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Development of Risk Management Framework for Digitalization and AI use in Engineering Projects

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Abstract

Background-The Inclusion of Artificial intelligence and other digitalisation technologies in Engineering projects has enormous potential to fulfil project objectives that prioritize low risks and better end quality. However, using Artificial Intelligence and other digital technologies in projects was being less implemented practically on-site, especially in the construction sector in some countries, for many Socio-technical reasons.

Purpose-Recently, many projects worldwide have undergone critical constraints; due to these, the stakeholders are much concerned with evaluating risk as the nature of constraints is unstable, making it challenging to execute existing risk management processes.

Proposed work-Therefore, proposed work in this paper can resolve the complex constraints with higher positive benefits and minimise adverse impacts has become imperative. The proposed work contains designing an Artificial Intelligence Risk Management Framework by the algorithm for Engineering projects which can identify and analyse all possible risks and their consequent range of impact, with a broader performance study of each component of the AI framework with high-quality, minimal negative impacts, and cyber security with a high-end response to any new risk generation. Out of all Risk Management techniques/tools for AI systems to choose the most appropriate risk management process which can balance all Socio-technical systems, especially for multi-constraint projects. Thirdly, working of the AI Risk Management Framework and its operation. Finally, designing AI Risk Management Framework with detailed functioning is the main and is in the scope of this paper. The comparison analysis of proposed framework to existing framework can be done which will help in identifying key characteristics of the framework. There are two main limitations that require attention in future, first is Adoption of the framework in the practical project, and second is the absence of validation processes.

Keywords: Multi constraints, Risk Management Framework, Stakeholders.

1 Introduction

Background:

Recently, many Industries and Engineering Projects have undergone some unstable and unpredictable constraints. These constraints were challenging to mitigate in keeping working people safe (Liu et al., 2021). For example, the COVID-19 pandemic has impacted in unstable Economic positions of companies worldwide, with the loss of critical employees. In addition, it is not feasible to ensure all the risk assessments are complete when an actual unpredictable constraint can create a financial loss in the project. Regarding the post-pandemic situations, the companies affected by the pandemic desire to have better and new risk management that can alert about all risks prior to start of Engineering projects.

Problem definition& Knowledge gap:

Digital transformation using AI in Engineering projects has many advantages, ultimately resulting in high positive and low-risk impacts. However, including AI in the Metallurgical & Materials sector might be challenging. Because as per the statistics, there is approximately 30-40% of employees worldwide face fatal accidents and injuries *(Pan and Zhang, 2021)* in construction projects. Therefore, it is imperative to design a new ethical risk management framework use of AI, which can keep accidents, and injuries at the project site minimal. The Risk Management Framework is vital in all significant large and small Engineering Projects. Currently, several Decision-making techniques are being implemented in projects around the world. There exist Standards, Operating Procedures, and *Codes* (Sadeghi, Zhang and Mohandes, 2023) for each risk that can cause accidents. However, implementing Artificial Intelligence in Metallurgy& Materials projects, specifically developing Risk Management frameworks under AI, is being followed in a fewer organisation. In addition, foreseen risk predictors such as COVID- 19 and others could not be able to predict before its impact on the project**.**

Aims & Objectives:

The main high-level aims are incorporated to resolve the primary crusts of this paper. To design a Risk Management Framework based on Artificial Intelligence algorithms for choosing the best Risk Management Process for Engineering projects particularly to Metallurgy and Materials Field. Working nature of all categories of the framework, specifically during uncertain risks such as Pandemics, others. The below objectives are developed and designed to resolve each above aim. To design an AI Risk Management framework using a comparative literature study of several research papers, British Standards. To design the basic functionality of the proposed framework using past and recent Case Profiles with relevant literature justification.

2 Research Methodology:

Implementing Artificial Intelligence by organisations for day-to-day business operations is essential for better productivity and quality. In the technology market, several AI techniques exist to develop AI systems in Organisations (Sarker,2022*)*. However, these techniques widely depend on the Application of AI.

Uncertainty of some of the risks in the project impacts project costs and human accidents. To regulate these unpredictable risks, it is evident to prioritize in Framework and select the appropriate model. The infographics below (Figure1) shows three categories: Decision making, Uncertainty modelling and Framework building. In each category several techniques/methods can be used to fulfil category goals. It is also evident that several other techniques can also be used for effective decision-making and Uncertainty of risks apart from those listed in the below figure. However, the listed techniques are best suited for expecting maximum profit and minimum risk (Boix-Cots, et al. 2023). Therefore, below (Figure 2) is a comparative study to select one technique/method for the Decision-making category.

