A submission to the:

NASA
GAME CHANGING DEVELOPMENT (GCD) PROGRAM

---

of a proposal for the:

RISKY SPACE BUSINESS:
NASA AI RISK PREDICTION CHALLENGE

by

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WHITEPAPER

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3. Submission Title

Proposed Design of a Comprehensive Program Risk Assistance Tool with an AI Interface for Predictive Guidance

Submitted on February 4th, 2022.

4. Executive Summary

This whitepaper proposes a design for a comprehensive 'Digital Assistant Tool' with a suitable GUI interface, together with concepts, terminologies, methods and processes in response to NASA's AI Risk Prediction Challenge (see Figure 1 for solution overview). It answers that call for whitepapers and algorithms to help identify, predict and mitigate the potential risks of new or currently active projects by using AI to compare them with previously learned lessons and historical information available from past GCD (Game Changing Development) projects and other sources.

It does that by explaining how all four main requirements described on page one of the challenge document can be addressed, and suggests how the capabilities of this tool can also be extended to include engaging with both the positive and negative challenges generated by the consequences of issues, and follow through with their resolution (for example, by risk mitigation), to help secure the intended outcomes of projects. Thereby enabling NASA, and potentially anyone managing a project, to use the knowledge accumulated from past (heritage) projects to improve how they identify and assess the challenges of future projects before they materialize.

I believe this is a game-changing solution proposal that truly matches the aspirations of NASA's GCD Program, by applying innovative new approaches to its requirements. In the remainder of this executive summary, I will try to provide a little context around my claims, and describe how I have presented those approaches within the submission requirements of this whitepaper.

My research efforts are focused on the strengths and weaknesses in conventional notions of risk, and where current approaches limit possibilities for practical disciplines such as program and project management, and mission-critical decision making. The relevance of AI/ML in those efforts has focused my research attention on a two-way human interface between AI/ML and risk management.

The ideas presented here are a composite of the best that current risk management and data science can offer, together with new notions I teach in training courses to online students, and solutions I have implemented for numerous client organizations around the world over the past 30 plus years. Most of these ideas are embedded in a software tool I have developed for training and client assignment interactions, which I use in this whitepaper to illustrate what a comprehensive ‘Digital Assistant’ tool incorporating solutions to all four requirements might look like. This is currently a highly configurable tool intended for educational use, and not packaged for commercial release. But I am upgrading it based on operational features requested by clients and partner organizations, which include an improved AI/ML interface for project risk management within its primary role of providing a ‘situation room interface’ for mission-critical decision making.

Meanwhile, I emphasize it is presented here as a prototype, for illustration purposes, to show the viability and full potential of implementing a comprehensive solution if that is considered the preferred option.

Finally, key aspects of this proposal can be found under the headings prescribed in section 5 of submission requirements. They aim to satisfy the four categories of judging criteria, while placing an emphasis on explaining the proposed solution, instead of providing example code algorithms and testable scripts. Although coding is an important part of solving this challenge, I will attempt to show it is not the ‘game-changing’ part.

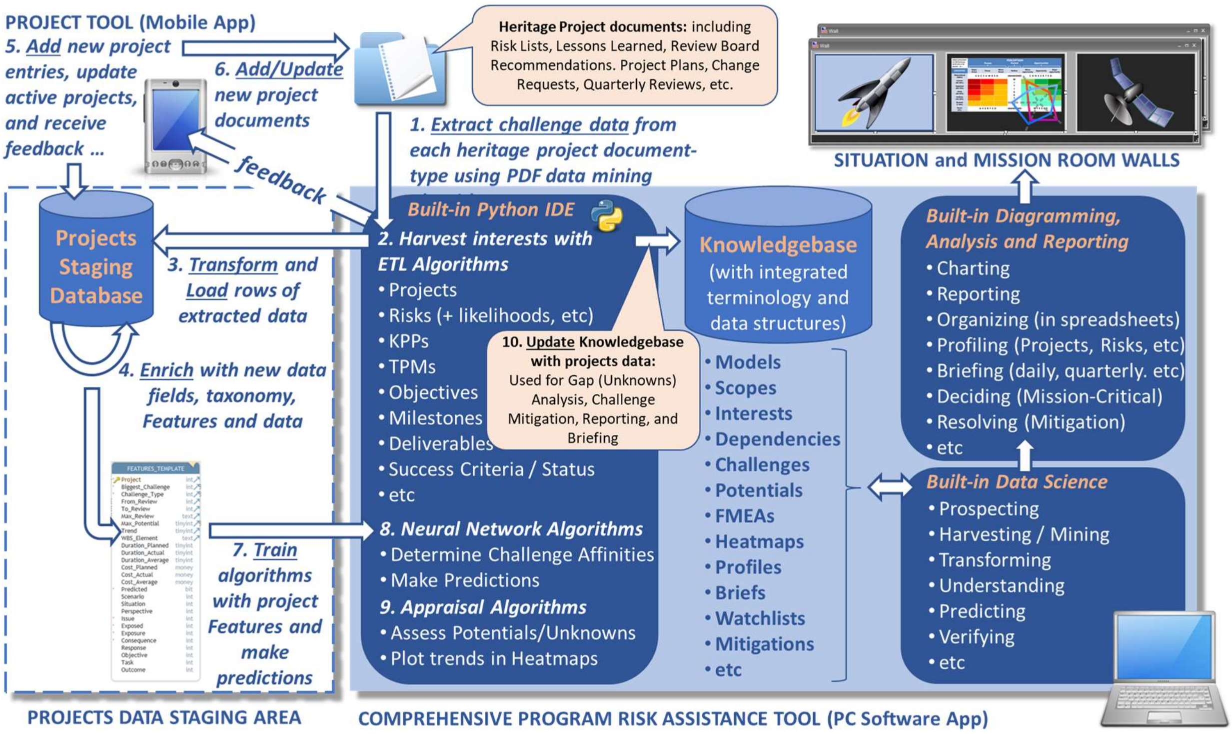

Figure 1: Outline of a comprehensive solution based on using a Digital Assistant Tool

Figure 1 provides an overall visual reference for this proposed solution, whereas some later sections include specific diagrams, and further details are shown in the appendices.

