Swedish Cultural Heritage in the Age of AI
Exploring Access, Practices, and Sustainability

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Abstract: This thesis aims to explore and gain an understanding of the current AI landscape within Swedish Cultural Heritage using purposive interviews with five cultural heritage institutions with ongoing AI projects. This study fills a knowledge gap in the practical implementation of AI at Swedish institutions in addition to the sustainable use of technologies for cultural heritage. The overarching discussion further includes related topics of ethical AI and long-term sustainability, framing it from a perspective of Information Practices and a socio-material entanglement. Findings show that AI technologies can play an important part in cultural heritage, with a range of practical applications if certain issues are overcome. Moreover, the utilisation of AI will increase. The study also indicates a need for regulations, digitisation efforts, and increased investments in resources to adopt the technologies into current practices sustainably. The conclusion highlights a need for the cultural heritage sector to converge and find collectively applicable solutions for implementing AI.

Keywords: Artificial Intelligence, Cultural Heritage Institutions, Large Language Models, Ethical AI, Information Practices, Sustainability, Socio-material Entanglement
Acronyms

AI       Artificial Intelligence
BERT     Bidirectional Encoder Representations from Transformers
CH       Cultural Heritage
CHI      Cultural Heritage Institutions
DIGG     The Agency of Digital Government
DL       Deep Learning
GPT      Generative Pre-trained Transformer
HTR      Handwritten Text Recognition
ICT      Information and Communication Technologies
KB       Kungliga Biblioteket (The National Library of Sweden)
LIS      Library and Information Science
LLM      Large Language Models
ML       Machine Learning
NER      Named Entity Recognition
NLP      Natural Language Processing
NN       Neural Networks
OCR      Optical Character Recognition
XAI      Explainable Artificial Intelligence
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1. Introduction

“*It was the best of times, it was the worst of times, it was the age of wisdom, it was the age of foolishness, it was the epoch of belief, it was the epoch of incredulity, it was the season of light, it was the season of darkness, it was the spring of hope, it was the winter of despair.*” – Charles Dickens, A Tale of Two Cities

“*Nature never appeals to intelligence until habit and instinct are useless. There is no intelligence where there is no need of change.*” – H.G. Wells, The Time Machine

Discussing Artificial Intelligence (AI) tends to reflect a dystopian and utopian discourse where AI is seen either as a great, all-encompassing solution or as ‘the greatest peril’ (Crawford, 2021, p. 214). This is reflected in the public debate across newspapers, blogs, opinion pieces and news programs (e.g. Knight, 2023; Serena Silver, 2023; Fawzi, 2023). More so, it has divided the professional field of AI research (Douglas Heaven, 2023). No matter where one falls in the debate, one thing is for sure: AI is at the front and centre of the public consciousness, not least since the launch of ChatGPT by OpenAI in November last year. In its first three months, ChatGPT reached approximately 123 million monthly active users, making it the fastest growing app in history (Wodecki, 2023)¹. ChatGPT is part of what is known as generative AI, a group of Large Language Models (LLMs) that use training data to produce a new output in various media such as text, movies, audio and source code. Creative tools like these open up previously inconceivable possibilities for various professions and purposes. The flexibility and ease of use of LLMs make them powerful tools for Natural Language Processing (NLP) tasks, for instance, information extraction and text summarisation (Drenik, 2023), and other applications suitable for the Cultural Heritage (CH) sector.

In fact, according to Bawden and Robinson (2022), we have entered a time when the physical and digital seamlessly blend into what is known as the infosphere and where Information and Communication Technologies (ICTs) have become an intrinsic part of society. Sometimes characterised as the fourth industrial revolution, it represents an inextricable entanglement of human day-to-day life with advanced technologies and computers (Rubin & Rubin, 2020; Bawden & Robinson, 2022). As new technologies rapidly emerge and evolve, a more aware digital culture is required to best utilise their functions (Floridi & Chiriatti, 2020). Furthermore, as algorithms and AI integration play a vital part in many decision-making

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¹ ChatGPT has since been surpassed by Meta’s app Threads (Ray, 2023).
processes, there is a strong need for transparency and accountability (Stuart, 2020). Currently, it is not always clear how algorithmic models reach their conclusions, and some companies choose to be purposefully opaque about technical specifications. With LLMs being stochastic processes that use training data to make predictions, any output of the model will reflect what it has been trained on and potentially advance inherent biases (Drenik, 2023). This can cause mistrust and misunderstandings, resulting in an inflamed AI debate and unsuitable implementations across businesses and organisations. Therefore, Stuart (2020) argues that it is important to understand the hype cycle surrounding new technologies, looking at their potential with a proper degree of critical evaluation.

Research has shown that adopting state-of-the-art technologies has the possibility to improve internal operations, performance, and user devices (Rubin & Rubin, 2020; Wang et al., 2022). Additionally, access to LLMs could likely see new tools and technologies emerging (Drenik, 2023), resulting in a need to identify which tools and functionalities most effectively meet specific needs and workflows (Stuart, 2020). Technological advances are changing the role and culture of libraries and disrupting practices across a wide range of professions, including the CH sector (e.g. Drenik, 2023; Rubin & Rubin, 2020; Haffenden et al., 2023). Apart from necessitating new work roles, AI implementation can warrant staff of Cultural Heritage Institutions (CHIs) to acquire new skill sets and knowledge areas, such as content management, communication, and technology (Rubin & Rubin, 2020; Stuart, 2020). In a conference paper from 2021, employees at Swedish CHIs indicated an existing knowledge gap concerning digital tools and resources (Carozzi Bjurström et al., 2021). This is mirrored in statistics identifying lack of knowledge and expertise as the biggest hindrance to AI adoption (SCB, 2023). At the same time as librarians in Sweden highlight competencies in technologies, bibliometrics, and data management as a priority, they seem wary of the potentially negative effect it might have on commonplace tasks and the librarian expertise (Carozzi Bjurström et al., 2021).

Systems and services provided by CHIs, from chatbots to collection management, are already reliant on technologies like Machine Learning (ML), which subsequently affect Information Practices (IPs) of both users and staff (Ridley, 2022; Andrews et al., 2021). For example, AI technologies may assist with classification, organisation and searchability of vast digital collections (Haffenden et al., 2023). With advancing technologies and large-scale digitisation\(^2\), new opportunities emerge for both libraries and their users (Snickars, 2018).

\(^{2}\) Digitisation refers to the process of transferring analogue materials to digital formats. This differs from the term digitalisation, which is used to describe the overall societal increase of IT. (SOU 2019:58, p. 113)
However, the consensus within the CH sector is that Sweden is behind on overall digitalisation and that a large-scale initiative is needed (e.g. SOU 2021:77; Summanen, 2021; Burman et al., 2022). Some key obstacles in the above-mentioned discussion are the division of responsibilities nationally, funding structures and a general lack of resources, indicating a need for Swedish CHIs to consider a broad overhaul. According to Summanen (2021), an additional hindrance is the fragmented and complex organisational structure of the CH sector in Sweden, where there seems to be a lack of an established communication network. While still in an early, exploratory stage, practical implementation and meshing of AI with CHIs seem likely to increase over time (Bawden & Robinson, 2022; Haffenden et al., 2023). Even though widespread implementations of AI in Swedish CHIs are limited, a few examples can be noted. Two recent MA theses conducted case studies on the implementation of algorithm-based logistics system IMMS at the libraries in Malmö and Copenhagen, respectively, concluding that the how of implementation should drive the conversation as there seems to be no doubt that AI will have a part in the future practices of libraries (Liljegren, 2021; Rodriguez, 2022). Other examples are Bibbi and UNO, two conversational AI robots employed at different libraries adaptable to meet organisational needs with functions such as ChatGPT, multilingualism and a connection to internal databases to assist with collection searches and administrative tasks (BTH, 2023; Clemens, 2023).

