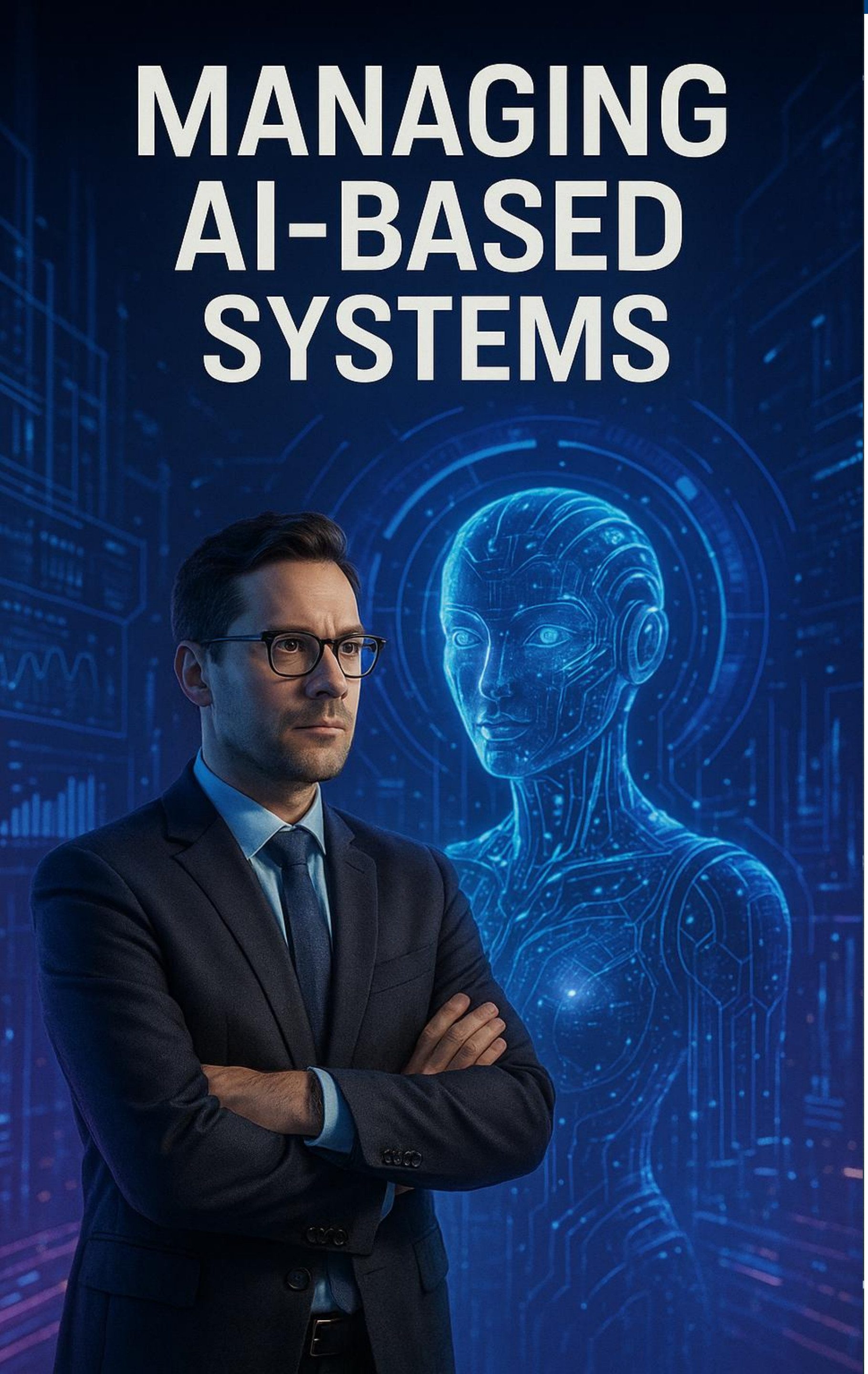

Session 12: KPI-based Monitoring and Change Management

Managing AI-based Systems

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Course navigator

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Basic understanding of AI and its business potential

AI Ideation	AI Strategizing	AI Design & Development	AI Operations at Scale
5 Application potentials of AI technologies	7 Evaluation an organization's AI readiness	9 Architectures of AI applications	12 KPI-based Monitoring and Change Management
6 Identification, design and evaluation of AI use cases	8 Management and governance of AI	10 Data Management and Model Transparency	13 Ethical, legal and social implications of AI
		11 Design of human-AI interactions	

Implementation

Objectives of today’s lecture

1. Learn how to select appropriate KPIs for AI initiatives
2. Understand the ML monitoring phases
3. Dive into the change management phases

Agenda

01 | Key performance indicators for AI

02 | Machine learning monitoring

03 | Change Management

Agenda

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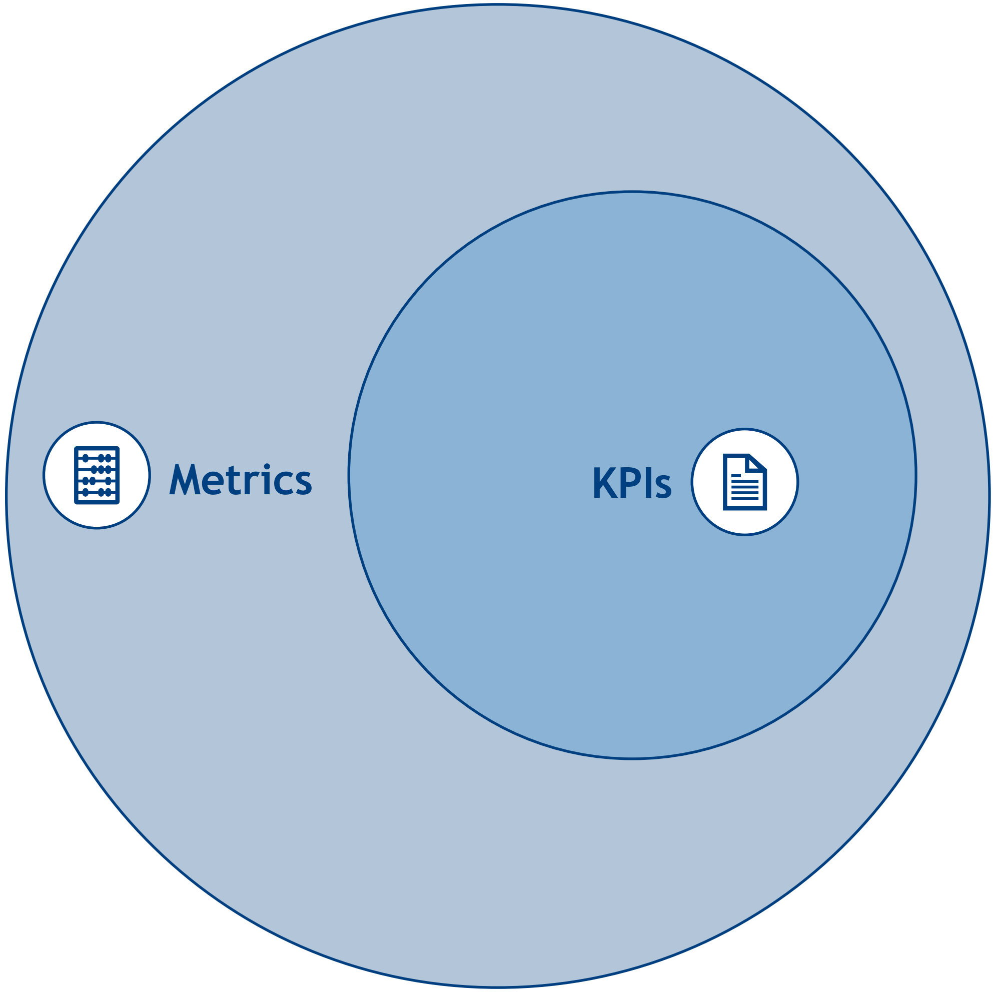
Recap lecture 4 - Definitions of AI metrics and KPIs



