A. JAMES CLARK SCHOOL OF ENGINEERING
Institute for Systems Research
APPLIED RESEARCH LABORATORY FOR INTELLIGENCE AND SECURITY

Moving Beyond 3D PDFs: *Envisioning AI-Powered, Data-Driven Product Lifecycle Management*

Thomas Hedberg, Ph.D., P.E.
Associate Director for Education Programs, Institute for Systems Research
Mission Director, Acquisition & Industrial Security, ARLIS

PLM Road Map™ & PDT North America 2024
Value Drivers for Digitalization of the Product Lifecycle
Insights for the PLM Professional—Why the investment, what are the returns, and how are they achieved?
May 8 & 9
CIMdata eurostep

"The purpose of a business is to create a customer."

-- Peter Drucker

Drucker, P. F. (1954). *The practice of management* (1st ed.). Harper.

2

Presentation Outline

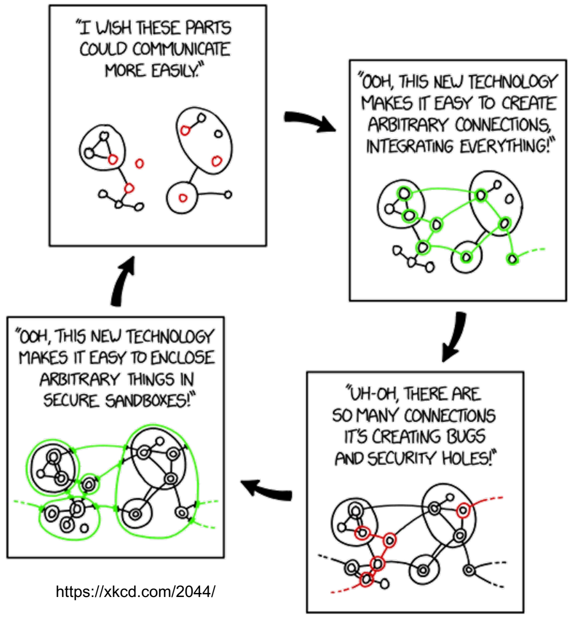
- What is the problem?
- What are we doing now?
- What can we do to improve our future?

3

The Problem

The Connection Interoperability Paradox

"All I want is a secure system where it's easy to do anything I want. Is that so much to ask?"

