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A Survey on the Challenges Hindering the Application of Data Science, Digital Twins and Design Automation in Engineering Practice

S. Rädler [1,2,✉] and E. Rigger [1]

[1] V-Research GmbH, Austria, [2] TU Wien, Austria

✉ simon.raedler@v-research.at

Abstract

Digital Engineering is an emerging trend and aims to support engineering design by integrating computational technologies like design automation, data science, digital twins, and product lifecycle management. To enable alignment of industrial practice with state of the art, an industrial survey is conducted to capture the status and identify obstacles that hinder implementation in the industry. The results show companies struggle with missing know-how and available experts. Future work should elaborate on methods that facilitate the integration of Digital Engineering in design practice.

Keywords: artificial intelligence (AI), design automation, digital design, computational design methods, product lifecycle management (PLM)

1. Introduction

Companies are facing challenges such as an increase of competition and pressure on prices because of global markets (Spence, 2011), new regional regulations towards green production and development to decrease global warming and climate change (Hannappel, 2017; Shen et al., 2017; Shi et al., 2016) or the reduced workforce caused by the COVID-19 crisis and economic shutdowns (Ozili and Arun, 2020). Therefore, the companies experience an increasing need to improve their products and processes in the design regarding quality and efficiency, respectively (Ehrlenspiel et al., 2007). One such means is the application of digital engineering methods. Digital engineering builds upon product lifecycle management (PLM, (Stark, 2011)) by exploiting the resulting data and process maturity of PLM's holistic approach for managing data, workflows and tools. In particular, digital engineering focuses on leveraging design performance (Duffy, 2005) based on the application of computational methods such as design automation (DA), data science (DS) or digital twins (DT). These terms are defined as follows:

- Design automation refers to computational methods for supporting design tasks based on automation to reduce errors and costs, minimize lead times or explore solution spaces. Design automation accounts for software solutions that combine product knowledge and algorithms, such as configuration solutions, CAD macros for automating routine processes and the application of optimization algorithms for design optimization (Rigger et al., 2018).
- Data science refers to the extraction of information and knowledge from unstructured and structured data. The procedure to analyze and understand the data is based on methods and theories from many fields like mathematic, computer science and statistics. The application results in opportunities to develop solutions based on (large) amounts of data, such as predicting production costs or machine maintenance. (Cao, 2017)

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- The digital twin comprises the digital representation of a physical object throughout the product lifecycle, making it possible to simulate the behaviour of a product during development or to analyze and optimize the behaviour of a finished product. The focus is on the exchange of data between the physical product and the digital twin. (Grieves and Vickers, 2017)

To foster the integration of digital engineering in design practice, methods have been proposed in the context of design automation (Curran et al., 2010; Zheng et al., 2012) and data science (Bitrus et al., 2020; Rädler and Rigger, 2020; Wiemer et al., 2019). Design automation studies show that the potential and the opportunities in industry are still not entirely reflected (Rigger and Vosgien, 2018). Similarly, the main challenges of implementing and utilizing configurators show that configuration technology is not widely applied in the industry (Kristjansdottir et al., 2018). However, a more comprehensive study of the current state of applying digital engineering methods in the context of design performance improvement is missing. Therefore, the following research questions are posed:

- What obstacles hinder the application of digital engineering in practice?
- What means are required to foster the integration of digital engineering in practice?

The research questions are addressed using a sequential explanatory survey (Creswell, 2009, p. 211) designed to broadly assess the current state of digital engineering practice. The study is conducted as a quantitative online survey, followed by a qualitative interview to bridge the interpretation gaps of the quantitative results. The results are then used to derive ways forward in digital engineering research so to foster the transition of methods from academia to industrial practice.

The remainder of this publication is structured as follows: Section 2 reviews surveys and existing methods supporting the implementation and application of digital engineering in practice. Section 3 depicts the applied research method for the conducted survey. Section 4 illustrates the findings that are discussed in Section 5. Finally, in Section 6, a conclusion is drawn, and an outlook is given.

2. Related Work

Digital engineering is a concept that implements digital technologies to support the engineering design process by taking the entire product lifecycle into account (Huang et al., 2020; Tsui et al., 2018). To incorporate data from PLM and extend engineering methods, digital engineering uses various approaches such as digital twins (Tao et al., 2018), design automation (Rigger, Lutz, et al., 2019; Verhagen et al., 2015) or data science (Dogan and Birant, 2021).

The considered topics DA/DT/DS are fast evolving in academia and industry. For example, the number of publications related to data science applications in engineering (e.g. predictive maintenance, quality assurance) increased rapidly in the past five years, as depicted in Figure 1, showing the importance and relevance of this topic in the scientific community as well as the market (Dogan and Birant, 2021).

