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C ^{3} AN: Custom, Compact and Composite AI Systems - A NeuroSymbolic Approach: 4th-Generation Evolution of Intelligent Systems

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C^{3}AN: Custom, Compact and Composite AI Systems - A NeuroSymbolic Approach: 4$^{\text{th}}$-Generation Evolution of Intelligent Systems

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Artificial Intelligence (AI) systems continue to evolve rapidly. From the architecture perspective, it is evolving from large, monolithic models trained on massive internet data to complex, multi-component "compound" systems and "agentic" frameworks capable of semi-autonomous decision-making. These systems show immense promise yet face numerous challenges in reliability, consistency, transparency, and alignment with user goals. In this article, we propose *Custom, Compact and Composite AI with Neurosymbolic (C^{3}AN)* approach, a framework that paves way to 4$^{\text{th}}$-generation of AI that integrates **data**, **knowledge**, and **human expertise** to build **robust, intelligent and trustworthy** AI systems defined by 14 foundation elements.

Custom emphasizes the focus on high-quality, domain-specific data and knowledge, along with tailored workflows and user or application-specific constraints.**Compact** highlights resource-conscious implementation that does not require extreme scale to achieve reliable domain adaptation. **Composite** refers to the integration of multiple AI modules that collaboratively perform domain-specific tasks, handling data, knowledge, and human expert feedback within a cohesive Neurosymbolic framework. Together, these qualities address longstanding issues in large, monolithic, or purely black-box models. We illustrate the foundation elements of C^{3}AN in two complex AI systems with demands representative of enterprise class and/or mission critical applications: (1) *Nourich*, a disease-specific diet management system that recommends recipes based on users' health condition and food preferences, and (2) *MAIC* (*MTSS AI Concierge*), which operates in the Multi-Tiered System of Supports (MTSS) domain for mental health and behavioral interventions to support health workers with different roles. We conclude by outlining practical challenges and future research directions to foster robust, multi-domain adoption of C^{3}AN.

Additional Key Words and Phrases: Neurosymbolic AI, Compound AI, Trustworthy AI, Agentic frameworks, Enterprise Grade AI.

1 INTRODUCTION

AI has reached an inflection point. From the rise of massive language models that can generate human-like text to the emergence of tool-integrated, multi-component solutions, AI has demonstrated remarkable capabilities in natural language processing, content generation, writing assistance, and conversation-based search. Despite these advances, there remains a significant gap between research demonstrations and robust, reliable, production-grade solutions.

In many real-world scenarios—healthcare, education, finance, governance—AI systems must satisfy stringent requirements for enterprise-ready use. Although large, monolithic models often perform well on general tasks, they frequently lack the domain specificity, transparency, and alignment with enterprise-grade standards required in these high-stakes domains. This shortfall stems in part from the vast and imprecise nature of their statistical representation spaces, which makes it challenging to retrieve contextually relevant information and integrate it for informed decision-making.

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Beyond monolithic models, so-called "agentic" approaches aim to automate decision-making processes by delegating tasks to individual agents. However, these agentic methods raise their own set of concerns about accountability, safety, and consistent performance—especially since, at their core, they often rely on the same opaque mechanisms as large, monolithic systems.

We posit that such limitations demand AI systems which are:

- **Custom**: Adapting effectively to domain-specific knowledge, workflows, or user-defined constraints from domain expertise,
- **Compact**: Maintaining domain-appropriate performance without indefinite scaling of data or model size,
- **Composite**: Orchestrating multiple components such as neural modules, knowledge-bases, and decision processeswithin a coherent framework.

As an implementation strategy, *Neurosymbolic AI* emerges as an effective means to unify **data-driven** neural networks with **symbolic knowledge representations** and **human expertise** in a single, coherent framework. Neural models excel at learning from raw data, while symbolic approaches enable the incorporation of domain knowledge and explicit workflows in a transparent, adaptable manner. By establishing robust feedback loops for expert oversight and guidance, Neurosymbolic systems can deliver stronger guarantees on consistency, accuracy, and alignment with enterprise requirements [1, 2].

This article presents *Custom, Compact and Composite AI Systems with Neurosymbolic Approach (C^3AN)* as a structured way to integrate **data**, **knowledge**, and **human expertise** leveraging Neurosymbolic AI. C^3AN is structured on three core pillars – intelligent, robust, and trustworthy, built on fourteen foundation elements as shown in Figure 1.

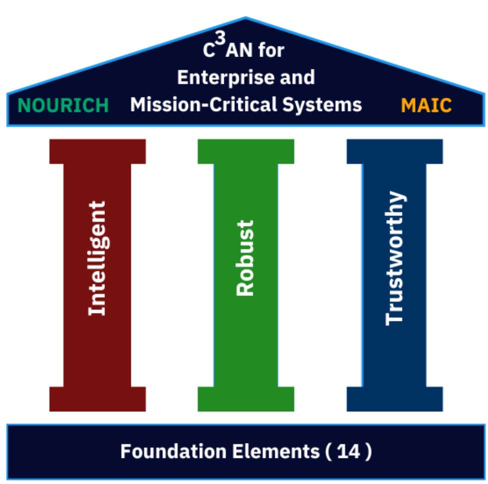


Fig. 1. The proposed AI framework C^3AN is structured around three core pillars: Intelligent, Robust, and Trustworthy, which are built upon fourteen foundation elements (Section 4).

We first review the four *generations* of AI systems—monolithic, compound, agentic, and copilot. We then motivate a new, 4^{th} generation—C^3AN—and detail 14 core foundation elements that lead to the pillars of robust, intelligent and trustworthy AI system, illustrating how each foundation element exploits the synergy of data-driven learning, explicit domain knowledge, and iterative feedback from human experts. Next, we show how *Nourich* and *MAIC*, two representative systems clarify the implementation of C^3AN's approach. We conclude with an overview of practical implementation challenges and future directions.

Custom, Compact and Composite AI Systems - A Neurosymbolic Approach (C^3AN)

Custom: Tailors domain-specific constraints, knowledge, and workflow structures to the enterprise-user's needs.
Compact: Emphasizes resource-conscious deployments, avoiding the pitfalls of massive, unbounded scaling.
Composite: Integrates multiple AI modules under a unifying, Neurosymbolic design.
Neurosymbolic: Integrates data-driven neural networks with symbolic knowledge and robust human feedback loops.