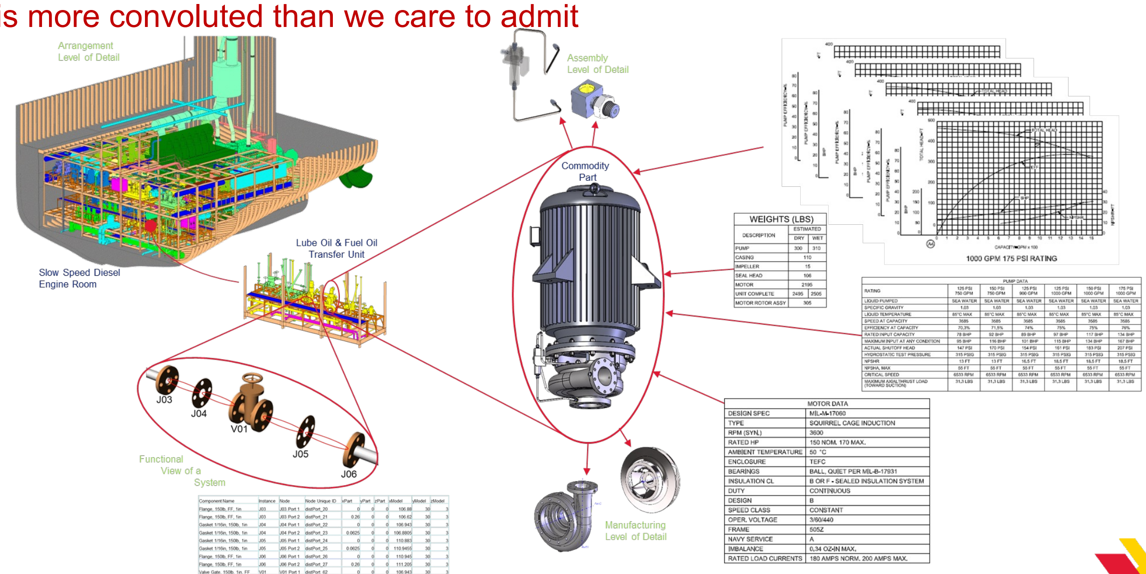


https://xkcd.com/2044/

5

3D Model-Based Definition

is more convoluted than we care to admit

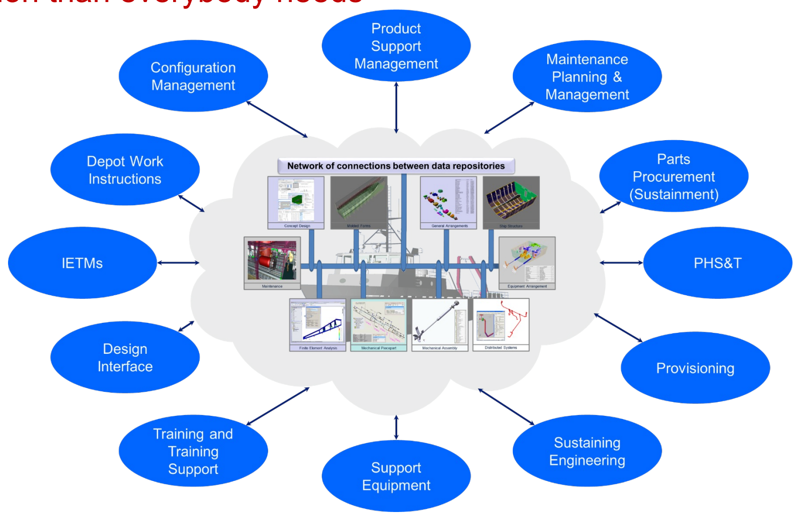


Do we really think there is a SINGLE Authoritative Source of Truth?

6

3D Model-Based Definition

has more information than everybody needs



Do you really want to expose all data to all processes?

7

Digital Thread is an Information Supply Chain

Thousands of Threads
Thousands of Opportunities for Gains
Thousands of Opportunities for Errors

8

But we've been saying it for years…

- DoD Digital Engineering Strategy says digital transformation will address challenges associated with complexity, uncertainty, and rapid change in deploying and using systems
- McKinsey recommends using a holistic and systematic analysis in making decisions on how and where to best deploy and maintain technologies and capabilities
- MITRE says U.S. needs better use of its existing resources to identify, protect, detect, respond to, and recover from network and supply chain threats – we must protect systems as much as we try to deploy them.

9

Digital Thread is an Information Supply Chain

So how can we expect a 3D PDF to be the interface to all of that?

Thousands of Threads
Thousands of Opportunities for Gains
Thousands of Opportunities for Errors

