# Are you ready to engineer and sustain AI systems?

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# About me

Carnegie Mellon University


PhD in Computational Design from CMU
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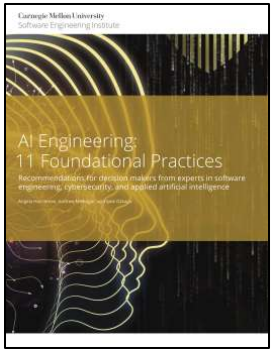


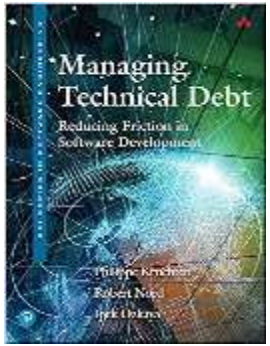


Body of work at the intersection of architecture design, analysis and tradeoffs


IEEE Software Magazine
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# Carnegie Mellon University Software Engineering Institute

## CMU – Global Research University

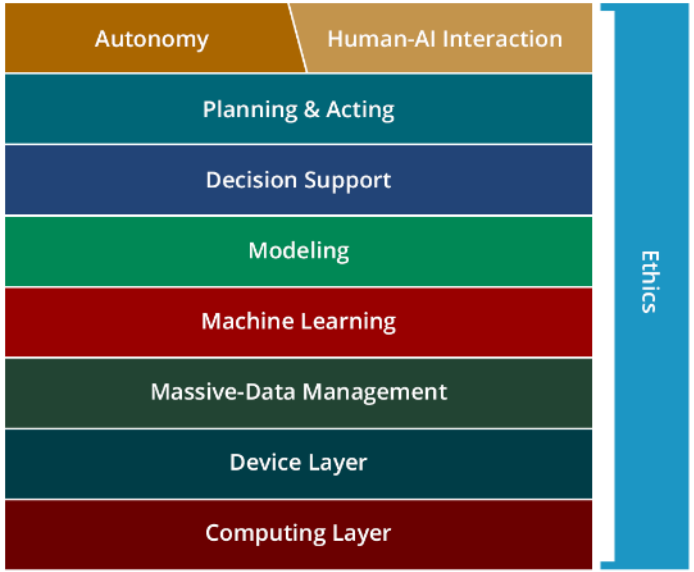
- CMU challenges the curious and passionate to imagine and deliver work that matters
- 1,442 total faculty, 13,285 students, 130 research centers
- Ranked #17 U.S. university, #1 for Computer Science, #1 for College of Engineering[1]
- Main campus and research centers in Pittsburgh, PA; Silicon Valley, CA; and Doha, Qatar

## CMU – Software Engineering Institute

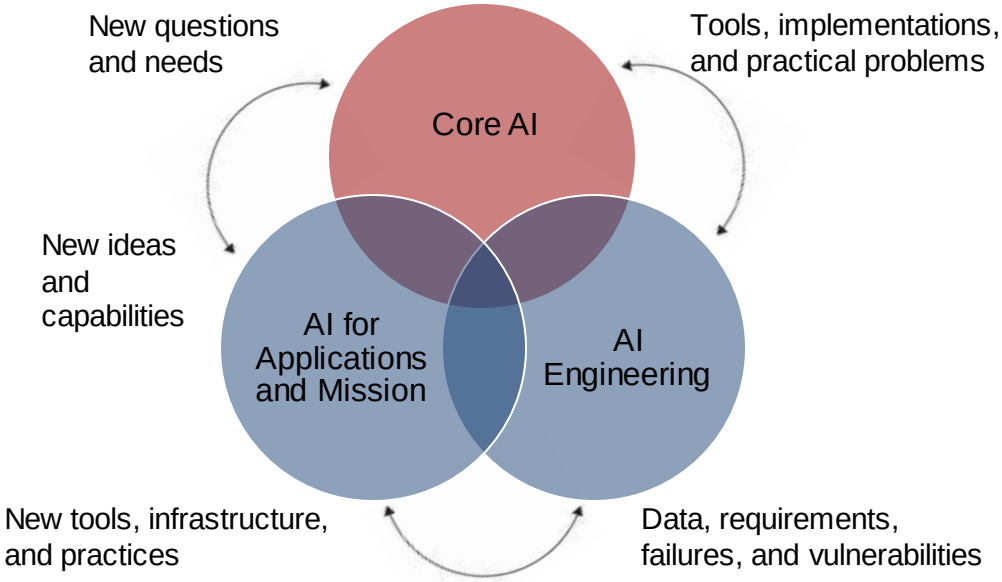
- Founded in 1984 as a DoD R&D Federally Funded Research and Development Center
- Focused on software, cyber, and AI
- 730 employees
- HQ in Pittsburgh, PA; other offices in DC and CA
- ~$145M annual funding / ~$21M DoD (USD R&E) 6.2 and 6.3 Line funding

