ARTIFICIAL INTELLIGENCE BASED BUSINESS TRANSFORMATION PROJECTS-THE ROLE OF DATA SCIENCES IN MIXED-METHODS PATTERNS (RDSMMP)

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ABSTRACT

The Applied Polymathical/Holistic Mathematical Model for Integrating Data Sciences in Mixed-Methods (AHMM4MM) supports Business transformation projects (simply Project*). The AHMM4MM uses various Polymathic Mathematical Models (PMM), that abstract, incorporate, and integrate Data Sciences (DS), AI-Subdomains, Intelligence based Information Communication System (IICS) components with* Project*'s transformed resources. Transformed resources can be services (and artefacts), success factors (or calibration variables), business processes (and scenarios), mixed-methods, AI-Models (AIM), and adequate Enterprise Architecture (EA) Models (EAM). PMMs, AI based services, resources/artefacts, and EAMs can be used to establish set of Mixed-Methods Patterns (MMP) that include DS technics/capabilities, data-platforms' access (and management), algorithms-functions, mapping concepts, unbundled services; to model and implement Decision Making System's (DMS) Processes (DMSP) related infrastructure, data-storage(s), components-models, and end-users' integration. The integration of MMPs enforces and automated MMP based DMSPs,* Project*'s validity-checking, and Gap Analysis Processes (GAP); which all need adapted dynamic interfaces to manage and access Enterprise,* Project*, Data-storage(s), IICS, EAMs, pool(s) of Artificial Intelligence (AI) services, and other types of artefacts and resources. On the other hand, MMPs communicate with other, by using* Project*'s and AI components; and can use also various medias-types formats, like the eXtensible Markup Language (XML) format, and others. Implemented, imported (or exported) AI or Data-Sciences (DS) contents and structures are combined with other* Project*'s and IICS artefacts, services, and components, to deliver MMPs for various AI-Subdomains.*

KEYWORDS

Advanced Mixed-Methods, Qualitative and quantitative research, Data Sciences, AI-Subdomains, Polymathical mathematical models, Business and common transformation projects, Enterprise architecture, Artificial intelligence, and Critical success factors/areas.

1. INTRODUCTION

AI-Subdomains include BigData (BD), Machine Learning (ML), Deep Learning (DL), Operations Research (OR), and other. The AHMM4MM is used for Project's AI-Subsystems' classifications, integrity-checking, algorithms' implementation (and integration), GAP, financial risks analysis, Project-risk-management, and many other types of strategic DMSP related activities/operations. MMPs use PMMs (where an AHMM4MM is a set of PMMs); and hence In-memory Distributed DataSets (IDDS) that are interrelated with MMPs. These methods are in-turn based on mainly qualitative and associated quantitative methods. The RDSMMP adopts a transformative enterprise-view and not just a simplistic DS' usage; which is in fact a specific case of statistics. RDSMMP promotes MMPs which uses a central reasoning-engine for the central

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qualitative Heuristics Decision-Tree (HDT). Knowing that Projects are complex and have an eXtremely High Failure Rates (XHFR) [1,65]. PMMs and hence the AHMM4MM, support AI usage by aligning AI-Subdomains, Projects, EAMs, AIMs, and other related artefacts. In this article the focus is on DS in the context of MMPs, related MMPs, and their relations with other AI-Subdomains, services' architectures, interface-variables, qualitative methods' interfaces, and APplication Domain (APD) functionalities, EAMs, data management-platforms… AI-Subdomains like DS, ML, DL, DP, and other, are the fundaments of an efficient DMSP that constitutes the basis of enterprise DMSPs. As already mentioned, MMPs are used for validity-checking, GAP, and optimization activities, and DMS activities. Before reading this article, the valuable reader can consult In-House Implemented (IHI) Polymathic Transformation Framework (IHIPTF) related documentation, and Projects fundamental works, like: 1) The IHIPTF Guide [2]; 2) The IHIPTF Glossary [3]; 3) A related syllabus [4]; 4) The AHMM4PROJECT [5]; and 5) The AI based Projects [6]. A Project is a set of Critical Success Areas (CSA) where a CSA corresponds to a MMP; and the first CSA is the Research and Development Project (RDP).

2. THE RDP'S USAGE

2.1. The Research Question

This article and RDP's Research Question (RQ) is: "Which RDSMMP and related AI-subdomains features, and structural inter-action are needed to support AI-based Projects and Entity's sustainable evolution(s)?" The RDP's Polymathic Resources and Literature Review (PRLR) uses AI literature, IHIPTF's knowledge DataBase (DB), Conceptual Proof of Concepts (CPoC), and previous articles repository, and gives advantages to the authors' relevant works and professional consulting-projects, like:

- AI and DS based Projects [49].
- The Polymathic set of PMMs or the AHMM4PROJECT(s) [5].
- Deep Learning Integration for Projects (DLI4P) in Projects [22].
- Machine Learning Integration for Projects (MLI4P) [7].
- The Business, Societal, and Enterprise Architecture Framework: An Artificial Intelligence, Data Sciences, and Big Data-Based Approach [8].
- An Applied Mathematical Model for Business Transformation and Enterprise Architecture: The Holistic Organizational Intelligence and Knowledge Management Pattern's Integration … [9].
- Enterprise Transformation Projects: The Polymathic Enterprise Architecture-Based Generic Learning Processes (PEAbGLP) [10].
- The Business Transformation and Enterprise Architecture Framework-The Applied Holistic Mathematical Model's Persistence Concept (AHMMPC) [12].
- An Applied Mathematical Model for Business Transformation and Enterprise Architecture-The Holistic Mathematical Model Integration (HMMI) [13].
- Using Applied Mathematical Models for Business Transformation [14].
- The Polymathic approach for Projects that use a Meta-Model [15].
- Applied Holistic Mathematical Models for Dynamic Systems (AHMM4DS) [16].
- … and others.

2.2. The Set of PMMs for RDSMMP

The Project, IICS, AIMs, EAMs, and other, are in fact sets of PMMs and IDDSs. The RDSMMP uses the most relevant PMMs which are [5]:

- PMM for U4MP (MM4UP) which supports unbundling.
- PMM for Factors (MM4FC) which structure and checks Factors.
- PMM for GAP (MM4GP) which supports GAP's estimations.
- PMM for PRWC (MM4PR) which supports PRWC's estimations.
- PMM for Expectations and Constraints (PEC) (MM4PE) which structures PEC.
- PMM for Polymathic Enterprise MtM (PEMtM) (MM4PM) which is base for PEMtM.
- PMM for Methodologies and IICS (MM4MD) which supports and checks OOM/UM, Archimate, and other.
- PMM for MDTCAS (MM4MT) which supports and checks MDTCAS.
- PMM for APDs (MM4AD) which supports and checks APDs and its problem-types.
- PMM for Intelligence (MM4IN) which supports and checks AI and decision-making.
- PMM for AHMM() (MM4AH) which constructs the for a specific topic .
- And others.

