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Enabling Federated Interoperability in Enterprise Models with Artificial Intelligence and Simulation

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ABSTRACT

Enterprise interoperability is crucial for modern companies survival and market competitiveness. Progress in this field has stalled due to a lack of suitable techniques and technology. However, the rise of generative AI and language models now enables automation of various interoperation processes. This vision paper reviews the limitations of previous interoperability methods and suggests enhancements through the use of language models and simulation.

1 INTRODUCTION

Enterprises started opening stores internationally at the end of the 20th century, which led to the materialization of globalization. This created a competitive environment for businesses given that foreign organizations were vying for a share of the market (Dollfus, 2001). The competitiveness witnessed in these scenarios force enterprises to improve their performance so that they can stay in the market. In some cases, enterprises cannot compete and bring enough amelioration alone and they need to cooperate with other organizations. This allows them to obtain multiple advantages such as improved performance, new business opportunities and new potential products. It also allows them to survive in the global industry (Lecerf, 2006).

Such a partnership needs to consider various aspects, including communication, coordination, cooperation, and collaboration across different concerns of the enterprises (Lauras, 2004; Forest, 2003; Seguy, 2008; Winer et al., 1994). Hence, the participants need to work together harmoniously to achieve these requirements. This gave rise to the concept of interoperability that joins these necessities together and structures them. It is defined as the ability of two or more enterprises to interact, communicate and exchange information on four concerns: data, services, processes, and business (IEEE, 1990; IDEAS, 2003; ATHENA, 2003; INTEROP, 2007). In order to help enterprises achieve this collaborative state and understand what is needed, a standardized schema was developed, and ISO 11354 was put in place (ISO/DIS11354-1, 2009). It is based on the work done by European projects such as INTEROP (INTEROP, 2007) and ATHENA (ATHENA, 2003). This standardized the collaborative process and put guidelines on the different concerns where enterprises must implement the interoperability demands, the different barriers they might face, and a categorization of the approaches that might be used. Subsequently, this interoperability framework became a key solution to numerous problems in multiple domains such as healthcare (Lezcano, 2011; Blackman-Lees, 2018), mobility (Hussain, 2018; Hussain 2019), and manufacturing (Ramnath et al., 2020; Canciglieri et al., 2018).

Similar to the prospects brought by the inclusion of the interoperability framework, these domains have greatly benefited from the advancements in artificial intelligence (AI). AI can be defined as the capability of machines to execute tasks in a manner that approximates human behavior (McCarthy et al, 2006). AI solutions, i.e. models, were developed by IBM to aid physicians in disease diagnosis through image recognition (Davenport & Ronanki, 2018). These models also helped multiple manufacturing firms in multiple situations such as digitalizing some of their process models and designs through computer visualization systems and identifying defects in the manufacturing process through machine learning models (Björkdahl, 2020). Other solutions were also proposed regarding mobility such as point-of-interest recommendation, next-location prediction, and traffic-flow prediction while maintaining the privacy and security of the data used of the parties involved through federated learning (Gecer & Garbinato, 2024). Studies were conducted as well to develop more advanced AI models in order to progress the field of automated translation between multiple languages and formats (Popel et al., 2020; Shashin & Ismail, 2024).

Alongside the advancement of AI and the benefits it brings, as well as the standardization of the interoperability concept, we observe a possibility of integrating AI models into the collaborative process between enterprises and enhancing the existing interoperability capabilities. This would allow interoperations to happen on the fly without significant prior work and would advance the interoperability approach called federated. Hence, we investigate previous studies in the interoperability domain to consider the integration of AI models, specifically LLMs, to develop the federated interoperability approach and resolve previous problems encountered in this domain explained in Section 3. Subsequently, we discuss in the Related Work section some of the previous studies done on the interoperability domain as well as the beneficial advances of AI regarding data mapping and transformation. Afterwords, we present the limitations of the previous work on interoperability and the improvements that can be brought by the integration of AI models in the Previous Limitations and Innovations section. Finally, we conclude and summarize the ideas presented in the Conclusion section.

2 RELATED WORK

1.1 INTEROPERABILITY

An interoperability framework has been put in place by INTEROP (INTEROP, 2007) and then standardized in the

ISO 11354 (ISO/DIS11354-1, 2009). As shown in Figure 1, we can see that interoperability can occur on four concerns: data, service, process, and business. In this case, it is a vertical hierarchy where services need data to operate, processes use multiple services to obtain a certain outcome, and the business ideas and requirements need multiple processes to execute trades, manufacture products, and perform collaborations. However, there are also three common barriers to achieve interoperability on each of these concerns: conceptual, technological, and organizational. These mainly affect the syntax and semantics used in each concern, the tools used to perform the collaboration, and the authorities involved, respectively.

