

# **MLOps Adoption in the Manufacturing Industry**

A Case Study With Zeiss SMT

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- Production deployment of machine learning (ML) remains rare<sup>1</sup>
- ML Operations (MLOps) promises a solution
  - Extending DevOps principles to ML-based systems
- Adopting MLOps involves a plethora of options and trade-offs<sup>23</sup>
  - Practitioners lack guidance and feel overwhelmed

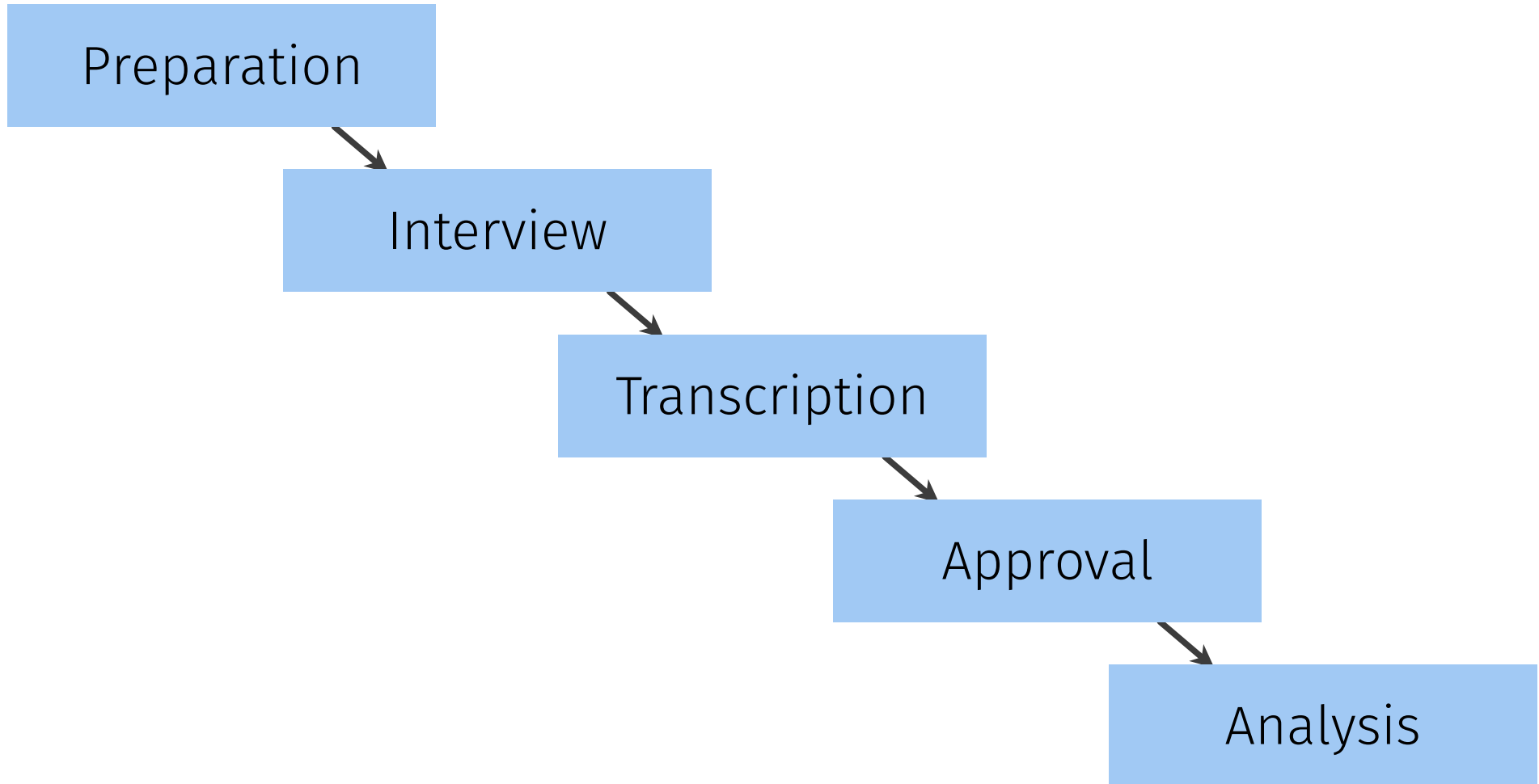
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<sup>1</sup> Meulen R van der, McCall T (2018) Gartner Says Nearly Half of CIOs Are Planning to Deploy Artificial Intelligence. <https://www.gartner.com/en/newsroom/press-releases/2018-02-13-gartner-says-nearly-half-of-cios-are-planning-to-deploy-artificial-intelligence>. Accessed 4 Mar 2025