2.3. The AMM4MM

The RDSMMP needs Polymathic organizational-intelligence and knowledge-management capabilities offered by the AHMM() [9]. Which restructures (or transforms) an Entity in the optimal manner, by applying AI/DS modules and MMPs. That needs a concept that is based on standards, patterns, mapping-mechanisms, and interoperability. MMPs respect standards, and methodologies to support AI based Projects. Transforming Entity's legacy IICS and DMSPs into an AI based atomic service-oriented environment.

2.4. RDP's Hypothesis

This RDP uses hypotheses (or assumptions and even constraints) that are in fact linked to Project's CSAs and the RDSMMP corresponds to the main CSA and RQ. RQ's real-scope and feasibility, and RDP's credibility, depend on the perceived hypotheses (and assumptions). Where RQ's main hypotheses depend on the following Project's transformational-activities (and phases) successful finalizations:

- Project's start, budget, contracting, goals, AI/RDSMMP vision (and roadmap) developments were hammered and documented.
- There is the needed a sufficient level of political support and AI/DS skills/experiences.
- Disassembling strategies were implemented to offer AI/DS services and The IHI methodology is the Methodology, Domain, and Technology Common Artefacts Standard (MDTCAS) artefacts.
- The Entity and Project have successfully implemented MDTCAS, Factors Management System (FMS), Polymathic Rating and Weighting Concept (PRWC), HDT, and In-House Implement (IHI) Polymathic Transformation Framework (IHIPTF).
- The Project uses the DB Centric Concept (DBCC) (or DB first) for data operations [17]; and the DB Centric Implementations (DBCI) [18].
- The Entity privileges IHI solutions and AI-Subdomains' integration.
- The Project's team has the needed skills for AI/DS modelling and development.
- The Project (and Entity) has implemented the AHMM() or AHMM4MM (and its PMMs) fundaments and interactions [5].
- A hypothesis (assumption) corresponds to a CSA, which are selected using the PRLR.

2.5. The PRLR and FMS' Integration

This RDP localized an important research-gap that is due to: 1) There isn't anything similar to the RDSMMP, AHMM4MM, and PMMs, and IHIPTF; 2) XHFRs and their possible prediction; 3) There isn't a MMP similar to the HDT that includes the Polymathic Quantitative-Qualitative Research Mixed Model (PQQRMM); 4) A concrete Weightings-rating (Wgt) based PRWC and FMS that are related to AI/DS, GAP, PMMs, IICS and IHIPTF; 5) The use of CSA Decision-Tables (CSA_DT) to qualify Project's CSAs; and 6) A structures approach to AI-subdomains and the DS' integration. As shown in Figure 1. GAP is applied to all CSAs, but in this article only one GAP/CSA_DT will be presented. The AHMM4MM supports DSs and MMPs by inter-relating PMMs for Factors (MM4FC), where Critical Success Factors (CSF), and Performance Indicators (KPI) are used for Project's and DSs basic-evaluations, and Optimization-Functions (OF). The AHMM() (and PMMs) support AI-Subdomains and DS' MetaModels (MtM) and a Polymathic Enterprise MtM (PEMtM). The PEMtM perform Entity's validity-checking and also uses the FMS and its underlying Factors that offer [19,20]:

- They can be used in Natural Programming Languages (NLP) scripts.
- The FMS incorporates CSAs, CSFs, KPI, and IICS VARiables (Var) (simply Factor).
- A CSA maps to a set of CSFs (and Project's resources), and a CSF is a set of KPIs.
- The Team manages and tunes the initial-sets of Factors.
- A KPI maps to a unique requirement and problem-type.
- CSFs are used for solving problem-types, in DMS/Knowledge Management System (KMS) (simply Intelligence), and other.
- FMS ensures that: 1) A CSA maps to an Entity APD (or a common functional-domain); 2) A CSF maps to a set of requirements (and directly linked problem-types); and 3) A KPI maps to a IICS' item-variable or Var.

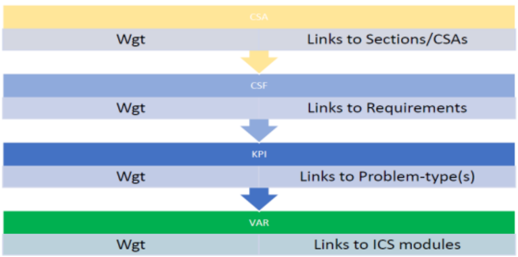

Figure 1. The evaluations for IHIPTF and AHMM() that process CSA_DTs.

2.6. The PRWC, CSA_DT's Evaluation, and GAP

The PRWC interacts with the FMS and Intelligence to offer [21]:

- An Entity standard for CSA-DTs' evaluation method like the Decision-Making Notation (DMN).
- CSAs are evaluated using CSA_DTs, where a CSA corresponds to a Project topic.
- CSA_DTs deliver RDP's Phase's 1 evaluations which constitute Project's DT (Prj_DT).
- The AHMM4MM and MM4PR are supported by the PEMtM.
- Is used to evaluate Project's integrity and used by MMPs.
- Uses the FMS that includes: Factors like VARs that are accessed by MMPs.
- GAP evaluates Projects, DS' modules, and other components statuses; by using HDT based Intelligence to eliminate gap(s).

- The PEMtM enables GAP's processing in all Project's phases which are synchronized by the Transformation Development Method (TDM).
- The TDM uses The Open Group's Architecture Framework (TOGAF) and its Architecture Development Method (ADM).
- GAP uses Factors like CSFs which can be: 1) Project's resource; 2) Disassembling outcomes; 3) MMPs' evolutions; 4) PRWC's outcomes; 4) TDM's synchronization; 6) AI/DS' outcomes; and 7) Use of KPIs to link VARs to concrete components.

3. IICS, EAMS, DATA-DBS AND OTHER

3.1. Introduction and Distributed IICS

The AI-Generic and Common Constructs (AI-GCC) is common layer for all AI-Subdomains, where an Entity and a Project can implement an IHI AI-GCC, which is the largest and critical part of AI-Subdomains' integration and/or implementation. Building a robust AI-GCC for transformed IICS (or modern applications) ensures scalability and reliability for AI-Subsystems. The AI-GCC: 1) Includes hardware, software, data-access components, and platform-networking components, which are crucial for transforming, implementing, deploying, and managing Projects and AI-Subsystems components; 2) It is the backbone of AI-Subsystems, that enables AI-Subdomains like, ML algorithms to process huge data-volumes and to generate data-insights; 3) Supports the integration of patterns like MMPs; 4) Avoids just using commercial products that cause a hairball; and 5) Offers a robust infra-structure and necessary resources for AI-Subdomains, so Entities can integrate complex algorithms like ML and BD for data-insights and data-driven DMSPs. The different and extensive processing of AI-Subdomains requirements and AIMs, is strongly related to large IDDS (used in launching complex computations). The use of various types of massive IDDSs is a considerable challenge. Distributed IICS (DIICS) and related computing-processing, need parallel processing-steps which enables AI-Modules to be scalable and supports the demands for massive data-driven environment [23,26].

