Classify AI Implementation

▼ Current Framework on AI Complexity

What she did in the report is give people to try the algorithms and assess the complexity based on different elements that are: ———————- Autonomy and Impact

And then we complete this work to build this five scale point complexity framework.

1. Low Complexity:

Description: AI systems in this category rely heavily on predefined rules, decision trees, or simple statistical models. They perform tasks that are well-structured, with limited variability, and typically don’t evolve or learn from new data over time.
Technologies:
Rule-based systems: These systems operate on clear “if-then” logic. There is no learning involved, and all decisions are based on static rules set by developers.
Simple regression models: Linear or logistic regression models that work well with small, structured datasets and don't require advanced computational power.
Characteristics:
Minimal or no autonomy: Human intervention is needed to define parameters, interpret results, and modify the system.
Structured data: Operates on clean, labeled datasets.
Examples: Administrative automation (e.g., appointment scheduling), simple clinical decision support systems that follow predefined clinical guidelines.
2. Moderate Complexity:

Description: Systems in this category incorporate basic machine learning techniques that involve some level of training and adaptation. These models

are still highly reliant on structured data but exhibit improved pattern recognition capabilities.
Technologies:
Supervised learning models: Algorithms like support vector machines (SVMs), decision trees, and random forests. These models can generalize patterns from labeled data but require consistent supervision and tuning.
NLP models for structured text: Basic natural language processing for text classification and sentiment analysis.
Characteristics:
Limited autonomy: These models need to be re-trained regularly and may require human intervention to handle outlier cases or novel inputs.
Moderate complexity in handling structured data, with some capability to generalize.
Examples: Diagnostic tools for analyzing radiology reports, basic chatbots that provide information based on predefined responses.
3. High Complexity:

Description: Systems at this level utilize deep learning or neural networks capable of working with large datasets and unstructured data, such as medical images or genomic data. These systems are often applied in healthcare for more complex tasks such as medical imaging analysis or predicting disease progression.
Technologies:
Convolutional Neural Networks (CNNs): Commonly used in computer vision applications for image analysis in radiology, dermatology, or pathology.
Recurrent Neural Networks (RNNs): Used for time-series data or longitudinal patient records, especially in monitoring patient vitals or disease trajectories.
Characteristics:
Moderate to high autonomy: These models can adapt to new data but may require periodic re-training and validation by human experts.
Ability to handle unstructured data: These models can process and make sense of complex, high-dimensional data such as MRI scans or EHR records.
Examples: AI-based diagnostics (e.g., detecting tumors in MRI scans), AI for personalized medicine using patient history and genomics.
4. Advanced Complexity:

Description: Advanced AI systems use techniques like transfer learning, multimodal AI, or reinforcement learning. These systems can combine disparate data sources (e.g., text, images, and clinical notes) and adaptively improve their performance with little human intervention.
Technologies:
Transfer Learning: This allows models to leverage knowledge from one domain to improve performance in another domain, reducing the need for extensive training on new tasks.
Generative Adversarial Networks (GANs): Often used to generate synthetic medical images or simulate patient outcomes.
Characteristics:
High autonomy: Systems can operate with minimal human intervention and adapt quickly to new data inputs.
Handles both structured and unstructured data: These models excel at integrating data from multiple sources to make comprehensive predictions or assessments.
Examples: Personalized treatment planning combining genetic data, medical history, and lifestyle factors, advanced surgical assistance systems that provide real-time feedback during operations.
5. Pioneering Complexity:

Description: These systems represent the cutting-edge of AI technologies and include neurosymbolic AI, federated learning, and edge AI. They are often deployed in environments where real-time decision-making and adaptive learning are critical.
Technologies:
Federated Learning: AI models are trained across decentralized data sources (e.g., hospitals), improving privacy and scalability while leveraging large-scale data without needing centralization.
Neurosymbolic AI: Integrates symbolic reasoning with deep learning to create models that can reason more abstractly and handle more diverse cognitive tasks.
Characteristics:
Full autonomy: Systems are capable of real-time decision-making and can adapt without human intervention.
Ability to operate in low-latency, distributed environments: These systems can

work with real-time data streams in critical care settings.
Examples: AI systems in ICUs that predict patient deterioration in real-time, federated AI systems for global pandemic monitoring and response.w

▼ Prompt for LLM Analysis of Healthcare AI Startups Using Framework C:

Analyze the provided content about healthcare AI startups, which includes a short description and, if available, a landing page. Classify each startup according to **two dimensions**:

1. **Autonomy**: Determine the level of autonomy exhibited by the AI system used by the startup:
   - **Action Autonomy**: The system operates independently, processing inputs, making decisions, and taking actions without human intervention (e.g., fully autonomous diagnostic or treatment systems).
   - **Decision Autonomy**: The system processes inputs and provides decision outputs (e.g., recommendations or predictions), but a human must act based on these outputs (e.g., clinical decision support tools).
   - **Perception Autonomy**: The system processes inputs and flags information that requires human evaluation or further action (e.g., AI used to detect anomalies in medical images for doctors to review).
2. **Impact**: Assess the potential impact of the AI system based on its risk level and influence on healthcare outcomes:
   - **High Impact**: The system's actions or decisions could significantly affect patient safety, medical outcomes, or the functioning of critical healthcare systems (e.g., AI systems used in emergency interventions or high-risk surgeries).
   - **Medium Impact**: The system influences clinical decisions, patient care, or operational efficiency but presents mitigable risks (e.g., AI for optimizing hospital workflows or assisting in routine diagnostics).
   - **Low Impact**: The system has minimal risk and may affect non-critical aspects of healthcare (e.g., AI used for patient scheduling or administrative tasks).

For each startup, classify its system into one of the three levels for both **autonomy** and **impact** based on the provided information. If only partial information is available (e.g., no landing page), use the short description to make a classification. Additionally, provide a rationale for your classification.

Based on the CSET Report, Framework C

https://cset.georgetown.edu/publication/classifying-ai-systems/