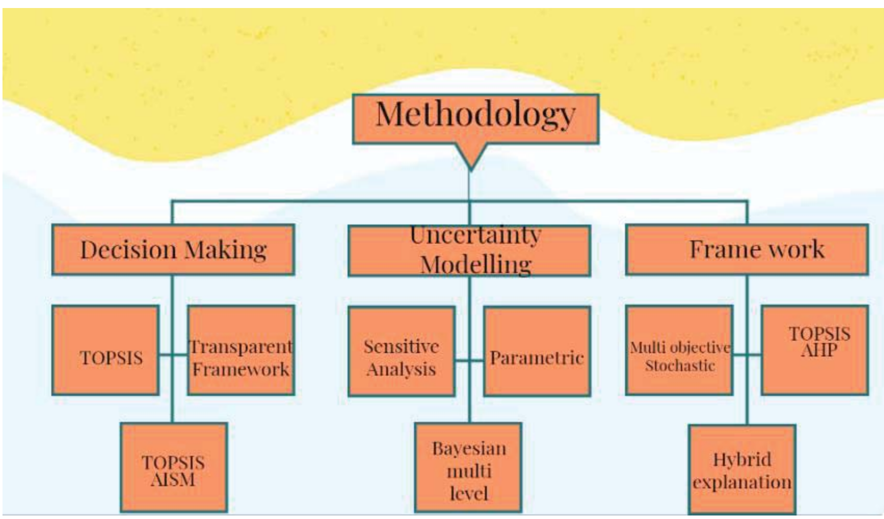

Figure 1: Methodologies of AI (Boix-Cots, et al. 2023).

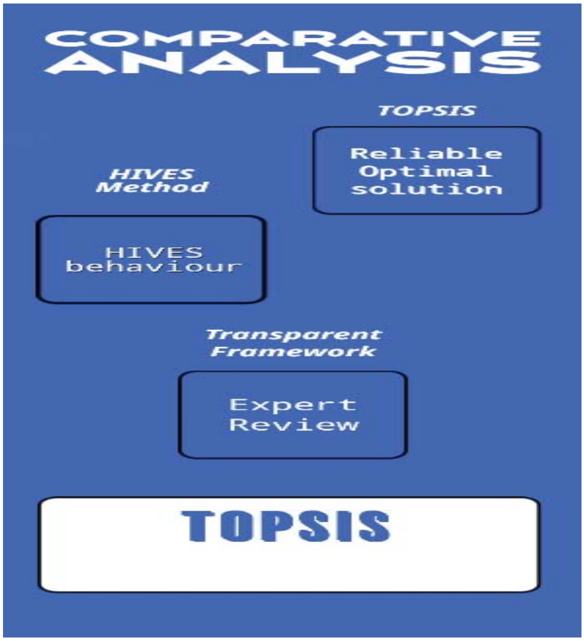

Figure 2 Comparative analysis of methodologies for Decision making capability

The effective decision making mainly depends on the requirements fed as Input to AI systems. So, it is important to induce desired requirements in the AI system (Berscheid and Roewer-Despres, 2019), to avoid data overlap and any other AI system complexity. The Transparent framework starts with an AI Validation document and ends with an Expert review. However, this methodology could not be considered because data collection and other steps involves expert review or Interviews. Instead, data collection in this paper is only achieved through literature data and the development of new reviews. Secondly, the HIVES method also cannot be considered because the HIVES process consists of a process called HIVES behaviour, which involves a task such as the Vote Casting technique for considering previous influences (Boix-Cots, Pardo-Bosch and Pujadas, 2023). Hence Technique for order preference by similarity to an Ideal Solution (TOPSIS) can be used, as it is easy to apply and efficient in resulting in the optimal decision (Sun *et al.*, 2022) on suitable Risk Assessments.

For Uncertain risks, the Sensitive analysis is a suitable modelling technique that helps identify and rank the influencing attributes (Dwivedi, Kumar and Goel, 2023). For designing AI Risk Management Framework, the Hybrid explanation model is not considered as this model involves a combination of two models with complex algorithms, which are sometimes tricky to interpretable *(Amini, Bagheri and Delen, 2022).* On the other hand, the AHP-TOPSIS framework is Analytic Hierarchy process Technique which makes decision effectively on the importance of project and risk impact. Secondly, combination of AHP with TOPSIS ranks the alternatives solutions required to overcome Complex Uncertainties in Engineering Projects (Magableh and Mistarihi, 2022*)* and reach a suitable risk assessment stability.

