Instructor Resources Sample

This is a sample of the instructor materials for *Information Technology for Healthcare Managers, Ninth Edition*, by Gerald L. Glandon, Detlev H. Smaltz, and Donna Slovensky.

The complete instructor materials include the following:

- PowerPoint slide presentations
- Answers to the end-of-chapter discussion questions
- Test bank
- Transition guide to the new edition

This sample includes the PowerPoint slides and answers to the end-of-chapter discussion questions for chapter 11.

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Chapter 11

Analytics
Learning Objectives

• Describe the difference between traditional analytics and big data analytics.
• Articulate analytics capabilities that characterize more advanced or mature analytics organizations.
• Describe different ways that a healthcare organization can establish and structure an enterprise analytics function.
• Articulate staffing considerations when establishing an enterprise analytics function.
• Describe typical governance requirements of an enterprise analytics function.
Analytics Defined

In an organizational context, such as a healthcare payer or provider organization, analytics are the processes, people, and technology that leverage data to glean information and insights to make sound business, operational, and clinical decisions.
### Traditional Analytics and Big Data Analytics

<table>
<thead>
<tr>
<th>Traditional Analytics/Business Intelligence (BI)</th>
<th>Big Data Analytics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic report generation to monitor an organization’s clinical and business performance</td>
<td>Advanced analytics approach using data sets so large and complex that traditional data management methods and data processing tools are challenged</td>
</tr>
<tr>
<td>Generally descriptive and retrospective in nature</td>
<td>Often is predictive and/or prescriptive in nature; its ultimate goal is to achieve personalized medicine</td>
</tr>
<tr>
<td>More advanced traditional analytics or BI allows users to reformulate data visualizations; e.g., “drill-down” capabilities to ever more specific organization units</td>
<td>Typically leverages advanced parallel processing computing infrastructures</td>
</tr>
<tr>
<td>Typically leverages structured data</td>
<td>Typically characterized by large (volume), dynamic (velocity), complex, unstructured (variety) data sets not well suited to traditional enterprise data warehousing technologies and techniques</td>
</tr>
<tr>
<td>Typically leverages analysts adept at writing report queries, spreadsheet manipulation, and data visualizations</td>
<td>Typically leverages data scientists, statisticians, and mathematicians adept at scientifically gleaning meaning from complex data sets</td>
</tr>
</tbody>
</table>
Analytics Maturity in Healthcare

• HIMSS Analytics’ Adoption Model for Analytics Maturity (HIMSS-AMAM)
• Serves as a way of assessing a healthcare organization’s level of maturity with respect to its own analytics capabilities
• Just like the HIMSS EMRAM discussion in Chapter 8, the HIMSS-AMAM has 8 levels of maturity (0–7)
<table>
<thead>
<tr>
<th>Stage</th>
<th>Cumulative Capabilities</th>
</tr>
</thead>
<tbody>
<tr>
<td>7</td>
<td>Personalized medicine and prescriptive analytics</td>
</tr>
<tr>
<td>6</td>
<td>Clinical risk intervention and predictive analytics</td>
</tr>
<tr>
<td>5</td>
<td>Enhancing quality of care, population health, and understanding the economics of care</td>
</tr>
<tr>
<td>4</td>
<td>Measuring and managing evidence-based care, care variability, and waste reduction</td>
</tr>
<tr>
<td>3</td>
<td>Efficient, consistent internal and external report production and agility</td>
</tr>
<tr>
<td>2</td>
<td>Core data warehouse workout: centralized database with an analytics competency center</td>
</tr>
<tr>
<td>1</td>
<td>Foundation building; data aggregation and initial data governance</td>
</tr>
<tr>
<td>0</td>
<td>Fragmented point solutions</td>
</tr>
</tbody>
</table>

*Source: HIMSS Analytics (2020)*
HIMSS-AMAM – Stage 0

All organizations started their analytics journey at stage 0, with a desire to learn about developing analytics capabilities in response to business demands, market pressures, and the need to develop further insights into the important decisions they make every day.
HIMSS-AMAM – Stage 1

• Organizations are just beginning to accumulate and manage data in centralized locations such as an operational data store or data warehouse supporting historical reference and consolidated access.

