Trends, Patterns, and Insights on the Use of Artificial Intelligence-Based Knowledge Management Tools in Private Enterprises

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Abstract

Despite the widespread adoption of new artificial intelligence (AI) technologies, there is a notable lack of information on how they're being used to manage knowledge within organizations. This study aims to fill this gap by examining how various companies are leveraging knowledge management software tools foundationally built upon new AI technologies (AI-KM tools) to enhance their businesses. The purpose of this is to identify any trends in the adoption of AI-KM tools, particularly ones that elucidate the nature of why certain companies may adopt different types of AI-KM tools across different teams, as well as find any trends that may predict future developments for how knowledge management is used in the private sector.

This study was carried out in three parts: A literature review, interviews with executives, and a thorough analysis of AI-KM tools and the companies who use them. The literature review yielded elucidations about the potential role of AI in the field of knowledge management, including an overview of the potential use, potential causes of slow adoption, and possible reasons for future widespread use. The interviews yielded the insight that the best way to examine AI-KM tool

use and collect meaningful data is to follow/use a software-customer research taxonomy. After 5 software companies were identified as ideal candidates for examination, their customers' usage data was analyzed across several metrics. The metrics fell into two categories: Tool use data describes what tools were used by which teams for each company; Company qualities include employee count (size), customer base, sector, industry, and location. The study demonstrates several distinct correlatory effects of most of these qualities on AI-KM tool usage:

1. Small companies tend to use AI-KM tools on a needs-based basis, medium companies tend to use AI-KM tools that can boost sales as much as possible, and large and giant companies spread utilization across teams and tool types.

2. Different sectors and industries show varied patterns in adopting AI-KM tools, with the technology sector leading the adoption of learning tools while healthcare and professional services led utilization of analysis and automation tools.

3. With respect to team utilization, service-based organizations tend to shift resources to external-facing teams such as sales and customer support, while internal teams like engineering and HR use AI-KM tools more in product-centric companies.

4. The tools that external teams use tend to be more complex than the ones internal teams use, but internal teams' tools have a significantly stronger correlation between complexity and usage than external teams' tools.

Broadly, this study's findings confirm previous findings of other researchers included in the literature review. All indications point towards further adoption of AI-KM tools over the next several years, particularly at larger companies where cost savings meets improved worker performance, which has yielded higher net productivity in the case studies examined. While this has potentially negative effects for current knowledge managers' future employment prospects, it confirms predictions that large enterprises are not seeking to replace knowledge workers with AI, but instead supplant them by automating away busywork, strengthening existing human-based support systems, and freeing up time for completing complex tasks.

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1 Introduction

Since the public release of ChatGPT in late 2022, there has been a flurry of both small and large companies integrating Artificial Intelligence/Machine Learning tools into their employees' workflows to boost productivity. The most common type of AI used are Large Language Models (LLMs), such as OpenAI's GPT, Anthropic's Claude, Google's Gemini, and Meta's LLaMa. Over the past year, hundreds of companies have started using these LLMs out-of-the-box to increase worker throughput, but little information exists on whether any are using AI to keep tabs on tacit knowledge used by employees (this can be done via creating custom LLMs with data lakes of employee data and metadata). This tacit knowledge can be mined from company documents, emails, phone calls, meeting recordings (audio transcripts), and other metadata, elucidating information about individual employees and processes that they may not even be aware of, such as instructions that can be added to reference documents, sales call performance, and more.

This study examines how AI is being used for enterprise knowledge management (KM) by analyzing how 120 companies of all sizes are using various software-based KM tools. The primary method of research is by reading and extracting data from hundreds of case studies posted onto blogs and other virtual platforms by the softwares' developers. Additionally, interviews with executives, articles, books, blogs, other forms of published media, and other materials were used to supplement research findings. By doing so, I analyzed how AI-KM tools are used and by whom.

1. Initially, this study had several goals, in the form of questions to be answered:

2. Do any companies use AI to analyze their employees' tacit knowledge?

3. If so, what is the company size (headcount) threshold where an organization starts to use AI to analyze its employees' tacit knowledge?

4. Is there a method by which an organization- above or below the threshold- can use AI to turn tacit employee knowledge into explicit data (and explicit data into qualitative analysis)?

However, after digging into the data, it became clear that company size was not a determinant of AI-KM software use, but instead was merely a factor in determining what features of each software was useful for any given company's needs. It became clear that there were several other factors- in addition to size- that determined use: Sector, Industry, Customer Base, Team, and Tool Type. 6 sectors, 18 industries, 4 customer bases, 4 sizes, 7 teams, and 11 tool types were identified.

The main questions then transformed into a more general: "Are there trends that emerge when examining how different companies use AI-KM tools and if so, what are they?" Leaving the question broad, in my opinion, allowed a wider net to be cast, which was crucial in an area in which no academic research has been done before. In fact, that aspect was a major contributor to the motivation for this. Since the field of knowledge management is dominated so heavily by industry, there isn't much academic research done; furthermore, AI/ML is a highly disruptive technology to the field and threatens to render knowledge managers near-obsolete. I believe that by examining how AI tools (which are currently in their infancy) are disrupting the field of knowledge management, I could obtain more insight as to what the future of KM could look like, and what roles both people and machines will play in it.

The research portion was conducted in three distinct phases: Discovery, Construction, and Analysis. The discovery phase consisted of a literature review followed by interviews with executives of various companies. I then proceeded to construct my dataset in the following order: Find software companies that fit my criteria, make a list of who their clients (other companies) are, record how those companies use the software, and then dig deep into traits of each company. The final phase, analysis, involved transforming the data I collected, creating a bunch of pivot tables, and making dozens of graphs that could help me make sense of the data.

2 Background

2.1 Literature Review

Explicit and tacit knowledge are known as the two forms of knowledge in the business KM taxonomy that oppose each other. Explicit knowledge is explicit and material, that is, it can be (and in most cases, is) written down, codified, or otherwise accessed and interpreted through traditional methods (indexing). Because of this nature, it is both easily integrated into existing business workflows, as well as easily commodified: "...even if nominally protected by law, experience suggests that such explicit knowledge may not remain a source of distinctive competence for long, as competitors strive to find ways to access or otherwise counter that which is transparently such a valuable commodity" (Fowler, 2000). This shift is starting to be the case with several new AI tools: Chatbots/virtual assistants, natural language content indexers, and meeting notetakers. Previously, being able to access internal information quickly was an edge over the competition; before computers, companies even developed proprietary systems to find the right document faster than their rivals, as that was seen as an edge. With the advent of search engines and better digital indexing algorithms, that "edge" shifted to having the skill to know how to search for the right thing; still, this was not a distributed skill, being most often held by researchers, knowledge managers, lawyers, and librarians – not necessarily anyone in an organization. Often, a differentiating factor in the productivity of an employee has been 'being good at Googling,' but with the advent of LLMs, and more specifically, natural language interfaces with indexing algorithms and search engines, that skill has been automated away, and in the process, commodified by technology. Because of this, it isn't the ability to find internal information quickly that is an edge, but not having that ability has become a technical liability; as such, it is reasonable to expect this less complex form of AI-KM tool to be widely adopted at scale before other types. Similarly, being able to find external information through a chatbot further pushes knowledge finding skill into a commodified state. As these LLM- and Neural network-based AI knowledge tools gain access to more user inputs (latent metadata), particularly from experts, they get more powerful, with the ability to inference and have predictive behavior, being able to come up with an answer in the absence of specific information. Fowler predicted this over 20 years ago: "...the creation of hybrid systems comprising combinations of rule-based expert systems and NNs may offer access to embedded knowledge coupled with an ability to function in the partial absence of certain data. Such systems may also exhibit a capacity to learn and subsequently improve their performance over time" (Fowler, 2000).

