The SECI-MaP Model: A Human-Machine Integrated Model for Organisational Knowledge Creation

Susanna du Plessis and Katarina Britz
Stellenbosch University, South Africa

santieduplessis@gmail.com
abritz@sun.ac.za

Abstract: While the human-focused SECI model of Nonaka and his colleagues captures their widely recognised theory of organisational knowledge creation, we live in an era of rapid technological advancements and Artificial Intelligence (AI). AI and in particular Machine Learning (ML), show great potential for organisations to support their learning and to discover and create new knowledge. This leaves the question of how AI and ML impact the SECI model. This study performs a theoretical investigation on integrating human- and machine contributions for organisational knowledge creation. A Design Science Research (DSR) approach is followed to design, develop and propose the conceptual SECI-Machine Partnership (SECI-MaP) model. The SECI-MaP model extends Nonaka's SECI model and captures a human-machine symbiotic and synergistic partnership for enhanced organisational knowledge creation. It implies that sufficiently mediated and applied combined efforts of humans and machines could be greater than the sum of their individual contributions.

Keywords: Knowledge creation, Knowledge-Enriched machine learning, Human-Machine partnership, SECI-MaP model

1. Introduction

Healthy, well-functioning organisations undertake intentional initiatives to create, develop and use knowledge to achieve business success (Davenport and Prusak, 1998). Since the 1990s, the SECI Model and theory of organisational knowledge creation, per Nonaka and Takeuchi (1995), has gained vast popularity and is often referred to as seminal and highly respected. While it has been revised and enhanced several times by introducing additional concepts and dimensions, it remains primarily human focused. The essence of the SECI model illustrates that the spiral of interactions and conversions between tacit and explicit knowledge, facilitated through four knowledge conversion modes (socialisation, externalisation, combination and internalisation), creates new knowledge.

Socialisation is the conversion of tacit knowledge into more tacit knowledge. Since tacit knowledge is embedded in the minds of people and is often context-specific and difficult to formalise, individuals exchange tacit knowledge through social interaction and shared experiences, while trust plays an important role. *Externalisation* is the conversion of tacit knowledge into explicit knowledge. As tacit knowledge is articulated through reflection and dialogue, it becomes crystallised and easier to codify and share and, therefore, tacit knowledge is translated into explicit knowledge. *Combination* is the conversion of explicit knowledge into more explicit knowledge. It involves the gathering, editing, integration and diffusion of explicit knowledge to compose systematic and more complex sets of explicit knowledge. *Internalisation* is the conversion of explicit knowledge into tacit knowledge, which closely resembles the concept of learning. Individuals need to identify within the explicit knowledge what is relevant to them and embody it through practice and action. New knowledge integrates with the person's existing knowledge and could restructure the existing knowledge. Tacit knowledge that becomes part of a person's knowledge base, leads to another spiral of knowledge creation, starting again with socialisation.

From a data-driven technology perspective, we have seen significant advancements since the 1990s. Artificial Intelligence (AI), in particular Machine Learning (ML), is used increasingly and offers significant potential for organisations to support their learning and to discover and uncover knowledge. Advancements in Automated Machine Learning (AutoML) make ML solutions more accessible to organisations, while the impressive results of ML in the form of Generative Artificial Intelligence (GenAI) have taken the world by storm since 2022. However, these technologies present challenges regarding the creation of organisational knowledge.

Firstly, there is the challenge of integration with tacit knowledge that is embedded in the human mind. Secondly, insufficient data and data quality concerns are common. It also became increasingly important to understand, interpret, explain and trust ML models. Research on integrating external knowledge into ML pipelines proved that Knowledge-Enriched Machine Learning (KEML) not only assists in addressing these challenges but could also improve performance and knowledge conformity of models (von Rueden *et al.*, 2021). An interesting perspective is that KEML closely resembles the human KM perspective, where knowledge creation is a product of integrating existing knowledge with newly acquired knowledge (Dasgupta and Gupta, 2009). Since KEML can combine human knowledge (represented for consumption by machines) with machine intelligence to develop new knowledge, this sparks the research question: *"How does KEML impact the SECI model of organisational knowledge creation?"*

To address the main research question, two supporting questions contribute from this background. Firstly, *"How can KEML address limitations of Nonaka's theory of organisational knowledge creation?"*, considers limitations highlighted by critical reviews of Nonaka's theory and the SECI model. The second supporting question, *"How can KEML unlock new potential for enhancing the SECI model?"* provides an opportunity to explore the research problem from a clean basis, uncovering further potential of KEML to enhance the SECI model.