3.Framework Design:

3.1 Decision making:

The below conceptual proposed framework consists of three main Risk categories: Known risks, Past lessons learnt and Unknown risks. In general, for any Engineering project, the Project Portfolio risks are categorised into six categories such as Organisation, Time, Cost, Quality, Human Resource Management, Stakeholder management (Zhang et al., 2023*) etc*. However, here the categories are listed based on cause of risks that could occur depending on Machineries, Environment/Project location, and Chemicals and Fire systems used throughout the project. In addition, a specific cause of risks, known as shut down safety rules, is also incorporated in the framework, as some projects may be pause work for couple of months under unexpected or External cause (Zhang et al., 2023*)*. Therefore, it is crucial to recognise all possibilities of causes of risks, whether Internal or External, for an accurate output of optimised Risk Management Process.

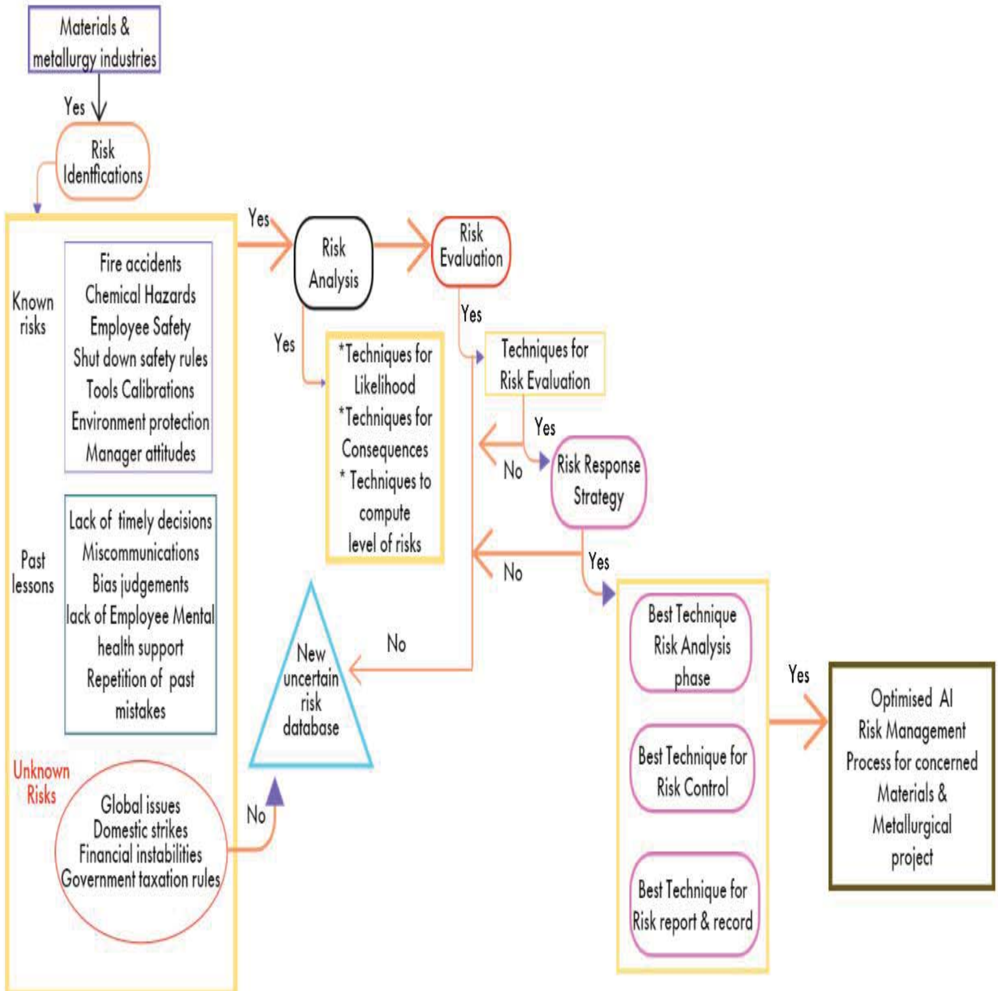

Figure 3 Design of Risk Management Framework (Risk part) (BS: EN 16991:2008)

From the above conceptual proposed framework, unknown Risks is equally important. It is also evident that predicting risks at various project phases and considering past risks (Filippetto, Lima and Barbosa, 2021*)* will help the Manager acquire more knowledge before starting a new project (Filippetto, Lima and Barbosa, 2021*)* timely. Finally, any new uncertain risks or causes occur at any project stage. In that case, the AI framework also possesses a system known as New Uncertain risk database which integrates with existing risk identifiers and stored there accordingly. Finally, the decision-making capability can balance Technical, Socio- Economic and Ethical values and could give an output which is Optimised Risk Management process from this framework. However, the decision-making framework need to run under a positive and ethical AI Lifecycle which is as shown below.