3.2. DIICS and High-Performance Computing (HPC) Systems

As shown in Fig. 2, the AI-GCC recommends Graphics Processing Unit (GPUs) and Tensor Processing Units (TPU) usage, [23,24,25] because:

- Graphics based processing technologies have enforced AI computing capabilities.
- GPUs offer new possibilities in complex domains like AI and were originally created/designed for graphics and video-rendering.
- But they are also suitable for accelerating AI-Subdomains computations, where their architecture is based on hundreds of cores which can handle thousands of threads simultaneously. That makes it exceptionally capable for parallel-processing requirements of ML algorithms.
- As it is designed for parallel processing/multi-threading, the GPU can used for various types of applications, whereas TPUs are Application-Specific Integrated Circuits (ASIC) used for ML and DS.
- TPUs are designed to support and accelerate the processing of TensorFlow's framework, which is mostly used for DL; and they are optimal for high-throughput used by matrix-operations that are dominant in Nural Networks (NN) processing-calculations, which offers efficient alternative to GPUs for specific AI-Subdomains.
- TPUs are AI-accelerators, which are optimal for large AIMs training, in a variety of use-cases (or APDs), like chatbots, code-generation, media content-generation, synthetic-speech, vision-services, recommendation engines, personalization-models…

- Entities use DIICS (or Clouds) based TPUs for IDDSs for real-time DA and DS tasks.
- Clouds' services and APIs enable Entities to adapt to AI-Requests, ensuring optimal-performances and robust Projects.

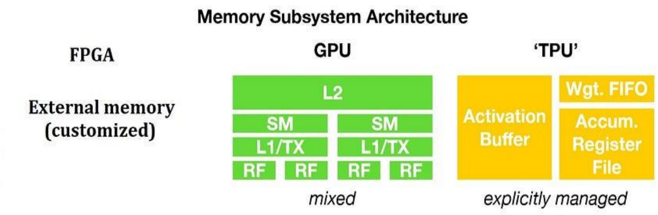

Figure 2. The IICS processing setup.

3.3. The Setup of High-Performance Data Storage Management Solutions

The AI-GCC recommends high-performances Data Storage Solutions, [23] based on:

- Distributed File Systems (DFS) like the Hadoop Distributed File System (HDFS) and Google Cloud Storage (GCS) are crucial for managing and coordinating large/huge IDDSs across IICS' multiple nodes.
- HDFS splits (or breaks) large/huge files into smaller blocks, which are distributed and can be replicated across IICS-nodes, which support scalability, and high-throughput.
- It persists-stores data (or IDDSs) near to computation-processing nodes, enhancing performances for various types of tasks like batch-processing.
- High-Speed Solid-State Drives (SSD) are important for data-intensive applications, like in AI-Subdomains, due to extremely fast read/write speeds.
- SSDs have outperformed legacy Hard Disk Drives (HDD) in speed, which is crucial vital for fast data-processing, application-launches, and real-time DS and Data-Analysis (DA) activities.
- The AI-GCC recommends Data Management, based on [23]:
- Data-ingestion and preprocessing are important steps in the data-pipeline, which ensure that raw-data is transformed into a request data-format that is ready for AI-Subdomains like DA, DA, ML…
- Extract, Transform, Load (ETL) pipelines, that are shown in Fig. 3, are applied to manage data-flows from multiple data-sources.
- In the extraction-phase, data is gathered from different data-sources like DBs, APIs, and system-files. In this data-transformation phase, the data is formatted, including Quality of Data (QoD) topics like missing values, duplicates, and inconsistencies.
- The loading phase is responsible for storing the processed-data in a Data Warehouses (DW) or DB, to be accessible by DS.
- ETL pipelines ensure data-integrity and efficient DS operations.
- Data labelling tools are used for implementing annotated IDDSs, which are important for supervised learning; the mentioned tools enable tagging and categorizing data, like images, text, or audio, providing la-bels for training ML models.

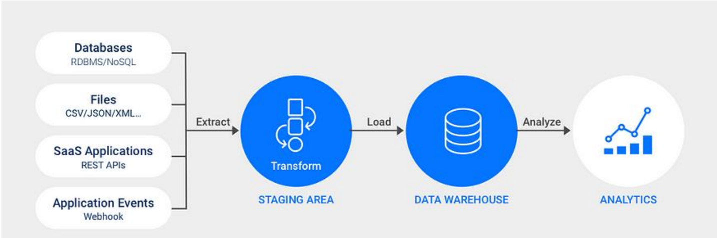

Figure 3. The ETL pipelines [23].

3.4. The DB Centric Strategy and Use of IDDSs

In AI there are various streams and probably the most important ones are:

- A DBCC and DBCI are Data (or DB) oriented approach which is the most popular concept in AI-Subdomains, especially in APDs like business, marketing, logistics [17, 18]… Such an approach is known Quantitative methods and statistics.
- A heuristics approach (like the proposed HDT) uses an Actions-Research (AR) engine is and experiences oriented, which is adapted to PEAbGLPs.
- Enterprise oriented which a mixture, which is combination of the two previous approaches, and is represented by the AHMM4MM, PQQRMM, IHIPTF, and Entity AI Concept (EAIC); which need an AI generic and basic constructs strategy.

3.5. Design for AIMs and AI-Subdomains Architectures

AIMs and AI-Subdomains that define a specific AI-Architecture is considered in the context of the Entity's EA-Models and has the following characteristics [39]:

- EA or Unified modelling language can be used for these purposes.
- Based on the Project's requirements and problems, specific algorithms can be selected to design AI-Architecture integration and interactions.
- The selected algorithms can include rule-based learning, DL, and NLP.
- AI-Architecture affects performance in an important manner, so there is the need to tweak different AI-Platform configurations to find the most effective one.
- Various learning technics are very efficient for different APDs.
- NLP models like transformers would be better for managing complex contextual relationships.
- AIMs and AI-Subdomains architectures must be secured;

3.6. Secured AIMs and AI-Subdomains Architectures

The DIICS uses internal and standard resources and artifacts that can include: 1) Computing systems that have processors, memory, hard-disk…; 2) Clusters for automation; and 3) Entity-wide security services like Identity and Access Management (IAM). The IAM service allows the DIICS to allocate operations and resources to a user; and main IAM's artefacts are: Identities and groups, Resources, Permissions, Roles, and Policies; where:

- Identities and groups are objects which grant access-rights to users.
- Resources are objects which can be accessed by authorized users.
- Permissions are the rights to execute an action on an DIICS resource.
- Roles are permissions used by the IAM and are set by administrators.