2 BACKGROUND: WHY AI NEEDS A PARADIGM SHIFT

Early AI systems relied heavily on heuristic rules and expert systems, focusing on symbolic representations of world knowledge. With the advent of increased computing power and massive datasets, statistical approaches like deep learning and Large Language Models (LLMs) surged in popularity. While these developments have delivered state-of-the-art performance in tasks such as content generation, image recognition, speech processing, and natural language processing, they also introduced new challenges:

- **Opaqueness.** Deep neural networks often function as "black boxes," making it difficult to trace why a particular decision or output was produced.
- **Data Hunger.** Modern LLMs require huge amounts of data to achieve high performance. They may fail or hallucinate in scenarios lacking adequate training data.
- **Hallucinations:** The LLM class of models seems to have an innate limitation of hallucination. While it can be mitigated to a certain extent, it cannot be prevented completely [3, 4]
- **Misalignment.** Without careful curation, large models can produce outputs misaligned with user values, ethical standards, or domain requirements.
- **Limited Domain Adaptability.** While broad LLMs are impressive generalists, they may struggle to incorporate specialized domain knowledge without extensive fine-tuning or large-scale customization.

Notable Industry Shifts Toward a New Paradigm

Demand for Domain-Specific (focused) Models: Industry forecasts indicate that over 50% of Enterprise Generative AI models will be domain-specific by 2027. Furthermore, two of Gartner's three bold and actionable AI predictions focus on reducing energy and resource consumption in AI training and development. [5].
Khanmigo: Khan Academy's AI-powered teaching assistant illustrates the growing role of Small Language Models (SLMs) in specialized domains. By leveraging SLMs, Khanmigo delivers efficient, scalable, and cost-effective educational support, enhancing student learning experiences and streamlining teacher lesson planning [6].

Analysing the Current Landscape of Generative AI for Enterprise Use

Success of Generative AI. Generative AI, marked by its remarkable ability to generate coherent text, summarize and retrieve content, generate images and videos, and simulate conversations, has transformed creative and content-based work. This innovation has transformed creative and information-centric fields, capturing the imagination of both the public and business communities. As a result, models quickly gained adoption across a wide spectrum, from everyday users and knowledge workers to large enterprises. From customer support automation to content creation and data analysis, generative models have brought innovation to workflows, introducing efficiencies and scalability. As these technologies evolve and permeate various industries, enterprises are increasingly adopting AI-driven solutions to enhance efficiency, drive innovation, and gain a competitive edge. The very large models have been used for engaging conversations (e.g., ChatGPT) and as a complimentary tool for search. They have also been used to generate content. They have succeeded in supporting language translation. However, all these collectively translate to serving informational and creative content-related needs. Analysis of 1 million ChatGPT prompts [7] found that the most frequent uses were for writing assistance, search, research, and coding support.

The Scaling-cost Fallacy. Generative models are designed on a large scale to serve general-purpose applications, necessitating extensive data from diverse domains. Training on such large-scale, multi-domain inputs significantly bloats the parameter space of these models. As a result, the intended outcomes may be located in areas of the parameter space that the models find challenging to reach. As a result, these models are sometimes not able to deliver results as expected, often producing non-sensical yet believable outputs. Furthermore, the models show a propensity for producing outputs that are misaligned with the ethical and operational standards of the organization. The lack of transparency, reliability, and cost of these models pose a severe concern over the value-to-cost ratio of these models. Crucially, the current large models do not seem to solve many high-value tasks – tasks that require models customized and tailored to enterprise knowledge and data. For example, in the manufacturing domain, usually the data is in the format of sensor values and images. The widely-adapted transformer models or foundational models may not fit this use case [8]. Each manufacturing domain is different and there is no universal pattern in anomalies. Even if a foundational model is implemented for this use case, the anomalies are unique to several manufacturing settings. Similarly, in a nutrition assistance setting, the underlying pattern in evaluating recipe suitability for each chronic condition is different, necessitating the need for custom models.

Cost Implications and ROI. The cost of training frontier AI models has increased exponentially, with projections suggesting the largest models will exceed a billion dollars by 2027 [9, 10]. Training trillion-parameter LLMs requires approximately 25,000 GPUs over three months, costing over $100 million and consuming energy comparable to that of entire nations[11]. This high-cost limits model retraining to a few major corporations, with most organizations unable to afford even fine-tuning.

OpenAI's recently released o1 model aims to enhance processing and reasoning capabilities but is significantly slower, offering only incremental performance improvements while requiring significantly more computational resources. Despite costing up to 40 times more than alternatives, o1 Pro mode does improve complex math and vision tasks. However, reports suggest it remains less cost-effective than models like Claude Sonnet 3.5 and continues to struggle with issues such as hallucinations. OpenAI also introduced a $200/month ChatGPT Pro subscription, granting access to the o1 model, though its high cost and increased token usage raise concerns about its practicality for widespread adoption. In a fast-paced environment, keeping LLMs and their training data up to date presents a significant challenge for enterprises. DeepSeek-R1, released in January 2025, focuses on reasoning tasks and challenges OpenAI's o1 model with its advanced capabilities [12], at a reduced cost leveraging model optimizations that lead to smaller model sizes (referred to as model distillation). This demonstrates that solving a specific task does not always necessitate the use of a large model. Maintaining such a large model is often redundant for handling a few smaller tasks. Model distillation enables the transfer of advanced capabilities from LLMs to SLMs, meeting specific requirements in vertical domains[13, 14]. Additionally, in various scenarios, deploying these models on edge or resource constraint environments is preferable for more efficient utilization. This requires smaller models targeted for specific tasks.

Generative AI's Deficiencies in Enterprise Use Cases. Successfully integrating Generative AI into business operations requires that such systems deliver value and align with organizational objectives. The systems must not only be accurate but also transparent, reliable, and ethically aligned with enterprise needs. As mentioned earlier, the current state of generative AI systems risk producing errors such as hallucinations or generating outputs misaligned with the intended goals. In mission-critical tasks, relying on general LLMs can be problematic, especially if the model has not been trained on domain-specific data [15]. For example, pharmaceutical companies need to identify appropriate and safe chemical disposal procedures. An incorrect recommendation could be detrimental to human society and the environment. To address this, businesses must focus on customizing every stage of AI development— from data selection and preparation to model selection and training—ensuring the system is tailored to solve the specific problem at hand.

The Promise of Knowledge-based Composite AI

Most real-world problems are complex and cannot be modeled as a single pattern recognition task alone. Instead, they require a modular approach involving multiple models collectively drawing on knowledge for making decisions based on model coordination. Crucially, the process of gathering insights by the individual models often necessitates specialized knowledge. For instance, while Vision-Language Models (VLMs) can efficiently generate cooking instructions from recipe images, identifying cooking methods from these instructions requires a separate model trained to learn the underlying data distributions and patterns. For example, the nutrition-related task of analyzing a recipe necessitates leveraging external knowledge, such as understanding the cooking method (e.g., grilling meat may produce traces of carcinogens). This highlights that solving complex problems often requires multiple models incorporating extensive knowledge and working together to address various sub-problems, ultimately enabling an informed and comprehensive final decision.