[1] 2021 *US News and World Report*

# AI at CMU and AI at the SEI



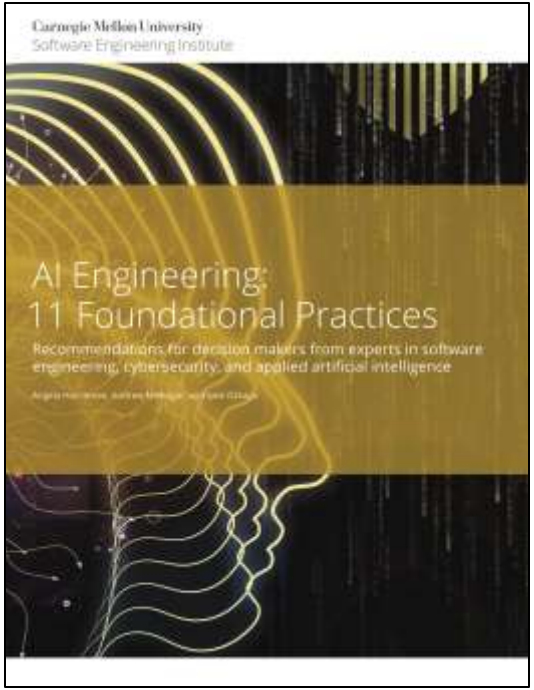

**CMU AI Stack***




**AI at the SEI**

* A. W. Moore, M. Hebert, S. Shaneman, "The AI stack: a blueprint for developing and deploying artificial intelligence," Proc. SPIE 10635, Ground/Air Multisensor Interoperability, Integration, and Networking for Persistent ISR IX, 106350C (4 May 2018); https://doi.org/10.1117/12.2309483

# AI-enabled systems are software systems!

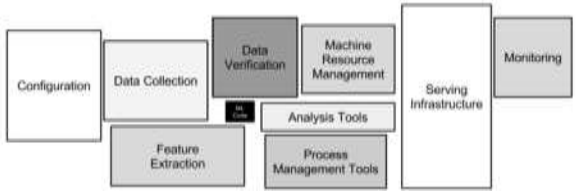



A. Horneman, A. Mellinger, I. Ozkaya. *AI Engineering: 11 Foundational Practices*. Pittsburgh: Carnegie Mellon University Software Engineering Institute, 2019.

An **AI-enabled system** is a **software system** with one or more **AI component(s)** that need to be developed, deployed, and sustained along with the other software and hardware elements of the system.

- **Disciplined software engineering** and **cybersecurity practices** are essential starting points in adopting AI.
- The interaction between **software, data, and AI components** (e.g., ML models) creates unique challenges and requires software design and architecture approaches to be incorporated early and continuously.

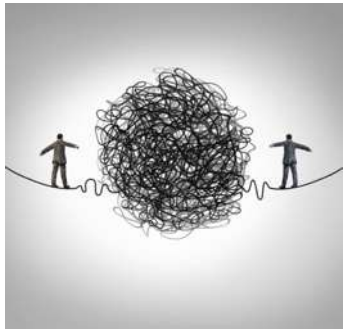
# Can we Design and Analyze AI-Enabled Systems Predictably?




What are ML components' dependencies?