- Policies link roles and permissions with DIICS resources.
- Data-security needs various mechanisms to secure data in addition to IAM's defined policies, which manage user-accesses by encryption.
- RDSMMP needs an Entity-wide security's implementation and Security Design Principles (SDP), like the Separation of Duties (SoD), least privileges, and defense in-depth.
- The implementation of General Data Protection Regulation (GDPR) for privacy-protection mechanisms.
- Use complex AI-Subdomains like Generative AI (GenAI) for supporting Entity-wide security.

4. AI-GCC ADVANCED TOPICS

4.1. The Design, Setup, and Implementation of IDDSs

IDDS is based on data artefacts and accesses mechanisms; and IDDSs' major characteristics, features, parts, components, and components/modules are [27,48,49]:

1. They enable AIMs training and learning.
2. Standardizing DIICS interfaces.
3. They can manage different data formats depending on the applications of AI-Subdomains, which can range from images, binary, text, complex sensor-io...
4. The QoD and quantity of IDDSs are important CSFs in estimating AIMs.
5. QoD must ensure that used data is errors-free, otherwise IDDSs will be full of biases, or irrelevant information; which will cause the AIM to deliver erroneous predictions.
6. QoD needs: 1) Data cleaning of inaccuracies and inconsistencies; 2) Data labelling and tagging with correct-labels for supervised learning; and 3) Data augmentation helps AIMs and EAMs to improve generalization.
7. Quantity of data improves predictions (and prediction-accuracies), because, more data/IDDSs means better AIMs, but that can prove itself wrong… Data quantity has to correspond to the AIM's problem-space, which means that it should have enough variation and samples of different classes/outcomes needed for AIM's PEAbGLPs.
8. IDDSs preparations are important for AI-Subdomains like ML includes: 1) Irrelevant-data identifying and discarding; 2) Duplicated data detection; 3) Noise data filtering; 4) Incorrect data-types correction; 5) Missing-values corrections; 6) Multi-collinearity improvements; 7) Outliers are managed; and 8) Unacceptable format are discarded.
9. Applying a PMM for business scenarios and EAMs.
10. AI and AIMs based Projects where DS plays a central role.

4.2. The Application of AIMs

An EAM and AIM are programs (or structured logic) which autonomously support specific business and common tasks, in an automated way. Like the Human Brain (HB), it learns/mimics, solves problems, and tries to make predictions. It does learn from experience like the HB, but it acquires knowledge from massive IDDSs and applies PMM-techniques and algorithms to derive insights. An example case, is an AIM that is used to compare pictures of tele-phones and PCs/laptops, using training on labelled images of both. To find differences, the AIM analyses the inputted images to detect patterns, like size, keyboard, used building materials, and screen's design. When the AIM is sufficiently (or highly) trained, it can be used for decision making for new objects, as shown in Figure 4. AIMs can be used for different Apart from this image recognition task, you can apply AI models to different workflows; that includes Apart from this image recognition task, you can apply AI models to several workflows; that include NLP, anomaly-detection, predictive-modelling, and forecasting… These include natural language processing (NLP), anomaly detection, predictive modelling and forecasting, and robotics. to several workflows. These include natural language processing (NLP), anomaly detection, predictive modelling and forecasting, and robotics [39].

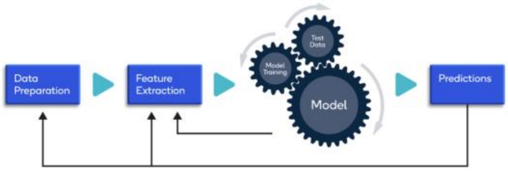

Figure 4. An AIM [39].

As shown in Figure 5, supporting an AIM needs [39]:

- Identifying the problem to be solved and defining goals to be achieved.
- Data preparation and gathering IDDSs that reflect the workflows. Where data can be structured, unstructured, static, or streaming, and inconsistencies must be removed.
- Execute AI-Architecture tasks.
- Training, validation, and testing data splitting into three IDDSs as follows:
- Training IDDS, which can be up to 70% of the total IDDS.
- Validation IDDSs use 15% of remaining data for validation, and AIM's enhancements.
- Testing IDDS, reserves the final 15% to evaluate the AIM performances.
- AIM training uses backpropagation to incrementally tune its internal parameters; and requires important IICS-resources and efficient frameworks like PyTorch.
- Hyperparameter tuning of batch-size, learning-rate, and regularization methods keeps the balance between underfitting and overfitting.
- Model assessment by using validation IDDSs, to evaluate the AIM's effectiveness. Various Factors (or Metrics) like accuracy, precision, recall, and F1-score will provide insights in AIM's performances.
- Testing and deployment use testing IDDSs and the AIM has to to meet defined use cases; and if the results are satisfactorily, then deployment processes are initiated.
- Continuous evaluation and enhancements are supported by the applied AIMs to adapt to the transformation of data-patterns. Received reports helps in understanding AIM's performances and how to make needed adjustments to keep it relevant.

Figure 5. The creation of an AIM [39].

4.3. Needed Support

Supporting an AIM needs [27]:

- AIM's training process includes improve PEAbGLPs to offer predictions or decisions based on inputted IDDS, that includes various steps.
- The selection of the Right-Model step, offers an algorithm that corresponds to the IDDS and the problem to be solved.
- The Preparation step, splits the IDDS into training, validation, and test sets of data.
- The Feeding step, inputs IDDSs into the AIM in batches, during the training-phase.
- The Backpropagation step, adjusts AIMs by PRWC (weightings and reatings) that is based on predictions' errors.
- Validation steps, use validation IDDSs to tune AIMs' hyperparameters.
- Testing steps, evaluate AIMs' performances on unseen IDDSs to ensure generalization.
- AIMs' training faces many challenges, and overfitting, underfitting, and ensuring AIM's interpretability are barriers that AI-Engineers face [27]:
- Overfitting is the case AIM learns too much, from the training IDDS too well, which results in including noise and outliers, and causes poor performances on new IDDSs.
- Underfitting is the case when the AIM is very simple to capture the underlying-trend(s) in the IDDSs.
- Interpretability refers to the ability to understand AIMs' made decisions, which is determinant.
- To overcome these challenges, AIMs can use best practices [27]:
- Regularization: Techniques like dropout or L1/L2 regularization can prevent overfitting.
- Cross-Validation: Using different parts of the data to train and validate the model helps in assessing its performance.
- Feature Engineering: Selecting and transforming the right features can improve the model's learning ability.
- Model Explainability: Tools and techniques that help explain the model's decisions can build trust and aid in debugging.
- AIMs use AI-Services and Application Programming Interfaces (API).

4.4. AI-Services and APIs Inclusion

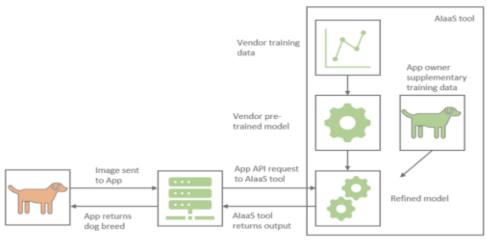

Figure 6. An AIaaS based application that recognizes objects [28].

