# Frontiers of Predictive Oncology and Computing

From Pathology to Computation The Path to Dynamic Models of Cancer

Carlos Cordon-Cardo, MD, PhD Chair System-Wide, Department of Pathology Mount Sinai Health System

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#### FROM PATHOLOGY TO COMPUTATION THE PATH TO DYNAMIC MODELS OF CANCER

#### THEMATIC DEVELOPMENT

Sick Care	Health Care	Integration of Multidimensional Studies to Precisely Classify Disease and Optimize Treatment
Data 📩 🛁 🛁 🛁 🛁	Knowledge	Development of Comprehensive Platforms (From Workflow and Data Flow to "Solutions-as-a-Service")
Treating <b>Symptomatology</b>	Treating Causation	Management of Knowledge (From Personalized Medicine to Population Management)

Transform Practice into a Dynamic Interactive Learning Experience

# A NEW PARADIGM IN PATHOLOGY INTEGRATED APPROACH TO DISEASE MANAGEMENT

		Molecular & Systems Pathology
Diagnosis & Staging	<u>Descriptive</u> analysis of clinical variables, histology, and biomarkers to categorize patients into broad disease stages; minimal to no predictive value to inform treatment selection.	<u>Objective, quantitative</u> and multidimensional analysis of clinical variables, tissue/cellular morphometrics, and molecular signatures to define individual patient tumor phenotype and genotype, guiding treatment decisions.
Prognostic Evaluation	Traditional population and cohort-based classification used to deduce disease progression and likelihood of treatment response; non-specific.	Patient-specific characteristics and molecular tumor profiles used to predict drug sensitivity and radiation response, thus optimizing treatment efficacy and outcome.
Treatment Selection	Group management approach that stratifies patients into disease categories, assigning therapies on pre-determined population- based protocols instead of being patient- specific.	Personalized and integrated care model drives selection of evidence-based treatment protocol to optimize clinical outcome; patient-tailored treatments improve survival and quality of life.

Diagnostic and prognostic approach that "groups" patients into disease categories.

Precise, predictive, and cost-effective; individualized patient management.

# **CENTER FOR COMPUTATIONAL AND SYSTEMS PATHOLOGY**

**Systems Pathology** represents a novel, comprehensive approach to personalized medicine, based on the development of highly accurate predictive algorithms. Integrates clinical variables, histological/cellular features & molecular profiles through innovative technologies in the areas of image analysis, quantitative biomarker multiplexing, and deep learning.

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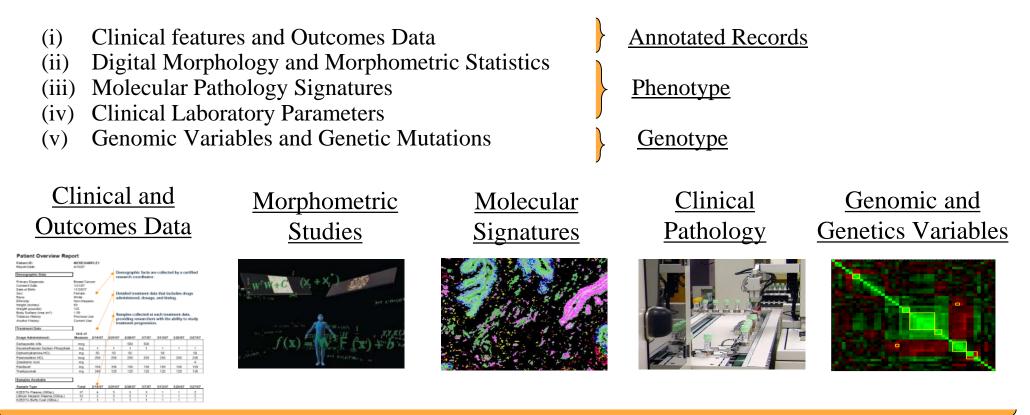
Computational Pathology: Mathematical characterization of phenotype. Systems Pathology: Analytical combination of multiple data sources.

