured data (e.g., tweets, images). These tools shape the **beliefs** within organizations about AI's ability to enhance operational decision-making. However, the overreliance on algorithmic outputs based on biased or incomplete data reinforced concerns about misinformation, surveillance, and reduced human empathy—especially in unpredictable, high-stakes environments. The belief that AI can "replace" nuanced judgment was repeatedly critiqued, raising doubts about its role in humanitarian settings.

The incorporation of AI in Human and Social Capital (HSC) enhances efficiency with negative repercussions on both micro and macro scales (Min, 2010; Longoni et al., 2019). Cognitive computing on a micro level enables personalized humanitarian aid (Karuppiah et al., 2025; Barari et al., 2024). Unlike classical systems with fixed protocols, cognitive tools provide adaptive suggestions based on the unique needs and situation of a crisis or region (Karuppiah et al., 2025; Barari et al., 2024). Cognitive computing technology enhances decision-making by predicting weather, geography, and population needs (Ivanov and Dolgui, 2020) to aid in disaster management, resource allocation, and distribution. Advances in IT and networking are continually required. Our results show the imperative for using cognitive computing software to process unstructured data for HSC (Parlangeli et al., 2024; Zellner et al., 2021). In addition, AI systems trained on biased historical data could reproduce discriminatory recruitment or promotion policies (Karuppiah et al., 2025; Barari et al., 2024). It is feasible only with records; even this might not hold true for humanitarian SC.

Due to unprecedented situations, relief distribution and resource allocation can be done based on a skewed algorithm (Madianou, 2022; Ozdemir et al., 2021). Cognitive computing programs examining unstructured data like tweets and facial expressions raise privacy issues, creating the sense of constant monitoring that undermines worker trust (Blecken, 2010). Overreliance on algorithms can also dehumanize HSC processes in a way that workers get isolated and disrespected. AI's reading of unstructured data, including social media and pictures, may be inaccurate, without sarcasm, context, or emotion, leading to false conclusions (Sandvik et al., 2014; Behl and Dutta, 2019). At a macro scale, the pervasiveness of AI utilized in HSC operations has the ability to intensify the digital divide, as per the hypothesis of the BAO model (Madianou, 2022).

This gives large firms with advanced AI an edge over smaller ones, increasing labor market inequality (Longoni et al., 2019; Karuppiah et al., 2025). Interviewees confirm prejudices influence the needs of the individuals concerned (Longoni et al., 2019; Karuppiah et al., 2025). Cognition-driven plans and interactions are evolving to revolutionize lives by beneficial utilization (Bicrel and Delagoutte, 2024; Esmaeilzadeh, 2020). More use of AI in labor analytics can destroy social capital within firms by replacing interpersonal relationships with algorithms (Dash et al., 2019; Pournader et al., 2021). Social networking, blogging, podcasting, and bookmarking sites are now commonplace due to rapid online development (Jain et al., 2022). These services allow individuals to upload and share data within groups. IBM claims that "2.5 quintillion bytes of data" are generated annually, and the number is growing (Jain et al., 2022).

6.2. Theme 2: deficiency in human judgment (action)

This theme captures the **actions** taken by organizations when AI recommendations are followed without critical human oversight. Respondents highlighted that decision-making in HSCs demands contextual sensitivity, moral reasoning, and cultural intelligence—all of which AI currently lacks. These misplaced actions (e.g., automation without oversight) often emerge when belief in AI's objectivity is overinflated, displacing human intuition and adaptability in crisis response. The humanitarian field is fragmented, and as a result, decision-making becomes less straightforward (Behl and Dutta, 2019). The BAO model delineates how humanitarian supply chains can be made more responsive and resilient (Madianou, 2022; Zellner et al., 2021). Respondents further noted AI's negative effects like overuse, concentration issues, and insensitivity (Behl and Dutta, 2019).

Humanitarian practitioners must properly interpret AI outputs (Karuppiah et al., 2025; Barari et al., 2024). Decision-makers should critically analyze AI recommendations, instead of presupposing them (Hurwitz et al., 2015; Parlangeli et al., 2024). Humanitarian supply chains try to reduce suffering and save lives, while AI is based on predefined data and does not have empathy (Mishra et al., 2022; Kwon et al., 2016). Humanitarian crises require prompt, transparent human responses—something that hard AI systems tend to fail at (Mishra et al., 2022; Kwon et al., 2016). One key limitation of AI, as identified by BAO, is the lack of human judgment (Behl and Dutta, 2019). While AI is comfortable processing data, it is not able to process subtle human behaviors, cultures, and ethical considerations that are essential in humanitarian action (Dubey et al., 2022). Large data must be filtered to speed up AI training, yet resource allocation has to remain under human discretion (Mishra and Sharma, 2020). Over-reliance on AI can degrade this essential human judgment (Behl and Dutta, 2019). Data preprocessing is important because the majority of datasets contain redundant or "noisy" data that may disturb AI predictions (Hurwitz et al., 2015; Parlangeli et al., 2024; Zellner et al., 2021).