5. Solution

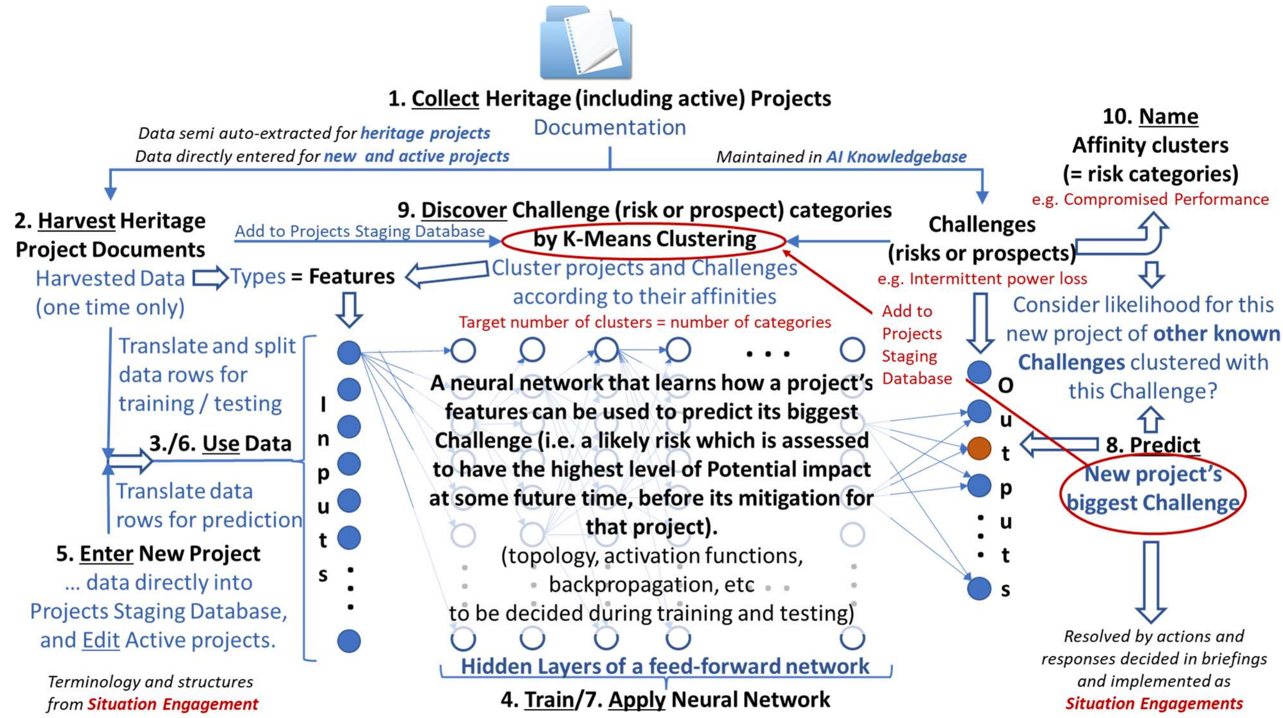

Figure 2: Known risk predictions

The above figure is provided here as a specific visual reference for sub-sections **a** and **b** below, to help explain why their data proposals are relevant (see sub-section **c** for a detailed explanation). It shows a solution overview for one of the main objectives of this submission: how to predict the potential of known risks for new projects from past (heritage) data. Prediction of previously unknown risks will be covered later.

a. Proposed data to be collected

i. Recommended data fields and data structures to be used based on past data.

As recommended for this type of data science initiative, I first reviewed the project documentation provided, and identified the following concerns that suggest options, priorities and required work-arounds for making recommendations in collecting and structuring past (heritage) data.

[1]. The equivalent project documents provided from two projects (Astrobee and SynBio) are a small sample for representing a large heritage of projects from various research centers and directorates over an unspecified period of time, each with their own documentation standards.

[2]. Although those provided documents try to apply the same terminology and conventions of Continuous Risk Management for risk identification, tracking and mitigation, while complying with NPR 8000.4A procedures, their individual

approaches are sufficiently different to make some data harvesting techniques unreliable. For example:

- **The two sample projects have distinct identification schemes and naming standards for risks, and provide further details inconsistently in the form of differently expressed risk statements or descriptions.** Which has implications for correctly interpreting a coherent meaning from risk text during data collection.

- **Relevant information is fragmented among each project's documentation**. So, for example their 'Risk List', which is maintained as a separate data source for the risk information in monthly and quarterly review presentations, does not contain additional useful information about the context of each risk, which can only be found where it is added later in the risk slides of those reviews.

- **Risks are categorized differently.** In Astrobee they are categorized by Performance, whereas SynBio categorizes them by Affinity, with no cross-reference or translation available.

- **Lessons learned are not recorded in a way that relates them back to specific project documentation content.** Which results in a disconnect between those lessons and documented project risks, mitigations or other observations that enables useful feedback.

- **Expressions of risk in this sample documentation sometimes confuse a risk with something else,** such as an issue, the thing at risk, or an exposure. If those expressions are confused, then AI-based interpretations are likely to be wrong. A work-around mentioned in a subsequent section of this whitepaper will recommend that the proposed data structure for past (heritage) data will be based on an improved terminology, and expressions will be translated accordingly.

- **Risks are logged and cumulatively retained in risk summaries, along with indications of how they are currently trending and their latest criticality**. So, it would be tempting to only collect risk data about a project that is provided by the latest summary. However, the solution recommended by this submission (see sub-section 5.c) argues that more accurate results can be achieved by predicting a project's biggest risk, with the highest level of potential impact over time, and then identifying other relevant project risks (both known for that project, and know for similar projects through affinity analysis). Which requires a longitudinal analysis of the changes in criticality of all risks in a time series of risk summaries for a project. But this assumes that risks have been consistently logged over time, and are comparable in their assessed criticality.

[3]. The current capabilities of machine-learning algorithms for predictive guidance generated from structured 'features' data about project risks are much better than algorithms for automatically extracting meaning from raw unstructured data. The

latter requires very large volumes of data. Although NASA and its partner organizations have a large collection of project documents, they are unlikely to provide enough clean data for automated risk categorization to be viable without any manual intervention.

Given all of the above-mentioned concerns, it will not be until the testing phase of implementation when the full diversity of how project risks have been reported in the entire collection of documents becomes known. Only then will proposals for automatic and semi-automatic AI/ML methods be realistically assessed for collecting, cleaning, populating and transforming heritage data sourced from among alternative, inconsistent and fragmented project documents. Therefore, at that time, target data structures in proposed staging database designs should also be revisited, when adjustments may be necessary.

Meanwhile, in pre-implementation attempts at designing a database for that purpose, a balance must be achieved between the features needed for addressing GCD's AI Risk Prediction Challenge, and a design capable of supporting all aspects of project management. This proposed solution is not intended to replace existing general-purpose project management software and databases. Instead, it focuses on NASA-specific 'project risk assistance' requirements. But, while keeping that caveat in mind, the 'Thermal-vacuum testing' example given in the description section of GCD's challenge calls for significantly more than basic data covered in the 'Risk Summaries' of project reviews.

So, the data fields and structures for collecting data about heritage projects proposed in this sub-section are designed to satisfy that type of broad requirement, while achieving a balanced approach regarding data coverage. Figure 3 begins explaining how to satisfy that requirement by describing where the data goes and how it is used.

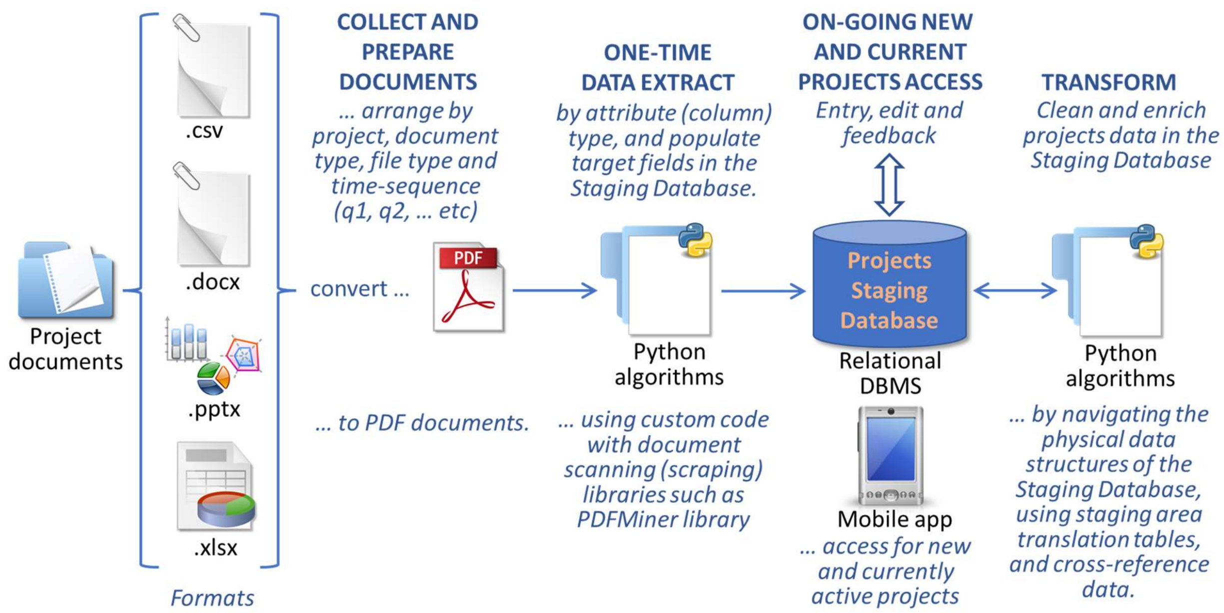

Figure 3: Collecting data about heritage projects from multiple document types

It shows that, based on documents provided for the Astrobee and SynBio example projects, four main file formats can be expected.