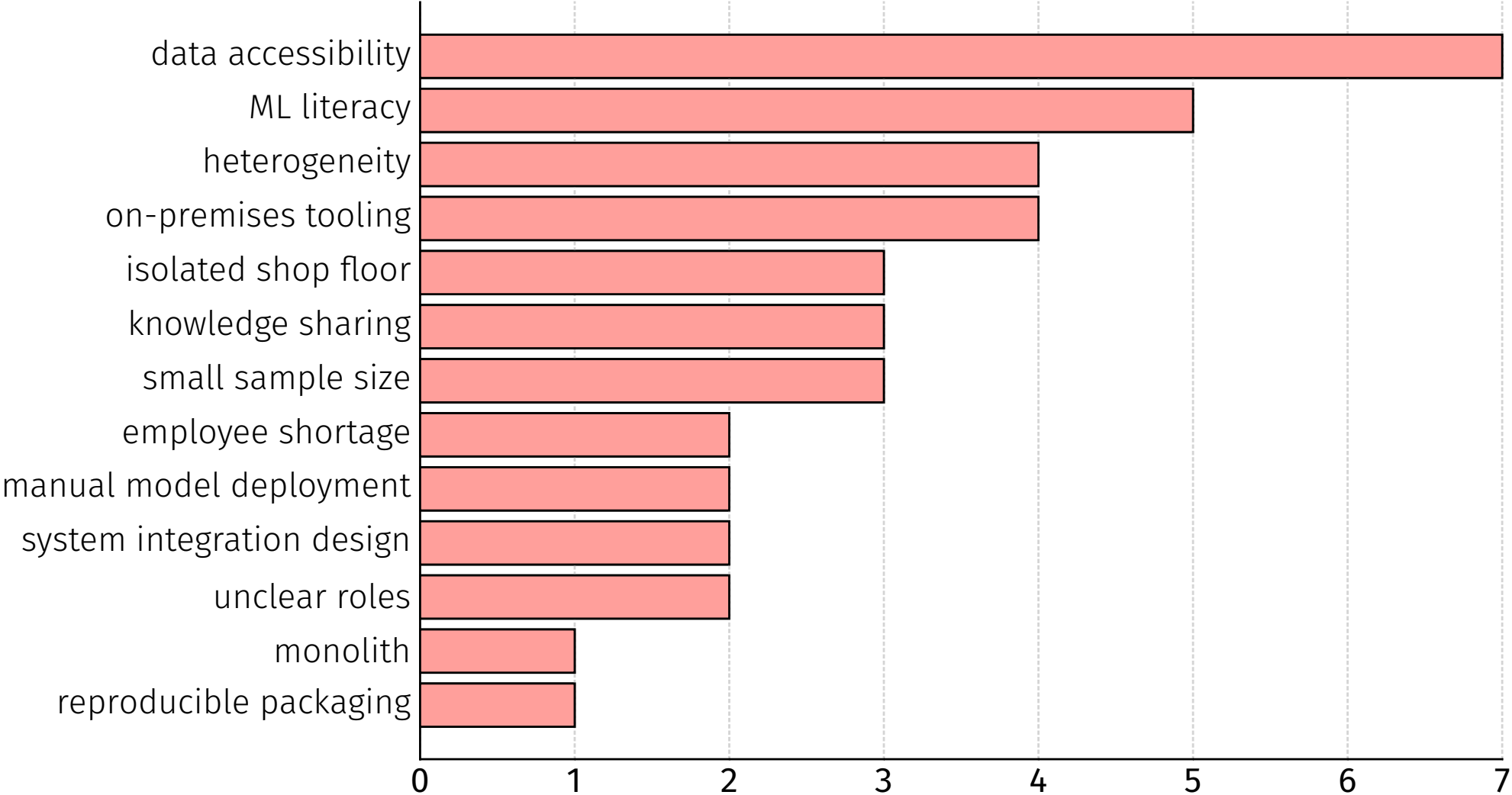
<sup>2</sup> Lewis GA, Ozkaya I, Xu X (2021) Software Architecture Challenges for ML Systems. In: 2021 IEEE International Conference on Software Maintenance and Evolution (ICSME). IEEE, Luxembourg, pp 634–638