How to model and analyze high-priority quality attributes of AI-enabled systems

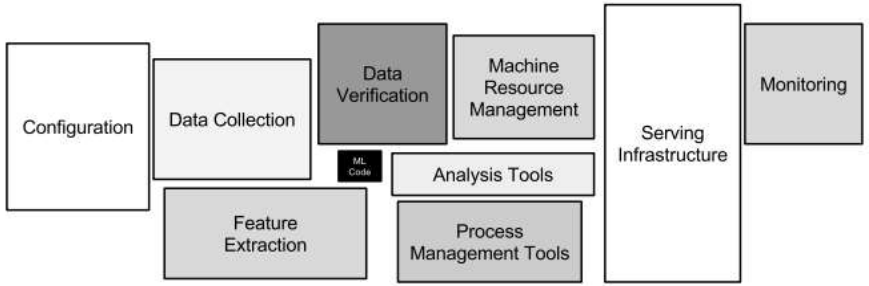
How can different aspects of monitorability inform ML-enabled system evolution?



How can we model for changing anything changes everything principle?

# Architecture Challenge #1: Lack of Systems Perspective

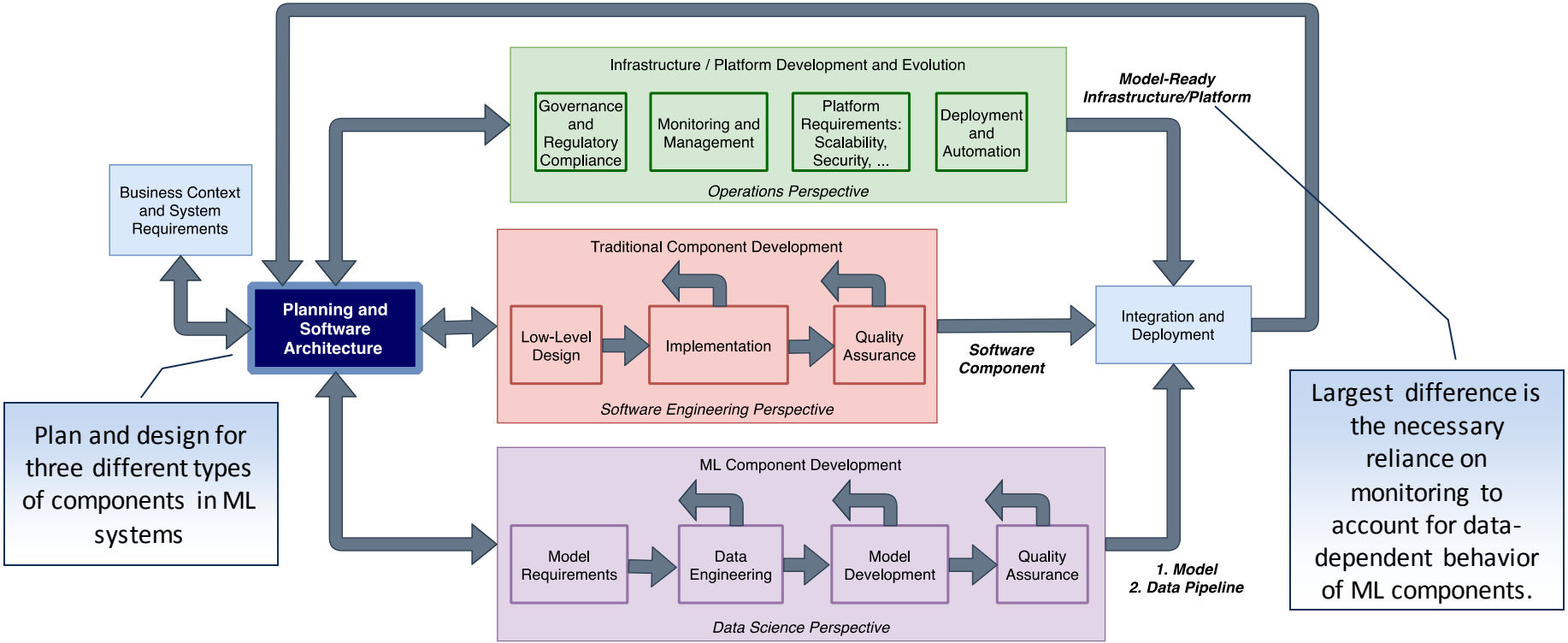
We fail to elicit, design for, and sustain the vast amount of other software components that AI components need to interact with




*"Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex." [Sculley 2015]*

Source: Sculley, D., Holt, G., Golovin, D., Davydov, E., Phillips, T., Ebner, D., ... & Dennison, D. (2015). Hidden Technical Debt in Machine Learning Systems. In Advances in neural information processing systems (pp. 2503-2511).
http://papers.nips.cc/paper/5656-hidden-technical-debt-in-machine-learning-systems.pdf

# Recommendation: Manage AI Component, Data, and Architectural Dependencies




Grace A. Lewis, Stephany Bellomo, Ipek Ozkaya:
Characterizing and Detecting Mismatch in Machine-Learning-Enabled Systems. WAIN@ICSE 2021: 133-140

# Architecture Challenge #2 : Inability to separate data and system attributes

Key AI-specific concerns, when not approach with a systems perspective, create unanticipa system-level failures, e.g.