For AI adoption to be successful and sustainable, decision-making should be evidence-based in both experience and current research (Wildemuth, 2017). In fact, Wildemuth (2017) argues that research within Library and Information Science (LIS) is often aimed at improving practices. This is especially important for new technologies where a foundation of practical application at CHIs is limited. Moreover, AI is identified as a highly significant area and an emerging trend in information science research (Bawden & Robinson, 2022; Rubin & Rubin, 2020). For professionals within the infosphere, it is not only necessary to understand digital technologies and data systems but also to be able to use them effectively (Bawden & Robinson, 2022). This is partly why professional practices and scientific research are so closely intertwined in information science. According to Saracevic (2010), this dual focus is central to the field and drives the research forward. As an interdisciplinary field, information science has various definitions (Rubin & Rubin, 2020), but at its core, information science considers the complete information process from collection to use regardless of format or context (Saracevic, 2010; Rubin & Rubin, 2020), with IPs playing a key role.
1.1. Problem Statement
There is no denying the entanglement of technology and humans, where so much of society is dependent on, or built around, advancing data systems. New technologies and their effects on everyday life are explored over many research disciplines and in relation to various business sectors. This is also true for CHIs, where AI is a topical issue (e.g. Nyberg Åkerström & Andersdotter, 2021; Colavizza et al., 2021), with a range of possible applications, as discussed above. However, it seems to be a gradual and slow progress to practically implement the technologies into current practices and services. This seems to be the case within LIS research as well. AI can be considered an interdisciplinary research topic, and while some research fields have come further, for example, medicine (Fiorucci et al., 2022) and journalism (Pavlik, 2023), within LIS, it is still in its infancy. As such, further studies on AI and ML are necessary. Haffenden et al. (2023) highlight a gap in both theoretical and practical studies, pointing to the potential such research could offer in altering current ways to work and in the development of AI itself. Thus, there is a need to enrich the field with research from various perspectives.

In light of both topicality and research gap, this thesis intends to contribute to existing research on AI technologies within CH and their impact on current practices. It does so from a perspective grounded in IP research and socio-technological entanglement. Additionally, it seeks to discuss adjacent issues of AI ethics and long-term sustainability. This will be touched upon to place the thesis in a broader context and provide a snapshot of the present state of knowledge. The study will be conducted using interviews with representatives from Swedish CHIs where ongoing projects concerning the implementation of AI and ML to CH materials and the development of models are taking place.

1.2. Aim and Research Questions
The aim of the study is to explore and gain an understanding of the current AI landscape within Swedish cultural heritage. Using purposive interviews with five institutions, ongoing projects, organisational adoption and related issues are discussed, compiled and placed within the broader theoretical research context.

RQ1. In what ways have AI technologies been implemented into the work of cultural heritage in Sweden, and what prospective work practices can be identified?
RQ2. What implications for long-term sustainability and relevance for said technologies can be discerned regarding socio-technological entanglement and cultural heritage materials?

1.3. Thesis Structure

Chapter 2 introduces the thesis’ conceptual framework by presenting the theories of IP and socio-technological entanglement and briefly recounting the technological developments leading up to modern AI. Thereafter, ethical aspects of AI are presented, such as the importance of regulations and long-term sustainability. Chapter 3 presents the current state of knowledge. This is done by discussing research that has been deemed relevant and substantiates this study. Chapter 4 outlines methodological choices made to suit the aim and research questions best. Following a critical discussion on online interviews and the sampling approach is a presentation of the participants. The chapter also describes this thesis’ ‘bricolage’ approach to the analysis of the collected data. The final two chapters, 5 and 6, present the results, analysis and concluding discussion that brings the thesis together. Lastly, the suggestions for future research are presented.

1.4. Limitations

This thesis has two main limitations. First, there is a modest number of participating institutions, which in part can be attributed to the specific criteria for inclusion and the current low AI adoption rate in Swedish CHIs. This hinders the possibility of finding suitable projects to include, as supported by Cox (2022) and Jaillant and Caputo (2022). The sample size may affect possible generalisations of the findings as it may not be fully representative of the CH sector. However, the purpose of this study is to provide a more in-depth insight into ongoing AI efforts within Swedish CHIs, for which the participating institutions are well suited. Future studies might benefit from a larger sample, as it could yield a more comprehensive understanding of this topic, either confirming or disputing the results from this thesis. The second limitation concerns the choice of interviews. While suitable for gaining in-depth insights, interviews have the inherent limitation of being reliant on what respondents know and share. As such, observations could be a valuable data collection method, allowing the researcher to observe IPs and discern informal interactions directly. The possibilities are for a deeper understanding where new, relevant aspects come to light. Therefore, this limitation highlights potential future research to enrich the conclusions made in this thesis.
2. Conceptual Framework

2.1. Information Practice

IP has many definitions but can generally be described as a concept used to frame how information, from a communicative and an operational standpoint, is embedded in social practices (Bawden & Robinson, 2022) and contextually bound (Savolainen, 2007). IP detail how people interact with information (Savolainen, 2007), including information use, sharing, seeking (Pilerot & Limberg, 2011), identification, creation and management (Zhao et al., 2020). Alternatively, Lloyd (2011) refers to the concept of IP as

information related activities and skills, constituted, justified and organised through the arrangements of a social site, and mediated socially and materially with the aim of producing shared understanding and mutual agreement about ways of knowing and recognizing how performance is enacted, enabled and constrained in collective situated action (p. 285).

As interpreted by Lloyd’s quote, IPs are inherently impacted and bound by the structures, arrangements and workplace frameworks of organisations. This concurs with the viewpoints of Bawden and Robinson (2022). For CH institutions, information and data are central parts of their mission, and in turn, they play a key role in the IPs of society at large.

As society has become more digital, technology has become an integrated part of everyday life and ways of work (Allen et al., 2019; Manhoff, 2015) and is part of a diverse range of research fields (Manhoff, 2015). ICTs are an essential part of practices due to the opportunities and limitations they provide (Pilerot & Limberg, 2011), not least in the workplace (Huizing & Cavanagh, 2011). Technology can thus either be part of making information accessible or hinder access. The wide variety of ways we use technologies for information purposes is part of an information infrastructure (Haider & Sundin, 2022). This focus within IP research concerned with socio-technical relationships refers to how practices, technologies and objects mutually shape and influence one another (Pilerot & Limberg, 2011; Haider & Sundin, 2022) in practically all aspects of information. IPs are thus intertwined with material objects and the larger social contexts surrounding them (Pilerot & Lindberg, 2018). They could be considered a relevant lens to view the adoption of new AI technologies into CHIs. Moreover, as algorithms play an increasing part in society's information infrastructure, they have a profound impact in shaping information whilst in itself being reorganised with use (Haider & Sundin, 2022). They could, therefore, be considered a key feature in the relationship between people, information and technology.
2.1.1. Socio-technical Relationships

Several concepts are used to describe socio-technical relationships. Knorr-Cetina (1997) coined the term *objectualisation* to describe a situation where objects are displacing or mediating human relationships. She argues that this results in reinforced object-relations, which lead to an increased object-dependence (Knorr-Cetina, 1997). *Technicisation* is a similarly defined term to describe the phenomenon of pervasive intelligent systems making room in social spaces; she argues that the rise of intelligent technology affects knowledge processes in professional and social settings where machines take the place of the specialist (Knorr-Cetina, 1997). Within CHIs, a recognised social space, a discussion of the role and implications of new technological tools and applications is valuable for analysing IPs and their impact on CH material.