- Board Certification in Clinical Informatics.
- Enhancing the development and funding of scientific research and clinical applications related to individualized and predictive medicine.



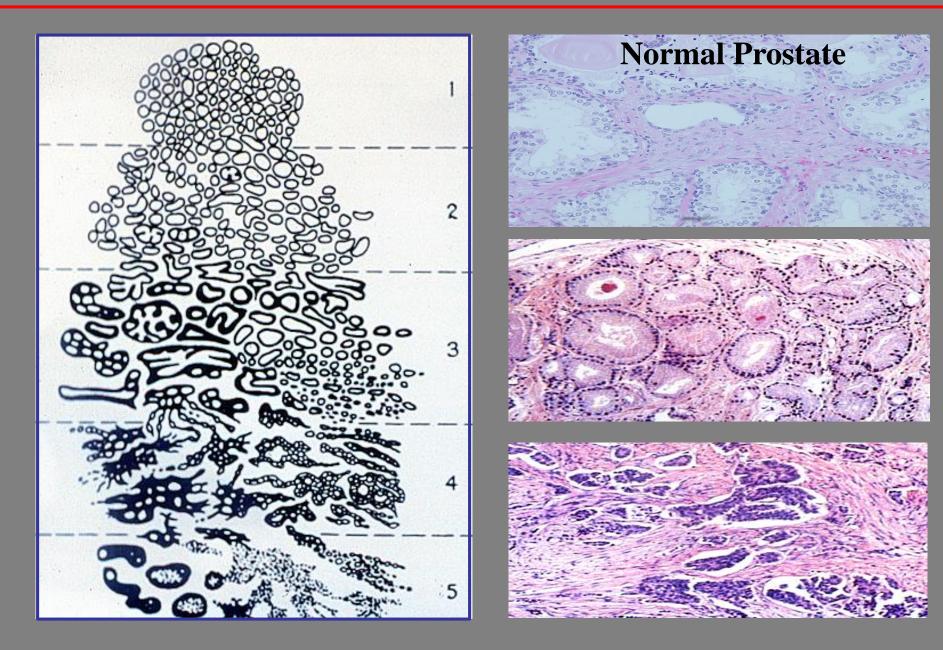
# **CENTER FOR COMPUTATIONAL AND SYSTEMS PATHOLOGY**

**PRECISE Medical Diagnostics** is a novel diagnostics platform to launch predictive/prognostic oncology-focused tests using deep learning and proprietary algorithms that combine:

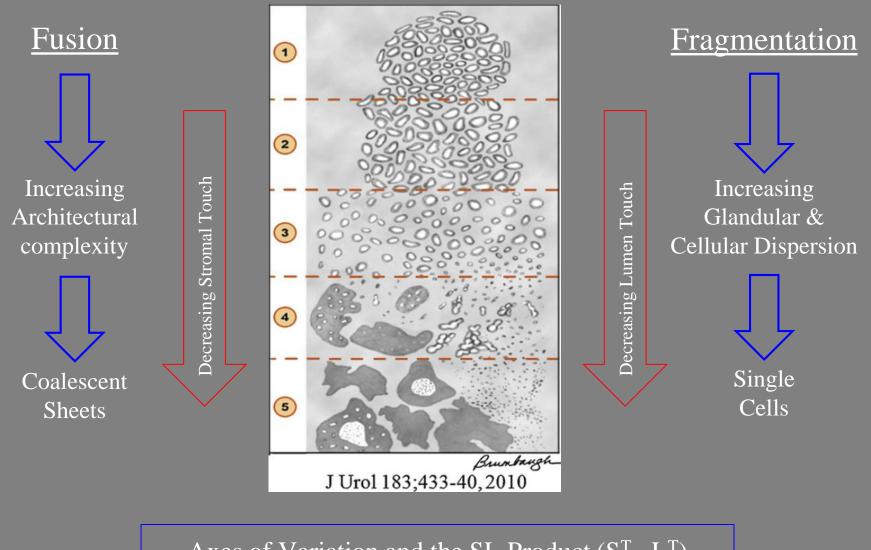


Algorithm-Based Platform for the Accurate Diagnosis and Better Management of Cancer Patients. Tests with higher precision to render more effective and efficient patient care.