10

Data-Driven PLM: Expectations vs. Reality

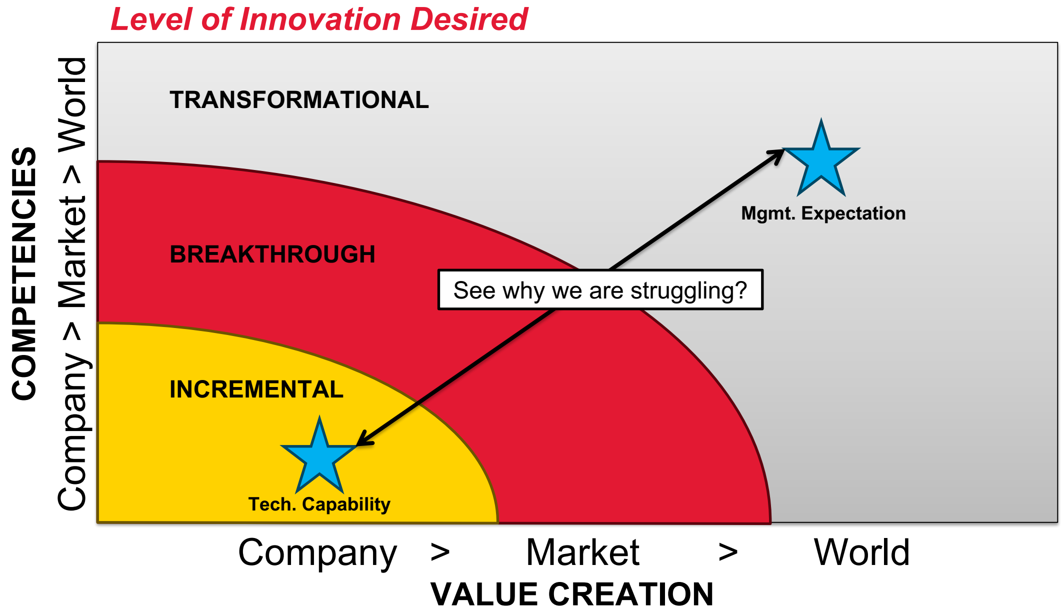


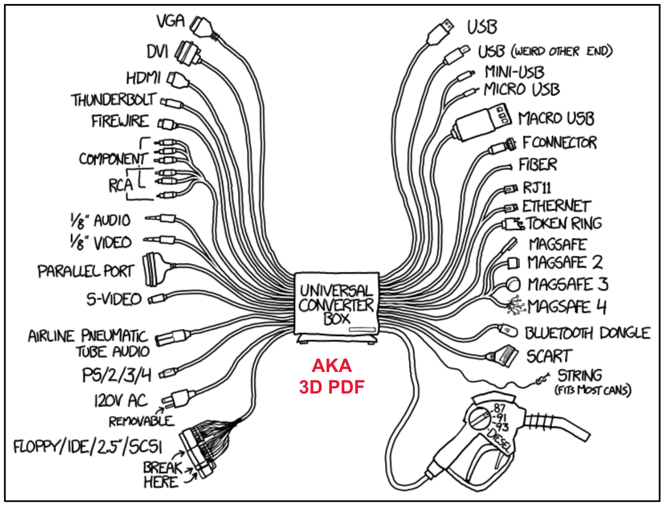
Figure: https://www.creativerealities.com/innovationist-blog/bid/49954/the-three-levels-of-innovation