A significant application of artificial intelligence to KM is for automating people-finder (PF) systems, a type of knowledge repository with information that "points" to an expert that possesses tacit organizational-specific knowledge. A case study by Becerra-Fernandez revealed that at various large organizations, such as Hewlett-Packard, Microsoft, and the National Security Agency, the purpose of PF systems within an organization depends on the nature of the organzaiton (Becerra-Fernandez, 2000) At HP, the development of a PF system ("CONNEX") was crucial for connecting customers to the right support expert. At the NSA, a PF system ("KSMS") was implemented to create an internal taxonomy of worker knowledge and skills, such that workloads on any given project could be distributed more effectively and efficiently. At Microsoft, a PF system ("SPuD") was implemented to identify employee competencies, manage employee quality assurance and performance assessments, and link incompetencies to educational opportunities. All of these purposes– customer support, workload management, people routing, competency evaluation, and employee training– are areas in which AI can be used to automate KM processes. In the past, these processes have always been enabled and enhanced by new technologies, from telephones to computers to the internet, so it is a near certainty that the next wave of technological progress (in this case, AI) will do so as well.

Outside of Becerra-Fernandez' study, several others identified overlapping and separate areas and practices for AI integration in knowledge-based processes. These include employee training and development (Maity, 2019), advertisement content creation and marketing (Bag et al., 2021), human resource management (Murali and Kumar, 2014), customer relationship management (Chatterjee et al., 2020), secure knowledge management (SKM) and cybersecurity (Samtani et al., 2023). Jarrahi et al. (2023)have suggested AI can be applied to knowledge management processes: Knowledge creation, storage, retrieving, sharing, and application all are applicable processes for the aforementioned areas/practices when they are used to support human KM practices. Others have suggested that AI won't just affect the various application/practice areas of KM, but also will cause dramatic changes to the way in which certain processes are computed. Knowledge graphs– and in particular, hierarchical decision trees and similar knowledge ontologies such as entity-event knowledge graphs – can be ingested, 'detangled,' and then interpreted by an AI system (Asman, n.d.).

Although these new AI-based smart technologies have been commercially available for a few years, but rollout [and in particular, commercial adoption] has been slow. Moertl and Ebinger (2021) suggest that this may be "due to increasing lack of user trust and acceptance of these technologies." Because of recent controversies surrounding privacy, developing frameworks for integrating ethical and trustworthy systems is essential, especially for people who are "out-of-the-loop" and may fear being unconsensually surveilled or replaced altogether by new technologies. In particular, European and North American regulators have espoused ethical use-centered frameworks that apply certain rigid standards to AI systems, particularly with respect to systems with surveillance and bias potential ((Gupta and Lanteigne, 2020). In response, many have pointed to encouraging the human-centric design of AI systems as a possible solution to prevent unethical artificial intelligences from being built (Rhem, 2021). Soleimani et al. (2021) point out that while AI can be used in recruitment processes to reduce implicit and explicit bias by recruiters, it is also a large potential risk that biases may be learned by machine learning models and are codified instead of reduced.

AI can be used to make KM more effective, and KM can be used to strengthen AI. Liebowitz (2001) suggests that managers may disregard KM as an overhyped combination of business process reengineering and information management, which is accentuated by a lack of methodical rigor applied to KM practices and systems. It is fully possible that machine learning models may bring KM the rigor it needs for universal adoption. AI projects fail for a few main reasons: "1) lack of knowledge among managers, 2) poor handling of the data and 3) poor planning and organization" (Haugen, 2021). By implementing KM processes to AI projects, risk of adoption failure can be mitigated.

Furthermore, adoption of AI-KM tools may be retarded by the lack of executives' understanding of underpinning machine learning mechanisms. However, this may be counterbalanced by the introduction of AI as a mission-critical risk/imperative in corporate governance; as such, a board with limited understanding artificial intelligence technologies "hinders the company's capacity to address adaptation challenges," and thus it may constitute a fiduciary duty for board members to be familiar with the basics of it (Orbach et al., 2023). This should particularly push adoption of AI in public companies, in which boards and executives are more stringently beholden to shareholders and reducing potential systemic risk and maximizing competitiveness. Therefore, it may be the case that larger companies push for widespread adoption of AI-KM tools more aggressively than smaller ones. Using PLS-SUM and fsQCA methodologies, Al-Emran et al. (2024) have found that there isn't any one deterministic factor that drives AI chatbot usage [among college students], but it is very possible that adoption is simply medium-dependent– that is, adoption rates of AI tools depend on who is adopting them. Jöhnk et al. (2021) suggest five factors that may contribute to the AI readiness of an organization (but notably not of an individual): Strategic alignment, resources, knowledge, culture, and data. To a large extent, this points to the same characteristics of all organizations that are forward-looking and operationally capable and poised to transform with evolving technological tides. These factors may combine to lead one to believe that AI adoption is more pull (organization) than push (individual) -based.

2.2 Executive Interviews

At first, I performed a set of interviews with several small company executives. Since there was no initial direction of research, a varied list of questions was used to find a lead:

1. Company Name
2. Company Headcount
3. Company Industry/Sector
4. Does your company use data analysis to assess performance (in any way)?
5. What software and how is it used?
6. Does your company use AI in any of its processes?
7. What AI software does it use?
8. Does your company use any software for knowledge management?
9. How does your company store employee knowledge (documentation, reports, etc.)?
10. How does your company assess the quality of submitted reports?
11. Does your company use any software to extract tacit knowledge from its employees?
12. What software, if so?
13. Follow-up question

Most of the interviews didn't yield substantive results, with the interviewees giving below-expected quality answers for my search. For the first several interviews, nobody was putting any conscious effort into knowledge management processes, and the few people who were actively using AI were mostly just using Otter to transcribe calls or ChatGPT to bounce ideas around and make drafting short documents and emails faster. After a few weeks of interviews, I had a Zoom call that gave me a bit of direction.

JL (name abbreviated for privacy) is an executive at a marketing firm with 20 employees. He shared that he uses an AI Zoom/Google Meet transcription software for making detailed call notes and shorter call summaries. This was not unordinary, since several other executives mentioned using call transcribers. What did stick out, however, was how he used it. Usually, services like Read.ai (the one he mentioned) are used to make workflows faster and more efficient. What JL was doing, however, was linking that product with a separate LLM (ChatGPT) and his marketing software (Hubspot), and then using their combined information repository to compare and assess the quality of other reports made by freelancers. Essentially, JL was using AI to encode and decode information so that he could break down large chunks of information into more digestible bites, as well as combining small, less coherent bits of information into longer, more understandable summaries. While this was an inefficient process, it became clear that at least one person (him) has a need for a tool that uses AI to transform (expand/shrink) the size and nature of information and knowledge.

This was a breakthrough for the search, indicating that there might be other software that had the desired functionality. A key part of knowledge management is not only knowing how to access certain information, but also getting it into a form where it can be accessed, so the software search started with looking for tools that could "intercept" knowledge as it left the mind (via chats, voice/calls, pieces of writing, etc.).

3 Methodology

3.1 Company Research

3.1.1 Software/Features

After the breakthrough, I stopped one-by-one interviews, as they were not time-efficient. Instead, I found a handful of different software companies that were each used in a commercial setting and then analyzed their publicly-viewable customer case studies.

A major problem encountered at first was that nearly all of the software marketed for knowledge management simply used LLM chatbots as an add-on so customers could interface more easily with their existing products but weren't fundamentally built on AI. This type of product is more akin to "putting lipstick on a pig" than truly creating a new product. The first suitable software discovered was Invoca, which markets itself as the "conversation intelligence AI leader." Conversation intelligence is the key phrase I desired, as it implied the software took human communications and used AI to extract insights. After confirming that Invoca was the correct type of software, I soon created a short list of 5 different software companies which not only serviced hundreds of customers, but posted exactly how many of those customers used their AI tools. Here is a summary of them:

Dashworks:

- Designed for companies in the technology sector that need to share more technical information between engineers, operators, and other internal staff.
- Synthesizes and ingests information from different sources and allows teams to share and access the information and insights from it.

Deephow:

- Improves workforce onboarding, training, and knowledge capture by centralizing knowledge sharing and access within one platform.
- Industrial environment-focused video and voice recordings → step-by-step instructions, with indexing and auto-translation features.

