Mass General Brigham

Automation and Artificial Intelligence in Cytology

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Disclosures

No relevant financial or personal disclosures related to this session.

Learning objectives

- Understand the historical context of AI in cytology
- Recognize the key success factors that enabled cervical cancer screening automation
- Distinguish between different AI technologies: ML vs DL
- Evaluate current AI systems and their clinical performance
- Assess implementation challenges and best practices
- Apply evaluation frameworks for new AI tools

The cervical cancer success story

Historical impact:
- 1930s: cervical cancer = #1 cancer killer of women in US
- Today: not even in top 10 cancer deaths in developed countries

Key success factors:
- Screening efficacy proven: 80% mortality reduction with intensive screening
- Clear clinical need: 500K+ cases worldwide annually
- Binary decision: Normal vs abnormal (screening context)
- Standardized preparation: Liquid-based cytology (1996) enabled automation
- High volume: 89% of US women screened

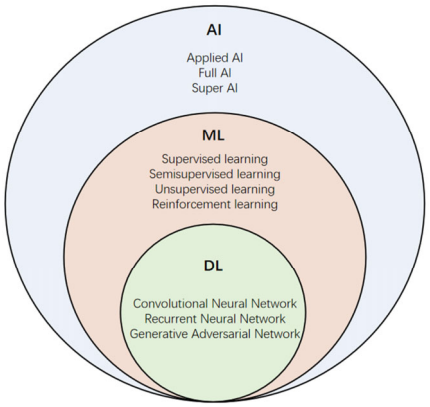
Perfect storm for AI: Clinical impact + standardization + volume = automation success

What is AI, ML, and DL?

Artificial Intelligence is the overall goal
- making machines intelligent

Machine Learning is how we train the machines
- using data and statistical models

Deep Learning is the most powerful recent technique
- using layered neural networks

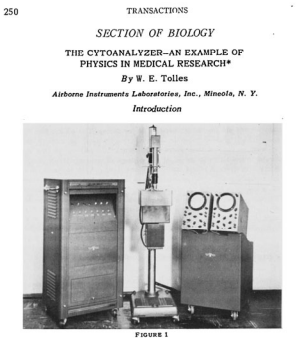


AI timeline

- **1956:** AI field officially founded at Dartmouth College
- **1960s:** Massive government funding, predictions of human-level AI "within a generation"
- **1970s:** Reality check – researchers "grossly underestimated the difficulty"
- **1974:** Government funding cut due to unmet promises ("AI Winter")
- **1980s-1990s:** Boom and bust cycles continued
- **2000s:** Machine learning breakthrough with better hardware + big data
- **2010s:** Deep learning revolution
- **2020s:** Current AI boom with ChatGPT and transformers

Cytology automation timeline

- **1950s:** Cytoanalyzer (Airborne Instruments)
- **1960s–1980s:** TI-CAS, Quantimet, BIOPEPR, CYBEST, CERVIFIP, DIASCANNER, FAZYTAN, LEYTAS
- **1990s:** Venture capital era, consolidation through mergers
- **2000s:** ML-based FDA-approved automation
  - ThinPrep Imaging System
  - AutoPap / FocalPoint Guided Screening Imaging System
- **2024:** DL-based FDA-approved automation
  - Genius Digital Diagnostics System



250 TRANSACTIONS

SECTION OF BIOLOGY

THE CYTOANALYZER—AN EXAMPLE OF PHYSICS IN MEDICAL RESEARCH*

By W. E. Tolles

Airborne Instruments Laboratories, Inc., Mineola, N. Y.