The research aim is to guide and contribute to enhanced organisational knowledge creation in dynamic business environments, by capitalising on the best of both human- and machine contributions, in an era of rapid technological advancements and AI. An intuitive connection between organisational knowledge creation as per traditional Knowledge Management (KM), and ML as part of AI, supports this aim – both are intrinsically concerned with knowledge and the nature of learning.

To this end, the objective of this study is the development of a human-machine integrated model for explaining, understanding and guiding enhanced organisational knowledge creation. Nonaka, Von Krogh and Voelpel (2006) highlight that open boundaries and the evolution of their theory prove to be of great benefit to the field. They encourage different approaches and perspectives and aim to inspire new development around the theory. Considering this open invitation and the prominence of Nonaka's SECI model within the KM field, it is used as springboard for this study. The proposed SECI-Machine Partnership (SECI-MaP) model, therefore, extends the SECI model and enhances it towards supporting organisations in their efforts to create new knowledge in a data- and technology-rich era, contributing towards innovation, organisational agility and prosperity.

2. Methodology

This study follows the Design Science Research (DSR) paradigm. DSR aims to enhance human knowledge via the design and development of artefacts. The output of DSR is both the newly developed artefact(s) and design knowledge (DK). The aim of DK is to provide an understanding of how and why an artefact changes (either enhances or disrupts) the context of where it is applied (Vom Brocke, Hevner and Maedche, 2020).

In this study, the artefact, the SECI-MaP model is designed and developed as a conceptual model. For this study, a conceptual model is regarded as a simplified visual representation that explains and supports the understanding of key elements, their interactions and relationships. Design knowledge includes perspectives of how and why the model explains and guides enhanced organisational knowledge creation.

While several DSR approaches exist, the methodology per Peffers *et al.*, (2007) as illustrated by Figure 1 has been adopted for this study. It provides a well-suited process model, but simultaneously flexibility in execution, such as different possible entry points and iterative possibilities. The following steps summarise the activities followed for this research.

- *Problem Identification*: The research problem is identified, defined and its importance justified. Primary- and supporting research questions are formulated as noted in the Introduction.
- *Objective Definition:* The aim and objective of the study is inferred from the defined problem. Supported by background- and theoretical knowledge, a feasible objective is defined.

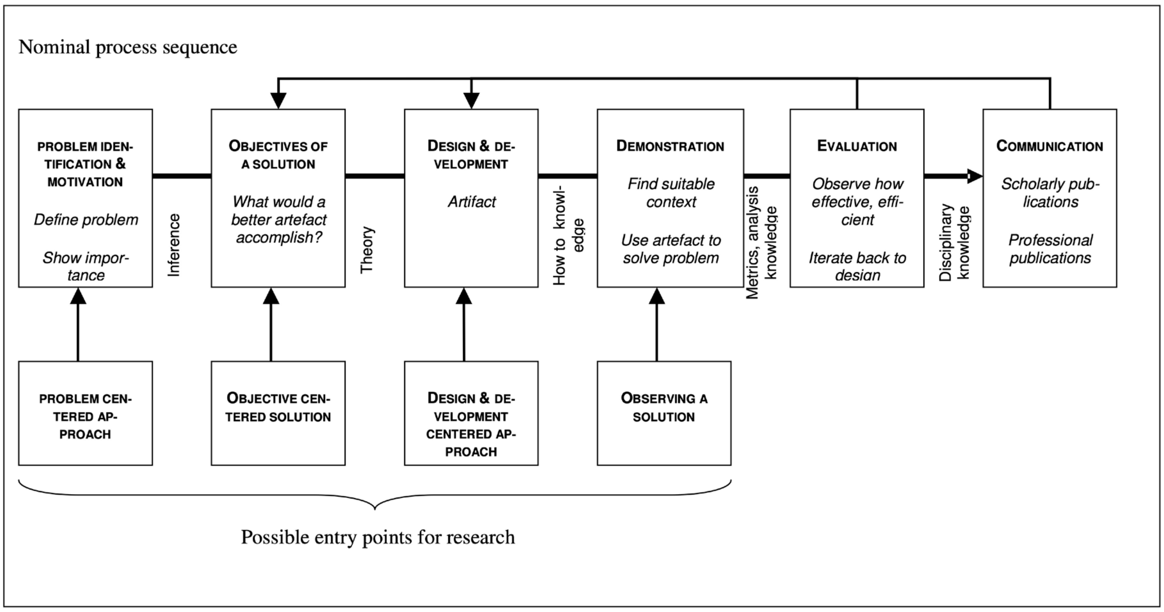

Figure 1: DSR Methodology Process Model (Peffers *et al.*, (2007))

