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Exploring the Role of Grey Knowledge in Enhancing Knowledge Management Practices in Finnish SMEs

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Abstract

This research examines the impact of grey knowledge on knowledge management practices in Finnish SMEs, with a particular focus on its role as a linkage between explicit and tacit knowledge. It employs a mixed method, integrating qualitative thematic analysis with quantitative machine learning models. Findings highlight the necessity for Finnish SMEs to capture and integrate grey knowledge into organisational processes. The integration of grey knowledge is perceived positively by managers and employees for its effect on enhancing performance. The theoretical contribution of this study lies in expanding its application in the context of Finnish

SMEs to create more balanced and effective KM practices. Despite being focused on Finnish SMEs, further interdisciplinary and cross-cultural industry-wide research is essential for understanding the role of grey knowledge in various KM paradigms. Such research could explore how organisations can utilise grey knowledge to strengthen resilience, foster innovation, and enhance competitiveness in markets.

Keywords

Knowledge management; grey knowledge; Finnish SMEs; mixed method; G-SECI.

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1. Introduction

Business organisations, particularly small and medium-sized enterprises (SMEs), predominantly utilise both explicit and tacit knowledge in their operations. However, the challenges of effective knowledge transfer (Biloslavo and Lombardi, 2021) raise the question of the possible existence of intermediate knowledge that can facilitate this transition (Terhorst et al., 2018). In SMEs, the use and transfer of knowledge are integral parts of their operational practices (Syed Mustapha, 2023; Escoz Barragan et al., 2025), but this importance has been examined mainly in larger companies, and its application in SMEs has not yet been thoroughly recognised. The lack of comprehensive research in the field of knowledge management (KM) programmes (Beek, 2017) often leads to the loss of knowledge (Pinto et al., 2023), especially when employees leave the organisation (Cerchione et al., 2016; Foli et al., 2023) or deliberately retain their acquired knowledge and conceal it from others who

need it (Su, 2020). In addition, this lack of research causes SMEs to face significant obstacles in implementing a formal KM system, and existing tools in this area fail to effectively integrate into formal KM strategies (Egwunatum and Oboreh, 2022; Paolone et al., 2024). Due to the presence of significant gaps in the systematic approach to KM in SMEs (Beek, 2017; Kianto et al., 2018; Saratchandra and Shrestha, 2022), this clearly demonstrates the need to adopt more structured KM systems in SMEs. This study adopts a constructivist paradigm, which emphasises the social processes of knowledge creation and sharing, particularly relevant in the context of SMEs.

Implementing structured KM systems in SMEs necessitates leadership involvement and the effective utilisation of knowledge from various sources (Child and Shumate, 2007; Polas et al., 2023). In this context, leadership involvement supports the execution process (Centobelli et al., 2017; Mubuyaeta and Ngulube, 2024), while efficient knowledge utilisation can help reduce implementation barriers through resource-effective KM practices (Cerchione et al., 2015). Unlike rational perspectives, which may overlook the nuances of informal knowledge dynamics (Garrrick and Chan, 2017), the constructivist approach allows for a deeper understanding of how effective knowledge facilitates knowledge transfer and innovation. Although structured KM can enhance system quality (Niese and Sasidharan, 2022), many SMEs still do not fully capitalise on this capability. For instance, Finnish logistics SMEs that rely on informal, tacit knowledge encounter difficulties in maximising employee potential and leveraging knowledge for long-term growth (Kianto et al., 2018). The personnel in these companies often depend on peer networks to address system-related challenges, expecting that coworkers will share solutions or workarounds (Niese and Sasidharan, 2022). This highlights the need for structured KM systems to be utilised more effectively to enhance knowledge utilisation and integrate seamlessly into SMEs (Bloem and Salimi, 2023; Zakery and Saremi, 2021). Hence, SMEs are significantly reliant on the knowledge of their staff. By focusing on the interplay between tacit and explicit knowledge, this paradigm effectively addresses

the identified gaps in existing research, particularly regarding the integration of informal knowledge channels in SMEs.

Tacit knowledge is deeply rooted in human resources and not in formal systems (Cerchione et al., 2016), and its transmission is hardly possible (Child and Shumate, 2007). Consequently, knowledge is typically stored informally at the operational level, which leads to inadequate sharing or codification. However, it is evident that tacit knowledge can be valuable to organisations, especially when externalised (Heaton and Taylor, 2002). This situation carries the risk of knowledge disappearance (Hoe, 2006). To mitigate these challenges, it is crucial to explore more cohesive KM models that can effectively manage and safeguard this vital knowledge. An exploration of an innovative model is particularly important for Finnish SMEs, as it can bridge gaps in formal knowledge systems and enhance innovation and competitive advantage by effectively leveraging informal knowledge channels (Henttonen and Lehtimäki, 2017). This study initially examines a systematic model of KM that focuses on both maintaining tacit knowledge and creating new knowledge. The primary objective of this research is to examine the impact of KM practices on Finnish SMEs, particularly in improving their knowledge transfer. This focus on a constructivist framework will provide valuable insights into the mechanisms of knowledge transfer and the role of informal networks in enhancing organisational performance. Additionally, the research evaluates the efficiency of an innovative model in addressing the challenges associated with KM and helps advance KM methods in the field of SMEs.

The primary foundation of this research is the SECI model, which systematically converts implicit and explicit knowledge into each other and creates new knowledge (Jayasekera et al., 2022). This study used the improved SECI model, known as the G-SECI model. Developed by Li et al. (2018), this model focuses on a specific type of knowledge called grey knowledge. This knowledge, which is half-tacit and half-explicit, is referred to as know-why and can be extracted from individual understanding through expression and communication (Gao and Tang, 2010). In other words, grey

knowledge serves as a bridge between informal knowledge sharing and formal KM practices. This is particularly significant for SMEs because grey knowledge includes the reasons and logic behind the decisions and actions that are made (Jordão and Novas, 2017). Although this type of knowledge is not officially recorded, it is effectively transmitted through dialogues, shared experiences, and practical observations, ultimately helping to improve decision-making processes and organisational learning. However, in traditional KM frameworks, this type of knowledge is often overlooked. For this reason, employees may have valuable insights into operational performance or customer preferences that are not officially registered but are informally shared through experience and conversation (Abubakar et al., 2019). The study applies the G-SECI model to examine the challenges facing SMEs in Finland. Aiming to evaluate the effectiveness of the model, the research contributes to a broader discourse in the KM field. It also provides insights into effective strategies for exploiting grey knowledge in Finnish SMEs. The main question this research seeks to answer is: “How does grey knowledge affect KM practices in Finnish SMEs? Understanding the role of grey knowledge in these practices can bring valuable insights. This paper offers a unique contribution to the field of KM by focusing on the often-overlooked concept of grey knowledge within Finnish SMEs, utilising the innovative G-SECI model to bridge the gap between tacit and explicit knowledge, and providing actionable insights that enhance both competitive advantage and innovation. Hence, in Secs. 2 and 3, we review the literature comprehensively and provide the theoretical framework for the current state of research. After that, in Sec. 3, we explain the research plan, data collection methods and analytical strategies in detail. After all, we present the findings and interpretations in Secs. 4 and 5 and suggest pathways for future research.