Bridging Symbolic and Subsymbolic Approaches

Classical symbolic AI excelled in explicit reasoning and domain knowledge representation but struggled with noisy, unstructured data. In contrast, subsymbolic methods (e.g., neural networks) perform robustly on pattern recognition tasks yet typically lack inherent explanation or domain constraint mechanisms. Researchers have long sought a "best of both worlds" paradigm, now commonly referred to as *Neurosymbolic AI* [16]. However, many existing Neurosymbolic methods do not emphasize the *custom, compact, and composite* nature that real enterprise scenarios demand. Likewise, not all approaches systematically incorporate **human expertise** beyond minimal preference signals. C^3AN explicitly addresses these gaps by integrating:

- **Customization:** Unlike purely neural models that require large-scale retraining to adapt to new domains, C^3AN integrates symbolic constraints (e.g., knowledge graphs, rule-based logic) to inject domain-specific constraints and reasoning, allowing tailored adaptations.
- **Compactness:** Symbolic knowledge structures allow the system to incorporate expert-driven priors, enabling efficient learning with targeted domain data rather than brute-force statistical modeling.
- **Composite orchestration:** C^3AN unifies specialized AI modules—such as neural embeddings for perception, knowledge graphs for reasoning, and process workflows for task execution—under a single reasoning layer. This layered approach enables modular, interpretable decision-making that balances statistical generalization with structured symbolic inference.

Why Neurosymbolic AI for C³AN?

Neurosymbolic AI merges data-driven pattern recognition (*subsymbolic*) with explicit knowledge representation and reasoning (*symbolic*). C³AN extends this by ensuring:

- *Domain Customization:* Knowledge graphs, process structures, and user constraints updated with minimal overhead.
- *Resource Compactness:* Focus on relevant domain data and iterative feedback from human experts to refine decisions without ballooning model sizes.
- *Composite Integration:* Multiple neural modules plus symbolic knowledge orchestrated via a unifying engine.

3 GENERATIONS OF AI SYSTEMS

The rapid development of generative AI since the emergence of early LLMs (e.g., BERT) to contemporary ones can be summarized in a series of "generations." Each generation builds upon lessons learned from the previous ones, while introducing new capabilities and new challenges. The conceptual depiction of models archetypes belonging to different generations can be found Figure 2.

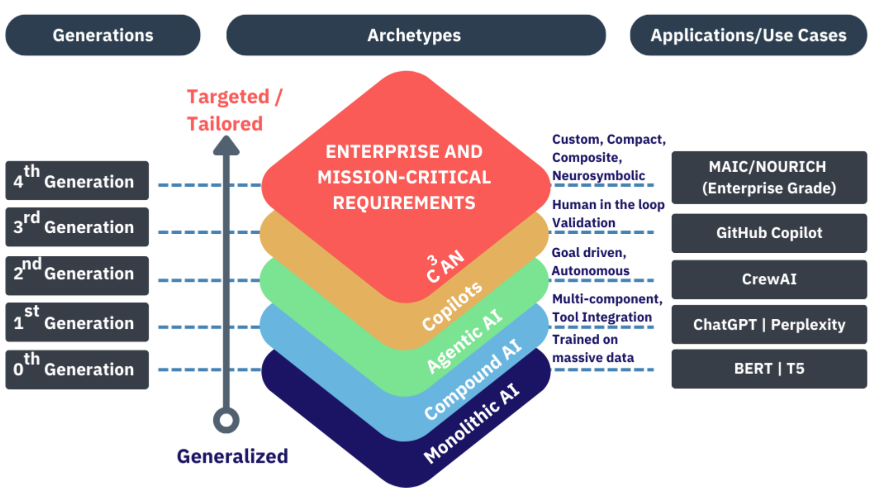


Fig. 2. **Evolution of AI Generations: From Monolithic AI to Mission-Critical Enterprise Systems**. This diagram traces AI's progression from generalized monolithic models (0th Gen) to enterprise-grade mission-critical AI (4th Gen). The *Generations* column outlines increasing complexity, from data-trained models (e.g., BERT, T5) to multi-agent AI (e.g., GitHub Copilot, CrewAI). The *Archetypes* column highlights key features, culminating in C³AN, integrating neurosymbolic reasoning, human-in-the-loop validation, and enterprise workflows. The *Applications* column maps real-world examples, with MAIC/NOURICH representing the highest level of customization, efficiency, and composability.

0th Generation: Monolithic AI Models

The **0th Generation** is characterized by language models and deep neural networks trained on massive internet-scale data. Although this generation of models showed success on several natural language processing tasks (e.g., machine translation), they didn't make drastic gains toward solving long-standing natural language processing tasks in a general way (e.g., across whole suite of benchmarks).

1st Generation: Compound AI Systems

The **1st Generation**, for the first time, introduced generalist language models that could be instructed to perform well across a wide variety of natural language processing tasks[17]. Although this generation of AI systems demonstrates significantly more flexibility in instruction following through prompting, they often require extensive prompt-engineering, suffer from extreme sensitivity to even the smallest prompt changes, ultimately leading to substantial overhead and human oversight to function correctly using the appropriate background knowledge.

2nd Generation: Agentic AI Systems

The **2nd Generation** sets up autonomous agents that leverage prompting for planning and orchestrating workflows coordinated by multiple language agents, sometimes even involving tool augmentation (e.g., search and math tools). This generation of systems showed promise in integrating language and structure (e.g., text-to-sql or text-to-math through Wolfram API), and automating simple workflows. However, such systems have often led to unnecessarily complex workflows, introducing overwhelming safety and reliability check-related overheads stemming from stringent code review and debugging requirements for checking the individual agent functions. Such checks are needed (e.g., compliance to the appropriate knowledge and procedures) due to the mission-critical nature of the majority of real-world enterprise use cases.

3rd Generation: Copilot

Due to the necessity for oversight in agentic systems, the **3rd Generation** involves human experts rejoining the loop as *copilots*, tasked with verifying an agent's decisions and refining workflows to enhance focus and precision. While this approach improves both efficiency and safety, it raises significant questions about the optimal way to integrate human expert feedback and address resource constraints (for instance, is reinforcement learning or other statistical methods the most effective choice?). Importantly, this leads to the fundamental question: *Why not integrate relevant knowledge and human expertise alongside the data during system development, rather than only at inference time?*

4th Generation: C^{3}AN

To address the issues across the different generations, our proposed **4th Generation** systematically incorporates:

- **Custom** adaptation: Unlike generic models or instruction-tuned systems, C^{3}AN integrates domain knowledge (e.g., knowledge graphs, rule-based constraints) directly into learning and reasoning, ensuring the solution is customized to domain needs.
- **Compact** deployment: Instead of depending on massive, internet-scale data or complex multi-agent setups, C^{3}AN leverages targeted domain data, structured knowledge, and iterative expert feedback to ensure efficient knowledge distillation during training, keeping models compact.
- **Composite** orchestration: Rather than treating reasoning as a monolithic or agentic process, C^{3}AN unifies symbolic and neural components into a structured framework, ensuring modular, expert-guided, and explainable decision-making without unnecessary complexity.
- **Neurosymbolic** design: C^{3}AN systematically combines data-driven learning with explicit symbolic reasoning, ensuring that human expertise and structured knowledge are incorporated throughout development—not just at inference time.

