Where is Technology Taking Us in Diversion Detection?

National Association of State Controlled Substances Authorities (NASCSA)  
2017 Annual Meeting  
San Antonio, Texas  
October 18, 2017
Invistics: Who We Are and What We Do

- Cloud-based software solutions
- for pharmaceutical manufacturers, distributors, laboratories, R&D, and
- for healthcare facilities
- to reduce inventory costs and compliance risks,
- within a single facility or across the extended enterprise.
Invistics Prescription Drug Supply Chain Experience

Drug Supply Chain

Manufacturing
- Drug Substance
- Domestic Chemicals

Manufacturing
- Drug Product
- Repackagers

Distributing
- Wholesalers
- Repackagers

Dispensing
- Retail Pharmacies
- Hospital/Clinics
- Practitioners
- Teaching Institutions
- Narcotic Treatment Programs

Patients

Other Elements of Supply Chain

Importers
Researchers
Analytical Laboratories
Reverse Distributors & Authorized Collectors
Exporters
Agenda

- Introductions
- Emerging Technologies Drug Diversion Detection
  - University of Michigan’s Diversion Detection
- Current Diversion Detection Technologies
  - NIH Study: Advanced Analytics for Diversion Detection
  - Other Emerging Technologies for Diversion Detection
- Group Discussion
How Prevalent is Drug Diversion in Healthcare?

“Rates of substance abuse and dependence are similar to those of the general population”

• 6-8% of Physicians, with higher rates for Anesthesiologists, e.g., 9.8% of Nurse Anesthetists.
• 9% of Pharmacists
• 4.7-8.8% of Registered Nurses

So for a typical, mid-size, 500 bed hospital, expect roughly 25-75 people to be diverting at any one time:

• 6-10 physicians, anesthesiologists or CRNAs,
• 4-5 pharmacists, and
• 15-60 nurses

Sources: Baldisseri, “The Impaired Healthcare Provider”
American Nurses Association (ANA) & the National Council of State Boards of Nursing (NCSBN)
Striking Results in 2017 Survey by Porter Research

- 140 hospitals were surveyed about drug diversion
  - Within their hospitals
  - Across the country

- Broad Mix of Roles:
  - Executives, Chief Nursing Officers, Directors of Pharmacy, Anesthesiologists, Drug Diversion Investigators, etc.
97% Agree – Diversion Occurring Across US Hospitals
88% Agree – Most Diversion Goes Undetected
Current Diversion Detection Technologies

- Lock-up drugs in Automated Dispensing Cabinets (ADCs)
- React to tips, incidents, or monthly “anomalous usage” reports
- Dedicate person(s) to conduct manual investigations
- Investigations require painful reconciliation of ADC vs. Electronic Medical Records (EMR)
Berge’s Law of Drug Diversion

Addicts are smart.
We are smart.

They are desperate.
We are not.

Therefore:
They are going to outsmart us every time.

- Dr. Keith H. Berge, Anesthesiologist, Mayo Clinic
Currently, a majority of drug diversion in US Hospitals is detected reactively using “low-tech” methods

Q11. Within your organization approximately what percentage of drug diversion cases are initially identified via the following? Please allocate 100 points:

![Bar chart showing percentages of drug diversion cases initially identified via different methods.]

- 1. Tips from coworkers suspecting diversion: 13.97%
- 2. Automated systems to detect diversion: 17.99%
- 3. Behavior changes observed by supervisor: 18.50%
- 4. Internal data analysis, e.g., an anomalous usage report: 29.44%
- 5. Discovery of missing controlled substances: 19.28%
- 6. Patient complaint: 3.60%
- 7. Other: 5.22%
Hospitals Can’t Keep Up

An investigation takes on average 7.8 hours to complete

A majority of investigations do not confirmed diversion

84% of hospitals investigated <10 cases last year.
65% of hospitals investigated <5 Investigations

Even though a typical hospital would expect 25-75 people to be diverting
Limitations of Current Technologies

- Reactive vs. Proactive
- ADC shows dispensing and wasting only. Other sources required to see total picture:
  - Electronic Medical Record (EMR) data: administration, pain scores, etc.
  - Employee Time Clocks
  - Wholesaler Purchasing Systems
  - Internal Inventory System(s)

- Current systems miss most diverters yet flag non-diverters:
  - Motivated diverters can “trick” the system with falsified entries.
  - “Anomalous usage” reports contain too many “false positives” to investigate
  - Several large healthcare systems building advanced algorithms to reduce these errors
Assessing Current Technologies

Not Effective
• Diverters falsify records to “cover tracks”
• Most diverters go undetected

=> addiction & loss of license
=> patient injuries
=> DEA fines, etc.