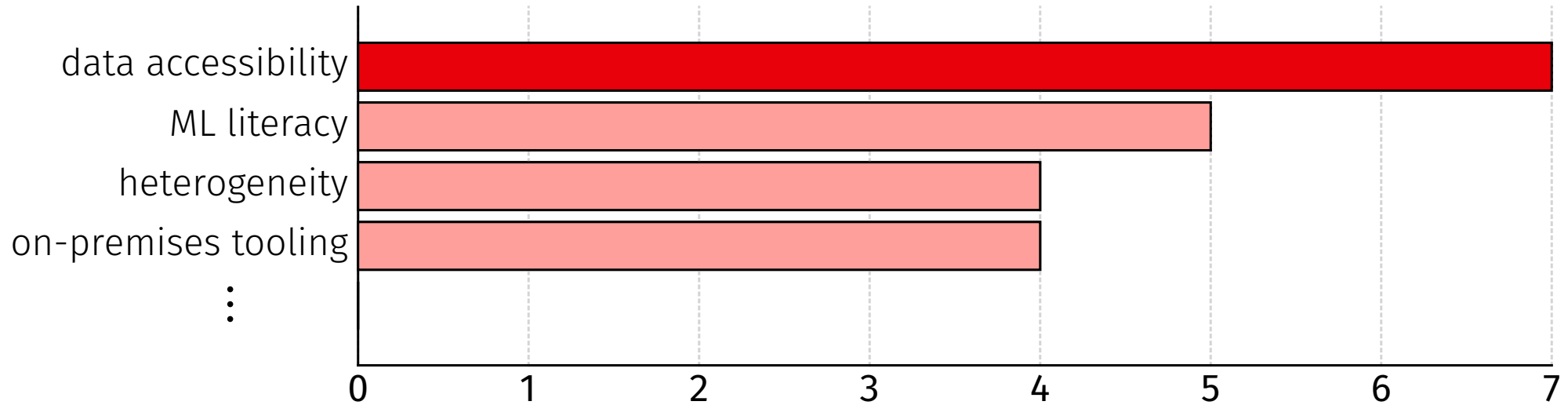
<sup>3</sup> Nazir R, Bucaioni A, Pelliccione P (2024) Architecting ML-enabled systems: Challenges, best practices, and design decisions. *Journal of Systems and Software* 207:111860. <https://doi.org/10.1016/j.jss.2023.111860>

- RQ1** Which challenges do practitioners face when implementing MLOps in practice, especially when integrating ML-based components into existing software systems?
- RQ2** How do practitioners deal with these challenges?
- RQ3** How does integrating ML-based components impact the software architecture of the existing software system?



ID	Role	Experience (years)					
		Role	SE	Ops	DevOps	ML	MLOps
P01	data scientist	1.0	0.0	0.0	0	3.5	0.0
P02	software developer	4.0	25.0	0.0	4	8.0	1.0
P03	software developer	1.0	2.0	0.0	2	2.0	1.0
P04	system developer	2.5	5.0	0.0	0	5.5	0.5
P05	data scientist	3.0	4.0	0.0	0	3.0	0.0
P06	data scientist	0.5	10.0	0.0	0	5.0	0.0
P07	process engineer	5.0	0.0	0.0	0	5.0	0.0
P08	ML engineer	2.0	12.0	1.5	0	6.0	0.0
P09	data scientist	6.0	10.0	0.0	2	13.0	0.0
P10	data scientist	3.0	10.0	0.0	2	3.0	0.0
P11	data scientist	2.5	7.5	1.5	1	7.5	1.0
P12	physicist	2.0	9.0	2.0	2	7.0	0.0





