Unlocking AI-based Knowledge Management Potential for SMEs: Exploring Semantic Search Adoption

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Research Paper

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Abstract. Small and medium-sized enterprises (SME) thrive on knowledge-intensive operations, making effective knowledge management critical to their success. Contemporary developments, such as semantic search applications (SSA) leveraging artificial intelligence (AI), promise significant benefits for knowledge management. However, the adoption of such AI-based applications in the context of SME remains still notably limited. Building upon the groundwork laid by previous research on the socio-technical dimensions of AI adoption, we thus investigate the adoption of SSA in a multiple case study within the German manufacturing sector. Hence, contextualizing the adoption of SSA in SMEs using a grounded theoretical framework. Our findings highlight the intricate interplay of organizational readiness, external support, and user satisfaction in facilitating SSA adoption. We believe our framework holds significant potential to guide the adoption of SSA and thus offers valuable insights for navigating the complexities of harnessing the potential of AI-based applications for effective knowledge management in SMEs.

Keywords: Semantic Search Application Adoption, Small and Medium-sized Enterprises, Knowledge Management, Multiple Case Study

1 Introduction

In the digital era, the rapidly expanding volume of information makes it increasingly difficult for organizations and humans alike to manage and make sense of information effectively. However, the ability to quickly navigate knowledge is crucial for organizational success as the productivity of corporations is predominantly contingent upon their intellectual capabilities rather than tangible assets (Quinn et al. 2005). This enforced the evolution of information technology to effectively capture, store, and disseminate knowledge across the organization. Integrating Artificial Intelligence (AI) marks a pivotal shift, offering unprecedented opportunities to provide intelligent ways for capturing, retrieving, and transmitting data and information (Fowler 2000). Emerging AI-based technologies offer novel knowledge management solutions within the framework of digital transformation. This is particularly pertinent due to the rising complexity and volume of data (Berente et al. 2021). Within this framework, semantic search applications (SSA) are regarded as a unique form of AI-based knowledge management. They supersede traditional lexical search methods by employing intelligent search systems based on semantic text analysis, representing a promising technological advancement in knowledge management practices (Formica et al. 2013; Pustejovsky & Boguraev 1993).

Particularly in the digital realm, knowledge management emerges as a critical area for small and medium-sized enterprises (SMEs) as it facilitates the capture, dissemination, and effective use of knowledge, which is crucial for sustaining innovation and competitive advantage in rapidly changing markets (Buck et al. 2021). Especially as SMEs, which constitute the backbone of the economy, particularly in Germany, are renowned for their specialized niche expertise and global market dominance, often being recognized as hidden champions. SMEs, thrive on technologically innovative manufacturing practices, significantly contributing to an advanced technological innovation landscape (Rovira Nordman & Tolstoy 2011). Nevertheless, in SMEs, where competitive advantage is rooted in specialized and knowledge-intensive processes and products, notable shortcomings emerge concerning knowledge management, particularly within the digital realm (Despres & Chauvel 1999; Durst et al. 2023). Despite the promising technological advancement of AI-based knowledge management, such solutions see little practical application in the context of SMEs (Majumder & Dey 2022).

Regardless of SMEs' leading role in production-related technology innovation, they show only limited structured work processes, inadequate data infrastructures (resulting in data fragmentation across various databases and formats), and dependence on external Information Systems (IS) expertise (Garbellano & Da Veiga 2019; Teece 2018; Thong et al. 1996). Thus, the technological capabilities of AI-based knowledge management implementation are often hampered by SME-specific technological barriers and capacity constraints. This technological aspect is magnified in recent developments where large corporations devote billions to technical AI development and adoption annually (Marr & Ward 2019) whereas SMEs struggle to catch up with implementing and using AI, having limited internal resources, capacities, and knowledge in that domain (Statistisches Bundesamt 2023).