As mentioned earlier in points [2] and [3], there are many issues with the data contents of those documents which are likely to stretch current AI/ML capabilities. Rather than suggesting unrealistic solutions informed by marketing hype, this submission offers a more practical approach to GCD requirements with the intentions:

- To keep things simple, and not suggest overkill in methodology and/or tools usage.
- To avoid past issues by changing how new projects are handled.
- To minimize or eliminate repeated references to original project documents.

Those intentions manifest themselves in where the data collection process of Figure 3 fits into the overall solution outline shown in Figure 1 (in steps 1 to 4), and how the neural networks contribution of Figure 2 connects them both (in steps 7 and 8 of Figure 1) in a design which aims to be antifragile as projects become more complex and risk exposures escalate. The objective of doing things this way is to focus on a once-only extraction and transformation of as much risk meaning from heritage source documents as possible. It will be achieved by using custom-built prospecting algorithms for document scanning (a.k.a. scraping) and database insertion algorithms targeted on populating a relationally structured staging database, with a little manual intervention where necessary.

Then all new project risk specifications are first entered directly into the staging database, which is also used as the primary source of all subsequent risk analyses by projects, and exported as tables or lists of data for import into the documents used for their management reviews (see steps 5 and 6 in Figure 1). Thereby eliminating the need to extract and transform new project data from the unstructured data in its documents for entry into the staging database, because it now originates from there. This satisfies the broad risk-data requirements of GCD's challenge in a way that is most efficient, less vulnerable to ongoing changes and variations in project documentation, and more adaptive to future project risk management innovations.

Queries on that staging database are then used to build rows of project features, which form the inputs used by a proposed neural network to learn how to predict potential risks of new projects (for more detail on this overall solution, see sub-section **c**). All of which helps to explain the proposed relational data structure for the staging database shared in Appendix 4. But before discussing specific fields in that structure, a few of its design principles are probably worth sharing.

- It is a relational database design, although that is not a necessary characteristic of data staging areas in data science. Data can also have other types of structure in these areas, including no structure (i.e. original unstructured data content in raw document formats).
- A relational approach was selected to capture as much meaning from source documents during once-only extraction and transformation.
- The database design presented in Appendix 4 is meant to illustrate the scope of data proposed to be collected, with examples of how it is transformed.
- It is represented by an entity-relationship model of risk data items identified in heritage project documents, merged with new data items considered useful for risk prediction which can either be sourced in a similar way, or derived somehow. The former are mostly shown on the left side of that diagram, and the latter on the right.

With those design principles in mind, a few key examples of recommended heritage data fields are examined here. This is not expected to be a complete list due to the implied broad scope of data requirements (mentioned earlier), and content variations likely to be found when the complete collection of project documents is analyzed. However, it should offer a good basis for understanding the range of predictions this proposal can generate.

The first observation worth noting is that this staging database uses a mixture of both new and heritage terminology to name data items (i.e fields and tables). Names that apply familiar terminology can be found on the left side of that diagram. They generally represent items of heritage data with the same name in source project documents, such as 'PROJECT', 'SCHEDULE', 'WBS_ELEMENT', and 'KPP_PARAMETER'. Whereas new names can be found on the right side, such as 'INTEREST', 'CHALLENGE', 'POTENTIAL' and 'SIGNIFICANCE'. But more of a mixture of name types can be found in the middle of that diagram, such as a data table with the new name 'AFFINITY_CLUSTER', or the familiar item of data called a 'Risk List' which has been re-named a 'CHALLENGE_LOG'.

Although the 'CHALLENGE_LOG' table represents the familiar notion of a 'Risk List', it contains a list of less familiar data fields (or data columns). This is a consequence of merging heritage and new data items in a meaningful relational structure. See the next section for more explanations of new data items.

As mentioned earlier, the purpose of arranging data items of the Projects Staging Database in this way is to capture as much meaning as possible from source documents during 'once-only' extraction, transformation and subsequent addition of new projects data. Therefore, innovative new ways of interpreting that data can be developed in the future without the necessity of extracting from source documents every time. Although, that will always remain an option.

So, due to their familiar names, the heritage or 'past' data items shown in the Appendix 4 diagram can be understood without much explanation, because their meaning is the same. However, this is not intended to be a complete representation of those data items to be included in this staging database. Only items relevant for predicting future risks have been included, and more will be added after a full analysis of all project documents.

ii. Recommended new data fields to improve risk analysis.

From the review of project documentation mentioned in item [1] above, some of the data items missing in the risk data of the Astrobee and SynBio projects are:

[1]. Although results (consequences) are usually associated with the risks mentioned in project documents, their **risk titles, statements or descriptions often fail to express any timescales or urgency of the exposures involved**. Furthermore, it is unlikely they can be accurately inferred from the dates associated with planned mitigations, and therefore should be made explicit.

   a. The current notions of 'Consequence' and 'Criticality' are enhanced by the new data items 'PERCEPTION' and 'SIGNIFICANCE' respectively in the proposed data design.

b. Which can then be automatically incorporated in the 'Statement' field of the new data item 'CHALLENGE' to express the timescales or urgency of exposures.

[2]. **Distinctions are not made between 'issues' that arise and the 'risks' they invoke**. Making such distinctions, instead of simply identifying risks (some of which are actually the same risks expressed in different ways by multiple projects), can be useful in guiding AI/ML to identify similarities between projects better, so that existing and new risks can be predicted more accurately.

a. A hierarchy of fundamental concepts from Situation Engagement is shown in the speech bubbles associated with the new 'INTEREST' and 'INTEREST_TYPE' data items, along with real examples from the AstroBee project. They provide powerful insights into a risk (/prospect) context, and greater precision of meaning.

b. The problem of fuzzy naming standards for risks and other concepts is also addressed by the definitions of those fundamental concepts, as shown by the examples mentioned in **a.**

[3]. **Key assumptions are rarely mentioned.** They can critically impact risk identification, assessment and possible revision after mitigation, and should be made part of any core considerations of risk assessments.

a. An 'Assumptions' text field is included in the new 'CHALLENGE' data item. But it can be expanded into a lookup relationship with dependencies if projects decide to include those considerations in future reviews.

[4]. **An improved taxonomy of risks may require extensive cross-references to heritage categorizations**. These will be a key input for data transformations performed during ETL processing, and may be needed for other purposes such as integrating with other information systems that have not converted their categorizations.

a. A comprehensive taxonomy of terms related to risk is offered in the Situation Engagement approach (see the Index tab shown in the screen capture image of Appendix 8).

b. New risk categories are dynamically created during the K-Means Affinity Analysis proposed for risk prediction. They are only increased in number when the required number of clusters is changed, at which time names can be allocated to them appropriate to the risks contained in each cluster.

c. Meaningful naming of risks (i.e. not ambiguous or too fuzzy) is handled by pre-implementation training (see Appendix 9).

iii. Describe the proposed structure.

Mostly incorporated in **i** and **ii** above.

The way this structure helps to predict risks is shown in Figure 3. Heritage project documents are collected and prepared by arranging them by project, document type, file type and time sequence. Then they are converted to PDF documents, and scanned (a.k.a. scraped) for data by prospecting algorithms that are custom written for each document type.

Finally, this data is cleaned and enriched by navigating its relational data structures using translation and cross-reference tables (between heritage and new terminology) to ensure the Projects Staging Database contents reach a level of data quality fit for using as the basis for AI/ML prediction of known risks (for unknown risks see subsection **c**).

iv. Describe how the structure supports program management needs, isn't overly constraining, and is easy to adopt.

Apart from providing a relationally structured Projects Staging Database for extracting, transforming and loading heritage project data, it is also the data structure on which data entry and analysis feedback solutions are constructed for all new projects after the implementation of this proposed solution.