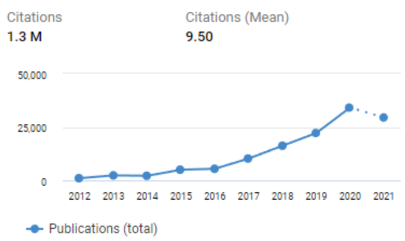

Figure 1. Fast-evolving number of publications related to data science in engineering[1]

Also, recent studies show the trend to intensify the work in digital engineering-related IT fields, e.g. artificial intelligence and smart factory (Russegger et al., 2015; Schneider et al., 2020). The authors of Russegger et al. (2015) assessed the usage of big data in SMEs (small and medium-sized enterprises) and reported that 80% of the interviewed SMEs think that big data is relevant for the future. According to Schneider et al. (2020), 23% of the companies report data science experts are essential for their field, this number will increase to 43% in future. The corresponding numbers for automation & artificial intelligence are 22% nowadays and 39% in future.

[1]Accessible on https://app.dimensions.ai/discover/publication?search_text="data%20science"%20"engineering"

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Due to the interdisciplinary aspects of digital engineering, knowledge from different research fields is required to apply approaches like the CRISP-DM methodology (Riepl, 2012) from data science. Although these methods are generally applicable, domain-specific difficulties concerning data collection or processing are not explicitly depicted. Therefore, methods have been proposed to extend CRISP-DM for the applicability in engineering (Huber et al., 2019; Rädler and Rigger, 2020; Stanula et al., 2018) by better align with the requirements in the specific domain, e.g. extension of the data understanding to gather knowing about tribological experiments (Bitrus et al., 2020). Similarly, methods to develop support for the engineering design by applying design automation (Rigger, Lutz, et al., 2019; Verhagen et al., 2015) or digital twins (Lu et al., 2020; Miller et al., 2018) are proposed in the literature. Although several methods are proposed supporting the integration of digital engineering methods and activities in research demonstrate the importance of the topic, there is still a growing gap between academic research and practice in industry (Berman et al., 2018; Rigger and Vosgien, 2018). Despite best practice for innovation in German industry (Meyer et al., 2022) have been reviewed, but no survey in literature observes the combination of the three selected digital engineering topics in an industrial context. Therefore, this work aims to obtain a holistic view of the state of practice to support future research in digital engineering and reduce the gap between academia and industry.

3. Research Method

In this section, first, the survey questions used to answer the research questions are introduced. Next, the pursued method, including the experimental setup, is depicted.

3.1. Survey Questionnaire

The questionnaire consists of 24 closed questions with some open answers to provide additional insights and are based on a literature review in collaboration with the IWI[2] Institute. To increase reliability of answers, the participants are asked about the relevance of the topics in their respective companies. Meaning, one or multiple answers are possible and therefore enable a preselection of relevant questions. Consequently, the response rate varies for each topic and question. The actual number of asked questions varies per participant based on an initial question of interest. Based on the participants' interest, the following questions are asked:

1. To what extent is DA/DT/DS used in your company?
2. What is the motivation behind the (planned) deployment of DA/DT/DS in your company?
3. What are the biggest challenges to implementing and using DA/DT/DS in your company?
4. How is a machine learning algorithm pre-selected as part of DS applications/projects in your company?
5. How would you rate your experience with projects using DA/DS/DT in your company?
6. Where do you get the necessary know-how for the development of DA/DT/DS?

3.2. The Experimental Setup

The method applied for this research is a mixed-methods study (Creswell, 2009). The chosen strategy is the sequential explanatory survey, characterized as weighted to the strong quantitative learning and explained with the insights from the qualitative part (Creswell, 2009, p. 211; Patton, 2002). The quantitative survey is executed as an online survey using closed answers based on literature review, completed by experts. Additionally, open-answers are possible. At the beginning of the questionnaire, the definitions from Section 1 are depicted. The online survey allowed gathering answers from more companies and enabled to identify trends in the industry. To support the interpretation of the given answers, a single-person interview was conducted by an expert for interview studies with a background in market research and a digital engineering expert. The participants are selected based on NACE[3] categorizations. The selected categories are related to engineering products and industries with a high

[2] Industriewissenschaftliches Institut - IWI: https://iwi.ac.at/

[3] The Statistical Classification of Economic Activities in the European Community (short NACE from French) is a system that enables the classification of industries in the European Union.

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demand for engineering products, e.g. food companies using automated machines to produce and fill goods.

4. Results

In this section, the findings of the study are presented, starting with study relevant metrics, e.g., response rate or characteristics of the participants. Next, the main findings of each survey question is given.