Multiple solutions have been proposed to implement interoperability in business collaborations and, according to the ISO 11354 (ISO/DIS11354-1, 2009) framework, they can

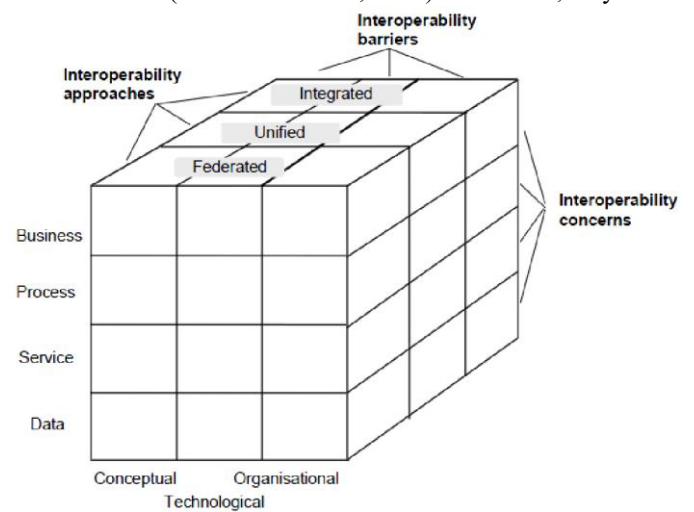


Figure 1 Interoperability Framework INTEROP (INTEROP, 2007)

be categorized under three types of approaches: integrated, unified, and federated. We subsequently discuss these three types:

- **Integrated Approach:** The integrated approach dictates that a common form or a single data model at the ecosystem level be designed and used to align the different concerns of an enterprise so that the interoperability demands be met. This type of solution requires that the services used during the collaboration, whether already in place or yet to be developed, follow the same format, even if it is not an international standard. This ensures that the partnering organizations can achieve seamless cooperation without the need for any mapping between the communicated elements. One attempt at achieving a standard to be used during the interoperability is the ISO 10303 (ISO10303, 1994)

which provides a comprehensive method to represent data including syntax and semantics. The use of this standard enables the actualization of the integrated approach.

- **Unified Approach:** The unified approach dictates that a non-executable metamodel needs to be defined so that the enterprises generate the required services or modify pre-existent ones in a manner that conforms to it. In this case, no common format between the partnering organizations is required as a mapping takes place between the enterprises different formats through the metamodel and leads to a transformation between them. One such example was developed by a study (Ethier et al., 2013) which developed an ontology-based framework called the general information model as well as appropriate mapping sets in order to unify structural models and terminologies between the different partners. In this case, it was implemented in a clinical setting with different organizations possessing heterogeneous formats.
- **Federated Approach:** The federated approach dictates that the enterprises models and systems do not undergo any changes during the duration of the interoperability process. Any conversion from one format to another that needs to be done during an exchange of information is done directly without a reliance on a metamodel or a standardized ontology between the organizations. Furthermore, any preparatory steps taken prior to the collaboration to enable this interoperability are also required to be kept at a basic level to not shift the approach into the other two possible ones. Earlier attempts at implementing this type of approach did not fully adhere to its definition due to the lack of techniques and technology to make it possible. One such example is the use of short-lived ontologies for mapping purposes (Zacharewicz et al., 2009). These ontologies were used similarly to a metamodel which is used to map data from one format to another. However, to remove the finality of the same metamodel governing the structure of the enterprise models, these ontologies are created when needed and deleted after their purpose has been completed. A more recent attempt is Data Spine (Deshmukh et al., 2021) which creates a distributed system that the enterprises can access without changing their models and processes. This platform makes use of multiple services that can be chained together depending on the requirements and performs conversions from one format to another so that interoperability can take place. Furthermore, in the event that a new enterprise with its own ontology joins the collaboration, custom services

and processes can be added to the platform where it can interact with previous ones to continue interoperations.

Among these three approaches, the integrated and unified solutions are well documented and easier to implement than the federated approach (Tu et al., 2016). This is due to the fact that the implementation of the latter requires that the interoperations be done automatically without a good amount of prior knowledge and modifications such as metamodels or ontology in the case of the former approaches. However, it requires less time and resources to be implemented since no modifications to the enterprise systems take place.