In short, C^{3}AN aims to avoid the pitfalls of the previous generations and take concrete steps towards supporting the features required for solving real-world use cases. The next section details the features, which we refer to as *foundation elements*.

Table 1. Summary of AI Generations with C^{3}AN's Distinct Qualities

Generation	Key Features	Challenges
0th: Monolithic	Large Neural Network or LLM	Hard to customize, lacks transparency, huge resource demand.
1st: Compound	Tool-integrated, multi-model	Complex orchestration, not necessarily compact [17].
2nd: Agentic	Autonomous agents, goal-driven	Safety, debugging, domain adaptation overhead [18].
3rd: Copilot	Human-in-the-loop Verification	Slower iteration, specialized interfaces.
4th: C^{3}AN	**Custom:** domain- and user-specific **Compact:** minimal overhead, targeted data **Composite:** multiple modules unified **Neurosymbolic:** merges data + knowledge + expert feedback	Implementation overhead, ensuring synergy among data, knowledge, and experts.

4 THE 14 FOUNDATION ELEMENTS AND 3 PILLARS OF C^{3}AN

The C^{3}AN paradigm supports 14 foundation elements leading to the pillars of Intelligent, Robust, and Trustworthy AI systems. Table 2 provides a summary of the foundation elements. Each element requires an implementation necessitating a blend of symbolic knowledge and data-driven learning while incorporating domain customization and use case requirements provided by expert humans. Humans remain essential in providing rich feedback, ensuring the system remains **custom** (data, knowledge, and human expertise specific to the domain, industry, or application), **compact** (efficient usage of resources and mechanisms), and **composite** (neural + symbolic + feedback modules).

5 EXAMPLE SCENARIOS: NOURICH AND MAIC

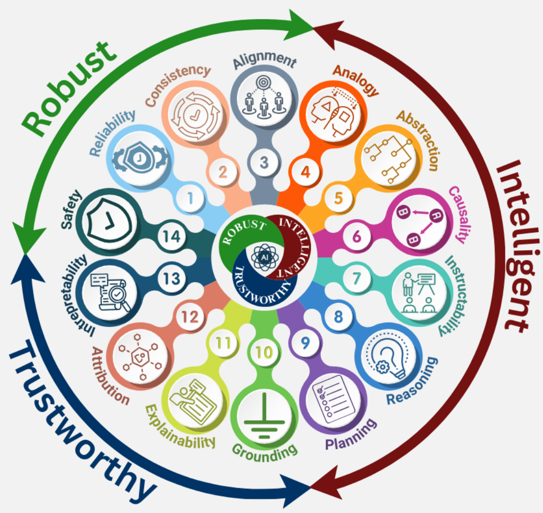
To demonstrate how C^{3}AN can be applied to mission-critical, complex enterprise applications, we present brief overviews of two representative systems: (1) *Nourich*, a disease-specific diet management system to recommend meals as per users' health condition and food preferences, and (2) *MAIC* (MTSS AI Concierge), which operates within the MTSS domain. Each system showcases **custom** domain knowledge with tailored workflows, maintains **compact** resource usage, and employs a **composite** implementation approach that integrates multiple AI modules, diverse data sources, and a human feedback loop.

5.1 Nourich: Disease Specific Diet Management System

Objective: The goal of the system is to analyze whether a given recipe is suitable for specific chronic conditions (diabetes) or not. In addition, the system aims to provide alternative recipes or a revised recipe through ingredient and cooking method substitutions.
Challenges: Analyzing the suitability of a recipe requires investigating ingredients, cooking methods and the effect of their interactions. This requires extracting ingredients, cooking methods

Neurosymbolic AI: 14 Foundation Elements to achieve 3 Pillars of C^3AN Framework

Neurosymbolic AI combines the pattern recognition and generalization strengths of neural networks with the abstraction and reasoning capabilities of knowledge graphs for symbolic inference. Our proposed **Neurosymbolic** approach enhances the C^3AN framework by integrating 14 foundational elements, ensuring it is *intelligent, robust, and trustworthy*. By leveraging the right *knowledge* alongside data-driven models, Neurosymbolic AI systematically captures these foundational elements to build reliable and adaptive C^3AN systems.



Reliability is critical for ensuring dependable, error-free operations *(Robust)* while also building user trust by meeting expectations persistently *(Trustworthy)*.
Consistency ensures coherence and uniformity in outputs *(Robust)*, which enhances trust in the system by avoiding contradictions *(Trustworthy)*.
Alignment ensures outputs adhere to user goals and domain requirements *(Trustworthy)* while enabling the system's ability to reason about these goals *(Intelligent)*.
Analogy enables the system to recognize patterns, draw parallels, and reason across contexts *(Intelligent)*, a hallmark of cognitive adaptability essential for complex problem-solving.
Abstraction elevates low-level data to high-level construct aiding both efficient reasoning *(Intelligent)* and stable processing *(Robust)*.
Causality reflects the system's capacity for causal reasoning by uncovering cause-and-effect relationships *(Intelligent)*.
Instructability shows how the system can learn from user input *(Intelligent)* while enhancing trust through adaptability to user needs *(Trustworthy)*.
Reasoning reflects the system's logical inference capabilities and its ability to derive meaningful insights from knowledge *(Intelligent)*.
Planning demonstrates the system's logical structuring of steps to achieve goals (Intelligent), while enhancing trust by providing actionable, realistic plans *(Trustworthy)*.
Grounding ensures decisions are tied to real-world entities *(Trustworthy)* while showcasing reasoning abilities to maintain context relevance *(Intelligent)*.
Attribution ensures the system clarifies the source of its decisions, fostering trust and accountability *(Trustworthy)*.
Interpretability Interpretability fosters user understanding of the system's internal reasoning (Trustworthy) while reflecting advanced modeling capabilities *(Intelligent)*.
Explainability Explainability ensures transparency by providing clear reasons for outputs, directly fostering user trust *(Trustworthy)*.
Safety ensures the system adheres to ethical guidelines and avoids harm, building trust *(Trustworthy)* while operating within stable boundaries *(Robust)*.

and their interactions explicitly from unstructured data such as natural language or recipe image. Then inferences has to be drawn on each ingredient and cooking method in the context of suitability on diabetes. Finally, these individual decisions needs to be composed together to form final decision. This is often referred as compositional reasoning [19] where the problem is decomposed into multiple sub-problems and final decision is made by composing the results of individual sub-problems. Investigating an ingredient requires several contextual knowledge about the ingredients and cooking methods such as nutrition information, disease contextual knowledge, glycemic index and effect of cooking methods. The ingredients and cooking methods need to be elevated to high-order abstractive concepts such as *potato is a healthy carbohydrate and it can be recommended* to analyze the suitability.

