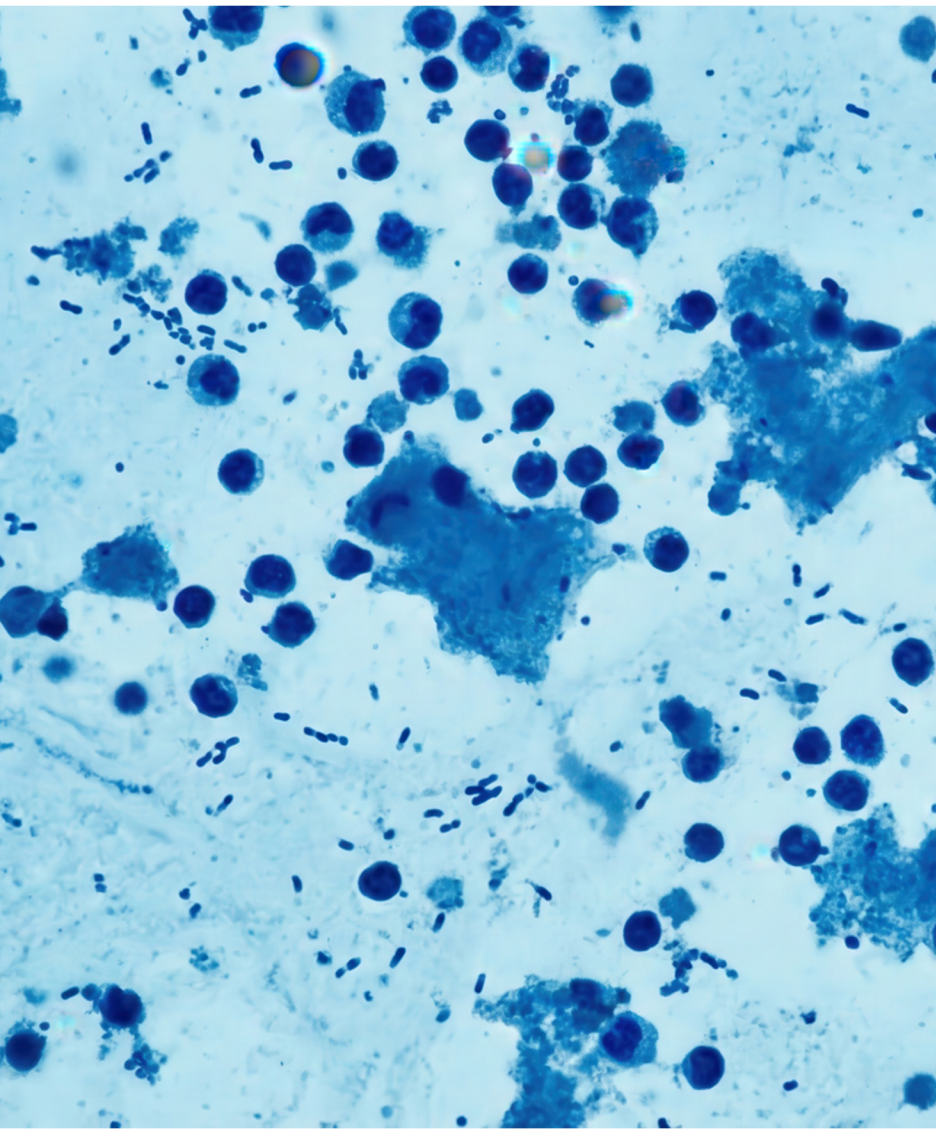


# HITLAB



## Transforming Diagnostic Imaging Through éo Vision's AI-Driven Visual Intelligence

**AN EVALUATION BY HITLAB**



This report presents HITLAB's evaluation of éo Vision, an AI-powered platform enabling clinician-led, end-to-end management of diagnostic intelligence across imaging workflows.

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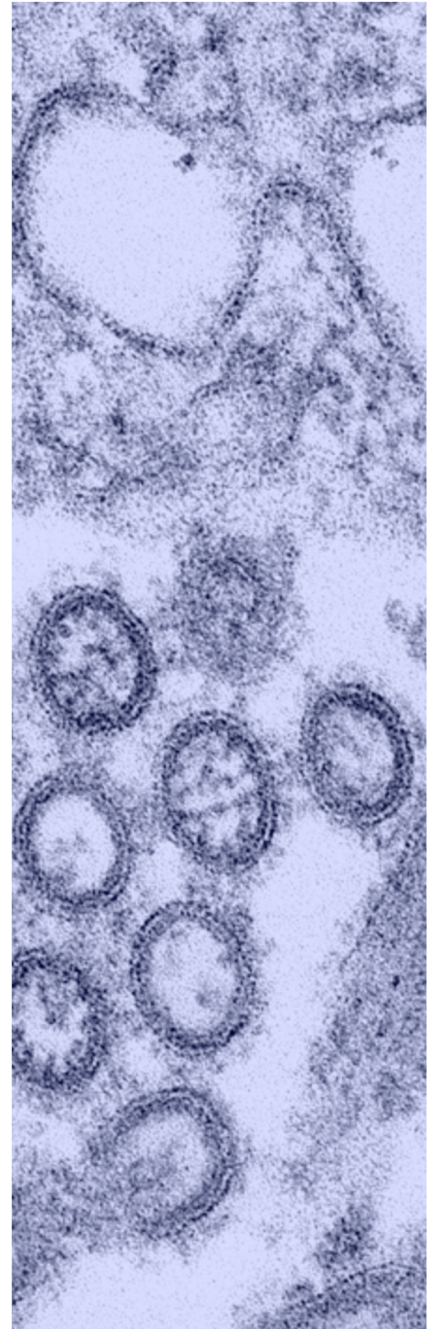
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# Executive Summary

This white paper presents an independent usability and workflow evaluation of *éo Vision*, an AI-enabled imaging platform designed to support clinical decision-making by enhancing how medical images are analyzed, compared, and interpreted. *éo Vision* is built to reduce clinician cognitive burden, increase diagnostic confidence, and improve efficiency in high-pressure clinical environments through intelligent image management and model-assisted insights.