In addition to the technological aspects, research found the adoption of AI to be two-sided: besides the technical component there is a social component as AI adoption includes culture and workforce (Madan & Ashok 2023). Concerning AI-based knowledge management, it is, therefore, essential to recognize that AI is not a static or closed digital technology in the traditional sense. Instead, it represents a dynamic and ongoing boundary shift across all levels, extending beyond conventional digital technologies (Berente et al. 2021). The dynamic characteristic of AI, thus, requires a reevaluation of adoption strategies (Berente et al. 2021). To fully exploit and convert the existing potential into value, socio-technical aspects regarding the willingness and motivation of individuals and organizations to utilize the technology must, therefore, be considered, extending beyond purely technical aspects. To give guidance for AI-based knowledge management adoption in SMEs, our research question is as follows:

How is the adoption of semantic search applications, as a form of AI-based knowledge management in SMEs, affected by socio-technical dimensions?

To answer our research question, we developed a grounded theoretical framework for SSA adoption in SMEs. Since the results of empirical studies in the IS literature cannot be easily generalized to SMEs (Dutot et al. 2014), we conducted a multiple case study including three SMEs located in the German manufacturing business-to-business (B2B) sector following Eisenhardt's (1989) case study approach. In addition, we investigated stakeholder needs in its natural setting in SSA adoption to unleash the potential of AI-based knowledge management for SMEs. We focused on a specific AI technology: Natural Language Processing (NLP) (Li et al. 2020).

The paper is structured as follows: We first provide an overview of knowledge management in SMEs and AI adoption. Then, we describe our multiple case study design, the data collection, and the data analysis. Subsequently, we present and interpret our main findings by developing a grounded theoretical framework for SSA adoption in SMEs. We close with the discussion and conclusion of our key findings, limitations, and possible directions for future research in the field of SSA adoption.

2 Theoretical background

2.1 Knowledge management in small and medium-sized enterprises

As SMEs face significant challenges in managing knowledge, SSAs are becoming increasingly important as part of the digital transformation of SMEs (Berente et al. 2021; Cambria & White 2014; Garbellano & Da Veiga 2019; Thong et al. 1996). The already existing complexity of the environment SMEs are embedded in is rising due to digitalization and requires careful and strategic management of knowledge (Majumder & Dey 2022). Especially in SMEs, searching with conventional knowledge management tools, e.g., intranet, can be frustrating due to insufficient user training, implementation obstacles, and data-related issues (Bergamaschi et al. 2015; Ulrich & Frank, 2021). In comparison to conventional knowledge management systems, AI-based knowledge management systems not only handle the complexity but also unlock new potential for the company (Majumder & Dey 2022). Knowledge management is characterized as a prerequisite of productivity in SMEs and includes the implementation, perception, and transfer of knowledge (Depres & Chauvel 1999; Durst et al. 2023; Quinn et al. 2005). The soaring success of AI changes the implementation, perception, and transfer of knowledge significantly by providing new AI technologies, such as NLP (Majumder & Dey 2022). NLP is a convergence of computer science, AI, and linguistics involving a range of methods and tasks designed to empower computers to understand, interpret, and generate human language (Hirschberg & Manning 2015; Li et al. 2020). Herein, SSAs are a subfield within the broader field of NLP (Cambria & White 2014; Hirschberg & Manning 2015; Li et al. 2020). Compared to lexical search, SSAs provide a more advanced and intelligent information retrieval method, giving users more precise, pertinent, and customized search results (Bast et al. 2016). SSAs involve information extraction by entering a search query and receiving a response with the information that most closely matches the search query (Cambria & White 2014). Thus, users can understand the context of a search query and the relevance of search results increases (Cambria & White 2014; Grant & Conlon 2006). To unlock the potential of new and promising knowledge management tools in the context of SSAs, the successful adoption of AI becomes increasingly important for SMEs.