Glean:

- Similar to Dashworks, but instead of finding specific documentation or technical information for you within a central repository, it focuses on simplifying the process of finding the right person, documents, plans, OKRs, or other internal company information so everyone can get on the same page.

Invoca:

- Suite of tools built around capturing information from phone calls and turning that information into useful insights for marketing, call centers, and customer experience teams; is industry-agnostic, but tends to cater to businesses that rely more heavily on phone calls (outbound and inbound).

Moveworks:

- Geared towards allowing employees to look up information technology (IT) processes without having to go to any IT staff for help.

- Focuses on automating basic knowledge-sharing processes for IT teams and replacing some of their functions with AI copilots.

3.2 Qualitative Methods

The "Qualitative Methods" section primarily refers to how data categories were conceived and then researched. These definitions and methods are in the qualitative section because in the end, they relied heavily on subjective judgments made in the research process. That is not to say the research was performed haphazardly without method or reason, but the only definitive metrics (100% certainty) for each company were the softwares used and headquarter locations. Something of note is that the term use case is used throughout this paper. Generally, a use case can be interchangeably understood in two ways, both in the context of AI-KM: As an instance of a specific tool used by a specific team for an unspecified (but often easily assumed) purpose; or as an instance of unspecified tool used by an unspecified team for a specific purpose.

3.2.1 Tools

A tool is a specific function, part, option, or feature of a software that does a specific thing. In other words, a software is a collection of tools operating under a single brand that often work synchronously.

Initially, over 20 types of tools across the 5 software were identified, but some were seldom used, and others were inconsistent to define, so the tools were separated by function and use case and then recombined. After landing on 11 different tool types that covered everything, they were split into 3 different categories that could be used to classify how they are used (and see if there are any correlations with other variables).

Table I: Detailed Description of Tools and Their Relation to Knowledge Management

Tool	**Category**	**Description**	**Relation to KM**
Knowledge Access	Learning	Tools that make it easier to find information within a company's knowledge base, database, Slack channels, email repositories, etc. Often this is in the form of an indexing tool that is connected to an LLM interface.	Previously, this task was done by a person knowledgeable of how to access certain internal company information.
Knowledge Sharing	Learning	Tools that allow people to submit or encode information and knowledge into the company's general data repository. This may come in the form of explicit instruction videos, software documentation, FAQs and internal blogs, etc. and is often linked to a knowledge access tool for easier recall.	This tool enables tacit knowledge to be encoded and/or documented, making it explicit.

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Tool	Category	Description	Relation to KM
Employee Onboarding	Learning	Tools that leverage LLMs to answer questions that new employees may have, but HR or their managers don't have the time to answer.	Subset of Knowledge Access & Sharing.
Employee Training	Learning	Tools that make training existing employees easier, allow managers to track their progress with learning new skills, and reduce the time it takes for them to learn things. These often utilize the same features as the other learning tools, but with an added progress tracking aspect.	Subset of Knowledge Access & Sharing.
Quality Assurance	Automation	Tools that automate the evaluation of calls. LLMs are used to transcribe call transcripts and then the transcripts are checked with evaluation criteria uniformly against all calls; previously, this quality checking was done manually on 2% of calls.	Previously, this task was done by a person with specialized knowledge of how to check the effectiveness of call center staff.

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Tool	**Category**	**Description**	**Relation to KM**
Call Center Routing	Automation	Tools that automatically route calls to the right person or location, instead of a human determining where to transfer a caller to.	Previously, this task was done by a person who knows where to route someone's call.
Lead Qualification	Automation	Tools that determine the nature of certain inbound call or email leads in real-time, so a salesperson doesn't have to figure that out themself.	Previously, this task was done by a person who knows how to determine an inbound source.
Regulatory Compliance	Automation	Tools that allow companies to automate compliance with regulations, such as HIPAA and SOC 2.	Previously, this task was done by a person with specialized knowledge of regulatory processes.
Data Aggregation	Analysis	Tools that bring together multiple streams of data for the purpose of further analysis. LLMs are used to allow humans to control how the data streams aggregate.	Previously, someone with specialized knowledge of how, where, and when to link different types of data together had to perform this task.

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Tool	**Category**	**Description**	**Relation to KM**
Ad Performance Analytics	Analysis	Tools that use data from advertisement feedback to simulate the performance of future ad campaigns and discover insights about current ones (using machine learning).	This tool facilitates increased effectiveness of advertising and marketing staff by supplementing their knowledge base with new information.
Call Tracking/Analytics	Analysis	Tools that use LLMs to transcribe calls, then an algorithm ingests multiple different types of data from the transcripts that a data analyst can then use to learn more about their customers and make more informed decisions.	This tool turns tacit knowledge into explicit insights by analyzing call transcripts and transforming the data into useful, usable knowledge.

Table I: **Learning Tools**: AI-KM tools that facilitate learning and sharing of knowledge. **Automation Tools**: Tools that automate existing (usually manual) knowledge-based processes using AI. **Analysis Tools**: AI-KM Tools that analyze knowledge itself or analyze knowledge-based processes.

3.2.2 Teams

From the case studies analyzed, there were clear delineations of which teams currently use the AI-KM tools. Of the seven identified, they could be split into 2 categories: Internal- and External-facing teams. For certain types of companies, unique professional roles were grouped into the most similar team type to the nature of the work (detailed below).

Table II: Detailed Description of Teams and Their Functions

Team	Category	Function
Sales*	External	Sells a service or product (directly) to a customer.
Marketing & Advertising	External	Attracts new customers (indirectly).
Customer Support	External	Helps existing customers solve their problems with the service/product.
Engineering**	Internal	Develops the technical aspects of a product or service.
Operations	Internal	Develops the technical aspects of a company.
Human Resources	Internal	Helps employees solve non-technical problems.
Information Technology	Internal	Helps employees solve technical problems.

Table II: **Internal**: Primarily interfaces directly with customers or potential customers. **External**: Primarily interfaces with other employees.

* In healthcare, legal, and finance/consulting companies, licensed professionals (doctors, lawyers, etc.) are considered part of the sales teams because they directly interface with customers (patients, plaintiffs, defendents, etc.).

** In manufacturing and infrastructure companies, trained technical staff are considered part of engineering teams; although no data was found regarding scientists' use of AI-KM tools, they would also be included under the Engineering Team umbrella.

3.2.3 Size

Company "size" is dictated by the number of employees it has. The employee count listed on each company's LinkedIn page was used for this data. If the company's size seemed off (sometimes the case for conglomerates with multiple subsidiaries), this number was sourced from the companies' 2023 Q4 earnings reports or 2023 annual report (10-K). Luckily, all the smaller, private companies had LinkedIn pages. The employee counts were clustered into sizes for convenience:

- **Small**: Fewer than 100 employees
- **Medium**: 100 to 1,000 employees
- **Large**: 1,000 to 10,000 employees
- **Giant**: More than 10,000 employees

3.2.4 Sector

Each company was assigned to a "sector" according to the sector definitions. As a result, several industries ended up being split between multiple sectors. For example, the Automotive, Consumer Discretionary, and Media industries ended up being split between 3 different sectors each. Certainly, there is often a relationship between Sector and Industry (SaaS companies are always in the tech sector, for example), but it is not a definite one. Here is how each sector is defined:

- **Technology**: Companies in this sector offer services or products whose users can access their features on their own digital devices.
- **Healthcare**: Companies in this sector offer services or products focused around health, wellness, or caretaking. This includes elderly care.
- **Professional Services**: Companies in this sector offer services that are carried out by specially-trained, often licensed, professionals, (excl. healthcare workers).
- **Manufacturing**: Companies in this sector transform raw materials into products in large-scale factory settings. They are creation-driven in nature.
- **Consumer**: Companies in this sector are focused on selling products to their end users. They may manufacture their own goods, but are sales-driven in nature.

- **Infrastructure**: Companies in this sector operate servers, pipelines, power lines, internet lines, and other transmission/storage equipment critical to society.