2. Theoretical background

2.1. Harnessing knowledge: The strategic imperative of knowledge management in SMEs

KM as a strategic asset improves how organisations create, share, and utilise information. KM encompasses systematic processes for identifying, capturing, organising, and leveraging knowledge

to drive organisational success (Chan et al., 2016; Valdez-Juárez et al., 2018). KM integration with enterprise structure enhances systems and processes for generating information that promotes individual and collective learning (Santoro et al., 2018; Jabeen and Al Dari, 2020). In a knowledge-intensive society, KM systems grow the global economy (Mubuyaeta and Ngulube, 2024). For SMEs, KM not only enhances operational efficiency but also fosters innovation by enabling faster decision-making and problem-solving through accessible knowledge resources. KM includes the creation, dissemination, sharing, and utilisation of knowledge, enhances organisational efficiency, particularly in SMEs (Almuayad and Chen, 2024). Enterprises engaging in all KM capabilities are expected to achieve the highest organisational performance, supported by Silva and Fain's (2024) findings. As a strategic approach, KM facilitates novel business processes that augment creativity, efficiency, and quality of system (Nakash and Bolisani, 2024). However, successful KM implementation often faces challenges such as employee resistance to sharing knowledge or inadequate technological infrastructure, which can be mitigated through leadership support and user-friendly platforms. This journey ameliorates through knowledge sharing among members, fostering collaboration towards organisational goals (Su, 2020) and improving the development of new competencies (Cheikh-Ammar et al., 2024). By fostering a culture of trust and collaboration, organisations can overcome barriers to knowledge sharing, ensuring that critical insights are effectively utilised across teams. This broad applicability underscores KM's critical role in SMEs, as knowledge sharing and application become core objectives of effective KM practices (Idrees et al., 2023).

2.2. Bridging the knowledge gap: The importance of KM practices in SMEs

While the theoretical foundations of KM are well established, its practical implementation in SMEs presents unique challenges and opportunities that warrant careful examination (DiPasquale and McInerney, 2010; Kishore and Sundaram, 2018). The scholarly literature emphasises the significant role KM plays in bolstering the competitiveness of both large corporations and SMEs (Cerchione and Esposito, 2017). However, it is crucial to acknowledge the differences that exist between SMEs and

larger enterprises. As per the research conducted by Kianto et al. (2018), SMEs are distinct not only in terms of their resource constraints but also in their organisational structures, management system, customer proximity, and market responsiveness. Comprehending these differences is of utmost importance, particularly considering the pivotal role SMEs perform in the global economy. In SMEs, KM is essential for facilitating technical innovation. It is crucial to realise that innovation depends on efficient KM and vice versa (Scuotto et al., 2023). Grey knowledge, often perceived as unstructured or informal knowledge, assumes an innovation in the decision-making process within SMEs. It facilitates the flow of both tacit and explicit knowledge, thereby enhancing the overall performance of the organisation (Almuayad and Chen, 2024).

Playing a pivotal role in the economic fabric, SMEs constitute approximately 90% of global businesses, thereby making a substantial contribution to job creation (over 50%) and economic development (40% of GDP). The World Bank (2019) projects a requirement of 600 million jobs by 2030, which underscores the criticality of SME development for the integration of the global workforce. In the context of Finland, SMEs contribute 59.6% of value-added and 65.2% of employment. There has been a consistent growth in value-added from 2014 to 2018. However, a slight decrease in SME employment is forecasted by 2020 (European Commission, 2019). To address these challenges, the implementation of KM systems can significantly enhance the capabilities of SMEs and contribute to their overall success. KM systems, as part of the broader organisational knowledge framework, facilitate knowledge sharing within the enterprise, thereby fostering innovation and competitiveness, enhancing creativity, and hindering reinventing the wheel (Child and Shumate, 2007). In essence, the strategic deployment of KM systems can equip SMEs to navigate the complexities of the modern business landscape and achieve sustainable growth. However, Beek (2017) discovered that Finnish SMEs often fall short in managing knowledge effectively, lacking systematic approaches to fully harness the potential of KM. To bridge these gaps, further exploration and research are needed

for a structured framework in Finnish SMEs. It is supported by the research of Silva and Fain (2024), highlighting the importance of a robust KM infrastructure in achieving organisational objectives.

2.3. Leveraging the SECI model for effective knowledge management in SMEs

The effective implementation of KM in SMEs requires addressing challenges and a robust conceptual framework as well (Zyl et al., 2022). SMEs utilise both tacit and explicit knowledge, which informs the selection of suitable KM models. Explicit knowledge, which is formal or codified, encompasses documents, formulas, contracts, process diagrams, and manuals. This type of knowledge is crucial for a firm's competitive advantage and profitability, as noted by López-Cabarcos et al. (2020). Moreover, explicit knowledge can be articulated, captured, stored, edited, and shared by organisations much better. In contrast, tacit knowledge resides in human minds as individual know-how, fundamentally embedded into a person's actions and expertise (Heaton and Taylor, 2002) and often expressed through innovation. It remains unwritten and unspoken, making it the most challenging type of knowledge to manage across all sectors, particularly in the assembly sector (Mohajan, 2016). A significant challenge in KM is capturing and sharing knowledge and converting tacit knowledge into explicit forms and vice versa (Jghamou et al., 2022), especially tacit knowledge, which can rarely be fully transferred (Walsham, 2002). Knowledge undergoes four phases during its transformation: tacit–tacit, tacit–explicit, explicit–explicit, and explicit–tacit (Jghamou et al., 2022) and employing this knowledge spiral affects the organisation's overall success (Heaton and Taylor, 2002). Based on this premise, Nonaka and Takeuchi's dynamic KM model views knowledge as a fluid entity, focusing on organisational creation and transfer (Adesina and Ocholla, 2019). This model emphasises continuous knowledge transfer, combination, and conversion through user interaction and practice, supported by relevant data to enhance decision-making and create new knowledge. Knowledge creation, particularly from tacit to explicit forms, is pivotal for organisational competitive advantage (Kaur, 2015). SMEs, where knowledge is predominantly tacit and embedded in employees, require mechanisms to create, share, and disseminate knowledge effectively. This provides a competitive

edge and fosters innovation (Anand et al., 2021). To address these con-version processes, Nonaka and Takeuchi's SECI model, shown in Table 1, outlines a structured approach through the four stages. Based on Table 1, the SECI model represents a dynamic knowledge creation framework that operates through four distinct yet interconnected conversion processes, each occurring within specific shared spaces or "ba" (Kaur, 2015). Socialisation facilitates the transfer of tacit-to-tacit knowledge among individuals, primarily through direct interaction and shared experiences in an originating ba (Strode et al., 2017).