Not Efficient
• Investigations manual and very time consuming
• Most following a tip or obvious clinical mistake(s)

=> typical hospital investigating < 5% of diverters
=> leading hospitals investing $ millions
Advanced Analytics was rated by HCWs as the most effective way to decrease drug diversion

Q10. Using the scale from 1 to 5, where 1 equals not at all effective and 5 equals very effective, please rate the overall effectiveness of each item in the identification and/or preventing drug diversion.
In Summary: We Have a Problem

- Numerous surveys, the American Nurses Association (ANA) & the National Council of State Boards of Nursing (NCSBN) say approximately 10% of health care workers are dependent on drugs, consistent with U.S. population.

- Hospitals agree:
  - Diversion is occurring universally
  - Most goes undetected
  - Diversion that is detected is usually too late, after:
    - deterioration in clinical performance
    - after most of the damage to the Health Care Worker, Patient, and Hospital is already done.

- Current methods for detection are both ineffective and inefficient,
  - 84% of hospitals investigate <10 cases annually
  - Even though a typical hospital would expect 25-75 people to be diverting

- Hospitals see Advanced Analytics would be more effective and efficient

2017 Porter Research Survey of 140 Hospitals
What Can a Hospital Do?

- Ignore the problem?
- Hire more investigators?
- Use advanced analytics & machine learning?
  - Build in-house detection systems?
  - Invest in commercial software?
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Overview of NIH Study

- 30 Month Study
- at 7 Hospitals
- Diversion Detection using Advanced Analytics & Machine Learning
- Expanding on research with MIT & U.S. Patent 7499766
Support Letters from 129 Hospitals, plus Law Enforcement, Schools of Pharmacy, etc.
Our NIH Fast-Track Study: Three Phases

- **Phase 1**
  - One Hospital

- **Phase 2**
  - Additional Six Hospitals

- **Phase 3**
  - Roll-out
  - In Collaboration with State & Federal Stakeholders
  - Expanding beyond hospitals to all healthcare facilities
Focus of NIH Study for Diversion Detection

• Proactive, real-time monitoring

• Transaction integration and reconciliation of
  • all healthcare workers, and
  • all drugs at risk of diversion
  • across multiple systems and departments

• Advanced analytics and machine learning

• “Alerts” signaling suspicious or non-compliant behaviors
NIH Hypotheses for Scientific Study

More Effective
- Detect diversion sooner (before addiction/injury)
- Detect diversion missed by current methods (as measured by fewer false negatives)

=> Lower risks to patient safety, DEA fines, etc.

More Efficient
- Automated reconciliation of all HCWs
- Manual investigations drop from hours to seconds (as measured by fewer false positives)

=> Lower costs to stay compliant
Data Integration: Looking Beyond the ADC

**EMR** (EPIC, AllScripts, Cerner, etc.)

**ADC** (Omnicell/Accudose, Pyxis, etc.)

**Add’l Data Sources**
- Wholesaler(s)
- HR/Payroll
- Reverse Logistics, etc.
- Invistics Data Vault™ (conversion of paper to electronic data entry)

**Drug Diversion Detection**
- Machine-learning algorithms and other advanced analytics to detect diversion
- With real-time alerts
Phase 1 Results to Date

- Partnered with leading hospital with mature diversion prevention
- Extracted data from health IT systems
- Consolidated data
- Built advanced analytics & machine learning
- Detected suspicious/non-compliant behaviors
- Discovered novel approaches for alerting
- Replicated results at a second hospital
Diversion Detection Examples
## Diversion Detection Example