- *Design and Development:* The SECI-MaP model (the artefact) is designed and developed. This is supported by a focused literature study, as guided by the scope and the needs of the investigation. Key inferences then guide the development of the SECI-MaP model as summarised in Section 3.
- *Demonstration:* The SECI-MaP model is demonstrated from both a conceptual and an applied perspective. The demonstration which shows how the SECI-MaP model enhances organisational knowledge creation, forms part of the design knowledge.
- *Evaluation:* The SECI-MaP model is evaluated against two diverse use cases. Due to the scope of the study, this is a theoretical and conceptual evaluation. In future projects, this can be advanced in practical organisational settings.
- *Communication:* Key elements of this study are communicated through this paper and more detail pertaining to the full research project through the original Masters thesis (du Plessis, 2025).

3. The SECI-MaP Model for Organisational Knowledge Creation

Organisational knowledge creation, as defined by Nonaka and his colleagues, remains relevant – even decades later in an era where data, technology, and artificial intelligence play prominent roles. In organisations, we are still interested in collective knowledge and expertise, knowledge about the organisation's processes and systems, successes and failures, risks and challenges, potential inefficiencies and areas of improvement, opportunities for growth, customer insights and industry trends – to name a few. We still need the new knowledge to support decisions and, where relevant, distribute it throughout the organisation and embed and embody it in products, services, and systems.

The research question *"How does KEML impact the SECI model of organisational knowledge creation?"* is addressed by designing and developing a human-machine integrated model for organisational knowledge creation. This section, therefore, represents the 'Artefact Design and Development' phase of the DSR Methodology per Peffers et al. (2007).

Leading up to addressing the research question, an overview of key arguments and inferences that guided the development of the proposed SECI-MaP model is presented. These arguments and inferences are based on the focussed literature study, the evaluation of a selection of applications of KEML, and supported by practical experiences in an organisational context. KEML, for this study, is defined as any application of ML where any form of knowledge is integrated into any stage of an ML process to improve the model and/or results. Exploring two supporting questions that further contribute to the SECI-MaP model concludes the section.

3.1 Key Contributing Arguments and Inferences

3.1.1 A partnership between humans and machines capitalises on the best of both.

The main design principle for the SECI-MaP model is a human-machine symbiotic- and synergistic partnership. Both humans and machines have much to offer, but both have strengths as well as weaknesses. The contributions of humans and machines could therefore be complementary, supplementary, sometimes re-enforcing, or even conflicting – in the latter case, serving as a flag that further work is required. The partnership is defined to be symbiotic as it should be mutually beneficial to the contributions of both humans and machines. This means that the strengths of humans should compensate for the weaknesses of machines and vice versa. The partnership is also defined to be synergistic, where humans and machines co-create outcomes that could be greater than the sum of their independent contributions. A few contributing perspectives are summarised below.

From an overarching perspective, the continuously increasing ability of machines to process higher volumes of data at greater speed filters through various attributes. The ability of humans, in comparison, is significantly limited, and without the use of machines, large amounts of data collected by organisations would remain unutilised and potentially wasted. However, human input generally improves the quality of results and outputs produced by machines (von Rueden *et al.*, 2021).

Related to machines' distinguished processing capabilities, are the exceptional levels of complexity that they can deal with. However, the more sophisticated and complex these systems become, the harder it becomes to interpret and explain the inferences generated by them (Calegari, Ciatto and Omicini (2020); Angelov *et al.* (2021)). Human understanding plays a critical role in testing the validity of results and interpreting and deriving contextualised meaning.

On a more specific level, machines have a lot to offer as far as predictive power is concerned. Machines can uncover new (currently unknown) knowledge and information from existing sources and data, based on discovering patterns and making connections. However, due to common challenges such as overfitting, underfitting, data imbalances, dimensionality-, and feature selection issues etc., outcomes can be greatly improved by human judgment and the integration of pre-defined knowledge (von Rueden *et al.*, 2021).

A human-machine integrated model for organisational knowledge creation should, therefore, first provide opportunities to capitalise on the best contributions of both humans and machines. Secondly, it should support the effective balancing of such efforts towards a symbiotic and synergistic partnership to advance optimal knowledge creation outcomes.

3.1.2 Humans remain central and in the driving seat.

While machines provide numerous possibilities, it is ultimately human intelligence that will determine the outcome. While machines can superbly take care of the tasks that they are designed for, and aid, strengthen, and augment human efforts, it frees up humans to focus on tasks that require human general intelligence such as creativity, adaptability and intuition.