Table 1 - The SECI model (Source: Authors)

Component	Knowledge Conversion Process	Participants	Direction	Key Activities	Shared space
Socialization	Tacit to Tacit	Individual to Individual	Face to face	•Mentoring practices •Knowledge sharing	Originating ba
Externalization	Tacit to Explicit	Individual to Group	Team reflexivity	•Team reflexivity •Organizational memory •Dialoguing	Dialogue ba
Combination	Explicit to Explicit	Group to Organization	Organizational communication	•Organizational communication •Technological support •Group collaboration	Systemizing ba
Internalization	Explicit to Tacit	Organization/Group to Individual	Human resources focused	•Human resources training	Exercising ba

Component	Knowledge Conversion Process	Participants	Direction	Key Activities	Shared space
				•Human resources development •Exercising	

Externalisation converts tacit to explicit knowledge within teams, using dialogue, organisational memory, and team reflexivity in a dialogue ba (Farnese et al., 2019). Combination changes explicit to explicit knowledge at the organisational level, supported by communication, technology, and collaboration in a systemising ba (Bartolacci et al., 2016). Internalisation transforms explicit to tacit knowledge indi-vidually, facilitated by HR training, development, and exercising in an exercising ba (Farnese et al., 2019; Tynjälä, 2022). According to SECI theory, knowledge creation and knowledge sharing can be achieved through four spiral stages of socialisation–externalisation–combination–internalisation (Farnese et al., 2019), representing the dynamic process of knowledge conversion within organisations.

2.4. The G-SECI model: A new paradigm for knowledge management in SMEs

While the SECI model has gained significant traction in KM literature, empirical validation of its effectiveness across different organisational contexts remains limited (Tammets, 2012). Hence, current research endeavours are directed towards investigating its utility and advantages for SMEs (Kishore and Sundaram, 2018). Bandera et al. (2017) postulated that the principles of the SECI model could elucidate the high failure rates of small businesses. They attribute these failures to the challenges encountered in the conversion of tacit knowledge into explicit forms, particularly in the face of resource constraints. Notwithstanding its extensive usage, the SECI model has not been exempt from criticism (Willman et al., 2022).

Li and Gao (2003) draw a distinction between different types of knowledge, warning against the model's indiscriminate application beyond its initial context of Japanese manufacturing. Powell et al. (2007) critically examines the model's philosophical underpinnings, positing that its perspective on the essence of knowledge constrains its capacity to promote knowledge growth and learning. Richter (2011) argues that Nonaka's theory prioritises the articulation and transformation of information over the generation of novel knowledge. Farnese et al. (2019) contend that the SECI model's conversion modes are abstract and necessitate operationalisation via organisational processes such as mentoring, knowledge sharing, team reflexivity, and organisational memory. Moreover, scant research has investigated the SECI model's predictive validity or its efficacy in generating new knowledge across diverse enterprise sizes, signifying a research gap (Tammets, 2012).

The limitations of the SECI model in addressing the fluid nature of knowledge in modern organisations have led to the development of alternative frameworks that better account for the complexity of knowledge dynamics. In response to these limitations, Li et al. (2018) introduced the concept of grey knowledge. This term serves to distinguish various types of knowledge that are critical in the knowledge-based economy, such as know-what, know-why, know-how, and know-who. These categories extend our understanding of knowledge beyond mere information, emphasising the tacit aspects that are challenging to codify (Lundvall and Johnson, 1994; OECD, 1996). These four types of knowledge are the components of the

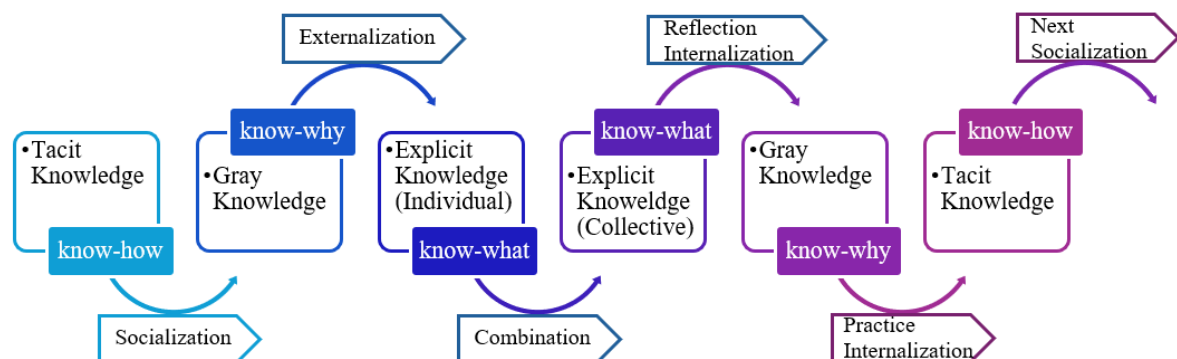


Fig 1 - Conceptual Model for Gray Knowledge (Source: Authors)

G-SECI model, as shown in Fig. 1, which illustrates the spiral sequence of these components. This figure provides a more comprehensive framework for knowledge creation, serving as the conceptual model for this research.

Based on Fig. 1, the conceptual model illustrates knowledge sharing in a spiral way as follows: Socialisation converts tacit knowledge (know-how) into grey knowledge (know-why). In the context of SMEs, the importance of socialisation cannot be overstated. It serves as the conduit for the transfer of knowledge from owners to employees and among peers (Bandera et al., 2017). Therefore, the implementation of an effective onboarding programme is paramount. Such a programme should seamlessly integrate new employees into the organisation's existing KM systems and facilitate their appropriation of relevant knowledge-sharing platforms (Cheikh-Ammar et al., 2024). However, it is crucial to note that, according to the G-SECI model, this knowledge remains in a state of flux, or grey, until it is tested in practice (Li et al., 2018). This highlights the importance of practical application in the process of knowledge acquisition and management. In essence, knowledge, until applied and tested, retains a degree of uncertainty, underscoring the need for practical application as a component of the learning process.