Metrics: Metrics are quantifiable measures used for assessing, comparing, and tracking the performance of an application
e.g., accuracy of storage predictions

KPIs: Key performance indicators are quantifiable measurements used to gauge a company's overall long-term financial, strategic, and operational performance
e.g., turnover ratio of a product

Understanding Key Performance Indicators

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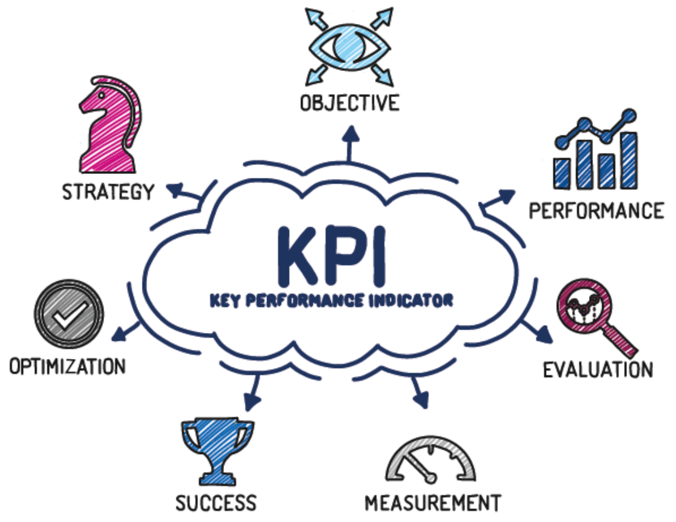
- **Direct Strategic Alignment:** Key performance indicators are specifically chosen to measure the progress of the company's strategic goals, such as increasing market share or improving customer retention rates.
- **Critical Performance Indicators:** KPIs focus on the most vital metrics that signify the organization's success, such as achieving a set profit margin or reaching a targeted number of users.
- **Broad Categorization:** They encompass both financial measures like return on investment (ROI), net profit, cost per acquisition, and non-financial measures like employee engagement levels, brand awareness, or customer loyalty.
- **Leading vs. Lagging:** KPIs include lagging indicators, which reflect past results (e.g., quarterly sales revenue), and leading indicators, which predict future outcomes (e.g., new signups indicating future sales potential).



https://www.campaign-services.de/glossar/kpi/

www.qlik.com; www.klipfolio.com

Key Questions Before Establishing KPIs

Ensure your organization is strategically aligned, goals are clear, and potential risks are considered:

1. **What's Your Strategy?**	Align your data initiatives with a well-defined business strategy
2. **What Are Your Objectives?**	Develop clear objectives and key results to underpin your KPIs
3. **What's the End Goal?**	Always start with the business decision you aim to make
4. **What Data Do You Need?**	Define the data elements required for your KPIs
5. **How Valuable Is the Information?**	Assess the impact of knowing versus not knowing
6. **Who Are Your Stakeholders?**	Consider the audience that will benefit from the insights
7. **What Risks Exist?**	Identify potential data, analytics, and AI risks

towardsdatascience.com (2022)

Effective KPIs

It is important distinct between goals and KPIs. KPIs are only indicators that measure progress towards and achievement of certain goals. Each indicator should be based on criteria that make it suitable for further analysis. The set of criteria most often referenced is that of SMART which is used for effective goal setting:

Specific → well-defined, answering "What, why and how?" for clear focus to avoid misunderstandings

Measurable → quantifiable to track progress and achievements

Attainable (aggressive) → realistic but still challenging goals with the given resources and time

Result-oriented (realistic) → alignment with bigger objectives, realistic in the given environment

Time-sensitive → specific timeframe for a sense of urgency and structure

Shahin, Mahbod (2007)

KPI dimensions

Financial

Expansion in revenue, cash flow, gross profit, and expenditure pace.

Support & Service

Time for resolution, mean resolution time, compliance with service level agreements, and quality.

Governance, Risk, & Compliance

Percentage compliance with processes, audit adherence, and incidents unrelated to security.

Customer

Participation levels, net promoter scores, costs of acquisition, and conversion rates.

Employee

Attrition and retention rates, satisfaction levels, and engagement.

towardsdatascience.com (2022)

KPI categories

	Strategic KPIs	Operational KPIs	Functional KPIs	Leading/ lagging KPIs
Characteristics	High-level, overview	Detailed, process-oriented	Department-specific, detailed, strategic or operational	Trend or result-analyzing
Timeframe	Long-term	Short-term (monthly, daily)	Strategic or operational	Leading: Future-oriented Lagging: Past-oriented
Users	Executives	Middle Management	Department Heads	Management, Analysts
Examples	ROI, Profit Margin, Total Company Revenue	Monthly Revenue Growth, Product-specific Sales, Regional Performance	New Vendor Registrations (Finance), Click-through Rates (Marketing), Department-specific Efficiency Metrics	Leading: Overtime Hours (indicating potential manufacturing issues) Lagging: Profit Margin (reflecting past operational performance)

investopedia.com (2023)