This further implies that humans require the skills to interact with their intelligent machine partners. It naturally suggests that traditional roles of humans in an organisation are changing. This prompts organisations to invest in upskilling or hiring to take advantage of an effective human-machine partnership. Yet, the realisation of such a partnership requires organisational foresight and intervention. Humans are therefore not only critical as part of an effective human-machine partnership, but also central and in the driving seat.

3.1.3 A sustainable model should consider continuously evolving technology.

Since the 1990s, the rapid rate of advancements in technology and AI has been transformative in many regards. With ongoing research, development and increasing investment in AI, it is not only expected that the pace of technological advancements will not slow down, but is likely to continue reshaping the world and, therefore, organisations in the future.

Against this backdrop, it is important to consider the continuously evolving role of technology in the design of the model. Process models that generally focus on a sequence of activities might be too restrictive. Process models are also often geared towards goal-oriented processes, while knowledge creation utilising KEML is generally more exploratory in nature. Thus, we steer away from a process model and propose a flexible conceptual model that focuses on the principles and interconnections of concepts.

3.2 From SECI to SECI-MaP

The research question "*How does KEML impact the SECI model of organisational knowledge creation?*", is addressed by extending and enhancing the SECI model towards a human-machine partnership. The resulting SECI-MaP model is visually represented in Figure 2.

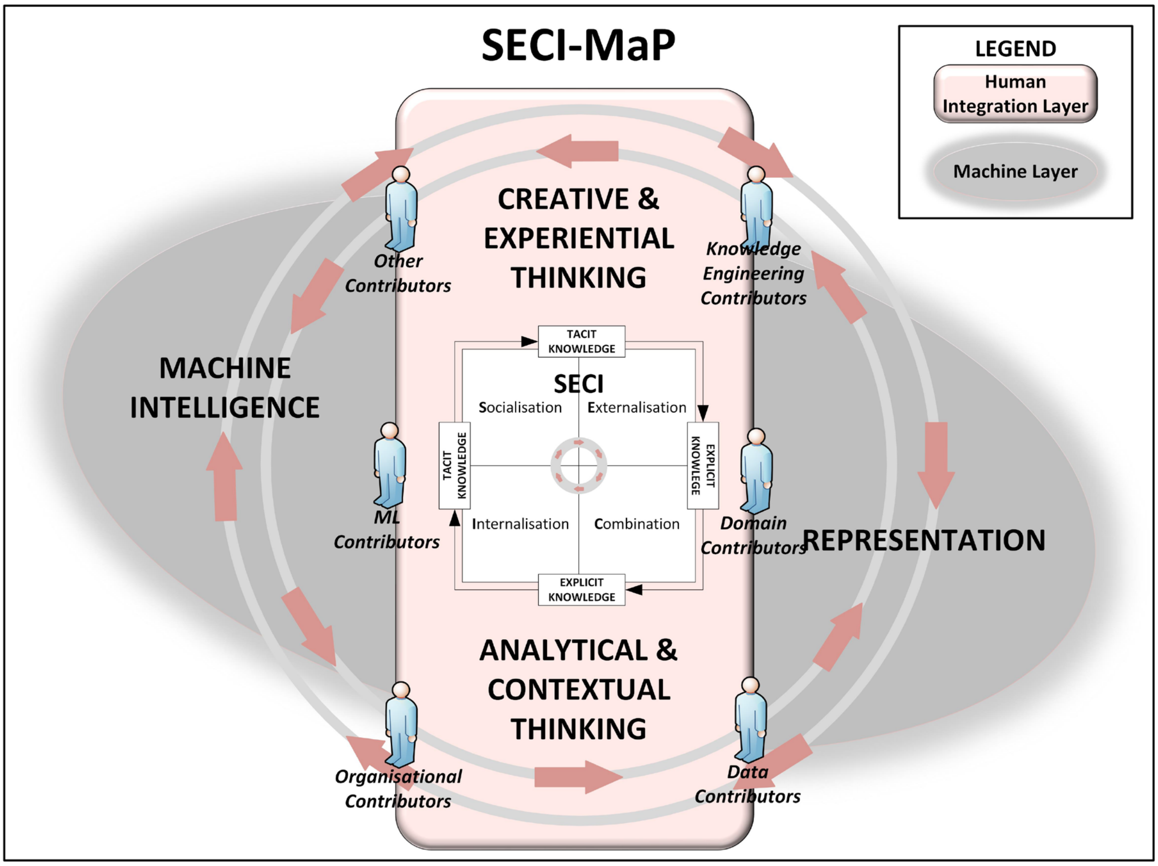

Figure 2: SECI-MaP Model

The SECI-MaP model consists of three layers. At the core, it captures the essence of the human-focused SECI model (Nonaka and Takeuchi, 1995). The spiral of continuous conversions between tacit and explicit knowledge facilitated through the four knowledge conversion modes (socialisation, externalisation, combination and internalisation) remains relevant.