Externalisation transforms tacit knowledge into explicit knowledge, and then the process of combination comes into play. This involves the processing of explicit knowledge to form new knowledge, a process that leverages documents and databases (Kaur, 2015). In other words, as Li et al. (2018) states, combination organises explicit knowledge, generating new explicit knowledge by integrating existing information. Following this, reflection internalisation involves absorbing explicit knowledge to form a deeper understanding, converting it into grey knowledge. Practice internalisation turns grey into tacit knowledge through practical application. As considered, the G-SECI model distinguishes between reflection and practice in the process of internalisation. It underscores the importance of transforming grey knowledge into tacit knowledge through hands-on activities (Li et al., 2018).

Considering the challenges Finnish SMEs face in KM and the limited research conducted on grey knowledge (Chaikovska, 2022), our research probes into how grey knowledge impacts KM practices in Finnish SMEs. The ensuing section of this paper will elucidate our approach to investigating this issue. We will elaborate on the research methods we employed and how we collected data to delve deeper into this topic.

3. Research Methodology

3.1. Overview

Using a mixed-method approach, the study examines the role of grey knowledge in improving KM practices in Finnish SMEs. This study aligns with Nonaka and Takeuchi's knowledge spiral model, which emphasises the dynamic interplay between tacit and explicit knowledge as a foundation for knowledge creation and management. To understand this more comprehensively, both qualitative and quantitative methods have been used. In the qualitative sector, themed analysis has been used to identify common patterns associated with grey knowledge. In a small part, machine learning techniques are also used to validate and reinforce the findings. This combined approach allows triangulation and helps increase the accuracy and reliability of research results.

3.2. Research Design

A case study method has been used to more closely examine the impact of grey knowledge on KM practices in Finnish SMEs. This method is especially suitable when we want to understand complex phenomena dependent on certain conditions (Paparini et al., 2020). In this research, our focus is on 10 Finnish SMEs chosen for their active use of KM practices and willingness to share experiences related to grey knowledge. This research design helps us to conduct deeper analysis and gather rich, condition-dependent insights. Ethical approval was obtained for data collection, and informed consent was secured from all participants, ensuring confidentiality and anonymity in the reporting of findings.

3.3. Data Collection Methods

In this study, instead of using large samples, we decided to use deep, semi-structured interviews as the main method of data collection. An interview guide was developed, consisting of open-ended questions focused on the “know-why” as a clear interpretation of grey knowledge identification, utilisation, and its impact on KM practices. To that end, we conducted interviews with 10 key people in 10 SMEs. Each interview lasted at least 60 min and was conducted via MS Teams. All interviews were audio-recorded and transcribed verbatim for analysis. The reason for choosing this number of interviews was the principle of “data saturation”. Based on this principle, conducting more interviews will likely lead to recurring information (Weller et al., 2018). Participants were selected considering their roles in KM within their SMEs, which represented diverse industries, including technology, manufacturing, and services, ensuring variability in perspectives. In this way, instead of expanding the sample size, our focus was to get accurate and in-depth data from these interviews.

Table 2 provides information about the interviewees, indicating the diversity of their fields of study. They have a variety of qualifications, from master’s to post-docs, as well as work experience in managerial and specialised roles in the field.

Table 2 - Overview of Interviewees Participating in Research

SME No.	SME Size	Sector	Interviewee (Sample) No.	Education Level	Work Experience	
					Manager	Expert
1	4	Industrial inspection	1	Doctorate	2	2
2	3	Inspection services	2	Master's	2	4
3	223	Advertising and media	3	Master's	0	2
4	48	Digital advertising	4	Master's	0	3
5	53	Gaming and entertainment	5	Post-Doctorate	0	2
6	70	Software and automation	6	Post-Doctorate	0	3
7	115	Cybersecurity and IoT	7	Post-Doctorate	0	2

8	10	Education institute	8	Doctorate	3	2
9	6	Inspection services	9	PhD Student	2	4
10	3	AI	10	Doctorate	2	2

This diversity in academic background and work experience has helped us to better understand grey knowledge in Finnish SMEs. In KM qualitative research, it is very useful to use small but rich examples of information. These types of samples allow researchers to examine the subject in detail and in depth. Indeed, if there were more samples, the generalisability of the results could be increased. But our qualitative approach is designed to identify and analyse the complexities of grey knowledge well.

3.4. Data Analysis Methods

For data analysis in this study, we chose Python because of its straightforward and flexible nature. Python stands out for its simplicity, modular design, object-oriented programming capabilities, and excellent tools for profiling and testing. Additionally, it is portable and comes with robust self-documentation features. The numeric libraries available in Python also make it incredibly effective for handling large volumes of numerical data (Khadka, 2019; Nagpal and Gabrani, 2019; Bektosh and Misliddin, 2024). Our analysis includes various methods: Frequency Analysis to identify common patterns, Thematic Analysis to explore recurring themes, Sentiment Analysis using machine learning models, and eventually Latent Dirichlet Allocation (LDA) for topic modelling to uncover hidden topics within the data.

The data analysis involves the following:

3.4.1 Textual and Content Analysis

We apply textual and content analysis to extract further insights from the dataset, while it is supported by Natural Language Processing (NLP) techniques (Tunca et al., 2023). Variables such as weighted percentages, word counts, and keyword frequencies are computed. N-gram

analysis, including unigrams and bigrams, is conducted to identify patterns and correlations between words and indicators (Dahiya et al., 2023; Saura et al., 2023).

3.4.2 Thematic analysis

We conduct thematic analysis to identify core themes within the dataset, following methodologies outlined by Bennetts et al. (2024), Dawadi (2021), and Varma et al. (2022). This process involves examining word frequencies and identifying recurring patterns to construct meaningful insights and themes aligned with the study's objectives (Perannagari and Chakrabarti, 2020; Goh and Wilk, 2024). Given that the analysis begins with specific observations (such as word frequencies and patterns) and progressively moves toward broader generalisations (the core themes), this approach is inductive (Peel, 2020).