Using Jakob Nielsen's Usability Heuristics for User Interface Design, a structured review of the *éo Vision* platform was conducted, focusing on system feedback, interaction flow, navigation clarity, accessibility, error handling, and user control. The assessment examined critical workflows including login and onboarding, image selection and model training, and overall interface consistency.

The findings demonstrate that *éo Vision* demonstrates strong potential to address real-world clinical needs. The platform's AI-supported image workflows, structured annotation tools, and model-assisted analysis reduce reliance on manual image comparison and support more consistent, efficient interpretation across users. These capabilities position *éo Vision* as a valuable enabler of scalable, intelligent imaging workflows across clinical and research environments.



Overall, HITLAB evaluation reflects *éo Vision* as a promising, clinician-centered platform with a solid technical foundation. By addressing the identified usability and interaction design gaps, *éo Vision* can significantly improve learnability, trust, and workflow efficiency. These enhancements will strengthen *éo Vision*'s readiness for scalable clinical deployment and maximize its impact on diagnostic accuracy and user experience.

# The Clinical Gap in Diagnostic AI

## The Need For Clinician-Driven, Scalable Solution

Healthcare diagnostics are increasingly strained by growing imaging volumes, fragmented AI tools, and workflows that impose high cognitive demands on clinicians. Manual image review in time-pressured settings contributes to fatigue, inter-observer variability, and elevated diagnostic error risk (Norman, 2005; Croskerry, 2013).

At the same time, many AI solutions are developed as narrow, externally controlled point products that fail to align with real clinical workflows or local standards of care, limiting trust and adoption (Longoni et al., 2019; Amann et al., 2020). As a result, the gap between the promise of AI and its practical impact in everyday diagnostics continues to widen. Without scalable, clinician-driven approaches, these limitations continue to hinder meaningful AI integration into routine diagnostic practice.

### Challenges

#### Growing Diagnostic Demand vs. Shrinking Expert Capacity



Medical imaging volumes are rising faster than the clinical workforce needed to handle it, particularly in pathology and radiology, creating structural capacity gaps. This imbalance contributes to reporting delays, burnout, and increased diagnostic risk in high-volume care settings (McDonald et al., 2015; Shanafelt et al., 2016).

#### Ineffective “Black-Box” AI In Clinical Practice



Opaque “black-box” AI systems lack explainability, limiting clinician trust and adoption in high-stakes diagnostics. When AI outputs cannot be interpreted or justified, clinicians are less likely to rely on them for clinical decision-making (Rudin, 2019; Tonekaboni et al., 2019).

#### Cognitive Overload and Constrained Clinician Control In AI-Assisted Diagnostics



Clinicians experience high cognitive load from manual image review, especially in time-pressured diagnostic settings, leading to fatigue and increased error risk (Norman, 2005; Croskerry, 2013). When AI systems are deployed without clinician oversight, this burden intensifies, as externally developed models often misalign with local standards of care. Limited transparency and control erode trust, hinder adoption, and prevent AI from effectively reducing workload or strengthening diagnostic confidence (Longoni et al., 2019; Amann et al., 2020).

# The Clinical Gap in Diagnostic AI

## The Need For Clinician-Driven, Scalable Solution

### Inconsistent Image Interpretation Across Clinicians



Substantial inter-observer variability exists in medical image interpretation, even among experienced clinicians. Such inconsistency is a major contributor to diagnostic error, malpractice risk, and preventable patient harm (Elmore et al., 2015; Makary & Daniel, 2016).

### Shortage of Trained Staff In Clinical Laboratories



Clinical laboratories face persistent staffing shortages, limiting throughput and quality assurance. Understaffing increases turnaround times and contributes to burnout, further constraining diagnostic capacity (Garcia et al., 2019; Hawker, 2007).

### Limited Sharing And Monetization of Clinical AI Models



There is no scalable platform for clinicians and institutions to share, collaborate on, or deploy AI diagnostic models. Most AI tools remain disease-specific point solutions, limiting their ability to scale across diverse and complex clinical needs. As a result, clinically valuable AI innovations remain siloed within individual institutions, slowing innovation and reinforcing unequal access to advanced diagnostic support (Beam & Kohane, 2018; Topol, 2019).

### Data Sovereignty And Compliance Risks



Concerns around data ownership, privacy, and regulatory readiness remain major barriers to AI adoption in healthcare. Early integration of compliance and auditability is essential for institutional trust and scalable deployment (Price & Cohen, 2019; FDA, 2021).

There is a need for a solution that addresses fragmented and misaligned systems by offering a unified visual intelligence platform built around clinician workflows.

It should allow clinicians to build, train, and refine diagnostic models without technical expertise, while enabling institutions to share and deploy models across facilities. This will reduce reliance on rigid point solutions and improve transparency, trust, and local control. By aligning AI with real clinical practice, it can support more scalable, efficient, and clinically relevant diagnostic innovation.

# Diagnostic Uncertainty: A \$100+ Billion Annual Risk to U.S. Healthcare

U.S. diagnostic errors and misdiagnoses are estimated to cost the healthcare system more than USD 100 billion each year through additional testing, treatments, and downstream care.