While general-purpose generative models are trained on extensive data from the internet, including medical guidelines, extracting disease-specific dietary constraints and other required guidelines from vast embedding spaces remains a significant challenge. In a mission-critical high-stake domain, incorrect recommendations could be detrimental. The model should be able to explain and support its reasoning by being able to trace back to trusted knowledge sources.

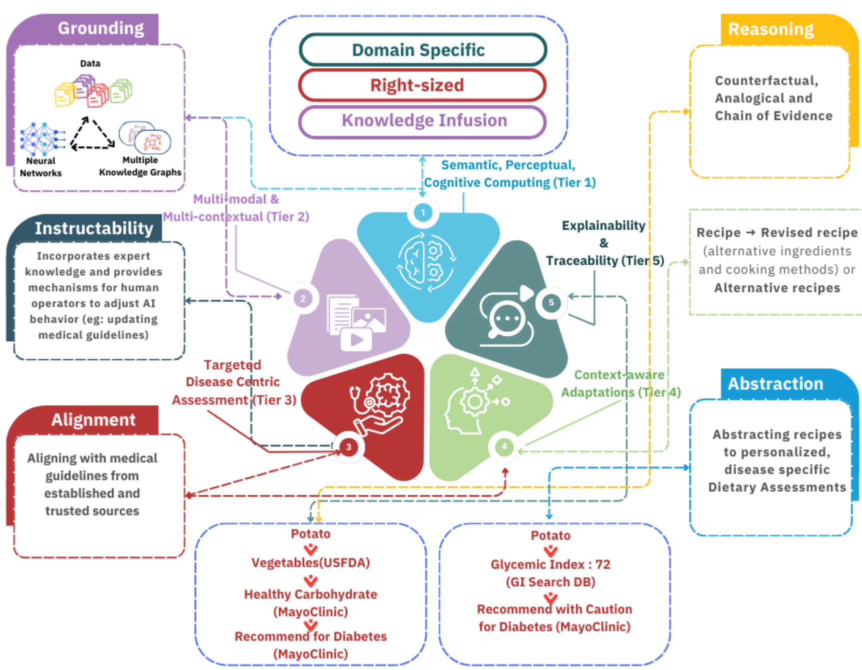


Fig. 3. **A domain-specific, right-sized, knowledge-infused AI framework for disease-specific dietary recommendations**, that requires Grounding, Instructability, Alignment, Abstraction, and Reasoning. It integrates data-driven modeling, symbolic knowledge, and human expert feedback. It adheres to domain knowledge (e.g., FDA categorizations, Mayo Clinic guidelines) to produce precise, disease-specific guidance.

Proposed Framework: C^{3}AN can accommodate the above-mentioned requirements along with modular pipelines to curate knowledge and data ensuring reproducibility. We propose ***Nourich*** designed to offer personalized dietary recommendations to individuals with specific constraints as described in Figure 3. The system consists of five tiers each one describing specific functionalities.

The proposed system consists of (i) **Custom data and knowledge** that are specific to dietary management and are multi-contextual and multimodal in nature (Tier 2 and Tier 3). The system adapts to a user's new instructions ("avoid peanuts") or rare dietary rules without re-training a massive model (ii) **Compact size** resulting from Nourich using domain specific data related to diet management verified through knowledge graphs and domain experts, instead of ingesting the entire internet, and a (iii) **Composite Engine** where several small neural networks perform specific pattern recognition tasks such as entity and relation extraction, rule-based models curating and integrating multi-contextual knowledge, symbolic models for reasoning and decision making at individual and global level, feedback models to refine borderline or newly encountered knowledge (Tier 1). Further, separate modules for explainable results (Tier 5) along with modified recipe recommendations (Tier 4). This yields a smaller operational footprint. Gathering mutli-contextual knowledge results in different kinds of knowledge as described below:

(1) **Taxonomy:** Taxonomy is a hierarchical relationship among entities. Cooking methods and ingredients categories are arranged with hierarchical relationships
(2) **Causal:** Causal knowledge captures the effect caused by an event. For example, the causal event of grilling meat produces traces of carcinogens (effect)
(3) **Logical Constructs:** Several logical constructs are curated for recipe analysis. An example would be, if ingredient is high in cholesterol, it is not suitable for diabetes
(4) **Rules:** Several rules were also employed to infer implicit knowledge. For example, if the carbohydrate to fibre ratio is 10:1, then the ingredient can be considered whole grain item which is suitable for diabetes. Else, it is not considered whole grain.

It can be noticed that the knowledge present in unstructured format from several sources need to be integrated to form a structured knowledge of different types to aid in higher-order reasoning. This necessitates a need for modular framework that can reproduce the knowledge curation pipeline along with data curation and model training. A Neurosymbolic approach can harness rich knowledge sources, facilitating accountable and explainable reasoning[20].

5.2 MTSS: Multi-Tiered System of Supports

Objective: Application of C^3AN in mental healthcare—a field with essential requirements for the three pillars of intelligent, robust, and trustworthy AI. Generative models alone might overlook critical details in patient data or produce insights that lack depth, which can be extremely problematic in contexts where accuracy of insights for patient health is of the utmost priority. A Neurosymbolic AI system, customized to recognize specific mental health patterns and behaviors, can help contextualize patient data with a high degree of understanding while maintaining reasoning accuracy. For example, such a system can incorporate symbolic knowledge from clinical guidelines and evidence-based therapies, leveraging human expertise through feedback loops to improve the system's diagnostic precision and recommendations over time. This approach not only enhances performance but aligns more closely with healthcare providers' objectives for safe, effective, and ethically sound patient care [21].

MTSS provides a tiered framework for academic, behavioral, and mental health needs. In this context, we introduce *MAIC*, an implementation of the C^3AN framework tailored to address the multiple tiers of support outlined in MTSS: Table 2 shows illustrative examples that *MAIC* is tasked with, spanning the 14 foundation elements.