The significance of KPIs in a data-driven world

Business Impact Assessment: KPIs align data, analytics, and AI initiatives with strategic goals, ensuring ongoing value

Timely Decision-Making: KPIs monitor the speed of data-to-insight conversion for competitive agility

Data Quality Assurance: KPIs ensure data accuracy and reliability for sound decision-making

Data Literacy: KPIs track data literacy progress, empowering informed decisions across the organization

Risk Management: KPIs quantify and mitigate risks in data, analytics, and AI projects

KPIs offer a comprehensive view of business performance, guiding strategic decisions and uniting the organization towards its goals. They are vital for handling vast data volumes and making data a competitive advantage, ensuring efficient and impactful data initiatives.

towardsdatascience.com

Import KPIs for AI initiatives

It's important to establish both quantitative and qualitative KPIs to enhance project efficiency and contribute to societal improvement. These KPIs are essential for quantifying the success of AI initiatives, providing insights into reliability, accuracy, user experience, and fairness:

1.Mean Time to Repair (MTTR): Evaluates how long it takes to rectify errors within an AI system.
Relevance: Measures system maintainability and reliability, crucial for swift response to errors.

2. Mean Absolute Error (MAE): Calculates the average disparity between predictions generated by a regression model and the actual values.
Relevance: Evaluates model accuracy in regression applications, vital for precise predictions.

3. First Contact Resolution Rate (FCRR): Indicates the proportion of issues resolved through initial support interactions.
Relevance: Key for customer support and user satisfaction, indicating efficient problem resolution and cost reduction.

4. True or False Positive Rate (T/FPR): A qualiy metric that assesses the sensitivity and specificity of predicted classifications.
Relevance: Essential for fairness, assesses the model's ability to distinguish between positive and negative classes, reducing biases.

pandata.co (2023)

Benefits of using KPIs in AI initiatives

Providing Measurable Goals

KPIs establish clear objectives for tracking progress and measuring success

Data-Driven Decision Making

Evaluate KPI data to identify areas needing improvement and optimize development efforts

Increased Efficiency

Identify and rectify inefficiencies and bottlenecks by measuring time and resource allocation

Greater Accountability

Clear goals and progress tracking encourage team accountability and effectiveness

Improved Customer Satisfaction

Track customer satisfaction through metrics like conversion rates and user engagement to enhance the product's alignment with user expectations

Addepto.com (2023)

Agenda

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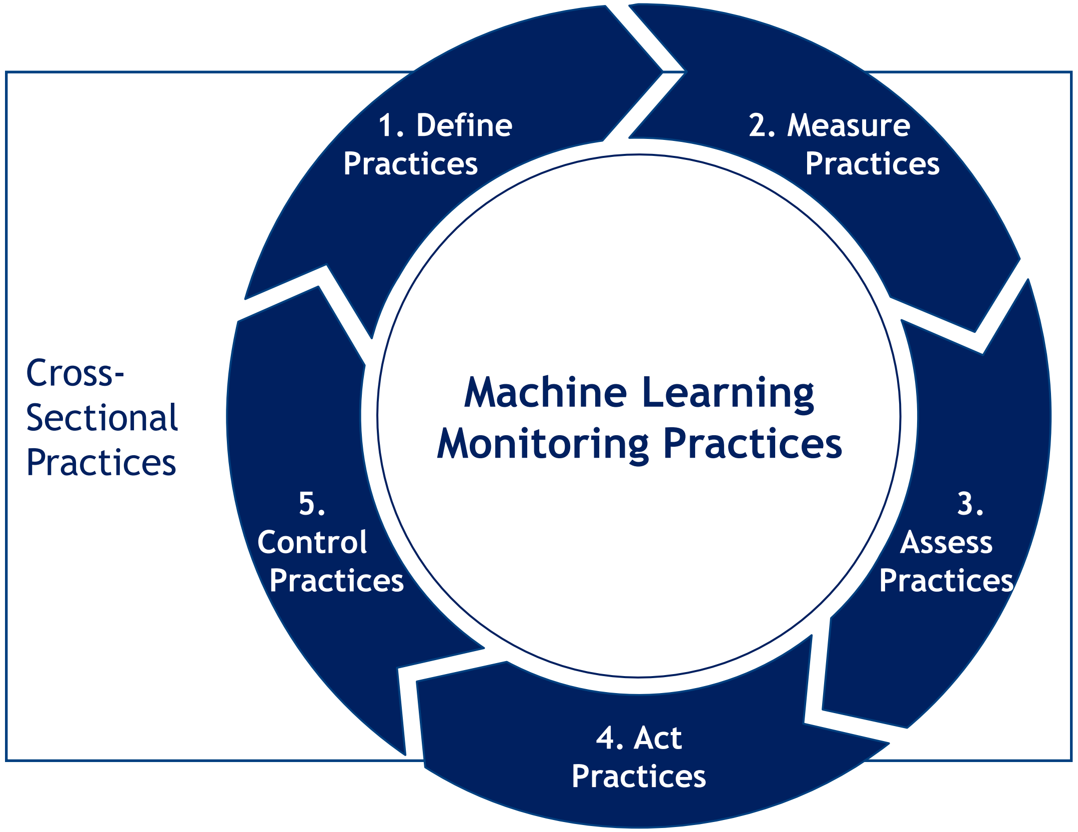
01 | Key performance indicators for AI