11

State of the Art

A look back at our historical journey

The Connection Interoperability Paradox

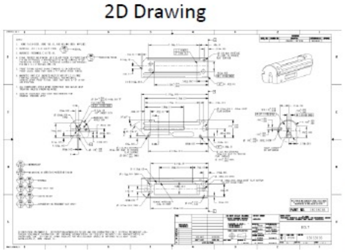


https://xkcd.com/1406

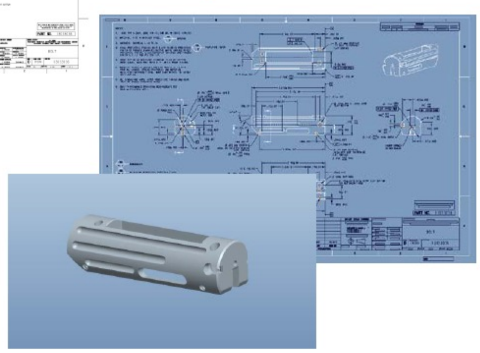
13

Tech Data Evolution

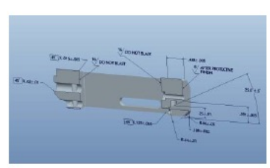
2D Drawing



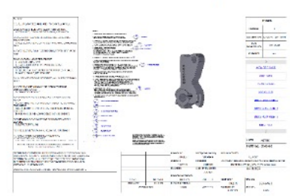
3D TDP



Fully Annotated Models

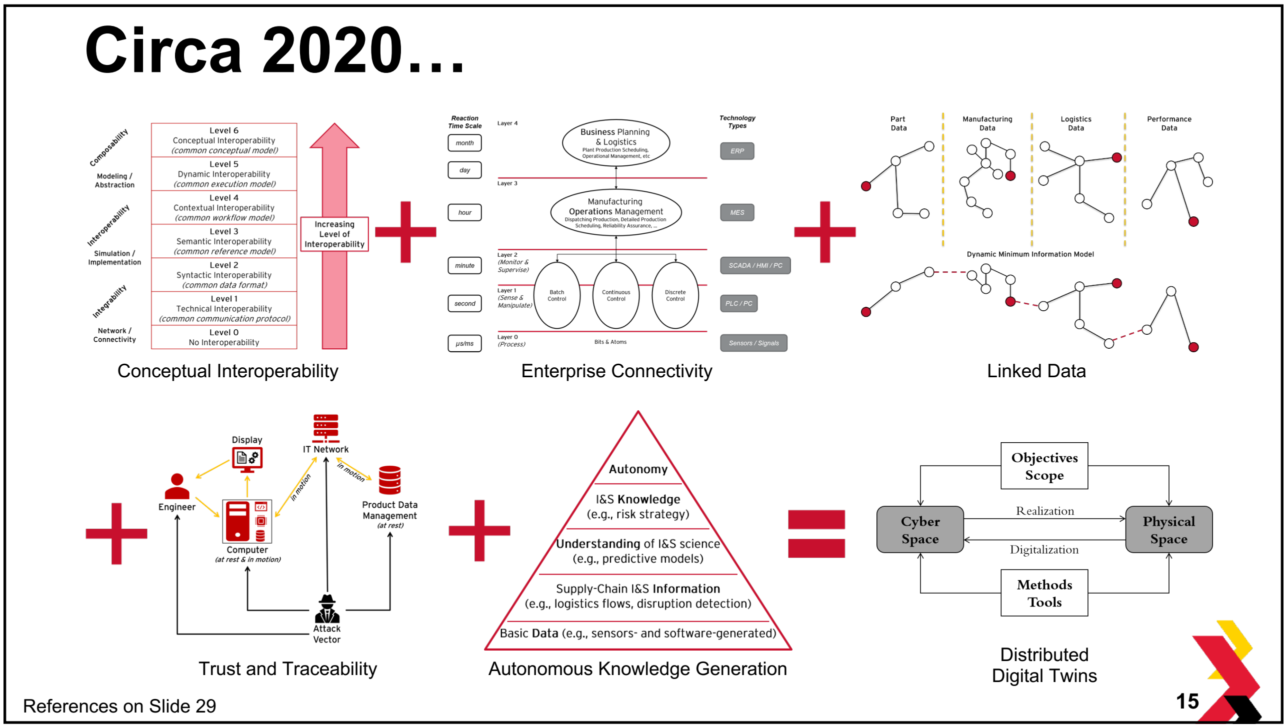


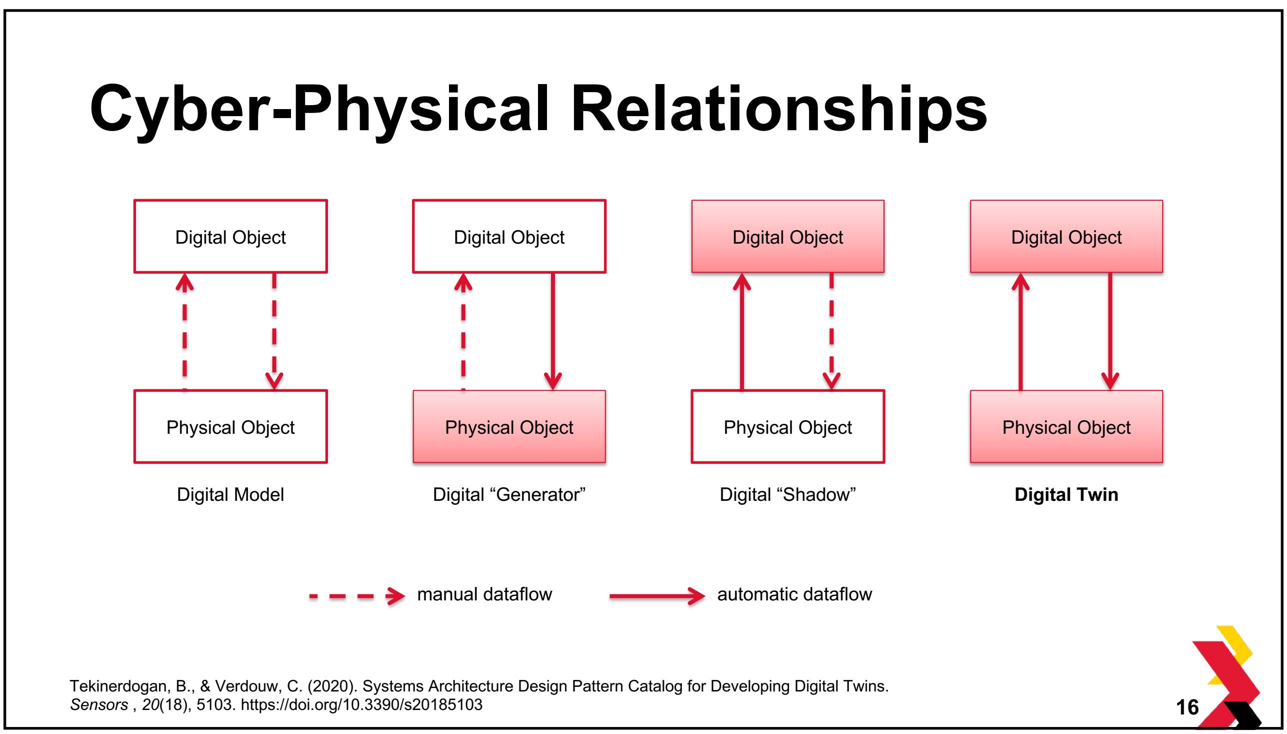
3Di pdf



Windham, J. (2019). MIL-STD-31000B Update and 3Di pdf Technical Data. In T. D. Hedberg Jr & M. Carlisle (Eds.), *Proceedings of the 10th Model-Based Enterprise Summit (MBE 2019)* (pp. 41–44). National Institute of Standards and Technology. https://doi.org/10.6028/NIST.AMS.100-24

14

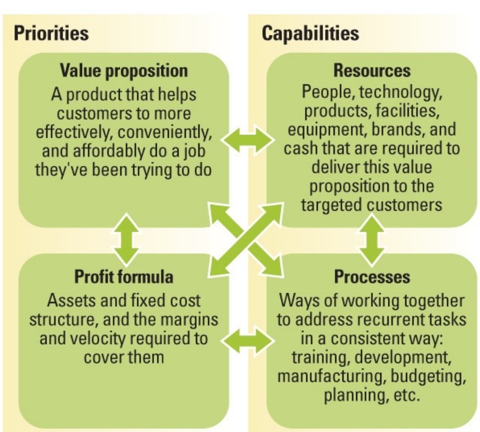

Circa 2020…
Level 6
Conceptual Interoperability
(common conceptual model)
Level 5
Dynamic Interoperability
(common execution model)
Level 4
Contextual Interoperability
(common workflow model)
Level 3
Semantic Interoperability
(common reference model)
Level 2
Syntactic Interoperability
(common data format)
Level 1
Technical Interoperability
(common communication protocol)
Level 0
No Interoperability
Composability
Modeling / Abstraction
Interoperability
Simulation / Implementation
Integrability
Network / Connectivity
Increasing Level of Interoperability
Conceptual Interoperability
Business Planning & Logistics
Manufacturing Operations Management
Batch Control
Continuous Control
Discrete Control
ERP
MES
SCADA / HMI / PC
PLC / PC
Sensors / Signals
Enterprise Connectivity
Part Data
Manufacturing Data
Logistics Data
Performance Data
Dynamic Minimum Information Model
Linked Data
Display
IT Network
Engineer
Product Data Management
(at rest)
Computer
(at rest & in motion)
Attack Vector
Trust and Traceability
Autonomy
I&S Knowledge
(e.g., risk strategy)
Understanding of I&S science
(e.g., predictive models)
Supply-Chain I&S Information
(e.g., logistics flows, disruption detection)
Basic Data (e.g., sensors- and software-generated)
Autonomous Knowledge Generation
Objectives Scope
Cyber Space
Realization
Digitalization
Physical Space
Methods Tools
Distributed Digital Twins
References on Slide 29
15


