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Please, defend your proposal by including not only technological, but also socio-economic, political, ethical and/or environmental aspects.

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EXECUTIVE SUMMARY

Logistics in **humanitarian interventions** represents one of the emerging topics of utmost importance in the logistics sector. Challenges such as **timeliness**, **lack of resources**, and **poor communication** can present opportunities to test emerging technologies and critically analyse the results. In this paper, the focus has been on the planning phase of relief interventions by designing PACE, a **data-driven method** to support the **decision-making** process that integrates an **artificial intelligence** model. The aim is to prioritize interventions to enable a more efficient allocation of resources and **ensure the success** of the intervention. Additionally, a series of strengths and challenges that may be encountered in the application of the method in real-world contexts are presented, as well as a stakeholder analysis.

SUMMARY

1 INTRODUCTION: CONTEXT

Over the years, **operations in the field of defence** have experienced a significant increase in complexity due to advances in technology, available resources, involved personnel, and growing interactions among stakeholders in play. A. Apte, P. Gonçalves and K. Yoho (2016) argue that it is usual for such organizations as "International non-governmental organizations (NGOs), UN agencies, inter-governmental humanitarian organizations (HOs), national societies, governmental organizations, military institutions, and many others […] to arrive at a disaster site or other affected area with limited understanding of the needs of the population, which other organizations are operating in the area, and what capabilities the different organizations on the ground possess". For these reasons, it is important to properly manage how **military** and **non-military organizations** collaborate with each other; thus, special attention must be given to processes related to **humanitarian logistics**, for which substantial resources are deployed and play a crucial role within humanitarian operations.

Indeed, as reported on the official DHL[1] website, "It is estimated nearly 132 million people will need humanitarian assistance in 2019. Funding requirements are likely to come in at around US$22 billion (€19.14 billion), just to meet the most urgent needs of over 93 million people in crises."

Humanitarian logistics has been defined as "the process of planning, implementing, and controlling the flow and storage of goods and materials, as well as related information, from point of origin to point of emergency, for the purpose of meeting the end beneficiary's requirements" (Van der Laan et al., 2009a, p. 365). Mitigating "the urgent needs of a population with a sustainable reduction of their vulnerability in the shortest amount of time and with the least amount of resources" (Van Wassenhove, 2006, p. 480) is typically the main performance target.

According to Thomas and Kopczak (2005), humanitarian logistics is a **critical** element of the disaster response process for three reasons:

1. It is the main driver for speed and effectiveness.
2. It is at the nexus of several information flows with the potential for process evaluation and improvement.
3. It is the most expensive part of the response process (Van Wassenhove, 2006), including procurement and transportation activities.

The main **causes of inefficiencies** related to humanitarian logistics processes, according to Balcik and Beamon (2008), include:

- **Irregularity of demand**, encompassing variations in timing, location, type, and quantity.
- **Sudden surges** in **demand**, often in significant quantities and with limited lead time, covering a wide range of essential supplies.
- High stakes linked to the **punctuality** of deliveries, where lives are in danger.
- **Scarcity of resources**: both human and financial resources including limited supplies and available technology.

Additionally, based on a study by van der Laan et al., it has been empirically demonstrated that humanitarian logistics is a **time-consuming** process **prone to errors** (2016), analysing the case of Médecins Sans Frontières (MSF) centre in Amsterdam. Moreover, misunderstandings between armed forces and humanitarian organizations concerning their respective capabilities may result in the **replication of efforts** and a **decline in operational efficiency** (Gourlay, 2000).

[1] https://lot.dhl.com/glossary/humanitarian-logistics/

To minimize inefficiencies, similar to industrial contexts where a considerable number of resources are involved, thorough and rigorous operational planning is necessary, outlining the operations to be carried out, their sequence, timing, and the elements required for their success (Farahani et al., 2011). In the industrial context, the goal has shifted from simply completing operations successfully to "*doing better*", following a continuous improvement logic (Imai, 1991). This concept can also be applied to defense operations. To achieve this, it is essential to identify appropriate **performance parameters** that allow assessing the completion status of desired objectives. A crucial factor that can influence the success of an operation is the **lead-time**[2]: the shorter the waiting-time between the beginning of a specific event and the start of the rescue intervention, the greater the chance of limiting both economic and physical damage and safeguarding as many human lives as possible.