4.1. Response and Participants' Characteristics

The questionnaire was sent to 1842 participants and the total set of companies is composed as follows: 3,4% of companies have more than 1000 employees, 27,5% between 250 and 1000 employees and 69,1% less than 250 but more than 80 employees. 81 participants filled out the survey, yielding a response rate of 4,4% and a margin error of 10,5% (Tanur, 2011). The respondents' positions are categorized as CEO (2), CTO (1), CDO (2), CFO (1), Business Unit Manager (3), Head of Department (Research (2), Sales (2), technical/engineering (4), Digitalization (5), IT (3), Shopfloor (1), Unspecified (17)), Process Manager (2), others (4). 60% are interested in design automation, 70% in data science and 63% in digital twins. The survey was comprehensively submitted by 66%, 16% partly and 15% after the first question of interest and 3% without any answer. The survey data is analysed as a single dataset using univariate analysis (Blessing and Chakrabarti, 2009). Further analysis based on separate economic sectors shown to be not significant (p-value > 0.4).
The second part of the survey was conducted with 7 companies (4 with more than 1000 employees; 3 with less than 250). The interview guide for the qualitative data was created based on the quantitative survey findings and aims to bridge interpretation gaps from the quantitative results. Although a definition for each domain was given prior to the interviews, respondents were sometimes unable to assign their projects to a single domain, e.g., is a CAD configurator with AI data science or design automation? One reason might be the possible overlapping of the areas, e.g. engineers are increasingly adopting data science for design automation applications (Camburn et al., 2020; Jiang et al., 2022).

4.2. Implementation Status

Figure 2 on the top left depicts the distribution of the digital engineering applications in practice.

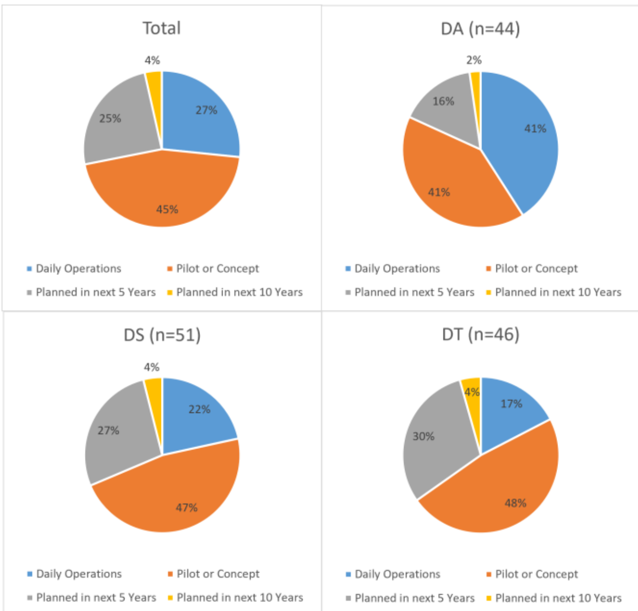

Figure 2. To what extent is DA/DT/DS used in your company? (Multiple answers possible)

About a quarter are using digital engineering methods in their daily business and nearly half of the companies are in a pilot or concept phase of integrating digital engineering methods. Comparing the subcategories, design automation is more often applied in the daily operations while the number of

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companies in the pilot and concept phase is comparable with the others. The long-term plans are equally distributed, while the next five years plan compensates design automation's advance in daily business.

4.3. Motivation

Figure 3 shows the companies motivations to apply digital engineering. For each topic, the main interest varies, while the overall focus is error reduction. The top five motivations are related to product or process improvement followed by reducing costs. To narrow down the scope of the question, not all answers were available for each topic.