Introduction

FIGURE 1

Parallel evolution – cytology and general AI

Period	Cytology automation	General AI development	Key parallels
1950s	Failed: Cytoanalyzer (Airborne Instruments)	AI field founded at Dartmouth College (1956)	**Early optimism**: both fields launched with high hopes
1960s—1970s	Multiple failed systems: TI-CAS, Quantimet, BIOPEPR, CERVIFIP, CYBEST, DIASCANNER, FAZYTAN, LEYTAS	Massive government funding, then reality check by 1974	**Overpromising**: both underestimated technical difficulty
1980s—1990s	Venture capital era, multiple company mergers needed	Boom and bust cycles, "AI Winter" periods	**Market consolidation**: survivor companies emerged from failures
2000s	First wave of success: ML-based FDA-approved automation, ThinPrep Imaging System (2003), FocalPoint Guided Screening Imaging System (2008)	Machine learning breakthrough with better hardware + big data	**Technical convergence**: hardware, algorithms, and data finally aligned
2010—2020s	Second wave of success: DL-based FDA-approved automation, Genius Digital Diagnostics System (2024)	Deep learning revolution, transformer architecture, ChatGPT boom	**Modern AI integration:** both fields now using deep learning

Early AI in cytology: rule-based machine learning

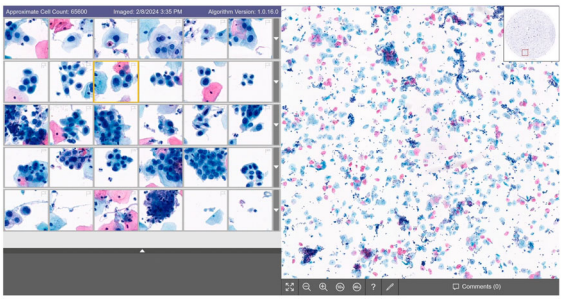
ThinPrep Imaging System (TIS), FDA-approved in 2003 as a primary screener

- Rule-based ML system using optical density and basic morphological algorithms
- Selects 22 fields of view (~25% of the slide) for manual review
- Physical microscope required
- Improved sensitivity over manual review but limited automation
- Still labor-intensive and subject to interobserver variability

Modern AI in cytology: deep learning

Genius Digital Diagnostics System (GDDS), first FDA-cleared digital cytology system in 2024

- DL neural networks
- Volumetric scanning (14 focal planes)
- 30-60 AI-selected tiles (100% slide analysis)
- 100% sensitivity for CIN2+ when ASC-US+ used as threshold
- Fully digital workflow
- Faster review (3.2 vs 5.9 minutes per case)
- Strong interobserver agreement



AI evolution in cytology

Feature	Early AI: TIS	Modern AI: GDDS
FDA clearance	2003	2024
AI type	Machine learning	Deep learning
AI output	22 pre-selected fields	30–60 AI-selected image tiles
Slide coverage	~25% (22 fields of view)	100% with 14-plane volumetric scan
Review modality	Microscope-based	Digital workstation
Regulatory counting (CMS/CLIA max: 200/day)	0.5–1.5 slides depending on review	0.5 slide per case

Evidence from clinical and operational studies

Study	Key finding
Cantley et al. 2024	GDDS vs manual: 3.2 vs 5.9 min per case → **46% faster**
Ikenberg et al. 2023	GDDS vs TIS: 44.8 vs 89.9 sec per slide → **45% faster**
Harinath et al. 2024	100% sensitivity for CIN2+ (ASC-US+ threshold)
Harinath et al. 2025	100% sensitivity for CIN1+ (ASC-US+); 74.7% with LSIL+ threshold
Cantley et al. 2024	Diagnostic concordance: GDDS 62.1% vs manual 55.8%

Implementation challenges: beyond performance metrics

What the studies also show

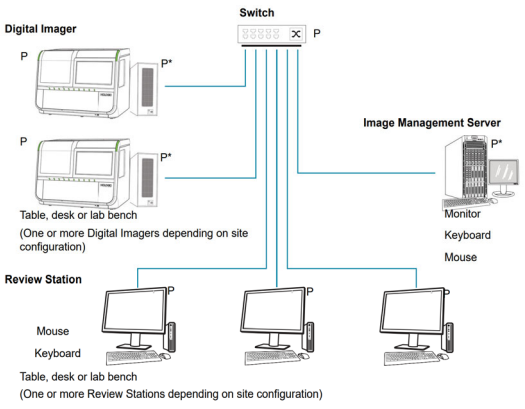
- **Training curve:** 1.5-2 days vendor-provided training; 3K+ cases of experience
- **Diagnostic shift:** 26% of LSIL cases reclassified as ASC-US
- **Context matters:** Performance affected when HPV status unavailable
- **Experience gap:** Steady-state use (~18K prior cases) vs. early-stage adoption with minimal training
- **Technical limitations:** ~5% of slides failed digital scanning

Reality check

- AI isn't just "better"—it's different. Implementation affects workflow, interpretation, and expectations.