02 | Machine learning monitoring

03 | Change Management

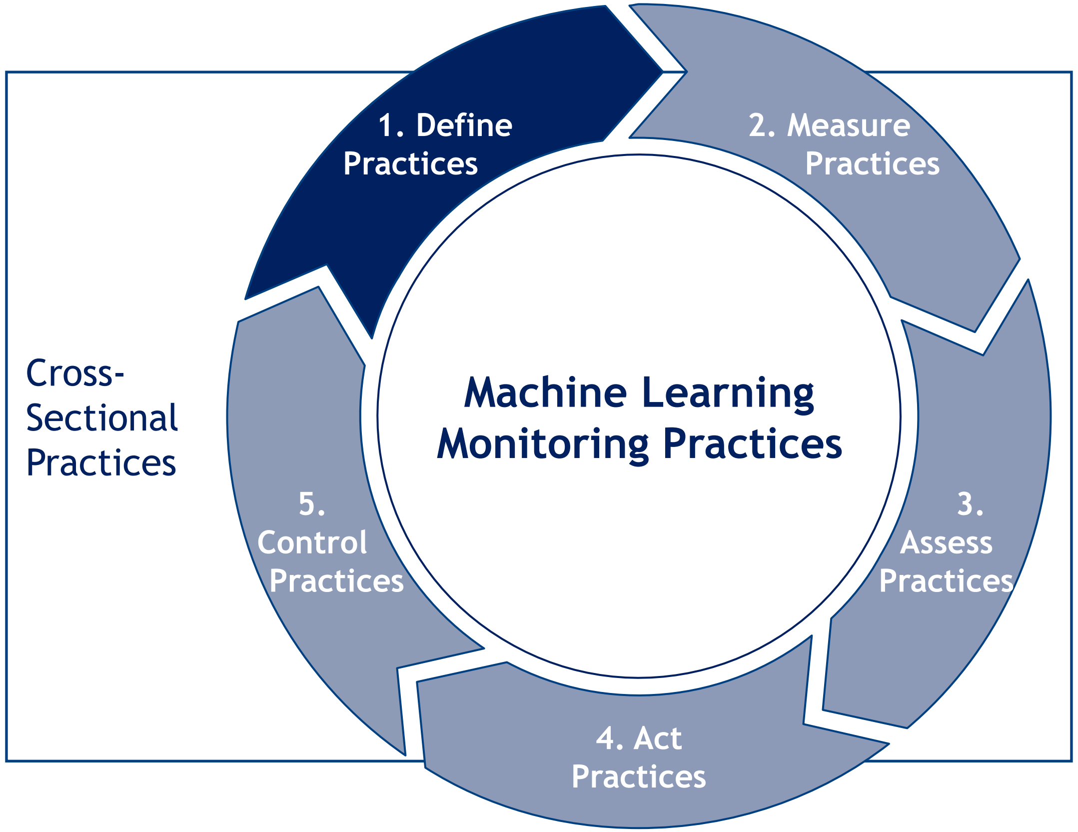
ML monitoring practice

We define **ML monitoring** as practices that include the systematic observation, performance measurement and analysis of ML applications' behavior in their production environments as well as appropriate actions when such behaviors deviate from their intended status



Mast and Lokkerbol 2012; Tonini et al. 2006

1. Define Practices



Define

(1) Define the ML application's weaknesses and compensatory workflows

(2) Select appropriate metrics from the range between technical and organizational metrics

- Cover the relevant information for all relevant stakeholders (computational, ML, business-driven metrics)
- Derive metrics from an organization's business objectives

(3) Model a metrics system for the selected technical and organizational metrics

- Identifying preferences for metrics and objectives in a collective metrics system specifies the trade-off space

2. Measure Practices

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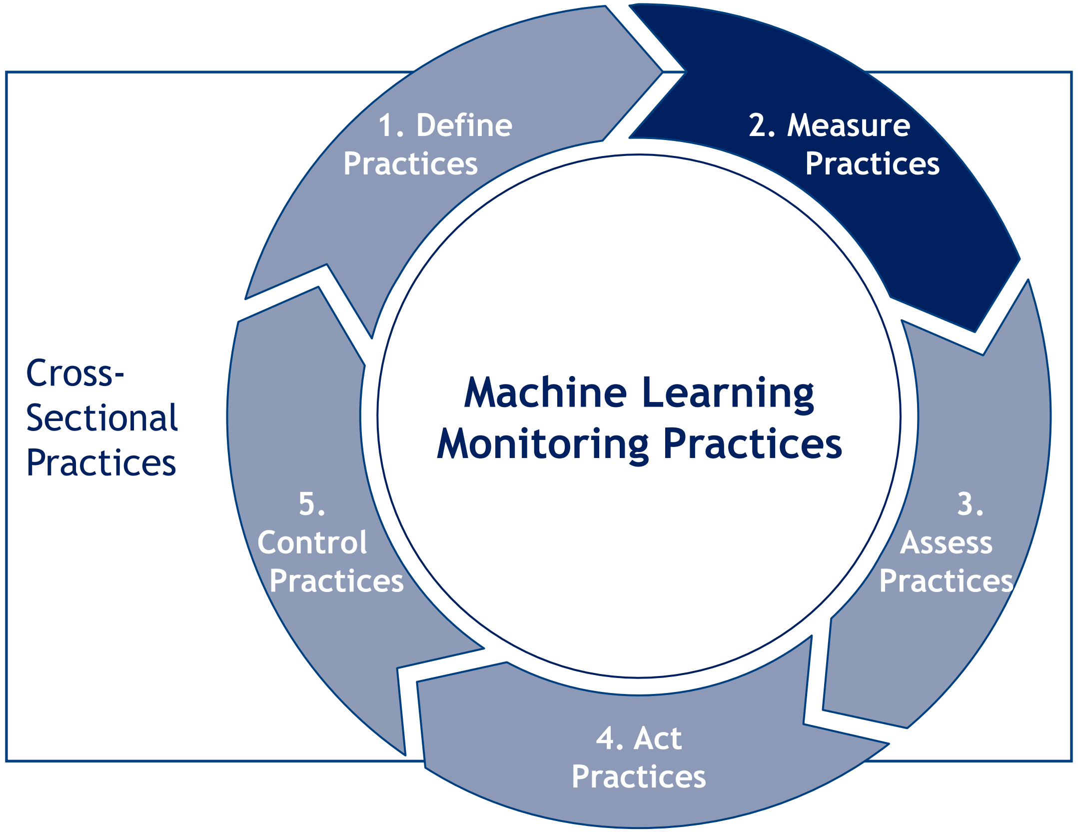