6.3. Theme 3: humanitarian goals and efficiency in supply chain (outcome)

The third theme concerns the **outcomes** of AI adoption, specifically when efficiency is prioritized over empathy. Participants noted tensions between algorithmic optimization and humanitarian ethics. For instance, the rigid application of AI may delay aid, overlook vulnerable groups, or exacerbate inequality. These outcomes indicate misalignment between the intended goals of humanitarian operations and the actual results of AI implementation.

At a macro-level, in alignment with the theoretical constructs of the BAO model, researchers have recently begun to pay attention to humanitarian performance assessments, much like practitioners have, and several metrics have been developed for application to humanitarian contexts (Zellner et al., 2021; Behl et al., 2023). We also found that humanitarian goals and efficiency were critical factors in AI-HSC operations (Mishra et al., 2022; Kwon et al., 2016). The increasing tension between AI-driven efficiency and human-centered flexibility in humanitarian crises signifies the dark side of AI in HSC operations (Mishra et al., 2022; Kwon et al., 2016). AI may not be able to forecast

humanitarian crises due to poor records. AI decisions may worsen disparities (Balcik et al., 2010; Efthymiou et al., 2025). Aligning humanitarian goals and performance in AI-HSC deployment is challenging (Madianou, 2022; Ozdemir et al., 2021). Over-reliance on AI in times of crisis may lead to resistance to change. AI's disregard for human judgment can retard essential decisions and reduce efficiency (Foysal et al., 2023).

6.4. Theme 4: the partnerships and networking (action)

Though there is no doubt that AI can exponentially improve operational efficiency, respondents cautioned against the potential risks inherent in this shift, most significantly the loss of trust, a homogenizing effect, and the removal of important contextualizing nuances that are paramount when relationship-building processes are allowed to become mechanized. The steps being taken in the process of forming effective partnerships are becoming more influenced and informed by the use of artificial intelligence tools, such as automated collaborator-matching systems and various digital coordination platforms. These network-level steps, often fueled by organizational faith in the functional applicability of AI, tend to overlook the relational depth that is categorically essential in humanitarian action aimed at establishing meaningful and effective collaborations.

Humanitarian Supply Chain (HSC) activities, such as partnerships and networking, can have a lot of unintended consequences (Balcik et al., 2010). While AI-powered communication tools and digital platforms are efficient, they often replace meaningful in-person interactions with impersonal or detached exchanges (Bicrel and Delagoutte, 2024; Esmaeilzadeh, 2020). In order to build strong partnerships, you need trust, mutual understanding, and close collaboration (Kovács and Spens, 2011).

Tools that match collaborators or map networks can unintentionally reinforce bias by promoting connections between similar actors, which can limit diversity and creativity (Shrivastav and Sareen, 2025). Employees may become overly reliant on AI suggestions, reducing their initiative to build and maintain professional relationships (Papagiannidis et al., 2023; Longoni et al., 2019).

From a BAO model perspective, using AI in relationship-building can centralize control and give larger, tech-savvy organizations a competitive edge (Balcik et al., 2010). However, partnerships are essential in HSC operations, especially during crises when no single actor can meet all needs alone (Madianou, 2022; Ozdemir et al., 2021). Effective humanitarian response requires coordination between governments, NGOs, private companies, and local communities (Kwon et al., 2016). These collaborations, built on trust and shared purpose, are key to reaching vulnerable populations quickly and effectively (Behl et al., 2023; Parlangeli et al., 2024).

Despite its ability to support certain operational aspects, AI lacks the emotional intelligence and contextual understanding needed to foster and sustain strong partnerships in humanitarian contexts (Behl et al., 2023; Kwon et al., 2016).

6.5. Theme 5: knowledge capabilities at the macro level within the organizations (belief and outcome)

This theme links **beliefs** about organizational readiness and **outcomes** in AI assimilation. Participants noted that the absence of necessary skills and data literacy often leads to underutilization of AI tools or inappropriate application. These mismatches result in poor decision-making, missed opportunities, or technological dependency without meaningful integration—ultimately diminishing long-term organizational adaptability.