2.2 ARTIFICIAL INTELLIGENCE AND LARGE LANGUAGE MODELS

Artificial Intelligence has been mainly used to aid and facilitate the work of experts in multiple domains. Given its ability to mimic human behavior and analyze patterns at a higher speed than humans can, it is able to categorize and predict certain information more efficiently (McCarthy et al, 2006). It has created breakthroughs in multiple domains such as healthcare (Davenport & Ronanki, 2018), mobility (Gecer & Garbinato, 2024) and manufacturing (Björkdahl, 2020). Additionally, various studies were conducted to also advance the natural language processing (NLP) domain where texts written in natural languages are treated by machine learning models to achieve a certain objective.

Even though attempts were made to create language models such as rule-based models (Liddy, 2001) and statistical language models (Liu & Croft, 2004), the most successful and accurate models are based on deep learning techniques-machine learning models that simulate brain mechanisms to allow fast computation and analysis. This is due to the fact that the two former model types had limitations in terms of semantic understanding and language context (Juang & Rabiner, 2005). In recent years, through the advancement of deep learning models, breakthroughs have been made in terms of language modeling. Specifically, the advent of large language models (LLM) made generating natural language texts possible. These models depend on and are trained on massive amounts of text to be able to extract the necessary patterns and rules of a language or format (Lund et al., 2023). One of the focuses of the studies conducted for language modeling is machine translation between different languages, which is a form of data mapping between different formats. The first model facilitating this was the Google Neural Machine Translation (GNMT) system which allowed translation between two languages (Wu et al., 2016). Afterwards, a new type of deep learning model Transformer was developed, and it was able to take into consideration the

relation between all words in a text whether they are placed before or after and put a weight on the relation between each pair of words through a new mechanism called attention (Vaswani, 2017). Subsequently, the Transformer model that obtained the largest amount of fame was OpenAI's Generative Pre-trained Transformer (GPT) model which represents an important breakthrough in NLP especially since it can contribute to multiple tasks such as summarization and translation in multiple domains depending on the query (Zhao et al., 2023). It is called a generative model as it falls under the generative artificial intelligence domain which is a type of model that can generate texts and data. Furthermore, in the case of the GPT model and its different versions, it is part of the most advanced and largest language models developed (Brown et al., 2020) to support the complex operations and diverse functionalities it offers.

3 PREVIOUS LIMITATIONS AND INNOVATIONS

The implementation of the two well explored and defined interoperability approaches -integrated and unified- requires of each of them different necessities or circumstances that might not be available or difficult to achieve for some of the enterprises that might take part in the collaborative process. As shown in Table 1, the integrated approach requires the shared information between the participating enterprises to have similar formats on the four concerns of interoperability. Furthermore, some new protocols and processes need to be created to increase the enterprises compatibility in a collaboration so that the interoperations proceed smoothly while existing ones need to be aligned. This is a time consuming and computationally expensive procedure as existing data, services and processes taking place in the collaboration must change their formats to conform to a chosen standard between the organizations and modify their modes of operation to make sure that their functionalities are not at risk of failure. Furthermore, these enterprises need to take into consideration one of the fundamental requirements of interoperability, which is reversibility and, unless measures were put in place before the collaboration takes place, is also arduous. This conversion also requires manual change, which requires time and resources that could be better utilized on other tasks. Subsequently, this forms a rigid architecture that increases the difficulty of adding new partners or removing them. The same situation is observed in the unified approach. In this case, given that a metamodel is required that is used to map all data formats used across the various collaborating enterprises. Even though the modifications made to the enterprise systems might not be as impactful as those performed if the integrated approach is adopted, it still suffers from the substantial time and resources that need to be

allocated. Additionally, the unified approach has higher restrictions and requirements to maintain the collaboration due to the metamodel used. This also increases the effort needed to ensure reversibility.