Measure

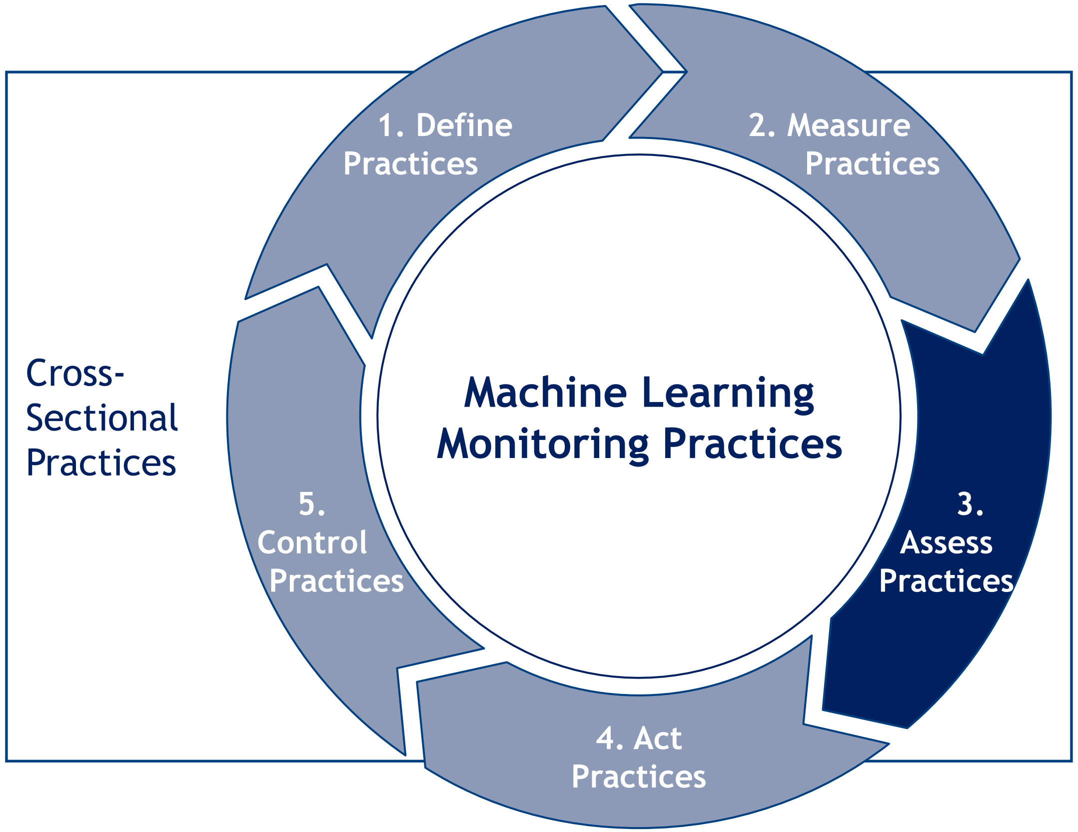
(1) Collect metadata from the ML application's context
- Collect logs, code versions, data, model and hyperparameter setting
- Get a clear overview of how the application is configured and how it runs

(2) Collect the ground truth label, if it is available
- Evaluate the ground truth label's availability
- Implement labeling mechanisms

(3) Collect metrics data for the ML application
- Collect required metrics data to calculate or receive the metrics using an adequate infrastructure
- Measure metrics in a useful interval

(4) Process collected data & metrics for assessment
- Join related metadata (from practice 1 in the measure step) and the ML application components in question to gain new insights
- Use statistical calculations for an ML algorithm's inputs and outputs

3. Assess practices



Assess

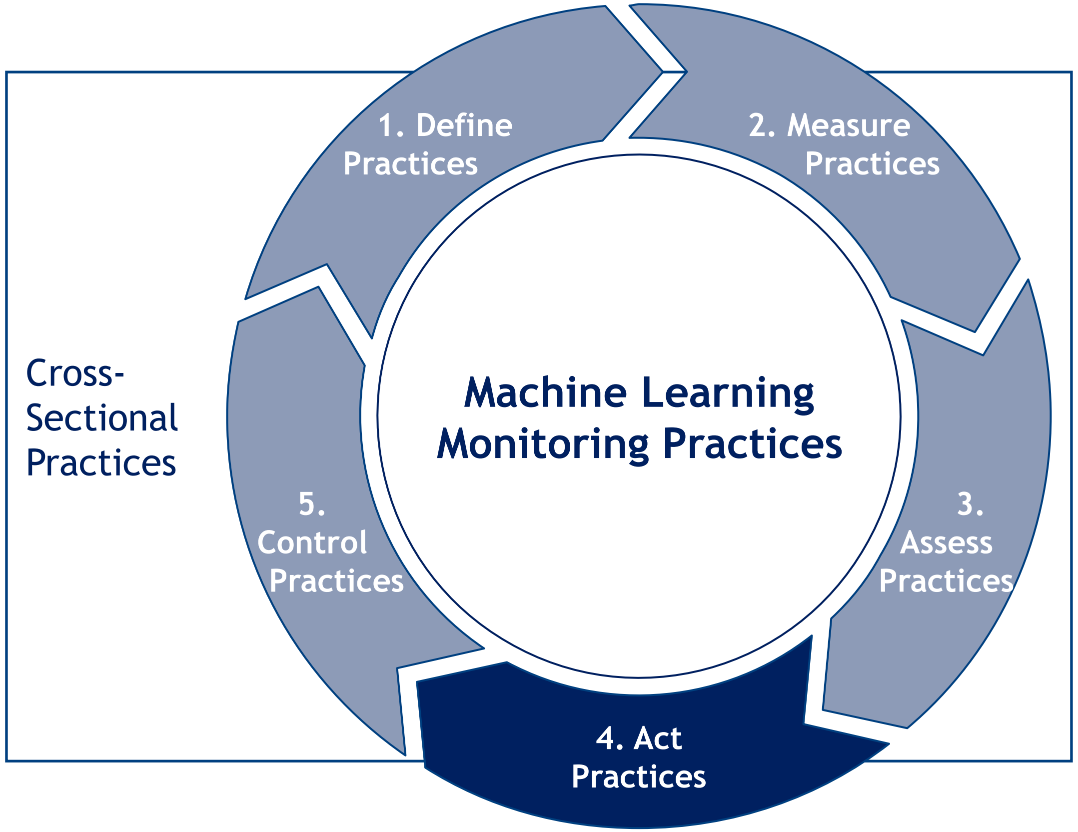
(1) Investigate the collected data to identify data quality issues
- Detection of data quality issues in data processing
- Check collected metrics against thresholds
- Check metrics on key data slices

(2) Investigate the collected data to identify drifts
- Identify changes in the input, output, and the relationship between input and output

(3) Conduct cause-effect analysis for identified data quality issues and drifts
- Track the dependencies between ML components over time
- Differentiate between model faults and external exceptions
- Determine the causes’ impacts on the key business metrics

(4) Determine adaptations for identified data quality issues and drifts
- Refer to prior versions of the ML application
- Determine an ML algorithm’s ideal retraining time
- Decide which adaptations (e.g., retraining or model substitution) in the ML applications are essential