The integration of AI systems without parallel investments in training and skill development may prevent us from taking advantage of AI's data-driven insights (Parlangeli et al., 2024; Zellner et al., 2021). As a result, AI's potential in HSC operations may remain underutilized without robust organizational knowledge capabilities (Parlangeli et al., 2024; Zellner et al., 2021). Further, we found that organizations must develop knowledge capabilities at the macro level, particularly in terms of their ability to handle data, develop skills, and enhance job-specific knowledge (Balcik et al., 2010; Kovács and Spens, 2011). Organizations invest heavily in AI assimilation for HSC operations in order to improve data-driven decision-making, but these investments can only be fully realized if employees possess the necessary skills and knowledge to adapt to changing circumstances. In addition to providing valuable insights into unforeseen crises, AI-driven predictive analytics rely on the workforce's ability to interpret and apply this information (Hurwitz et al., 2015). In humanitarian crises, an organization's ability to manage and use data effectively is crucial (Balcik et al., 2010; Kovács and Spens, 2011). As a consequence, although artificial intelligence can contribute to operational efficiency, its success is largely determined by the organization's ability to cultivate a knowledgeable and adaptable workforce able to utilize these technological advancements in real-world humanitarian situations (Hurwitz et al., 2015).

6.6. Managerial implications

This study provides practical and actionable directions for humanitarian supply chain managers involved in disaster relief and crisis response. Managers must first recognize the dual importance of agility and resilience in their operations. As opposed to traditional supply chains, HSCs are focused on minimizing human suffering and saving lives (Sandvik et al., 2014; Kovács and Spens, 2011). As a result, we have to adapt to the unpredictable nature of disasters, but also anticipate them by forecasting epicentres and damage severity (Damoah et al., 2021; Kwon et al., 2016). In spite of the fact that AI tools like warehouse automation, predictive analytics, and supply chain optimization platforms are becoming more and more popular, our results show that these technologies overlook important human factors (Min, 2010; Longoni et al., 2019; Karuppiah et al., 2025). The misalignment between AI's macro-level potential and humanitarian work's micro-level reality may lead to unsustainable and ineffective practices (Barari et al., 2024; Blecken, 2010).

We recommend the following actionable strategies for HSC managers to address these limitations. Instead of full automation, combine AI-driven recommendations with human expertise, especially for high-stakes or ethically complex decisions. In this way, human responders can override AI outputs based on field conditions, balancing speed and empathy. Managers should audit AI tools for algorithmic bias, especially in areas like aid allocation and beneficiary prioritization, to avoid reinforcing social inequalities. Managers can bridge the gap between technological capability and human-centered operations by taking these steps. Integrating AI in humanitarian supply chains must be done thoughtfully and transparently to enhance - not replace - human judgment, local knowledge, and compassion (Chukwuebuka et al., 2025).

6.7. Theoretical implications

In this study, the findings are based on the Belief-Action-Outcome (BAO) theory, which emphasizes that beliefs shape actions that ultimately determine outcomes (Behl et al., 2023). As a result of this framework, it is understood that negative attitudes toward artificial intelligence can lead to cautious or resistant behavior among humanitarian supply chain (HSC) professionals, particularly those who perceive the machine lacking empathy, its inability to process contextual nuance, and its potential to undermine human judgment (Shrivastav and Sareen, 2025; Singh, 2025). Typically, such actions can be seen as a reluctance to fully adopt or rely on Artificial Intelligence (AI) systems in decision-making, a reduction in collaboration with AI-supported logistics tools, or a selective use of AI outputs for operational planning.

It is understandable that some people are resistant to AI-driven processes, but such resistance can hinder timely and coordinated

humanitarian responses in times of crisis (Singh, 2025). In some cases, for instance, aid workers may delay implementation of AI recommendations or revert to manual processes if they question the credibility or ethical soundness of AI recommendations, especially in contexts requiring empathy, cultural sensitivity, or rapid judgment. In turn, these delays can lead to adverse outcomes, such as a slower delivery of aid, a misallocation of resources, and the missed opportunity to mitigate the consequences of the crisis (Aryatwijuka et al., 2024).

As a result of our study, we were able to demonstrate that these belief-driven actions are not isolated events, but part of a much broader pattern that can be observed at both micro and macro levels (Shrivastav and Sareen, 2025). On the micro level, it is increasingly difficult for employees to trust their employer due to concerns about algorithmic bias and surveillance; on the macro level, unequal access to AI capabilities can widen the operational gap between large international organizations and their local partners. Our research suggests, therefore, that in line with BAO theory, negative beliefs about the limitations of artificial intelligence directly influence key decision-makers' actions, which ultimately shape the effectiveness, as well as the unintended consequences, of the implementation of AI in humanitarian supply chains (Chukwuebuka et al., 2025).

7. Conclusion, limitations, and future research direction

We conclude in this study that humanitarian policies have significantly more complex performance consequences than have been previously investigated (Damoah et al., 2021; Kwon et al., 2016). A more individualised approach to humanitarian relief is primarily enabled by cognitive computing. In contrast to traditional systems that adhere to set procedures, cognitive tools can adapt their advice according to the circumstances and demands of a particular situation or area (Modgil et al., 2022; Ivanov and Dolgui, 2020). As a major limitation, the model we utilize in this paper underscores the mediating role of individuals in linking macro-level variables such as social structure and the behavior of the social system. Three types of relations are included: (1) macro-level variables such as social structure affect the psychic states (beliefs, desires, opportunities, etc.) of individuals; (2) psychic states affect individual action; and (3) combined individual action affects macro-level variables such as the behavior of the social system. This eventually helps us propose a framework to help organizations improve their social, organizational, and environmental operations.