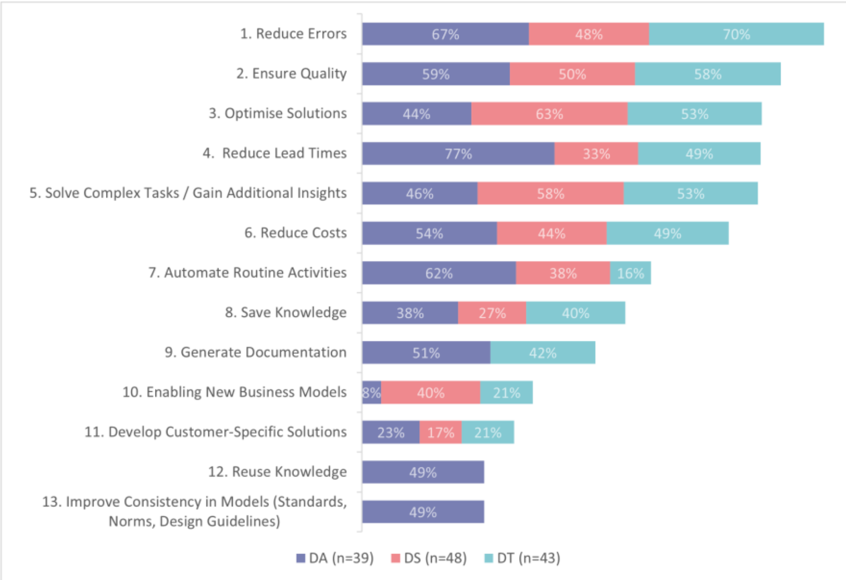

Figure 3. What is the motivation behind the (planned) deployment of DA/DT/DS in your company? (Multiple answers possible)

4.4. Challenges

The main challenges are the implementation effort, the lack of knowledge, and the shortcomings in data quality and availability. The problem of sufficient accuracy and integration into the daily processes of the production machines was cited as the reason for the implementation effort. For digital twins, the lack of a business model or financing is more challenging than the data quality and availability. Although the data is a challenge for the companies, the infrastructure requirements, both internal and external, and the lack of suitable tools seem to be no problematical factors.

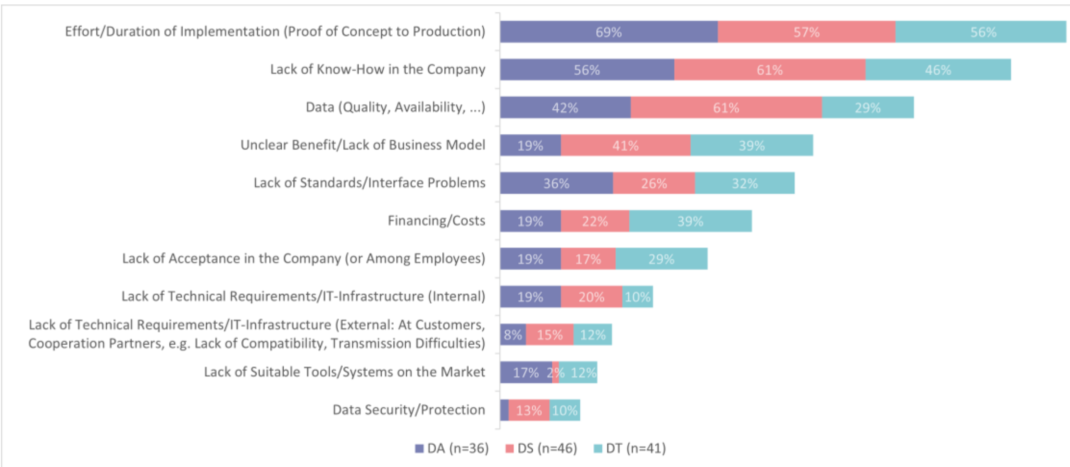

Figure 4. What are the biggest challenges to implementing and using DA/DT/DS in your company? (Multiple answers possible)

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4.5. Implementation Strategy

Figure 5 illustrates the strategy for selecting machine learning algorithms in the context of digital engineering applications. The companies are mainly relying on expert knowledge followed by a try-and-error approach adapting pre-implemented algorithms. Only a minority uses methods for the implementation. Optionally, the name of the method could be given. The only method was CRISP-DM.

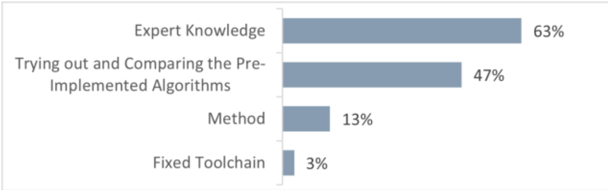

Figure 5. How is a machine learning algorithm pre-selected as part of DS applications/projects in your company? (Multiple answers possible; n=32)

4.6. Experiences

To assess the experience of the companies, a Likert scale from very negative to very positive in five steps was used. The results were added together, with very negative being minus 2 and very positive being plus 2, and the values in between each in one step. Figure 6 shows the overall impression of digital engineering realizations is positive except the satisfaction with the employees. The satisfaction with the availability of qualified employees is correlated with the Costs/ROI. If the availability is ranked less positive, the cost ranking is also less positive. Additionally, data science experiences are less positive.