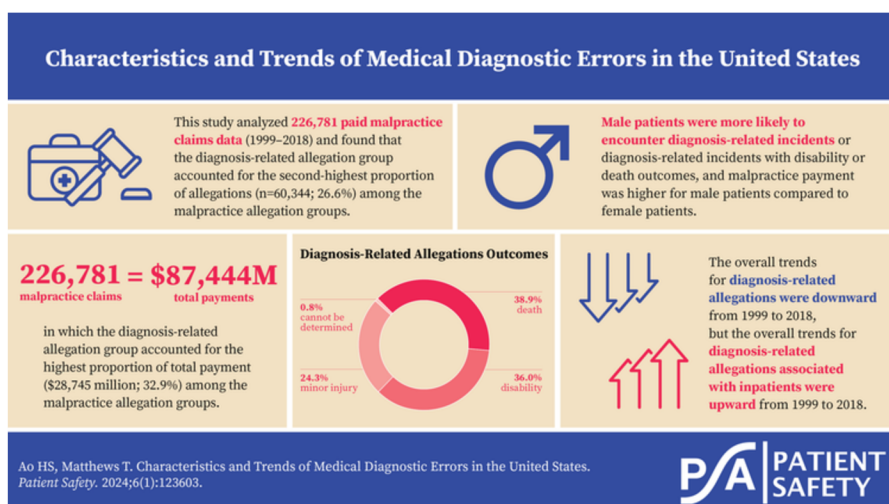
Diagnostic inconsistency in U.S. medical imaging is a major economic burden. Different interpretations of the same scan lead to misdiagnosis, delayed care, unnecessary procedures, and malpractice exposure, costing the healthcare system an estimated \$50 billion annually. A single percentage point of diagnostic variance costs a health system \$551K–\$1.27M per year. Hospitals could be facing \$5.5M–\$19M in annual financial risk tied to diagnostic variability.

Current AI solutions address only a small fraction of the problem. While more than 3,000 clinically relevant diseases rely on imaging, existing disease-specific AI tools cover less than 1% of them. At this pace, it would take over 2,300 years to achieve full diagnostic coverage, leaving hospitals exposed across most clinical cases.

This uncertainty drives massive spending on defensive medicine. U.S. hospitals spend \$46–\$300 billion per year on extra tests, scans, and procedures ordered primarily to reduce legal risk rather than improve patient outcomes.

AI has improved accuracy but has not reduced risk at scale. Poor workflow integration, limited transparency, and a lack of legal defensibility prevent clinicians from fully trusting or adopting these tools.

Hospitals buy AI to reduce risk, not for novelty. Every uncertain diagnosis creates financial, legal, and operational exposure—making reliable, scalable diagnostic confidence a critical economic need in U.S. healthcare.



# A Patient Safety Emergency Hiding in Plain Sight

## Rising volume, declining capacity, higher risk

There is a growing and unavoidable structural challenge in modern healthcare: while the volume of medical images is increasing rapidly each year, the number of qualified experts available to interpret them is steadily declining. This creates a widening gap between diagnostic demand and clinical capacity, leading to longer wait times, higher workloads, increased error risk, and greater reliance on defensive testing. It is not simply a workforce shortage, but a systemic scalability crisis—one that threatens the reliability, speed, and safety of medical decision-making. Without new infrastructure to amplify and distribute expert-level interpretation, healthcare systems will struggle to deliver timely and accurate diagnoses at scale.

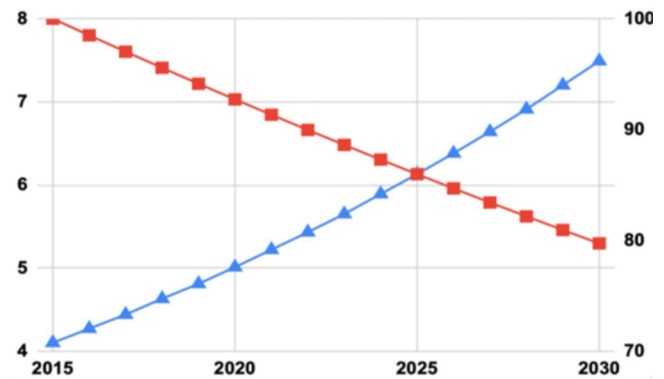


Figure: The two opposing trends from 2015 to 2030: Blue line (rising) → The volume of medical images is growing rapidly by about 4.1%. Red line (falling) is the number of experts available to interpret these (e.g., pathologists, radiologists), which is declining by ~1.5% per year.

The crises in modern healthcare: diagnostic error driven by human perception limits. Misdiagnosis being the third leading cause of death in the U.S. underscores that this is not a marginal quality issue, but a systemic patient-safety emergency. The fact that 80% of radiology errors are perceptual, meaning the abnormality was actually visible but simply missed, reveals that the core problem is not lack of data, but the limits of human attention, fatigue, and cognitive load in high-volume imaging environments.

# éo VISION

## Explainable, Clinician-Controlled AI For Medical Imaging

éo Vision is a clinician-centered, glass-box AI platform designed to transform how medical imaging intelligence is created, trusted, and used in real-world clinical care. It puts clinicians at the center of the AI lifecycle, allowing them to build, validate, and apply visual intelligence using their own data, own cases, and own standards of care, unlike traditional black-box AI tools that operate outside of clinical control.