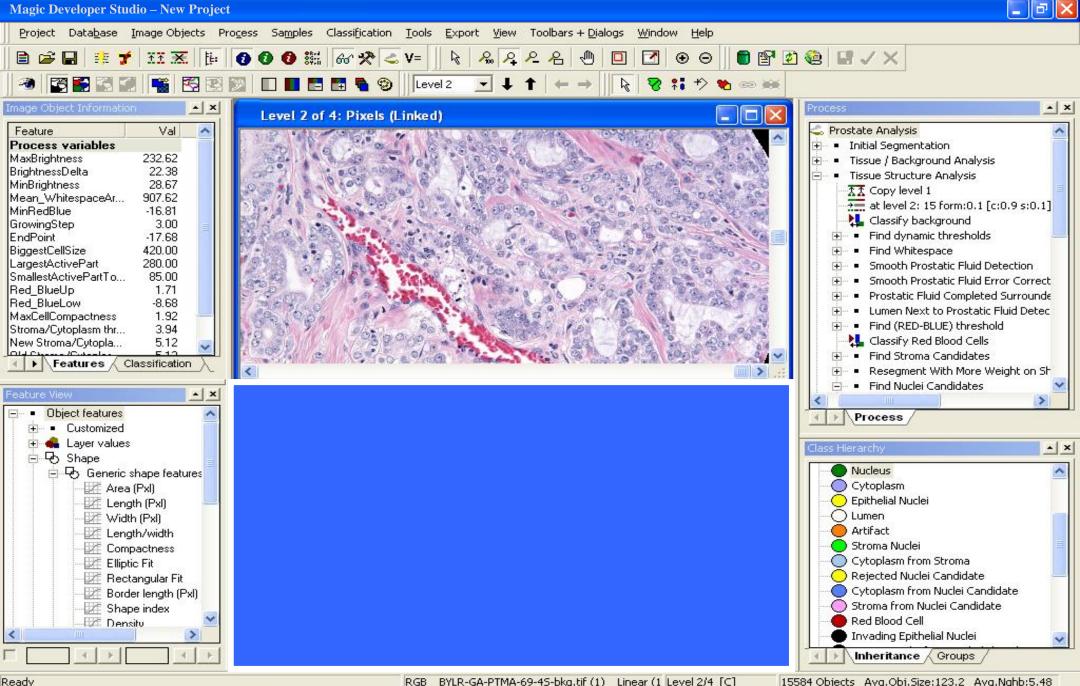
## PROSTATE CANCER ANALYSIS: GLEASON TUMOR GRADE



### **PROSTATE CANCER ANALYSIS: GLEASON TUMOR GRADE**



Axes of Variation and the SL Product ( $S^{T} \cdot L^{T}$ )