In contrast, the federated approach only requires data about the formats used for their data models as well as an environment that enables communication exchanges. Hence, the federated approach aims to solve the issues of the integrated and unified solutions as the required conversions or implementations needed are reduced to only the minimum necessities. This is due to its definition which states that no changes should be made to the enterprise's systems, and all exchanges and transformations of their content are done automatically and on the fly. Thus, there are no problems to stop the collaboration at any time without any effort needed for the reversibility aspect and return the enterprises full autonomy. However, as has been seen by previous studies (Zacharewicz et al., 2009; Tu et al., 2016), it was difficult to completely achieve it due to the lack of the proper techniques and technology. These studies utilized distributed systems through which enterprises could communicate information which is mapped there either through their access point or through a temporary collective mapping system that is deleted once it finishes its task. Although the enterprise systems and models themselves are not submitted to any changes, there are still manual implementations and modifications done when the data transformation and mapping take place, especially in the case of a new enterprise joining the collaboration. In order to reduce these manual interventions needed, the framework Data Spine (Deshmukh et al., 2021) was proposed. It is also based on a distributed platform but has different processes that can be used to map from one format to another. These processes can be automatically chained if needed without any manual input. However, the initial processes included are restricted to the known formats at the start of the collaboration. If any new structure is introduced, a new custom process needs to be done manually and then integrated with the other pre-existing ones.

Additionally, due to the federated approach's definition, some potential limitations can be extracted. As shown in Table 1, as a result of the automatic conversion, some potential information loss can happen which might lead to an inadequate exchange. Furthermore, depending on the method utilized to implement the federated solution, it can lead to resource-intensive requirements. As a result of these two limitations and the diversity of the solutions proposed, we cannot give a definitive reliability level of the federated approach.

Table 1 Necessities and limitations of the three interoperability approaches.

Approaches	Necessities	Limitations
Integrated	<ul style="list-style-type: none"> -Common form implemented between the enterprises -Unified service protocols require adapting or creating new protocols for system compatibility -Enterprises must align processes and workflows to the same standards for seamless integration 	<ul style="list-style-type: none"> -Time consuming -Resource-intensive -Substantial manual intervention -Rigid architecture -Difficulty in introducing new partners -Relatively difficult to maintain
Unified	<ul style="list-style-type: none"> -Enterprises must map and transform data into a common format for compatibility -A metamodel that defines the structure and relationships between data, services, and processes for uniformity is required -Enterprises must adapt services to the metamodel for smooth communication 	<ul style="list-style-type: none"> -Time consuming -Resource-intensive -Substantial manual intervention -Difficulty in introducing new partners -Extremely difficult to maintain
Federated	<ul style="list-style-type: none"> -Partnering enterprises must prepare some data about their format to adapt the transformation models -Set up the required environment to perform the automatic data mapping 	<ul style="list-style-type: none"> -Potential information loss -Potentially resource-intensive -Undetermined reliability level

These difficulties faced with the federated approach can be potentially solved through the use of generative artificial intelligence. This is also observed by Deshmukh et al. (2024) who proposed the use of LLMs for a federated interoperability regarding dataspace which are a standardized solution for sharing data in a trusted way. Specifically, these models can be used instead of the mapping processes that are normally used. Moreover, instead of utilizing only one LLM such as GPT (Zhao et al., 2023) to handle all mapping processes, multiple specialized LLMs can be used which would increase their efficiency and accuracy. This would also reduce the number of manual interventions needed even further. Previously, any new format that needed to be introduced had to have a custom mapping system manually done for it which wastes time and resources. On the other hand, given sufficient data, already trained LLMs can be fine-tuned to be able to take into account the new information and generate it in the correct structure. This does not necessitate human intervention and can be automated instead. Through an interface, the user would only need to

upload the dataset required and the model affected only needs to be fine-tuned using it. Given that not all enterprises are willing to share the data to a central server for privacy concerns, federated learning can be used to train or fine-tune the model. This takes advantage of the fact that most systems developed for the federated approach already utilize distributed systems which is an ideal platform for this type of model training. Additionally, this type of learning reduces the substantial computational power and time required to normally train and fine-tune LLMs by splitting the training data across multiple devices and servers which decreases the amount of input to be processed by the models. Subsequently, data quality and integrity also need to be verified. This can be done through two checks which are human control intervention and automated data profiling. The former allows manual intervention of a human expert to verify that the data quality is satisfactory, and the latter allows for some pre-defined verifications to be executed such as outlier detection and duplicate detection. Although manual intervention is required to prepare and validate the dataset, it adheres to the

principle of using minimal prior knowledge for interoperability. Moreover, the level of intervention needed is significantly lower compared to previous implementations of the federated interoperability approach. Finally, given that a distributed orchestration system needs to be used to optimize the collaboration, High-Level Architecture (HLA) standard provides support to interoperability of heterogeneous components (Zacharewicz et al., 2008) such as simulation systems based on the Simulation Data Distribution Service (Zhang et al., 2021) can be used to verify, model and display the processes and systems that are used in the platform. This approach can be used in any domain requiring interoperability. One domain that can benefit from it is mobility. It could enhance routing in certain areas where the existing systems are of poor quality. Effectively, this needs a collaboration between transportation companies is needed to obtain the data required as well as to utilize their services and processes in interoperations to achieve the enhancement.