- data-dependent behavior
- shared resource dependencies
- misaligned runtime environments for AI components

Key data concerns create unanticipated AI failure

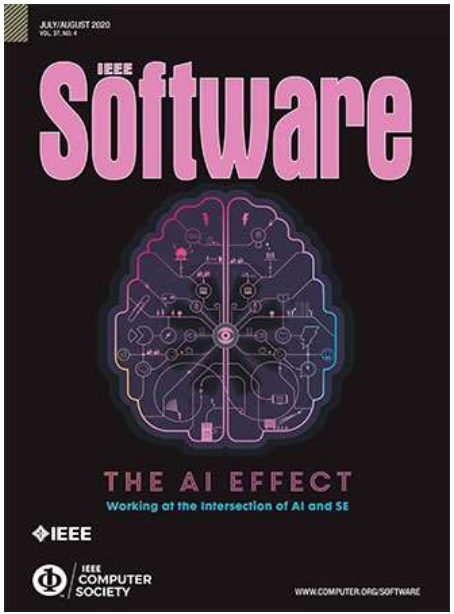
- ethics, bias, fairness
- incorrect outcomes

L. Pons, I. Ozkaya. Priority Quality Attributes for Engineering AI-enabled Systems. *Association for the Advancement of Artificial Intelligence AI in Public Sector Workshop.* Washington, DC, November 7-9, 2019.

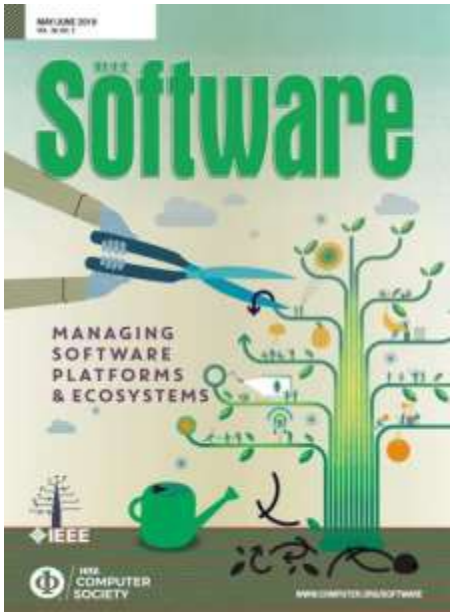
# Recommendation: Understand High-Priority Quality Attributes of ML-Enabled Systems

| ML-related software design challenge | You will desire… | At a minimum, you need to … |
|---|---|---|
| ML components need to be designed such that attributes can be observed | monitorability | • include monitoring components to observe and manage data changes over time<br>• identify attributes to expose |
| AI introduces new attack surfaces. | security | • decouple model changes from the rest of the system<br>• build in capabilities to modify the systems to ease deploying retrained models |
| Tight coupling of data and models may limit implementing privacy protections. | privacy | • decouple data stores and their interactions with other systems as much as possible<br>• isolate changes and updates to as few locations as possible |
| Software update cycles may not adequately address data changes and their impact. | data centricity | • ensure that uncertainty, availability, and scalability of data are key architecture drivers for system design |
| Output of AI components is not human interpretable. | explainability | • decouple model changes from changes to the rest of the system<br>• introduce observability mechanisms into the system |
| Rate of change that impacts software and AI components can vary significantly. | sustainability | • express rate of change as an architectural concern<br>• build in monitoring components for both the system and the AI components |

# Architecture Allows Improving Predictability of Data and Other System Component Interactions




I. Ozkaya. *What Is Really Different in Engineering AI-Enabled Systems*? *IEEE Softw. 37(4):* 3-6 (2020).




I. Ozkaya. *Ethics Is a Software Design Concern*. *IEEE Softw. 36(3): 4-8 (2019).*

Take your data seriously to prevent it from consuming your project – data pipelines will require architecting.