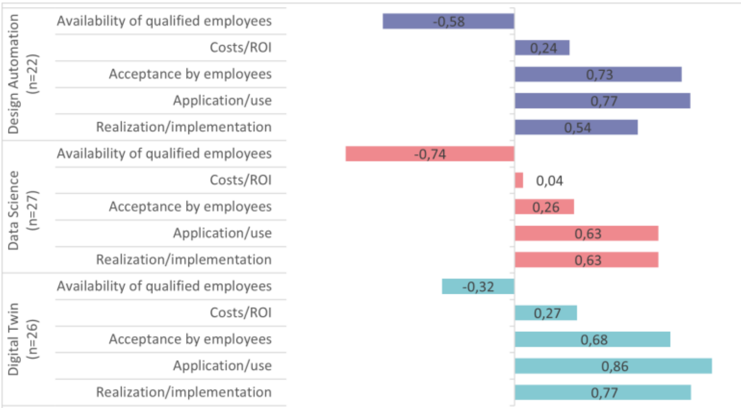

Figure 6. How would you rate your experience with projects using DA/DS/DT in your company? (Likert Scale)

4.7. Knowledge Acquisition Source

To enable digital engineering implementation streamlining, the sources used to gather the required implementation knowledge are determined. Figure 7 illustrates that external knowledge is more valuable for digital twins, while for the others, a mix of internal and external expertise is preferred.

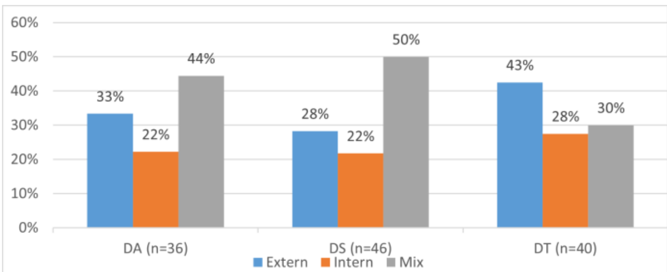

Figure 7. Where do you get the necessary know-how for the development of DA/DT/DS? (Multiple answers possible)

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5. Discussion

In this section, first, the results of the survey are critically discussed and justified. Second, the implications of the findings are used to derive avenues for future research.

5.1. Findings of the Survey

Generally, the motivation and the readiness to apply digital engineering can be seen in Figure 1. In addition, design automation has a greater degree of maturity and is more common in companies, both in daily business and in the conceptual phase. Comparing to a study in 2016 (Rigger and Vosgien, 2018), the daily used design automation increased by 4%, showing the results are comparable. Therefore, trends can be derived by assessing the findings of both studies.

Comparing the motivation with a study regarding the motivational drivers for the application of design automation in industry from 2016 (Rigger and Vosgien, 2018), reducing the errors stays as the primary goal. However, the remaining priorities shifted so the reduction of costs is not anymore part of the top five. Interestingly, these drivers are related to product and process optimization instead of costs or revenue. Solving complex tasks is now ranked dramatically higher when compared to 2016 (Rigger and Vosgien, 2018), being well aligned with the increasing challenges due to rising complexity in engineering systems.

Although the results of the survey show a trend of the companies for applying digital engineering, the following open challenges need to be addressed: First, human-based factors like the effort/duration of implementation or the lack of knowledge. Second, economic factors like the unclear benefit or the financing of the development. Finally, the system and infrastructure-related challenges like the lack of standards and interfaces, and the availability and quality of the data need to be tackled. Yes, these factors are related to each other. The quality of data, for instance, can be improved with the increased knowledge of the employees gathering the data. The number of integrated applications will further lead to an increased number of interfaces and standardization. And to close the circle: When the interfaces are defined and standardization is in place, the quality and availability of the data increases. Additionally, when employee knowledge matures through learning from existing interfaces and standardizations, the effort required to implement digital engineering is reduced and better benefit identification is made possible. To assess these benefits, the evaluation of the potential seems to be beneficial. In this respect, a method for the derivation of metrics to assess the impact of design automation in design practice has been proposed (Rigger, Vosgien, et al., 2019).

Although there are methods to assess the impact or those that support the implementation, the findings show that the companies rely on expert knowledge to choose the data science algorithm. As depicted in Figure 5, the second primary strategy to select an algorithm is to try out pre-implemented algorithms. These findings are supported by a survey from the tech community Stack Overflow ("Stack Overflow Developer Survey 2021", 2021), with 80.000 participants saying that 60% of the respondents learned to code from online resources. Additionally, the survey depicts that data scientists and machine learning specialists are the developer type with the least experience apart from students (average < 9 years). The few years of experience of data scientists is most likely the same as for digital engineering. Since the knowledge is mainly gathered from online courses and the lack of knowledge is a main problem for the companies, best practice needs to be established. In this respect, the elaboration of new methods is required to foster the derivation of best practices and gain experience.