The outer layer is the *Machine Layer*. It capitalises on the strengths and unique contributions of machines. The rounded shape with 'expandable' soft edges symbolises open-endedness and continuously evolving approaches, techniques, and technology. This supports the model's sustainability where continuously evolving technology is the order of the day. Guided by the needs of an organisation, any technique or approach can be used when applying the model in practice. Embedded in the machine layer, are the two key elements *Machine Intelligence* and *Representation*.

Machine Intelligence is loosely positioned towards the tacit side, as it refers to the ability of machines to learn, act, and even 'think' in a way that mimics human cognition. These are done by using algorithms and computational processes and include, recognising and analysing patterns, interpreting and 'understanding' complex data, learning from experience, predicting outcomes, and generating content.

Representation is positioned towards the explicit side and refers to the input into the machine learning process. Explicit input must be represented in some way for it to be consumed by machine intelligence. This could be structured- or unstructured data or formally represented knowledge. Per the taxonomy of informed machine learning (von Rueden *et al.*, 2021), representation can take on various forms such as algebraic- or differential equations, probabilistic relations, simulation results, logic rules, knowledge graphs, formal ontologies, and human feedback. Once represented, knowledge can be integrated into various stages of ML pipelines and thus be consumed by machine intelligence – an approach that has been proven beneficial by various studies. Benefits have been summarised and classified by Rueden *et al.* (2021) to include better performance, knowledge conformity, better interpretability as well as training with less data.

The *Human Integration Layer* is the middle layer. It does not only serve as the 'glue' that holds the model together, but it also drives the application of the model. The rounded edge of the rectangle symbolises the symbiotic and synergistic partnership between humans (symbolically square) and machines (symbolically rounded). Note that the human integration layer encapsulates the SECI core, implying that the contributions from the machine layer extend the SECI model via the human integration layer. The aspects of thinking incorporated in the human integration layer are derived from Sternberg's theory of adaptive intelligence (Sternberg, 2021). These are simplified from the aspects of creative, analytical and practical (or contextual) thinking, into two broader categories that are loosely aligned with tacit and explicit knowledge, respectively.

Creative and Experiential Thinking in the context of the SECI-MaP model refers to human cognitive processes that typically rely on tacit knowledge. It depends on knowledge gained through practical experience, intuition and judgement, and is a critical mediator to interpret and enhance the output from machine intelligence, or to refine, redirect and mould it towards more reliable, trustworthy, ethical and feasible solutions.

With *Analytical and Contextual Thinking* on the explicit side, humans need to consider the broader environment and context when analysing problems and making decisions. While the machine layer can greatly contribute and support human productivity by dealing with high levels of complexity and processing high levels of data at speed, outcomes must be contextualised, understood and trusted. This form of human mediation includes applying human judgement, ensuring quality, communicating explanations, context and causality, and integrating the machine contributions into human understanding.

Human contributors are represented as broad categories of knowledge and skill. These categories are not intended to be an exhaustive list, but rather a broad indication. Important to note is that these areas of contribution do not imply that people are ringfenced within these areas - the same person could contribute to more than one area.

The circular arrows that span across the human integration layer and the machine layer, are driven by the human role players from the human integration layer. The circular arrows move in both directions and symbolise the integration of human- and machine contributions in the partnership. Note that the positions of human contributors are not absolute or static. Human participants would typically 'move around' and often work closely together.

3.3 Addressing Limitations with Knowledge-Enriched Machine Learning

In response to the supporting question: "*How can KEML address limitations of Nonaka's theory of organisational knowledge creation?*" the potential for KEML as part of a human-machine partnership to address some of the noted limitations of Nonaka's theory and SECI model was investigated. Key findings from the analysis are summarised below.

- *Learning, diversity and bricolage*: Poell and Van Der Krogt (2003), note that the SECI model neglects the contribution of different actors and learning strategies. Furthermore, multiple perspectives that lead to knowledge diversity and better-informed decisions is overlooked (Powell *et al.*, 2007).

A typical KEML project brings (human) diversity when a project team draws together different skills, knowledge and backgrounds e.g. organisational-, domain-, data- and ML- expertise. When AI comes into play, the diversity added by machine 'actors' adds an additional dimension to the potential for knowledge creation.