3.2.5 Industry

Each company was assigned to an "industry" according to their LinkedIns. In the case one of the industries below was not in a LinkedIn about section of a given company, the closest one was chosen. For example, a company may be listed as a CRM tool, which would then be reclassified as SaaS. Similarly, a design firm and a news publisher both would be considered to be in the Media industry. In the cases where a LinkedIn-described industry was 1-of-1 on the data table (originally, there were over 20 of these), I combined the closest ones together and repeated the process until I was left with only industries of at least 2 companies. Here are all 18 Industries that I landed on as a result of this process:

- Automotive
- Chemical & Materials
- Consumer Discretionary
- Cybersecurity
- Digital Infrastructure
- Education
- Elderly Care
- Energy
- Finance & Insurance
- Healthcare
- Home Services
- Housing, Construction, & Hospitality
- Legal, Consulting, & Agencies

- Manufacturing
- Media
- Medical Devices
- SaaS
- Telecommunications

3.2.6 Customer Base

"Customer base" is a metric that describes the target market of a company. For small, service-based businesses, this is often local (or regional, if there are multiple locations). Franchised companies are often at the national level if they have locations in multiple regions, but sometimes extend into different countries or only exist in a single region within a country. The largest 13 companies are all multinational conglomerates, but the correlation between size and customer base reach is weak. There are even interesting edge cases: The largest non-multi-national company is local, not national or regional, while there is a multi-national company examined in the study that has under 100 employees. For SaaS and other software businesses, I determined their customer base reach by checking on their websites if there were any clues as to who their target market is, and if the target markets are geographically constrained; there was a clear difference between SaaS companies with no geographical constraints and those that targeted a certain area. Here is how each type of customer base was defined:

- **Local**: The company's target market is within a small geographic area, often a city or two in a single state or province.
- **Regional**: The company's target market is within a single large state or province (Texas) or a cluster of neighboring states or provinces (e.g. the American South).
- **National**: The company's target market is within a single country and has no singular geographic focus (2+ or non-neighboring states/provinces and/or regions).
- **Multi-national**: The company's target market extends to multiple countries.

3.2.7 Location

Similar to industry definitions, the "location" of a company is determined by where the company's headquarters is located (information sourced from their LinkedIn page, then verified via Google). For multi-national and national companies, only the country was recorded. For regional and local companies, the city, region, or state/province was also recorded. The definition of a region is a large, continuous area in a single country; it can encompass a single state/province or multiple.

3.3 Quantitative Methods

"Quantitative Methods" refers to the methodology used to collect, organize, and analyze the data.

3.3.1 Data Collection and Organization

First, every company mentioned as a customer on the softwares' websites was recorded – a total of 148 across the 5 different softwares. They were categorized, by employee count, industry, sector, customer base, and location. Following this, the tools used and which team(s) used the tools were recorded. As the list of tools and teams using them (together known as use cases) expanded, I took mental note of how each was being used. After going through all of the case studies, the terminology used to describe the tools were consolidated into 11 key phrases (with the help of those mental notes). The 28 companies that did not have any case studies posted were not included in this phase. With the primary dataset filled in, a few data transformations was the final step. First, the employee count was consolidated into size categories. Then the location information was split into a country column and a more specific location column. Following this, the industry and sector entries were cleaned using the iterative method described in the qualitative methods section. After the data was cleaned, a combination of if statements in excel were used to split the Team/Tool matrix apart – essentially making a filter that showed how many times each column header was used in any given matrix entry (the column headers being the names of each tool). The formula looks like this: [P2] = IF($I2=P$1,1,0) + IF($J2=P$1,1,0) + IF($K2=P$1,1,0) + IF($L2=P$1,1,0) + IF($M2=P$1,1,0) + IF($N2=P$1,1,0) + IF($O2=P$1,1,0), where P1 is the column header. This method allowed the easy (and scalable manner) breaking down and assigning of numerical values to which companies were using which tools and teams.

3.3.2 Data Analysis

With my AI-KM tool use data now prepared, the different combinations of columns were imported into pivot tables. Size, sector, industry, customer base, and location were all set on one axis (at different levels), while the tools or teams were set on the other. After cycling through the different combinations of categories, slicers were added to hide unnecessary parts of the data during visualization. This feature was especially useful when examining the trends of each size increment and sector.

4 Results

4.1 Qualitative

4.1.1 Software/Features

Primarily marketed to other tech companies, **Dashworks**' strength lies in riding a strengthening current: Remote work. As teams transition to being remote and communicating primarily through SMS, email, chats (i.e. Slack), phone calls, and video calls, the friction of obtaining information from others dramatically increases, making it much more difficult to obtain data quickly… you can't just ask someone in the office for a password when there is no office! Dashworks' place in the market is in using LLMs and indexing tools to make obtaining that information as frictionless as possible and shrinking that virtual-physical divide.

Going head to head with Dashworks, **Glean** also markets itself to tech companies and focuses on AI-KM learning tools. The primary difference between the two are their purposes. Dashworks is a tool that takes knowledge and provides it to a user instead of asking the person who has that knowledge, whereas Glean is a tool that directs the user to that person. In the context of AI being pushed to replace humans in knowledge processes, it is interesting to compare the success the two companies have: Glean is the older of the two companies and has raised over $200 million from leading venture capital firms such as Kleiner Perkins, Lightspeed Venture Partners, and Sequoia

Capital, which helped it achieve a $2.2 billion valuation and land customers such as Databricks, Plaid, Sony Electronics, and Vanta; Dashworks, on the other hand, has raised under $10 million (from Point72 Ventures, South Park Commons, and Y Combinator) and has fewer large-scale customers. The last part is interesting, especially because philosophically, this implies that larger companies prefer semi-automated processes (the software points to humans to go to for information) to fully-automated processes (the software provides the information directly). This is a strong signal that large enterprises still value – and trust – humans more than AI chatbots in the knowledge transfer process.

It is no secret that we are at the precipice of a large generational transition in manufacturing. As the baby boomer generation is exiting the workforce, they are bringing their knowledge with them to the retirement home. That knowledge, which in most cases is tacit, not explicit, is extremely valuable to companies, so **Deephow**'s solution is to offer a platform that makes recording, storing, and using that information significantly easier. New ML techniques in audio and language processing make the platform much easier to integrate, as its latest version can create audio transcripts even in a noisy factory setting.

Moveworks' purpose is to help its clients free up their internal help desks by automating the process of answering IT questions. It works by ingesting data from various sources – most notably company and external documentation (such as published documentation for the software they use) and IT staff emails and messages – and making it accessible via a chatbot. It operates like Dashworks in the sense that its target companies are those with teams distributed across geographies, but its cornerstone is the IT department and is expanding to other internal teams, as opposed to starting in customer support and expanding to other external teams.

Invoca is the easiest to understand of the 5 software companies (and potentially the most transformational): Its primary function is to turn phone calls into granular data that can be analyzed by different teams in an organization. As a result, its target market and the teams within its customers, are the ones who rely heavily on phone calls to do their jobs. Of the different software companies, it presents the deepest understanding of the knowledge transfer process: Because its primary differentiator is how it intercepts knowledge, it can do more with the information it ingests. The information encoded within its machine learning model(s) conceptually operates more similar to a second-order differential (latent knowledge vector + knowledge transfer vector) than a first-order one (only latent knowledge vector), which allows it to be more deterministic with its insights than the other software. From what I can tell, their algorithm is not currently using this aspect of their data collection fully, instead opting to use call metadata (the knowledge transfer vector) to help with digital logistics (routing the information to the right place). However, it should only be a matter of time before either they – or a competitor – use this insight to improve their model(s).