AI-Subdomains use specialized services, APIs, and AI as a Service (AIaaS) which include a wide-spectrum of required AI-Functions, like understanding hu-man-language(s), recognizing objects in images and videos, learning from data, understanding speech, analysing sentiments, suggesting personalized advices-recommendations… AIaaS offers [11,28,29,30]:

- The AIaaS platform ecosystem is optimal for fast commoditization in cloud-services. Cloud-vendors offer a range of standardized, pre-configured AI-Services. Like AI-services that supports the deployment of chatbots; financial-services, fraud-detection…
- Services-Oriented Architecture (SOA) and MSA which accompanied the decline of legacy monolithic IICS architectures. The emergence of SOA and MSA enable the implementation of cloud-services, like AIaaS.
- Legacy monolithic IICS architectures, an application is a set of unit, whereas, SOA and MSA support applications composed of atomic Blocks, which supports the implementation of AIaaS-Functions.
- Commoditization of AI-Functions in AIaaS offers: 1) Optimizing IICS-infrastructure costs; 2) 'pay as you go' model; 3) Reduction of special-ists' costs; 4) 'out of the box' pre-trained AI models can be used; and 5) Integration with other DIICSs.
- Supports various APDs like image-recognition as shown in Figure xxxx that enables a user to identify objects by taking a photo.
- There are many AI-Frameworks that deliver AI-Services and for various subdomains like Machine Learning as a Service (MLaaS).

5. MMP BASED LEARNING APPROACH

5.1. Generic Learning Approaches

There is a strong interaction between Projects, AI-Subdomains implementation and Entity Automated LPs (EALP), and therefore the Entity has to implement a Polymathic Enterprise Architecture based PEAbGLP. The PEAbGLP manages all EALPs' that includes ML, DL, DS, traditional-legacy LPs and other. The PEAbGLP proposes an IHI concept for a generic and transcendent EAIC. EAIC generic approach means that it supports and interfaces with all AI-Subdomains. The EAIC uses a Polymathic transformation framework that is specialized in Projects. Projects have XHFRs, and added to this complexity, AI-Subdomains implementations and related products can force a siloed-integration implementation approaches, which are the main reason for XHFRs [65]. The EAIC ensures Entity's sustainability, just-in-time decision-making, and operational efficiencies [10]. EALPs can include various AI-Learning fields and technics.

5.2. AI-Learning Fields and Technics

There various types of EALPs types: 1) Artificial Narrow Intelligence (ANI); 2) Artificial General Intelligence (AGI), and Artificial Super Intelligence (ASI). Where EALPs can be classified to its ability to function like the HB; and the main differences are [8,31]:

- ANI is used for simple AI-Subdomains and applies algorithms implemented by developers, which is equivalent to the implementation of a predefined-task, and it does not include autonomous-reasoning; like the AI for Voice (AI4Voice) commands, offer users appropriate responses, used in APDs such as fraud-detection, machine-translation…
- AGI is the case where AI can reason and offer decisions like the HB, where the level of precision is still to be defined. AI based problem-solving which HBs cannot solve like scientific research or mathematical-reasoning.
- ASI is in initial phases, and it is supposed to mimic HB's intelligence but for the moment AI is much more an enhanced statistics field. And the HDT is an ASI example.
- In AI related EALPs and more specifically the author's PEAbGLP supports various AI-Subdomains by offering like [7,31]:

- AI-Machines are today are the base of EALPs, where machines which DIICS based, interpret, process, and analyse IDDSs to diagnose or solve problems. It is mainly a Quantitative approach in which massive IDDSs are inputted to DIICSs to be processed.
- ML has different types of LPs, which are to: 1) Supervised; 2) Unsupervised; and 3) Reinforcement LPs.
- Supervised ML (SML) LPs are based on labelled data-samples; where machines executed specialized tasks on samples that have been labelled, such samples are known as Training-Data for AI (TD4AI), like for example in on image-recognition.
- SML's image-recognition the main concept is based on idea that a machine determines if the image belongs to a specific category and object. Once the machine learned to recognize object's image from TD4AIs, then it will be fed with new images to tune the knowledge related to the object; and at the end used to make predictions.
- Unsupervised ML (UML) LPs are based learning by comparing objects. UML is different from SML, because the machine will not use labelled samples to execute tasks like analysis. By using comparison, that depend on the characteristics of the objects' different elements, like in the case of image-segmentation.
- Reinforcement ML (RML) LPs are based learning from concrete user-experiences and interactions with the concerned environment(s) and APDs, where LPs correspond to HBs' way of reasoning. In this case the machine explores DMS options and offers feasible recommendations (or rewards) or penalties, depending on the selected Factors.
- DL LPs are based on NN, which is a subcategory of ML that in-turn uses Artificial NNs (ANN) to solve-process more complex IDDSs and deeper (more aggregated) AIMs.
- And afterwards iteratively, it tries to understand object's constructions from various viewpoints. So, DL LPs, develop a Virtual NN (VNN) from IDDSs to offer solutions.
- The VNN explores a number of layers, and data becomes hard to analyse.
- NLP based AI (NLP) is founded on scientific methods related to learning from NLP to implement machines capable of communicating, and developing businesses and their Business Processes (BP).
- Other Subdomains based AI (OS) like robotics, expert systems, fuzzy logic (and other) LPs include: 1) Robotics that uses AI on robots; 2) Expert systems that offers HB expertise to develop a well-defined reasoning-thinking capacity; 3) Fuzzy logic-based AI for machines/computers to understand topics, problems, and solution which are not just binary 0 or 1 ("true" or "false").
- AI-Subdomains like DS, BD, and other need a Project and Entity strategic roadmaps which defined AI based transformation processes to implement an Entity DMS where the role of DS and DS and the needed AI-Roadmap and MMPs [8,32].

6. AI-ROADMAP AND MMPS

6.1. AI-Roadmap

AI-Roadmap and (cartography) needs to define the real relations and interactions between various DIICS and AI-Subdomains, especially AI-Components, ML, DS, and DL. The mentioned AI-Subdomains are inter-connected to analyse large IDDSs. AI-Components, ML, DS, and DL are related, but they are applied for different goals and have different methods of practical operation [6,8,32]:

- AI-Subdomains need a generic concept to support DMSPs.
- The needed generic concept supports Projects to transform the legacy business environment into an automated one.
- AI-based business environment enhances control and monitoring.