Generally, while in industrial contexts some intervention alternatives can be discarded if they do not bring adequate advantages to organizations, when a defense stakeholder (such as a national army, the UN, etc.) is called upon for a specific type of intervention, it must act: the margin for error is very narrow; hence, resources must be ready. Therefore, the problem is no longer whether to take a particular action or not but when to take it. It is important to establish a certain **intervention priority** among various alternatives that may emerge simultaneously, in such a way as to optimize resource utilization and achieve the best result in terms of both effectiveness and efficiency.

2 PACE: AN INNOVATIVE DATA-DRIVEN FRAMEWORK

Challenges identified in humanitarian field need new approaches that enable targeted and effective actions, in order to get best results from **collaborations among parts involved during interventions**. The aim of this proposal is to introduce a new method for logistics of humanitarian interventions that aligns with the objectives of reducing time, costs, and errors. The solution proposed consists in a semi-automated methodology based on Data Science techniques, developed to support decision-making and logistics planning processes in humanitarian interventions. Automation is, indeed, one of the key features that allows reducing the time between the occurrence of the event and the intervention decision, as well as decreasing errors and costs. However, we consider it essential for the final decision to rest with the human decision-maker to neutralize any *biases* that the data might have induced in the model or classification errors.

The method we have developed is structured as follows.

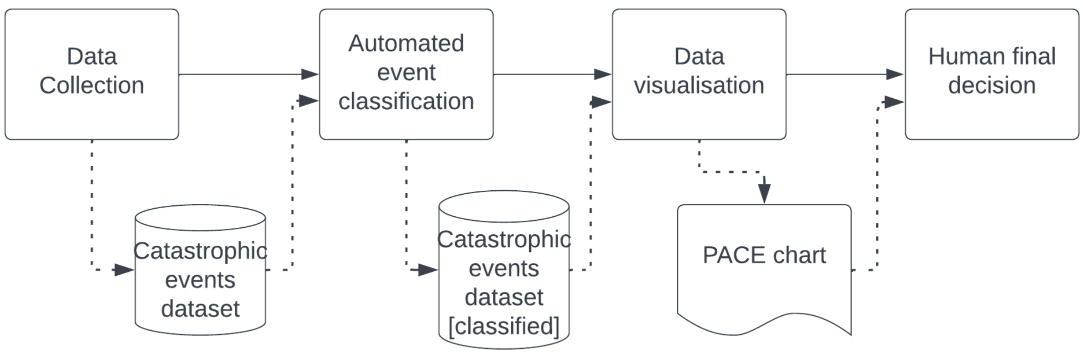

Figure 1: Process flow diagram.

[2] https://www.interlakemecalux.com/blog/logistics-lead-time

The process aims at training a **Machine Learning (ML) model** on a **multi-class classification task**. The input is catastrophic events with their descriptors, the output is the class of the event, which can take on four different values corresponding to the **action** suggested (i.e., **Plan, Analyse, Check, Exploit**). The class of the event is predicted using two KPI, namely *priority* and *difficulty*. The first KPI measures the event's priority compared to others, while the second KPI measures the potential difficulty of the rescue process.

Following the event classification, the results are **visually represented** using a PICK chart, appropriately adapted to the context of humanitarian emergencies. The x-axis represents the difficulty of intervention, while the y-axis represents priority. This way, a specific action can be associated with each event based on its level of priority and difficulty.

As last activity, the **final decision** rests with **decision makers** who have to analyse the results of PACE chart method in detail by quantifying distance among catastrophic events with each other and considering other possible potential factors that the model could not have considered, in order to take appropriate decisions in critical moments.

Each phase identified in the flow diagram will be explained in the following paragraphs.

2.1 DATA COLLECTION: VARIABLES AND MEASUREMENT

The first phase of the process involves collecting a large amount of data to train the ML model for a classification task. The idea is to use data related to real natural and artificial catastrophic events and manually label the target variable based on the action taken in response to the event or the action that should have been taken.

Data can be sourced, for example, from the *Centre for Research on the Epidemiology of Disasters* (CRED), which provides access to the **International Disaster Database**[3]. It is important to emphasize that these data alone are not sufficient to support correct decision-making and also suffer from various *biases* such as geographic, temporal, threshold, and risk biases (Khanken et al., 2021). This means that some events might be overlooked, for example, if they did not surpass the risk threshold to be considered as catastrophic events. Therefore, it is necessary to **integrate** them with **global**, **national**, and **regional databases**, as well as data from emergency reports, field surveys, and technologies like drones, satellites, and remote sensors.

Considering the defined objective, we aimed to enhance the efficiency of logistics planning by prioritizing events to allow better resource allocation. In the designed methodology, **PESTLE analysis** is exploited (Akman, 2020) to incorporate 6 fundamental dimensions (*Political, Economic, Social, Technological, Legal, Environmental*) as proxies for the measure of intervention priority. For each dimension, three Key Performance Indicators (KPIs) were further identified to provide a broader overview of the event and its characteristics, as shown in figure 2.