4.1.2 Teams

All team types use AI-KM tools to boost their productivity, but how they do so depends on their unique needs. Here is how each team type uses the tools available:

- **Sales** teams use AI-KM tools to be more prepared for customers and potential customers, target potential customers more efficiently, and evaluate performance.
- **Advertising and Marketing** teams use AI-KM tools to evaluate the performance of past, current, and future campaigns.
- **Customer Support** teams use AI-KM tools to be more prepared for calls, match customers with the right person, and evaluate performance.
- **Engineering** teams use AI-KM tools to share and access knowledge more quickly and make compliance processes less burdensome.
- **Operations** teams use AI-KM tools to share and access knowledge more quickly.
- Human Resources teams use AI-KM tools to improve employee on-boarding and training processes and access and share knowledge more intuitively.
- **Information Technology** teams use AI-KM tools to reduce their workloads, share knowledge with others, and maintain high-level insights about IT systems.

4.1.3 Sizes

Company size has a large effect on how companies adopt different tools – and more specifically, which teams do so. Each company size has its own unique traits, and therefore each requires a different distribution of AI-KM tools, even within the same sector. Smaller companies tend to choose one or two tools that improve the performance of their most important team(s), which depends on the nature of their business; Often this ends up being external teams. Since their budgets are smaller, this makes sense, as they are trying to squeeze the most out of their limited spending dollars. Large and Giant companies, on the other hand, tend to distribute access more and use a wider variety of tools, as they are less budget-constrained and prioritize maximizing efficiency/productivity per employee. This aligns with the general nature of larger organizations, as statistical methods (i.e. distributing resources according to group, instead of individual, needs) are more applicable for performance improvement as headcount increases. A notable pattern I noticed, however, is that medium companies in particular invest heavily in tools and teams that supercharge sales volume, even if that allocation of resources isn't necessarily the most aligned with their general business model and/or strategy. This implies that the most effective (or at least popular) way for a company to transition from a go-to-market-oriented organization focused on getting off the ground to an established, large, steady corporation is by focusing as much energy as possible on growing its customer base, a strategy commonly known as blitzscaling (Hoffman and Yeh, 2018).

4.1.4 Sectors

Qualitatively, the more entrenched a sector's labor force is in virtual processes, the more common the adoption of AI-KM tools. The technology sector, and large SaaS companies in particular, dominates adoption for internal teams, while there is no clear leader among external teams. Sectors in which external teams are more important, such as healthcare and professional services, tend to adopt tools that help their external teams more – especially analysis tools, which implies these sector value quality of customer interactions more than others (which makes sense, as the majority of these are service-based businesses where quality matters more than anything else). Sectors where internal teams are more important, such as technology and manufacturing, adopt internal-focused tools more – particularly learning tools, while likewise is logical, as they usually operate product-based business models where consumers are significantly more sensitive to price than quality.

4.2 Quantitative

Because of the nature of the dataset (mostly categorical, and with some industries having only a couple companies examined each), applying statistical methods is impractical and likely introduces error to results/conclusions. Instead, I chose a graphical approach, where the data is examined on a relative basis within each figure. Each figure (e.g. "**Figure 1**") represents a specific way of examining the data, while the different sub-figures (e.g. "**Figure 1.2**") allows for the isolation of specific conditions. **Figure 1** is an overview of the complete dataset not intended for analysis, so it is not included in the Quantitative Results section.

4.2.1 Analysis of Software Use

Immediately, Invoca sticks out from the rest in **Figure 2** because it is geared only to automation and analysis tools, which results in its proportionally higher adoption by internal teams than the other 4 software companies. Glean and Deephow both exclusively offer learning tools, but Deephow is used 100% by internal teams, while a third of Glean's base is external teams. Moveworks offers the widest variety of tool types, and perhaps as a result, has the most consistent and varied distribution of team types. Dashworks mostly focuses on learning tools, but also offers a data aggregation tool to some customers. Invoca and Moveworks exhibit a relative increase in internal team tool use as customer base reach grows, while the other three software companies don't exhibit a significant relationship between customer base and tool use. Moveworks' customers' adoption of AI-KM tools doubles with each category "increase."

Overall, the gross adoption of knowledge sharing and access tools in multinational companies is more widespread than among all other tool types, between all softwares except Invoca. Invoca's gross tool utilization is highest among national companies, with the ratio of analysis to automation tool use varying from 1:1 to 1:3, independent of customer base reach.

Glean has the lowest standard deviation of gross tool use between different customer base types (near identical adoption between national and multinational companies), while Deephow has the highest (Multinational companies dominate).

4.2.2 Analysis of Internal and External Teams

Figure 3 shows that large SaaS companies dominate adoption of AI-KM tools by both internal and external teams (but by internal to a greater degree). Healthcare, telecommunications, and other service-based industries lead total adoption by external teams in companies of all sizes, while total adoption by internal teams was roughly evenly distributed (with the exception of aforementioned large SaaS) between sectors and sizes. Adoption by external teams was more consistent across varying industries and sizes than adoption by internal teams. The difference is especially apparent among small and medium companies.

At large and giant companies, the industries that primarily use AI-KM tools for internal teams are: Consumer Discretionary; Media; Chemicals and Materials; Manufacturing; Finance and Insurance; Cybersecurity; Energy; and SaaS; the industries that use the tools for their external teams are: Housing, Construction, and Hospitality; Elderly Care; Healthcare; Automotive; Home Services; Legal, Consulting, and Agencies; Telecommunications; and Education.

Included is the figure for external team adoption for small and medium companies, but since there is not enough data for internal team adoption nor in all the industries examined, I am hesitant to draw conclusions.

4.2.3 Analysis of Learning, Automation, and Analysis Tools

Apart from a few isolated service-based industries, **Figure 4** shows that learning tools dominate total cases of tool adoption across all sizes. Once again, large SaaS companies dominate. Utilization is higher at large and giant companies than small and medium. Utilization of analysis tools is more consistent among small and medium companies, and less consistent among large and giant companies, with SaaS, Elderly Care, and Healthcare industries adopting more often than others. Automation tool use is the least frequent and exhibits no consistent, quantifiable trends between varying sizes, sectors, or industries.

4.2.4 Analysis of Tool Use Frequency for Different Teams

In **Figure 5**, total AI-KM tool use frequency (number of individual tool uses) is distributed differently across industries of different sizes based on the team type: External teams use AI-KM tools at similar frequencies regardless of size and industry, whereas internal teams adopt the tools at higher rates at larger companies. The average frequency of internal team adoption is greater than that of external teams, suggesting that they may be more enthusiastic about adoption or the tools geared towards them are easier to adopt. However, adoption between different industries is less consistent for internal teams than external, implying an underlying mentality difference in various industries of the value that AI-KM tools bring to internal and external teams.

4.2.5 Analysis of Tool Use Frequency for Different Tools

Figure 6 shows that in any given company, learning tools – and particularly knowledge sharing and access tools – are much more likely to be used by multiple teams, while analysis and automation tools, particularly call tracking/analytics tools, are typically used by only 1-2 different teams. AI-KM tool use frequency is highest for large companies (followed by giant companies), and heavily skews towards national and multinational companies. In fact, there appears to be a trend where tool use frequency increases proportionally with customer base (i.e. n(multi-national) >n(national) >n(regional) >n(local)), and within each customer base type, the individual use per company is normally distributed. The same relationship does not exist within each sector, size and customer base notwithstanding: Technology has the highest average total uses, followed by professional services, healthcare, manufacturing, infrastructure, then consumer; within the different sectors, professional services and healthcare most commonly use tools only once per company and total uses decrease with increasing uses per company (downward trend), infrastructure and consumer companies use tools on multiple teams more frequently than on single teams (increasing trend), and technology and manufacturing companies' distribution of tool use is more normally distributed (concentrated in the center).

4.2.6 Analysis of Tool Use Frequency for Different-Sized Companies

Figure 7 demonstrates that when companies adopt tools across more teams, the distribution of tools used stabilizes. That is, when companies only provide AI-KM tools to a few (1-3) teams, the distribution of which teams adopt them is more random, but then when introduced to many (4-7) teams within the same company, the distribution remains relatively constant. For the less frequent end of the spectrum, external teams are more used, but the use frequency appear to converge at around 40% external, 60% internal, and even more interesting, the boundary seems to be reminiscent of a sinc function (with noise transforming into convergence)! Even when the data is broken up by company size, the converging nature of increasing tool use frequency remained– an effect most pronounced in the graph of large companies (Figure 7.4). The approximate point of convergence is in the 40-50% range (of internal teams, so 50-60% for internal teams) for all sizes.