2.2 AI adoption

AI adoption is a preliminary stage for AI implementation (Frambach & Schillewaert 2002). Based on the adoption of innovation and technology, AI adoption can be defined as the preparedness related to integrating new AI innovations (Alsheibani et al. 2018). The process of AI adoption reflects the sequence of initiation, adoption decision, and implementation (Jöhnk et al. 2021). Initiation is characterized by the awareness, consideration, and intention to implement AI in the company to identify AI innovations (Damanpour & Schneider 2006; Jöhnk et al. 2021; Rogers 2003). SMEs in particular find it difficult to implement AI technologies due to a lack of AI expertise (Wei & Pardo 2022). The adoption decision includes evaluating innovation ideas and allocating resources (Damanpour & Schneider 2006; Jöhnk et al. 2021). Because of the SME-specific relevance of social factors (Jöhnk et al. 2021; Madan & Ashok 2023), the adoption decision is a crucial step in the adoption process for SMEs. Implementation involves adapting and integrating the innovation within the organization until it becomes routine for its users (Damanpour & Schneider 2006; Jöhnk et al. 2021). In SMEs, the strong dependence on external IT service providers hinders successful AI implementation (Thong et al. 1996). External IT support by IT service providers is a central factor for AI adoption in SMEs as SMEs depend on external support due to the sophistication of IS and the scarcity of IS staff (Bruque & Moyano 2007; Igbaria et al. 1997). Employee training is one factor through which external support (technology supplier) influences the adaptation of technological change in SMEs (Bruque & Moyano 2007; Premkumar 2003).

Besides technical drivers, Jöhnk et al. (2021) highlight the various challenges emerging from non-technical drivers. Within the context of socio-technical literature, assimilating AI into organizational frameworks demands a holistic approach that also considers organizational readiness (Jöhnk et al. 2021). Organizational readiness emerges as a central factor influencing the adoption process of AI within SMEs (Alsheibani et al. 2019; Bruque & Moyano 2007; Jöhnk et al. 2021) and can be defined as the organization's ability to execute digital transformation including AI-based technologies (Alsheibani et al. 2018). To ensure a successful AI adoption the assessment of the organizational readiness identifies potential gaps within the adoption process (Alshawi

2007; Jöhnk et al. 2021). Organizational readiness assessment includes the four steps of identification, prioritization, assessment, and adaption of organizational necessities and factors (Jöhnk et al. 2021). In sum, external support and organizational readiness are the crucial socio-technical factors for AI adoption.

3 Method

To examine how SMEs adopt AI, we conducted a qualitative case study research following Eisenhardt’s (1989) method for building theories from multiple cases. We firmly believe that qualitative research methodologies, as emphasized by Vogelsang et al. (2013) and Guggenberger et al. (2023), offer invaluable insights into the realm of SSA adoption research.

Aligned with Eisenhardt’s (1989) methodology, the cornerstone of our research lies in the specific use case scenarios observed within the participating companies and partners (see Table 1). Over a comprehensive two-year period, a consortium comprising three application partners (ID 1-3), two development partners, and two research partners (ID 4) investigated the intricacies of SSA adoption within SME environments. Each of the three application partners (ID 1-3) falls under the SME category, a demographic that constitutes a substantial portion of Germany’s economic landscape. The companies operate in diverse sectors including agriculture, mechanical engineering, metal processing, and the manufacturing of technical glass and ceramic beads. Their engagement with SSAs stems from a collective effort as part of a public initiative (KIWise) funded by the Federal Ministry of Education and Research. This collaborative endeavor sought to explore the practical implementation of SSAs as a knowledge access tool within SMEs, with a particular focus on enhancing knowledge accessibility for employees through AI-based tools.

Our research methodology encompassed both primary and secondary data collection to identify potential barriers hindering the effective utilization of SSAs. Primary data was gathered through in-depth semi-structured interviews conducted with representatives from the three SMEs in the manufacturing sector, as well as the company responsible for developing the SSA. These interviews, each spanning approximately 45 minutes, provided rich insights into stakeholder experiences, facilitated by follow-up questions to delve deeper into the phenomenon under study. An overview of the interview questions can be found here: https://doi.org/10.5281/zenodo.12581478. Additionally, secondary data analysis involved scrutinizing unsolicited and official project documents to uncover potential barriers that may not have surfaced during primary data collection (Flick 2018; Scott 1990).