[3] https://www.emdat.be/

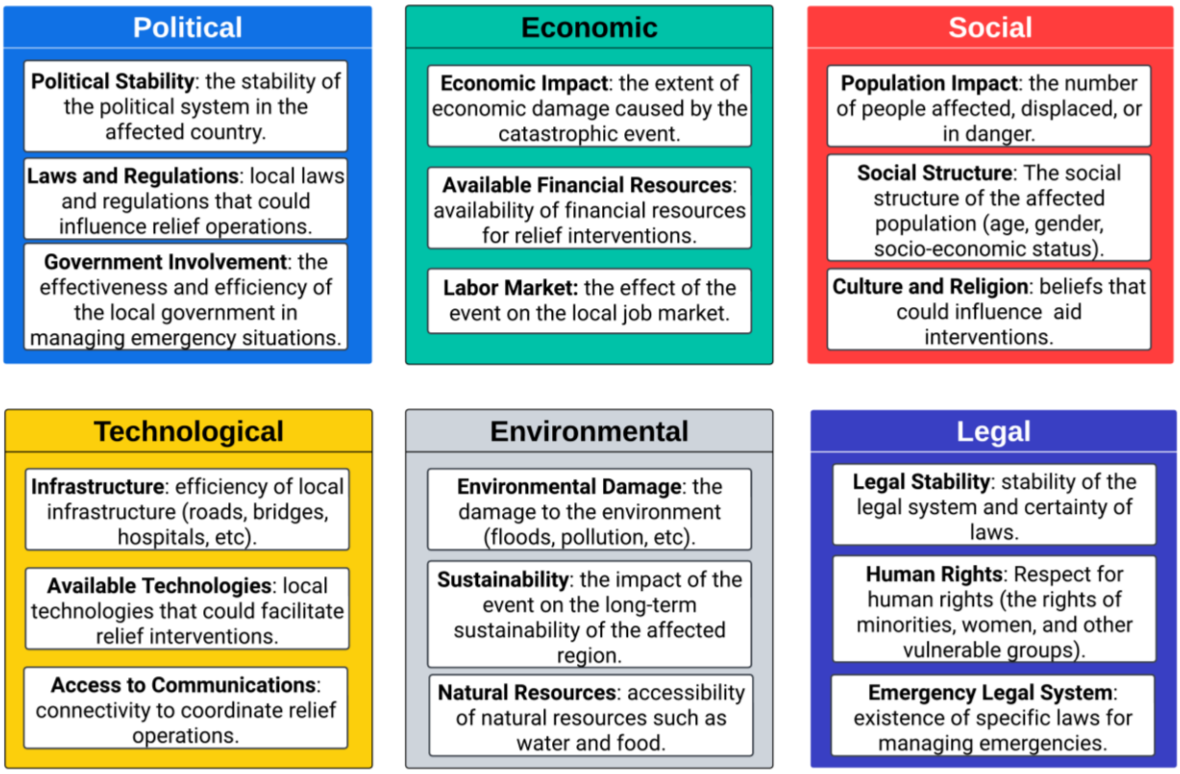

Figure 2: Identified PESTLE variables.

The other collected data, that aims to assess the challenges faced during the rescue process, are variables such as:

- **Demand and Supply**. Demand and supply reflect the **disparity between the needs** of the affected people (demand) and the **availability** of humanitarian resources and aids (supply). This discrepancy is crucial to understand the immediate needs of the population and the adequacy of rescue means. Demand can be estimated by analysing demographic data, the number of people involved, and their essential needs. Supply can be measured by evaluating human resources, medical supplies, equipment, and other aids available based on records from humanitarian organizations and rescue agencies.
- **Duration of Disaster**. The duration of the disaster impacts the **temporal planning** of rescue operations. Prolonged events require sustainable resource management and must address challenges such as long-term procurement and continuous support to the affected population. The duration of the disaster can be determined through historical data, field reports, and continuous monitoring. Analysing past trends can help predict the duration of future catastrophic events.
- **Location**. The geographic location of the catastrophic event directly influences the time required to reach the affected area (i.e., **lead time**) and can determine the ease or difficulty in accessing specific areas. Geographic conditions also influence the logistics of transporting rescue resources. Location can be assessed through geolocation systems, map data, and geographic information.