3.4.3 Sentiment Analysis

We perform sentiment analysis using Textblob and is supported by machine learning models, involving Support Vector Classifier (SVC), Multinomial Naive Bayes (MNB), Logistic Regression (LR), and Random Forest Classifier (RFC) (Nurcahyawati and Mustaffa, 2023; Saha, 2023). The analysis categorises the content into positive (1), negative (−1), or neutral (0) sentiments and computes an overall polarity score (ranging from 0.0 (very objective) to 1.0 (very subjective)) for a concise measure of sentiment. To enhance the accuracy of sentiment analysis, we trained and evaluated several machine learning classifiers. We utilised a labelled dataset, splitting it into training, validation, and test sets to ensure robust model evaluation. Each model underwent hyperparameter tuning and was assessed using metrics such as accuracy, precision, recall, F1-score, and AUC–ROC. This rigorous process allows for reliable sentiment classification, addressing and ensuring the models can generalise effectively to new data (Singh et al., 2017).

3.4.4 LDA

We employ LDA for topic modelling to uncover underlying themes in the SMEs' KM system.

3.5. Reliability and Validity

3.5.1 Reliability

We ensured the reliability of our work using standard and repeatable methods for data analysis. We pre-processed all the text equally, which meant we took steps like tokenisation, lemmatisation, stopword removal, and noise filtering using established libraries like NLTK and TextBlob. This allowed input data to be processed uniformly throughout the collection. Further, to minimise variance and increase reproducibility, we trained and evaluated various classification models such as SVM, LR, RFC, and MNB using the stratified train-test splits method and fixed random states. We also measured the performance of these models by criteria such as accuracy, precision, recall, and F1-score to ensure the stability of our results, confirming the strength of the sentiment classification.

3.5.2 Validity

To check the validity, we used several different layers. Predefined, literature-based keyword taxonomies for tacit, explicit, and grey knowledge supported content and construct validity. These classifications were systematically applied using pattern matching and thematic scoring to make sure the categories were meaningfully represented. Moreover, we applied LDA topic modelling while measuring its coherence score to discover new and hidden themes. This gave our predefined code an empirical basis and contributed to internal credibility. Sentiment analysis also deepened our understanding of tone and perspective in qualitative data. The simultaneous use of qualitative thematic analysis and quantitative machine learning techniques allowed us to triangulate a methodology that greatly strengthened the overall validity of our findings.

Thus, instead of seeing validity and reliability as just abstract concepts, we institutionalised them in the process of analysing our data to make sure our results were both robust and reliable.

4. Results

The results highlight grey knowledge as a bridge between tacit and explicit knowledge in Finnish SMEs. Thematic and sentiment analyses reveal their significance in decision-making, while topic modelling emphasises its application. These findings support the G-SECI model’s role in integrating why-know knowledge into formal KM practices. The following sections detail these findings.

4.1. Results of Word Frequency

Word frequency analysis, which involved counting the occurrences of each word in interviews, enhanced understanding of text patterns, keyword extraction, and content categorisation (Alhaj et al., 2022).

Figure 2 revealed the word frequency of interviews:

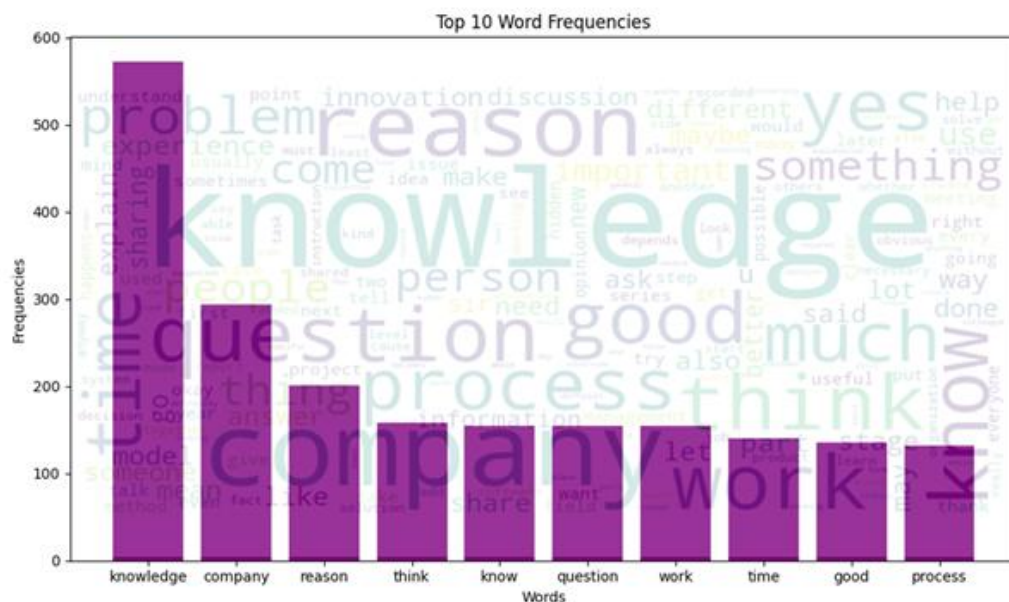


Fig 2 - Word cloud of interviews

Figure 2 shows a bar chart illustrating the top 10 words used in our text analysis. “Knowledge” led the list, appearing nearly 600 times, suggesting it played a major role in the dataset. Next was “company”, which showed up around 350 times. Other frequently occurring words included “reason”, “think”, “know”, “question”, “work”, “time”, “good”, and “process”, each appearing between 150 and 250 times.

4.2. Results of Overall Polarity and Subjectivity Scores:

Analysing the Overall Polarity and Subjectivity Scores gave us a deeper understanding of the sentiment and emotional tone of interviews (Bravo-Marquez et al., 2014). Table 3 presents the overall polarity and subjectivity scores derived from the data.

As shown in Table 3, the overall polarity score was 0.12, suggesting a slightly positive sentiment in the interview data. And the overall subjectivity score of 0.42 indicated that the interview data contained a moderate level of subjective viewpoints.