Localize uncertainity.

Incorporate user experience and interaction to constantly validate and evolve models and architecture.

Treat ethics as both a software design consideration to monitor for and a policy concern.

# Architecture Challenge #3 : Lack of Monitorability

AI components degrade at a different rate than the rest of the system components.

- Components that are responsible for detecting, e.g. ML model performance degradation, need to be clearly identified and designed
- Components that incorporate user feedback for ground truth need to be included
- Other system monitoring components may need to be adjusted

# Recommendation: Decouple Different Aspects of Monitorability

Understand what different monitoring techniques will be needed for data quality vs. model quality vs. software quality vs. service quality

Explore the relationship of monitorability and self-adaptation in ML systems*

- *of* ML — ML models self-adapt to system changes (one of the goals of MLOps)
- *for* ML — ML system adapts to changes that affect quality of service (QoS)
- *by* ML — system uses ML techniques to adapt (some of this research is already happening in the self-adaptive systems community)

* H. Muccini and K. Vaidhyanathan. Software Architecture for ML-based Systems: What Exists and What Lies Ahead. In 1st Int. Workshop on Software Engineering - AI Engineering (WAIN). IEEE, 2021.

# Recommendation: Integrate the analyses performed by the Data Scientist into the MLOps pipeline

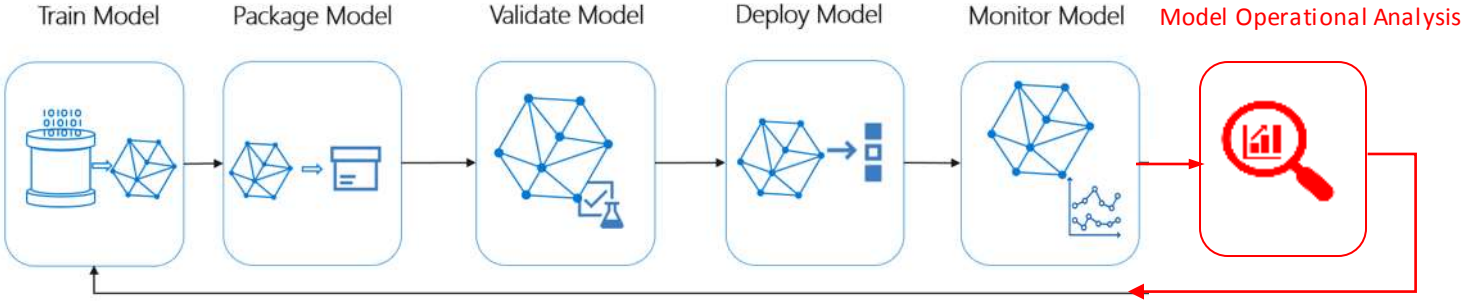



Diagram Adapted from MS Azure MLOps Pipeline

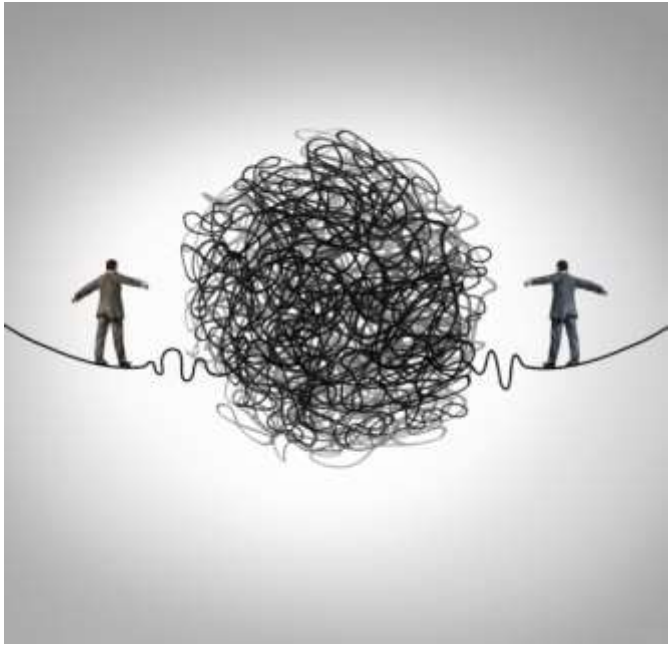
**MLOps automates model deployment, but creates a model retraining problem**