### What it offers

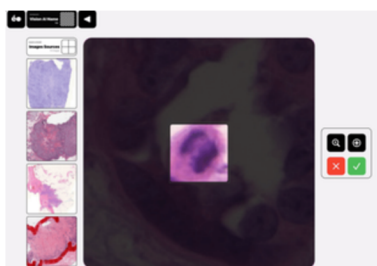
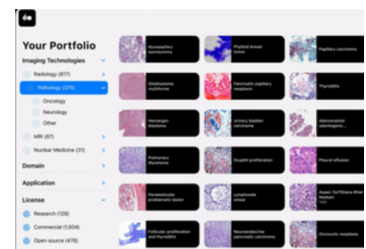


#### Scaling Clinical Expertise Through AI

It enables frontline clinicians to build and deploy clinical-grade AI models in days—not years—without needing data science expertise, while the secure Knowledge Hub allows teams to share and scale validated models across institutions, transforming individual expertise into a collective standard of care.

#### Commitment to Data Ownership, Sovereignty, and Clinical Trust

It is built on data sovereignty and regulatory readiness, ensuring clinician data and models never become the company's product; ownership remains with the creator, supported by transparent governance, full auditability, and controlled access at every stage.



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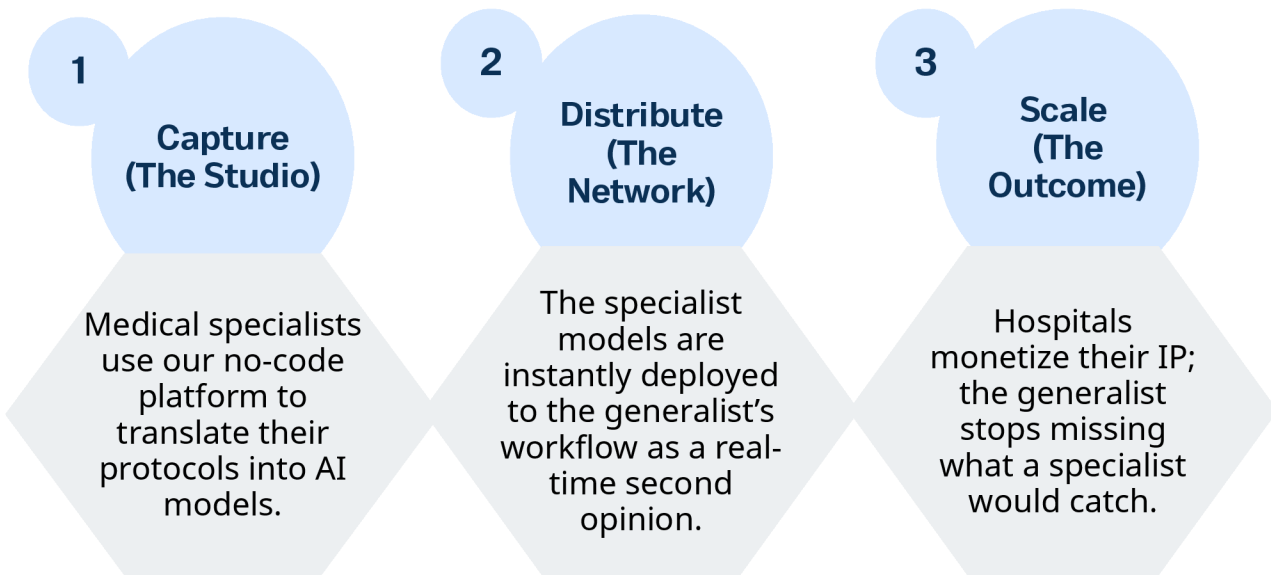
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# éo VISION

## Build models; build the factory (The TSMC\* of Clinical AI)



**The TSMC of Clinical AI: An AI Foundry for Medical Software**

**The Core Analogy: From Silicon Chips to Clinical AI**

**The Designer: NVIDIA vs. Mayo Clinic**  
 NVIDIA: Designs proprietary chip IP. | Mayo Clinic: Provides clinical expertise IP.

**The Factory: TSMC vs. The éo Foundry**  
 TSMC: Provides complex manufacturing infrastructure. | éo Foundry: Provides complex SaMD infrastructure.

**The Success Metric: Manufacturing Yield vs. Clinical Yield**  
 Manufacturing Yield: % of defect-free products. | Clinical Yield: % of safe, defect-free diagnoses.

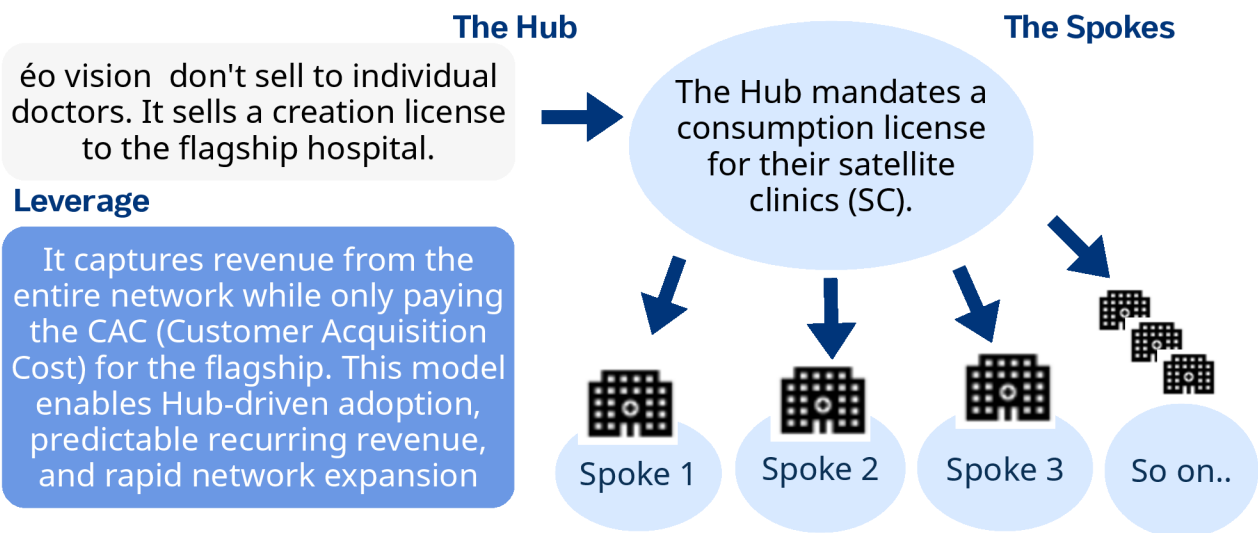
**Our Moat: The Clinical Yield Flywheel**