The dissatisfaction with the skills of companies' employees is also a widespread challenge, reflected in the low availability of employees in the market. In Figure 6, the data science available employees are worse ranked than for the other field, which might be in correlation with the findings of the Stack Overflow survey and the less academic research experience of the data scientist. While employee availability is rated negatively, the use of the technology and the resulting product are satisfactory and employee adoption is reasonable. The knowledge acquisition sources in Figure 7 show that many companies are aware that the knowledge can only partly be acquired internally.

The actual number of available employees cannot meet the industry's need to introduce digital engineering. Additionally, the knowledge of experts in enterprises is too low and the application of methods to support the implementation is not reasonable. In this regard, additional methods and more

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comprehensive methodologies need to be developed to further support the implementation of digital engineering and possibly solve the problems of applicability in practice.

5.2. Future work

To support the implementation of digital engineering and strengthen the growth of the research field, a comprehensive methodology needs to be developed to foster the implementation of digital engineering. In this respect, the Enterprise Architecture framework (Lankhorst et al., 2010; Lapalme et al., 2016; Zachman, 1987) realized in the ArchiMate language (The Open Group, 2019) seems to be beneficial. The Enterprise Architecture framework enables a model-driven approach to ensure the IT applications are compatible with the related business processes, and the infrastructure is satisfying.

Figure 8 depicts the ArchiMate Framework supporting the integration of applications and technologies in business processes. The main benefits of the framework are the integration of different points of view and the integration of domain knowledge with the related IT infrastructure (Lankhorst, 2017). Additionally, Enterprise Architecture adds model management to reuse specific parts and reduce redundancies and duplications.

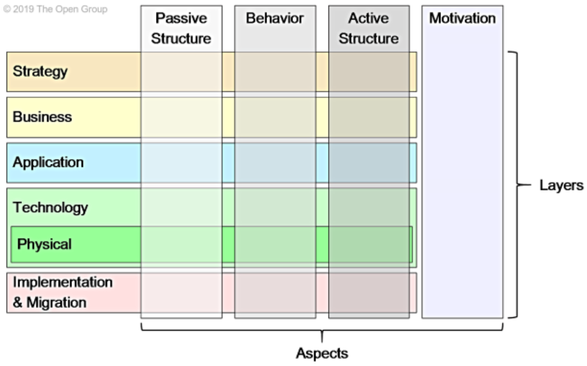

Figure 8. ArchiMate full framework (The Open Group, 2019)

Although the enterprise architecture framework provides necessary and beneficial features, additional detail is required with respect to data description, data quality evaluation, and digital engineering topics, like required features for digital twins or data science properties. In addition, future work on the specific aspects of digital engineering will need to be conducted depending on the various requirements of specific industries to ensure that the proposed methodology fits in the state of practice in each industry.

6. Conclusion

In this work, the current state of digital engineering practice in the industry is assessed based on quantitative and qualitative surveys with Austrian enterprises. Reviewing the factors pushing and hindering the application of digital engineering in industry and comparing to results obtained from 2016 shows a trend towards more extensive usage of IT systems in engineering practice and the use of digital engineering methods for solving complex engineering tasks. Independent on the particular domain of digital engineering, DT/DA/DS, the missing knowledge can be considered the major hindering factor in industry. In this context, the usage of Enterprise Architecture as a framework to support comprehensive digital engineering integration is suggested as focal point of future research to provide means to industry to compensate the most critical factor currently experienced, the missing knowledge regarding digital engineering methods.

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References

Berman, F., Rutenbar, R., Hailpern, B., Christensen, H., Davidson, S., Estrin, D., Franklin, M., et al. (2018), "Realizing the potential of data science", Communications of the ACM, Vol. 61 No. 4, pp. 67–72.

Bitrus, S., Velkavrh, I. and Rigger, Eugen. (2020), "Applying an Adapted Data Mining Methodology (DMME) to a Tribological Optimisation Problem", International Data Science Conference (IDSC 2020), presented at the international Data Science Conference (iDSC 2020).

Blessing, L.T.M. and Chakrabarti, A. (2009), DRM, a Design Research Methodology, Springer, Dordrecht ; London, available at: https://doi.org/10.1007/978-1-84882-587-1.

Camburn, B., He, Y., Raviselvam, S., Luo, J. and Wood, K. (2020), "Machine Learning-Based Design Concept Evaluation", Journal of Mechanical Design, Vol. 142 No. 3, available at:https://doi.org/10.1115/1.4045126.

Cao, L. (2017), "Data Science: A Comprehensive Overview", ACM Computing Surveys, Vol. 50 No. 3, pp. 1–42.

Creswell, J.W. (2009), Research Design - Qualitative, Quantitative, and Mixed Methods Approaches, 3rd edition., SAGE Publications Ltd., available at: https://uk.sagepub.com/en-gb/eur/research-design/book237357 (accessed 26 April 2018).