Considering these aspects, the use of artificial intelligence models to estimate demand, historical analysis to assess the duration of the disaster, and the use of geolocation technologies to evaluate location can significantly contribute to measuring and understanding the challenges of intervention in humanitarian emergency situations; in fact, the correct prediction of necessities demand and the emergencies duration based on historical data, enables organizations to minimize lack of preparation, reducing possible future damages and aggravations for people involved when a new event is recorded in the model, while the aware of its precise location and distance from organizations headquarters and warehouses helps the decision makers to planning the best path in terms of travel time and presence of obstacles.

2.2 DATA PROCESSING: EXPLAINABILITY AND HITL

The goal of the processing phase is to automatically classify a new event according to two metrics, both of which can take on high (H) or low (L) values:

- Priority
- Difficulty

A crucial aspect of our approach is the need for **explainability** (XAI) in the decision-making process. According to M.A. Kohl et al. (2019), "Explanations enable understanding and thereby foster trust and trustworthiness, justify actions and decisions, improve usability, help in locating sources of error, and can minimize the chance for human error. Particularly in "human-in-the-loop" scenarios, in which humans have to make a decision based on a system's recommendation, humans cannot reach an informed decision without having access to the system's reasons for its recommendation".

As technology progressed and the Internet became more complex with an higher and higher quantity of data, especially in the last ten years, the European Union recognized the need for modern protections; thus, the EU has introduced the **General Data Protection Regulation** (**GDPR**[4]) in 2018: according to it, the use of algorithms that influence human decisions are to be **transparent** and **explainable**; this means it is mandatory to explain how the ML model arrives at a specific prediction when its decisions impact the rights and freedoms of individuals, in order to make all the parts involved conscious about the implication of the use of the method. The implementation of explainability techniques is, therefore, a **legal necessity** as well as an **ethical** one (Coppi et al., 2021).

Moreover, traditional machine learning system development typically begins with data collection and labelling, followed by analysis, algorithm selection, etc., until the trained model can be deployed. **ML models** developed as described above risk becoming **static**, difficult to evaluate, and can degrade because of changes in the context in which they are implemented. When an unacceptable degradation is identified, the model needs to be updated, which can be complicated as machine learning experts and domain experts might be engaged in other projects, and many parts of training and feature engineering are difficult to document using traditional tools and processes (Holmberg et al., 2020).

An alternative path is represented by some approaches that involve domain experts in a brief training cycle and consequently allow continuously retraining the model so that it can adapt to changes in needs or implementation context. **Human-in-the-loop** (HITL) incorporates human experience and judgment into the decision-making process, enabling the decision-maker to evaluate the model's predictions in light of contextual information and their field experience. This hybrid approach, **combining artificial intelligence with human intervention**, ensures a flexible and adaptable response to the changing challenges of humanitarian emergencies.

For these reasons, we recognize the importance of a human-in-the-loop approach in our system (Mosqueira Rey et al., 2022).

[4] https://gdpr.eu/tag/gdpr/

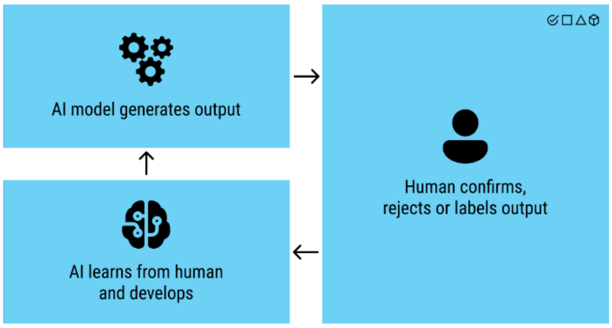

Figure 3: HITL approach representation.

2.3 DATA VISUALISATION: PICK CHART ADAPTATION

In the third phase of the proposed methodology, it has been chosen to graphically visualize the output of the ML model, adapting a tool typical of Lean Manufacturing to the context of humanitarian emergencies to guide humanitarian intervention decisions. The innovative methodology relies on the **PICK chart**.

In an industrial context, its use is attributed to the ease of identifying activities that are simple to implement but have a high payoff (i.e., to be implemented immediately, in the Implement quadrant), as well as activities that have a high payoff but require more time and resources (i.e., to be carefully planned, in the Challenge quadrant). This tool helps make informed decisions about **priorities**, **optimizing resource allocation**, and **maximizing** the overall **effectiveness** and **efficiency** of the project (George, 2009).