Similarly, in the field of museums and art, Hood and Kraehe (2017) discuss the power that exists in subject-object relationships, which does not solely reside with the subject or object but is an interdependence, or *distributive agency*, between two material bodies. The object is, therefore, not simply a facilitator or tool for human uses (Irvine-Smith, 2019) but an equal part of the dynamic. Agency as a concept extends to data, information systems, algorithms and design principles (Haider & Sundin, 2022). It is thus akin to the term *affordance*, which is central in information science and similar to objectualisation regarding subject-object relationships. It is a key concept to explain the dependence between people, sociocultural contexts and technology that affect IPs (Zhao et al., 2020). The relationship may concern the features of an object concerning how it is shaped and used within a context by the user, and the value of affordance with an object is thus contingent on its usefulness, as appraised by the subject (Zhao et al., 2020). As with distributive agency, Bobsin et al. (2019) argue that affordance is not a property that either object or subject possesses but rather exists in their relationship.

Affordance can be reframed and contextualised within the topic of AI interaction and work practices to correspond with socio-technical relationships and sociomateriality, as affordance concerns the mutual relationship and dependency between humans and machines. The term is applicable on a personal and organisational level (Bobsin et al., 2019), where the relationship between employees and machines, technologies or analogue tools can be viewed. This relationship is exemplified from a CH perspective regarding digital archives (Manhoff, 2015) and library technologies (Huizing & Cavanagh, 2011). Exploring affordance and technology through the lens of an organisational context is impactful for understanding socio-technical practices in professional settings and the implementation of new technologies.
2.1.2. Sociomateriality

When researching the adoption of technology in the workplace, Orlikowski (2007) found that materiality, a phenomenon of human dependence on material things, is not an occasional reaction in the implementation of new technology but is constant and integral to organisational life. Organisational studies is a divided science with a techno-centric and a human-centred perspective. Both perspectives are limited by their stance on humans and technology as opposites, thus lacking insight into the dynamic relationship between the two poles (Orlikowski, 2007). The techno-centric perspective argues that the function of technology is as a tool for human endeavours, making it purely instrumental; by way of contrast, the human-centric perspective recognises the existence of a human-technological relationship but reduces the part of technology in this relationship (Orlikowski, 2007). Orlikowski (2007) argues that the social and the material are inextricably entangled, and separating the two does not favour their positions within organisational studies.

Each of these concepts points to a concurrent view, a socio-material entanglement that is interdependent (Manhoff, 2015; Haider & Sundin, 2022; Huizing & Cavanagh, 2011) and so enmeshed in societal practices that they should not be viewed separately (Irvine-Smith, 2019; Haider & Sundin, 2022). Furthermore, this relationship is vital for all aspects of IP, not least within CH. This is exemplified by Huizing and Cavanagh (2011), who discuss storage, preservation, distribution and access regarding libraries as being continuously rearranged and managed with technological developments. ML is, therefore, an integral part of LIS and CHIs (Ridley, 2022).

2.2. Cultural Heritage

The Swedish National Heritage Board (n.d.) describes CH as all material and immaterial phenomena, such as objects, structures, traditions, or perspectives, impacted by human activities. CH includes a range of expressions given value in this subject-object interaction (The Swedish National Heritage Board, n.d). In this study, CH material refers to historical and cultural artefacts collected and preserved by archives, libraries, and museums. The material can be physical, born-digital\(^3\), or be made digital through digitisation.

Some key organisational goals of CHIs are preservation, accessibility, collection development, and supporting research (Borowiecki & Navarrete, 2017; Terras et al., 2021); this

\(^3\) The term born-digital differs from digitised in that it refers to materials that are digitally created, e.g. emails and social media.
can be seen reflected in the mission statements of The National Library of Sweden and The Swedish National Archives (KB, 2023; The Swedish National Archives, n.d.-b). Sufficient and sustainable funding is vital to achieve set goals, which in the CH sector tends to be an issue as multiple goals, limited funds and priorities might not be clear or work together (Borowiecki & Navarrete, 2017). CHIs, as repositories of knowledge, hold collections that help cultivate the information infrastructure and generate new knowledge (Borowiecki & Navarrete, 2017), and IPs are, hence, an integral part of these organisations.

2.2.1. Digitisation

Technological innovation and digitisation are imperative for CHIs to achieve their mission and are used across all organisational functions, from collection management to customer service and communication (Taormina & Bonini Baraldi, 2022). The work to digitise CH collections has been ongoing for the last few decades in Europe, with long-term strategies for preservation and availability becoming entangled with new technologies (Evens & Hauttekeete, 2011). For example, The National Library of Sweden started its digitisation process in the late 1990s (Snickars, 2018). According to Borowiecki and Navarrete (2017), national libraries and universities are the primary forces of digitising library collections, with the goal of improving availability, usability, and functionality across networked infrastructures (Borowiecki & Navarrete, 2017). However, the 2004 Google mass digitisation project and the 2007 initiative by the Internet Archive have been influential in the digitisation of books (Borowiecki & Navarrete, 2017; Snickars, 2018). While the accessibility of these collections is made possible by technological advances, the rapid pace also challenges the process, highlighting the need to view digital preservation as an ongoing activity (Evens & Hauttekeete, 2011).

2.3. AI Technologies

Advances and new developments in technology overall and AI specifically have been rapid, especially in the past decade. This has resulted in a widespread interest in implementation across nearly all sectors and personal life. Leading to the argument that we are in the middle of an ongoing ‘AI boom’, referring to the popularity of the field, which has been fueled not least by massive increases in data and computational power (Fazi, 2021). Whilst architectures will evolve and new models emerge, it is important to understand that these build upon historical advances in the field of AI (Rothman & Gulli, 2022). A range of terms and concepts are used in new ways or combinations, not always consistently, resulting in a somewhat fragmented and
unclear thesaurus when discussing AI. The term AI has various definitions and can come to refer to different things depending on context; AI can be seen as an umbrella term referring to computer systems that are developed to enact problem-solving (Gil et al., 2020), but may also include the wider context in which these technologies are developed, managed and used. Crawford (2021) distinguishes between the terms AI and ML, stating that the latter is frequently used in the technical field, whereas AI can be considered the more socially used term, often with a fluctuating meaning and application. By and large, AI reflects a junction of governance, technology and capital at the heart of power that is key in shaping collective knowledge and communication (Crawford, 2021).

2.3.1. Early AI

It was in the 1950s that the concepts of AI, machine learning, and natural language processing began. The term artificial intelligence was coined by John McCarthy in 1955 (Gil et al., 2020; Luitse & Denkena, 2021). However, it can be seen as somewhat misleading as, according to Crawford (2021), AI is neither autonomous nor rational but relies on considerable computational training based on rules, rewards, and sizable datasets. The birth of AI as we know it today dates back to Alan Turing’s Computing Machinery and Intelligence, where he questioned machine intelligence (Gil et al., 2020). This question was the basis for the Turing test, which was intended to see whether computers could display the same intelligence as humans or at least provide answers that seemed human. However, it has been argued that the test can not qualify an AI as ‘intelligent’ if it passes but simply disqualifies it from being so if the AI fails (Floridi & Chiriatti, 2020).