Curran, R., Verhagen, W.J.C., van Tooren, M.J.L. and van der Laan, Ton.H. (2010), "A multidisciplinary implementation methodology for knowledge based engineering: KNOMAD", Expert Systems with Applications, Vol. 37 No. 11, pp. 7336–7350.

Dogan, A. and Birant, D. (2021), "Machine learning and data mining in manufacturing", Expert Systems with Applications, Vol. 166, p. 114060.

Duffy, A.H.B. (2005), "Design process and performance", Engineering Design-Theory and Practice, Cambridge, U.K., pp. 76–85.

Ehrlenspiel, K., Kiewert, A. and Lindemann, U. (2007), Cost-Efficient Design, edited by Hundal, M.S., Springer-Verlag, Berlin Heidelberg, available at: https://www.springer.com/de/book/9783540346470 (accessed 25 September 2019).

Grieves, M. and Vickers, J. (2017), "Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems", in Kahlen, F.-J., Flumerfelt, S. and Alves, A. (Eds.), Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches, Springer International Publishing, Cham, pp. 85–113.

Hannappel, R. (2017), "The impact of global warming on the automotive industry", AIP Conference Proceedings, American Institute of Physics, Vol. 1871 No. 1, p. 060001.

Huang, J., Gheorghe, A., Handley, H., Pazos, P., Pinto, A., Kovacic, S., Collins, A., et al. (2020), "Towards digital engineering: the advent of digital systems engineering", International Journal of System of Systems Engineering, Inderscience Publishers, Vol. 10 No. 3, pp. 234–261.

Huber, S., Wiemer, H., Schneider, D. and Ihlenfeldt, S. (2019), "DMME: Data mining methodology for engineering applications - a holistic extension to the CRISP-DM model", Procedia CIRP, Vol. 79, pp. 403–408.

Jiang, S., Hu, J., Wood, K.L. and Luo, J. (2022), "Data-Driven Design-By-Analogy: State-of-the-Art and Future Directions", Journal of Mechanical Design, Vol. 144 No. 2, p. 020801.

Kristjansdottir, K., Shafiee, S., Hvam, L., Forza, C. and Mortensen, N.H. (2018), "The main challenges for manufacturing companies in implementing and utilizing configurators", Computers in Industry, Vol. 100, pp. 196–211.

Lankhorst, M. (2017), Enterprise Architecture at Work, 4th ed., Springer Berlin Heidelberg, Berlin, Heidelberg, available at:https://doi.org/10.1007/978-3-642-01310-2.

Lankhorst, M.M., Proper, H.A. and Jonkers, H. (2010), "The Anatomy of the ArchiMate Language":, International Journal of Information System Modeling and Design, Vol. 1 No. 1, pp. 1–32.

Lapalme, J., Gerber, A., Van der Merwe, A., Zachman, J., Vries, M.D. and Hinkelmann, K. (2016), "Exploring the future of enterprise architecture: A Zachman perspective", Computers in Industry, Vol. 79, pp. 103–113.

Lu, Y., Liu, C., Wang, K.I.-K., Huang, H. and Xu, X. (2020), "Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues", Robotics and Computer-Integrated Manufacturing, Vol. 61, p. 101837.

Meyer, T., Gracht, H.A. von der and Hartmann, E. (2022), "How Organizations Prepare for the Future: A Comparative Study of Firm Size and Industry", IEEE Transactions on Engineering Management, Vol. 69 No. 2, pp. 511–523.

Miller, A.M., Alvarez, R. and Hartman, N. (2018), "Towards an extended model-based definition for the digital twin", Computer-Aided Design and Applications, Vol. 15 No. 6, pp. 880–891.

Ozili, P.K. and Arun, T. (2020), Spillover of COVID-19: Impact on the Global Economy, SSRN Scholarly Paper No. ID 3562570, Social Science Research Network, Rochester, NY, available at:https://doi.org/10.2139/ssrn.3562570.

https://doi.org/10.1017/pds.2022.172 Published online by Cambridge University Press

Patton, M.Q. (2002), "Two Decades of Developments in Qualitative Inquiry: A Personal, Experiential Perspective", Qualitative Social Work, SAGE Publications, Vol. 1 No. 3, pp. 261–283.

Rädler, S. and Rigger, E. (2020), "Participative Method to identify Data-Driven Design Use Cases", Proceedings of the International Conference on PLM, presented at the Internation conference on product lifecycle management, Springer, Rapperswil, CH, available at:https://doi.org/10.1007/978-3-030-62807-9_54.