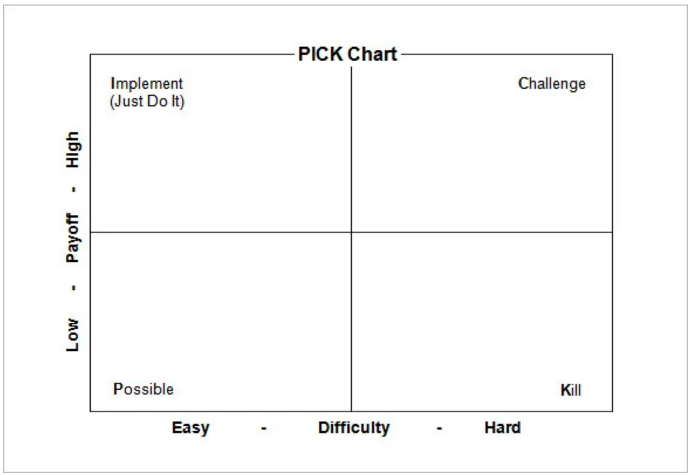

Figure 4: PICK chart.

In this context, the PICK chart focuses on evaluating the intervention priority and the associated difficulty of each event, synthesizing the structured data processing approach upstream of the rescue operations planning phase. Modifications to the tool were necessary, particularly regarding the y-axis, as it is not appropriate to speak of payoff resulting from the intervention in the context of humanitarian emergencies, given the strong moral and sense of duty matrix characterizing the stakeholders potentially involved in this tool.

The proposed framework is called the **PACE chart** (figure 5). Based on the values assumed by the priority and difficulty indicators, four distinct quadrants are identified: P (Plan), A (Analyse), C (Check), and E (Exploit).

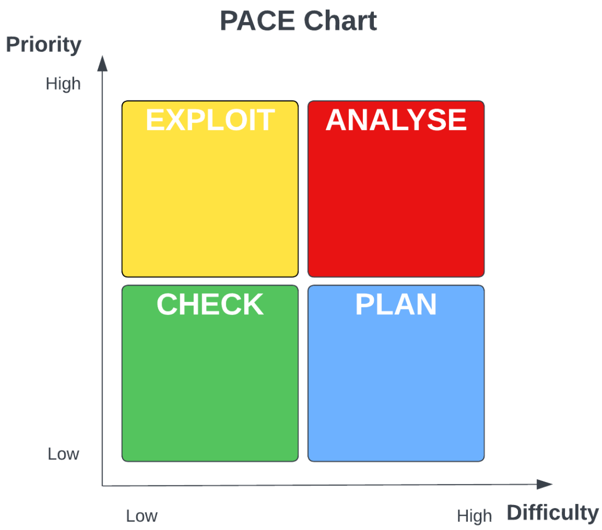

Figure 5: PACE chart.

1. **PLAN**: Interventions that can be carried out at a later stage compared to others as they require careful planning but are not particularly urgent.
2. **ANALYSE**: Interventions that require additional resources to be executed, necessitating a careful analysis of the missing resources.
3. **CHECK**: Monitoring activities for ongoing interventions that do not require significant resource involvement.
4. **EXPLOIT**: Interventions that already have all the necessary resources available and are ready to be implemented immediately.

2.4 Human final decision: technology-based support

In the final decision phase, the role of the human decision-maker becomes **crucial**. Despite the automation of the Machine Learning model, in the proposed methodology, the ultimate decision is made by a human. This hybrid approach combines artificial intelligence with human intervention to ensure that decisions are based not only on the data and predictions of the model but also on human wisdom and experience.

The PACE chart provides a clear visual representation of the priorities and difficulties associated with each event to support the decision-maker in a careful evaluation of the information provided by the chart, considering the specific context of the humanitarian situation. The strength of the graphical output consists in its ability to synthesize complex priority and difficulty data into a **visually intuitive format**. However, human experience and intuition play a crucial role in making informed decisions, taking into account not only numerical metrics but also the nuances and unique variables of each humanitarian emergency situation.

Moreover, human involvement allows for the consideration of **unmeasured ethical**, **cultural**, and **social factors** that can significantly influence the humanitarian response. The interaction between artificial intelligence and human intervention creates a flexible and adaptable environment, ensuring that decisions are timely, ethical, and effective in the face of the evolving challenges of humanitarian emergencies. This **synergy** between technology and humanity is essential to ensure a positive and meaningful impact in rescue operations within complex humanitarian contexts.

Lastly, it is important to recognize that behind each activity identified in the chart, there is a corresponding rescue action. Without human intervention to associate a specific action plan with each phase, the process could be paralyzed.

3 PACE: FRAMEWORK ASSESSMENT

This chapter is structured as follows: in section 3.1, a comprehensive SWOT analysis of the proposed framework is undertaken, providing a strategic overview. Subsequently, in section 3.2 an analysis of stakeholders potentially interested in the methodology is conducted.