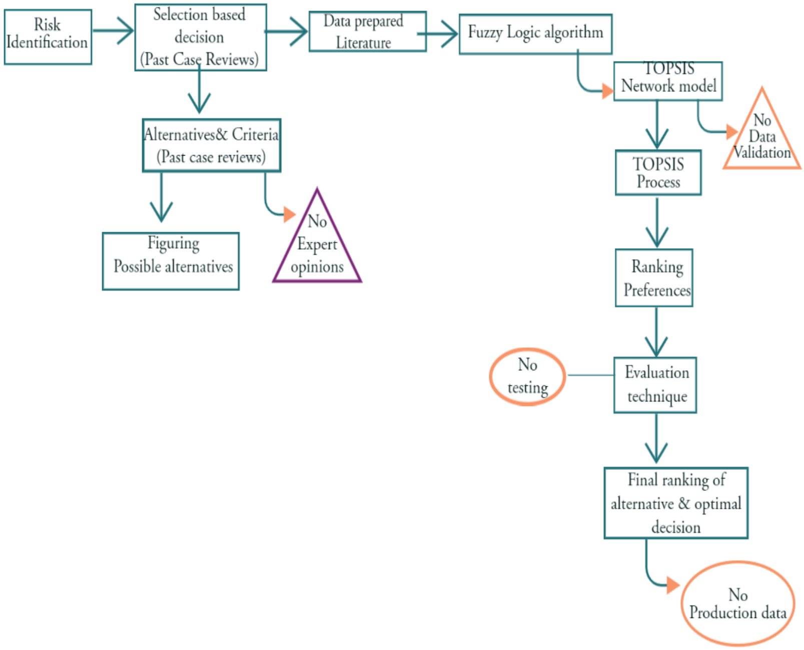

Figure 4 Ethical AI Framework using TOPSIS

The design of the above AI lifecycle was also developed using British Standards such as *(*BS ISO/IEC 23053:2022 Framework for Artificial Intelligence using Machine learning). The basic Artificial Narrow Intelligence (ANI) will only be used to achieve one specific task (Mezgár & Váncza, 2022*),* that is, to give the best Risk Management Process for Metallurgy & Materials Engineering projects, which starts with Data evaluation and Data preparation steps as shown in the above figure. However, Model deployment and operation have not been carried out. However, algorithm selection and its evaluation by TOPSIS techniques are performed to achieve the desired goal. The main reason for selecting the Fuzzy logic algorithm instead of another one is that it effectively makes decisions, specifically identifying risk (low, medium & high) by analysing all the data collected (Panja et al., 2023) *and* results in the best possible optimal output. A combined integrated model, Fuzzy-TOPSIS (Technique for Order preference by similarity to Ideal solution), is used in the model evaluation.

3.2 Data Collection:

The below is the data collection process for this framework under an Artificial Narrow Intelligence ANI type of system. The fundamental requirement is to select the appropriate platform for executing AI operations. In the market, some of the latest ANI examples use basic platforms like Google AI and Phone (Labeeuw,2022*).* Similarly, the same platforms can be used for this framework. For real-time practical execution, data such as updated risk register forms, inspection reports, accident reports, ethical decision records, etc. must be considered as Input. According to the ANI type, the collected data must be processed and then imported into the ANI system without any errors in the data formats. Usually, the data used for the ANI system can be in a format such as text, image, or video (Labeeuw,2022*).* Similarly, the same formats will be used for this framework. After the data creation stage is completed, the next stage is data evaluation, which begins with data cleaning and formatting (Opidi, 2020). The basic agenda of these steps is to avoid and eliminate unnecessary data and manage data in such a way that the format of the data does not deviate from ANI Data format settings.