The collected data underwent meticulous analysis using the coding approach outlined by Gioia et al. (2013), supported by MAXQDA. MAXQDA is a comprehensive tool that enhances the rigor of qualitative data analysis through efficient coding, annotation, retrieval, organization, and visualization of qualitative data, as well as offering features for mixed methods research from sources such as interviews, surveys, and focus groups. A total of 16 interviews were conducted across various functional roles within the participating companies supplemented by the analysis of 50 documents comprising presentations, manuals, protocols, and textual documents in various formats (pdf, excel, word). To ensure the reliability of our analysis, we conducted a second round of coding two months later, adhering to Mayring's (2010) framework. Our iterative coding process, conducted by established guidelines (Saldaña 2013), resulted in the identification of 357 labeled statements and text passages (256 from interviews, 101 from documents).

Additionally, we organized workshops involving multiple researchers within the IS discipline to validate our findings and facilitate an iterative process for theory development. Throughout this journey, we maintained a transparent and collaborative approach, providing feedback documents to the observed SMEs based on the insights gleaned from our interviews and document analysis.

ID	Case description and organization	Use case characteristics	Interviewee background and No. of interviewees (#)
1	**Agricultural and mechanical engineering:** Implementation of a SSA in service and sales of livestock farming technology for agriculture.	Technical training Sales enquiries Service enquiries	Service technician **(3)**
2	**Metal processing:** Implementation of a SSA to increase efficiency and effectiveness in production processes.	Improved work preparation Reduction of idle times Quick knowledge access	Assistance to the board **(1)** Machine operator **(3)**
3	**Technical glass and ceramic beads manufacturing:** Implementation of a SSA in the sales department and research and development.	Complaints management Procurement process Find visit and fair reports	IT **(1)** R&D **(2)** Sales **(3)**
4	**Development and research partner:** Support in the derivation of use cases for a SSA and support in the derivation of functional and non-functional requirements.	Technical support Identification of potential areas of application	Developer **(1)** Researcher **(2)**

Table 1. Overview of cases with use case characteristics and interviews.

4 Results

4.1 Main findings

The SSA adoption for AI-based knowledge management is intricately influenced by various socio-technical dimensions in SMEs. Our investigation has unveiled three primary dimensions driving this influence: organizational readiness, external support, and user satisfaction. Through a careful coding process, we initially identified 30 first-order concepts, which were then refined into eight second-order themes and eventually synthesized into three aggregate dimensions (Gioia et al. 2013). As we progressed with our analysis, we continuously refined our coding framework to ensure its alignment with the rich content we encountered (Mayring 2010). While repeating the theory building, we rearranged them into 18 first-order concepts, eight second-order themes, and three dimensions (see Table 2). In addition, tables 3, 4, and 5 list sample quotes from the interviews for each of the 18 first-order concepts.

1st order concepts	2nd order themes (# of codes)	Dimensions (# of codes)
Company size	Use case context (58)	**Organizational readiness (130)**
Industry sector		
IT-Infrastructure	Technology readiness (44)	
IT-Qualifications		
Expansion of the database	Data privacy and data security (28)	
Data storage location (online/offline)		
Access management to the database		
User-friendly interface	Onboarding (68)	**External support (179)**
Helpful introductions		
Reliability of search results	Technical capabilities (111)	
Technical improvements		
Explanations of search results	Interpretability of decision-making (26)	**User satisfaction (48)**
Restart duration		
Perceived Usefulness	User expectations (22)	
Trustworthiness		
Economy of time		
Accuracy of search results		
Compatibility with daily routine		

Table 2. Data structure. Own representation based on Gioia et al. (2013).