3.1 SWOT ANALYSIS

The proposed framework presents a series of **strengths** that goes beyond its innovative methodological approach. These points allow users of the framework to achieve planning goals and get a more effective management of humanitarian interventions. The main strengths of this proposal are:

- **Data-driven decision-making process.** Intervention decisions are guided by accurate and detailed data analysis, minimizing uncertainty and ambiguity in humanitarian operations. This data-driven approach not only enhances the effectiveness of decisions made but also allows an objective evaluation of intervention strategies, contributing to better coordination among the involved organizations.
- **Prioritization of activities**. The methodology not only classifies events based on their priority but also provides a comprehensive overview of the tasks necessary to respond to each event. This prioritization of activities enables the decision-maker to focus resources and efforts on the most crucial operations, optimizing the use of limited resources.
- **Graphic visualization**. This leads to an **ease of interpretation** which is crucial in emergency situations, where rapid understanding of information is essential for making timely and effective decisions.

The **weaknesses** faced by PACE methodology arise from specific implementation recommendations, which need to be effectively mitigated by leveraging its inherent strengths. These weaknesses, when addressed strategically, can be turned into opportunities for further enhancement and refinement of the methodology. Some of these challenges include:

- **Constant maintenance**. The ML model need to be constantly updated to be effective in response to new kinds of emergencies and changes in humanitarian situations. An action based on non-updated data could not be the best choice in specific situations; a wrong priority rate could be associated to them, that surely causes wastes and retards in interventions.
- **Margin of error in PESTLE**. Furthermore, concerning the calculation of the indicator measuring the execution complexity of interventions, it is important to note that this indicator is based on the PESTLE analysis of the operational context. The calculator uses scores assigned to evaluation parameters, which might carry a certain degree of uncertainty. This uncertainty constitutes a margin of error, although a small one.

Certain potential **threats** to the effectiveness of the PACE tool must be acknowledged and strategically addressed to ensure its successful implementation. Although decision makers must remain vigilant about these challenges when adopting PACE, the proactive identification and mitigation of the threats empower them to navigate humanitarian interventions with confidence and precision. Some of the major threats are:

- **Machine Learning Model Training**. It is crucial to pay particular attention to the data used during the training phase of the ML model. Training on inaccurate data can lead to not just suboptimal, but even misleading decisions. This could have serious consequences both on the costs of humanitarian operations and on the harm suffered by the people involved. It is essential to carefully consider data collection during the tool's usage phase as well, as errors can also emerge in this stage, negatively impacting the decisions made.

- **Boundary Events**. Additionally, because the calculator processes non-integer values, the output results are rounded to the nearest tenth. This poses the risk of excessive approximation, which might not significantly affect scores that are far from the PACE quadrant boundaries. However, issues could arise in the *borderline areas*, close to the centre of the 4 quadrants, both regarding the complexity and the priority obtained. Therefore, events located near one of the two boundary lines should undergo a more in-depth evaluation by experts.

Finally, the adoption of PACE could offer some **opportunities** to exploit. By leveraging these opportunities, decision makers can maximize the impact of their interventions and achieve positive outcomes. These opportunities include:

- **Collaboration between organizations**. The use of semi-automated classification model supporting the planning process can help collaboration between international organizations involved in the relief process: if all of them use the same evaluation system, they could get **more coordinated response** to humanitarian crisis.
- **Twofold utilisation**. On one hand, the matrix PACE provides a **holistic overview** of the events considering the entire interventions as a whole; on the other hand, by breaking down the relief process, it enables targeted planning of **individual tasks**. This demonstrates the versatility of the proposed method not only towards complex operations, but also specific steps of them. This optimizes the use of available resources and creates synergy between activities, allowing for efficient intervention even in more complex emergency situations. As in the industrial context it is possible to distinguish between macro-processes, processes and tasks, in humanitarian emergencies, intervention can be broken down into a series of specific tasks. Therefore, while designed to handle macro-interventions, the tool is equally valid for coordinating a series of activities related to a larger-scale emergency.

The results of SWOT analysis are shown in figure 6.