The next step in the data evaluation stage is the data scaling. Since data can vary in terms of its attributes, units, and other factors, So, it is highly important to set boundaries, especially with regards to the attributes. Therefore, the data scaling is the stage where its focus is to scale up all the data and apply the same sub criteria (Opidi, 2020) to each set of data evaluated for every run of the ANI system operation cycle so that there won't be any different data with different sub criteria get analysed, which could give an undesired output. Until here, the data evaluation stage completes, which then goes to the next stage, which is task definition *(*BS ISO 23053:2022). Here, the specific task is set, which is to evaluate all risks that could cause any metallurgy and materials engineering project and produce the best optimal risk management process. Finally, once the data has been evaluated, it will be subjected to fuzzy modelling and the TOPSIS methodology to evaluate risks.

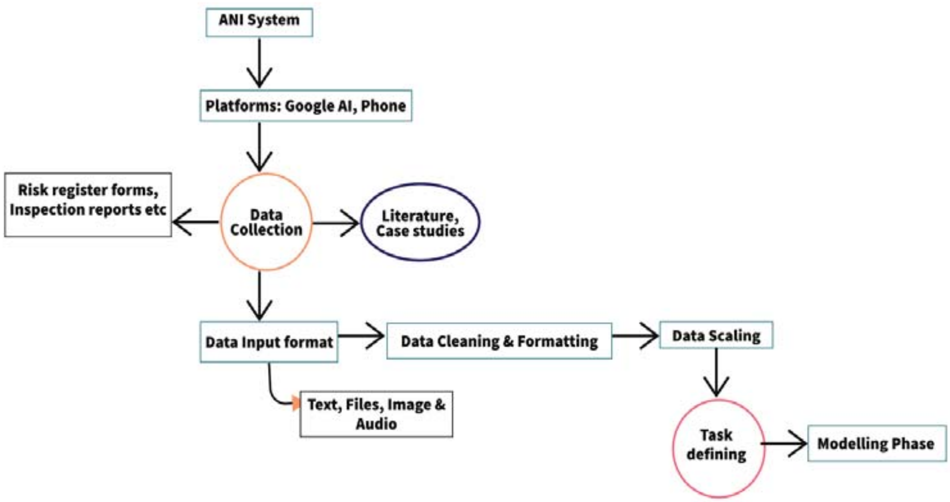

Figure 5: Data collection map for AI system

3.3 Framework Operation Map:

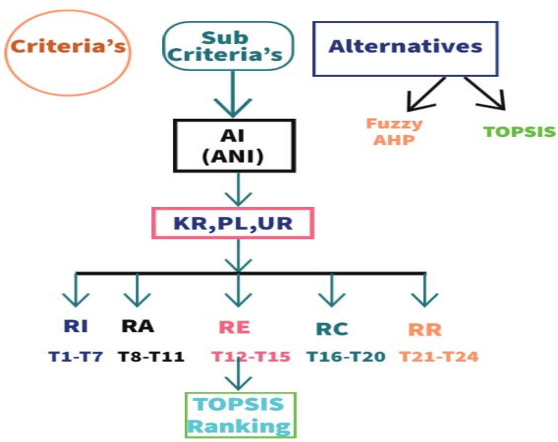

Figure 6: Framework operation map (Sheoraj and Sungkur, 2022)

The above figure is the flow of the framework operating procedure of AI under the fuzzy TOPSIS method. Firstly, the AI system evaluates the risks based on the input, such as criteria and sub-criteria, fed to it. Secondly, as this framework expects that desired output should control any sort of unfair decisions towards ethics and socioeconomic (De Silva & Alahakoon, 2022) rights of individuals, to manage these rights, the system needs to fix a standard weight for each criterion (Mathew,2018). The alternatives could also be considered as input, if there is a lack of data of sub-criteria. During the evaluation stage, the AI system checks all possible risks by using known risks (KR), past lessons (PL), and unknown risks (UR). Finally, as per the TOPSIS system, it does a specific task (Sheoraj and Sungkur, 2022), which is to generate the optimal risk management process for that project.

4 Decision attributes for Engineering Projects:

The main objective of the Risk register database is only to collect and store all necessary past risks of similar projects that occurred with the help of Artificial Intelligence techniques and produce an optimised Risk assessment. Finally, a significant benefit of this database is that it helps both Organisation and project team in segregating and identifying all risks, prior to the Project start date. Safety management is one of the crucial departments; as per statistics, it is observed that accidents in projects are caused due to poor safety management measures (Khalid, Sagoo and Benachir, 2021). In addition, accidents or significant risks could hinder project status and deadline. Therefore, the main aim is only to collect and store all necessary details, including Compliance with factors such as Personnel, Organisational, Environmental, Managerial, Social and Legislature (Khalid, Sagoo and Benachir, 2021*)*. that can cause safety issues at any Project stage. Finally, this inclusive way of considering the above factors can help to achieve desired Safety Performance.