Organizational readiness: We understand organizational readiness as the extent to which SMEs navigate the interplay between use case context, technology readiness, and data privacy and data security. Building upon our observations use case context encompasses the boundary conditions for defining and focusing on specific, practical scenarios in which the SSA is applied to solve real-world problems depending on the company size and industry sector. Regarding company size, we observed that smaller organizations struggle with identifying appropriate use cases for the SSA because of their limited data resources. In contrast, larger organizations have access to more extensive datasets, enabling them to explore a wider array of applications and leverage more advanced SSA capabilities. Additionally, the unique needs and regulatory challenges of different industry sectors give distinct contexts for how SSAs are selected and implemented. We observed that technology readiness refers to the degree to which an organization (IT-infrastructure) or individual (IT-Qualifications) is prepared and equipped to effectively utilize a specific technology. Regarding IT-infrastructure, we observed that data management and data preprocessing is a big issue in SMEs. In addition, we noticed that the IT-qualifications are medium-qualified in SMEs as users show only little interest in in-depth technological understanding. A reinforcing factor for insufficient IT-qualifications in SMEs is the inadequate IT infrastructure compared to large companies. As data privacy focuses on handling personal information and data security protects data from unauthorized access, in SMEs both are essential components of effective information management concerning the expansion of the data storage location, database, and access management to the database. The users want to know where data is processed, and they prefer local data storage. Local data storage significantly increases the sense of security as users feel more comfortable with it because the data remains within the company. When expanding the database, carefully managing access management is crucial as users were concerned that plenty of people have access to their data like e-mails.

Example Quotes	1st order concepts	2nd order themes
"So, my impression is that, of course, a lot more energy in SMEs had to be invested in finding the use case at the start because the data material is simply not as large as in large companies."	Company size	**Use case context**
"I would have expected to get more results. But as I said, that was probably mainly because of the tables [specific to the manufacturing industry]."	Industry sector	
"In general, you have to say that data management and data preprocessing is always a big issue and that was also a big issue here. It's simply not easy for many people."	IT-Infrastructure	**Technology readiness**
"Interested [in AI], but not in depth. You just get to see what is already working in, let us say, the popular media. You try the whole thing out for yourself."	IT-Qualifications	
"What do I upload to this whole thing, where does it all end up and who guarantees that it stays right there and that only I have access to it? Of course, that is one story, always the question, so as local as possible."	Expansion of the database	**Data privacy and data security**
"As long as it is limited to the server here, not really at all, because then I look for it and I know where [...]"	Data storage location (online/offline)	
"We once discussed whether the whole thing could be extended to include emails or other points. Then the question is again, who can find what?"	Access management to the database	

Table 3. Example quotes from the interviews for organizational readiness.

External support: Our findings suggest that external support relates to how effectively SMEs manage the interaction between onboarding and technical capabilities. Onboarding is the process through which the users in our study were introduced to the SSA. User-friendly interfaces and informative introductions were identified as key elements of effective onboarding, facilitating seamless user experiences. The user interface of the SSA was very intuitive and easy to understand for the users and the introduction to the SSA was helpful as it was self-explanatory. While some users expressed a desire for further education, the majority found the initial technical introduction provided by developers sufficient. We noticed that technical capabilities refer to the techniques, methodologies, and tasks of the SSA ensuring reliable search results and potential for technical improvements. Throughout the project's duration, the reliability of search results provided by the SSA experienced enhancements. Suggestions for improvement include tables and graphics to increase the reliability of search results.

Example Quotes	1st order concepts	2nd order themes
"The user interface and the general operation, as far as we have used it, is relatively intuitive and not that difficult to understand, at least for me."	User-friendly interface	**On-boarding**
"We had a very short briefing. It's relatively self-explanatory."	Helpful introductions	
"Partly, partly. So. Better than when I started using it. In any case."	Reliability of search results	**Technical capabilities**
"The only negative thing about the application is that it cannot display images or graphics."	Technical Improvements	

Table 4. Example quotes from the interviews for external support.