During this time, ML evolved as well. Foundationally, ML is a set of algorithmic approaches to make predictions that are made possible due to large amounts of training data. It is considered a subfield of AI with three main categories: supervised, unsupervised, and reinforcement learning. These types refer to how models are trained. Supervised learning describes algorithms that have been trained on and evaluated against pre-defined, labelled datasets, thus providing an answer sheet on how to make sense of the data (Tsourakis, 2022). In contrast, unsupervised learning can make use of unlabeled data for training, which in turn allows the algorithm to find hidden patterns and interpret the data (Tsourakis, 2022). Reinforcement learning uses an iterative trial-and-error reward system to train the algorithm to identify optimised ways to accomplish set goals (Tsourakis, 2022). The choice of how to train an algorithm comes down to several aspects, such as the types of available datasets, the purpose of the model, and the problem at hand.
2.3.2. Algorithms

Neural Networks (NNs), also called artificial neural networks, are mathematical models intended to imitate the intricate ways a human brain works. It does so by using interconnected layers of artificial neurons trained in iterative processes on large datasets to fine-tune the parameters to optimise the predictability and minimise errors. With more neurons and layers in a network, more complex problems can be solved. This complex network structure makes even the programmer unable to explain specific decisions and outcomes (Maclure, 2020). NNs have the ability to learn and adapt independently from data without a need for explicitly programmed instructions, which has proven suitable for various tasks, from pattern recognition, classification, and regression to optimisation. Thus, NNs excel in, for example, NLP tasks, such as speech recognition, computer vision, and image generation.

Deep Learning (DL) is considered a subset of ML algorithms built on a structure of numerous processing layers. It was developed, in part, to solve problems of generalisation in AI tasks where prior algorithms were inadequate (Goodfellow et al., 2016). It has resulted in massive improvements across several domains, not least due to its ability to learn complex functions and discover intricate structures (LeCun et al., 2015). NNs and DL can be applied in various new technologies to solve several kinds of complex problems (Mantri & Thomas, 2021).

During the 1970s and onwards, other important discoveries and research breakthroughs were made, not least regarding NNs, backpropagation, and reinforcement learning. The concept of backpropagation, which started in the early 1970s, was a decade later used with great success in NNs, resulting in further interest and advances in the technology (Mantri & Thomas, 2021). Backpropagation refers to a specific algorithm that computes what is known as the gradient by sending information backwards in the network (Goodfellow et al., 2016) and utilises recalibration of NNs to optimise performance and attain desired outcomes with greater precision (Maclure, 2020). In essence, this means that the parameters of a network are iteratively calculated and adjusted to improve performance and resulting outputs.

2.3.3. Natural Language Processing

NLP is a research field of its own, evolving parallel to AI research, but has, according to Kang et al. (2020), also been integrated into the AI field. It is an interdisciplinary field of study used in linguistics, AI, and computer programming (Kang et al., 2020) that provides an ability for machines to comprehend and process both textual data and spoken language similar to humans (Jaillant & Caputo, 2022; Kang et al., 2020). Early NLP was primarily rule–based and
capable of imitating natural language to an extent. This approach shifted in the 1980s with the introduction of ML to NLP tasks, made possible by increasing computational power. Moreover, the emerging models are swiftly changing and improving, optimising results. There are two directions of NLP: natural language understanding, which is focused on comprehension of human language, and natural language generation, which is focused on producing understandable text (Kang et al., 2020). These fields then contain a variety of tasks. Jaillant and Caputo (2022) exemplify speech recognition, Named Entity Recognition (NER) and sentiment analysis. This flexibility and range can explain why NLP plays a key role in today’s digital society. It is integral to, for example, search engines, email, social media, translations (Rothman & Gulli, 2022), and chatbots (Kang et al., 2020). Meaning that most people interact with these functions daily.

In turn, a key component in much of contemporary NLP is language models (LM). While not exclusively used for NLP, LMs are, according to Eovito and Danilevsky (2021), trained to emulate the linguistic manners of humans using three main approaches: manual, statistical and neural. As such, LMs are not necessarily NNs, but it is at least a fundamental part of state-of-the-art LMs today (Eovito & Danilevsky, 2021). In contrast to humans, LMs do not comprehend the meaning or context behind words and sentences as per the constraints of their construction. Three methods are utilised to achieve the best possible output: linguistic, probabilistic and embedding (Eovito & Danilevsky, 2021).

2.3.4. Text Recognition

Text recognition is a method of transcribing images of text to ‘machine-actionable text data’ (Cordell, 2020, p. 23). Through analysis of white and black areas of the documents, the technology identifies letters and digits and thus reduces the need for manual transcription (Chaudhuri et al., 2016), which can be time-consuming and expensive (Cordell, 2020). Within CH, Optical Character Recognition (OCR) is an established ML technique central to search and research (Cordell, 2020; Terras, 2022). Since OCR was developed specifically for printed texts, it does not achieve the same high accuracy when applied to other formats. Cordell (2020) exemplifies this with historical documents that have characteristics such as distinct typography and complex layouts. OCR is unable to distinguish between these features and simply marks these as feature differences (Romein et al., 2020). To improve OCR quality, it is necessary to further develop training data that are ‘more robust and diverse’ (Cordell, 2020, p. 24). Comparably, like with historical texts, OCR is not best suited for handwritten materials, where transcription progress has been slower due to their complexities. Handwritten Text
Recognition (HTR) combines AI, DL, human training, and the statistical analysis of language patterns to recognise and transcribe handwritten texts more successfully than OCR (Romein et al., 2020). This is because HTR is developed for the purpose of deciphering handwriting. In contrast to the low accuracy when utilising OCR on handwriting, an unexpected benefit of HTR is that it tends to yield high accuracy on printed texts because of its advanced technologies. Within CH, text recognition technologies are important for digitisation efforts as they enable document search, metadata inclusion, and the editing of text or layout options. Including AI in these technologies is especially useful for digitisation and metadata incorporation of large collections. These advances have led to HTR becoming more incorporated into the digitisation practices of CHIs (Terras, 2022; Romein et al., 2020). However, according to Terras (2022), standards and best practices are yet to be established.

2.3.5. A New Era

A new era started in the 2010s when NNs and DL became more readily used in AI and NLP. As NNs need vast amounts of data and computational power (Mantri & Thomas, 2021), the increased availability has, in combination with the transition to ML algorithms, been vital in driving this advancement (Maclure, 2020). It has proven successful for NLP tasks like topic classification, sentiment analysis, question answering, and language translation (LeCun et al., 2015). Around 2015, the concept of attention gained popularity as an optimised way to build and manage more efficient models that replace previous time-consuming and computationally heavy architectures. By yielding better results, the attention mechanism can take full sequences into account and utilise deeper relationships between words (Rothman & Gulli, 2022) to learn context and make predictions by focusing on relevant elements in that sequence.

In 2017, transformer models emerged, using NNs and attention (Rothman & Gulli, 2022). This followed the article ‘Attention is All You Need’ by Vaswani et al. (2017), which introduced the attention-based transformer architecture. Transformer models outperform other models regarding NLP tasks (Rothman & Gulli, 2022). By allowing parallel computations to take place, training speed in these architectures is accelerated (Luitse & Denkena, 2021), which paves the way for a new generation of ready-to-use AI models (Rothman & Gulli, 2022) and could be considered a paradigm shift in modern AI. Attention and transformers have led to state-of-the-art NLP advances (Mantri & Thomas, 2021) at a shocking speed from introduction to having little to no need for fine-tuning for such tasks (Rothman & Gulli, 2022). For example, over the last few years, the advances in the output of LLMs have been striking (Sejnowski, 2022), where the use and effectiveness of the transformer architecture in newer
LLMs is linked to higher performance of humanlikeness in texts due to its effectiveness in handling sequential data (Luitse & Denkena, 2021).

LLMs are an application of ML and can be seen as an evolution of LMs. They are sophisticated and powerful models that are often NN-based and trained with vast quantities of unclassified data in order to classify and generate text (Luitse & Denkena, 2021). Therefore, they are both memory-intensive and require large amounts of computational power (Luitse & Denkena, 2021). Moreover, LLMs are versatile, self-supervised, pre-trained models suitable for various specific NLP tasks when fine-tuned (Sejnowski, 2022). LLMs work as statistical representations of a language, predicting the probability of sentence syntax when producing output text (Luitse & Denkena, 2021). NLP is thus an essential factor of LLMs. Examples of LLMs that were both released in 2018 are the generative language model GPT (Generative Pre-trained Transformer) by OpenAI and the open-sourced architecture BERT (Bidirectional Encoder Representations from Transformers) by Google (Luitse & Denkena, 2021).