Cyber-Physical Relationships
Digital Object
Physical Object
Digital Model
Digital Object
Physical Object
Digital "Generator"
Digital Object
Physical Object
Digital "Shadow"
Digital Object
Physical Object
Digital Twin
manual dataflow
automatic dataflow
Tekinerdogan, B., & Verdouw, C. (2020). Systems Architecture Design Pattern Catalog for Developing Digital Twins. Sensors , 20(18), 5103. https://doi.org/10.3390/s20185103
16

Recommendations

Data-Driven PLM Needs a Business Model

Elements of a Business Model

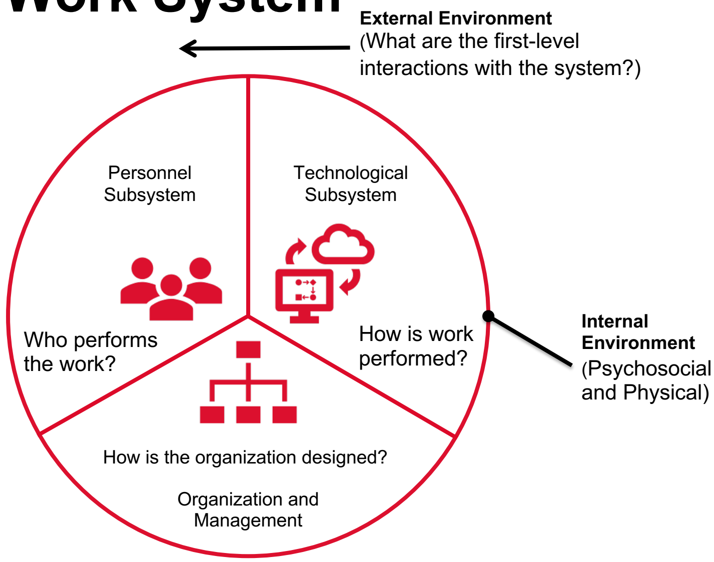


- How will AI-enabled, data-driven PLM processes improve value?
- What are the affects on resources and processes?
- Are our current work systems and business models still relevant?

Figure: https://sloanreview.mit.edu/article/the-hard-truth-about-business-model-innovation/

Redesign the Work System

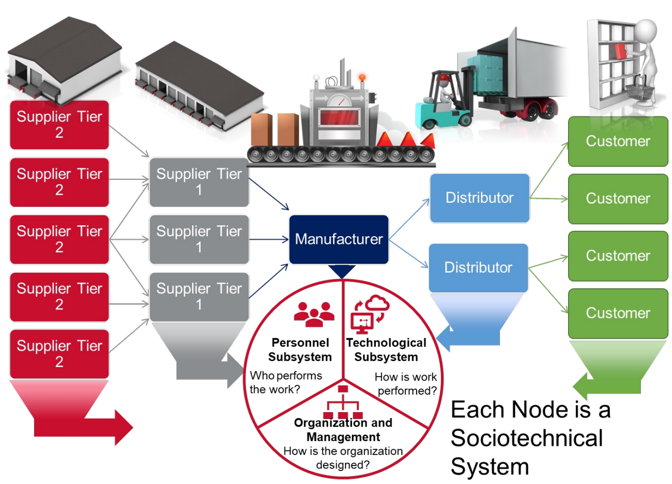
STS Elements



Kleiner, B. M. (2008). Macroergonomics: Work System Analysis and Design. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *50*(3), 461–467. https://doi.org/10.1518/001872008X288501

PLM Needs Information Supply Chains

Supply Chain Resilience
- Node-level
- Sector-level
- Network-level
- End-to-end
- Full-lifecycle



Each Node is a Sociotechnical System

IT/OT Validation
- Interface between humans, digital, and physical world
- Root of data and control

What is to be made? How to make it?