• The main focus of stage 1 is to document and begin execution of an analytics strategy that brings basic data together from appropriate systems of record (e.g., the EHR application(s), the ERP application(s), etc.) and then to learn to manage (data governance) and define data so that they can be used and referenced by a broad cross section of analysts.
HIMSS-AMAM – Stage 2

• Data is presented in a formal data warehouse as an enterprise resource (as opposed to a silo-oriented and narrowly used resource) with master data management (MDM) that supports ad hoc queries and descriptive reporting.

• The enterprise begins advancing data governance while leveraging this environment in support of basic clinical and operational tasks, such as patient registries.

• All activities should be aligned with the organization’s overall strategic goals.

• Analytic skills, standards, and education are managed through an analytics competency center.
HIMSS-AMAM – Stage 3

• A mastery of descriptive reporting is in place broadly across the enterprise.

• Varying and different parts of the organization are able to corral data effectively, work with it, and produce historical and current period reporting with minimal effort.

• Data quality is stable and predictable.

• Tools are standardized and broadly available, and data warehouse access is managed and reliable.
HIMSS-AMAM – Stage 4

• The organization directs analytical data assets, skills, and infrastructure squarely toward improving clinical, financial, and operational program areas.

• There is a concerted effort to understand and optimize data by honing analytics resources that support evidence-based care, track and report care and operational variability, and identify and minimize clinical and operational waste.
HIMSS-AMAM – Stage 5

• Organizations show expanded point-of-care-oriented analytics and support of population health.

• Data governance is aligned to support quality-based performance reporting and bring further understanding of the economics of care.
HIMSS-AMAM – Stage 6

• Stage 6 pushes the organization to mature in the use of predictive analytics and expands the focus on advanced data content (e.g., both structured and unstructured data perhaps) and clinical support.
HIMSS-AMAM – Stage 7

• This stage represents the pinnacle of applying analytics to support patient-specific prescriptive care.

• Healthcare organizations can leverage advanced data sets, such as genomic and biometric data, to support the uniquely tailored and specific prescriptive healthcare treatments of personalized medicine.

• Organizations can deliver mass customization of care combined with prescriptive analytics.
Structuring an Analytics Function

Five Basic Organizational Structuring Arrangements

Source: Adapted from Davenport, Harris, & Morison (2010)
## Organizational Structuring Options for Analytics

<table>
<thead>
<tr>
<th>Type</th>
<th>Potential Advantages</th>
<th>Potential Challenges</th>
</tr>
</thead>
</table>
| **Decentralized**  
(Analyst groups are associated with their respective functional departments with little or no corporate oversight.) | • Provides autonomy of prioritization of BI projects to each decentralized analyst group | • Difficult to accomplish cross-functional BI projects  
• Difficult to set enterprise priorities  
• Often creates added costs due to replication of services |

This is how virtually every healthcare organization typically started its initial foray into data analytics as individual functional departments attempted to leverage data to meet their own functional needs. However, it is very challenging to try to scale a decentralized approach into an enterprise-focused operational model.
### Organizational Structuring Options for Analytics (cont.)

<table>
<thead>
<tr>
<th>Type</th>
<th>Potential Advantages</th>
<th>Potential Challenges</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Functional</strong>&lt;br&gt; (A single analyst group resides in a primary data consumer’s department/business unit.)</td>
<td>• Negates need for a new central department</td>
<td>• May be viewed as being too parochial to its own functional department or business unit&lt;br&gt; • May lack functional analytics expertise needed by other departments</td>
</tr>
<tr>
<td><strong>Consulting</strong>&lt;br&gt; (Same as centralized, only not a shared service; instead departments “hire” analysts for projects in a “pay-to-play” way.)</td>
<td>• More market driven; prioritization is simplified as only projects that departments are willing to pay for are undertaken&lt;br&gt; • Leverages business metadata standardization and economies of learning</td>
<td>• Falts under weak enterprise focus or project selection criteria and/or poor executive leadership</td>
</tr>
</tbody>
</table>
Organizational Structuring Options for Analytics (cont.)