Furthermore, 35 respondents were interviewed using semi-structured interviews to gain a deeper understanding of the topic. Based on the theoretical framework of BAO framework in humanitarian supply chain systems, the interview questions examined the negative impact of artificial intelligence on HSC operations within an organization by considering the perspectives of the selected participants from both a micro- and a macro-level perspective (Modgil et al., 2022; Ivanov and Dolgui, 2020). While the sample is representative of the micro-level and macro-level workers in supply chain-based organizations, it does not accurately reflect the actual number of agencies involved in a disaster. Further, we think a line of inquiry based on the positivism research philosophy—that is, quantitative research design—would be beneficial to thoroughly examine the relationship between information complexity and humanitarian behaviors for future studies.

It is an organization's capacity to manage and effectively use data in humanitarian crises that plays a pivotal role in vulnerabilities, and as such, organizations need to develop knowledge capabilities at the macro-level that play a pivotal role in vulnerabilities. as such, organizations need to develop knowledge capabilities at the macro level (Ivanov and Dolgui, 2020; Barari et al., 2024). It is their capacity to manage and effectively use data in humanitarian crises that plays a pivotal role in these situations (Helo and Hao, 2022). Hence, employees of these organizations must possess or obtain the necessary competencies and knowledge to adapt to dynamic situations and without these capabilities, the application and utilization of AI in such scenarios would remain limited. Furthermore, it is advised to test these themes using an empirical study based on the positivism research philosophy—that is, quantitative research design—to thoroughly examine the relationship between information complexity and humanitarian behaviors for future studies.

CRediT authorship contribution statement

Abhishek Behl: Writing – original draft, Visualization, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **Shikha Bhardwaj:** Writing – original draft, Validation, Resources, Investigation, Data curation. **Nirma Jayawardena:** Writing – review & editing, Writing – original draft, Software, Resources, Methodology, Formal analysis, Data curation. **Vijay Pereira:** Writing – original draft, Validation, Supervision, Methodology, Conceptualization. **Mohammad Roohanifar:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology.

Appendix A

Interview guide

Exploring the Harmful Impacts of AI in Humanitarian Supply Chains through the BAO Framework

Section A: Background and Context

1. Would you mind describing your function in humanitarian supply chain operations briefly?

2. How many years have you worked within this field, and in what type of organizations or geographies?

Section B: Beliefs (Micro- and Macro-Level Perceptions of AI)

Objective: To explore individual- and organizational-level beliefs, attitudes, and perceptions about AI. Micro-Level (Individual Beliefs) What is the first thing that comes to mind when you think of AI in your professional work?

3. Do you believe that AI facilitates or complicates humanitarian work? Why? Did you ever feel anxious or skeptical about AI engagement in your work? If affirmative, why?

Macro-Level (Organizational and Systemic Beliefs).

4. What is generally the organizational attitude toward using AI for supply chain management?

5. Are there clear policies, strategies, or narratives about AI uptake within your organization?

6. Have you noticed contradictions between organizational AI initiatives and genuine frontline workers' values?

Section C: Actions (Responses and Behaviors Toward AI Use in HSCs)

Purpose: To record individual and organizational responses or adjustments after AI integration. Micro-Level (Individual Actions)

7. How have you individually reacted to the introduction of AI instruments or systems in your work?

8. No, have you ever resisted or struggled with the use of AI? Why or why not?

9. What (if any) changes in your role have you made due to the impact of AI? Macro-Level (Organizational Actions)

10. Can you describe any notable organizational actions taken in an effort to introduce or implement AI tools?

11. Were employees consulted or trained as part of the decision-making process?

12. Have there been any tension or harmonization issues between top-down AI roll-out and genuine operational needs?

Section D: Outcomes (Impacts of AI Adoption in HSCs)

Objective: To understand functional and ethical outcomes at micro (individual) and macro (organizational) levels. Micro-Level (Individual Impact)

13. Did the adoption of AI influence your job satisfaction, workload, or ability to make decisions? 14. Did you or your colleagues experience any unexpected impacts, for instance, exclusion or de-skilling? Macro-

Level (Organizational Impact)

15. What have been the positive and negative impacts that you have observed at the organizational level due to AI adoption?

16. Have there been any issues related to data bias, resource misallocation, or ethical dilemmas?

17. Are there feedback mechanisms in place to reflect on AI's impacts and adapt accordingly?

Data availability

Data will be made available on request.

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