### BATCH DETAILS

<table>
<thead>
<tr>
<th>NDC</th>
<th>Drug</th>
<th>Patient PHI</th>
<th>Dispensed By</th>
<th>Dispensed Date</th>
<th>Dispensed Time</th>
<th>Dispensed Quantity</th>
<th>Admin. Date</th>
<th>Admin. Time</th>
<th>Admin. Quantity</th>
<th>Status</th>
<th>Wasted Date</th>
<th>UOM</th>
<th>Invest</th>
<th>Location</th>
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<tbody>
<tr>
<td>00542-5...</td>
<td>Fentanyl IV, 2 mg/kg</td>
<td>[LINK] Nurse Smith</td>
<td>05/26/18</td>
<td>8:30 AM</td>
<td>4</td>
<td>05/26/18</td>
<td>5:45 AM</td>
<td>2</td>
<td>CS Accountability</td>
<td>05/26/18</td>
<td>CC</td>
<td>NO</td>
<td>Nursing Unit 4 East</td>
<td></td>
</tr>
<tr>
<td>00487-2...</td>
<td>Fentanyl IV, 4 mg/kg</td>
<td>[LINK] Nurse Jones</td>
<td>05/26/18</td>
<td>4:45 AM</td>
<td>2</td>
<td>05/28/18</td>
<td>8:15 AM</td>
<td>0</td>
<td>Manual inventory override</td>
<td>05/26/18</td>
<td>CC</td>
<td>NO</td>
<td>Nursing Unit 4 East</td>
<td></td>
</tr>
<tr>
<td>00220-3...</td>
<td>Fentanyl IV, 1 mg/kg</td>
<td>[LINK] Nurse Jones</td>
<td>05/31/10</td>
<td>7:00 AM</td>
<td>2</td>
<td>05/31/10</td>
<td>8:30 AM</td>
<td>1</td>
<td>Not Wasted within 30 min</td>
<td>05/31/10</td>
<td>NO</td>
<td>Nursing Unit 5 East</td>
<td></td>
<td></td>
</tr>
<tr>
<td>00542-5...</td>
<td>Fentanyl IV, 2 mg/kg</td>
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<td>05/31/10</td>
<td>10:00 AM</td>
<td>4</td>
<td>05/31/10</td>
<td>12:00 PM</td>
<td>2</td>
<td>Not Wasted within 30 min</td>
<td>05/31/10</td>
<td>NO</td>
<td>Nursing Unit 5 East</td>
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</tr>
<tr>
<td>00487-2...</td>
<td>Fentanyl IV, 4 mg/kg</td>
<td>[LINK] Nurse Smith</td>
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<td>9:30 AM</td>
<td>3</td>
<td>05/31/10</td>
<td>2:30 PM</td>
<td>2</td>
<td>Not Wasted within 30 min</td>
<td>05/31/10</td>
<td>NO</td>
<td>Nursing Unit 5 East</td>
<td></td>
<td></td>
</tr>
<tr>
<td>00220-3...</td>
<td>Fentanyl IV, 1 mg/kg</td>
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<td>05/31/10</td>
<td>11:00 AM</td>
<td>2</td>
<td>05/31/10</td>
<td>11:45 AM</td>
<td>1</td>
<td>Not Wasted within 30 min</td>
<td>05/31/10</td>
<td>NO</td>
<td>Nursing Unit 5 East</td>
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<tr>
<td>#434</td>
<td>Pump Key # 434</td>
<td>[LINK] Nurse Willis</td>
<td>05/26/18</td>
<td>6:00 AM</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td>Pump key not returned within 4 hrs</td>
<td></td>
<td>KEY</td>
<td>NO</td>
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<td></td>
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<tr>
<td>00542-5...</td>
<td>Fentanyl IV, 2 mg/kg</td>
<td>[LINK] Nurse Davis</td>
<td>05/26/18</td>
<td>7:00 AM</td>
<td>1</td>
<td>05/28/18</td>
<td>7:46 AM</td>
<td>0</td>
<td>Pyxis Count Discrep.</td>
<td>05/26/18</td>
<td>CC</td>
<td>NO</td>
<td>Nursing Unit 4 East</td>
<td></td>
</tr>
<tr>
<td>00220-3...</td>
<td>Fentanyl IV, 1 mg/kg</td>
<td>[LINK] Nurse Smith</td>
<td>05/26/18</td>
<td>6:45 AM</td>
<td>2</td>
<td>05/28/18</td>
<td>9:46 AM</td>
<td>2</td>
<td>Waste not reported in 4 hrs</td>
<td>05/28/18</td>
<td>CC</td>
<td>NO</td>
<td>Nursing Unit 4 East</td>
<td></td>
</tr>
</tbody>
</table>
Real-Time Alert Example e.g., for a Nurse Manager

- Highest priority alerts send a text to Nurse Manager
- Click the message to see the alert on your cell phone
Advanced Analytics & Machine Learning Example

Drug Reconciliation Dispensing - Hospital (Hospital Demo)

Select Date Range:
- 1/1/2017
- 12/31/2017

Select Location:
- AHOSP

Select Health Care Worker:
- Nurse Brown
- Nurse Davis
- Nurse Jones
- Nurse Moore