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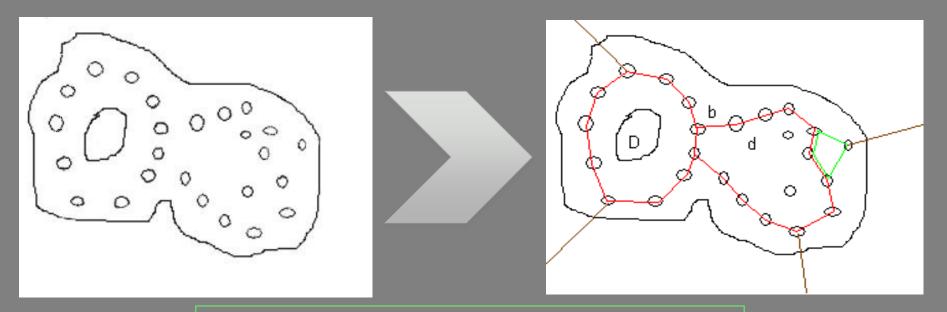
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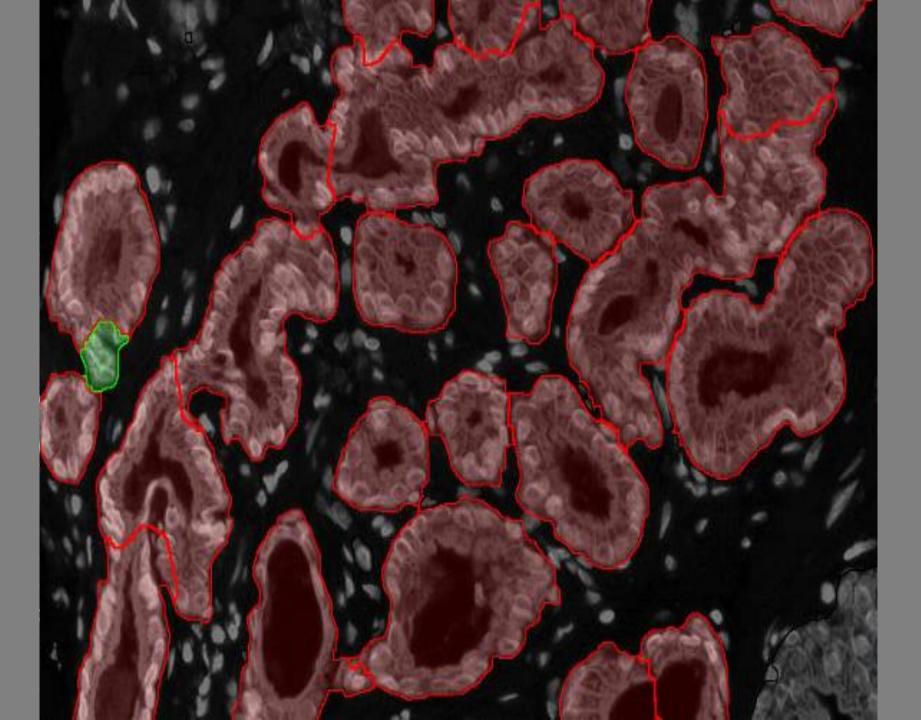
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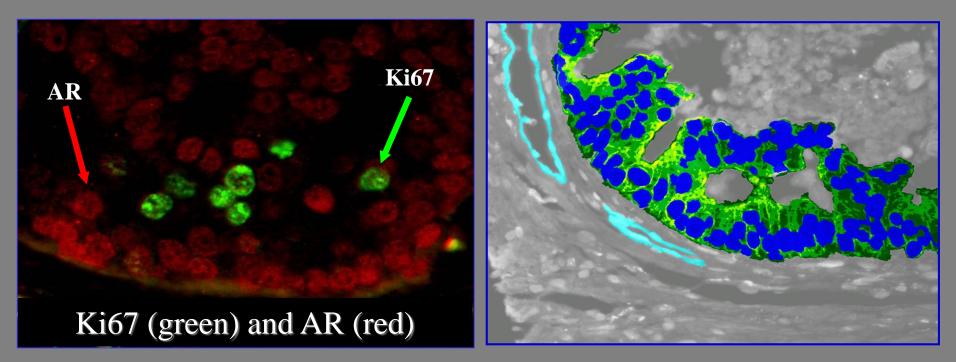
# MORPHOMETRIC AND AUTOMATED GLEASON GRADING GLANDULAR RING STRUCTURES

- Prostate cancer grading is based on morphological assessment of glandular differentiation (Gleason Grade).
- Gleason Grade notoriously lacks interobserver reproducibility.
- Glandular structures can be converted mathematically to "ring" structures
- <u>Technical definition</u>: A graph theory and "voronoi" diagram based algorithm for identifying gland rings as a basis for quantitating architectural structure, specifically degree of glandular differentiation.