**Figure 1**

*Relationship between AI, ML, DL, and Generative AI*

GPT models are part of what is known as *generative AI* (see Figure 1 for visualisation). These models do not follow a fixed, deterministic calculation but are probabilistic, which enables stochastic and novel output (Foster, 2019). Its possible output includes textual, visual and auditory content, which expands the uses of generative material to a wide range of domains,
such as advertising, architecture, and education (Alto, 2023). Alto (2023) argues that
generative AI has enabled alternative ways of creating and interacting with the world and
improved the efficiency of processes. Progress made in larger training data volumes and
advancing parameter counts has resulted in fine-tuning and reinforcement learning to
improve the models’ reliability, performance and utility (Eloundou et al., 2023). Smooth
integration of LLMs and other digital tools could improve these functions further (Eloundou et
al., 2023). In fact, LLMs, like a standard BERT model, tend to reach 85–90 percent accuracy,
and with additional improvements, it introduces a range of new uses in various professions
(Drenik, 2023).

Pertaining to the internal structures of the models, while both are pre-trained, GPT
adheres to the original transformer structure with encoders and decoders, whereas BERT
makes use of only multiple stacked encoders (Luitse & Denkena, 2021). The purpose of these
models differs in that GPT is primarily focused on generative tasks, such as creating images
and texts based on prompting, whereas BERT models are created with natural language tasks
in mind (Foster, 2019). BERT is bidirectional, which increases the caption of contextual
information from surrounding words (Sabharwal & Agrawal, 2021). Much like humans, it
considers all words in a sentence rather than only past words when making predictions
(Rothman & Gulli, 2022), performing well on NLP tasks such as classification, translation,
question answering and NER when purposefully fine-tuned (Sabharwal & Agrawal, 2021;
Eovito & Danilevsky, 2021). Unlike BERT, GPT is designed for complete sentence generation
tasks and has an output that is conversational in tone (Foster, 2019). Some distinctive
attributes of the later GPT models include that they require no fine-tuning and have a high
number of stacked decoder layers, whereas the latter implies that GPT models have a larger
context size of possible words with which to improve the accuracy of its output (Rothman &
Gulli, 2022). Since launch, LLMs, with ChatGPT in the forefront, have been integrated into a
range of products and services to meet user needs better. Therefore, this broad adoption
influences ML systems worldwide (Luitse & Denkena, 2021).

2.3.6. The Question of Intelligence

According to LeCun et al. (2015), ML is intrinsically meshed in modern society. The type of AI
presently available and implemented into a wide variety of applications is known as narrow AI,
which is pre-trained, task-specific and to some extent supervised by humans (Gil et al., 2020;
Luitse & Denkena, 2021; Maclure, 2020). On the other side of the spectrum lies true cognition
and complete autonomy, known as strong AI or superintelligence, and is predicted to possess
intelligence that supersedes what the human brain is capable of (Gil et al., 2020). This is still merely a theoretical concept (Gil et al., 2020), although arguments are being made that this type of intelligence is becoming more likely to develop. Research into artificial general intelligence and ‘common sense’ learning is ongoing, and AI, NNs and DL are an integral part of most research disciplines (Mantri & Thomas, 2021). In popular culture and some debates across news media, AI is often depicted as sentient robots almost indistinguishable from humans. However, while some models like ChatGPT, for example, might produce output that seems intelligent, it is not sentient in a human sense. As explained by Sejnowski (2022), LLMs do not recite the training data as these datasets are too vast to ‘memorise’; instead, an internal latent representation is formed, which allows novel responses to novel queries and provides generalisation. Sejnowski (2022, p. 317) further suggests that what is seen as LLM intelligence might instead be a reflection of the interviewer's intelligence and thoughts, calling it a “reverse Turing test”. It, therefore, mimics or strengthens our views and appears more intelligent when the input quality of prompts is higher (Sejnowski, 2022).

The question of intelligence affects how the impact of AI is viewed. From having a positive outlook and focusing on possibilities to seeing dangers and disruptions and a balancing point in between. Two opposite points of view that can be distinguished from the development of AI are described by Maclure (2020) as inflationism and deflationism. Where inflationary views exaggerate the risks and capacities of AI, sometimes to the point of urgent concern for an existential risk, deflationary views intend to discern what is reasonable and realistic with AI and its effect on human life (Maclure, 2020). As there is no consensus on the impact of AI, and the advancements are staggeringly rapid to the point where it is hard to grasp every aspect fully, transparency and regulatory debates are essential. One risk Maclure (2020) presents is that inflationary views might muddle the discussion on how to legislate AI ethically, focusing on what might or might not be over what actually is.

2.4. AI Ethics
With the increased use of AI for private and professional purposes, the topic of ethical AI has received much attention and is an essential part of the discussion of AI adoption. Ethical AI, also called responsible AI, can span a range of aspects; for example, complex copyright frameworks, technical concerns, skills and diversity among employees are all an intricate part of ethical concerns regarding digital technologies and CH, according to Terras et al. (2021). Within a professional setting, ethical AI is described by Eitel-Porter (2021) as having good intent and not endangering employees or customers.
2.4.1. Corporate Power and Regulations

Power disparities, where the crucial AI infrastructure is monopolised by a few corporations, can arise from a lack of regulation and transparency of necessary resources for AI advancement; this is referred to by Luitse and Denkena (2021) as the ‘political economy of AI’. However, where big tech has dominated the NLP market, smaller companies have started to gain attention – for example, Hugging Face, which provides both a free and paid service approach of models (Rothman & Gulli, 2022). Necessary resources to access or run models are at risk of becoming inaccessible to smaller companies, whereas large corporations with established infrastructure solutions are able to keep a hold on the market by offering cloud services – resulting in long-term consequential path dependencies (Luitse & Denkena, 2021; Crawford, 2021).

Apart from infrastructure privately owned by big tech corporations, there are publicly available open source repositories. This information is often free to study, use, or modify and published with accessibility in mind, which has led to an increase in the use of open access information (Birkinbine, 2020). Within LIS, examples of technologies made accessible through web-based repositories for source code are OCR and HTR software, as well as LLMs. Publishing openly accessible software can be viewed as a way to counteract monopolisation and increase the democratisation of technology, which is supported by large tech companies’ previous dislike for the concept (Birkinbine, 2020). However, the landscape has since shifted to where open source software receives contributions from larger corporations; additionally, Microsoft enabled interoperability with technologies from other companies in 2012 (Birkinbine, 2020). A reason why big tech would choose to invest in open source projects, Birkinbine (2020) explains, is because their goals are mutually beneficial. Much like competition is argued to initiate innovation, novel developments made by access to open source push the boundaries of technology and can thus be utilised and incorporated into corporate structures (Birkinbine, 2020). For the CH sector, this can drive innovative uses and enable the sharing of source code.