<table>
<thead>
<tr>
<th>Type</th>
<th>Potential Advantages</th>
<th>Potential Challenges</th>
</tr>
</thead>
</table>
| **Centralized** (All analyst groups report to one corporate executive as a shared service.) | • Easier to deploy analysts on strategic projects  
• Priorities easier to align with overall organizational goals  
• Leverages business metadata standardization and economies of learning | • Can be seen as an “ivory tower” group  
• May be seen as “bottleneck” if governance activities are not transparent and fair |
| **Center of Excellence** (Community of practice program office approach—analyst groups are decentralized but report in dotted line fashion to central corporate “program office”) | • Provides autonomy of prioritization of BI projects to each decentralized analyst group  
• Leverages business metadata standardization and economies of learning | • Can also falter under weak enterprise focus or project selection criteria, particularly in the absence of a formal “program office” or governance prioritization approach |

These two approaches tend to be more effective enterprise analytics structuring arrangements (Davenport, Harris, & Morison, 2010)
Staffing an Enterprise Analytics Function

Current State
- IT
- Finance
- Quality
- PI

Option A
- Enterprise Analytics
  - IT
  - Finance
  - Quality
  - PE

Option B
- Enterprise Analytics
  - New Hires
  - IT
  - Finance
  - Quality
  - PE
  - Consultants

Legend
- Non-Data Analyst
- Data Analyst
Staffing an Enterprise Analytics Function (cont.)

**Option A**

**Staffing Options**

**Pros**
- Enterprise Analytics has organizational knowledge on day 1; if you pick the right people to seed it, trust in Enterprise Analytics’ efforts/products should be higher
- Requires less net new resources

**Cons**
- Functional departments may not want to let their best report writers/data analysts go
- Functional departments may request backfill for these FTEs
Staffing an Enterprise Analytics Function (cont.)

Option B

New Hires

Enterprise Analytics

Consultants

Pros
- Functional departments FTEs or their work is not affected
- Jump starts the program with external expertise
- Creates limited disruption to workers in their existing roles and responsibilities

Cons
- New hires and outside consultants won’t know the “lay of the land”/longer learning curve
- Functional departments may not trust efforts of “newbies”
- Generally requires net new resources
Staffing an Enterprise Analytics Function (cont.)

<table>
<thead>
<tr>
<th>Staffing Option</th>
<th>Potential Advantages</th>
<th>Potential Challenges</th>
</tr>
</thead>
</table>
| **Option A** (mostly reassign resources from within) | • Enterprise analytics (EA) function has organizational knowledge on day 1  
• Departments that seeded the EA function with their own resources will tend to trust the efforts of the EA (instant credibility)  
• Requires less “net new” resources | • Functional departments may not want to let their best report writers and analysts be reassigned to an EA function that they don’t directly control  
• Functional departments may seek to backfill the resources that were reassigned to the EA function |
| **Option B** (mostly new hires and external consultants) | • Functional/departmental resources and productivity are not impacted  
• Jump-start the program with external expertise | • New hires and/or consultants won’t know the “lay of the land” and will have a longer learning curve  
• Functional departments/business units may not trust the efforts of “newbies”  
• Requires more “net new” resources |
Staffing an Enterprise Analytics Function (cont.)

Other factors that weigh into the staffing approach:

• **FTE growth policy of the healthcare organization.** Organizations that wish to keep their permanent FTE headcount down (i.e., fully burdened salary dollars) may favor leveraging consultants at least at the outset (Option B) prior to reassigning resources from functional departments into the EA function (Option A).

• **Historical level of trust and cooperation between business units.** In low trust organizations, leaders within specific functional business units may not want to see their departmental analytic resources reassigned to a corporate EA function (Option B).

• **Level of analytic expertise within the healthcare organization.** Organizations with little reporting writing/analytic skills at their disposal may desire leveraging new hires and/or consultants (Option B).

• **Level of leadership commitment to an enterprise approach to analytics.** Organizations without demonstrable C-level (CEO, COO, CFO, etc.) awareness and commitment to fostering an enterprise approach to analytics will find it difficult to reassign resources from functional departments into the BICC (Option A).
Roles in an Enterprise Analytics (EA) Function

Chief/VP/Director/Manager of the EA function

Typical titles include:

- Chief Information Officer
- Chief Analytics Officer
- Chief Data & Analytics Officer
- VP, Analytics
- VP, Data & Analytics
- Director Analytics
- Director Data & Analytics

- Typically reports to C-level executive or the executive with responsibility for enterprise-wide business performance management, continuous process improvement, or Lean Six Sigma
- Leads efforts to deliver analytics infrastructure and capabilities in support of organizational performance improvement efforts and strategic initiatives; leads an EA function (a department responsible for analytics strategy, projects, processes, training of end users, and ongoing analytics benefits realization efforts)
- In organizations with enterprise data warehouses (EDWs), owns the overall EDW project, ensuring sponsorship and funding are in place
- Able to articulate the business problems that will be addressed by the EA function or EDW
- Is knowledgeable about analytics technology and how it can be applied to solving business problems
- Is responsible for tracking return on investment/benefits achieved via various analytics projects
- Primary analytics service provider for executives, managers, functional champions, stakeholders, and end users
Roles in an Enterprise Analytics (EA) Function (cont.)