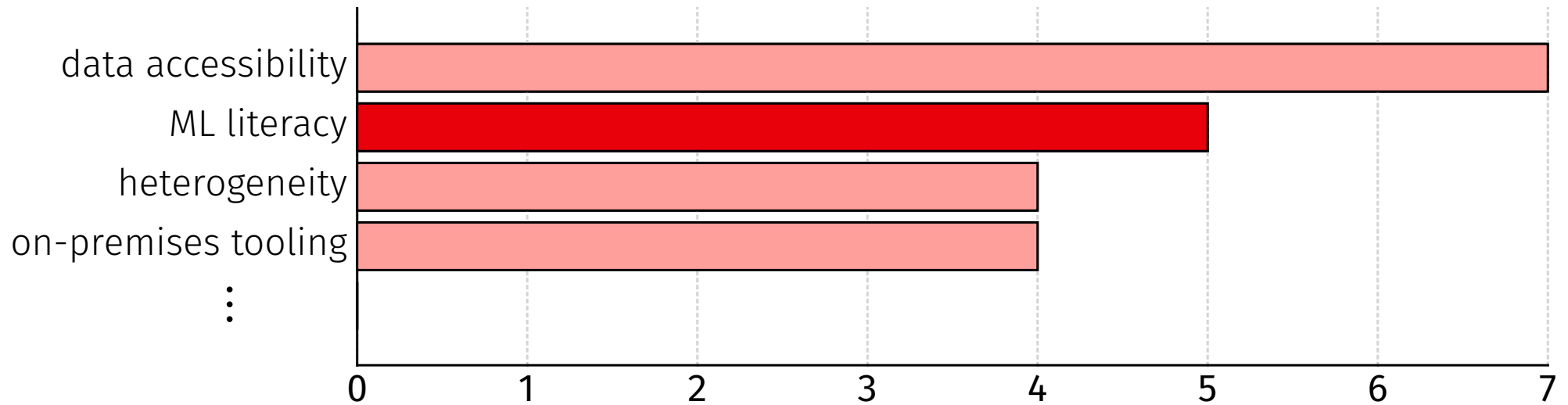
**Key Insight** Participants expressed difficulties identifying and accessing appropriate data sets for their ML projects.

## Sub Aspects

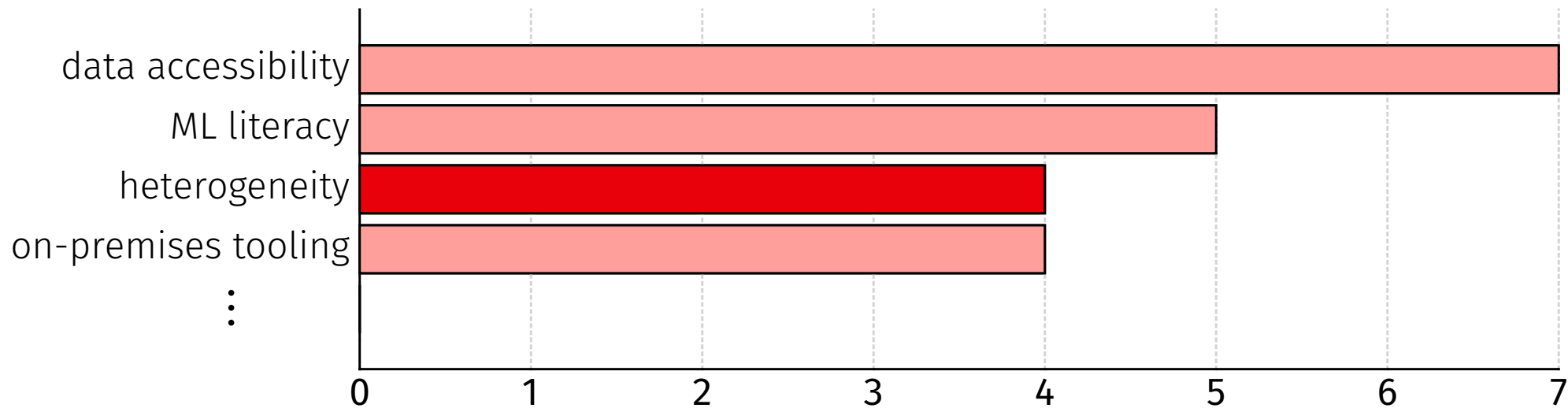
**data discovery** identifying an appropriate data set