- 1. Defect is Detected**  
AI model flags high-uncertainty diagnosis, like a "defective" chip.
- 2. Safety System Calibrated**  
Statistical signature of failure captured, updating the safety wrapper.
- 3. Improvement Deployed to Network**  
New safety parameter is pushed to all hospitals using the foundry.

éo Vision in Clinical AI acts as the manufacturing backbone for medical AI, just like TSMC is the manufacturing backbone for the chip industry.

\*Taiwan Semiconductor Manufacturing Company(TSMC) does not design chips. It manufactures chips designed by companies like NVIDIA, Apple, and AMD.

## Business Model





## What Makes éo Vision Different

### AI Infrastructure, Not A Tool

éo Vision provides a permanent AI foundation that hospitals continuously build upon rather than relying on disconnected, disease-specific algorithms.



### Clinician Knowledge At Scale

Doctors create and refine models that capture expert judgment and make it available across teams and institutions.

### Diagnostic Consistency

AI ensures the same patient would receive the same interpretation regardless of who reads the image or where it is reviewed.



### AI As A Second Opinion

Expert-built models validate findings in seconds, reducing uncertainty without replacing human judgment.

### Better Hospital Economics

Fewer misses, fewer re-reads, and fewer unnecessary tests improve throughput, reimbursement, and risk exposure.



### Less Clinician Burnout

Automated pattern recognition reduces fatigue, allowing clinicians to focus on decision-making instead of visual scanning.

### Global Clinical Intelligence

The Knowledge Hub enables expert models to be shared worldwide, raising the standard of care everywhere.



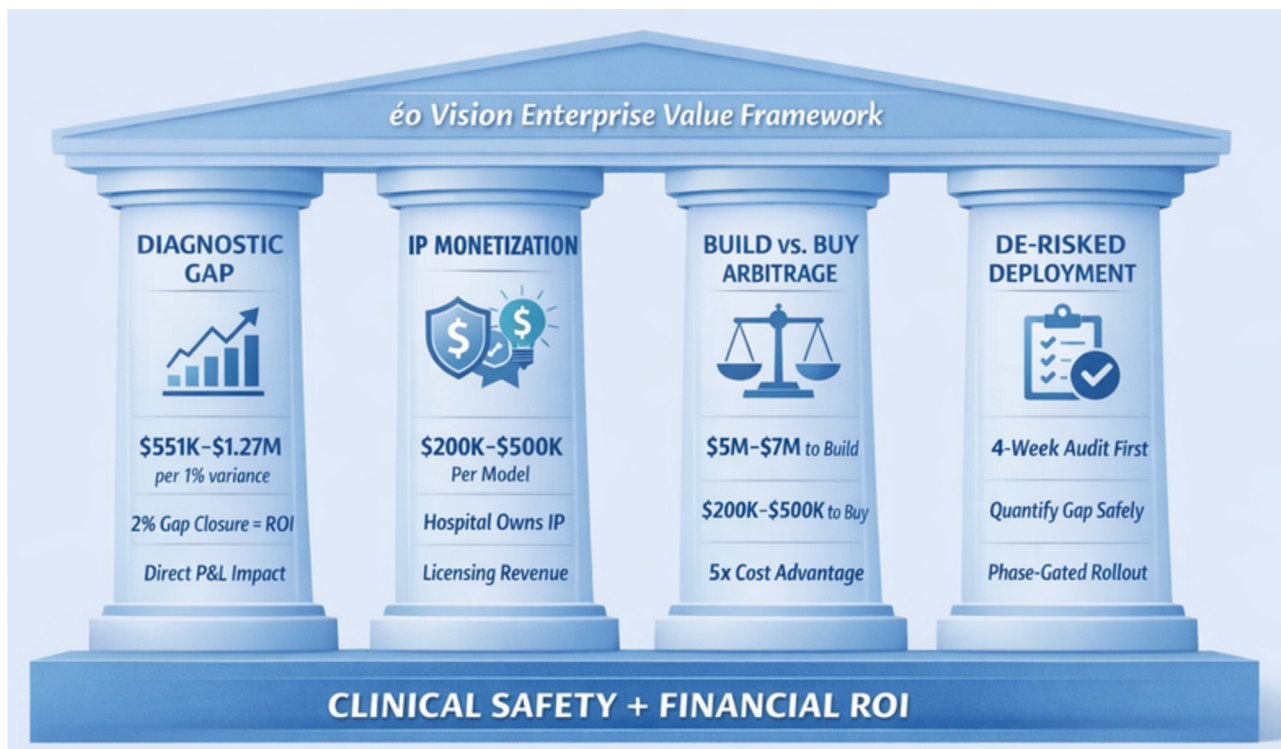
### Aligned Across Stakeholders

Clinicians, service-line leaders, and executives all benefit from improved quality, capacity, and financial performance.