Continuous Grading (e.g., 2.4+2.8 = 5.2)

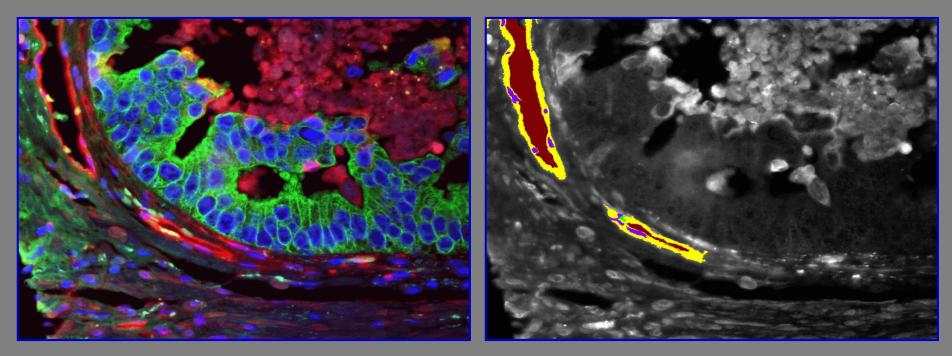




#### MULTIPLEXED IMAGE

#### EXTRACTED FEATURE

NUMBER OF EPITHELIAL CELLS (DAPI+ CK18) AVERAGE SIGNAL INTENSITY IN THE CYTOPLASM

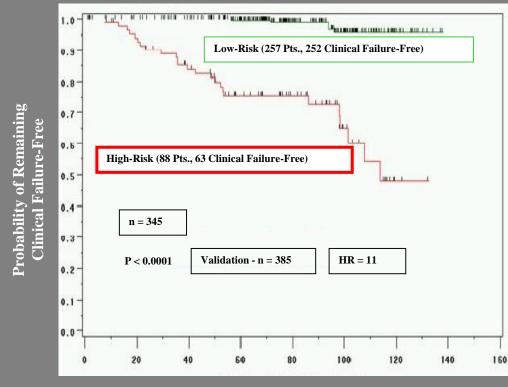


#### MULTIPLEXED IMAGE

EXTRACTED FEATURE

NUMBER OF LABELED VESSELS (CD34) TOTAL VESSEL AREA, PERIMETER, LENGTH, WIDTH <u>MICROVESSEL AREA (MVD)</u>

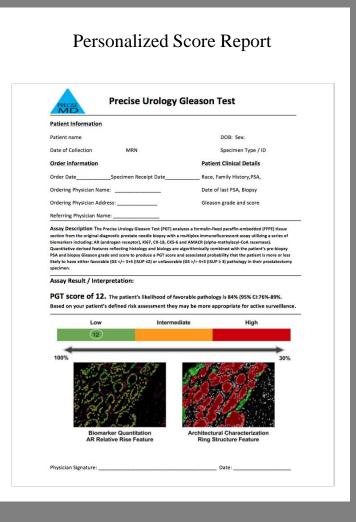
### INTEGRATION OF CLINICAL AND MOLECULAR VARIABLES RENDERS PRECISE DIAGNOSIS AND PROGNOSIS