**data ownership** identifying data owner & obtaining access

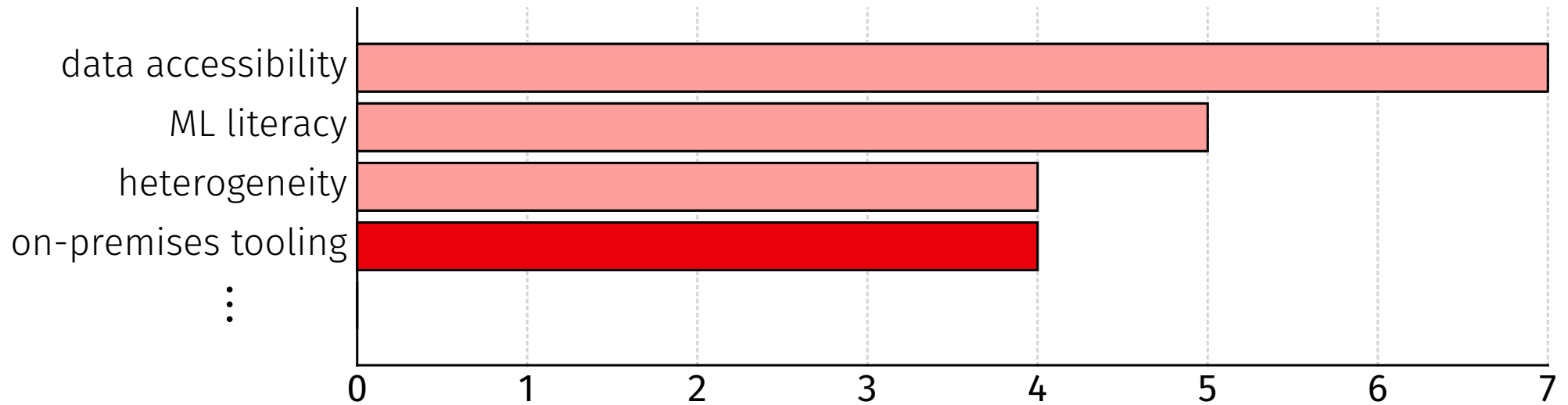
**data security** handling data securely (e.g., access to cloud resources)



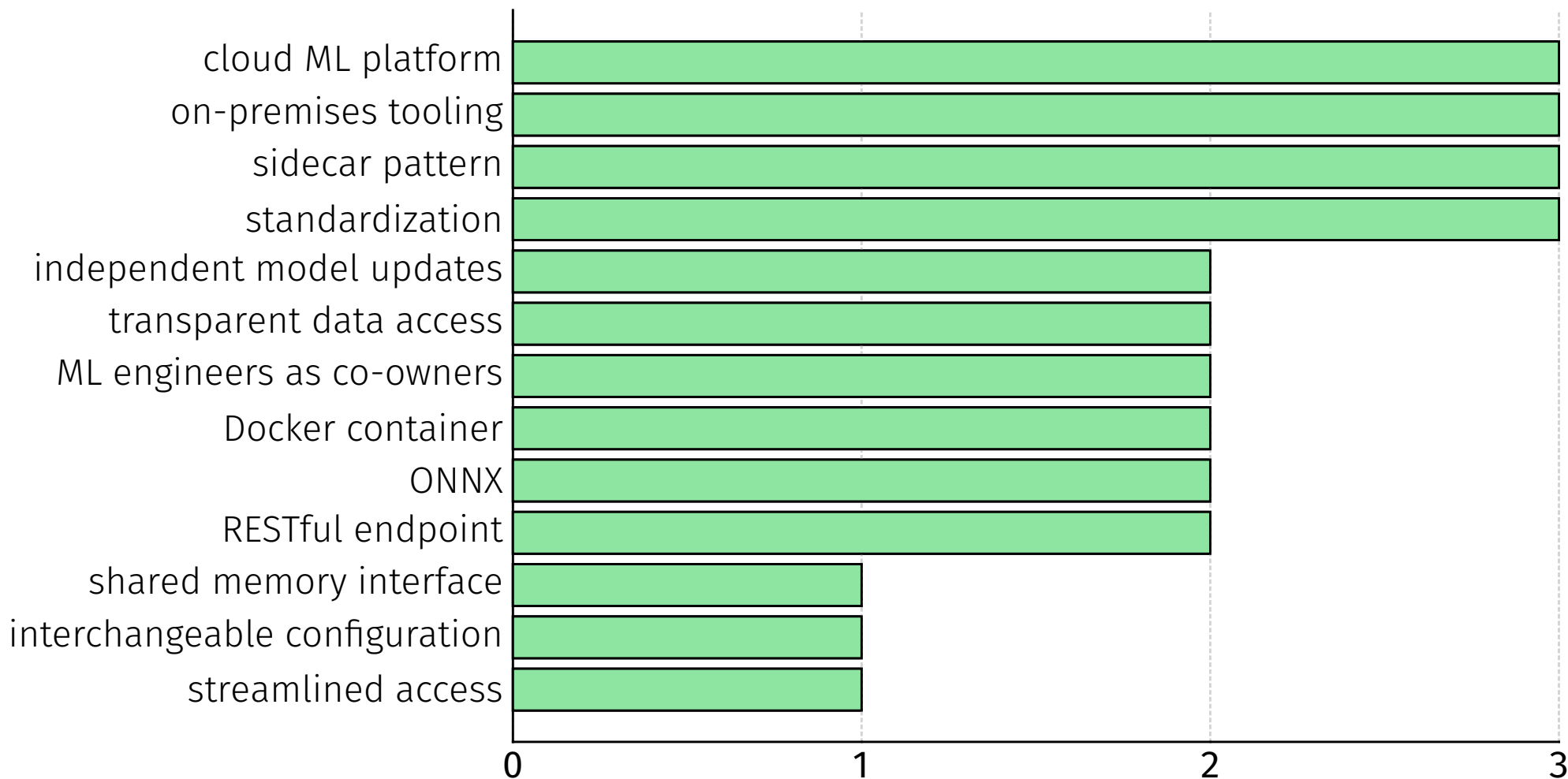
**Key Insight** Project stakeholders do not understand properties of ML (projects)