# éo VISION

## Commercial and Strategic ROI

### The Four-Pillars Supporting Clinical and Financial Performance



#### 1. The Micro-Economics of the Diagnostic Gap

Even a 1% diagnostic variance can cost a large health system \$551K–\$1.27M annually, and closing the gap by just 2% can offset platform costs and deliver measurable P&L impact.

#### 2. IP Monetization: From Cost to Revenue

Instead of paying \$200K–\$500K per vendor model annually, hospitals using éo own their validated AI models and can license them to networks, turning AI from a cost center into a scalable revenue asset.

#### 3. Build vs. Buy vs. éo Arbitrage

Compared to building internally (\$5M–\$7M + 18 months) or buying rigid vendor models (\$200K–\$500K per use case), éo delivers up to 5x cost advantage through flat-cost infrastructure and unlimited model creation.

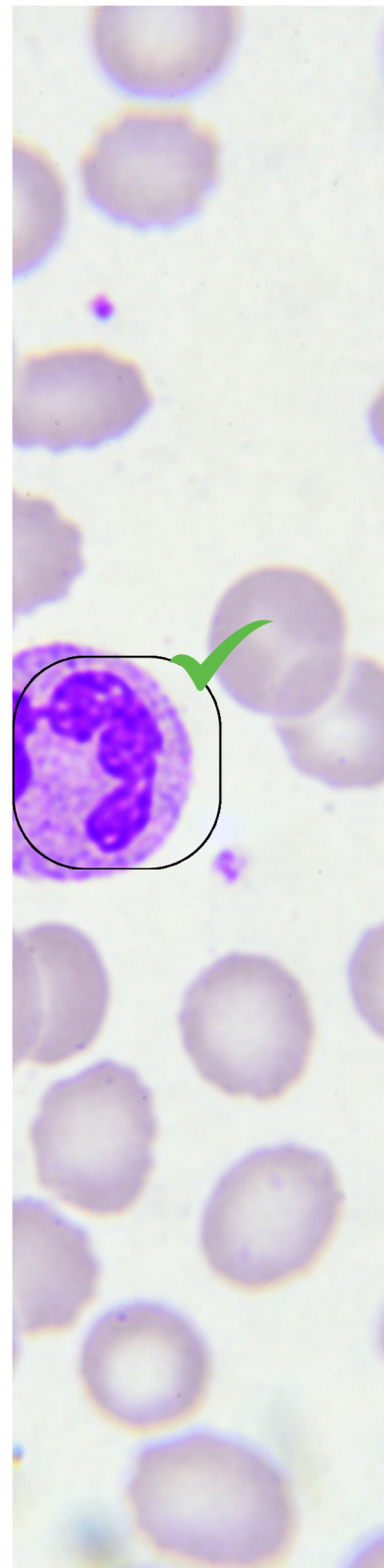
#### 4. De-Risked Implementation Model

A 4-week retrospective audit quantifies each hospital's exact diagnostic gap and financial exposure before live deployment, enabling data-driven adoption without major upfront risk.

# éo VISION

## Key features

- **Clinician-Driven AI Creation:** Clinicians can build, train, and deploy imaging AI models without data science or engineering expertise.
- **Dataset-Based Model Training:** Models are trained using real clinical image datasets for practical, case-based learning.
- **Multi-Specialty Imaging Support:** Supports radiology, pathology, dermatology, microbiology, and related clinical imaging fields.
- **AI-Powered Visual Workflows:** Provides detection, classification, and interpretation pipelines for complex medical images.
- **Explainable AI Outputs:** Delivers transparent, interpretable results to support trust and accountability.
- **Standardized, Auditable Results:** Produces consistent, traceable outputs across users and institutions.
- **Reduced Manual Review:** AI assistance lowers repetitive image comparison and review workload.
- **Continuous Model Optimization:** Includes onboarding, tuning, and performance monitoring to maintain accuracy.
- **Scalable AI Deployment:** Enables cost-effective expansion of diagnostic AI across teams and sites.
- **Seamless Workflow Integration:** éo Vision fits directly into existing imaging and data workflows.
- **High-Volume Image Handling:** It efficiently processes and trains on large-scale imaging datasets.
- **Clinician-Centered Platform Design:** éo Vision is built for fast, reliable use in real clinical environments.



# éo VISION

## The Core Team

**Jonathan Alexander Brown (CEO)**, Mathematician and global risk expert with a decade of experience quantifying complex risk for Berkshire Hathaway (TransRe), Tokio Marine, and Marsh



**Louis-Alexandre Etezad-Heydari (CAIO)**, PhD in Neuroscience, 2nd time AI founder, acquired by Twitter (**2014**) to build their AI dept(Twitter Cortex) and deliver AI at scale

**Kim Nilsson (CTO) (CAIO)**

World-class cybersecurity engineer who **solved the \$300M MtGox Bitcoin's breach**



## The Building Team



**Carrie Kengle, Founding Engineer**

NYU adjunct professor, specializes in human-computer interaction, ensuring clinicians can use éo Vision easily and safely.



**Thibaud Perriches Life Science Specialist, CBO / Head of Partnerships**

PhD in Biomedical Engineering (Nature-published), 10+ years in top research labs, Expert in identifying and commercializing healthcare innovation



# Heuristic Evaluation

## Conducted by HITLAB

HITLAB conducted a heuristic evaluation of the éo Vision platform by applying structured usability inspection methods to assess its interface design, navigation, and workflow clarity, identifying areas where the platform diverges from established usability standards or may introduce barriers to efficient clinical use.