4.2.7 Analysis of Tool Use Frequency for Companies in Different Sectors

According to **Figure 8**, both internal and external tool usage resembles a normal distribution within each count (e.g. n= 1, 2, ... 6, 7) for different customer bases and company sizes, but the highest totals are at the n=2 mark for external teams and n=5 for internal teams. For external teams, national customer bases are frequently the highest total, whereas for internal teams, multinational has spikes at nearly every n. Overlaying both internal and external teams, it is evident that different tool use frequency usually do not affect total minimum or maximum tool use; the lone exception is for n=5 (which implies usage across both internal and external teams), where the maximum is nearly 70% greater than the rest.

Breaking down tool use frequency by sector, technology has both the greatest maximum usages and the largest total usage across the largest distribution of different tool use frequencies. It, along with manufacturing (which coincidentally has the smallest distribution of different tool use frequencies), mostly exhibit internal team use. The other 4 sectors all have similar maximum use frequencies and total usage patterns: As n increases, the proportion of internal team usage increases; external team usage dominates in low-frequency companies in these sectors.

4.2.8 Side-by-side Analysis of Teams & Tools for Companies in Different Geographies

There are not enough European and Asian companies in the dataset to compare Asian, European, and North American companies accurately and insightfully. Of those examined in **Figure 9**, both Multi-national and Giant companies have the largest diversity of tool use and team type, compared to other categories, respectively. Other trends match those seen in **Figure 4** and **Figure 5**. It is also very apparent that across sectors and sizes, higher learning tool use correlates with internal teams and higher automation and analysis tool use correlates with external teams. The correlations are not always 1:1, but there is no distinct trend across different sizes, customer bases, and geographies that would make predicting deviation from a standard 1:1 correlation easier. Multi-national technology companies have more total recorded tool uses by over a twofold margin over the next largest category; what's interesting to note is that in the four largest sectors (in terms of total AI-KM tool uses) across different customer base reaches, there is more external team use than would be expected from the 1:1 trends, implying that "overperformance" (more widespread tool adoption) may be caused by external teams being more open to AI-KM tool use.

4.2.9 Side-by-side Analysis of Teams & Tools for Different-Sized Companies

In small companies, external teams account for most different industries' AI-KM tool users, but the tools they use are split roughly evenly between the three categories, as demonstrated in **Figure 10**. The professional services and healthcare sectors are both evenly split between automation and analysis tools, while the technology and manufacturing sectors lean more towards learning tools. For medium companies, except for the technology sector (which has an even internal/external split), nearly every company across the other sectors pours all of their AI-KM resources towards external teams, and nearly every industry uses analysis tools, with SaaS, Consumer Discretionary and Media being the only ones with ¿50% learning tool use (all 3 are in the technology sector). Large and giant companies have very similar usage trends with both the types of tools used and the teams that use them: The healthcare and professional services sectors are majority external team-use, while the manufacturing and technology sectors are majority internal team-use; the latter two additionally use almost exclusively learning tools, while the other sectors have more even tool use (large professional services and healthcare companies use analysis tools more than in other sectors, but it doesn't constitute a significant majority in many sectors). Overall, while the teams that use the various tools in large and giant companies are split evenly across most industries, learning tools constitute a safe majority of the type of tools used.

4.2.10 Side-by-side Analysis of Teams & Tools for Companies in Different Sectors

Figure 11 shows that for the majority of companies in the technology sector across different industries, learning tools are the most prevalent (and often the only tool type used) – an overall proportion higher than internal teams (which is expected to be closer to 1:1 relative proportion, a la **Figure 9**). In the professional services sector, external teams constitute most of the AI-KM tool adoption (¿75%) across different company sizes and sectors, but the tool type distribution is roughly evenly distributed between learning, analysis, and automation tools. Healthcare companies use the highest proportion of external teams and analysis tools of any sector, but also still use every tool type. Infrastructure companies' internal and external team use split is roughly 40%-60% and have a 50%-30%-20% split between learning, automation, and analysis tools, respectively. Consumer companies have roughly even adoption between learning and analysis tools as well as internal and external teams (external teams adopt the tools slightly more, but not significantly so). The manufacturing sector is the most homogeneous, as nearly all usage is learning tools – medium housing companies are the lone exception to tool type; Internal teams dominate these companies more than in other sectors, surpassing even technology.

4.2.11 Analysis of Tool Use for Companies in Different Sectors

Companies in the consumer, healthcare, and professional services sectors generally see increasing learning tool and decreasing analysis tool usage as size increases, as shown in **Figure 12**. Infrastructure firms have the opposite trend, with giant companies in the sector using more analysis tools and fewer learning tools than large ones. Companies in the technology and manufacturing sectors both have roughly a 3:1 ratio of learning-to-analysis tool adoption, with technology companies of all sizes using both tool types and manufacturing companies using all of one or the other (with analysis tools being used in medium-sized manufacturing companies).

4.2.12 Analysis of Tool Use for Different-Sized Companies

Small companies use all 3 tool types in a roughly even distribution across the different sectors examined in **Figure 13**. Medium companies use nearly exclusively analysis tools, with the only sector where it isn't the majority type used being technology. For large and giant companies, learning tools constitute a 3:1 majority of tools used, with analysis tools being used more than automation tools in a 2:1 ratio (for companies of both sizes). However, healthcare, infrastructure, and professional services sectors each use all 3 different tool types. Figures 13.7 and 13.8 show similar insights, except with more granular detail because they are also broken up by industry. Cybersecurity and chemical/materials manufacturing are the only two industries that exclusively use a single tool type across different sizes.

4.2.13 Analysis of Team Use for Companies in Different Sectors

While no specific industries exhibit any trends in **Figure 14**, companies in the technology sector have a similar ratio of internal-to-external team tool use across small/medium, large, and giant [categories] (2:1). In the professional services sector, small, medium, and large companies all have nearly only external team use in almost every industry; at giant companies in the sector, there is roughly equal AI-KM tool adoption in internal and external teams. In healthcare companies, this trend extends to all sizes. Manufacturing exhibits the opposite trend, with medium being the only external-majority size and over 70% of industries having exclusively internal teams adopt AI-KM tools. In infrastructure and consumer companies, the ratio of internal-to-external team tool use across all sizes is approximately 1:2 in total across multiple industries. External teams are the only ones that utilize AI-KM tools in the telecommunications industry, across all sizes.

4.2.14 Analysis of Team Use for Different-Sized Companies

Figure 15 elicits interesting results. External teams are used over $\frac{3}{4}$ of the time in both small- and medium-sized companies; excluding small manufacturing and medium technology companies, that number jumps even higher.

Large and giant companies have similar internal-external distributions across various sectors and industries, with the internal-external ratio standing at 1:2. Companies in the telecommunications, home services, elderly care, and the manufacturing industries are the only ones which had the same teams consistently adopt AI-KM tools across sizes.

Exclusively external: Small elderly care, small healthcare, small consumer discretionary, small home services, small media (professional services), medium consumer discretionary (consumer), medium elderly care, medium healthcare, medium housing (infrastructure), medium finance, medium home services, large automotive (consumer), large elderly care, large telecommunications, large education (professional services), large home services, large legal, giant housing (consumer), giant elderly care, giant telecommunications, giant home services, and giant automotive (technology) companies.

Exclusively internal: Small manufacturing, medium SaaS, large housing (manufacturing), large maunfacturing, large education (technology), large media (technology), giant consumer discretionary, giant chemicals, giant manufacturing, and giant automotive (professional services) companies.