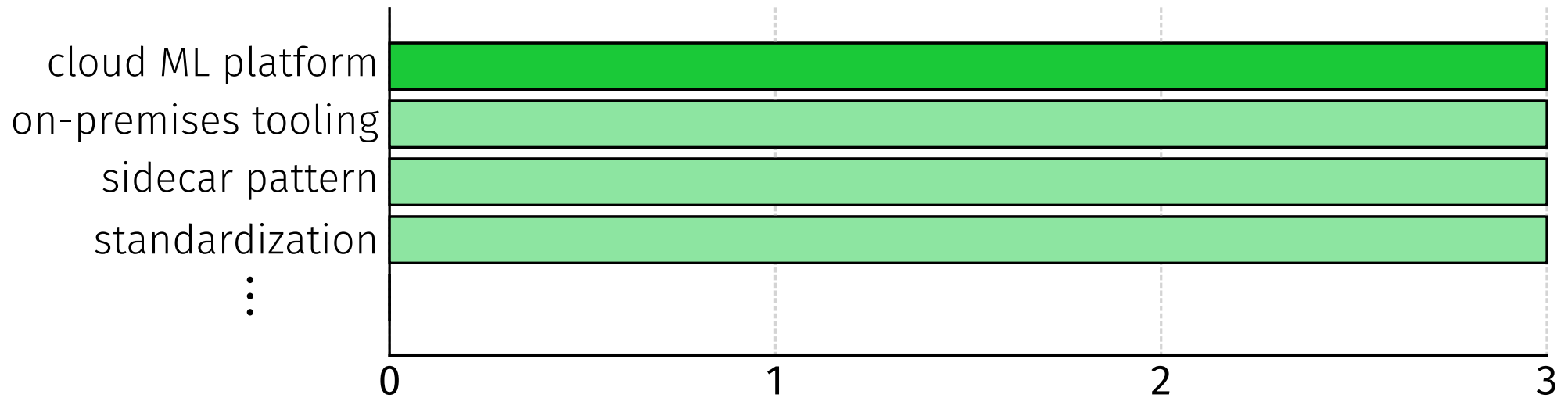


**Key Insight** Projects employ a multitude of different tools

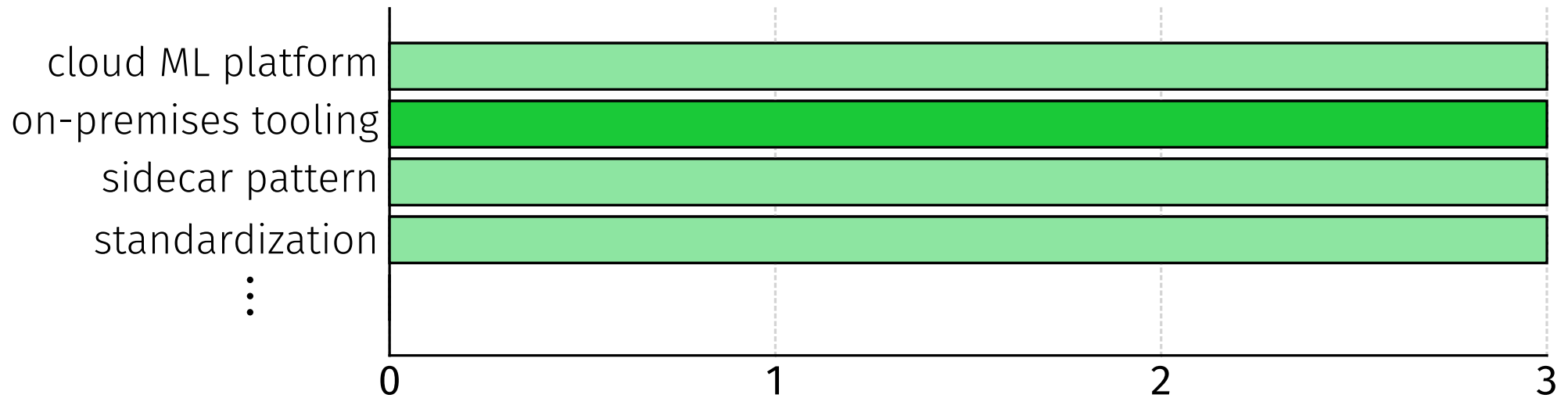


**Key Insight** Available on-premise tooling is not competitive with cloud offerings regarding user experience

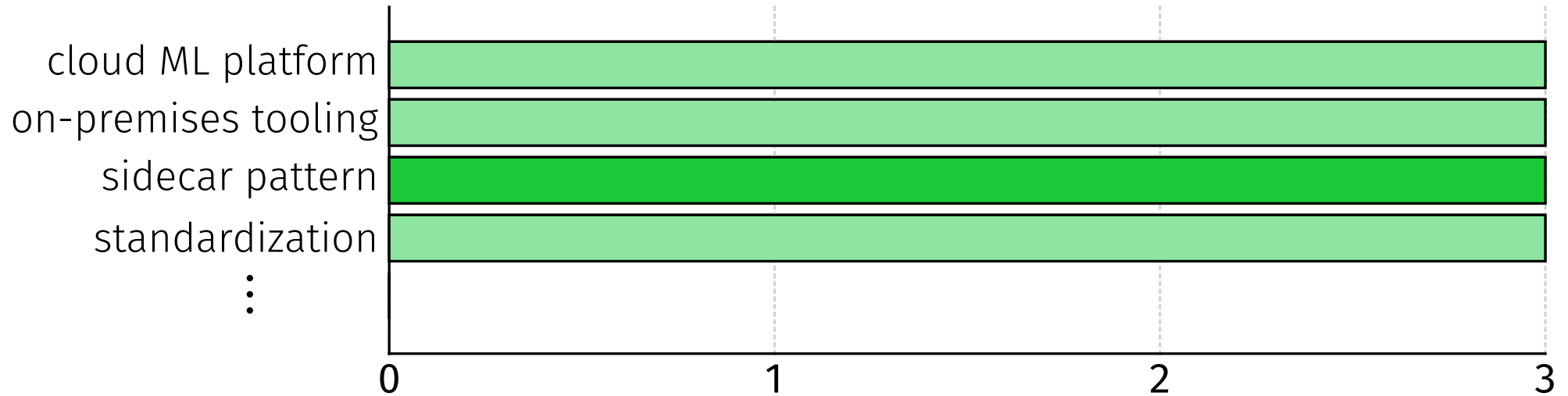




**Key Insight** Participants prefer cloud ML infrastructure for its usability and automation capabilities.

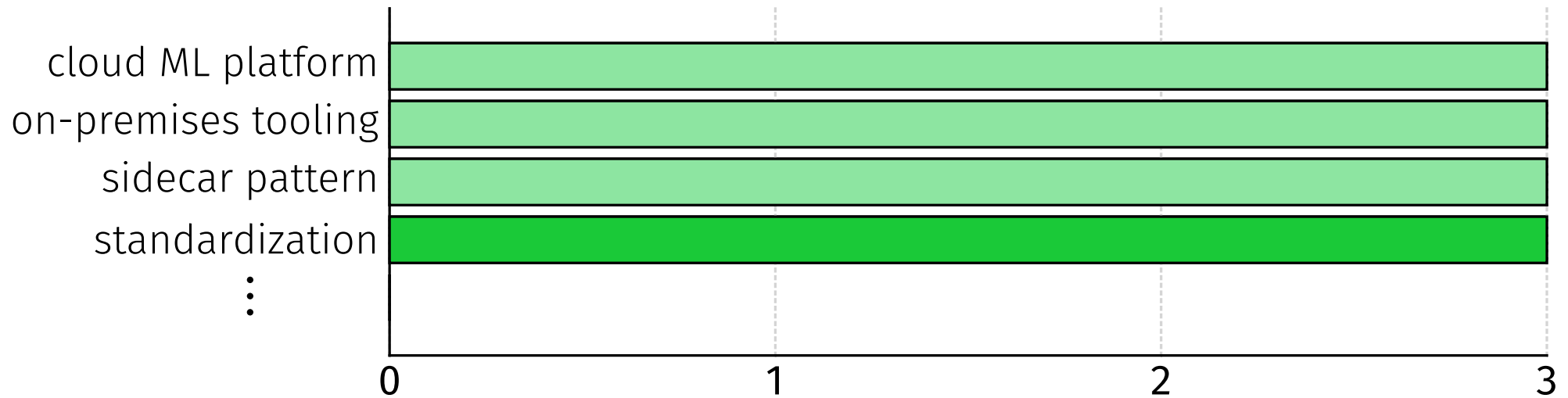


**Key Insight** After cloud ML infrastructure, participants prefer centralized on-premise ML infrastructure.



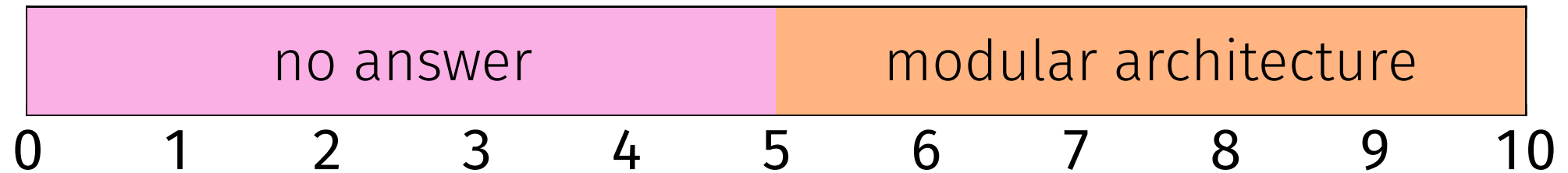
**Key Insight** As a last resort, participants fall back on the sidecar pattern for ML model deployment.

Model is deployed next to the system using its results.