Riepl, W. (2012), "CRISP-DM: Ein Standard-Prozess-Modell für Data Mining", Statistik Dresden, available at: https://statistik-dresden.de/archives/1128 (accessed 7 March 2020).

Rigger, E., Lutz, A., Shea, K. and Stanković, T. (2019a), "Estimating the Impact of Design Automation: the Influence of Knowledge on Potential Estimation", Proceedings of ICED 19, presented at the ICED 2019, Design Society, Delft.

Rigger, E., Stanković, T. and Shea, K. (2018), "Task Categorization for Identification of Design Automation Opportunities", Journal of Engineering Design, available at:https://doi.org/10.1080/09544828.2018.1448927.

Rigger, E. and Vosgien, T. (2018), "Design Automation State of Practice - Potential and Opportunities", DS 92: Proceedings of the DESIGN 2018 15th International Design Conference, presented at the 15th International Design Conference, pp. 441–452.

Rigger, E., Vosgien, T., Shea, K. and Stankovic, T. (2019b), "A top-down method for the derivation of metrics for the assessment of design automation potential", Journal of Engineering Design, pp. 1–31.

Russegger, S., Freudenthaler, B., Günter, G., Kieseberg, P., Stern, H. and Strohmeier, F. (2015), "Big Data und Data-driven Business für KMU", Salzburg Research Forschungsgesellschaft, May, available at: https://www.salzburgresearch.at/publikation/big-data-und-data-driven-business-fuer-kmu/ (accessed 2 July 2021).

Schneider, H.W., Brunner, P., Demirol, D., Luptacik, P. and Landendinger, P. (2020), "IT-Qualifikationen für die österreichische Wirtschaft", Vol. IWI-Studie, p. 115.

Shen, J., Wei, Y. and Yang, Z. (2017), "The impact of environmental regulations on the location of pollution-intensive industries in China", Journal of Cleaner Production, Vol. 148, available at:https://doi.org/10.1016/j.jclepro.2017.02.050.

Shi, B., Yang, H., Wang, J. and Zhao, J. (2016), "City Green Economy Evaluation: Empirical Evidence from 15 Sub-Provincial Cities in China", Sustainability, Multidisciplinary Digital Publishing Institute, Vol. 8 No. 6, p. 551.

Spence, M. (2011), "The Impact of Globalization on Income and Employment: The Downside of Integrating Markets", Foreign Affairs, Vol. 90, p. 28.

"Stack Overflow Developer Survey 2021". (2021), Stack Overflow, May, available at: https://insights.stackoverflow.com/survey/2021/ (accessed 27 October 2021).

Stanula, P., Ziegenbein, A. and Metternich, J. (2018), "Machine learning algorithms in production: A guideline for efficient data source selection", Procedia CIRP, Vol. 78, pp. 261–266.

Stark, J. (2011), "Product Lifecycle Management", Product Lifecycle Management, Springer London, pp. 1–16.

Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H. and Sui, F. (2018), "Digital twin-driven product design, manufacturing and service with big data", The International Journal of Advanced Manufacturing Technology, Vol. 94 No. 9, pp. 3563–3576.

The Open Group. (2019), "ArchiMate® 3.1 Specification", available at: https://pubs.opengroup.org/architecture/archimate3-doc/ (accessed 18 March 2020).

Tsui, R., Davis, D. and Sahlin, J. (2018), "Digital Engineering Models of Complex Systems using Model-Based Systems Engineering (MBSE) from Enterprise Architecture (EA) to Systems of Systems (SoS) Architectures & Systems Development Life Cycle (SDLC)", INCOSE International Symposium, John Wiley & Sons, Ltd, Vol. 28 No. 1, pp. 760–776.

Verhagen, W.J.C., de Vrught, B., Schut, J. and Curran, R. (2015), "A method for identification of automation potential through modelling of engineering processes and quantification of information waste", Advanced Engineering Informatics, Vol. 29, pp. 307–321.

Wiemer, H., Drowatzky, L. and Ihlenfeldt, S. (2019), "Data Mining Methodology for Engineering Applications (DMME) - A Holistic Extension to the CRISP-DM Model", Applied Sciences, Vol. 9 No. 12, p. 2407.

Zachman, J.A. (1987), "A framework for information systems architecture", IBM Systems Journal, Vol. 26 No. 3, pp. 276–292.

Zheng, P., Zhao, G., Torres, V.H. and Rios, J. (2012), "A knowledge-based approach to integrate Fuzzy Conceptual Design Tools and MOKA into a CAD system", 2012 7th International Conference on Computing and Convergence Technology (ICCCT), presented at the 2012 7th International Conference on Computing and Convergence Technology (ICCCT), pp. 1285–1291.

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