User satisfaction: The user satisfaction in our study encompasses the interplay between the interpretability of decision-making and user expectations. We see the interpretability of decision-making as the degree to which the users can understand, explain, and validate the rationale, process, and outcomes of decisions made within the SSA. The explanation of search results and the restart duration of the SSA are pivotal for the extent of interpretability of decision-making. Users desire to receive a notification if the SSA fails to find a satisfactory result or if the user needs to refine the query. The user expectations in our study refer to the anticipated standards, requirements, or desires that users have regarding the performance, features, and quality of the SSA. The extent of user expectations exists of the perceived usefulness, trustworthiness, economy of time, accuracy of search results, and compatibility with daily routine. We view perceived usefulness as how the users assess if the SSA will enhance their performance or well-being in achieving specific tasks and goals. The usefulness of the SSA is limited in everyday working life. Trustworthiness refers to the reliability of the SSA. Users were afraid of consequences when someone relied solely on the search results without scrutinizing them. In our understanding, economy of time is the efficient and effective use of time to achieve the users' desired objectives or goals. Dissatisfaction was particularly noted with the duration of SSA restarts, with users expressing frustration over extended wait times. The SSA's accuracy of search results is the perceived degree of correctness of the information retrieved by the SSA in response to a user query. Users were confused about the varying quality of search results. We see the compatibility with daily routine as the degree to which the SSA fits into the users' routine in their working lives. Users prefer the SSA for simple tasks, but they are not convinced of its compatibility with daily routine when it comes to more complex tasks.

Example Quotes	**1st order concepts**	**2nd order themes**
"I would like to see a little oops, we could not find that or something like that, for example. Or please ask the question differently."	Explanation of search results	**Interpretability of decision-making**
"When I need the application, I start it and then I have to wait two minutes. I don't know why, but it's extremely annoying. Even though you know it."	Restart duration	
"But it is less relevant for day-to-day production."	Perceived Usefulness	**User expectations**
"So how much can you trust a solution like that? Because you always have a machine with you. Very quickly, you have a machine breakdown."	Trustworthiness	
"Well, it actually has to be quick. I need more time to assess it than if I search in the table of contents myself."	Economy of time	
"Sometimes I had the feeling that I could search for the same thing three times and get different results three times, so that was extreme, for example."	Accuracy of search results	
"It can help us with the simple things, but it's not much use with the difficult things like technical documents we use in our daily routine."	Compatibility with daily routine	

Table 5. Example quotes from the interviews for user satisfaction.

In conclusion, our study highlights the multifaceted nature of SSA adoption in SMEs, underscoring the critical role played by socio-technical dimensions in shaping organizational readiness, external support, and user satisfaction. To enhance the utility of SSAs in the manufacturing SME context, our findings underscore the importance of addressing specific areas for improvement. These include optimizing the analysis of tables and graphics, automating the display of exact text positions in search results, and addressing issues related to SSA restart times to mitigate user dissatisfaction.