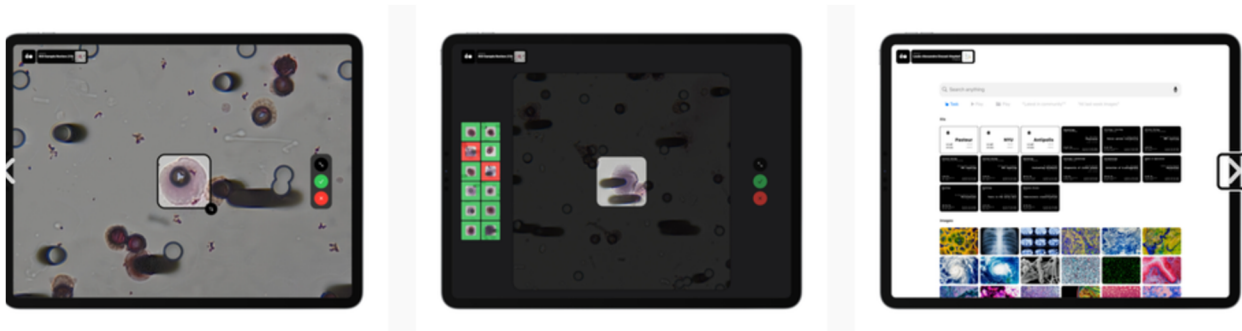


## Methodology

The evaluation was designed to reflect the perspective of end users, particularly clinicians and imaging specialists working in high-pressure diagnostic environments, while incorporating expert analysis of éo Vision’s design, functionality, and interaction patterns.

The assessment was guided by Jakob Nielsen’s Ten Usability Heuristics, a widely accepted framework for interface evaluation. Each heuristic—visibility of system status; match between system and the real world; user control and freedom; consistency and standards; error prevention; recognition rather than recall; flexibility and efficiency of use; aesthetic and minimalist design; help users recognize, diagnose, and recover from errors; and help and documentation—was systematically applied to identify strengths and areas for refinement.

The evaluation involved a structured review of éo Vision’s core workflows, including onboarding, image selection, model training, result interpretation, and navigation. Testing focused on how effectively the platform supports accurate, efficient, and intuitive image analysis workflows in real-world clinical contexts, where clarity, reliability, and cognitive load management are critical.



# Heuristic Evaluation

## Conducted by HITLAB

### Evaluation Persona

The expert evaluators from HITLAB conducted the review by simulating the role of a persona of a 44-years-old Radiologist working in a multispecialty hospital.



### Dr. Andrew Paton

**Occupation: Radiologist**

**Age: 44 years**

*“With the volume of images I review every day, I would expect that AI should be able to reduce complexity. I need tools to trust, understand, and adapt to my clinical practice, which would help me to see subtle patterns earlier and ensure consistency across cases, without disrupting the workflow, which should directly translate to better care for my patients under high pressure conditions.”*

<p><b>Background</b></p> <ul style="list-style-type: none"> <li>• Dr. Andrew is a board-certified radiologist who works in high-volume clinical setting where accuracy, speed, and consistency are critical.</li> <li>• He interprets complex visual data everyday such as imaging studies, digital pathology slides, or clinical photographs—often under time pressure and with increasing caseloads.</li> </ul>	<p><b>Goals</b></p> <ul style="list-style-type: none"> <li>• Deliver safe, timely care and make sound decisions under pressure</li> <li>• Document accurately without slowing patient flow</li> <li>• Maintain trust, transparency, and accountability in diagnostic decisions</li> </ul>	<p><b>Challenges</b></p> <ul style="list-style-type: none"> <li>• Juggling work, life, and a fast-paced, unpredictable environment</li> <li>• Making quick, accurate decisions under tight time constraints</li> <li>• Coping with stress and fatigue from limited time and energy</li> </ul>
<p><b>Motivations</b></p> <ul style="list-style-type: none"> <li>• Improve patient outcomes through earlier and more accurate diagnosis</li> <li>• Increase efficiency without compromising diagnostic quality</li> <li>• Stay current with innovation while retaining clinical control</li> </ul>	<p><b>Frustrations</b></p> <ul style="list-style-type: none"> <li>• Can't prioritize personal health due to demanding shifts</li> <li>• Fragmented workflows that require switching between systems</li> <li>• Lack of control over model performance, or updates</li> </ul>	<p><b>Needs</b></p> <ul style="list-style-type: none"> <li>• Intuitive platform for real-time documentation</li> <li>• Customizable and transparent models aligned with real clinical workflows</li> <li>• Seamless integration with existing imaging and data systems</li> </ul>

# Heuristic Evaluation Findings

## A solid foundation for clinician-centered AI diagnostics

The éo Vision platform demonstrates a solid foundational design, with strengths across key usability dimensions that support AI-assisted image analysis and clinical review workflows. The evaluation identified notable strengths in image-centric workflow structure, integration of AI-driven functionality, and alignment with real-world diagnostic practices.

The platform shows a value proposition in task-flow continuity, enabling clinicians to progress smoothly from exploration to confirmation. It demonstrates strong support for both exploratory and confirmatory diagnostic workflows, allowing clinicians to investigate findings, compare cases, and validate conclusions within a single environment. Results are presented consistently and predictably, supporting comparison, auditability, and clinical governance. The design reinforces clinician control over AI-assisted decisions, positioning AI as a supportive second opinion rather than an opaque decision-maker.