The polarity score helped measure the emotional tone of data, indicating whether it was positive, negative, or neutral. This metric was useful in assessing the over-all sentiment in interviews and comparing different datasets for deeper analysis. Chart 1 revealed the distribution of polarity scores. The polarity score chart, which measures sentiment on a scale from -1 (very negative) to 1 (very positive), shows that most responses fell in the neutral to

Table 3 – Overall Polarity and Subjectivity Scores in Interviews

Data\Score	Overall Polarity	Overall Subjectivity
Interviews	0.12	0.42

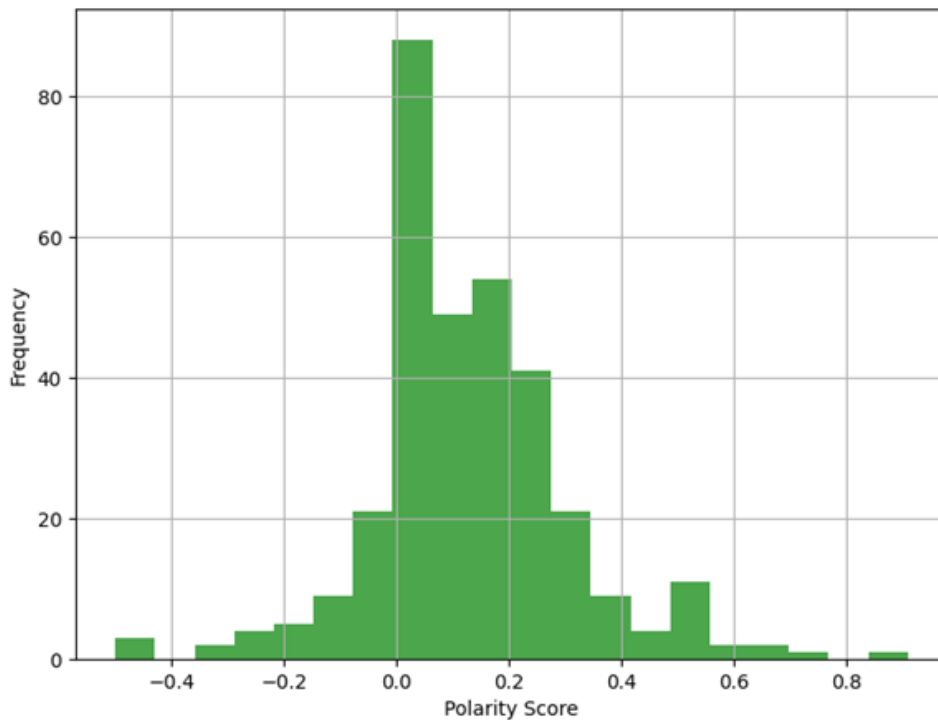


Chart 1 - Distribution of Polarity Scores

slightly positive range. When looking at the histogram, which displays the distribution of these scores, we saw that most people felt neutral or a bit positive about grey knowledge. A significant number of responses were between -0.1 and 0.3 , with the highest concentration around 0.1 . This indicated that respondents generally viewed grey knowledge in a neutral or slightly positive light when it came to their KM practices. Negative sentiments were rare, as few responses fell in the negative polarity range. Similarly, strong positive sentiments (scores above 0.5) were also uncommon.

4.3. Results of Machine Learning Model Results:

In this section, the performance of four different machine learning models was compared for predicting sentiment labels (Kumar Jha and Varkkey, 2018; Sharma et al., 2024) for interviews. First, the reliability and validity of models have been measured as they have been reflected in Table 4.

According to Table 4, the machine learning models exhibit strong reliability and validity. The precision, recall, and F1-score indicate that the models are generally effective in making accurate predictions, with acceptable levels of variability. The findings suggest that the models can be

confidently applied in practical scenarios. Then, the main metrics used were accuracy and sentiment label; the former was the proportion of correct predictions made by the model, and the latter was the sentiment predicted by the model. Table 5 shows this comparison.

Based on Table 5, all sentiment labels predicted were positive. The LR model had the highest accuracy, followed closely by the RFC model. The MNB model had

Table 4 - Reliability and validity of machine learning models

Machine Learning Models	Precision	Recall	F1-score
Average	0.7855 ± 0.06325	0.8035 ± 0.0385	0.7825 ± 0.0425

Table 5 - Comparing the performance of four different machine learning models in Banks

Data	Machine Learning Models							
	SVC		Multinomial Naive Bayes		Logistic Regression		Random Forest	
	Accuracy	Sentiment Label	Accuracy	Sentiment Label	Accuracy	Sentiment Label	Accuracy	Sentiment Label
Interviews	0.951	P	0.886	P	0.963	P	0.957	P

- **P = positive**

the lowest accuracy but still predicted the same sentiment label (“positive”), and SVC had intermediate performance between the MNB and Random Forest models.

4.4. Results of Thematic Analysis Scores:

Thematic analysis scores in content analysis systematically evaluate and quantify identified themes within qualitative data. These scores aid in identifying patterns and drawing meaningful conclusions, highlighting central themes (Crowe et al., 2015; Weisser et al., 2015; Neuendorf, 2018). The analysis revealed four primary themes: “Grey Knowledge”, “Tacit Knowledge”, “Explicit Knowledge”, and “Knowledge Management System”. Chart 2 revealed thematic analysis scores for data.

The results, as illustrated in thematic analysis (Chart 2), suggest that grey knowledge can strengthen the KM system, thereby supporting an effective KM system. Categories such as tacit knowledge and explicit knowledge were scored alongside grey knowledge, highlighting the relative importance and influence of each. In other words, grey knowledge significantly contributed to KM practices, often overlapping with both tacit and explicit knowledge. The scores indicated that while tacit and explicit knowledge were well-recognised, grey knowledge was crucial for bridging gaps and enhancing overall KM effectiveness:

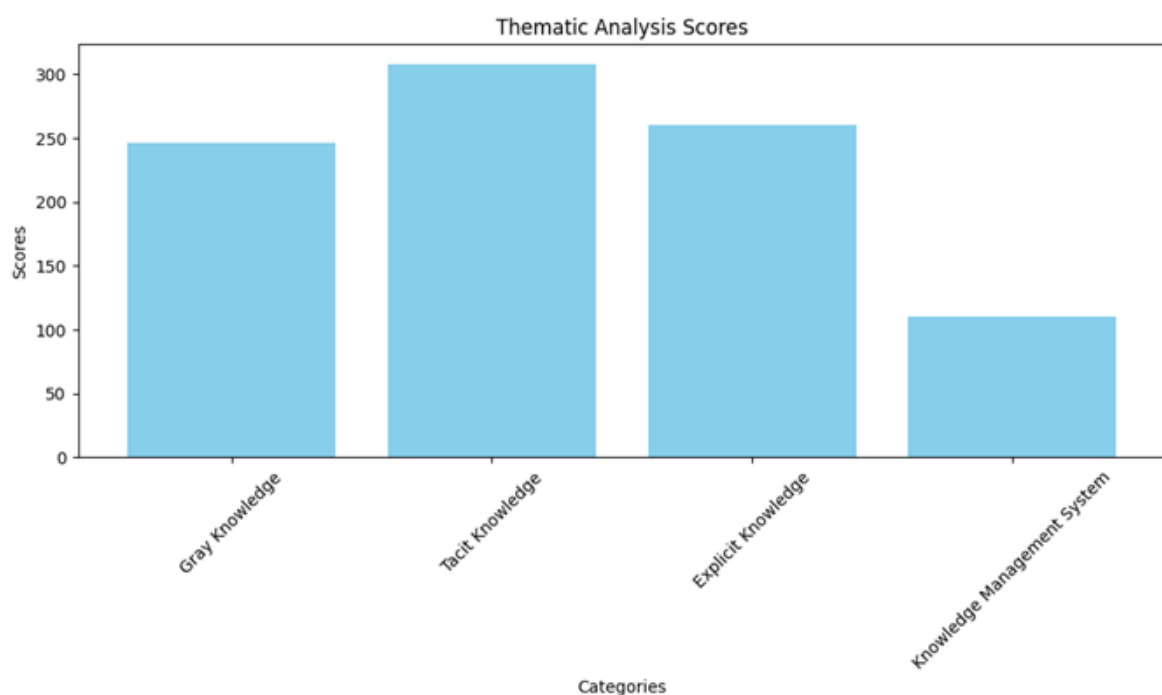


Chart 2 - Thematic Analysis Scores for interviews

4.5. Results of LDA Topics Results:

LDA was a technique used to uncover hidden thematic structures within reports using the top words for each topic (Chauhan and Shah, 2021). Table 6 shows the results of LDA Topics for interviews. These five themes, shown in Table 6, collectively offer a well-rounded perspective on KM in companies. They cover why sharing knowledge was important, how it has been applied in practice, how it evolved, how it solved problems, and the need for quality assessment. This multifaceted look provides a deep understanding of how knowledge operated and was managed within organisations.

Table 6 - Uncovering Thematic Insights through LDA Analysis

Topic	Top Significant Terms	Description
Topic 1	knowledge, company, reason, question, work, think, may, know, experience	This topic emphasizes the role of knowledge within companies, focusing on the rationale behind knowledge-sharing practices, the questions arising from these practices, and the experiences contributing to knowledge management decisions.
Topic 2	knowledge, thing, company, work, use, reason, important, come, know	The focus here is on the application of knowledge within companies, stressing the importance of using knowledge effectively, understanding the reasons behind its use, and recognizing critical elements of knowledge integration.
Topic 3	knowledge, company, time, much, reason, know, work, people, good, important	This topic addresses the temporal aspects of knowledge management, exploring how knowledge evolves over time within companies, the reasons for its evolution, and the importance of timely application and adaptation of knowledge.
Topic 4	knowledge, company, problem, think, process, person, way, question, reason, use	This topic centers on knowledge as a solution to company problems, focusing on the processes of thinking, questioning, and using knowledge to address issues, involving both individual and collective problem-solving approaches.
Topic 5	knowledge, good, company, reason, know, mean, much, important, question, make	The emphasis is on the qualitative aspects of knowledge within companies, considering how 'good' knowledge is recognized, the reasons behind its valuation, and the importance of understanding and questioning its meaning and impact.
Topic Coherence Score		1.0

Moreover, the topic coherence score of 1.0 indicates perfect coherence among topics, suggesting that the terms within a topic are highly related and meaningful. This score demonstrates reliability by consistently reflecting the underlying structure of the data and validity by accurately representing the intended themes, ensuring that the topics generated are both relevant and interpretable.

In our recent study, significant findings were made about the role of grey knowledge in shaping KM practices in Finnish SMEs. The thematic analysis showed that there is a deep connection between implicit, explicit and grey knowledge, and grey knowledge plays a vital bridge in the process of knowledge conversion in the G-SECI model. In more advanced analyses using word frequency techniques and LDA topic modelling, we found that grey knowledge has a significant impact on decision-making processes, problem-solving, and knowledge-sharing behaviours. This finding is especially important in the field of organisational learning. The results of the sentiment analysis showed that the overall attitude towards grey knowledge lies in the neutral to positive spectrum of weakness, indicating the importance of this type of knowledge, while the challenges are associated with its expression and integration. The machine learning models were able to accurately predict the emotions associated with grey knowledge, which indicates the tangibility of this concept in the knowledge ecosystem of SMEs. These findings provide strong empirical support for the theoretical foundations of the G-SECI model and show that this model can provide a suitable framework for integrating grey knowledge into formal KM practices. Evidently, we must emphasise that effective exploitation of this model requires the development of structured strategies for extraction, outsourcing and practical application of grey knowledge. According to our findings, by overcoming these challenges, Finnish SMEs can use grey knowledge as a lever to foster innovation, flexibility and sustainability of organisational knowledge. This can lead to improved performance in dynamic business environments and smarter use of capital knowledge.

5. Discussion

Questioning how grey knowledge affects KM practices in Finnish SMEs, the findings accentuate the unique value of grey knowledge in enhancing adaptability and decision-making in dynamic business environments. Grey knowledge appeared as an essential and flexible type of knowledge that connected explicit knowledge with tacit knowledge based on experience and intuition (Lin and Tan, 2022). This bridging role allowed for nuanced decision-making and continuous innovation, which

was particularly useful in SMEs, which often lacked extensive resources and established KM frameworks (Abidi, 2007). Our study highlighted grey knowledge as a critical but under-recognised part of KM that bridged the gap between tacit and explicit knowledge, especially in Finnish SMEs. As contributions to knowledge, through thematic analysis, we demonstrated that grey knowledge enables employees to navigate rapidly changing business environments, solve unexpected problems, and access knowledge that was not always documented or easily accessible (Lucero-Arias et al., 2024). Using LDA topic modelling, we identified deeper thematic patterns that emerged. We showed how grey knowledge worked in different dimensions in SMEs, equipping them to navigate the uncertainty of dynamic business environments. This function included understanding the reasons behind knowledge-sharing practices, recognising the evolution of knowledge over time, and addressing organisational issues through collective problem-solving approaches. By extracting these insights, we showed that grey knowledge not only complemented formal knowledge sources but also played a role as a core element in creating a comprehensive KM environment where all types of knowledge were integrated (Jackson, 2012). Building on the qualitative insights, quantitative analysis further supports the positive role of grey knowledge in KM. Through sentiment analysis, we showed that there was a neutral to slightly positive view of grey knowledge in KM practices. According to the average polarity and subjectivity scores, 0.12 and 0.42, respectively, the interviewees showed a relatively optimistic view towards grey knowledge. They recognised the importance of this knowledge, but at the same time, they looked at it realistically and did not exaggerate it. Using machine learning models, especially LR, which achieved 96.3% accuracy, we were able to quantitatively confirm these results of the qualitative analysis. This high accuracy was also present in other models such as RFC and SVC models. The high stability of the results of the models strengthened the positive opinion about grey knowledge. This balanced view was consistent with the results we obtained from the thematic analysis. In this regard, the findings of the thematic analysis showed that the interviewees, while accepting the benefits of this knowledge, were also aware of the