4.2 Grounded theoretical framework

Our investigation into the adoption of the SSA in SMEs has culminated in the development of a grounded theoretical framework, as illustrated in Figure 1. The framework serves as a comprehensive outline for understanding the interplay of the observed socio-technical dimensions influencing the adoption of SSA solutions in SMEs. The initial element of our grounded theoretical framework is the reciprocal relationship between organizational readiness and external support [1a.]. Within the realm of organizational readiness, our framework includes three key determinants: use case context, technology readiness, data privacy, and data security. In contrast, external support is characterized through the onboarding processes of both deployers and users, as well as the technical capabilities of the SSA. Our findings show that organizational readiness within SMEs is linked to the extent of external support it receives as organizational readiness can impact the utilization and effectiveness of external support. SMEs that are well-prepared and committed to the SSA are more likely to leverage external support effectively to achieve a successful adoption process. External support in turn shapes the organizational readiness to embrace SSAs effectively by providing technical capabilities and onboarding. On top of that, our framework delineates the separate influence of organizational readiness [1b.] and external support on user satisfaction [1c.] independently from their reciprocal relationship [1a.]. Organizational readiness sets the stage for a successful SSA adoption influencing user satisfaction directly by providing a fitting use case context, considering data privacy and data security, and being technologically ready. Similarly, our framework suggests that the quality and extent of support provided by developers significantly contribute to user satisfaction levels within SMEs. Our framework conceptualizes the influence of user satisfaction on SSA adoption [2.] based on how well the SSA aligns with user expectations and enables users to understand the decision-making process of the SSA. SSA adoption triggers a feedback process that leads to advanced organizational readiness [3a.] and external support [3b.]. By requiring adjustments to organizational infrastructure and procedures, the adoption of the SSA influences organizational readiness. SSA adoption also influences the requirement for external support to successfully guide the adoption process. To guarantee the effective adoption and integration of the SSA into their operations, SMEs need to evaluate their organizational readiness and ascertain the extent of external support needed. By employing this grounded theoretical framework, we aim to provide a holistic understanding of the complex dynamics underlying the adoption of SSAs in SMEs.

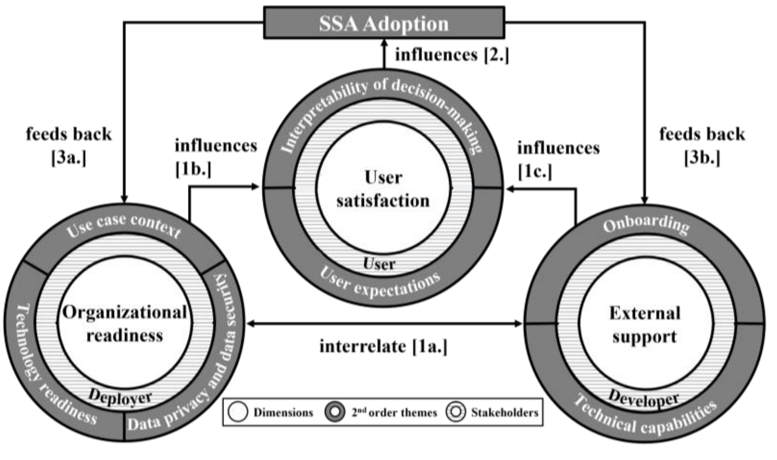

Figure 1. Grounded theoretical framework for SSA adoption in SMEs.

5 Discussion

Based on our socio-technical understanding of AI adoption (Jöhnk et al. 2021), we conceptualized the adoption of SSAs. Thereby, our research findings offer a novel perspective unveiling the central role of user satisfaction in fostering the successful adoption of AI-based knowledge management within SMEs.

Our findings resonate with the established discourse within IS literature, underscoring the interplay between organizational readiness and external support (DeLone & McLean 1992; Jöhnk et al. 2021; Lee & Chen 2019; Markus & Robey 1988). However, existing IS research has highlighted a direct correlation between organizational readiness and external support with the adoption of AI-based technologies (Bruque & Moyano 2007; Jöhnk et al. 2021). In contrast, our grounded theoretical framework suggests for SSAs, that organizational readiness and external support determine the adoption specifically indirectly through influencing user satisfaction. Hereby, we underscore the importance of focusing on end-user experiences and satisfaction as core elements for the adoption process of AI technology in SMEs.

In alignment with the findings of Jo & Bang (2023), our study has unveiled AI adoption drivers. Thus, applying as well as extending the body of knowledge about such drivers from the context of generative (e.g., ChatGPT) towards extractive AI (in the form of SSA). In this context, our research reveals that external support significantly drives user satisfaction during the adoption of an AI tool designed for knowledge extraction. Smooth onboarding processes and strong technical functionalities emerged as pivotal specific adoption drivers. Echoing Acton & Golden (2003), who explored the effect of IT training on user satisfaction, our research further underscores the vital importance of well-executed onboarding in enhancing user satisfaction. The effectiveness of the onboarding is, thus, paramount for SSA adoption, as it reduces the users' cognitive load upon technology contact and fosters the core intent to retrieve knowledge effectively supported by AI.