Step 5 in Figure 1 shows how the proposed project tool (possibly a mobile app) enables each project to enter and edit project details directly, and receive downloads of the risk analysis they need to enter into their monthly/quarterly reviews. In that way they no longer need to originate this analysis in their presentations, etc., and they will not depend on someone else to re-enter this information correctly for meaningful risk prediction and status feedback.

This does not require more effort than how they do such things currently, but it enables greater consistency and sharing of known risks, assumptions and dependencies between projects.

v. Describe how the output can be used by AI/ML to categorize and predict risk.

Once the Projects Staging Database is populated with both heritage projects data and begins to take on new projects, it is used to translate those contents into a Project Features Dataset (see Appendix 5 and the Phase 1 tasks of Appendix 9) for input into a predictive neural networks algorithm.

b. Proposed method to populate the existing data into the new format

i. Describe the data extraction process, approach to working with GCD documents, the methodology applied to the process

See Figure 3, the associated explanations that follow in that subsection, and Appendix 9.

ii. Describe sample algorithm/s

Not applicable.

c. Proposed method for predicting risks for each project in that format

i. Describe the process, approach, and methodology using GCD data.

An overview of the process is shown in Figure 1.

Whereas the extraction from GCD data is shown in Figure 3, and the overall methodology is described within the recommended phased implementation shown in Appendix 9.

In this section I explain how known risks will be predicted, and discuss a prototype of the 'Digital Assistant Tool' mentioned in the requirements document.

As mentioned earlier, the data extraction flow of steps 1 to 4 in Figure 1 feeds data into the neural networks contribution of Figure 2, which is shown as steps 7 and 8 of Figure 1, in a design which aims to be antifragile as projects become more complex and risk exposures escalate.

As data is harvested from heritage project documents, features are identified by content analysis (shown at step 2 of Figure 2) that are used as input for a custom-written predictive neural networks algorithm. The best choices of appropriate features is found by repetitive testing of that algorithm, known as its 'learning and testing process'. During that time of experimentation, selections are made from among various options of a suitable networks topology, activation functions, backpropagation, etc. until the accuracy of predictions reach a desired level. Various techniques such as data splitting are used along the way.

The objective of that algorithm is to predict a new project's biggest Challenge (i.e. a likely risk which is assessed to have the highest level of Potential impact at some future time, before its mitigation for that project). Which is why a full time-series of risk assessments is needed from heritage project documents.

Meanwhile, natural risk categories are discovered among the contents of the Projects Staging Database by performing K-Means clustering between its projects and their full set of risks.

Once the 'biggest risk' of a new project is finally predicted, it can be added to the clustering exercise. Then, when it is clustered together with all other projects, the risks that are clustered together with the new project's 'biggest risk' become further predictions for consideration by that new project.

Appendices 6, 7 and 8 show how many of these solution components can be provided by a comprehensive program risk assistant tool. A few of these can be seen as follows:

- Appendix 6 shows how a model can be built containing solution-specific designs for database schemas, algorithms and direct content building. It also has an embedded IDE (Interactive Development Environment) for writing SQL and Python code, which can be run to build and/or amend physical databases and functionality.

- Appendix 7 shows how processes can be defined and run in their correct sequence, such as the proposed risk prediction algorithm and its process dependencies. The output recommendations of that algorithm are show in the bottom ‘Output’ tab.

- Appendix 8 shows other functionality that may become very useful for GCD, according to Phases 2 and 3 of the implementation diagram in Appendix 9.

ii. Describe the method of building a library of risks and classifying risks from past projects.

Step 10 in Figure 1 shows how a ‘Digital Assistant’ could automatically build a Knowledgebase of project risk content, that extends the existing library of risk content collected in the Staging Area Database, capable of improving risk mitigation, mission-critical decision making, and promoting deeper involvement of GCD in project support, such as FMEA (Failure Mode and Effects) audits to catch unmitigated risks before a project’s go-live/launch authorization.

iii. Describe how you could use this to identify unknown risks.

Unknown risks would be addressed by the ‘Digital Assistant’ Knowledgebase, by tracking exceptional activities and data movements out of range as ‘Suspected Unknowns’ recommended for further investigation.

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6. External Sources

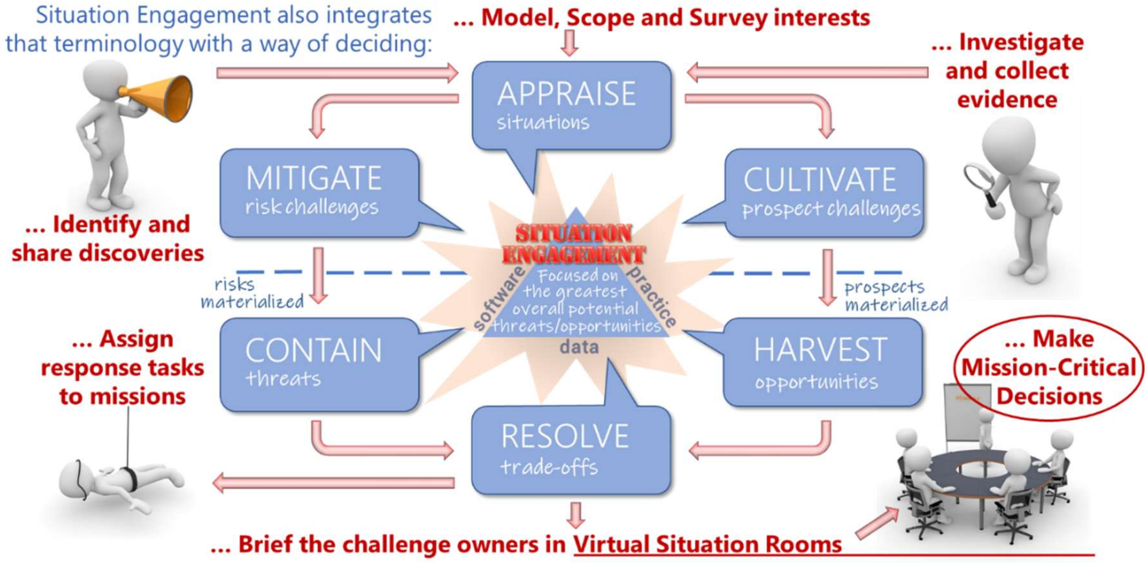
Not applicable.

7. GitHub repository access

Not applicable.

APPENDICES

Appendix 1: How to resolve program/project challenges



The Situation Engagement approach can be applied in a way that complements existing risk management notions and practices. It should be considered risk management 2.0 because it extends and improves risk management 1.0.

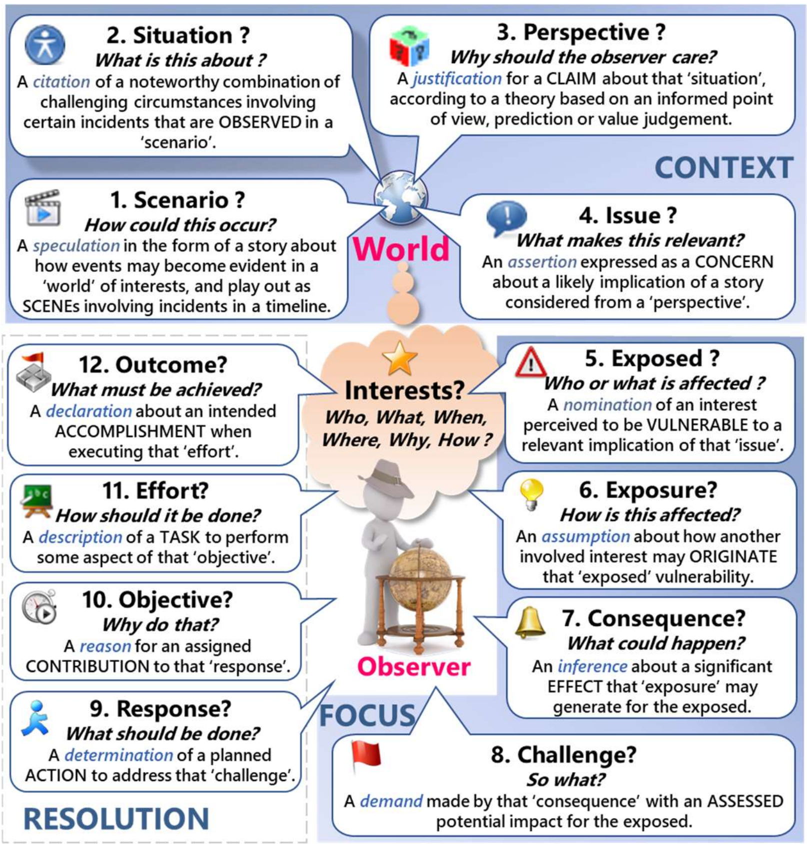
It extends conventional thinking by enriching and properly integrating the terminology currently used, and explicitly includes peripheral considerations that have a material effect on outcomes (such as environmental circumstances). It also factors in a time-dimension and perspective to risk assessments, which are often merely implied.