- The role of BD, DS, and data-modelling techniques are essential for DMSPs.
- EALPs for DL, and ML are based on Action Research (AR) approach can unify all AI-Subdomains related LPs.
- As already mentioned, DS deals with IDDSs using environments, and technics to extract hidden-patterns, meaningful-insights, and to offer optimal decisions.
- DS automated processes include: gathering, organizing, and analysing IDDSs. And can be considered a Polymathic (interdisciplinary approach) which merges different fields of DIICS, scientific processes (and methods), and statistics.
- For mining BD (associated with DS), DS uses various techniques, tools, and algorithms.
- DS uses mathematical statistics and ML to handle voluminous IDDSs.
- In ML, statistical-methods are used by DCIS to enhance their LPs, without being implemented by software packages.
- As already mentioned, ML have 3 LP types: Supervised; Unsupervised; and reinforced; and can be related by [32]:
- The Polymathic RDSMMP can put together capabilities from various APDs and AI-Subdomains ML, quantitative statistics, and visualization; to deliver APD-valuable insights from voluminous IDDSs, supporting robust DMS' processes in various areas, like DIICS/technology, scientific-research, and usual business oriented APDs.
- ML is a subset of both DS, and AI, which utilizes algorithms and statistical models to process IDDSs, that in turn support EALPs to be enriched without hard-coding.
- AI is a wider concept, and it focuses on creating DCISs which execute operations which are commonly done by the HB which has intelligence, reasoning, learning, and problem-solving capabilities.
- DS is the foundation for ML and AI that incorporate IDDSs for applied AIMs, and to learn from them. It integrates algorithms from ML and includes concepts from legacy traditional APDs' expertise, statistics, and mathematics to implement solutions.
- AI is a valuable resource for DS related fields, because it generates data-insights. The main difference with AI, lies in DS's comprehensive approach to data-collection, preparation, and analysis, transcending only algorithmic or statistical tools-facets.
- An ML case is predictive-maintenance, which is used to predict future results (or outcomes) based on historical-data. Predictive-maintenance includes analysing IDDSs from sensors to predict equipment's possible failure(s).
- NLP is the combination of the mentioned concepts and it involves analysing human language(s) to extract insights and their meaning.
- The NLP-Subsystem supports AI-Subdomains interactions.

6.2. Cases of AI-Subdomains Interactions

Cases in which AI, DS, and ML interact can be [32]:

- Recommendation systems, are AI systems, that represent algorithms, that delivers personalized recommendations based on IDDSs. DS participates in the collection and analysis of user IDDSs, while ML is used to implement algorithm(s) that supports the mentioned recommendation system.
- The Fraud detection system, uses DS and ML to analyse large data amounts and to identify (hidden) patterns and errors/anomalies that can include fraudulent actions. ML algorithms identify such patterns and anomalies, while DS collects and prepares IDDSs for DA.
- The NLP-Subsystem based chatbots which are designed to simulate conversations with people (clients). AI-Subdomains support chatbots, like ChatGPT, which uses ML

algorithms, and NLP-Subsystem techniques, to understand Natural Language Queries (NLQ), to provide personalized responses.

- General Electric’s (GE) predictive maintenance platform which uses ML, which collects sensor IDDSs from its equipment and analyses them to predict their statuses. The mentioned platform uses advanced ML’s algorithms to detect patterns in sensors’ IDDSs. It is designed to learn from historical-data, to improve predictions’ accuracy.
- The mentioned AI-Subdomains overlap and there are redundancies, which each Subdomain has a unique role in solving problems. The interdependence of Subdomains DS, ML, and AI leads to the use of adapted environments. Where Machine Learning Algorithms (MLA) play a central role.

6.3. MLAs Implementations and Integrations

There are different types of MLAs [33,40,41,42]:

- SML Algorithms (SMLA), consists of a target (or outcome) variable (also known as a dependent variable), which is used to predicted from a given set of predictors (independent variables). SMLAs for classification and regression include generating a function/module that maps input-data to corresponding outputs. Training is applied until the AIM achieves the defined or sufficient-enough level of precision. The most popular and used SMLAs are: 1) K-Nearest Neighbours (KNN) is a SMLA classifier, which uses proximity to create classifications (or predictions) on the grouping of individual data-points. Linear regression is the most common regression analysis method because it is simple to use in predicting and forecasting activities [35], like Logistic regression is a statistical algorithm applied to binary-classifications
- UML Algorithms (UMLA) acts on unstructured and unlabelled data, in which there are no target (or outcome) variable for predicting purposes. UMLAs for clustering and data-mining identify hidden-patterns (or possible structures) in data. Using the mentioned patterns, data-points are grouped by using “similar-characteristics”, that auto-generates a function for mapping input-data to clusters (or groups). This iterative process continues until the applied AIM identifies meaningful patterns in IDDSs. The most popular SMLAs are:1) K-Means clustering used for clustering-problems used in ML or DS contexts, where it groups unlabelled IDDS into different clusters. K defines the number of pre-defined clusters, created and as if K=2, creates 2 clusters, and for K=3, creates 3 clusters…2) Hierarchical Clustering, used to group the unlabelled datasets into a cluster and also known as Hierarchical Cluster Analysis (HCA). It develops the tree-hierarchy of clusters (a dendrogram).
- RML Algorithms (RMLA), consists of reinforcement EALPs’ algorithms, where the DIICS supports continuous-training (by trial & error) to offer recommendations and/or decisions. EALPs learn from past-experience and (try) to capture optimal knowledge used to offer precise decisions.

6.4. RDSMMP, MMPs, and EALPs Linkages

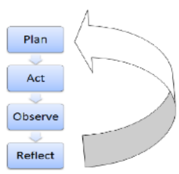

Figure 7. AR’s basic operations to support EALPs [53].

AR is optimal for implementing RDSMMPs and MMPs; where the main advantage is that is optimal for EALPs' management and integration.

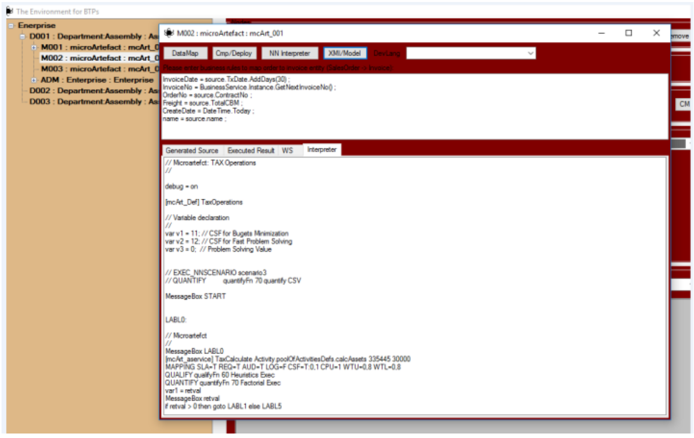

Figure 8. NLP's integration for EALPs.