existence of challenges in its implementation. The distribution of polarity scores showed that grey knowledge complemented explicit and implicit knowledge gradually and effectively, without having made fundamental changes in KM practices. In other words, this knowledge created significant added value, especially when dealing with complex and ambiguous issues (Lin and Tan, 2022). This showed that machine learning could help strengthen the validity of research results by accurately analysing sentiment in big data.

5.1. Theoretical Implications:

Our research on the G-SECI model in Finnish SMEs contributed to the understanding of this model and grey knowledge's role in KM. Grey knowledge bridged tacit and explicit knowledge, having made the SECI model more complete (Abubakar et al., 2019; Gao and Tang, 2010; Jordão and Novas, 2017). Findings suggested grey knowledge helped SMEs make better decisions and adapt with limited resources, supporting continuous innovation through effective knowledge sharing (Scuotto et al., 2023). Our study showed that SMEs should actively incorporate grey knowledge into their KM processes. The study's mixed methods - using thematic analysis and machine learning - contributed to highlighting that advanced analysis could deepen KM understanding within the G-SECI framework. By naming and systematising this knowledge, it was possible to prevent the loss of tacit knowledge, which is one of the weaknesses of SMEs (Child and Shumate, 2007; Heaton and Taylor, 2002) and help improve the long-term performance of the organisation (Cerchione et al., 2016; Almuayad and Chen, 2024). Researchers acknowledged limitations and suggested further exploring grey knowledge in other fields with new technologies to enhance the model (Powell et al., 2007; Willman et al., 2022).

5.2. Practical Implications:

Beyond theory, this research contributed practical advice for Finnish SMEs to incorporate grey knowledge into KM processes, having aligned with the G-SECI model's focus on combining knowledge types to improve performance. By using grey knowledge, these enterprises would have

more flexible and stable systems. Also, this method helped these businesses to make better decisions, create a more dynamic work environment, and strengthen innovation in the organisation. SMEs could practically institutionalise grey knowledge in their organisation by incorporating experiential knowledge of employees into recruitment processes, teamwork, and informal communication networks. To document grey knowledge effectively, SMEs can employ AI technologies, which are expected to be a perfect solution for capturing and organising grey knowledge; however, this area requires further research to fully understand its potential. Using proper technologies to record and categorise this knowledge would help these companies to be more flexible and better respond to market changes. This would greatly help to empower SMEs and improve their performance. These results benefited managers of SMEs, researchers, and policymakers.

5.3. Limitations and Future Directions

As limitations, while we offered comprehensive insights into the impact of grey knowledge on KM with this study, the scope was limited to Finnish SMEs, which could limit the generalisability of the findings.

For future research, scholars could continue to improve our understanding of grey knowledge and develop frameworks and tools that could help organisations capture and use this type of valuable knowledge more effectively in their KM practices. Extending this research to larger organisations or different industrial and cultural contexts could provide a broader understanding of the applications and benefits of grey knowledge. Furthermore, future research could explore technology-based solutions for capturing and using grey knowledge and examine how digital tools could ease their systematic integration into various KM structures.

6. Conclusion

Our research demonstrated that grey knowledge, as a valuable complement to tacit and explicit knowledge, plays a pivotal role in shaping KM practices in Finnish SMEs (Li et al., 2018). By employing a hybrid approach that integrates thematic analysis and machine learning, we highlighted

the strategic significance of grey knowledge in KM. The findings revealed that grey knowledge serves as a flexible tool, enabling SMEs to address complex challenges, foster innovation, and enhance decision-making efficiency (Centobelli et al., 2017; Niese and Sasidharan, 2022). This integration is particularly beneficial for SMEs, which often operate with limited resources and rely on informal KM frameworks (Kianto et al., 2018).

Our study underscores that grey knowledge can balance KM by bridging formal explicit knowledge and experience-based tacit knowledge, thereby creating a comprehensive KM environment. The interviewees in this study acknowledged the practical benefits of grey knowledge, aligning with prior studies that emphasise its role in enhancing adaptability, decision-making, and innovation (Cerchione et al., 2015; Santoro et al., 2018). Through sentiment analysis, we identified a balanced and realistic perspective on grey knowledge. While confirming its value and potential, the participants also recognised the challenges associated with its systematic integration into organisational processes.

The findings highlight the need for practical measures to leverage grey knowledge in building robust KM practices. Embedding this knowledge into organisational processes - such as onboarding programmes, team collaborations, and informal knowledge networks (Cheikh-Ammar et al., 2024) - and utilising technology to record, classify, and retrieve it (Cerchione et al., 2016) can effectively preserve and promote knowledge within SMEs. These efforts can strengthen the culture of continuous learning and enhance organisational performance.

This research contributes to the G-SECI model by affirming that grey knowledge acts as a bridge between tacit and explicit knowledge, thereby enriching the SECI framework. It aids Finnish SMEs in making better decisions with limited resources while fostering continuous innovation (Li et al., 2018). However, the focus of our study on Finnish SMEs limits the generalisability of the findings. Future research should explore the impact of grey knowledge across diverse industries, organisation sizes, and cultural contexts to achieve a more comprehensive understanding of its applications

(Tammets, 2012). Additionally, investigating technological tools to systematise grey knowledge could provide valuable insights, helping managers design KM systems that align with strategic performance objectives (Massa et al., 2023). These insights can contribute to more adaptable KM frameworks tailored to the varied needs of organisations.

As a key yet often overlooked element of KM, grey knowledge bridges the gap between tacit and explicit knowledge (Hoe, 2006; Niese and Sasidharan, 2022). Its role in enhancing decision-making, adaptability, and innovation makes it a critical asset for SMEs, especially in dynamic environments. Further research into capturing and integrating grey knowledge into KM practices can equip these organisations with innovative strategies to boost flexibility and achieve sustainable competitive advantage.

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