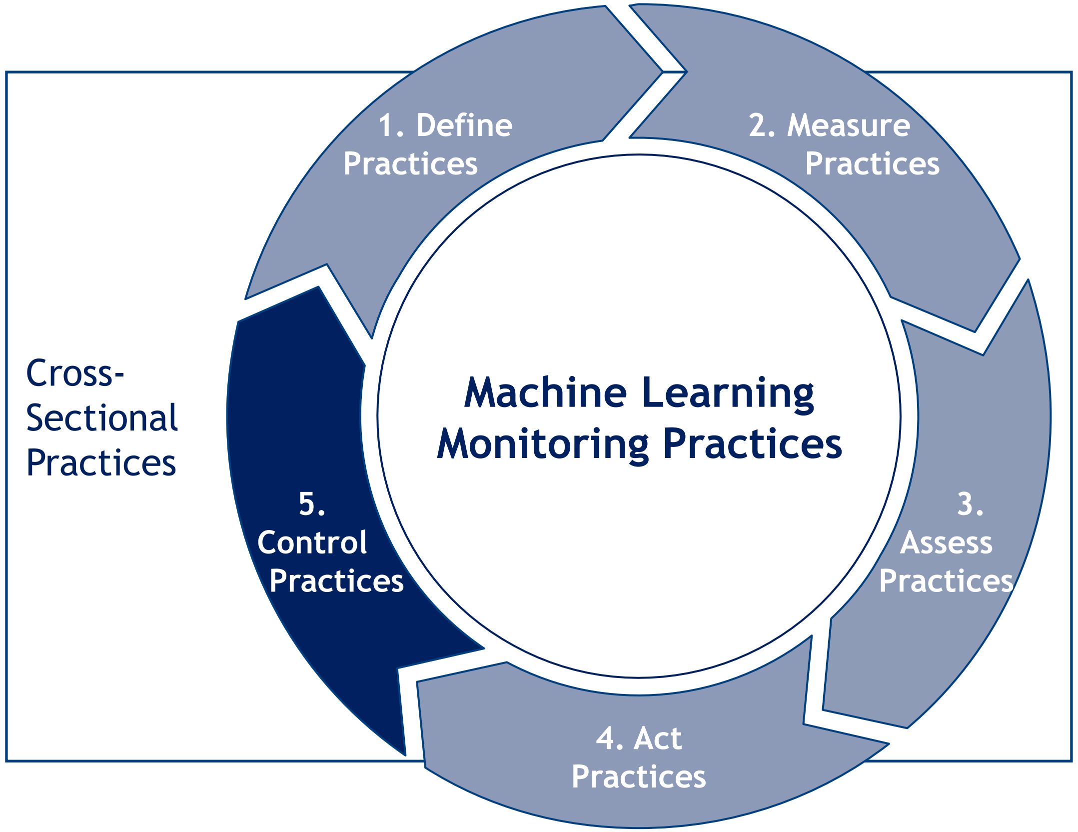
4. Act Practices



Act

Communicate adaptations to stakeholders
- Communicate the necessary adaptations to the development entity of the ML application
- Communicate the adaptations to the application’s stakeholders

5. Control practices



Control

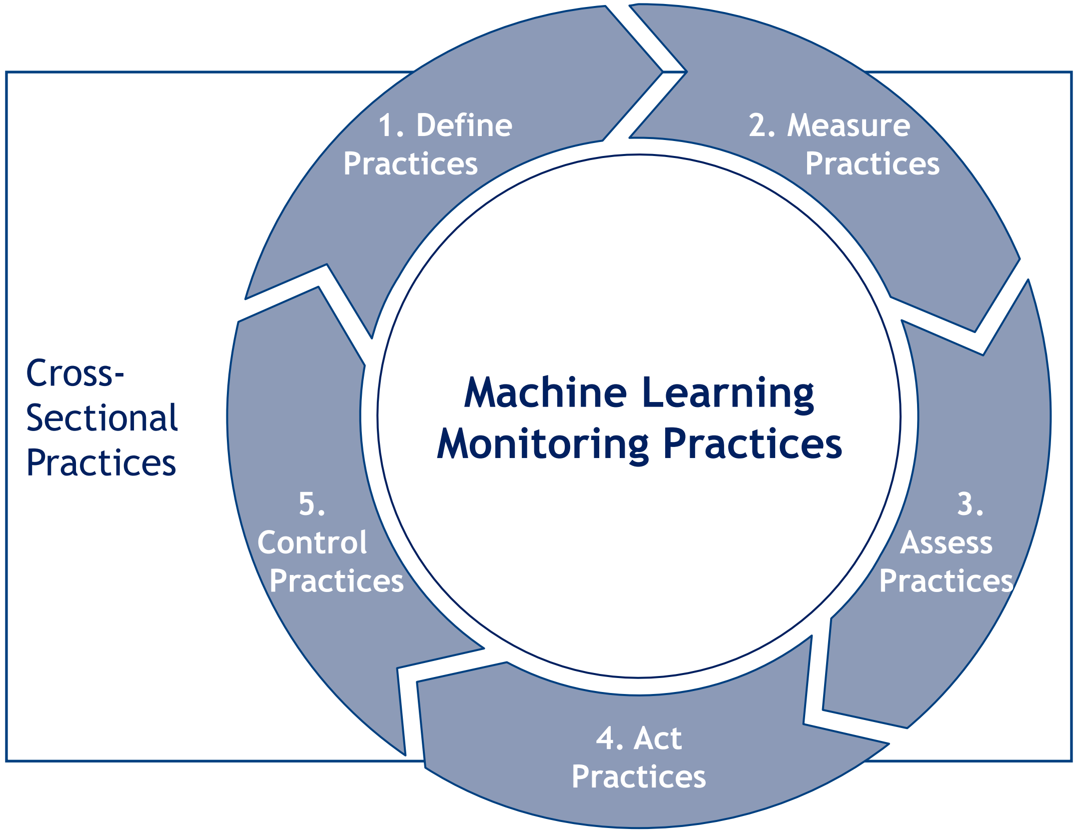
(1) Verify the adaptations made in the ML application from the act step

- To verify the adaptation, it is useful to give the necessary information to the define step so that, in the next monitoring cycle, the ML monitoring entity can observe the adaptation's impact

(2) Transfer the required adaptations in the monitoring process to the define step

- Bringing all the learned insights during a monitoring cycle (i.e., running through steps 1 to 5) back to step 1 (i.e., define) helps to improve the monitoring approach

Cross-Sectional Practices



Cross-Sectional

(1) Apply proactive mechanisms

- Seek to capture possible issues as early as possible and not just react to unfolding issues