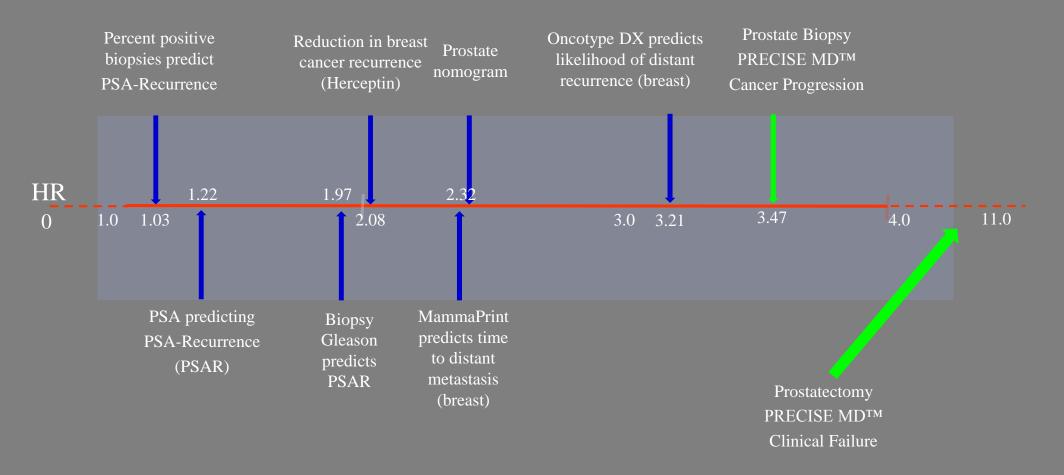
Actual Time to Clinical Failure (months)

PREDICTIVE ACCURACY: 92% - SPECIFICITY: 91%; SENSITIVITY: 90%

(More than 10,000 prostate cancer cases analyzed to date)

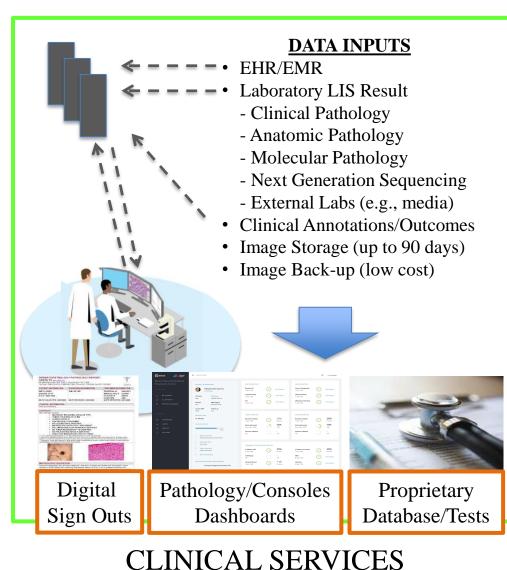


## INTEGRATION OF CLINICAL AND MOLECULAR VARIABLES RENDERS PRECISE DIAGNOSIS AND PROGNOSIS



NCI-Hazard Ration (HR) (definition): A measure of how often a particular event happens in one group compared to how often it happens in another group, over time. For example, a hazard ratio of one means that there is no difference in survival between the two groups. A hazard ratio of greater than one means that survival was better in one of the groups.

# **CENTER FOR COMPUTATIONAL AND SYSTEMS PATHOLOGY**



#### **CONTINUED EDUCATION AND INNOVATION**

- Clinical Applications of Digital Pathology
- New Developments in Clinical Laboratory Medicine
- Clinical Informatics: A Novel Area Board Certification

#### **GRADUATE MEDICAL EDUCATION**

- Pathology & Cell/Molecular Biology Courses
  - Medical Students
  - PhD Students
- Self Assessment Modules