**Key Insight** Participants wish for a best practice guidelines on ML system architecture & technology selection

**How did integrating an ML model into the system change the software architecture?**



**Key Insight** Generally, existing systems are so well-architected that ML-based functionality can be integrated without major changes to the software architecture.

**However** ML models may require specialized hardware (e.g., GPUs)

- Challenges mainly stem from the trade-off between **Security** and **Usability**
  - Focus on security is a key challenge
  - In some cases, data may be classified too conservatively

- Subjective bias
- Incomplete results
- Limited scope of case study

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## Conclusion

- Interview-based case study on MLOps adoption at Zeiss SMT
- Collected challenges & solutions from 10 interviews
- Key challenge is trade-off between **Security** and **Usability**

## Future Work

- Improved on-premise ML infrastructure
- MLOps guidelines
- Comparison with other manufacturing companies

# Appendix

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- Lewis GA, Ozkaya I, Xu X (2021) Software Architecture Challenges for ML Systems. In: 2021 IEEE International Conference on Software Maintenance and Evolution (ICSME). IEEE, Luxembourg, pp 634–638
- Meulen R van der, McCall T (2018) Gartner Says Nearly Half of CIOs Are Planning to Deploy Artificial Intelligence. <https://www.gartner.com/en/newsroom/press-releases/2018-02-13-gartner-says-nearly-half-of-cios-are-planning-to-deploy-artificial-intelligence>. Accessed 4 Mar 2025
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