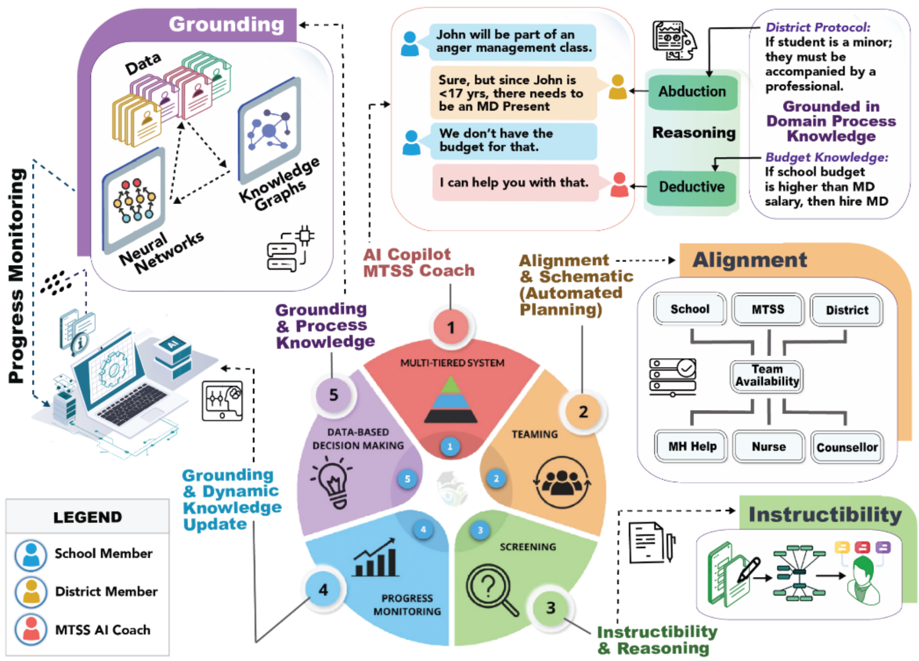


Fig. 4. **MAIC as a C^{3}AN system for the MTSS Framework.** Grounding integrates neural networks and knowledge graphs with district protocols and budget constraints. Automated planning (Alignment & Schematic) coordinates school resources, while Instructability & Reasoning enable abductive/deductive logic for tailored interventions. A multi-step workflow—information gathering, Teaming, Screening, Progress Monitoring, and Data-Based Decision Making—ensures dynamic updates, human oversight, and compliance with institutional guidelines.

- **Custom Workflow.** *MAIC* tailors interventions to each student by referencing local district policies and specialized knowledge of emotional/behavioral guidelines. This domain-specific encoding ensures alignment with the guidelines.
- **Compact Focus.** Only relevant data—such as attendance, teacher notes, and discipline logs—are processed. The knowledge base contains just the essential policy structures, enabling the system to run efficiently without massive resource demands.
- **Composite Data Fusion.** A neural module processes textual notes and patient records, while a symbolic layer encodes official policy constraints (Tier 2 vs. Tier 3). Teachers and counselors supply feedback, required for robust reasoning about patient outcomes.

By integrating multiple tiers of support with advanced AI reasoning, *MAIC* aims to enhance the decision-making process for educators and counselors, without overgeneralizing the successes of one student to another. Instead, it focuses on ensuring interventions remain context-specific, evidence-based, and aligned with the foundational MTSS principles.

> ***About the Use Cases.*** *We have prototyped and evaluated C^{3}AN framework to domains and applications encompassing behavioral and mental health, disease-specific nutrition, smart manufacturing, and additional ongoing efforts in library sciences and finance. For brevity, we provide two detailed examples:*

- *Nourich, a system providing dietary recommendations for individuals with specific nutritional or medical needs,*
- *MAIC, to assist with the multi-tiered system of supports for mental health and behavioral interventions in educational settings.*

All use cases harness the triad of data, knowledge, and human expertise, respecting resource constraints (compactness) and domain rules (customization).

5.3 Detailed Explanation and Illustration of the 14 Foundation Elements with Composite AI Use Cases

Reliability & Consistency. Reliability ensures the AI system produces *accurate outputs* under varied conditions. In *Nourich*, the system reliably identifies safe vs. unsafe recipes for diabetes, referencing domain knowledge graphs. Because it is *composite*, the solution can integrate a knowledge-based filter with a neural parser. Domain experts can customize thresholds for sugar levels, and the entire approach remains compact by focusing only on the relevant medical guidelines [22].

Consistency reflects the AI's ability to avoid *contradictory recommendations. Nourich* ensures ingredient substitutions across the workflow do not conflict with dietary constraints. In the custom environment of the MTSS domain, the system *MAIC* ensures it never proposes conflicting interventions for the same student without new data or feedback, thus exemplifying the synergy of a composite system (reasoning module with teacher feedback) [22].

Alignment. Alignment ensures outputs adhere to user or domain requirements. Because C^{3}AN is *custom*, the system can embed domain rules (e.g., healthcare protocols, educational policies) directly. For example, in the MTSS domain, *MAIC* references state education regulations to align behavioral interventions with established frameworks. *Compactness* is achieved by storing just the relevant rules, avoiding large, generic policy corpora.

Analogy & Abstraction. Analogy powers structured solutions by identifying parallel contexts across limited, domain-specific data. *Nourich* might map tofu to chicken as functional protein substitutes, verifying with knowledge constraints. In the MTSS domain, *MAIC* references local educational knowledge bases and teacher expertise to guide context-specific analogies, avoiding unsubstantiated generalizations [23]. A Neurosymbolic approach provides the means to draw analogies at multiple levels of abstraction [24].

Abstraction addresses complexity by grouping details into high-level categories. *Nourich* can reduce granular macronutrient profiles into "low-carb" or "high-protein" categories, while a domain expert might refine borderline cases. This approach remains *compact* by filtering out unneeded detail. In *MAIC*, behavioral risk indicators can be grouped into broader categories (e.g., "Tier 2" vs. "Tier 3"), making the system efficient without losing critical distinctions.

Causality. Causality underlines the ability to identify cause-and-effect relationships. *Nourich* links sugar intake to glycemic spikes, combining neural pattern detection with recognized medical guidelines. In the MTSS domain, *MAIC* identifies inconsistent parental involvement as a factor in negative behaviors, referencing local policy and teacher feedback to confirm the connection. A Neurosymbolic approach offers promise for facilitating mechanisms to ensure that the appropriate knowledge is used to guide cause-effect relationships [25].

Instructability. Instructability ensures the AI system remains adaptive to explicit user instructions. *Nourich* might exclude certain allergens globally, storing that constraint in a knowledge graph, thus customizing the approach. This is *compact* because it focuses only on instructions relevant to the user's domain. In the MTSS domain, *MAIC* shifts from one intervention to another per counselor instructions, updating its knowledge base with minimal overhead. A Neurosymbolic approach is essential for providing guarantees on the system adhering to instructions constrained by the knowledge [26].

Reasoning. Reasoning is the system's core inference engine, merging data-driven insights with symbolic constraints. *Nourich* might consider low-sodium limits, then confirm with dieticians if borderline items are acceptable. *MAIC* weighs risk factors gleaned from textual data and domain rules, plus teacher suggestions, to recommend interventions in the MTSS domain.