CONCLUSIONS

Interoperability solutions come in three types: integrated, unified, and federated. Despite the fact that the first two approaches have been researched extensively, issues in terms of computation time, resources, and reversibility arise since a form of standardization between the enterprises needs to be implemented. In contrast, the federated approach is not affected by the same issues as it does not need to modify the enterprise's components and performs the needed prerequisites of the interoperations automatically when they are needed. Even though current approaches can remove the need to modify the enterprises systems, either some elements belonging to the unified approach or substantial manual intervention remain.

We investigate a novel approach that utilizes a distributed system and LLMs that are trained through federated learning. This ensures that the mapping between different formats can be done automatically without any manual intervention. These models also eliminate the need for such interventions as the process of adding new formats can be automated given that the data is present for the LLMs to use. Additionally, since a distributed system and federated learning approach are utilized, privacy and data security are maintained. Due to the same reason, the simulation systems that can be used to verify and demonstrate the platform developed need to be based on the Simulation Data Distribution Service to obtain the best representations. Hence, the approach of integrating LLMs into the federated interoperability solution can solve multiple issues faced by the unified and integrated

approaches as well as advance the state of federated interoperability solutions.

REFERENCES

- Akman-Lees, S. (2018). Towards a conceptual framework for persistent use: A technical plan to achieve semantic interoperability within electronic health record systems. In *Proceedings of the 51st Hawaii International Conference on System Sciences*. Retrieved from scholarspace.manoa.hawaii.edu.
- ATHENA Integrated Project. (2003). Advanced technologies for interoperability of heterogeneous enterprises networks and their applications: Integrated project description of work.
- Björkdahl, J. (2020). Strategies for digitalization in manufacturing firms. *California Management Review*, 64(4), 17–36.
- Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., et al. (2020). Language models are few-shot learners. *Advances in Neural Information Processing Systems*, 33, 1877–1901.
- Canciglieri, M. B., Szejka, A. L., Canciglieri Junior, O., & Yoshida, L. (2018). Current issues in multiple domain semantic reconciliation for ontology-driven interoperability in product design and manufacture. In *Product Lifecycle Management to Support Industry 4.0. PLM 2018. IFIP Advances in Information and Communication Technology* (pp. 126–135). Cham: Springer.
- Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108–116.
- Deshmukh, R., Jayakody, D., Schneider, A., & Damjanovic-Behrendt, V. (2021). Data Spine: A federated interoperability enabler for heterogeneous IoT platform ecosystems. *Sensors*, 21, 4010.
- Deshmukh, R. A., Collarana, D., Gelhaar, J., Theissen-Lipp, J., Lange-Bever, C., Arnold, B. T., Curry, E., & Decker, S. J. (2024). Challenges and opportunities for enabling the next generation of cross-domain dataspace. *Proceedings of the Second International Workshop on Semantics in Dataspace co-located with the 21st Extended Semantic Web Conference*.
- Dollfus, O. (2001). *La Mondialisation* (2nd ed.). Presses de Sciences Po.