To ensure safe and ethical AI use in the workplace, governmental institutions and larger technological companies have released guidelines. In 2019, the EU Commission presented ethics guidelines stating that for AI to be classified as trustworthy, it should be lawful, ethical, and technically and socially robust (European Commission, 2022). When no formal norms or structures enforcing the ethical practice of AI exist, the accelerated expansion of these systems and legal responses risk becoming merely patches adapted after the assured social entanglement of AI (Crawford, 2021). It is thus up to each institution to construct their own ethical guidelines.
2.4.2. Principles

Seppälä et al. (2021) describe some of the most common principles of ethical AI use in professional settings as *privacy, fairness, authenticity, non-discrimination*, and *transparency*. Transparency of AI became a large focal point during the GPT-4 release in March of 2023, where the creator of the AI model, OpenAI, detained information about the model’s dataset construction and training method (McGowran, 2023). OpenAI (2023) argued that the decision was made on the basis of security in a competitive landscape, but Luitse and Denkena (2021) reason that by operating their GPTs as a closed system, OpenAI limit access and adaptability to the model’s fundamentals results in a ‘unique dependence’. However, Ridley (2022) highlights the difference between acceptable concealment to protect trade secrets and intellectual property and being intentionally opaque to mislead users. This issue can be mitigated with regulations and should be a focal point for libraries to ensure transparency (Ridley, 2022). The lack of clarity as to the construction, contents, and inner workings of AI models is often referred to as ‘Black Box’, which is an issue that can lead to a mistrust of the model and its output. Alternatively, Bunn (2020) suggests the metaphor of an iceberg rather than the black box, where there is more to the model than can be seen at first glance and which can be considered important in some instances but not others. Trust should, according to Langer et al. (2021), be calibrated as use can be negatively influenced by either undertrust⁴ or overtrust⁵ in the system, affecting its effectiveness.

AI affects rights, decisions and opportunities of everyday life, resulting in ethical issues concerning, for example, opacity, biases, privacy and the status of low-skilled workers (Maclure, 2020). This has led to the area of Explainable Artificial Intelligence (XAI) emerging (Bunn, 2020), with the intent to provide insight into complex artificial systems (Langer et al., 2021). It is especially important since, according to Ridley (2022), systems, services and collections are inherently ML and subsequently affect IPs. There is an intuitive connection between XAI and recordkeeping, as both consider transparency vital, and opaque models are considered disruptive for recordkeeping as they challenge existing practices and ideas of preservation (Bunn, 2020).

Bunn (2020) mentions two viewpoints of XAI influencing the key terms *interpretability* and *explainability*, where the former focuses on technical understanding of the model and the latter on concepts like accountability, transparency, trustworthiness and fairness.

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⁴ Undertrust indicates a distrust of a system’s process, often resulting in constant supervision and meddling, thus undermining the effectiveness (Langer et al., 2021, p. 4).

⁵ Overtrust refers to a lack of questioning and challenge of a system’s output, even when necessary (Langer et al., 2021, p. 4).
Explainability emerges as the focus shifts to become more human-centred (Bunn, 2020; Ridley, 2022). These concerns become prominent as the adoption of AI has an evident impact in the real-world (Bunn, 2020) and thus has the purpose of satisfying various stakeholders’ expectations, interests, needs and demands (Langer et al., 2021). Explainability can also be one way to distinguish between a system that is malfunctioning or exhibiting unexpected but correct behaviour (Langer et al., 2021).

Training data used for AI technologies is a debated area regarding fairness, privacy and bias. Bunn (2020) and Cordell (2020) state that AI is neither neutral nor objective, and can reflect as much bias and discrimination as the humans building it. In other words, the input affects the output. Both privacy and data protection concerns may be present in the historical datasets of CHIs (Terras et al., 2021), as well as their modern collections and documents. This data often forms the training data and is thus the foundation for representational sensemaking in the systems (Crawford, 2021).

2.4.3. Long-term Sustainability

Several aspects impact the long-term sustainability of technologies, organisations and collections. In this study, the focus will be on discussing environmental, technological, and financial sustainability. Luitse and Denkena (2021) identify potential social implications, environmental impact, and inherent biases as some of the issues connected to LLMs. For example, while much is still unknown about the required energy consumption of AI models, not least due to opaque business practices by tech corporations, it is clear that data centres are one of the largest electricity consumers in the world (Crawford, 2021). This contextualises the importance of talking about environmental issues in conjunction with the adoption of AI.

The sustainability of AI refers, in part, to its environmental sustainability as a technology, where one main aspect concerns clean energy consumption. Modern technological preservation structures require large quantities of energy to power physical servers and in-house storage locations (DIGG, 2023). The Agency of Digital Government, henceforth DIGG (2023), states that while estimations of global emissions caused by digitisation efforts are between 2 and 3%, the general carbon footprint of digitalisation remains unknown due to a lack of insight into the subsequent ways it has streamlined different sectors. Lack of knowledge of the energy use of digitalisation challenges the notion of the digital format as a sustainable practice. Preservation structures using modern technologies require large quantities of energy to power and maintain (DIGG, 2023). To address this issue, one suggested method is threefold: to increase energy and water efficiency by turning off devices when not in use, to schedule
increased energy consumption during off-peak hours, and to purchase energy from clean or renewable sources (Pendergrass et al., 2019). DIGG (2023) reports that similar solutions have improved energy efficiency for large computer servers in the last decades, in addition to utilising naturally colder climates to prevent overheating. Hence, storing and managing digital formats is associated with resource demands and an environmental impact that affects the integration of new technologies. For instance, cloud computing is often described as a key factor to a more climate-friendly digital transition and is considered to be something abstract rather than a physical infrastructure that is, to a large degree, powered by coal (e.g. DIGG, 2023; Cordell, 2020). The discussion demonstrates the duality of the environmental impact of digitalisation, where advances make utilisation more efficient at the same time as exponential growth requires vast amounts of energy and resources. Achieving environmental sustainability, thus, requires changes to current practices (Pendergrass et al., 2019).

Another aspect of sustainability is the technological longevity. Digital preservation, with the purpose of accessibility and long-term use, is concerned with policies, technologies and strategies (Xie & Matusiak, 2016). Where policies help with decision-making, standards tend to be technical and used in management to ensure consistency (Bryson, 2016). Policy development should not only work in the present environment but also take future demands, developments and long-term funding into consideration (Bryson, 2016), particularly due to the long-term implications that choices in digital preservation have on, for example, quality and maintenance (Xie & Matusiak, 2016).

Researchers are dependent on data being discoverable in order to reuse it. This can be negatively affected by a lack of standardisation in collection, description and sharing practices (Gregory et al., 2019). Discoverability is dependent on thorough metadata. Metadata is considered equally important to the data itself (Summanen, 2021; Gregory et al., 2019), as the contextual meaning of data is vital for long-term understanding, management and usefulness (Xie & Matusiak, 2016). Several schemas for metadata exist that can be used for digital objects depending on parameters such as format, content (Bountouri, 2017), needs and preferences. The risk of descriptive metadata becoming detached, altered, damaged or destroyed increases the complication of provenance and authenticity (Xie & Matusiak, 2016). Moreover, an increased use of modern AI in CH can assist with damaged or incomplete artefacts. AI is capable of rendering recreations of these artefacts by performing digital enhancements and can also help improve the legibility or quality of images (Manžuch, 2017). However, improvements challenge the concept of authenticity, and according to Manžuch (2017), digitally enhanced artefacts or images of an artefact cannot be deemed original or authentic.
Apart from storage solutions of digital CH, short lifespans of relevant technology can lead to unsustainable practices. As data formats, hardware, and software are subject to changes and degradation over time and become obsolete, the long-term usability of digital resources is complicated to maintain (Bountouri, 2017). The rapid development of new technologies consequently means shorter technological lifespans. This can result in incompatibility between formats and challenges with backward compatibility, finding devices that can read certain formats, and as such, it poses a significant issue in digital preservation (e.g. Xie & Matusiak, 2016; Bountouri, 2017). There are a few strategies to handle these challenges. CHIs often migrate resources when needed, in other words, copying or converting data to other updated formats or technologies for preservation (Bountouri, 2017). When technological failures do occur, it is hard for CHIs to recover lost materials as resources are limited to begin with (Terras et al., 2021).