Vendor dependence and integration limitations

- **Narrow scope**: Optimized for GYN cytology only — no current support for non-GYN samples
- **Unclear roadmap**: Expansion of GDDS into non-GYN remains uncertain
- **Hardware footprint**: Requires dedicated GDDS imager, server, and review station hardware
- **Review workflow impact**: Adds to existing microscope + computer setups
- **Dual-system burden**: In hybrid labs, users must toggle between GDDS station for GYN and other platform(s) for other WSI applications



AI for non-GYN cytology: current landscape

- **Urine cytology:** Paris System-based algorithms, promising early results
- **Effusion cytology:** Metastatic carcinoma detection models
- **FNA cytology:** Thyroid, lung, breast, pancreatic applications
- **ROSE applications:** Adequacy assessment automation
- **Current status:** Mostly research-stage, limited clinical deployment
- **Key barriers:** Lower volumes, higher variability, diverse workflows

AI for non-GYN cytology: barriers today, potential tomorrow

Current barriers:
- Low case volumes per institution
- Variable preparation methods
- Complex diagnostic criteria
- No FDA-cleared systems
- Unclear reimbursement

Future opportunities:
- Regional lab consolidation
- Integration with existing WSI platforms
- Multi-site training datasets
- Workflow optimization focus

Current state of AI adoption in cytology

- **Current usage:** 77% of labs don't use AI in cytology practice
- **Comfort with AI:** 49% comfortable with FDA-approved systems
- **Preferred applications:** 73% want AI for screening, 62% for biomarkers
- **Training needs:** Most want 100-200 cases for validation
- **Barriers:** Regulatory approval, integration complexity, cost
- **Future focus:** Workflow improvement over diagnostic replacement

Practical AI evaluation framework

Domain	Key questions
Clinical value	Does it improve sensitivity, specificity, or turnaround time?
Regulatory status	Is it FDA-cleared, CE-marked, or purely research?
Scalability	Is it viable for your volume and specimen mix?
Workflow fit	Can it integrate into existing processes and AP-LIS?
Hardware burden	Does it require proprietary scanners, review stations, or IT infrastructure?
Standards compliance	Does it support or plan for DICOM compatibility?
Training burden	What's the learning curve and ongoing education requirements?
Support model	Will the vendor assist with training, QA, and downtime?
Vendor roadmap	Will they continue development and support long-term?

DICOM for pathology: learning from radiology's success

- **DICOM:** Digital Imaging and Communications in Medicine
- **Current cytology state:** Most AI systems use proprietary formats, creating vendor lock-in
- **DICOM advantages:** Universal standard enables vendor-neutral image storage
- **Interoperability benefits:** Mix and match scanners, AI algorithms, and viewing software
- **Hospital IT integration:** Leverage existing imaging archives, and radiology infrastructure
- **Future flexibility:** Avoid vendor dependency
- **Action item:** Ask vendors about DICOM roadmaps during evaluation

AI in cytology: where we are—and what comes next

- GYN cytology shows that modern AI tools can succeed (see note)
  - Note: it took 20+ years of refinement
- New platforms (e.g., AIxMed, VisioCyt) are exploring urine, thyroid, pulmonary cytology, etc.
- True adoption depends on more than accuracy:
  - Workflow integration
  - Infrastructure readiness
  - Regulatory and reimbursement alignment
- Cytopathologists must stay engaged to guide development that fits practice

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