The following three conventional definitions of risk illustrate these inadequacies and gaps (see Appendix 2 for the Situation Engagement alternative):

> A **'chance or possibility'** of danger, loss, injury or other adverse consequences. *The Oxford English Reference Dictionary*.
>
> Risk is the **'effect of uncertainty on objectives'**, and an *effect* is a positive or negative deviation from what is expected. *Uncertainty* (or lack of certainty) is a state or condition that involves a deficiency of information and leads to inadequate or incomplete knowledge or understanding. In the context of risk management, uncertainty exists whenever the knowledge or understanding of an event, consequence, or likelihood is inadequate or incomplete. *ISO 31000*.
>
> Risk can be defined as **'a combination of the answers to the four questions'**: (1) What can go wrong?, (2) How likely is it to go wrong?, (3) If it does go wrong, what are the outcomes? (4) How do you feel about it? *Kaplan and Garrick, 1981 and 2011.*
>
> Risk is **'a real, measureable uncertainty'** relating to some formally-expressed logical proposition. *Knight, 1921.*

And finally, the process of Situation Engagement incorporates the opposite of a risk (a prospect), and resolves trade-offs between threats and opportunities. For project risks that helps to ensure optimal choices are made, and takes dependencies between project deliverables into account when balancing their objectives for overall program success.

Appendix 2: The 12 Fundamental Concepts of Situation Engagement



The 12 Fundamental Concepts shown above are used for making mission-critical decisions of any kind in the new discipline of Situation Engagement. They are part of a comprehensive, fully integrated terminology, which enables greater clarity of thinking and more precise communications than are conventionally achieved for such purposes. When applied in next-generation approaches to project management, they can shine a new light on old limitations and reveal breakthrough solutions.

A simple example of how that terminology can bring more clarity and precision to the meaning of the term risk (and its opposite) is given below:

Risk definition (*defined by* **fundamental concepts** and related terms):

A risk is a *negative* perception of a **challenge** created by a **consequence** of an **exposure** to an **issue** raised by a **situation** observed in a **scenario**, with the potential of being a threat for someone or something of **interest** when viewed from a **perspective** on a **world** of circumstances.
However, a risk is individually ***expressed*** as the likelihood at a particular time of that threat **materializing** by some later time, when all known circumstances are considered, in the absence of any new intervention **effort**.

Prospect definition (opposite of risk *defined by* Situation Engagement as above):

A prospect is a *positive* perception of a **challenge** that is created in a similar way to a risk, with the potential of being an opportunity for someone or something of **interest** when viewed from a **perspective** on a **world** of circumstances.
However, a prospect is individually ***expressed*** as the likelihood at a particular time of that opportunity **materializing** by some later time, when all known circumstances are considered, in the absence of any new intervention **effort**.

Reward definition (for comparison with the above definitions)

Is simply a *beneficial* **consequence** of taking a risk or converting a prospect.