(2) Learn iteratively and continually

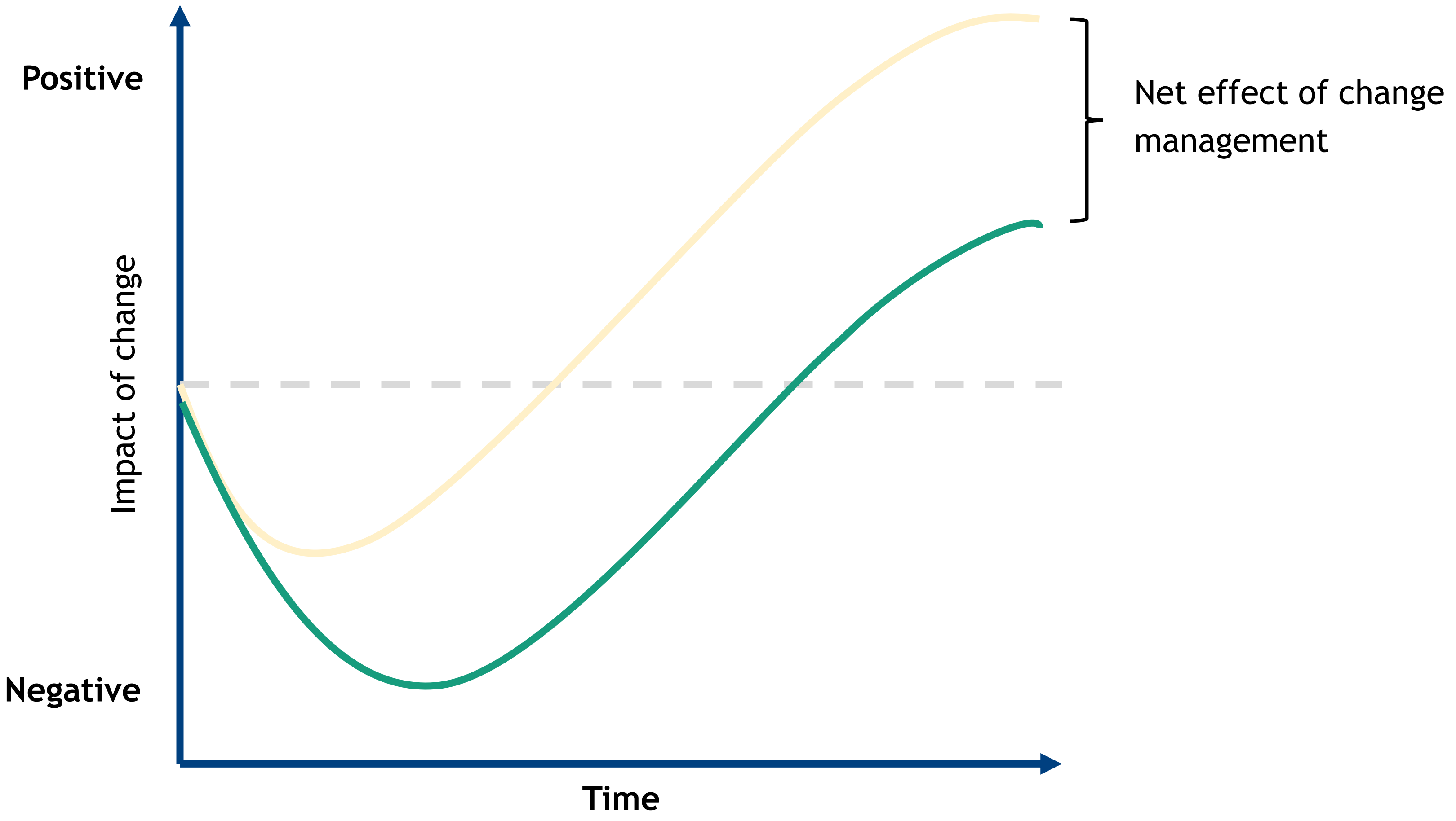
- Establish a virtual cycle that enables ML applications to continually learn from the production environment, improve, and expand their scope

(3) Design monitoring tailored to use cases

- Tailor ML applications to the organization's and use case-specific circumstances as well as the monitoring entity