Information Flows

What was made? How was it made?

Technical Information Assurance
- Digital Engineering
- Digital Twin
- …

Let's Discuss Use Cases

…in less than 2 minutes!

<<domain>> Design: Design and Simulation

- **Use Case:** AI-driven tools assist in the design process by offering automated suggestions for material choices and design modifications based on desired product performance characteristics and regulatory compliance. AI can also simulate how a product will perform under various conditions, reducing the need for physical prototypes.
- **Benefits:** Speeds up the design process, reduces costs associated with physical prototyping, and improves product performance and compliance.
- **Ready for Production?** 

22

<<domain>> Realize:
Predictive Maintenance and Quality Control

- **Use Case:** AI algorithms analyze real-time data from production equipment to predict maintenance needs before failures occur, reducing downtime and maintenance costs. Similarly, AI can analyze product quality data to identify potential issues early, ensuring high-quality output.
- **Benefits:** Minimizes unplanned downtime, extends equipment life, and ensures consistent product quality.
- **Ready for Production?**

23

<<domain>> Realize:
Supply Chain Optimization

- **Use Case:** AI models forecast demand more accurately by analyzing market trends, past sales data, and external factors like economic conditions or weather patterns. This enables more efficient inventory management and optimized production planning.
- **Benefits:** Reduces excess inventory costs, improves delivery times, and enhances responsiveness to market changes.
- **Ready for Production?**

24

<<domain>> Service:
Post-Sale Product Monitoring and Feedback

- **Use Case:** AI tools analyze data gathered from product usage in the field to provide insights into how products perform over their lifespan, which can inform future design improvements and proactive customer service interventions.

- **Benefits:** Enhances product development with real user data, improves customer service, and supports predictive maintenance services.

- **Ready for Production?**  With caveats

25

Closing Thoughts

- AI-driven PLM systems may enable rapid adaptation to market changes and technological advancements, fostering innovation through predictive analytics and personalized product development.

- It also introduces complexity in integration and potential information assurance concerns around data CIA* and decision-making transparency. It's crucial to approach AI integration with a balanced understanding of its capabilities and limitations

- Implementing AI effectively demands strong data governance, skilled talent, and continuous investment in technology upgrades. Organizations must manage these foundational elements before fully leveraging AI capabilities.

*CIA: Confidentiality, Integrity, Availability

26

Snapshot About Me

Education

Ph.D., Industrial and Systems Engineering
from Virginia Polytechnic Institute and State University, Blacksburg VA

M.Eng., Engineering Management
from The Pennsylvania State University, University Park PA

B.S., Aeronautical & Astronautical Engineering
Minor in Political Science focused on Science and Technology policy
from Purdue University, West Lafayette IN

Professional Experience

- Current: Research Engineer (VPR & ISR)
- 2014-2020: Program Manager, NIST
- 2005 to 2014, Aerospace Sector, Phoenix AZ

- Internationally known as the Model-Based Enterprise (MBE) Evangelist

More on LinkedIn

27

Thank you. Questions?