And the related issues are [50,51,52]: 1) It supports iterative and continuing LPs; 2) Offers a predefined sets of applicable actions in HDT's context; 3) It can configured for various types of problems like the ones related to APDs, DIICS, Project, AI…; 4) Problem-types are the HDT in a participatory, collaborative, and cyclical manner; 5) Capable of using positivist, interpretive, and critical concepts; 6) Applies basic actions, as shown in Figure 7 [53]; and 7) It is mainly a qualitative-heuristics reasoning pattern that can punctual qualitative DS methods. AR and EALPs' based RDSMMP is a qualitative reasoning-mechanism that appeared as a major AI-Subdomain in the 20th century. In 1950, Alan Turing implemented the basics of automated machine-based logic or the *Turing Test*. And the term AI, was hammered in the proposal for an AI-Subdomains conference in 1956, at Dartmouth [54]. Qualitative support for AI-Subdomains includes: 1) HDT's cognitive-processes that use NLP scripts, as shown in Figure 8; 2) Sets of problem-types actions; 3) Sets of actions are applied to search and find optimal-solution(s) (or a goal-state in the HDT); 4) HDT processes start at a root-node and create a tree of states; 4) The HDT interface the PRWC; and 5) The found solution-state (or node), includes the actions needed for executing the changes and are persisted in EALPs [55].

6.5. A Qualitative and HB Concept

By convened definitions, AI tries to mimic or simulate HB's functions. And HB functions are mainly experiences based or qualitative, and not DS based. Therefore, the RDSMMP is a qualitative-empirical concept and not a simplistic DS or quantitative one. That implies that EALPs, adopt AR, which is optimal for education and hence LPs. The HDT and hence the qualitative based EALPs, which are not simplistic quantitative methods, is optimal for solving complex problems and learning from them, as shown in Figure 9. The best solutions depend on the PRWC and selected Factors, and primarily on the RDSMMP's Objective Functions (ROF).

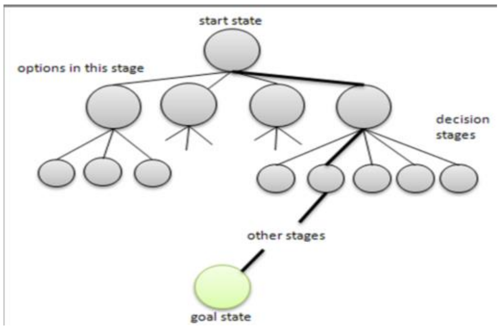

Figure 9. IHIPTF's HDT tree structure.

EALPs map to concrete to APDs' cases that need to be abstracted by AIMs and EAMs; and as there are many methodologies that change quickly, the Entity has to implement an IHIPTF's Methodology (IHIPTFM). The IHIPTFM is expected to enable inter-operability which in-turn enables HDT to solve problem-type(s) and improves EALPs [66].

6.6. A Polymathic Approach and Hyper-Automation

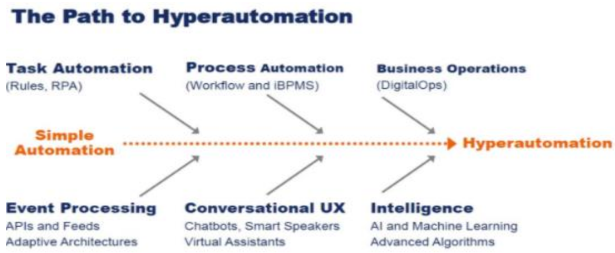

Figure 10. EALP's interfaces AI/OR Hyperautomation [61].

Projects must enable an efficient management of EALPs that need constant enhancements which demands [46]: 1) Evolutive an quality processes; 2) Enhancements' coordinate management; 3) An IHI Polymathic implementation's roadmap; 4) The use of RDSMMP; and 5) RDSMMP, AIMs, and DIICS inter-linking; 5) Defining DIICS' evolution roadmap; 6) Building RDSMMP metamodel; 7) RDSMMPs' interfaces with TDM [56]; 8) Managing concurrent EALPs; 9) Using the IHIPTFM for modelling; 10) Implement RDSMMP's vision(s); 11) Defining levels of granularity, and abstracting problem-types; 12) Enabling hyper-automation as shown in Figure 10; and 13) Complexity Management Framework (CMF) and Strategy (CMFS). The CMF [58]. The CMFS relates Entity's DIICS, RDSMMP, AI-Subdomains, and APDS; which can be weighted and controlled by the Global Simplicity Index (GSI). The GSI presents the level of Project's and RDSMMPs' complexities and their possible reductions; and the enhancements to EALPs [58,59]. The RDSMMPs offers abstraction-levels and interfaces to implement AI-Subdomains like OR, ML, DL, and others. Where the HDT is supported by: 1) Modelling of AIMs; 2) Implementing generic for ML, OR … as shown in Figure 11; 3) RDSMMPs' integration; 4) EALPs abstracts OR, ML… methods; and 5) The integration of complex algorithmics, as shown in Figure 11.

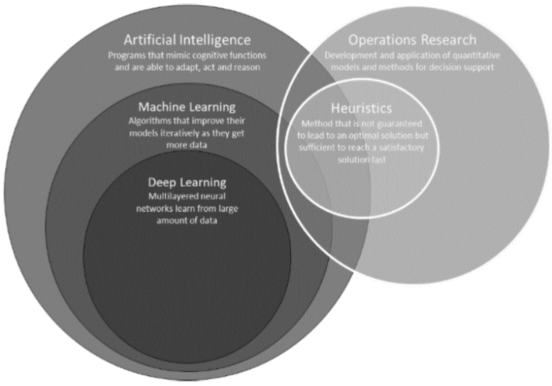

Figure 11. Various AI domains [56].

The RDSMMPs' uses ROFs to optimize and persist solutions/results in EALPs which support Entity's transformation and reorganization [61,64]. EALPs and their associated NLP-Scripts show GAPs (or inconsistencies) and use RDSMMPs to offer actions to transform/(re)organize Entity departments. RDSMMPs' iterative approach can improve success-rates, because the used EALPs actions are based on "organizational routines or known actions" and proven reorganizational models (and associated NLP-Scripts) [63,64]. Entity's departments transformation/(re)organization improves its robustness by prediction problem sources like resistances to change. AIMs and EAMs include (re)organizational models [57, 61, 62].

7. Complete Proposition and Prototype-The CPoC

7.1. Preparing DIICS' Platform

The CPoC's first step is to prepare the optimal RDSMMP platform that includes:

- An IHI Cloud based DIICS.
- Support for AI-Accelerators, which are optimal for AIMs' training …
- HPC support for DBs based on DFSs that in turn enable scalability, fault-tolerance…
- Use DB centric concepts and design for AIMs and AI-Subdomains.
- All RQ's hypotheses are fulfilled and the Entity is transformation ready.

7.2. Preparing IDDSs

Figure 12. Scatterplot of the IFDS [45].

The CPoC is a concept that is based on patterns that support IDDSs for this undertaking and the CPoC is mainly based on [44,45]:

- The Iris Flower IDDS (or Fisher's Iris IDDS, IFIDS), is a multivariate IDDS.
- It uses MLA’s LDA to process IFIDSs and to quantify the morphologic variation of Iris flowers (of related “n” species).
- The IFIDS consists of 50 samples for each of 3 species of Iris (Iris setosa, Iris virginica and Iris versicolor), as shown in Figure 12.
- The selected “m” or 4 features were used and were measured for each data-sample: Length and width of sepals and petals, in centimetres.
- The combination of 4 features used by LDA-Model compares the species.
- These IFIDS can be used in AI-Subdomains basic constructs.