For organizations it is deemed crucial to mobilize and deploy IT-based resources for the rapid development and implementation of new technologies (Bharadwaj 2000), thereby enhancing their ability to respond promptly to internal or external changes (Buck et al. 2021). However, Nevo et al. (2007) highlight the importance of external technical support, which is in line with our observations. In our context, the external support provided by developers reduced the prohibitive effect of making upfront investments associated with developing, deploying, and maintaining sophisticated AI systems. Furthermore, in-house specialized knowledge is superfluous, as the technological expertise to effectively deploy and maintain AI-based systems can be leveraged while maintaining focus on the primary core business.

Supporting current research, we emphasize the vital importance of the use case context in connection with organizational readiness (Venkatesh et al. 2003). Our insights, therein, echo the perspectives expressed by Burton-Jones & Grange (2012) and Orlikowski (2000), emphasizing the foundational role of understanding the specific use case context for driving effective technological utilization. The meticulous and especially purposeful selection of AI use cases is of utmost importance (Hofmann et al.

2020), particularly within the SMEs investigated in our research. We found that comprehending the context, pinpointing domain-specific issues, and aligning AI solutions with the scale of the companies' use cases play a pivotal role in configuring and ultimately adopting SSA. Moreover, our research underscores the critical importance of data privacy and data security considerations in fostering organizational readiness, especially within the initial stages of SSA adoption within SMEs (Fu et al. 2017; Guan et al. 2020). Our findings highlight the significant impact of these considerations, which we observed to result in increased user satisfaction, particularly arising from factors such as the location of data storage, expansion of the database, and access management (Bélanger & Crossler 2011; Yang et al. 2020).

Throughout phases of creation, delivery, and utilization of SSA adoption in SMEs, users, developers, and deployers emerged as the relevant stakeholders from our study. The relationship between them is defined by a feedback loop in which decisions about the development and deployment of the SSA are influenced by the user's satisfaction based on how the SSA matches the user's expectations and allows the user to interpret the SSA's decision-making. Recognizing the importance of involving all relevant stakeholders, we advocate for a collaborative approach to prevent costly errors and maximize the benefits of AI-based initiatives within the SME environment (Humpert et al. 2023).

In essence, our study advances our understanding of the complex dynamics underlying SSA adoption in SMEs, offering valuable insights into the interplay between organizational readiness, external support, and user satisfaction. Through our nuanced exploration, we aim to pave the way for informed decision-making and effective implementation strategies in leveraging SSAs within SME.

6 Conclusion

Given the pivotal role SMEs play in the German economic landscape, embarking on a successful digital transformation journey becomes imperative. In our endeavor to catalyze the adoption of the SSA within SMEs, we crafted a grounded theoretical framework. This framework includes a dynamic interplay between organizational readiness and external support, resulting in increased user satisfaction, a cornerstone for driving the SSA adoption. Our framework gives guidance to practitioners by offering an overview of the diverse stakeholders crucial for the seamless adoption of SSAs within SMEs. It delineates their interactions, empowering practitioners with invaluable insights into the needs and nuances of each stakeholder group. Armed with this comprehensive understanding, practitioners can navigate the SSA's implementation journey with confidence, ensuring a successful outcome. However, it is important to acknowledge the limitations of our study. Our observations were confined to the developer of the SSA, along with the user and deployer of three SMEs within the sector of German manufacturing. As such, our insights are bounded by the scope, industry sector, company size, and stakeholder composition of the observed entities. Future research should aim to broaden the scope of analysis, encompassing a diverse array of stakeholders and exploring SSA adoption dynamics across various industries.

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