4.2.15 Effect of Complexity

As a final attempt to elucidate the precise nature of the relationship between tool complexity and adoption, two metrics were developed for **Figure 16**: One to represent the degree of complexity of AI-KM tool use by a company (Y), and one to represent the total usage of a tool (X), using the following formulas:

X = log (Employee Count) * (Total Learning Tool Uses / 4 + Total Automation Tool Uses / 4 + Total Analysis Tool Uses / 3)

Y = sum (Individual Tool Uses * Complexity Score) / Total Tool Uses

Complexity scores were valued 1-11, in ascending order: Knowledge Sharing, Knowledge Access, Employee Onboarding, Employee Training, Call Center Routing, Data Aggregation, Lead Qualification, Quality Assurance, Regulatory Compliance, Ad Performance Analytics, Call Tracking.

Companies that used the tools for internal (green), external (orange), and both (black) types of teams were all colored consistently with other graphs. The results were clear. External teams' tools tend to be more complex and exhibit a loose correlation with increasing usage. Internal teams' tools tend to be less complex than external teams', but they show a significantly stronger positive correlation with increasing usage. Interestingly, in the dataset, companies whose tool use was spread to all types of teams tended to use less complex tools, but gross/total usage was greater than the other two categories.

5 Discussion

5.1 Interpretation of Results

Each company size has its own unique traits, and therefore each requires a different distribution of AI-KM tools, even within the same sector. Small and medium companies tend to use AI-KM tools to boost revenue and improve external functions, while large and giant companies tend to use AI-KM tools to increase internal productivity and process efficiency. Small and medium companies generally have a smaller variance in the tools that they use within each sector, whereas large and giant companies use both more tools and a larger variety of tools. Similar to the prediction made in the literature review, it appears that there is a "pull" effect of widespread adoption of AI-KM tools across different teams for larger companies (perhaps as a result of competitive forces), while there is a "push" effect of targeted adoption of certain AI-KM tools to boost performance in certain areas for smaller companies. In other words, the reasoning behind the adoption of AI-KM tools is reliant on the size of the companies: Small companies, where individuals make decisions that affect the whole organization, are more likely to have tool adoption based on individual needs; Medium companies which are hyper focused on growth are more likely to adopt tools that can boost sales (and those tools are more likely to be adopted by external teams); large and giant companies, while to a different degree each, are more likely to adopt a wide variety of tools to improve efficiency and stay competitive and distribute those tools relatively equally to different teams. Another non-mutually-exclusive interpretation is that smaller companies with more concentrated talent can use more complex tools to maximize high-end productivity, while larger companies with more distributed teams need simpler tools that cut down on organizational inefficiencies. The same logic here for size differences also applies to differences in use for varying degrees of customer base reach.

Generally, adoption of AI-KM tools was highest in the technology sector (and specifically for SaaS companies), which is no surprise since this is a new technology, after all. Tech uses learning tools more than any other sector does and uses learning tools more than any other tool type; both are by a wide margin. Analysis tool use also sits at around 20% for all sizes except large, where learning tools- and in particular knowledge access tools- dominate over 2/3 of the market. Professional services and healthcare companies exhibit similar AI-KM tool use patterns (both in the tool types and teams that use them), which makes sense given that both are service-based in nature. Healthcare uses analysis tools more than any other tool type, and external teams dominate adoption. Companies in the professional services sector use all types of tools, also mostly by external teams. In both sectors, learning tools are also used more frequently as size increases (i.e. in large and giant companies). In consumer sector companies, analysis tool use decreases with size, while learning tool use increases with size (no consumer companies in the study used automation tools). The manufacturing sector mostly uses learning tools, with the exception of medium manufacturing companies, which utilize call analytics tools. Lastly, infrastructure companies use all 3 AI-KM tool types, with automation tool use of around 15% for both sizes, learning tools dominating large companies, and learning and analysis tool use being roughly equal in giant companies (small and medium infrastructure companies generally don't exist, and none were included in the study). The fact that there are such stark differences in tool use between companies in different industries/sectors implies that they value different things for improving their businesses. A positive note from comparing usage in different sectors is that since AI-KM tools are focused on helping employees do their jobs better (i.e. as a virtual facilitator), they generally avoid the ethical, ontological, and complexity (with regards to people being able to understand and implement them) issues that other AI applications have.

5.2 Comparison with Previous Research

The literature review and software/company research have significant qualitative alignment. This is an unexpected result, as little explanatory coherence was present in the executive interviews, and the data types collected were chosen out of availability more so than literature-informed direction; that is to say, the conclusions drawn from both types of data converge independently. In fact, even the majority of use cases presented in the literature review– customer support, quality assurance, employee training, human resource management, marketing/advertising, people routing, knowledge sharing, and knowledge retrieval (access)– are congruent with available AI-KM tools. The remarkable part about this is that several studies mentioning these use cases were published well over 2 decades ago! This validates the study in the sense that the correct software to examine were chosen, as the preliminary research showed most enterprise adoption of AI tools for knowledge management aren't fundamentally AI-KM tools, they're merely existing KM tools with an AI interface on top, an important distinction.

5.3 Limitations and Future Work

First, since this is a cross-sectional study, it is unknown how each of the examined companies will change over time, particularly with respect to how they apply new AI tools to different KM processes inside various teams and for different purposes. In the future, this can be elucidated by surveying the teams in the companies repeatedly over an extended period [that includes before, during, and after the adoption/transition period].

Second, more data should be collected; in particular, an uneven number of companies across different sectors and sizes were examined because of the availability of data. In future research, there should be a minimum of 30 companies for each size-industry combination. Potential cultural or regulatory effects were unable to be examined because there weren't enough non-American companies examined; a larger number of European and Asian companies in the dataset would allow such a study to be possible. Additionally, different types of AI-first software can be examined as more AI-KM tool types emerge.

Third, the data collected was categorized manually by examining posted case studies of each company into different teams and tool types that was found on the software websites. Ideally, this information would be supplied directly from the companies themselves and usage data (i.e. time saved by each tool, number of employees using the tools, number of teams using the tools, etc.) would be more granular. Furthermore, the relative complexity of both the tools and the nature of the tasks the tools help with is non-quantified.

Currently, there does not exist a benchmark for AI-KM use case complexity: There are currently agent evaluation methods based on model fidelity (Rosenfeld, 2021) and performance relative to other models, but none that quantify the complexity of a tool (that may link multiple models) based on its qualitative application. A method to do so must be developed more rigorously to make any definitive conclusions about the relationship between an

AI-KM tool's nature and the nature of its adopter(s).

5.4 Future Implications

With regards to future technological progress, the current form of AI-KM tools is likely to reach market saturation in white-collar industries where employees do their jobs from a computer (i.e. knowledge workers), as this is where existing explicit knowledge currently exists. However, in industries/sectors where employees' jobs' main functions are fundamentally in-person, such as food service, retail, and labor, adoption will only start to catch up once there is a tool/device/technology available to intercept tacit knowledge as it is formed. With such a device, tacit knowledge can be ingested and codified into explicit knowledge, at which point it can have all sorts of analytical processes done to it.

Over the next few years, as the cost of running AI models decreases (Pilz et al., 2024), the barrier to adopting AI-KM tools will fall, leading to more unified, resilient, efficient enterprises. A common fear among artificial intelligence skeptics (also known as "AI doomers") is that AI will replace and displace humans from their jobs. For the teams that AI-KM tools support, this is simply untrue, as the results of this study clearly show AI is not only used almost exclusively to assist people, but semi-automation is significantly more commercially successful than full automation, as companies prefer to do away with simple busywork while making complex (but manual) tasks easier. This applies to nearly all teams, from sales and marketing to HR and IT. However, the same fate does not necessarily hold true for knowledge managers. The future of the profession is being threatened, because while the tacit knowledge practitioners hold may be incredibly helpful to organizations, those organizations may be hard-pressed to justify spending hundreds of thousands of dollars on knowledge managers when a set of AI-KM tools can do 90% or more of the job for less than 10% the cost. In this scenario, knowledge management professionals may find that the value of their skillset and knowledge lies in working in fields where current AI-KM tools can't be used (i.e. in businesses where nearly all employees' functions are non-digital) or applying their experience and expertise to other fields.