- Assumes new training data should be treated the same as the initial training data
- Assumes model parameters are constant and should be the same as those identified on the initial training data
- Has no information to understand why the model performed as it did
- Has no informed procedure of how to combine the production and development data set into a new training data set

https://insights.sei.cmu.edu/blog/improving-automated-retraining-of-machine-learning-models/

# Architecture Challenge #4 : Different Paces of Change

AI systems have several kinds and rates of change that we do not yet fully understand and have techniques for to manage.



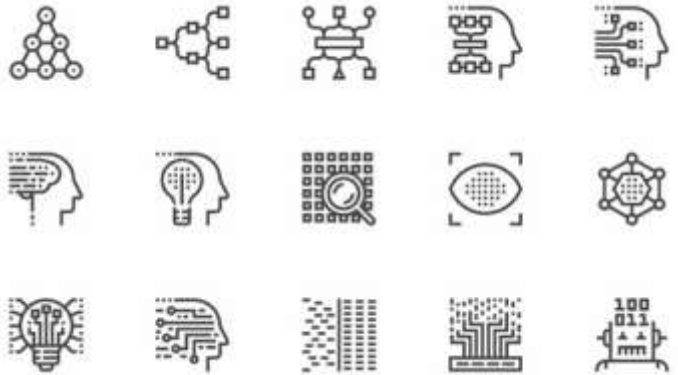
# Recommendation: Embrace Changing Anything Changes Everything Principle*

Architect data pipelines to support incorporating rate of change in data, retraining models, and incorporating new data from training to deployment to maintenance and evolution.

Decouple routine change from highly-coupled data changes, which are often the source for unpredictable change propagation.

Design instrumentations to enable traceability of recommendations to improve explainability.

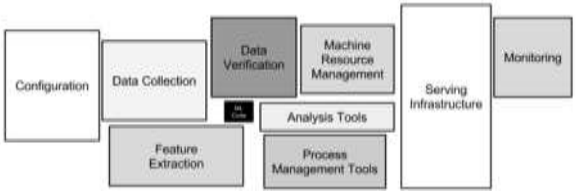
Do not forget changing environment conditions.



Ipek Ozkaya. *What Is Really Different in Engineering AI-Enabled Systems? IEEE Softw. 37(4): 3-6 (2020).*

* Sculley, D., Holt, G., Golovin, D., Davydov, E., Phillips, T., Ebner, D., ... & Dennison, D. (2015). Hidden Technical Debt in Machine Learning Systems. In *Proc. 28th Int. Conf. Advances in Neural Information Processing Systems, Vol. 2* (pp. 2503-2511). ACM, 2015.

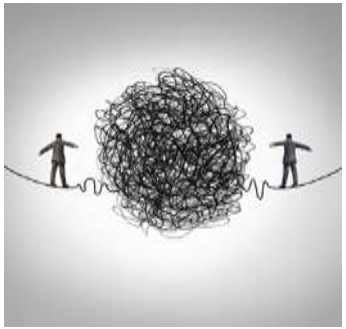
# Summary Recommendations




Manage ML components' architectural dependencies

Understand high-priority quality attributes of AI-enabled systems

Decouple different aspects of monitorability



Embrace changing anything changes everything principle

# Connecting Communities – Upcoming


J. Bosch, H. Holmström Olsson, B. Brinne, I. Crnkovic
AI Engineering: Realizing the Potential of AI, Nov/Dec 2022 IEEE Software

I. Ozkaya,
An AI Engineer Versus a Software Engineer
Nov/Dec 2022 IEEE Software

https://www.computer.org/digital-library/magazines/so/cfp-expainable-ai-software-engineering

## Call for Papers: Explainable AI for Software Engineering (XAI4SE)

*IEEE Software* seeks submissions for this upcoming special issue.

### Important Dates

**Submissions Due:** 15 November 2022

**Publication:** May/June 2023

# Connecting Communities – Upcoming


https://conf.researchr.org/track/cain-2023/cain-2023-call-for-papers
Abstracts due: 11 January, 2023
Papers due: 18 January, 2023

# THANK YOU!

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