The ability of LLMs to perform true reasoning has been debated [27, 28]. While they can produce seemingly logical responses (e.g., chain-of-thought reasoning), LLMs lack the deeper cognitive capabilities to handle genuinely novel or complex scenarios. Current tests typically focus on limited forms of reasoning (commonsense, math-based, etc.) [29], but real-world solutions require multiple types of reasoning (abductive, deductive, analogical, inductive, counterfactual, syllogistic, causal, compositional, and so on). For instance, to analyze a given recipe, a system like *Nourich* may need several types of reasoning:

(1) **Counterfactual Reasoning:**
Actual Condition: Grilled Chicken (given recipe) is not suitable
Counterfactual Condition: Oven-Roasted Chicken is a better alternative (recommended recipe)
(2) **Analogical Reasoning:**
Source: Grilled Chicken
Target: Oven-Roasted Chicken
Inference: Instead of Grilled Chicken, Oven-Roasted Chicken can be recommended as they have similar ingredients and cooking actions
(3) **Chain of Evidence Reasoning (Path-based reasoning):**
Sequence of Premises: $Chicken \rightarrow Poultry\ Products \rightarrow Animal\ Protein \rightarrow Recommend$; $Chicken \rightarrow Poultry\ Products \rightarrow Medium\ Cholesterol \rightarrow Caution$
Inference: Though chicken is a good protein source, it has notable cholesterol. Hence, recommend with caution.
(4) **Procedural Reasoning:**
Procedure: Grilling + Meat → Traces of Carcinogens
Input: Chicken is Meat
Inference: Grilling + Chicken → Traces of Carcinogens

Planning & Grounding. Planning organizes solutions into actionable steps. *Nourich* generates multi-day meal plans that combine knowledge from nutritional guidelines, neural analysis, and dieticians' feedback. In the MTSS domain, *MAIC* forms a phased intervention plan, referencing local resources for an efficient, *compact* sequence of tasks. Multi-step planning in composite systems requires Neurosymbolic mechanisms to ensure accuracy and mechanistic correctness, offering reliable and trustworthy plan construction for mission-critical goals [26].

Grounding ties abstract representations to real-world entities. *Nourich* references USDA daily intakes for nutrients, while a domain expert can override them in unusual cases. In the MTSS domain, *MAIC* ties interventions to actual class schedules, ensuring the approach is *custom* to each school's constraints. A Neurosymbolic AI approach enables verifiable grounding, which positively affects all components of a composite AI system (e.g., robust analogies, fewer hallucinations) [30].

Explainability & Attribution. Explainability fosters transparency by clarifying the rationale behind each recommendation. *Nourich* might say, "High sugar content can lead to blood glucose spikes," citing explicit knowledge and data examples. In the MTSS domain, *MAIC* references local educational frameworks, preserving *composite synergy* between data-driven inferences and domain rules [22].

Table 2. Overview of 14 foundation elements in C^3AN illustrated in the context of Nourich and MAIC domains introduced in Section 5.

Foundation Element	Nourich Example	MAIC (MTSS Domain) Example
Reliability	Uses a knowledge-based filter + neural parser to flag unsafe recipes for diabetics; domain experts confirm borderline cases.	Provides accurate interventions for each student, referencing a local policy knowledge base + teacher input.
Consistency	Ensures no contradictory advice across recipe constraints; if a user excludes peanuts, that flows throughout the workflow.	Never proposes conflicting interventions for the same student unless new data or feedback justifies a change.
Alignment	Recommendations reflect user-specific dietary goals (vegan, diabetic), referencing known guidelines.	Adheres to a student's behavioral objectives, referencing district frameworks and teacher counsel.
Analogy	Maps tofu to chicken via pattern recognition + domain knowledge on protein roles.	Identifies parallels in local educational settings, guided by teacher feedback to ensure context-specific analogies.
Abstraction	Groups nutritional details into high-level "low-carb," "high-fiber" categories; dieticians refine borderline cases.	Categorizes behaviors into risk tiers, with counselors adjusting boundaries if needed.
Causality	Understands sugar $\longrightarrow$ glycemic spike, combining neural data with medical guidelines.	Recognizes inconsistent parental involvement $\longrightarrow$ negative behaviors; teachers confirm the causal link.
Instructability	Adapts if the user says "avoid peanuts," updating the knowledge base and focusing on relevant recipes.	Shifts interventions per counselor instructions, implementing minimal updates in its knowledge framework.
Reasoning	Infers best ingredient combinations for low-sodium diets; domain experts confirm borderline items.	Weighs multiple risk factors + local policy constraints, plus teacher input, to recommend interventions.
Planning	Generates multi-day meal plans; rechecks with small domain knowledge modules to avoid bloat.	Outlines a phased intervention plan, referencing available local resources; teacher feedback finalizes steps.
Grounding	Ties recommended meals to USFDA guidelines, with expert override if necessary.	Aligns each suggested intervention to the student's schedule and local resource availability.
Interpretability	The system provides a step-by-step breakdown showing how nutritional factors (e.g., sugar content, fiber levels, user preferences) influence the final recommendation for each recipe.	Offering a transparent view of how student performance data and prior interventions factor into recommended strategies, allowing educators to trace the system's reasoning.
Explainability	Clearly states sugar content impacts blood glucose, referencing medical research and recipe data.	Explains recommended behavioral strategies by citing local policy references and historical success data.
Attribution	Cites nutrition databases + dietician oversight in final suggestions.	References validated MTSS frameworks, state board policies, and teacher feedback logs.
Safety	Ensures no harmful ingredient combos for at-risk users (symbolic checks with expert sign-off).	Prohibits psychologically harmful interventions by combining domain rules + counselor approval.

Attribution cites sources, data sets, or domain knowledge references. In *Nourich*, each recommendation might link to recognized medical research, ensuring *customization* for a user's dietary needs. In the MTSS domain, *MAIC* similarly cites local policies or teacher-approved strategies, reinforcing trust [31].

Safety ensures the system avoids harmful outcomes. *Nourich* enforces constraints to protect high-risk users (e.g., renal patients). In the MTSS domain, *MAIC* references mental health guidelines, verifying with experts that no psychologically damaging intervention is prescribed. Both are *composite* in that they combine data checks, symbolic constraints, and human oversight [22].

6 IMPLEMENTATION CHALLENGES FOR C^{3}AN

While C^{3}AN holds promise, implementing a system with the 14 foundation elements and the 3 pillars that is **custom**, **compact**, and **composite** can pose significant difficulties. Key challenges include:

Complex Integration

The *Neurosymbolic* layer must unify data-driven insights with symbolic knowledge for constraints and domain customizations in a tractable manner. Human expertise must be solicited without overwhelming end users. Achieving a seamless interplay of these modules (i.e., the *composite* synergy) requires well-defined interfaces and effective representations [32, 33].

Scalability vs. Compactness

Designers must balance the push for large models with the need for an efficient, domain-focused footprint. Overly broad knowledge bases can become unwieldy. Distillation techniques or "just-in-time" knowledge retrieval can keep the system *compact* by focusing on contextualized knowledge and data only.

Knowledge Base Maintenance

AI systems in rapidly evolving domains must integrate new findings without re-training entire subsystems. This is core to the *custom* approach: ensuring updates can be swiftly encoded in domain-specific workflows or knowledge, with minimal overhead.