- *Problem finding*: As highlighted by Engeström (1999), this important success factor for the creation of knowledge for innovation is not included in the SECI model.

Due to the unique way that machines raise questions compared to their human counterparts, machines could identify unnoticed correlations in data and find problems that may be missed by human cognitive processes. Machines could also discover knowledge that is not question-driven (Martinez-Plumed et al., 2021). Due to these differences, humans and machines in a partnership could arrive at different questions from the same context, which further creates more diversity and opportunities.

- *Socialisation challenges*: Employees often resist full participation and share selectively due to caution related to trust issues and fear of judgement (Au and Chan, 2008).

Machines are not human, and hence, they do not judge. Various studies found that trust plays an important role and that humans are more willing to share honestly with machines where the interaction is anonymous or non-judgmental. This opens the door for the human-machine partnership to promote more open and honest sharing during socialisation phases.

- *Externalisation and Internalisation challenges*: Issues related to knowledge hoarding and superficial articulation of knowledge exist due to attempts by employees to be indispensable and thus preserve knowledge for themselves (Au and Chan, 2008). They further highlight the over-reliance on memory compared to understanding as an internalisation challenge.

The playing field changes in an era where AI plays a prominent role. Information and knowledge that individuals would typically try to preserve for themselves are becoming more readily available. Individual competitive advantage is increasingly driven by other factors such as creativity, critical thinking and the ability to discriminate effectively. Interesting to note is that these skills that drive individual competitive advantage are also key human skills required for an effective human-machine partnership.

- *Combination challenges*: Human nature to resist change and stick to old practices, often leads to combination efforts resulting in the 're-inventing of old wheels' (Au and Chan, 2008).

Machines have no preference for the old versus the new. They have no emotions or natural tendency to stick to old habits. This counters and balances combination challenges in the human-machine partnership.

3.4 Unlocking new Potential with Knowledge-Enriched Machine Learning

To address the second supporting question: "*How can KEML unlock new potential for enhancing the SECI model?*", new opportunities and potential for KEML as part of a human-machine partnership towards organisational knowledge creation were investigated.

The first relates to knowledge creation to support organisations to excel in times of rapid change. An organisation needs to be a 'learning organisation' and therefore be adaptable and flexible to survive and thrive in times of rapid change (Senge, 1990). That, while learning from a human perspective is subject to 'Learning Myopia' in the form of the human tendency to overlook distant times, overlook distant places and overlook failure (Leventhal and March, 1993). These challenges are embedded in the organisational challenge to find the appropriate balance between exploration (creation and invention of new knowledge) and exploitation (re-use of existing knowledge in new contexts). The natural human tendency is to favour exploitation over exploration (Lavie, Stettner and Tushman, 2010; Levinthal and March, 1993). Exploration and exploitation in organisations also compete for (human) resources that are often short in supply. Sturm *et al.* (2021) found that machines can reduce the need for human exploration as ML is particularly suitable for exploration. KEML as part of the human-machine partnership, therefore, exhibits great potential in this context.

A second opportunity relates to the codification and subsequent retrieval of knowledge. Knowledge codification is needed to organise knowledge and make it explicit, re-usable and accessible (Davenport and Prusak, 1998) and is also a key component of externalisation in Nonka's SECI model. However, organisations face challenges in achieving these goals. A key challenge is the extensive time required from subject matter experts to codify knowledge. This is due to the volumes, complexities and the need for an iterative process of recodification and refinement (O'Meara and Kelliher, 2021). Knowledge is also context-dependent (Cohendet and Edward Steinmueller, 2000) and a 'phenomenon in motion' (Patriotta, 2004). This is where KEML in the form of genAI applications, customised for the organisation, shows significant potential. Although the use of genAI presents challenges and risks, many of these relate to sociotechnical issues (Fui-Hoon Nah *et al.,* 2023) and can therefore be largely mitigated by the human-driven partnership between humans and machines.

Finally, machines could alleviate pressure on one of the scarcest resources in organisations – time. As per Davenport and Prusak (1998), the lack of adequate time is regarded as the biggest threat to the successful generation of knowledge in organisations. While time is limited and impossible to replicate, machines can take care of tasks that are time-consuming for humans, and hence, 'create' more time for humans to focus on their unique contributions.

4. Evaluation

During the evaluation phase of the DSR process, the artefact was theoretically evaluated using two diverse real-world organisational scenarios. Two scenarios from development areas that capture significant interest from organisations (AutoML and GenAI) were used for the evaluation. Key aspects and findings from the detailed evaluation of the SECI-MaP model (du Plessis, 2025), are summarised below.