Financial sustainability considers the secure, long-term funding ability of institutions, projects and services. It ensures durability over time for CH projects within the constraints of available finances (Jelinčić & Šveb, 2021) and is necessary for continuous management. Due to the complexity of funding structures, maintaining sustainable financing can be challenging (Eschenfelder et al., 2021). CHIs are often subject to several types of revenues, including structural funding, project grants, host institution support and consulting (Eschenfelder et al., 2021). When funding is centred around periodic ‘applying and approving’, revenues can vary over time. In turn, this affects the sustainability of other resources, such as staffing and investments in technology (Eschenfelder et al., 2021). In fact, the development of infrastructures can not be based chiefly on short-term funded projects into new technologies but rather a combination of both short-term and long-term investments (Karasti et al., 2010). As such, new creative ways of funding are being explored globally in an attempt to mitigate risks of financial sustainability. One example is the participatory approach of crowdfunding, which museums of all sizes have been exploring for the last couple of years (Jelinčić & Šveb, 2021). As a funding method, it can bring a sense of communal inclusion but is highly uncertain and should, when applied in CH, be considered a supplement to a larger funding policy (Jelinčić & Šveb, 2021).

2.5. Brief Chapter Summary

This chapter has presented the conceptual framework for the study. The entanglement of technologies, individuals and practices is a relevant lens through which to look at advancements in AI technologies and their adoption into CHIs. As AI is rapidly evolving and
being integrated into software solutions, organisational practices and day-to-day life, it has, according to Haider and Sundin (2022), a profound impact on the informational infrastructure. Furthermore, it is described as thoroughly enmeshed in societal practices (Irvine-Smith, 2019; Haider & Sundin, 2022). Several terms were used to describe socio-technical entanglement, indicating a concurrent view of its importance. It is to be considered constant and integral in organisational life (Orlikowski, 2007) and is relevant for CHIs whose mission of preservation and accessibility is dependent on technological innovation and advances.

The rapid advances in the fields of ML, AI and NLP have opened up new possibilities and challenges, made possible not least by the massive improvement in computational power and advancements with attention and the transformer architecture. According to Mantri and Thomas (2021), this has led to state-of-the-art advances in NLP. Transformers are also effective in newer LLMs, optimising their performance (Luitse & Denkena, 2021). These models are integrated into a range of products, and NLP is thus a vital part of societal IPs. Moreover, algorithms are key in shaping decision-making, opportunities and rights (Maclure, 2020). One primary downside is the lack of transparency of the inner workings of algorithms. This is closely tied to what Luitse and Denkena (2021) called the ‘political economy of AI’, where some large corporations monopolise the AI infrastructure.
3. Related Research

Many facets from adjacent research fields can be considered when studying AI implementation into CHIs. Therefore, the structure of this chapter uses three main perspectives to present the current state of knowledge: the relationship between technologies and work practices in CHIs, the significance of staff expertise and attitudes, and lastly, the ethical and sustainable issues surrounding AI technologies. The composite findings will be presented in a concluding section.

3.1. AI and Practices in CHIs

Technologies are entangled in the work practices of practically all sectors, governments and personal lives in ways that seem irrevocable. It affects how information and CH are shaped, shared, accessed and interacted with. Moreover, AI is becoming a more prevalent part of how we work and the tools utilised. Between the years of 2019 and 2021, Sweden saw an increased use of AI with 1.1% up to 6.5% in businesses and 4.1% up to 26.6% in the public sector (SCB, 2023), presented in Figure 2 below.

**Figure 2**

*Statistics of the use of AI in Sweden*

![Graph showing the use of AI in Sweden between 2019 and 2021 for businesses and public sector.*

*Note. Statistics adapted from SCB (2023).*
The two main reasons for adopting AI in 2021 within the Swedish public sector were described as ‘improving existing products or services’ and ‘develop or improve internal processes’ (SCB, 2023). These reasons correlate with current research initiatives and tests of AI implementation in CH. For tasks and services, AI and, in particular, DL can be used broadly, as discussed regarding using transformer architectures to detect fake online reviews (Catelli et al., 2023), crowd–AI collaboration systems for damage assessment (Zhang et al., 2022), extracting semantic relationships for management (Christou & Tsoumakas, 2021) and era estimations of documents (Yoo & Kim, 2022), classification models for Cantonese opera (Chen et al., 2022), as well as protection and inheritance of cultural landscape heritage (Wang, 2022) and textile art (Wenji et al., 2022). It can thus apply to tangible and intangible CH of all formats, from accessibility, services, and preservation to management. This versatility might be one of the contributing factors for the accelerated research and gain in popularity seen in AI.

3.1.1. Accessibility

AI technologies are suggested to play a vital role in increasing accessibility to vast amounts of CH collections, both digitised and born-digital (e.g. Terras et al., 2021; Colavizza et al., 2021), as it is one of the primary approaches to how staff and users of institutions benefit from AI implementation. Accessibility refers to making information available but also how people are given the opportunity to interact with CH. This is suggested by Pisoni et al. (2021) to include both site-specific and digital resources. Further, Pisoni et al. (2021) argue that AI, like natural language explanation generation, can provide personalised methods of accessing CH, for instance, tailored interfaces, thus making institutions more inclusive. This notion is shared by Agostino et al. (2020), who, in addition, state that based on the perceived effects of digital technologies in museums, these new technologies will most likely play a key role in changing the ways of cultural appreciation. Personalised experiences, both physical and digital, can, for instance, become more adaptable and creatively incorporated than they currently are. In fact, while the opportunities for personalised CH experiences have been explored since the late 90s, and advancements in technological infrastructures subsequently present better tools to integrate for this purpose, it has yet to become widely adopted (Not & Petrelli, 2019). This new way of interacting with and experiencing culture is expressed by Andrews et al. (2021) as a growing entanglement of libraries and technology. Entanglement of CHIs, their materiality and the technologies they use, such as AI and ML, is an important context to consider, according to Griffin et al. (2023), because of the intrinsic use of technology and systems. Current work practices and services at CHIs are not only dependent on technology but are
constructed around it. To this point, Not and Petrelli (2019) highlight the collaborative relationship that exists between users and personalised CH systems when designing and experiencing them. For example, interactive experiences could ‘complement what is on display’, shift passive consumption of CH to ‘active visiting’, put the visitor in charge of their own experience and provide something unexpected and memorable for the visitor (Not & Petrelli, 2019, p. 76).

Another aspect of increased accessibility is digitisation. Making collections digitally available can, according to Terras et al. (2021), contribute to new ways to use and draw value from CH datasets, suggesting, for instance, co-creative processes with AI technologies. This is exemplified by discussing cases where new art is created, and interactive visitor experiences are produced by the reuse of CH, resulting in the historical datasets generating new forms of value for all parties involved (Terras et al., 2021). Moreover, as digitised collections are turned into datasets, in what is often referred to as ‘collections as data’ it becomes available for digital humanities research, which relies on high-quality data (Wittman et al., 2019, p. 1). Openly available large sets of high-quality data open up new approaches to research and ways to analyse the data, which might consequently generate new forms of value and understanding (e.g. Gregory et al., 2019; Wittman et al., 2019; Borowiecki & Navarrete, 2017). In addition, high-quality datasets can benefit AI models as training data, giving CHIs a central role in AI research (e.g. Cox, 2022; Colavizza et al., 2021; Cushing & Osti, 2022). The statistics of SCB also indicated that a lack of relevant data or poor data quality hinders AI implementation within Swedish businesses (2023). Accessible collections can, therefore, be argued to benefit innovation across all sectors (Borowiecki & Navarrete, 2017), where digitisation and LLMs in CH materials can provide a high societal value.