UPDATE RESULTS

Nurse Dispensed Over Time

![Graph showing nurse dispensed over time]

<table>
<thead>
<tr>
<th>Nurse Brown</th>
<th>DISPENSED DATE</th>
<th>DISPENSED TIME</th>
<th>DISPENSED QUANTITY</th>
<th>ADMIN DATE</th>
<th>ADMIN TIME</th>
<th>ADMIN QUANTITY</th>
<th>WASTED DATE</th>
<th>WASTED TIME</th>
<th>WASTED QUANTITY</th>
<th>STATUS</th>
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</thead>
<tbody>
<tr>
<td>Fentanyl IV, 1 mg/kg</td>
<td>1/3/2017</td>
<td>11:00 AM</td>
<td>2200</td>
<td>12/2/2017</td>
<td>11:50 AM</td>
<td>2200</td>
<td>6/3/2017</td>
<td>12:00 PM</td>
<td>2200</td>
<td>OK</td>
</tr>
<tr>
<td>Fentanyl IV, 1 mg/kg</td>
<td>1/5/2017</td>
<td>10:00 AM</td>
<td>2200</td>
<td>12/5/2017</td>
<td>10:50 AM</td>
<td>2200</td>
<td>6/5/2017</td>
<td>10:00 AM</td>
<td>2200</td>
<td>OK</td>
</tr>
<tr>
<td>Fentanyl IV, 1 mg/kg</td>
<td>1/7/2017</td>
<td>10:30 AM</td>
<td>2200</td>
<td>12/7/2017</td>
<td>10:45 AM</td>
<td>2200</td>
<td>6/7/2017</td>
<td>10:30 AM</td>
<td>2200</td>
<td>OK</td>
</tr>
<tr>
<td>Fentanyl IV, 1 mg/kg</td>
<td>1/9/2017</td>
<td>4:00 PM</td>
<td>2200</td>
<td>12/9/2017</td>
<td>4:45 PM</td>
<td>2200</td>
<td>6/9/2017</td>
<td>4:00 PM</td>
<td>2200</td>
<td>OK</td>
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<tr>
<td>Fentanyl IV, 1 mg/kg</td>
<td>1/11/2017</td>
<td>4:00 PM</td>
<td>2200</td>
<td>12/11/2017</td>
<td>4:45 PM</td>
<td>2200</td>
<td>6/11/2017</td>
<td>4:00 PM</td>
<td>2200</td>
<td>OK</td>
</tr>
<tr>
<td>Fentanyl IV, 1 mg/kg</td>
<td>1/13/2017</td>
<td>10:30 AM</td>
<td>2200</td>
<td>12/13/2017</td>
<td>10:45 PM</td>
<td>2200</td>
<td>6/13/2017</td>
<td>10:30 AM</td>
<td>2200</td>
<td>OK</td>
</tr>
<tr>
<td>Fentanyl IV, 1 mg/kg</td>
<td>1/15/2017</td>
<td>4:00 PM</td>
<td>2200</td>
<td>12/15/2017</td>
<td>4:45 PM</td>
<td>2200</td>
<td>6/15/2017</td>
<td>4:00 PM</td>
<td>2200</td>
<td>OK</td>
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<tr>
<td>Fentanyl IV, 1 mg/kg</td>
<td>1/17/2017</td>
<td>3:00 PM</td>
<td>2200</td>
<td>12/17/2017</td>
<td>3:15 PM</td>
<td>2200</td>
<td>6/17/2017</td>
<td>3:00 PM</td>
<td>2200</td>
<td>OK</td>
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<tr>
<td>Fentanyl IV, 1 mg/kg</td>
<td>1/19/2017</td>
<td>8:00 AM</td>
<td>2200</td>
<td>12/19/2017</td>
<td>8:15 AM</td>
<td>2200</td>
<td>6/19/2017</td>
<td>8:00 AM</td>
<td>2200</td>
<td>OK</td>
</tr>
</tbody>
</table>
Advanced Analytics & Machine Learning Example

Hospital Pain Scores V2 (Hospital Demo)