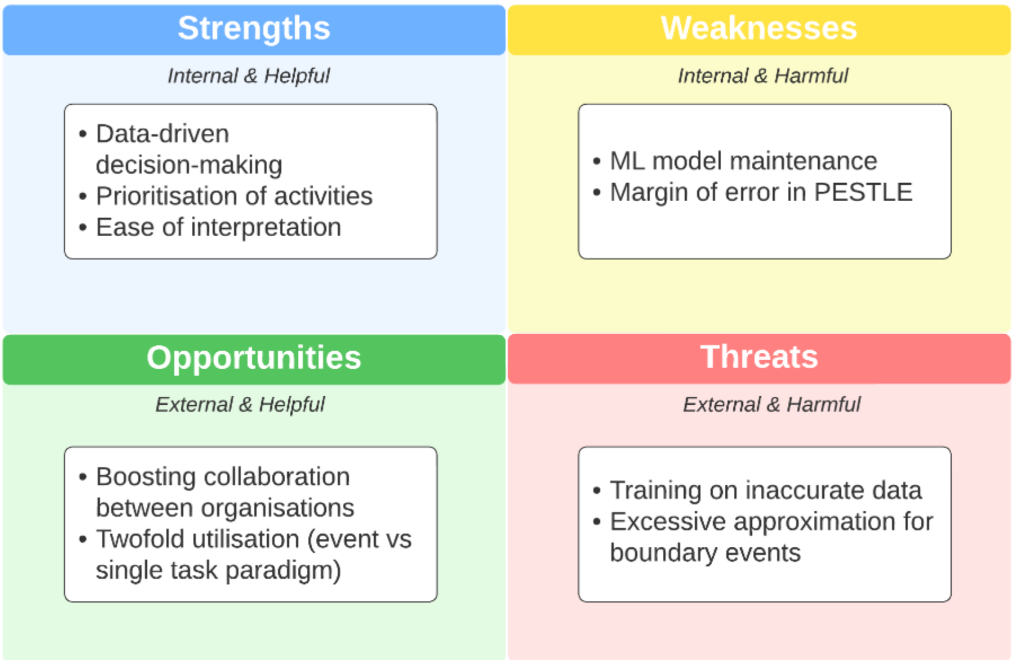

Figure 6: PACE framework SWOT analysis

3.2 STAKEHOLDERS ANALYSIS

As mentioned earlier, the PACE tool is intended to be used by **decision makers in the context of humanitarian intervention planning**. However, the use of the tool has effects not only on the users but also on other parts. These effects could be both positive and negative; moreover, some of these parts might oppose the use of the tool and hinder its implementation. Stakeholders can be classified in four groups as shown in Figure 6, which are:

- **Direct Stakeholders**. For humanitarian organizations and armed forces directly engaged in field humanitarian operations, our PACE tool offers fundamental advantages. They benefit from quicker and more efficient responses to humanitarian emergencies, optimizing the allocation of limited resources and minimizing errors. This translates into increased effectiveness in reaching affected communities and mitigating damages.
- **Positive Stakeholders**. Affected communities, local and national governments, donors, and sector experts gain from the swift and well-coordinated response to emergencies provided by our PACE tool. This translates into enhanced safety and reduced suffering for people involved, better coordination among humanitarian organizations, and increased donor confidence in the effectiveness of humanitarian operations.
- **Negative Stakeholders**. Although some humanitarian operators not directly involved might perceive our tool as a threat, the adoption of PACE can, in fact, contribute to greater efficiency and transparency within humanitarian operations. Communicating the potential of the system to these stakeholders can be helpful in mitigating their concerns and reducing resistance to change. Moreover, there needs to be continuous evolution of the process to include marginalized communities, for example, those not present in the datasets.
- **Enemies**. Hostile actors, such as armed groups, criminal and terrorist organizations, might show resistance to the implementation of our PACE tool. Their opposition could translate into direct actions aimed at hindering the use of PACE, with the goal of hindering resources supply and information flow within the context of humanitarian operations. Therefore, it is essential to carefully monitor these dynamics and adopt preventive strategies to safeguard the integrity of the PACE system and ensure that humanitarian operations remain efficient, safe, and capable of responding promptly to emergencies.

It is important to be aware of the stakeholders and the type of interest they have regarding the tool, in order to understand the expectations of the involved parties, engage them in case of positive interest. The goal is to further improve the tool, quantify the risks associated with its use, and adopt defence strategies well in advance.

