MACHINE LEARNING FOR HEALTH

The Future of AI-Based Medicine

Personalized systems, distributed computing, and the human role

TECHNICAL HANDOUT · SESSION 16

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Academic teaching material based exclusively on the PDFs available in the project

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Introduction

Envisioning the future of AI in health requires distinguishing technical possibilities from established evidence. The local materials support trends such as multimodal data, distributed intelligence, personalization, education, and human–machine collaboration but do not justify deterministic predictions. [1]

This final session revisits infrastructure, evaluation, and governance as conditions for new interfaces to produce benefits. [1]

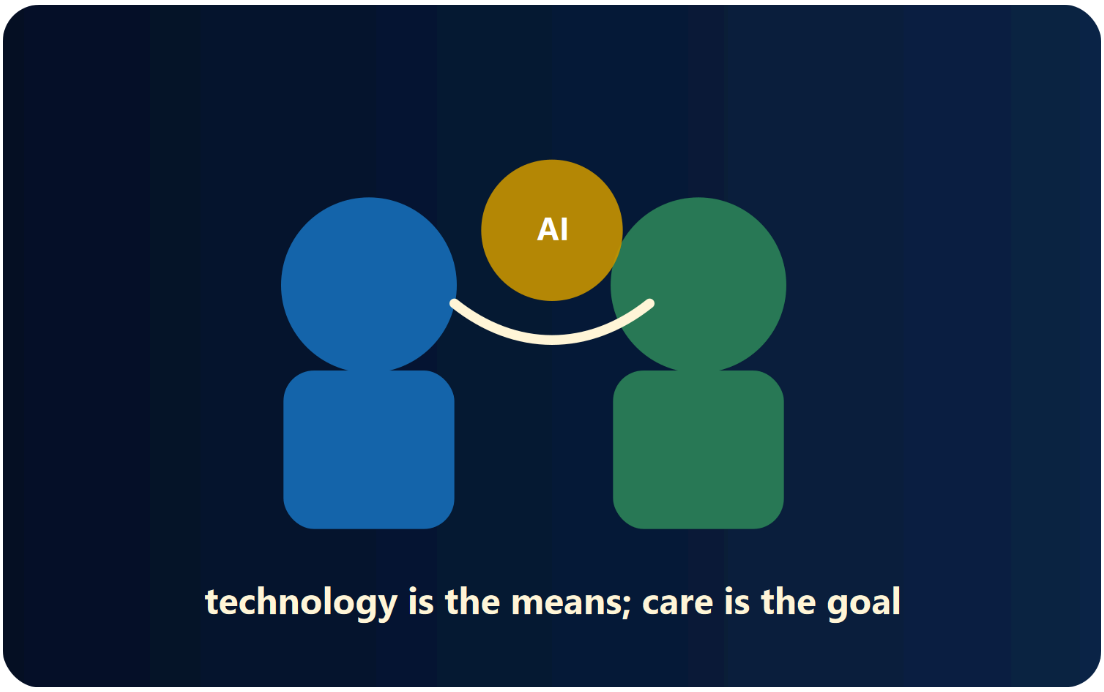

Figure 1 — Technology as a means of supporting human care. Source: original illustration based on [1] and [5].

1. From evidence to operational intelligence

The expansion of digital data and computing capacity opens possibilities for systems that integrate observation, knowledge, and decision support. Progress depends less on a single technique than on interoperability, quality, implementation, and evaluation [1].

Data-driven intelligence must remain connected to clinical evidence. Future systems will need to show the origin of information, uncertainty, and limitations so that users can understand when to trust, verify, or reject an output [1].

KEY CONCEPT
The expansion of digital data and computing capacity opens possibilities for systems that integrate observation, knowledge, and decision support.

2. Personalization and patient representations

Personalized models seek to adapt predictions to an individual's characteristics rather than rely only on average relationships. This adaptation faces a tradeoff between specificity and data volume: the narrower the context, the less evidence may be available [2].

A digital twin in health is a dynamic representation of a patient fed by clinical, behavioral, and sensor data to observe state, simulate trajectories, and explore possible responses. A conceptual architecture separates acquisition; integration and preprocessing; modeling or simulation; and the clinical interface [7].

The promise of continuous updating does not remove limitations: temporal quality, semantic interoperability, validation, privacy, and governance determine whether the representation is clinically useful. Simulations remain computational hypotheses and are not equivalent to evidence of patient benefit [7].

3. Edge AI, learning, and the environment

Mobile and wearable sensors enable continuous, contextual data collection. Processing some of the data near the source can reduce latency and transfer, but energy, capacity, updating, and security constraints shape the design [3] [6].

Edge computing moves processing and decisions closer to the data source, which may favor real-time response and reduce traffic. The appropriate architecture may be hybrid: light or urgent tasks remain on the device, whereas storage and heavier analyses use remote infrastructure [6] [7].

Intelligent systems can also support personalized and just-in-time education. Evaluating this use requires measuring learning and transfer into practice in addition to interface acceptance [4].

4. Ambient interfaces and continuity of care

Ambient scribes combine speech recognition and NLP to transform an encounter into a proposed note. A safe workflow separates capture, processing, proposal, and review: the professional corrects, completes, and signs the note before incorporating it into the health record [7].

Automation can reduce mechanical work but creates new control points for consent, recording, speaker identification, omissions, attribution of speech, and audio retention. Performance must be evaluated in the setting and population of use, not only on clean transcripts [7].

5. Human–machine synergy and final projects

The sustainable contribution of AI depends on complementarity: machines can search, organize, and recognize patterns, whereas professionals integrate context, values, responsibility, and communication. The team and its environment constitute the unit of design and evaluation [5].

In the final project, a mature proposal should connect the problem, population, data, method, evaluation, integration, risks, and governance. A technical demonstration is a starting point; the argument must show how the solution would be challenged, tested, and maintained [5].

SOURCE LIMITATION **TinyML remains presented only at a conceptual level; the new sources support a deeper discussion of edge computing, digital twins, and ambient scribes without claiming clinical effectiveness that has not yet been demonstrated.**

Session summary

From evidence to operational intelligence: the expansion of digital data and computing capacity opens possibilities for systems that integrate observation, knowledge, and decision support.
Personalization and patient representations: personalized models seek to adapt predictions to an individual's characteristics rather than rely only on average relationships.
Edge AI, learning, and the environment: mobile and wearable sensors enable continuous, contextual data collection.
Ambient interfaces and continuity of care: ambient scribes combine speech recognition and nlp to transform an encounter into a proposed note.
Human–machine synergy and final projects: the sustainable contribution of ai depends on complementarity: machines can search, organize, and recognize patterns, whereas professionals integrate context, values, responsibility, and communication.

References

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