User Trust and Adoption

Explainability, *Attribution*, and *Safety* features must be emphasized for stakeholders to trust the system. Because the solution is *composite*, different modules (neural or symbolic) might produce partial explanations that must be aggregated coherently. Iterative feedback from experts fosters acceptance but demands a well-designed UI.

Multi-Stakeholder Environment

Balancing conflicting objectives from teachers, parents, or domain experts requires robust alignment. A *custom* C^{3}AN approach must handle these different perspectives in its inner workings. This synergy can be complex to manage—particularly in large institutions.

Validation and Benchmarking

Beyond accuracy, C^{3}AN requires *comprehensive* evaluation for the 14 foundation elements, e.g., reliability, alignment to user needs, etc. Resource consumption and compliance with domain constraints must also be tracked to confirm the *compact* approach is delivering actual efficiency.

Practical Implications for Enterprise AI

C^3AN aims to incorporate:

- **Custom Implementation:** Domain-specific constraints and knowledge can be added or updated with minimal overhead.
- **Compact Deployment:** Rather than relying on ever-larger models, C^3AN focuses on targeted data and relevant knowledge, reducing costs and resource demands.
- **Composite Framework:** Domain experts, symbolic reasoning, and neural modules all integrate seamlessly to tackle complex tasks.
- **Neurosymbolic Intelligence:** Data-driven inferences are continually refined by effective and efficient symbolic mechanisms (e.g., knowledge graph updates) and iterative human feedback loops.
- **Agile Model Development:** Agile methodology facilitates achieving outcomes through composite systems by enabling iterative data augmentation and incorporating end-user feedback loops, ensuring models remain current, relevant, and aligned with dynamic requirements.
- **Secure Model Hosting:** C^3AN can be deployed within high-assurance environments, including on-premises infrastructure and security-controlled cloud ecosystems. This ensures compliance with stringent regulatory frameworks, making it suitable for federal institutions, financial systems, critical government applications, and healthcare environments handling sensitive patient data. By maintaining both the model and inference layers within the security perimeter, organizations can uphold the highest standards of security, privacy, and compliance while ensuring full control over data and access.

7 FUTURE DIRECTIONS

We discuss a representative set of research topics to realize the broader vision of C^3AN.

Formal Semantics for Composite Workflows

C^3AN's composite architecture can benefit from more rigorous formalisms, clarifying how multiple modules (neural and symbolic) combine, share data, and exchange partial inferences. High-level languages or frameworks could help specify such composite workflows more systematically.

Adaptive Customization via Continual Learning

In many domains, new rules or policies emerge frequently. Future work may explore dynamic updates to knowledge graphs or process workflows without significant human and training costs. Continual learning approaches can keep the system *compact* by only updating relevant modules.

Scalable Yet Resource-Efficient Deployments

Further investigation is needed on how to maintain a *compact* approach across large enterprise systems that handle diverse tasks. Hybrid methods combining prompt engineering with specialized knowledge modules can prevent unconstrained model growth.

Multi-Stakeholder Governance and Ethical Compliance

Ensuring safe AI adoption in regulated environments demands explicit alignment with regulatory frameworks (e.g., HIPAA, FERPA). The customizability of C^3AN can incorporate these constraints in the symbolic layer, but robust governance processes are crucial for production-grade deployments.

User Interfaces for Explainability and Feedback

Future research must develop adaptive UIs enabling domain experts to provide structured feedback, override certain rules, or revise knowledge graphs. By capturing expert insights efficiently, the system can continuously refine neural predictions and symbolic constraints without losing *compactness*.

Empowering AI Development with a Platform-Centric Approach

User communities and businesses of all sizes should not depend solely on major technology providers for the development of AI systems, as this often leads to affordability challenges and implementation inefficiencies. Instead, a platform-centric approach empowers communities to create task-focused composite AI systems using streamlined boilerplate templates, enabling effective outcomes with limited resources.

AI for Everyone

Ensuring AI benefits everyone, including underserved populations, requires providing solutions deployable in a wider variety of settings—even those without continuous internet connectivity. By using **custom**, **compact**, and **composite** strategies, AI systems can remain both accessible and efficient.

Re-evaluating *Intelligence* & Expanding Benchmarks

The future generation of AI systems requires broadening our conception and measurement of "intelligence."[34] Current benchmarks in the GenAI community often rely on narrowly targeted evaluations (e.g., MMLU for multitask language understanding) and conflate performance on these tests with general intelligence. However, we must look to disciplines such as cognitive science and neuroscience for richer perspectives on what constitutes intelligence—including abstraction, creativity, and contextual understanding. Developing more representative benchmarks that move beyond basic question-answer tasks will be pivotal in guiding AI toward deeper capabilities and addressing the long path that remains in achieving truly robust, general intelligence.

8 CONCLUSION

C^3AN represents a coherent 4^{th}-generation framework, addressing the limitations observed in monolithic, compound, agentic, and copilot systems. By adopting domain-specific knowledge or workflows (**Custom**), maintaining a resource-focused strategy (**Compact**), weaving together multiple modules (**Composite**), and bridging neural and symbolic reasoning with explicit feedback loops (**Neurosymbolic**), C^3AN targets enterprise-grade requirements for the three pillars of intelligent, robust, and trustworthy AI supported by the 14 foundation elements.

We illustrated these concepts through two example domains, *Nourich* and *MAIC*, each highlighting the specifics of C^3AN system features. The custom, compact, and composite nature of C^3AN offers a promising path for real-world AI deployments. We encourage researchers and practitioners to adapt the C^3AN framework to new application contexts and to refine its integration of data-driven learning, symbolic constraints, and expert oversight.

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Resources for Techniques and Use Cases related to 14 Foundation Elements

C^{3}AN Use Cases:

(1) *MAIC*: https://tinyurl.com/MTSSAIConcierge-Video
(2) Nourich: Disease-specific Diet AI System: https://tinyurl.com/Nourich-Video
(3) SmartPilot: Co-pilot for Next-Gen Manufacturing: https://tinyurl.com/SmartPilot-Video

Project Pages - AIISC Wiki:

(1) Neurosymbolic Research at AIISC: https://tinyurl.com/NeurosymbolicResearchatAIISC
(2) Mental Health Projects: https://tinyurl.com/MentalhealthProjectatAIISC
(3) Food Computation: https://tinyurl.com/FoodComputationatAIISC
(4) Smart Manufacturing: https://tinyurl.com/SmartManufacturingatAIISC

Tutorials/Talks:

(1) Neurosymbolic Customized and Compact CoPilots, ISWC, November 2024: https://tinyurl.com/ISWC-2024-Tutorial
(2) Keynote - 1st International Workshop on Responsible AI for Healthcare and Net Zero: https://tinyurl.com/KeyNote-ResponsibleAI-Video
(3) Robust & Trustworthy AI: https://tinyurl.com/robust-trustworthyai

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