Pain Score & Admin. Quantity by Day

<table>
<thead>
<tr>
<th>HEALTH CARE WORKER</th>
<th>Average Pain Score</th>
<th>Average Admin. Quantity Per Day</th>
<th>Average MEQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nurse Brown</td>
<td>2.25</td>
<td>2.30</td>
<td>14.20</td>
</tr>
<tr>
<td>Nurse Davis</td>
<td>2.63</td>
<td>5.00</td>
<td>7.50</td>
</tr>
<tr>
<td>Nurse Jones</td>
<td>2.75</td>
<td>1.25</td>
<td>8.75</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>PROCEDURE NUMBER</th>
<th>HEALTH CARE WORKER</th>
<th>DIAGNOSTIC CD</th>
<th>DRUG</th>
<th>ADMIN_DATE &amp; TIME</th>
<th>ADMIN_QUANTITY</th>
<th>MORPHINE EQUIVALENT_DOSE</th>
<th>PHLEMR #</th>
<th>PAIN SCORE</th>
</tr>
</thead>
<tbody>
<tr>
<td>204-1345</td>
<td>Nurse Brown</td>
<td>K44</td>
<td>Morphine 15 MG Oral Dosage</td>
<td>1/1/2017 9:00:00 AM</td>
<td>2</td>
<td>20.00</td>
<td>XYZ-215</td>
<td>3.00</td>
</tr>
<tr>
<td>204-1346</td>
<td>Nurse Brown</td>
<td>K44</td>
<td>Morphine 15 MG Oral Dosage</td>
<td>1/1/2017 9:00:00 AM</td>
<td>2</td>
<td>20.00</td>
<td>XYZ-215</td>
<td>3.00</td>
</tr>
<tr>
<td>204-1347</td>
<td>Nurse Davis</td>
<td>K44</td>
<td>Morphine 15 MG Oral Dosage</td>
<td>1/1/2017 6:00:00 PM</td>
<td>2</td>
<td>20.00</td>
<td>XYZ-215</td>
<td>3.00</td>
</tr>
<tr>
<td>204-1348</td>
<td>Nurse Brown</td>
<td>K44</td>
<td>Hydrocodone 5 MG Tablet</td>
<td>1/2/2017 8:00:00 AM</td>
<td>4</td>
<td>20.00</td>
<td>XYZ-215</td>
<td>8.00</td>
</tr>
</tbody>
</table>
Interested in Collaborating on this NIH Study?

- **Phase 1**
  - One Hospital

- **Phase 2**
  - Additional Six Hospitals

- **Phase 3**
  - Roll-out
  - In Collaboration with State & Federal Stakeholders
  - Expanding beyond hospitals to all healthcare facilities

National Institute on Drug Abuse
Agenda

- Introductions
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On-site inspection to physically count (selected) controlled substances

Compare this quantity to the following:

• Start with most recent biennial inventory listing form, quantity and strength of each medication.
• Add quantity received, and subtract quantity dispensed/administered, returned, destroyed, reported lost/stolen, or otherwise disposed of
• The result is the closing inventory expected

If the two don’t match, expect:

• “accountability audits revealed shortages or overages”
• Memorandum of Understanding with DEA
• $$$ Fines
Challenges with DEA Accountability Audits

• Biennial inventories are time-consuming and difficult
• Discrepancies will occur as a result of:
  • Diversion
  • Or any mistake in purchasing, movements, wasting, etc.
• Very difficult to assemble all the data from various hospital systems (Purchasing, EMR, ADC, reverse distributors, etc.)
Automated DEA Accountability Audits in Health Care: Closed Loop Inventory Management & Diversion Detection

- Wholesaler
- Drug Manufacturer
- Other Hospitals/Pharmacies
- CII Safe
- ADMs
- Compounding
- Repackaging
- Satellite Pharmacies
- Disposal
- Waste
- wastes

forward flow of product
reverse flow of product

Patient
Automated DEA Accountability Audits in Health Care: Example of Streamlined Biennial Inventory & Audits
Numerous Organizations Using Machine Learning to Detect Diversion on Social Media Sites

- Non-for-profit Consortiums, e.g., Researched Abuse, Diversion and Addiction-Related Surveillance (RADARS®) System, including Web Monitoring, Impaired HealthCare Worker Program and StreetRX.com
- Hospital Systems, e.g., Kaiser Permanente's effort to detect resold prescriptions on social media and dark web sites.
- For-profit Companies, e.g., Pondera software to detect drug diversion by merging private, public, and social media databases
- Plus active research, largely NIH-funded, e.g.,
  - Sarker & Gonzalez “A corpus for mining drug-related knowledge from Twitter chatter” Data in Brief 10 (2017) 122–131
Questions? Suggestions? Collaborations?

- We welcome questions, suggestions, and collaboration!

- Thank you,

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  (770) 559-6386 x209