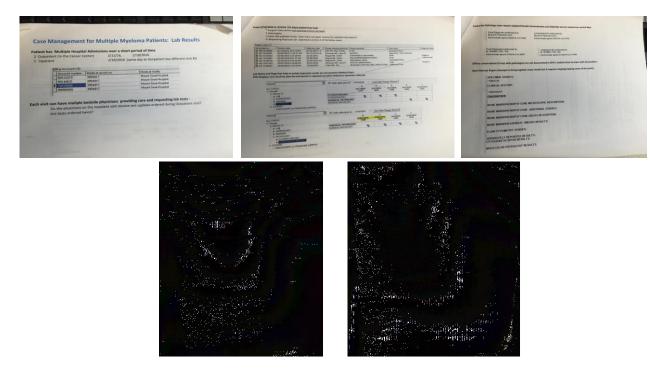
#### **POST-GRADUATE EDUCATION**

- Residency/Fellowship Training Modules
- Post-Doctoral Training Modules

# EDUCATIONAL DIMENSIONS

## THE NEED FOR COMPREHENSIVE PLATFORMS TEST REPORTING (MULTIPLE MYELOMA AS EXAMPLE)

# FRACTIONATED and MANUAL DATA FLOW

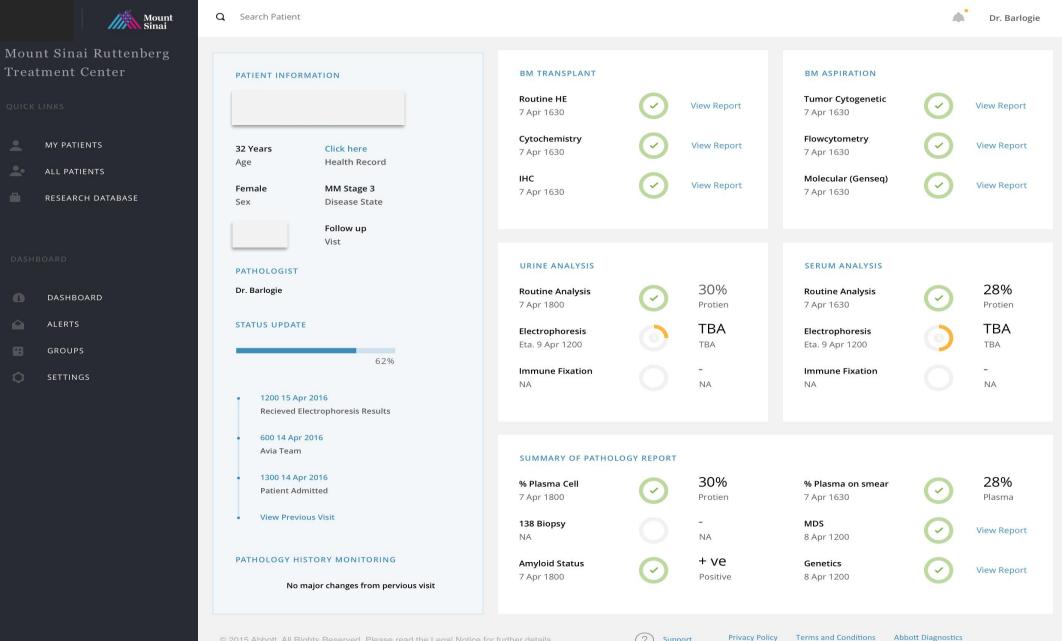


The MM clinic manually aggregates +20 Clinical Results per case for the oncologist to review in 15-20 minute

#### **CHALLENGES:**

- Data residing in different systems and formats.
- Long TAT (1 to 3 wks).
- Significant manual process (risks of diagnostic errors).
- Every Hospital develops internal procedures that are not standarized and are not harmonized.

# **MULTIPLE MYELOMA PATHOLOGY DASHBOARD**



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Support

# THE NEED FOR COMPREHENSIVE PLATFORMS

### PATHOLOGY DASHBOARDS

- 1. Consolidation of all Pathology Results.
- 2. Real-time Updates on Pathology Results.
- 3. Streamlined Access to stored Pathology Results.

## **DIRECT BENEFITS:**

Reduced TAT and reporting times. Improve Documentation/Reporting. Translate Data into Knowledge.

# **INDIRECT BENEFITS:**

Improves Patient Management/Outcomes. Improves Physician Satisfaction. Increased Accountable Care.

To assist Personalized Treatments and Improved Outcomes

### INTEGRATION OF DIAGNOSTIC SERVICES: MAXIMIZING EFFECTIVENESS, IMPROVING OUTCOMES, AND MITIGATING RISK