6 Conclusion

This study offers an exhaustive analysis of the deployment and impacts of AI-based Knowledge Management (KM) tools across various organizational contexts, delineating a paradigm shift in the domain of knowledge management facilitated by artificial intelligence technologies. By meticulously examining the utilization patterns across a spectrum of industries and organizational sizes, the research reveals substantial transformations in KM practices, fundamentally driven by the integration of AI capabilities. This study's findings articulate how enterprises are not merely supplementing existing KM systems with AI tools but are fundamentally redefining their KM strategies through such integrations. This transition towards AI-enhanced KM systems is marked by an increased capacity for processing and leveraging tacit knowledge, transforming it into a strategic asset that significantly augments decision-making processes and fosters innovation.

Distinct adoption patterns emerge, delineated by the size of the organization, the sector of operation, and the nature of the workforce. Larger enterprises exhibit a propensity to implement a diverse array of AI-KM tools, aimed at enhancing internal efficiencies and managing complex, multi-faceted processes. These tools are leveraged to automate data analytics, optimize communication flows, and refine operational methodologies, thereby sustaining competitive advantage in a digital-first economy. Conversely, smaller firms adopt AI-KM tools with strategic focus, primarily enhancing external functionalities such as customer engagement and competitive analysis. This judicious use of AI in smaller enterprises significantly amplifies their market responsiveness and adaptability, thereby enhancing their competitive stance in a dynamic business environment. Industry-specific deployment of AI-KM tools further elucidates tailored applications of AI technologies. In sectors like technology and SaaS, there is a notable emphasis on learning and knowledge access tools to support rapid development cycles and innovation demands. In contrast, sectors such as healthcare and professional services prioritize analytical tools to ensure regulatory compliance and maintain high standards of customer care.

This granular utilization of AI-KM tools underscores their adaptability and the strategic imperatives that drive their adoption across different sectors. The ability of AI to transform KM practices into more agile, efficient, and competitive business processes highlights the strategic value of AI in modern organizational contexts. Looking ahead, the research anticipates a pervasive increase in the adoption of AI-KM tools as the technologies mature and become more cost-effective. This trend suggests a future where AI integration in KM will be as ubiquitous and essential as information technology in contemporary organizational environments. However, it also necessitates a critical consideration of the evolving role of human capital– and in particular, knowledge managers whose traditional roles are both being transformed and displaced by AI.

By adopting AI-KM tools, firms can not only enhance the function of existing organizational knowledge capabilities, but also implement new transformative changes to their operations. The insights from this study contribute significantly to both academic discourse and practical applications in knowledge management, offering a robust foundation for future research and development in this rapidly evolving field.

7 References

References

Al-Emran, M., AlQudah, A. A., Abbasi, G. A., Al-Sharafi, M. A. and Iranmanesh, M. (2024), 'Determinants of Using AI-Based Chatbots for Knowledge Sharing: Evidence From PLS-SEM and Fuzzy Sets (fsQCA)', *IEEE Transactions on Engineering Management* **71**, 4985–4999.
URL: *https://ieeexplore.ieee.org/document/10033095/*

Asman, J. (n.d.), 'Entity Event Knowledge Graphs for Data Centric Organizations'.

Bag, S., Gupta, S., Kumar, A. and Sivarajah, U. (2021), 'An integrated artificial intelligence framework for knowledge creation and B2B marketing rational decision making for improving firm performance', *Industrial Marketing Management* **92**, 178–189.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0019850120309044*

Becerra-Fernandez, I. (2000), 'The role of artificial intelligence technologies in the implementation of People-Finder knowledge management systems', *Knowledge-Based Systems* **13**(5), 315–320.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0950705100000915*

Chatterjee, S., Ghosh, S. K. and Chaudhuri, R. (2020), 'Knowledge management in improving business process: an interpretative framework for successful implementation of AI–CRM–KM system in organizations', *Business Process Management Journal* **26**(6), 1261–1281.
URL: *https://www.emerald.com/insight/content/doi/10.1108/BPMJ-05-2019-0183/full/html*

Fowler, A. (2000), 'The role of AI-based technology in support of the knowledge management value activity cycle', *The Journal of Strategic Information Systems* **9**(2-3), 107–128.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S096386870000041X*

Gupta, A. and Lanteigne, C. (2020), 'Response by the Montreal AI Ethics Institute to the European Commission's Whitepaper on AI'. Publisher: [object Object] Version Number: 1.
URL: *https://arxiv.org/abs/2006.09428*

Haugen, K. S. (2021), Failure in AI Projects: What organizational conditions and how will managements' knowledge, organization and involvement contribute to AI project failure, Master's thesis, University of South-Eastern Norway, Kongsberg, Norway.
URL: *https://hdl.handle.net/11250/2783842*

Hoffman, R. and Yeh, C. (2018), *Blitzscaling: The Lightning-Fast Path to Building Massively Valuable Companies*, HarperCollins Publishers. Google-Books-ID: HH5QDwAAQBAJ.

Jarrahi, M. H., Lutz, C., Boyd, K., Oesterlund, C. and Willis, M. (2023), 'Artificial intelligence in the work context', *Journal of the Association for Information Science and Technology* **74**(3), 303–310.
URL: *https://asistdl.onlinelibrary.wiley.com/doi/10.1002/asi.24730*

Jöhnk, J., Weißert, M. and Wyrtki, K. (2021), 'Ready or Not, AI Comes—An Interview Study of Organizational AI Readiness Factors', *Business & Information Systems Engineering* **63**(1), 5–20.
URL: *http://link.springer.com/10.1007/s12599-020-00676-7*

Liebowitz, J. (2001), 'Knowledge management and its link to artificial intelligence', *Expert Systems with Applications* **20**(1), 1–6.
URL: *https://linkinghub.elsevier.com/retrieve/pii/S0957417400000440*

Maity, S. (2019), 'Identifying opportunities for artificial intelligence in the evolution of training and development practices', *Journal of Management Development* **38**(8), 651–663.
URL: *https://www.emerald.com/insight/content/doi/10.1108/JMD-03-2019-0069/full/html*

Moertl, P. and Ebinger, N. (2021), The Development of Ethical and Trustworthy AI Systems Requires Appropriate Human-Systems Integration: A White Paper, Whitepaper 0.2, InSecTT.
URL: *https://www.insectt.eu/wp-content/uploads/2022/11/Trustworthiness-Whitepaper-InSecTT-Format-v02-1-1.pdf*

Murali, A. and Kumar, S. K. (2014), 'Knowledge Management and Human Resource Management (HRM): Importance of Integration', *FIIB Business Review* **3**(1), 3–10.
URL: *http://journals.sagepub.com/doi/10.1177/2455265820140101*

Orbach, B., Boettcher, S. and Zan, O. (2023), 'AI Adaptation: A Primer for Corporate Directors', *SSRN Electronic Journal* .
URL: *https://www.ssrn.com/abstract=4662300*

Pilz, K., Helm, L. and Brown, N. (2024), 'Increased Compute Efficiency and the Diffusion of AI Capabilities.', *Centre for the Governance of AI* .

Rhem, A. J. (2021), 'AI ethics and its impact on knowledge management', *AI and Ethics* **1**(1), 33–37.
URL: *https://link.springer.com/10.1007/s43681-020-00015-2*

Rosenfeld, A. (2021), *Better Metrics for Evaluating Explainable Artificial Intelligence: Blue Sky Ideas Track*.

Samtani, S., Zhao, Z. and Krishnan, R. (2023), 'Secure Knowledge Management and Cybersecurity in the Era of Artificial Intelligence', *Information Systems Frontiers* pp. s10796–023–10372–y.
URL: *https://link.springer.com/10.1007/s10796-023-10372-y*

Soleimani, M., Intezari, A. and Pauleen, D. J. (2021), 'Mitigating Cognitive Biases in Developing AI-Assisted Recruitment Systems: A Knowledge-Sharing Approach', *International Journal of Knowledge Management* **18**(1), 1–18.
URL: *https://services.igi-global.com/resolvedoi/resolve.aspx?doi=10.4018/IJKM.290022*

8 Appendix

8.1 Figures

8.2 Dataset