- Ethier, J.-F., Dameron, O., Curcin, V., McGilchrist, M. M., Verheij, R. A., Arvanitis, T. N., Taweel, A., Delaney, B. C., & Burgun, A. (2013). A unified structural/terminological interoperability framework based on LexEVS: Application to TRANSFoRm. *Journal of the American Medical Informatics Association*, 20(5), 986–994.
- Forest, C. (2003). *Empowerment skills for family workers: A worker handbook*. Cornell University.
- Gecer, M., & Garbinato, B. (2024). Federated learning for mobility applications. *ACM Comput. Surv.*, 56(5), Article 133, May, 28 pages.
- Hussain, S. M., Yosof, K. M., & Hussain, S. A. (2018). Interoperability issues in Internet of Vehicles—A survey. In *Proc. 3rd Int. Conf. Contemp. Comput. Informat. (IC3I)* (pp. 257–262).
- Hussain, S. M., Yusof, K. M., & Hussain, S. A. (2019). Interoperability in connected vehicles—A review. *International Journal of Wireless and Microwave Technologies*, 9(5), 1–11.
- IEEE. (1990). *A compilation of IEEE standard computer glossaries*. Standard computer dictionary. New York.
- IDEAS Project Deliverables. (2003). WP1-WP7. Public reports.
- INTEROP. (2007). *Enterprise interoperability-framework and knowledge corpus—Final report*. INTEROP NoE, FP6 – Contract No. 508011, Deliverable DI.3, 21 May.
- ISO/DIS 11354-1. (2009). *Advanced automation technologies and their applications. Part 1: Framework for enterprise interoperability*.
- ISO 10303. (1994). *Industrial automation systems and integration—Product data representation and exchange (STEP)*.
- Juang, B.-H., & Rabiner, L. R. (2005). *Automatic speech recognition—A brief history of the technology development*. Georgia Institute of Technology.
- Lecerf, M. (2006). *Les petites et moyennes entreprises face à la mondialisation*. L'Harmattan.
- Lauras, M. (2004). *Méthodes de diagnostics et d'évaluation de performance pour la gestion de chaînes logistiques: Application à la coopération maison mère – filiales internationales dans un groupe pharmaceutique et cosmétique*. Doctoral dissertation, National Polytechnic Institute of Toulouse.
- Lezcano, L., Sicilia, M.-A., & Rodríguez-Solano, C. (2011). Integrating reasoning and clinical archetypes using OWL ontologies and SWRL rules. *Journal of Biomedical Informatics*, 44(2), 343–353.
- Liddy, E. D. (2001). *Natural language processing*.
- Liu, X., & Croft, W. B. (2004). Statistical language modeling. *Annual Review of Information Science and Technology*, 39, 1.
- Lund, B. D., Wang, T., Mannuru, N. R., Nie, B., Shimray, S., & Wang, Z. (2023). ChatGPT and a new academic reality: Artificial intelligence-written research papers and the ethics of the large language models in scholarly publishing. *Journal of the Association for Information Science and Technology*, 74(5), 570–581.
- McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A proposal for the Dartmouth summer research project on artificial intelligence, August 31, 1955. *AI Magazine*, 27(4), 12.
- Popel, M., Tomkova, M., Tomek, J., et al. (2020). Transforming machine translation: A deep learning system reaches news translation quality comparable to human professionals. *Nature Communications*, 11, 4381.
- Ramnath, S., Haghghi, P., Venkiteswaran, A., & Shah, J. J. (2020). Interoperability of CAD geometry and product manufacturing information for computer integrated manufacturing. *International Journal of Computer Integrated Manufacturing*, 33(2), 116–132.
- Seguy, A. (2008). *Décision collaborative dans les systèmes distribués*. Doctoral dissertation, University of Toulouse.
- Shahin, N., & Ismail, L. (2024). From rule-based models to deep learning transformers architectures for natural language processing and sign language translation systems: Survey, taxonomy and performance evaluation. *Artificial Intelligence Review*, 57, 271.
- Tu, Z., Zacharewicz, G., & Chen, D. (2016). A federated approach to develop enterprise interoperability. *Journal of Intelligent Manufacturing*, 27(1), 11–31.
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gómez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems*, 30.

Winer, M., & Ray, K. (1994). *Collaboration handbook: Creating, sustaining, and enjoying the journey*. Ed. Amherst H. Wilder Foundation.

Wu, Y., Schuster, M., Chen, Z., Le, Q. V., Norouzi, M., Macherey, W., Krikun, M., Cao, Y., Gao, Q., Macherey, K., et al. (2016). Google's neural machine translation system: Bridging the gap between human and machine translation. arXiv preprint arXiv:1609.08144.

Zacharewicz, G., Chen, D., & Vallespir, B. (2008). HLA supported, federation oriented enterprise interoperability: Application to aerospace enterprises. In 2008 International Simulation Multi-conference, Edinburgh, United Kingdom.

Zacharewicz, G., Labarthe, O., Chen, D., & Vallespir, B. (2009). A HLA multi-agent/short-lived ontology platform for enterprise interoperability. In Proceedings of the IFIP Advances in Information and Communication Technology, 338, 350–357.

Zhang, G., Wang, Y., Ren, J., Liu, W., & Gao, K. (2021). Distributed simulation system based on data distribution service standard. In 2021 International Wireless Communications and Mobile Computing (IWCMC) (pp. 440–445), Harbin City, China.

Zhao, W. X., Zhou, K., Li, J., Tang, T., Wang, X., Hou, Y., Min, Y., Zhang, B., Zhang, J., Dong, Z., et al. (2023). A survey of large language models. arXiv preprint arXiv:2303.18223.