Thomas Hedberg, Ph.D., P.E.
Associate Director for Education Programs
Institute for Systems Research
Mission Director, Acquisition and Industrial Security
Applied Research Laboratory for Intelligence and Security

thedberg@umd.edu

A. JAMES CLARK SCHOOL OF ENGINEERING
Institute for Systems Research
APPLIED RESEARCH LABORATORY FOR INTELLIGENCE AND SECURITY

28

Slide 15 References

- **Conceptual Interoperability**
  - Tolk, A., & Muguira, J. A. (2003). The levels of conceptual interoperability model. Proceedings of the 2003 Fall Simulation Interoperability Workshop, 7, 1–11. https://www.sisostds.org/DesktopModules/Bring2mind/DMX/API/Entries/Download?Command=Core_Download&EntryId=24721&PortalId=0&TabId=105
  - Wang, W., Tolk, A., & Wang, W. (2009). The Levels of Conceptual Interoperability Model: Applying Systems Engineering Principles to M&S. Proceedings of the 2009 Spring Simulation Multiconference, 1–9. https://dl.acm.org/doi/abs/10.5555/1639809.1655398
  - Helu, M., Sprock, T., Hartenstine, D., Venketesh, R., & Sobel, W. (2020). Scalable data pipeline architecture to support the industrial internet of things. CIRP Annals. https://doi.org/10.1016/j.cirp.2020.04.006
- **Enterprise Connectivity**
  - Hedberg, T. D., Jr, Manas, B., & Camelio, J. A. (2020). Using graphs to link data across the product lifecycle for enabling smart manufacturing digital threads. Journal of Computing and Information Science in Engineering, 20(1), 1–29. https://doi.org/10.1115/1.4044921
- **Linked Data**
  - Bernstein, W. Z., Hedberg, T. D., Jr, Helu, M., & Feeney, A. B. (2017). Contextualising manufacturing data for lifecycle decision-making. *International Journal of Product Lifecycle Management*, *10*(4), 326. https://doi.org/10.1504/IJPLM.2017.090328
  - Hedberg, T. D., Jr, Feeney, A. B., Helu, M., & Camelio, J. A. (2017). Toward a Lifecycle Information Framework and Technology in Manufacturing. *Journal of Computing and Information Science in Engineering*, *17*(2), 021010. https://doi.org/10.1115/1.4034132
  - Hedberg, T. D., Jr, Manas, B., & Camelio, J. A. (2020). Using graphs to link data across the product lifecycle for enabling smart manufacturing digital threads. *Journal of Computing and Information Science in Engineering*, *20*(1), 1–29. https://doi.org/10.1115/1.4044921
- **Trust and Traceability**
  - Hedberg, T., Jr, Helu, M., Krima, S., & Feeney, A. B. (2020). Recommendations on Ensuring Traceability and Trustworthiness of Manufacturing-Related Data (AMS 300-10). National Institute of Standards and Technology. https://doi.org/10.6028/NIST.AMS.300-10
  - Hedberg, T., Jr, Krima, S., & Camelio, J. A. (2019). Method for Enabling a Root of Trust in Support of Product Data Certification and Traceability. Journal of Computing and Information Science in Engineering, 19(4), 041003. https://doi.org/10.1115/1.4042839
- **Autonomous Knowledge Generation**
  - Feng, S. C., Bernstein, W. Z., Hedberg, T., Jr, & Barnard Feeney, A. (2017). Toward Knowledge Management for Smart Manufacturing. Journal of Computing and Information Science in Engineering, 17(3), 031016. https://doi.org/10.1115/1.4037178
- **Distributed Digital Twins**
  - Shao, G., & Helu, M. (2020). Framework for a digital twin in manufacturing: Scope and requirements. Manufacturing Letters, 24, 105–107. https://doi.org/10.1016/j.mfglet.2020.04.004

29

Disclaimer

Any opinions, findings, conclusions, or recommendations expressed in this publication do not necessarily reflect the views of the Department of Defense (DoD). Additionally, neither the DoD nor any of its employees make any warranty, expressed or implied, nor assume any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, product, or process included in this publication.

Certain commercial entities, equipment, or materials may be identified in this document to describe an experimental procedure or concept adequately. Such identification is not intended to imply recommendation or endorsement by the ARLIS, the University of Maryland, or the DoD, nor is it intended to imply that the entities, materials, or equipment are necessarily the best available for the purpose.

30