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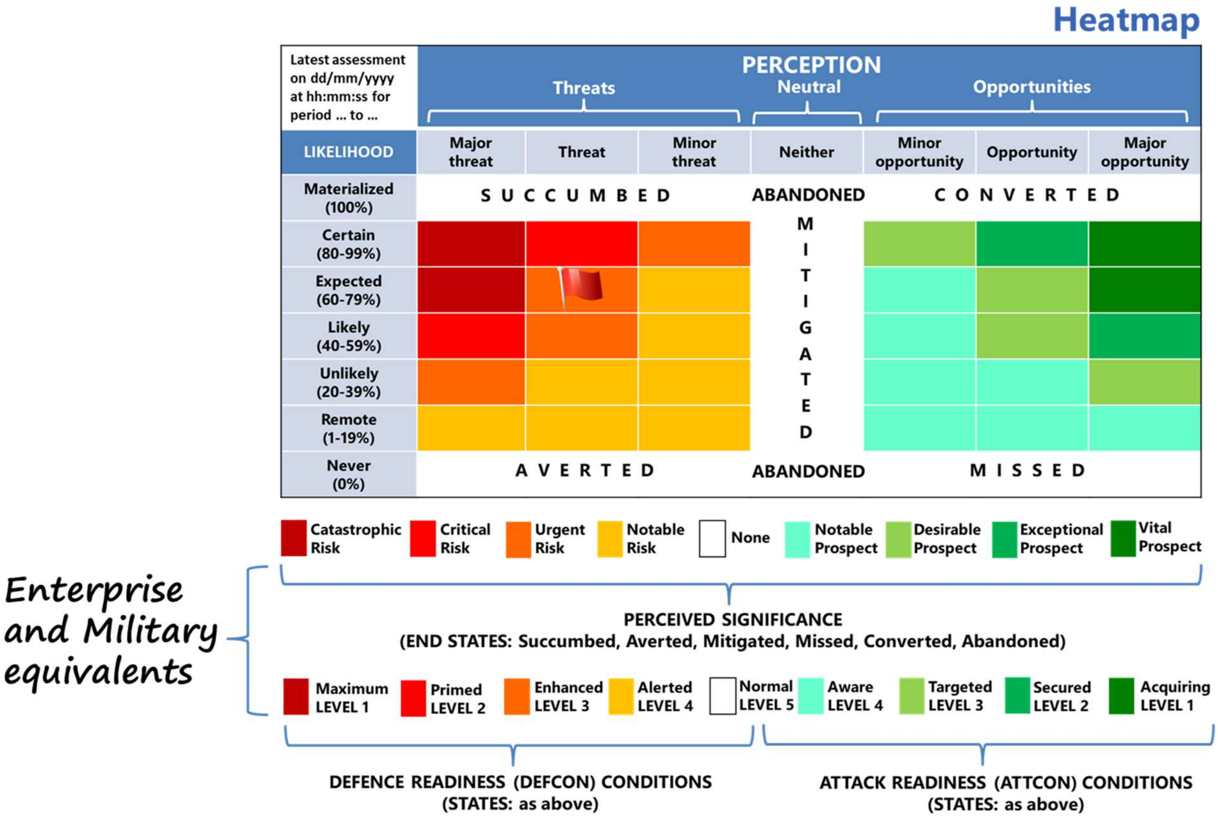
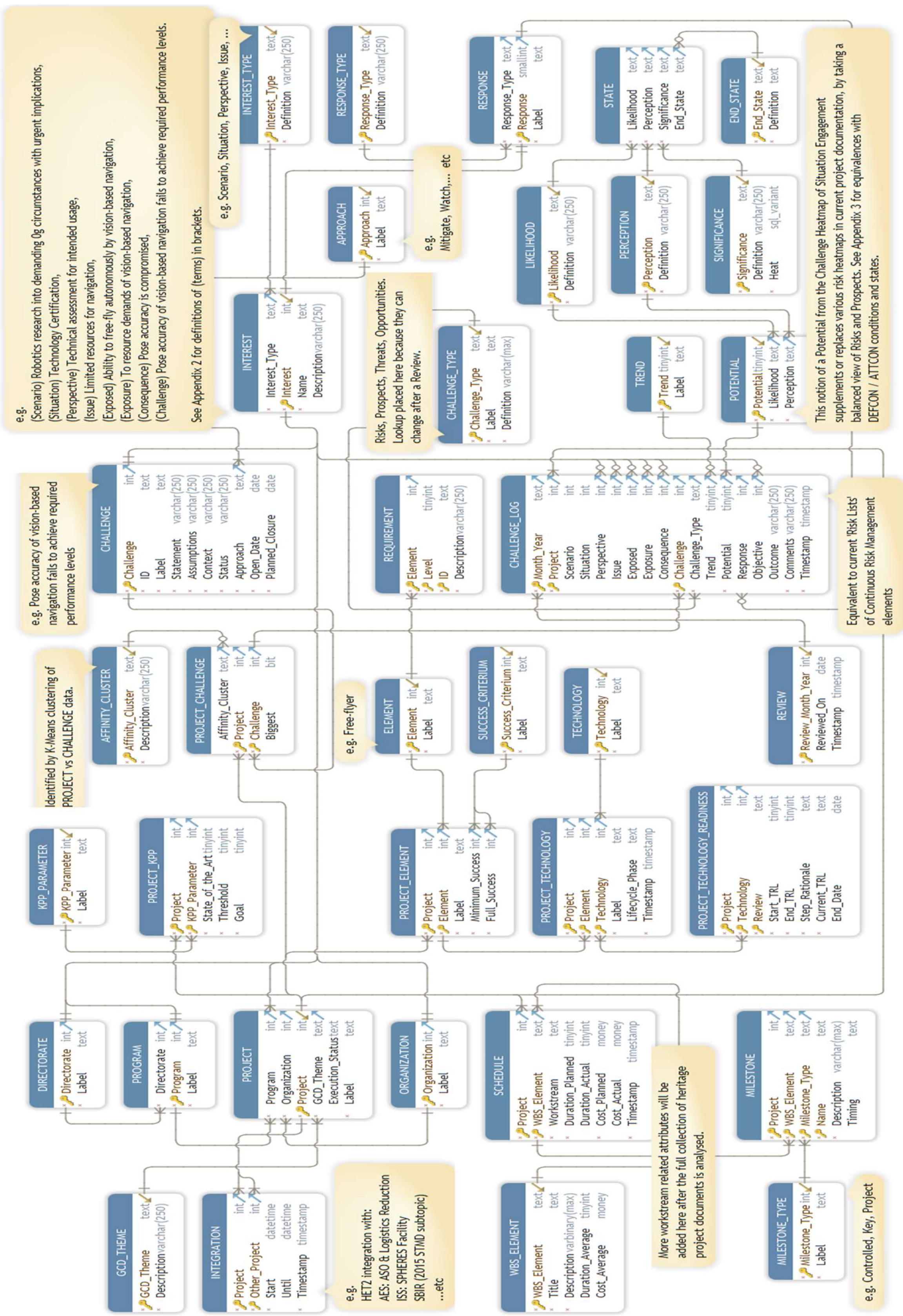
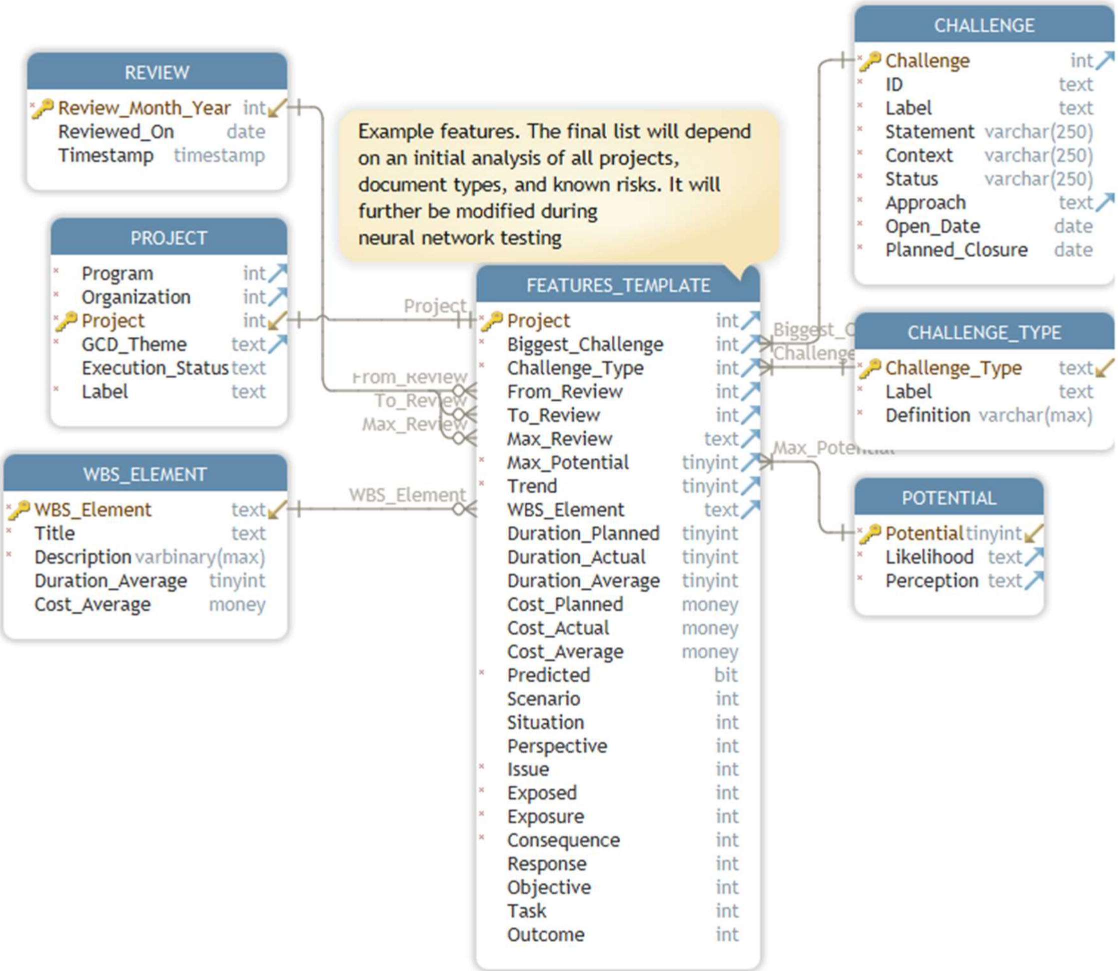
Appendix 3: DEFCON / ATTCON style heatmap for Challenge Potential