**Enterprise Data Architect**

- Typically reports to EA function leader
- Is responsible for managing the healthcare organization’s overall data architecture, data standardization, data dictionary, and metadata associated with enterprise data (e.g., in maintaining an EDW)
- Has an overall understanding of both hardware platforms and all software products being used to support analytics projects
- Understands relational databases, physical/logical data models, middleware, metadata, and end-user tools
- Works closely with business analysts to define data incorporated into logical data model
Roles in an Enterprise Analytics (EA) Function (cont.)

**Data Integrator (extraction, transformation, and load developer or data parser)**

- Typically reports to enterprise data architect
- Writes extraction, transformation, and loading (ETL) scripts and parser scripts (e.g., HL7 parsing).
- Adept in graphical user interface–based ETL tools
- Focuses on strategic data integration issues, such as data quality/stewardship, real-time/event-based data integration, and crafting a service-oriented vision for data integration
Roles in an Enterprise Analytics (EA) Function (cont.)

Database Administrator (DBA)

• Creates, tunes, and otherwise maintains the databases associated with the key data repositories used by the EA function (e.g., data marts, EDW)
• Reports to project manager for task management
• Maintains an in-depth knowledge of database technology
• Understands physical data models
• Is an expert in data structure (including parallel data structure)
• Works closely with enterprise data architect
Roles in an Enterprise Analytics (EA) Function (cont.)

**Project Manager**

- Reports to the EA function leader (either directly or indirectly if healthcare organization has a centralized project management function)
- Understands EDW and analytics project management methodology
- Manages the project plan for completeness and timeliness
- Manages the resource plan, ensuring the correct individuals are working toward project completion
- Reports on project status
- Interfaces with both EDW project team and functional stakeholders
Roles in an Enterprise Analytics (EA) Function (cont.)

**Business Analyst/Data Analyst**

- Possesses expertise in a particular functional business unit and thus serves as a credible point of contact with those business users of analytics resources (such as the EDW or various reporting products)
- Responsible for training end users on how to navigate EA function tools and resources to find information
- Run reports and performs analysis
- Works closely with business managers to identify requirements
Roles in an Enterprise Analytics (EA) Function (cont.)

**Analytics Developer**

- Works closely with business analysts/data analysts to develop and publish enterprise reports, dashboards, and scorecards
- Works closely with data scientists to potentially help develop products and services based on predictive models
Roles in an Enterprise Analytics (EA) Function (cont.)

Data Scientist

- Typically trained in statistics or biostatistics
- Performs data mining to detect and identify patterns in the data to inform management decision-making
- Leverages published predictive models or creates new predictive models and algorithms to inform management decision-making
- Works with analytics developer to develop products and services based on predictive models as well as prescriptive models
Analytics Governance

A Typical Governance Structure for Enterprise Analytics

**Oversight & Prioritization**
- **Charge/Charter**
  - Align projects with strategic goals
  - Guide prioritization
  - Monitor project progress
  - Ensure transparency
  - Advocate technologies
  - Oversee data governance and ad hoc project efforts as needed
- **Membership**
  - Representative Functional VPs
  - Representative Service Line VPs
  - CIO
  - CAO
  - Others as needed

**Senior Leadership Executive Committee**

**Enterprise Analytics Steering Committee**

**Ad Hoc Task Forces & Projects (as needed)**

**Data Governance Sub-Committee**

**Data Governance**
- **Charge/Charter**
  - Identify Data and KPIs owners
  - Standardize reporting
  - Resolve data quality issues
  - Resolve data definition conflicts
  - Contribute to business rules
  - Contribute to data strategies
  - Enforce data policies
- **Membership**
  - Representative Functional Dir/Mgrs.
  - Representative Service Line Dir/Mgrs.
  - Representative from Analytics Dept. & IT
  - Others as needed
The Relationship Between Analytics Governance and Analytics Operations