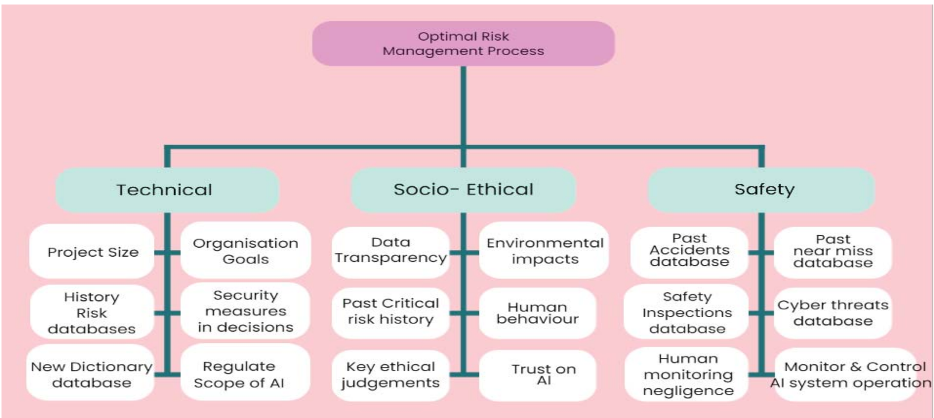

Figure 1 Decision attributes for AI (Dwivedi, Kumar and Goel, 2023)

It is clear from the below figure that the main objective of the framework is to result in the best optimum Risk Management process for Engineering projects, especially for the Metallurgy & Materials sector. Secondly, this AI Framework predominantly focuses on three main criteria: Technical, Socio Ethical & Safety data inputs before the resulting outcome. In addition, the sub-criteria for each criterion will also be considered in the *process* (Zubayer, Mithun Ali and Kabir, 2019*)* and are the main constituents; however, if the Organisation does not comply with all the data required to the framework as Criteria and Sub Criteria's. In that case, some of the Alternatives such as Text, Image & voice (Kanade et al., 2022*)* recording of a person about a Project can also be utilised in the system as Basic Alternative, as they are easily compactable with AI systems.

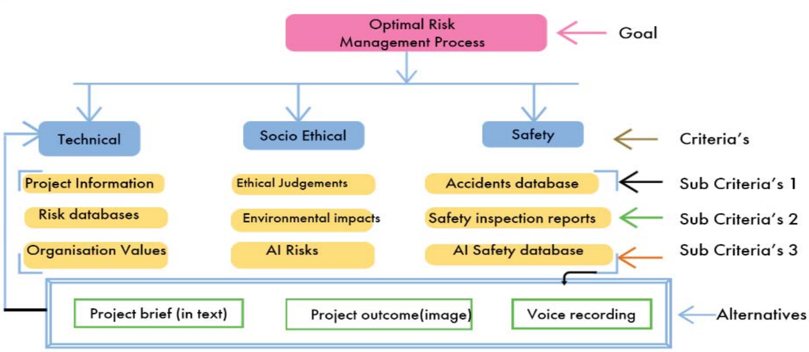

Figure 2 Decision hierarchy Structure for AI (ISO/IEC 9126-1(2001))

5 Conclusions & Future work:

Based on several pieces of literature, it is concluded that the urgency and need for an artificial intelligence system in metallurgy and materials engineering projects have been identified to tackle new uncertain risks in projects as well as keep individuals safe and prevent any accidents. Moreover, due to a tight project schedule, it is sometimes hard to pay attention on risks and perform risk techniques practically on a timely basis. So, this paper proposes a Risk management framework run under an Artificial narrow intelligence system that evaluates all possible risks by taking into three categories of data input to AI: known risks, past lessons, and unknown risks, and gives out an optimum risk management process with a balance of Socio-ethical of one's individual rights before start of project which helps organisation to plan Risk Management. The main operation of the framework depends mostly on two main parameters: one is data input such as sub-criteria and alternatives. The second is the evaluation of all three categories of data: known risks, past lessons, and unknown risks. Three alternatives such as the project brief (in text), the project outcome (in image), and voice recording were used in this framework. In this project, the design of the AI Risk Management framework is divided into two parts: the Risk part and the AI part. However, the integration of these two parts into one could be future work.

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