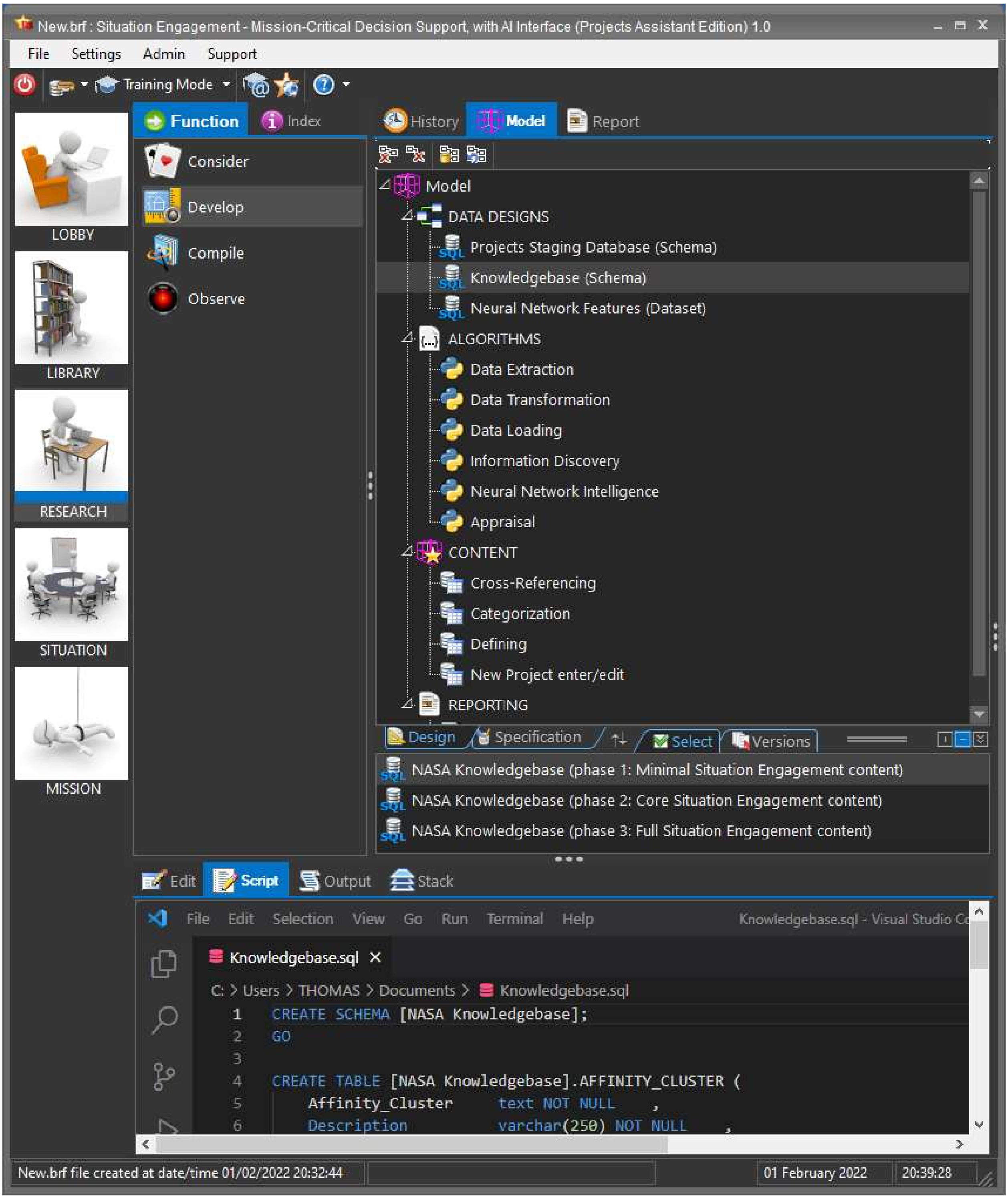
Appendix 4: Data structure for the Projects Staging Area



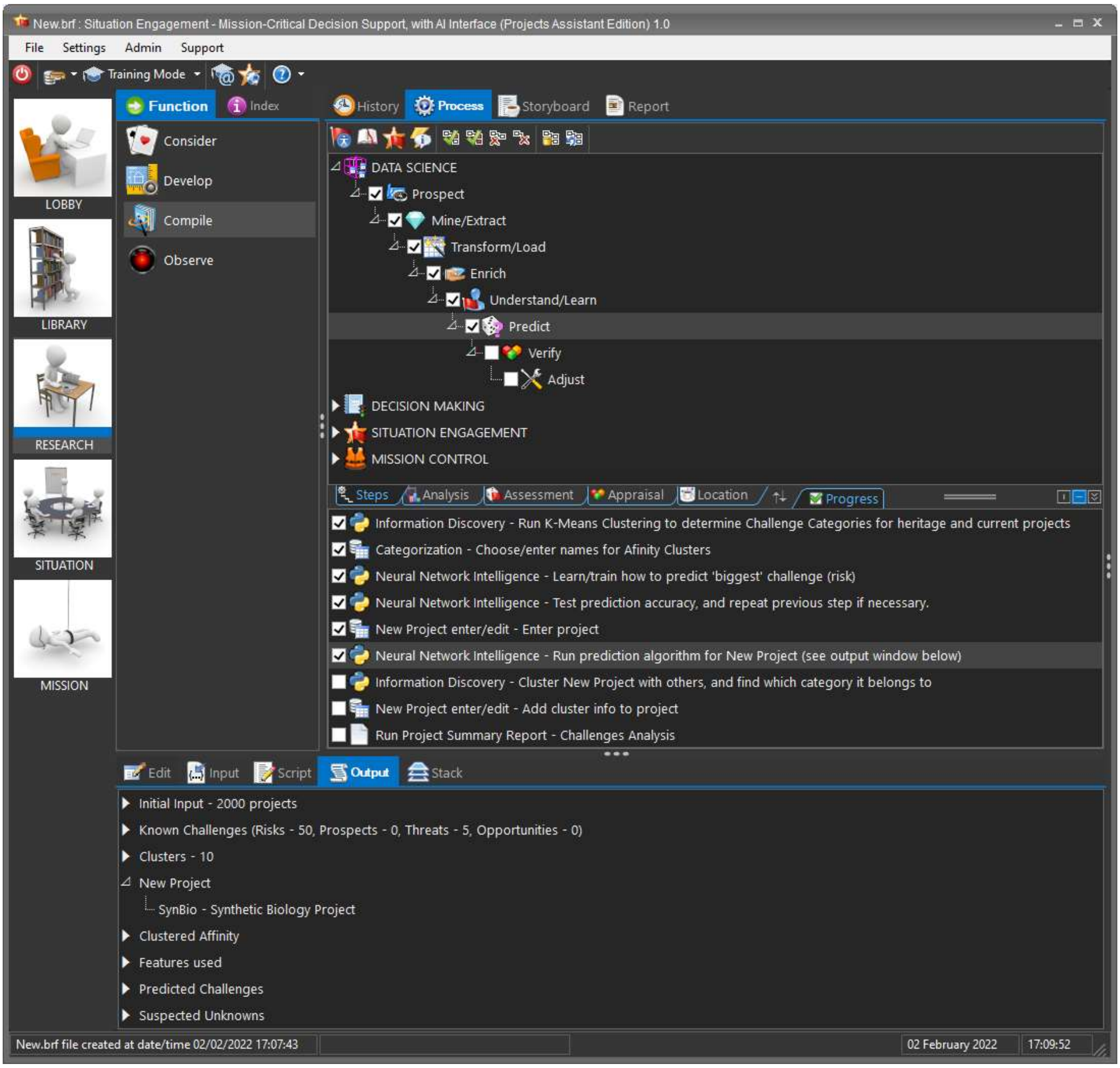
Appendix 5: Data structure for the Neural Network Features Dataset