7.3. Basic Constructs (Quantitative)

This prototype’s main characteristics are [45]:

- Uses a DT and Working DTC (WDTC) are ML-Prediction system that generates rules.
- Uses an ML-Library which is a customized library for DT, which carries out the following tasks: 1) Implementing functions which split training-data into small IDDSs depending on their disorder; and 2) Implementing source-code that calls/uses splitting-functions to create a DT from IFDS and processes/computes a predicted-class.
- Setting-up the CPoC with n=50 data items that are a subset of the data-store.
- The objective is to predict object-types (tagged with 0, 1 or 2).

7.4. The Execution-Setup (Quantitative)

This PoC’s setup has the following steps [45]:

- There isn’t a standard format for WDTC and the Project must define its IHI version as shown in Figure 13 below.
- Each WDTC node contains 6 values defined in a Node class:
  s
  1) The List<int> is the nodes’ collection.
  2) The root-node’s nodeID has the value: “0”. The source-rows are the rows of the entire 30-item dataset with the values: [0, 1, 2. . . 50].
  3) The splitCol and splitVal attributes determine where the source-rows in the node are split in 2 subsets (having small average Gini-impurity).
  4) The selected splitCol is set to “2” and splitVal to “3.3”, that implies that rows with column [2] has the values strictly-less than “3.3”, are shifted (or assigned) to the left-child (or side) of the root-node.
  5) The classCounts is an attribute collection that has the numbers of classes related with source-rows in nodes. Root-node’s classCounts contains numbers of every class that is associated with source-rows.
  6) The predictedClass attribute is used for the prediction which is associated with the actual/current node.
  7) root-node’s predictedClass is a class that maps/corresponds to classCounts’ highest value. As all 3 class-counts is equal, implies that the predicted class is a tie between classes 0, 1, and 2. In cases of ties, PoC’s WDTC randomly selects the 1st of the tied classes, which implies that the predicted class is “0”.

public class Node

```
{
  public int nodeID;
  public List<int> rows;
  public int splitCol;
  public double splitVal;
  public int[] classCounts;
  public int predictedClass;
}
```

Figure 13. The class Node structure.

7.5. The Execution-Conditions (Quantitative)

This PoC's execution conditions, and constraints [45]:

- The use of splitting (and disorder) scripts creates WDTC.
- The WDTC is ML based and predicts and then generates rules like IF Budget < 10000.0 AND Project_Status >= 2.0 THEN RiskFactors = 10 (which is high).
- The WDTC is ML must be customized and standard-library for DTs offer a huge set of complex functions. Therefore, it is better to use an IHI DWTC.
- For this PoC 30 (training/reference data items) to implement the IHI WDTC which has 7 nodes; which enables 100% accuracy.
- The PoC proves by predicting the class/species of a new (unkown iris-flower with sepal and petal values of (6.0, 2.0, 3.0, 4.0).
- The WDTC predicts that the class is 0, corresponding to the rule: IF (column 2 < 3.1) AND (column 0 >= 5.1) THEN class = 0.

7.6. The Execution-Prediction Process (Quantitative)

This PoC's prediction process [45]:

- In the case of external tools or libraries WDTC, and specifically the environments that apply recursions, makes it complex and difficult to define the set of rules.
- PoC's WDTC ignores this complex topic and bypasses using sets of rules (as string-collections) in prediction processes.
- Sets of rules for WDTC's root-node is: IF (any value in all column of the item to be predicted, THEN it is anything.
- The PoC labels this condition using the snippet-string: IF (*) THEN […].
- In some simple cases the root-node is sufficient.
- The prediction_accuracy of a minimal WDTC is the comparison-etalon value; like for a collection of 30 items includes 22 class_1 items, 4 class_0 items, and 4 class_2 items, which means that root-node's class-counts is [4, 22, 4].
- The WDTC predicts class_1 for all items and related prediction_accuracy is 22 / 30 = 0.73 (rounded). The result that corresponds to the prediction_accuracy of a root-node is achieved by simple guessing.
- Therefor a credible WDTC offers prediction_accuracies that is better (>) than its minimal root-node version.

7.7. The Execution-Prediction Process (Qualitative)

Selected Factors are linked to NLP-Scripts and the HDT contains relationships between the RQ and RDSMMPs. CPoC's interfaces were implemented using Microsoft Visual Studio .NET environment and the IHIPTF. The RDSMMP uses calls to resulting AI-Services, IHIPTFM, to launch HDT actions. Factors were selected and evaluated by the PRWC.

7.8. Problems Processing in a Concrete HDT Node (Qualitative)

The DMSP solves Project's problems, where Factors inter-link EALPs, Problem-type(s), with sets of actions which are processed in an HDT-Node. And in this context, the action *CSF_RDSMMP_Extraction_Procedure* was executed and offered solution(s). Solving Problem-types involves the selection of actions and solutions for multiple Project's activities. The HDT applies the PQQRMM and uses the following steps:

- In Phase 1, IHIPTF*'s* interface implements HDT-Scripts to process Factors. And then relates CPoC's resources to *CSF_RDSMMP_Extraction_Procedure*.
- The PRWC and DMSP are configured to weight and tuned to support the HDT.
- Link the selected node to HDT to deliver the root-node.
- The HDT starts with the *CSF_RDSMMP_Extraction_Procedure* and proposes solution(s) in the form EALPs' improvements.
- HDT scripts support AHMM4MM's instances which are processed in IHIPTF's background to offer solution-value(s).

8. CONCLUSIONS

RDSMMPs support reasoning-engines for Projects which are complex. The RDSMMP aligns AI-Subdomains, Project components, EAMs, AIMs, and other artefacts. In this article the focus is on DS, other AI-Subdomains, services' architectures, EAMs, DIICS-platforms… AI-Subdomains like (R)DS, ML, DL, DP, OR, and other, are the fundaments of a DMSPs. This articles main RDSMMP conclusions are:

- The RDSMMP takes a transformative enterprise-wide view and not just DS' or AI.
- IDDSs' contents and structures are combined with AI-Subdomains.
- IDDSs can be interrelated with mixed-research methods, like the presented PQQRMM.
- Has to build a DIICS Platform to support AI-Computing and ML algorithms.
- Apply a DB, AIaaS, and IDDS centric concepts.
- Use EALPs that includes ML, DL, DS, traditional-legacy LPs that results in implementing EALPs.
- RDSMMP's approach means that it supports and interfaces with AI-Subdomains.
- An AI-Roadmap defines the relations between various DIICS and AI-Subdomains, AI-Components, AI-Services…
- An RDSMMP supports the interaction of AI, DS, and ML components.

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This article is a part of a series of research works related to AI, Projects, and EAMs. It is an intersection of the mentioned fields that are interconnected using a Polymathic methodology and framework.

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