The findings also highlighted targeted opportunities for refinement to further improve system feedback, navigation clarity, icon consistency, accessibility, and user guidance. Addressing these areas will enhance usability, reduce cognitive load, and strengthen clinician confidence as éo Vision scales across diverse clinical settings and use cases. As the platform scales across more users, institutions, and clinical use cases, targeted future enhancements can further strengthen this solid foundation.



Overall, the findings indicate that éo Vision is well-positioned for real-world clinical adoption, with a robust design foundation that can be further optimized to support scalable, safe, and clinician-centered AI-enabled diagnostics.

# Strengths Identified

**Built for trust, governance, and long-term adoption**



- **Clinical Credibility:** éo Vision is designed around how clinicians actually work, making it far more likely to be trusted, adopted, and used in real diagnostic settings.
- **Market Differentiation:** Unlike single-disease or black-box AI tools, éo Vision is a general-purpose visual intelligence platform that scales across specialties and use cases.
- **Lower Barriers to AI Adoption:** By removing the need for technical teams, éo Vision allows hospitals and research groups to move from idea to usable AI in days, not years.
- **Faster Innovation Cycles:** Clinician-driven development enables rapid iteration, validation, and improvement of models, accelerating clinical discovery and deployment.

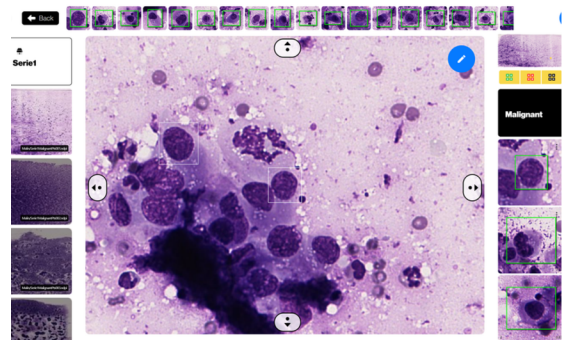


- **Ecosystem Advantage:** The Knowledge Hub turns isolated expertise into a growing network of shared clinical intelligence, compounding value over time.
- **Regulatory and Enterprise Readiness:** Built-in governance, traceability, and validation data make éo Vision suitable for regulated healthcare environments and large institutions.
- **Trust and Transparency:** Explainable, glass-box AI strengthens clinician confidence and supports safe clinical decision-making.
- **Sustainable Business Model:** Model ownership and monetization create incentives for clinicians and institutions to contribute, ensuring long-term platform growth.

# Opportunities for Improvement

## From strong foundation to enterprise-ready platform

- **Enhanced Clinician Onboarding:** Expanding guided onboarding and walkthroughs can help clinicians realize value even faster.
- **Richer In-Platform Guidance:** Additional contextual prompts, workflow guidance, and more detailed and intuitive model performance dashboards can further simplify advanced tasks.
- **More Transparent System Feedback:** Enhanced progress indicators and real-time status updates can strengthen user confidence.
- **Greater Personalization and Accessibility:** Customizable views and display settings can better support diverse clinical roles and working preferences.
- **Deeper Clinical Workflow Integration:** Broader integration with PACS, EHRs, and laboratory systems can further reduce friction and embed *éo* Vision seamlessly into daily practice.
- **Stronger Collaboration Capabilities:** Enhanced tools for versioning, comparison, and team collaboration can amplify cross-institutional knowledge sharing.
- **Growing Support and Knowledge Resources:** Expanding documentation, best-practice libraries, and live support options can strengthen long-term engagement and success.



## Recommended Next Steps

To systematically enhance the platform, HITLAB recommends a phased approach:

- **Immediate (0–2 months):** Improve system feedback, onboarding, icon labels, and accessibility to make image selection and model training easier and clearer.
- **UX Optimization (2–4 months):** Add contextual help, tutorials, clearer navigation, better error messages, progress tracking, and customization to improve clinical efficiency.
- **Pilot & Scale (4–6 months):** Test in real clinical settings, refine AI workflows, and support rollout with training, documentation, and performance validation.

# Conclusion

The HITLAB heuristic evaluation confirms that *éo Vision* is a clinically grounded, intelligently designed AI imaging platform built to meet the real demands of modern healthcare. Its image-centric workflows, AI-assisted interpretation, and intuitive interaction design demonstrate a strong alignment with how clinicians actually think, work, and make diagnostic decisions. By emphasizing clarity, structure, and clinical relevance, *éo Vision* reduces cognitive burden while strengthening diagnostic confidence, specially in fast-paced, high-risk environments.



*éo Vision* enhances their expertise, enabling more efficient image review, more consistent interpretation, and better-informed clinical judgment. The platform's ability to streamline image selection, comparison, and AI-supported analysis reflects a mature understanding of both usability principles and real-world diagnostic practice.

HITLAB's findings also identify focused opportunities to further elevate the experience—particularly in system feedback, onboarding, accessibility, and interaction clarity. These refinements do not signal foundational weaknesses, but rather represent the next step in transforming a strong platform into a truly best-in-class clinical AI infrastructure.

With its robust design foundation, clinician-centered philosophy, and evidence-based roadmap for improvement, *éo Vision* is well positioned to scale across specialties, workflows, and healthcare systems—delivering trusted, interpretable, and high-impact AI for diagnostic confidence worldwide.

“

*éo Vision* reflects a fundamental shift in clinical imaging and diagnostic workflows—replacing fragmented, manual image review and comparison with a unified, AI-enabled, and workflow-driven platform designed to support scalable, efficient, and clinician-centered decision-making.

— Stan Kachnowski, Chair,  
HITLAB

”

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