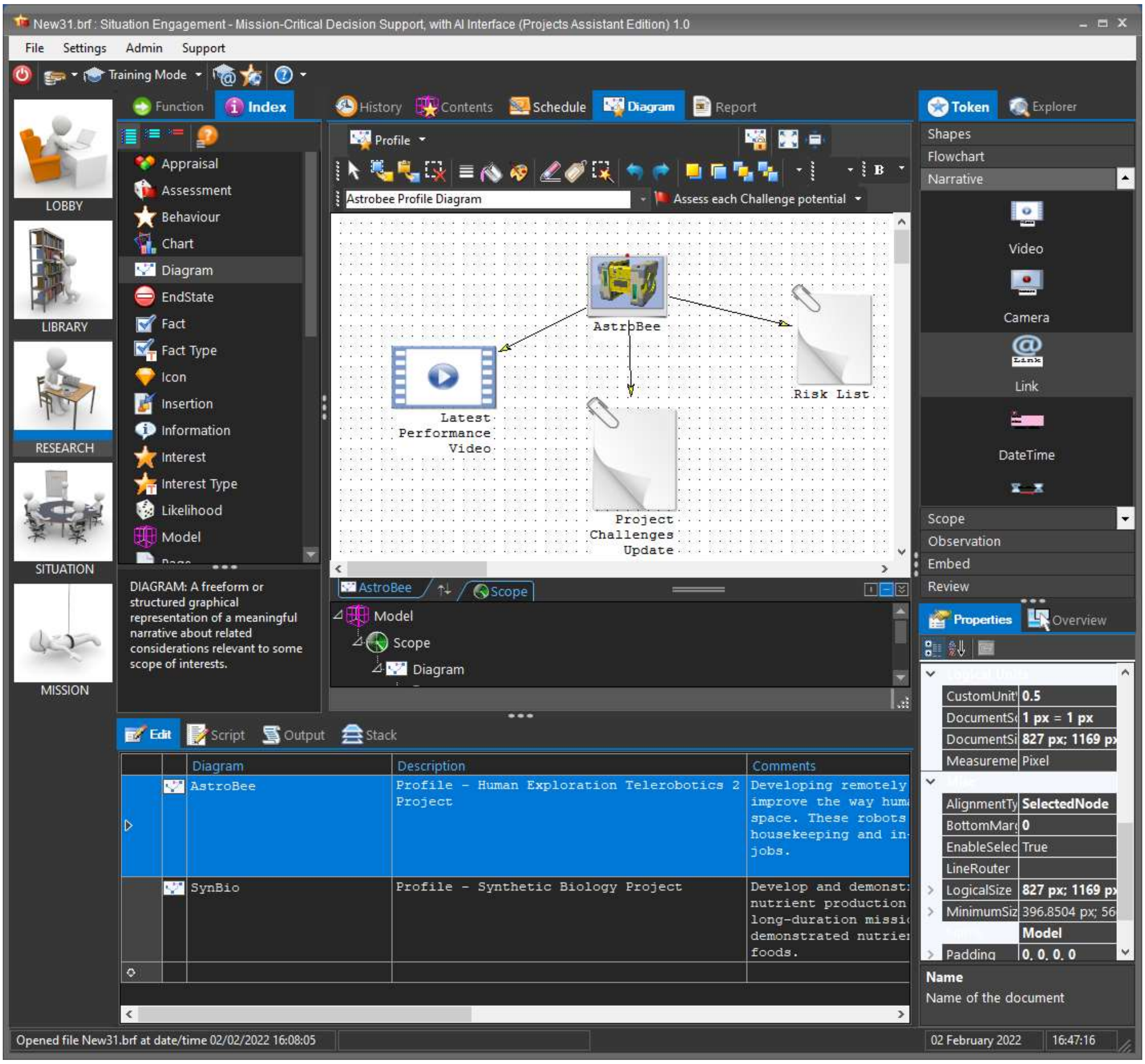
Appendix 6: Example of a Comprehensive Program Risk Assistance Tool (shows model-building aspects)



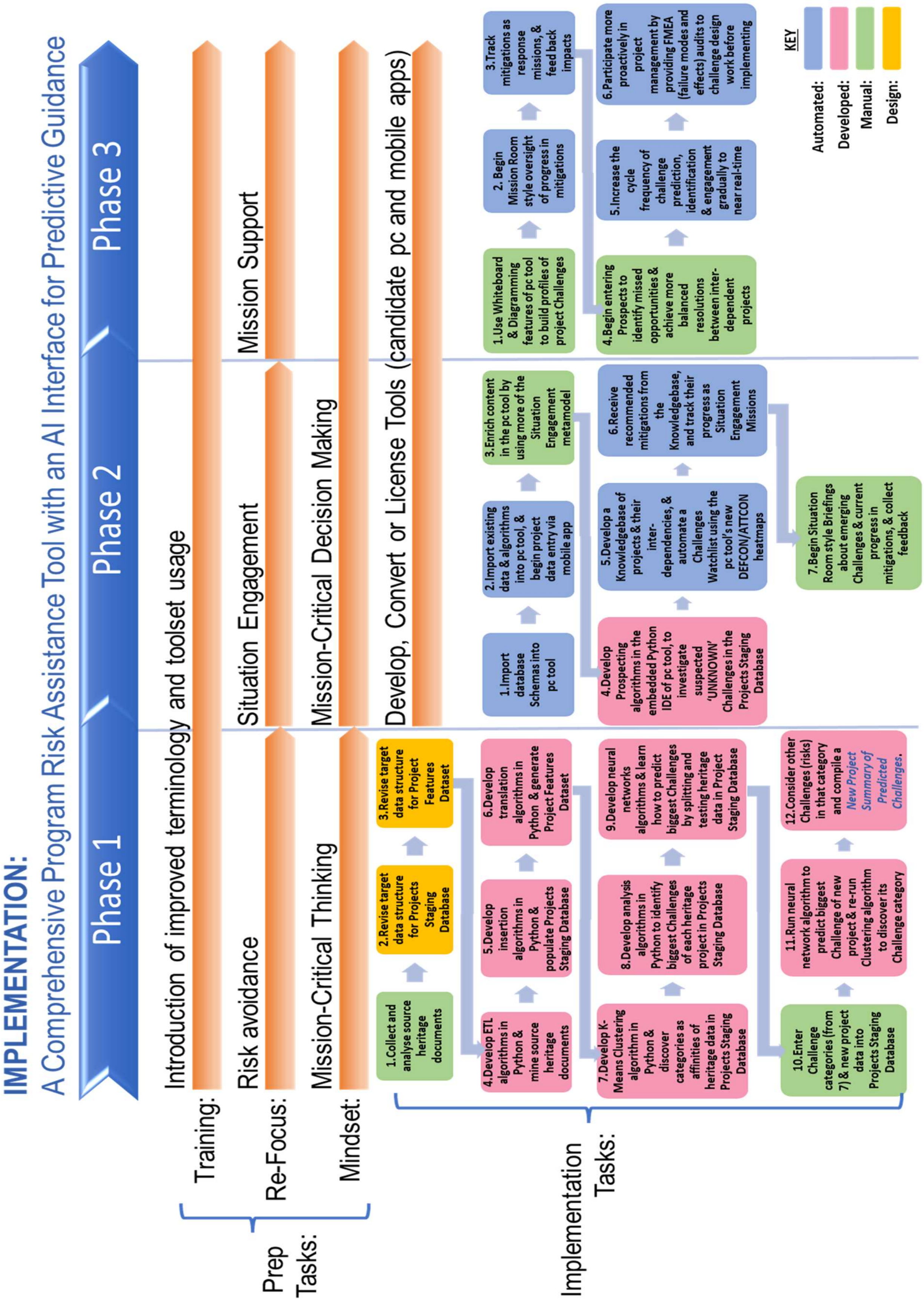
Appendix 7: Example of a Comprehensive Program Risk Assistance Tool (shows data science process and AI predictions interface)



Appendix 8: Example of a Comprehensive Program Risk Assistance Tool (shows whiteboard / diagramming interface)



Appendix 9: A Recommended Phased Implementation



Appendix 10: Resumé

Dr THOMAS ILIN PhD (Cranfield University, School of Management, UK)

- Acknowledged expert in Risk, Crisis and Situation Management.
- With special interests in Decision Making and Problem Solving.
- Actively researching their integration into a new discipline called Situation Engagement, incorporating a unique perspective on how to engage with challenging situations for commercial, scientific and military purposes.
- Practical experience includes 15 years as an IBM Data Warehousing and Business Intelligence data scientist, solution architect and principal consultant, developing and implementing solutions for clients worldwide.
- Continues to provide international consulting and coaching services, based on over 30 years of experience at senior levels to Financial Services, Energy and Defence (/Defense) industries.
- Also teaches through the Situation Engagement Academy online school.
- Currently focused on implementing innovative mission-critical solutions as founder and CEO of the startup firm Surveylant Inc, a research firm and publisher of the Situation Room+ pc software apps and data services.
- Author of the 'Operational Definition of Systemic Risk', summarized in the paper titled 'The uncertainty of systemic risk' published in the academic journal: *Risk Management (2015) v17, p240-275.*