The first scenario is summarised from an Amazon Web Services (AWS) 'Online Tech Talk' dated 16 August 2022 (AWS, 2022). KEML in the form of AutoML is used by a mobile phone service provider for insights and predictions on customer churn. The marketing analyst has access to high volumes of tabular data related to customer history, as well as information on customers who left. He uses the user-friendly no-code interface of AWS SageMaker Canvas to interact with his machine partner. Canvas analyses the data by identifying data types, missing and mismatched values, and visually presenting it to the user. The user further interacts with Canvas to select the column to predict and evaluate recommendations on how to deal with anomalies before selecting a model. The promising results from the model in Canvas motivate getting weigh-in from the data science team, where they enrich the model with formally presented knowledge, using AWS SageMaker Studio. The final model results are analysed, refined and communicated by the marketing analyst.

We observe a close interaction between the human and the machine layer. It requires tacit as well as explicit knowledge from the marketing analyst to 'socialise' with his machine counterpart. The machine layer plays an externalisation role as results are presented as user-friendly visualisations. Further human mediation takes place when the data science team feed additional external knowledge to the representation side of the machine layer, for further consumption by the machine intelligence. Both combination and internalisation take place as the marketing analyst gets to understand the relationship between features. As the marketing analyst shares the output of the model with other organisational users, socialisation and internalisation take place as they learn more about their customers and what services are important to them. It takes advantage of the contributions of both humans and machines, saving valuable time towards creating new knowledge about their customers' needs, and enables them to do root cause analysis on potential issues.

The second evaluation is on a genAI tool, developed for conversational guidance to customer support agents. (Business scenario summarised from Brynjofsson *et al.* (2023).) Agents require problem-solving skills, thorough product knowledge and the ability to handle contentious conversations and deal with frustrated customers. The genAI tool was enriched with additional training on a large set of customer-agent conversations from the organisation that have been labelled based on outcomes and customer satisfaction. The tool provides real-time suggestions to agents on how to respond, while agents remain responsible for their conversations and are free to use, amend or ignore suggestions from the tool.

To interpret this scenario in the context of the SECI-MaP model, it is important to note that the human ability to respond 'appropriately' is based on tacit knowledge gained through experience. This underlies the conversations with customers that are integrated into the explicit/representation side of the machine layer. This serves as training input for the machine intelligence that ultimately displays these skills and tacit knowledge when providing conversational guidance and suggestions. We can argue that a form of 'socialisation' takes place between the machine and the humans when suggestions are made. Humans use their judgement (tacit knowledge) to reject, alter, or accept the machine guidance. This could be a particularly effective way of 'socialisation' as machines are not human and do not judge. Humans can therefore freely decide what to do with the machine suggestions without fear of judgement or pressure to use the suggestions.

We can conclude that the evaluation indicate that the SECI-MaP model is generic enough to remain valid for the diverse scenarios. It is also specific enough to explain how enhanced organisational knowledge creation is facilitated through the human-machine partnership in the scenarios.

5. Conclusion and Future Work

Nonaka's widely cited SECI model has attracted considerable interest from researchers in the field of KM. Various studies provide critical assessments, while others aim to integrate varying additional aspects, such as complexity theory, knowledge enablers and sensemaking - to name a few. Several studies also propose alternative models and suggest different focal points regarding organisational knowledge dynamics. More recent studies consider the role of different technologies, each with its unique contribution. This study relates to the latter.

In alignment with the objective, the primary contribution of the study is the proposal of the conceptual SECI-MaP model that explains how machines, as represented by KEML, impact the SECI model of Nonaka and Takeuchi (1995). Extending and enhancing the SECI model in consideration of rapidly advancing technology and AI, advances our understanding of the increased potential that emerges when human- and machine efforts are effectively integrated. It explains the unique strengths of machines versus humans and how they complement and supplement each other to create a partnership that is both symbiotic and synergistic. This feeds into the longer-term aim of the research, which is to guide and contribute to enhanced organisational knowledge creation in dynamic business environments, taking advantage of AI.

The demonstration and evaluation of the SECI-MaP model, indicates theoretical validity and the potential for the model to support the longer-term aim of the study. Since the 'Evaluation' phase of the DSR Methodology of Peffers *et al.* (2007) aims to observe the effectiveness and efficiency of the developed artefact, a limitation of this study is that it does not include empirical validation. While empirical research was beyond the scope of this study, the promising theoretical results justify the need for further empirical research.