Figure 7: Stakeholders

4 CONCLUSION

In conclusion, the innovative PACE framework offers a transformative approach to humanitarian intervention planning by **leveraging advanced data science techniques** and **human expertise**. The ease of interpretation of the visual results of this method allows decision makers of most important humanitarian organizations to not only optimizes resource allocation, but it also guarantees a **swift** and **coordinated response** in the face of critical situations, setting a **hierarchical order of interventions** and reducing time-decision. This order is established by an objective evaluation, made using a **XAI Machine Learning model** trained with historical data of previous emergencies, in such a way to ensure an accurate forecast of the future events. The high flexibility of the instrument enables its application to a wide range of different kind of interventions in **different scenarios**, such as **humanitarian aid, humanitarian war emergency, natural disasters** and many others. However, challenges, such as data accuracy and potential biases, require careful consideration. Moreover, understanding the wide range of stakeholders and their interests is crucial for successful implementation. Overall, **PACE** represents a significant advancement in humanitarian logistics, offering a **versatile solution** to the complex challenges faced in emergency response operations.

5 REFERENCES

- Apte, A., Gonçalves, P., & Yoho, K. (2016). Capabilities and competencies in humanitarian operations. *Journal of Humanitarian Logistics and Supply Chain Management*. https://www.emerald.com/insight/content/doi/10.1108/JHLSCM-04-2015-0020/full/pdf?title=capabilities-and-competencies-in-humanitarian-operations;
- Van der Laan, E. A., Brito, M. P. D., Fenema, P. C. V., & Vermaesen, S. C. (2009). Managing information cycles for intra-organisational coordination of Humanitarian Logistics. International Journal of Services Technology and Management, 12(4), 362. https://doi.org/10.1504/ijstm.2009.025814;
- Van Wassenhove, L. N. (2006). Humanitarian Aid Logistics: Supply Chain Management in high gear. Journal of the Operational Research Society, 57(5), 475–489. https://doi.org/10.1057/palgrave.jors.2602125;
- Thomas, A.S., Kopczak, L.R., 2005. From Logistics to Supply Chain Management: the Path Forward in the Humanitarian Sector. Tech. Rep. Fritz Institute, San Francisco CA. http://www.fritzinstitute.org/pdfs/whitepaper/fromlogisticsto.pdf;
- Balcik, B. and Beamon, B.M. (2008), "*Facility location in humanitarian relief*", International Journal of Logistics: Research and Applications, Vol. 11 No. 2, pp. 101-21;
- Gourlay, C. (2000), "Partners apart: managing civil-military co-operation in humanitarian interventions", Disarmament Forum, Vol. 3 No. 2000, pp. 33-44. https://www.academia.edu/761052/Partners_Apart_Managing_Civil_Military_Cooperation_in_Humanitarian_Interventions;
- Van Der Laan, E., Van Dalen, J., Rohrmoser, M., & Simpson, R. (2016). Demand forecasting and order planning for humanitarian logistics: An empirical assessment. Journal of Operations Management, 45(1), 114–122. https://doi.org/10.1016/j.jom.2016.05.004;
- Farahani, R.Z., Rezapour, S. and Kardar, L. (2011) *Logistics Operations and management: Concepts and Models*. San Diego, CA, USA: Elsevier Science;
- Imai, M. (1991) *Kaizen, the key to Japan's competitive success.* Singapore: McGraw-Hill;
- Khankeh, H., Mazhin, S., Farrokhi, M., Noroozi, M., Roudini, J., Hosseini, S., Motlagh, M., & Kolivand, P. (2021). Worldwide disaster loss and damage databases: A systematic review. Journal of Education and Health Promotion, 10(1), 329. https://doi.org/10.4103/jehp.jehp_1525_20;
- Akman, M. K. (2020). Defense Management and PESTLE Analysis. Ante Portas. https://doi.org/10.33674/3201910;
- Coppi, G., Moreno Jimenez, R., & Kyriazi, S. (2021). Explicability of humanitarian ai: A matter of principles. Journal of International Humanitarian Action, 6(1). https://doi.org/10.1186/s41018-021-00096-6;
- Mosqueira-Rey, E., Hernández-Pereira, E., Alonso-Ríos, D., Bobes-Bascarán, J., & Fernández-Leal, Á. (2022). Human-in-the-loop machine learning: A state of the art. Artificial Intelligence Review, 56(4), 3005–3054. https://doi.org/10.1007/s10462-022-10246-w;
- Explainability as a Non-Functional Requirement, Maximilian A. Köhl, Kevin Baum, Markus Langer, Daniel Oster, Timo Speith, Dimitri Bohlender, 2019 IEEE 27th International Requirements Engineering Conference (RE). https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8920711;
- Holmberg, L., Davidsson, P., & Linde, P. (2020). A feature space focus in machine teaching. 2020 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops). https://doi.org/10.1109/percomworkshops48775.2020.9156175;
- George, M. L. (2003). Lean six sigma for service how to use lean speed and Six sigma quality to improve services and transactions. McGraw-Hill.