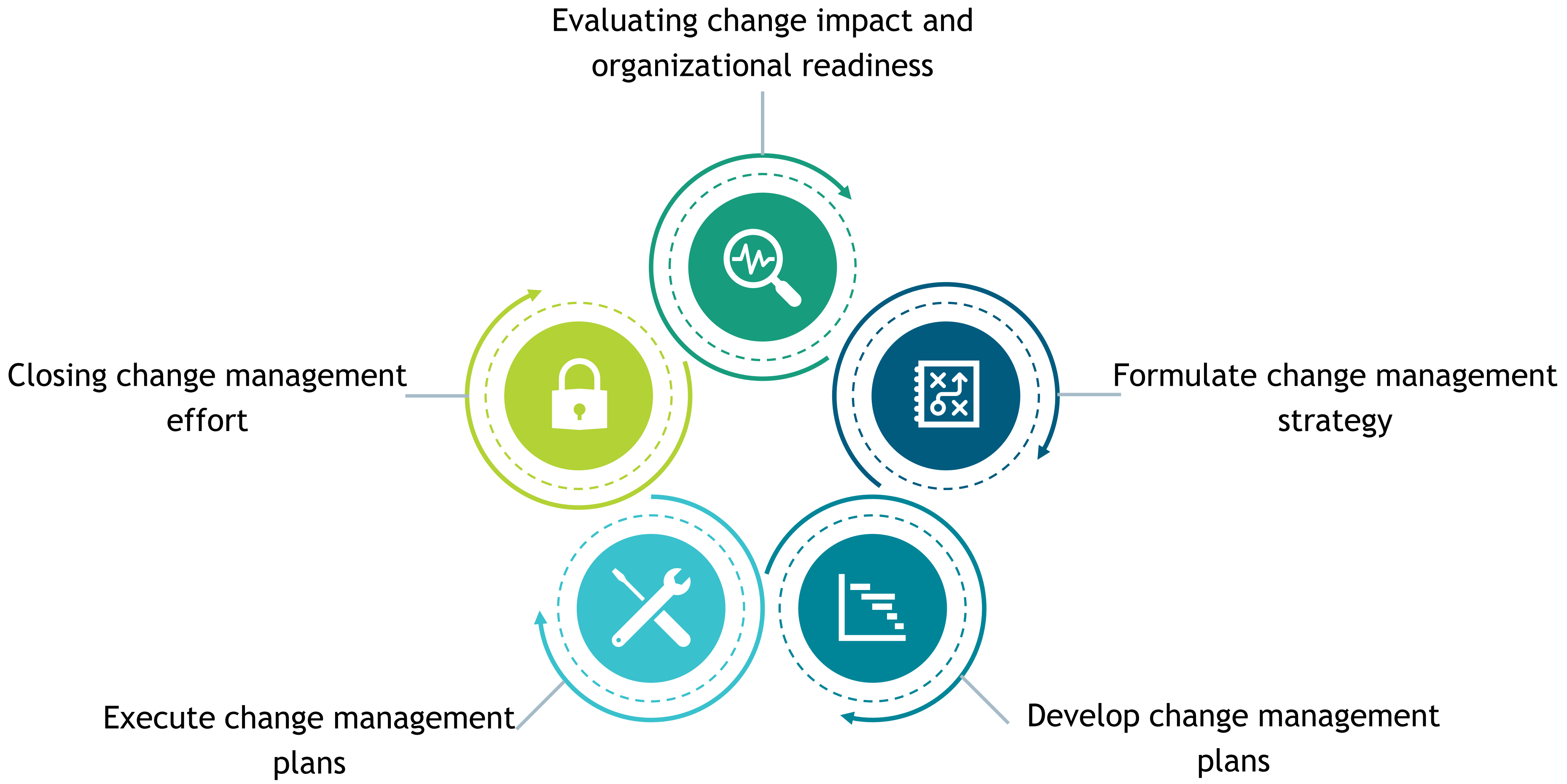
Agenda

Managed change is essential for the successful implementation of AI applications



Wrenn & Sohn (2021)

Five steps for a successful AI change management



ACMP (2019)

Five steps for a successful AI change management
1. Evaluating change impact and organizational readiness

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- Develop definition and vision and identify key objectives
- Determine necessity and drivers
- Identify success criteria and KPIs
- Identify responsibilities and affected stakeholders
- Assess AI readiness and readiness to change
- Derive expected impact for people, processes and organization
- Derive suitable education and communication measures

ACMP (2019)

Five steps for a successful AI change management
2. Formulate an AI change management strategy

- Develop communication strategy
- Develop education and development strategy
- Develop stakeholder engagement strategy
- Develop sustainability strategy

ACMP (2019)

Five steps for a successful AI change management
3. Develop AI change management plans

- Develop holistic change management plan
- Resource plan: human, technological and financial resources
- Communication plan: steering and influencing of employees
- Education and development plan: areas of improvement
- Stakeholder engagement plan: leverage participation
- Sustainability plan: ensure long-term adoption

ACMP (2019)

Five steps for a successful AI change management
4. Execute AI change management plans

- Executing, administrating and monitoring change mgmt. plan
- Resource plan: ensuring availability and allocation of resources
- Communication plan: preventing and managing resistances
- Education and development plan: execution and evaluation
- Stakeholder engagement plan: feedback implementation
- Sustainability plan: track, observe and reward progress

ACMP (2019)

Five steps for a successful AI change management
5. Closing AI change management effort

- Evaluate and document results
- Derive Lessons Learned and Best Practices
- Share resulting resources and knowledge
- Transfer of ownership

ACMP (2019)

Unmanaged vs. managed change -perspective of employees
From insecurities to resistance

unmanaged change

- **How** is AI supposed to **help** me and the organization?
- Will AI **replace** my job? Do I have to **upskill**?
- I **do not understand** the technology and how it will **affect** my job
- I don’t know **where to find information** about change projects

- I do not think that AI will **support** my job but will only make it more difficult
- I **fear** that AI will **replace** my job and that I need to **change my job profile**
- I do **not feel qualified** to use AI
- I do not **trust** AI and its results
- **I will not use AI applications**

Pirard and Cartwright (2023), Power (2018), Wrenn & Sohn (2021)

Unmanaged vs. managed change -perspective of employees
From resistance to advocacy

managed change

- **How** is AI supposed to **help** me and the organization?
- Will AI **replace** my job? Do I have to **upskill**?
- I **do not understand** the technology and how it will **affect** my job
- I don’t know **where to find information** about change projects

- My **leaders** shared our **vision** for AI and I **understand** how we will get there
- I understand how AI will **support my job**
- **Me and my input** have been **included** in the design of our AI solutions
- Me and my coworkers **discuss updates** and announcements to **stay up to date**

Pirard and Cartwright (2023), Power (2018), Wrenn & Sohn (2021)

Addressing insecurities with the right change strategies

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Education & upskilling

- Identify existing competencies and areas of improvement
- Develop individual upskilling and competency development roadmaps
- Offer workshops and training programs
- Lower the barriers for education offers
- Offer safe spaces to test applications and collect experiences

Skill & qualification concerns

Techno-logical under-standing

Employee involvement

Sense of ownership

- Collect requirements together with end users
- Form focus groups to understand user needs
- Involve your experts in testing
- Encourage and implement feedback of your employees
- Reinforce AI enthusiasts and reward intended behavior
- Address employee concerns and develop strategies to overcome them

Intrinsic motivation

Transparency & communication

Trust and job security

- Communicate AI strategy and vision through all available channels
- Show benefits of AI for the organization
- Show expected consequences of the change
- Inform employees about their roles and what you expect from them
- Celebrate quick wins and milestones
- Give regular updates

Under-standing the role of AI

Pirard and Cartwright (2023), Power (2018), Wrenn & Sohn (2021)

Our tips for successful AI change management

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Think big, start small

- Define **vision, objectives & timeline** with stakeholders
- Start with **small pilot programs** and **identify early adopters**
- Continue incrementally with **lessons learned** from pilots
- **Organization-wide communication** for awareness

Put your people front and center

- Form **focus group** to understand user needs
- Involve **end users** in **development**
- Encourage involved end users to **advertise project**
- Include **end users** in pilot **testing**
- Encourage and **implement user feedback**

Equip them with knowledge

- Offer **crash courses and workshops** according to employee concerns
- Assess skills and competencies to **tailor training plan**
- Use **train-the-trainer model** to further improve experts
- Create **ongoing exchange** and training opportunities

Tell it like it is

- Draft **communications plan**
- Identify and communicate **through ambassadors** across all levels
- Use **all** communication **channels** (All-Hands, newsletter, Brown Bags,…)
- Allow and **communicate anonymous feedback**

Connect people to one another

- Create **shared online platform** to allow knowledge and resource exchange
- Use **AI enthusiasts** so spark community engagement
- Host **AI-themed events** (Hack-a-thon, podium discussions,…)
- Host events to **showcase and celebrate milestones**

Wrenn & Sohn (2021)

Today’s lecture at a glance

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- We have discussed different categories and dimensions of KPIs
- We have understood the five step cycle of the ML monitoring cycle
- We have worked out the change management process to ensure successful AI change management

Questions, comments, observations

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