While this study serves as a theoretical foundation and merely a starting point to guide, navigate and contribute to enhanced organisational knowledge creation in a partnership between humans and machines, it leaves organisations with promising prospects and opportunities to explore.

Ethics statement: Ethical clearance was not required for the research referred to in this paper.

AI statement: AI tools were not used in the development of this paper.

References

Angelov, P. P., Soares, E. A., Jiang, R., Arnold, N. I., & Atkinson, P. M. (2021). Explainable artificial intelligence: an analytical review. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *11*(5), e1424.

AWS. (2022) Make better business decisions with ML using Amazon SageMaker Canvas, without code. Online Tech Talk, August 2022. Available at: https://aws.amazon.com/events/online-tech-talks/

Au, A. K., & Chan, I. (2008). Knowledge Creation–Presumption Versus Actual Practice. *Contemporary Management Research*, *4*(2).

Brynjolfsson, E., Li, D., & Raymond, L. R. (2023). *Generative AI at work* (No. w31161). National Bureau of Economic Research.

Calegari, R., Ciatto, G., & Omicini, A. (2020). On the integration of symbolic and sub-symbolic techniques for XAI: A survey. *Intelligenza Artificiale*, *14*(1), 7-32.

Cohendet, P., & Edward Steinmueller, W. (2000). The codification of knowledge: a conceptual and empirical exploration. *Industrial and corporate change*, *9*(2), 195-209.

Dasgupta, M., & Gupta, R. K. (2009). Innovation in organizations: A review of the role of organizational learning and knowledge management. *Global Business Review*, *10*(2), 203-224.

Davenport, T. H., & Prusak, L. (1998). *Working knowledge: How organizations manage what they know*. Harvard Business Press.

Du Plessis, S. J. (2025). Towards a human-machine integrated model for organisational knowledge creation: A case for knowledge-enriched machine learning. *Masters Thesis.* Stellenbosch University.

Engeström, Y. (1999). Innovative learning in work teams: Analyzing cycles of knowledge creation in practice. *Perspectives on activity theory*, *377*, 404.

Fui-Hoon Nah, F., Zheng, R., Cai, J., Siau, K., & Chen, L. (2023). Generative AI and ChatGPT: Applications, challenges, and AI-human collaboration. *Journal of Information Technology Case and Application Research*, *25*(3), 277-304.

Lavie, D., Stettner, U., & Tushman, M. L. (2010). Exploration and exploitation within and across organizations. *Academy of Management annals*, *4*(1), 109-155.

Levinthal, D. A., & March, J. G. (1993). The myopia of learning. *Strategic management journal*, *14*(S2), 95-112.

Martínez-Plumed, F., Contreras-Ochando, L., Ferri, C. *et al*. (2021). CRISP-DM twenty years later: From data mining processes to data science trajectories. *IEEE transactions on knowledge and data engineering*, *33*(8), 3048-3061.

Nonaka I, Takeuchi H (1995) The knowledge-creating company: How Japanese companies create the dynamics of innovation. Oxford University Press, New York.

Nonaka, I., Von Krogh, G., & Voelpel, S. (2006). Organizational knowledge creation theory: Evolutionary paths and future advances. *Organization studies*, *27*(8), 1179-1208.

O'Meara, M., & Kelliher, F. (2021). Knowledge codification. In *Knowledge Management and Learning Organizations* (pp. 25-50). Cham: Springer International Publishing.

Patriotta, G. (2004). On studying organizational knowledge. *Knowledge Management Research & Practice*, *2*(1), 3-12.

Poell, R., & Van der Krogt, F. (2003). Learning strategies of workers in the knowledge-creating company. *Human resource development international*, *6*(3), 387-403.

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. *Journal of management information systems*, *24*(3), 45-77.

Senge, P. M. (1990). *The fifth discipline: The art and practice of the learning organization*. Doubleday/Currency, New York.

Sternberg, R. J. (2021). *Adaptive intelligence: Surviving and thriving in times of uncertainty*. Cambridge University Press.

Sturm, T., Gerlach, J. P., Pumplun, *et al.* (2021). Coordinating Human and Machine Learning for Effective Organizational Learning. *MIS quarterly*, *45*(3).

Vom Brocke, J., Hevner, A., & Maedche, A. (2020). Introduction to design science research. *Design science research. Cases*, 1-13.

Von Rueden, L., Mayer, S., Beckh *et al.* (2021). Informed machine learning–a taxonomy and survey of integrating prior knowledge into learning systems. *IEEE Transactions on Knowledge and Data Engineering*, *35*(1), 614-633.