• EA Steering Committee oversees and prioritizes the work of the EA function
• Just like any other project, when approved a project team executes the work; it is made up of:
  ➢ Project champion or sponsor
  ➢ A team leader (can be from any functional area)
  ➢ A representative number of project team members from the key functional areas that the project encompasses as well as members of the EA function
• Project status is reported to EA Steering Committee or Data Governance Sub-Committee (as applicable)
Answers to Discussion Questions for

Chapter 11

Analytics

1. **Distinguish between traditional analytics and big data analytics.**

Analytics generally comprises the processes, people, and technology that leverage data to glean information and insights to make sound business, operational, and clinical decisions.

Traditional analytics, or business intelligence, is generally descriptive and retrospective reports that monitor an organization’s clinical and business performance. Analysts are adept at writing reports, manipulating spreadsheets, and visualizing data.

Big data analytics employs collections of data sets so large and complex that they become difficult to process using traditional data management tools or traditional data-processing applications, often requiring advanced parallel-processing computing infrastructures and data scientists, statisticians, and mathematicians adept at scientifically gleaning meaning from complex data sets.

2. **What is the advantage of using technologies such as Hadoop and NoSQL for big data analytics rather than typical data warehousing analysis approaches?**

These technologies are better able to deal with large, unstructured data sets and are able to effectively leverage the parallel-processing computer servers needed to analyze those data sets.
3. **The HIMSS Analytics Adoption Model is based on a cumulative capability structure. What does this mean?**

A lower-level stage is an essential precursor to a higher-level stage. In other words, achieving each successively higher stage requires that all of the capabilities of that particular stage as well as those of each lower stage are met.

4. **How is achieving stage 7 of the HIMSS Analytics Adoption Model expected to affect clinical care?**

Healthcare organizations can leverage advanced data sets, such as genomic and biometric data, to support the uniquely tailored and specific prescriptive healthcare treatments of personalized medicine. Organizations can deliver mass customization of care combined with prescriptive analytics.

5. **The authors suggest that healthcare analytics models are “immature” with regard to managing data as a strategic asset. What is the basis for this assertion?**

The current predominant model for analytics in healthcare organizations is decentralized; thus, analysts often are not tasked solely with the most important analytical projects and may not have the needed enterprise perspective. Many healthcare organizations do not manage data as a strategic asset.
6. **What analytics capabilities characterize more advanced or mature analytics organizations?**

   A centralized or center-of-excellence model; a high level of data mastery; an enterprise approach to data governance; a cross-functional team that has defined tasks, roles, responsibilities, and processes for supporting and promoting the effective use of analytics across an organization.

7. **Describe different ways a healthcare organization can establish and structure an enterprise analytics function.**

   *Centralized:* All analyst groups report to one corporate executive as a shared service.

   *Consulting:* Same as centralized, except no shared service; instead, departments “hire” analysts for projects in a “pay-to-play” way.

   *Functional:* A single analyst group resides in a primary data consumer’s department or business unit.

   *Center of excellence:* Community-of-practice program office approach; analyst groups are decentralized but report in dotted-line fashion to a central corporate “program office.”

   *Decentralized:* Analyst groups are associated with their respective functional departments with little or no corporate oversight.

8. **What are key staffing considerations when establishing an enterprise analytics function?**

   At a minimum, the sum of the individuals that an organization assigns to the enterprise analytics function should possess representative subject matter expertise that spans the
key data consumers of the healthcare organization. Analysts must have a broad understanding of the business of healthcare (ideally, both clinical and financial) and a background in data analysis or informatics. Additionally, solid “people” skills to effectively facilitate the kind of cross-functional coordination necessary to complete successful enterprise analytic projects are essential.

9. **What are the two primary facets of governance for an enterprise analytics function?**

   1. Prioritization and strategic alignment
   2. Data standardization and data quality improvement to ensure that the data can be used to maximal beneficial value

10. **What is a common barrier to democratizing data analytics across the enterprise?**

    Unfortunately, there continues to exist a generalized data illiteracy among many business and clinical colleagues in the healthcare organization. While these colleagues generally have an adept understanding of the business, clinical, and/or operational processes that drive their respective parts of the healthcare organization, they are ignorant about the underlying data that are generated by those same operations how that data may be needed and used by other functional areas of the organization, or how to effectively use that data for performance improvement initiatives.