While digitisation has many benefits, it is a resource-intensive process, requiring staff, time, technology and finances. For CHIs, the high costs can be challenging to commit to as financial allocations decrease (Bountouri, 2017). Apropos limited resources, Wittman et al. (2019) lift the question of the subsequent effect on how to prioritise collections to be converted into data, suggesting it can either be based on demand or the anticipated need and use. Furthermore, the need for prioritisation expands not only to what, or even if, to digitise but also which level of metadata to include and what standards to follow. Rich metadata of high quality enhances digital accessibility (Bountouri, 2017), especially when it adheres to established standards, suggesting that metadata extraction is a good example of a task where AI can be efficiently utilised.
AI is also proposed as a managerial tool for the archival backlog of both libraries and archives by Cushing and Osti (2022). This argument is supported by Andrews et al. (2021), who state that AI technologies suit collection and inventory management. This could involve adding AI and ML to automated tasks to improve efficiency and free up staff for other qualified tasks, opening up for CHIs to utilise their resources better. Colavizza et al. (2021) exemplify viable automated tasks, such as providing intelligent support and assisting with identifying, classifying and manually reviewing materials for content affected by copyright or regarded as sensitive. Within the archival sector, implementing AI for automated tasks has, in the last decade, gone from being experimental to effectual early adoption (Colavizza et al., 2021). Libraries and museums might not be in the same phase as archives, and progress can vary between countries and institutions. In Sweden, work with AI is not widely adopted in CHIs; however, some ML methods can be considered more commonly used and discussed than others, for example, OCR, HTR, NLP and automated metadata extraction (e.g. Grönkvist, 2018; Griffin et al., 2023). In addition, a positive impact of AI on OCR accuracy can already be seen (Summanen, 2021), indicating the possibilities for efficient AI use in CH. Successful implementation of, for example, HTR technology into work practices is dependent on aspects from digitised materials and staff engagement to institutions having a stable, long-term management plan (Terras, 2022). Thus, the questions of accessibility and management stress the need for a broad contextual view of CHIs and their available resources when considering AI implementation.

3.1.2. Obstacles for Implementation

Research suggests that insufficient financing and internal knowledge limit the adoption progress in CH (e.g. Evens & Hauttekeete, 2011; Summanen, 2021). When there are not enough allocated resources from higher up in the organisation, it only allows for partial testing or exploratory projects and is rarely enough for long-term management, argues Summanen (2021) and Cox (2022). Given this, Eschenfelder et al. (2021) claim that flexibility is key to achieving and maintaining financial sustainability. This refers to both funding structures and cost-effective work practices. For smaller institutions, collaborations can play a part in financial sustainability as it allows for a shared workload when infrastructures are developed and maintained, rather than having to take on this cost independently (Shankar & Eschenfelder, 2015). As such, Shankar and Eschenfelder (2015) argue that networks are essential for institutional sustainability.
So, despite a large agreement among researchers on AI’s usefulness, practical implementation remains low (e.g. Cox, 2022; Andrews et al., 2021; Grönkvist, 2018). Especially for Swedish CHIs, where AI implementation is still in an early stage (Griffin et al., 2023). This is argued by Cox (2022) to be predominantly credited to the large resource investment it requires. Institutions must, as a consequence, weigh the options of where to invest their resources best. Cox (2022), therefore, suggests that institutions are more likely to participate in external AI efforts and utilise third-party licence models due to cost efficiency rather than developing them in-house.

Implementation of technology will also require relationships with external partners (Taormina & Bonini Baraldi, 2022) and invite collaborations between institutions regarding access to resources, for example, supercomputers, LLMs, or software. Kann-Rasmussen et al. (2019) and Summanen (2021) go further, arguing that the whole CH sector should converge, especially concerning digitalisation and technological advancements. One of the advantages of converging would be the possibility to use the combined resources and insights of the CH sector to meet the rapid technological advances before falling so far behind that the cost to catch up becomes too great. At the moment, this is a challenge to CHIs, where organisational changes and implementation of new technologies tend to be gradual and less disruptive than the pace of AI advances (Taormina & Bonini Baraldi, 2022).

In addition to the aspect of long-term resource management, many CH materials require continuous management as well. Digital formats are fragile and unstable and thus at risk for information loss (Xie & Matusiak, 2016). This increases the need for routines and work practices to be clearly defined to ensure consistency. Clear guidelines must be in place for detecting and documenting this loss during migration, as well as determining what level of loss is deemed acceptable (Bountouri, 2017). Ambiguity can deepen the risk of misunderstandings or faulty practices, which might result in higher costs down the line or even information and materials being lost. In order to support sustainable practices of digital artefacts, Stuermer et al. (2016, p. 249) propose two conditions: transparency of code for transmutability into new formats to reduce loss and distributed storage locations to minimise the risk of data loss due to server or software crashes.

3.2. Staff Expertise and Attitudes

AI technologies have the potential to be utilised within a range of professional sectors, changing the way we work and, consequently, the roles and knowledge needed. AI and LLMs are steadily becoming more incorporated in workplaces and are considered adaptable to a
variety of tasks and social contexts (Luitse & Denkena, 2021; Terras et al., 2021). While this flexibility may create opportunities, it also challenges existing dynamics in power and ownership as well as established procedures and internal practices, indicating a need for clear digital strategies to be developed (e.g. Terras et al., 2021; Taormina & Bonini Baraldi, 2022). This is helpful as strategies can provide guidance during phases of change, ensuring that the organisation’s long-term digital vision is well established and thus mitigating misunderstandings and discontent among employees. AI technologies are predicted to reshape current jobs and the needed skills, resulting in new roles like AI specialists and prompt engineers to best make use of the models (e.g. Floridi & Chiriatti, 2020; Rothman & Gulli, 2022; Taormina & Bonini Baraldi, 2022). With that prediction comes a concern that advanced technologies will inevitably change the structure of the CH sector and current work roles, perhaps even make them obsolete, as it is not adapted for digital infrastructures (e.g. Carozzi Bjurström et al., 2021; Cox, 2022; Summanen, 2021). It is, however, hard to predict how exactly the changes will turn out. To give one example, Sejnowski (2022) argues that rather than replacing us, LLMs will make us both smarter and more productive by having the ability to generate first drafts, provide new insights, and thus improve and speed up processes, among others.

While services using AI have been implemented to some degree at Swedish libraries, more effective use of AI is argued to be dependent on an increase in continuous competence development to follow the rapid technological changes (e.g. Nyberg Åkerström & Andersdotter, 2020; Griffin et al., 2023). Griffin et al. (2023) specifically point out the lack of continuous skills training and expertise as an issue in Swedish CHIs, particularly as personnel tend to stay in their roles long-term and as there seems to be a collective under-staffing in digitality functions. Institutions with low staff turnover risk becoming stagnant and having more difficulty possessing the necessary skills for new technological advances. As observed by Carozzi Bjurström et al. (2021, p. 24), librarians are a largely ‘homogenous’ occupational group that requires personnel with new knowledge and backgrounds. One way to achieve this is to recruit young people with up-to-date perspectives and insights (Summanen, 2021). However, according to Cordell (2020), this could prove problematic as most LIS programs do not provide sufficient training in ML methods. There is, thus, a disconnect between what is needed in the sector and what is taught at universities. Additionally, cultivating the skillsets internally ‘requires substantial investments of time’, and in turn, it could become necessary to hire ML specialists who often request salaries unattainable to CHIs (Cordell, 2020, p. 38). This is important as the level of knowledge about technologies correlates with an increased level of
trust in AI (Wang et al., 2022). Recruiting from external sectors might hinder internal knowledge from developing, thus increasing the risk of impacting internal attitudes negatively. Consequently, this affects if and what projects and technologies will be undertaken. It is, therefore, pertinent to understand how changes are instituted in organisations and how these changes are entwined with internal conditions.

Attitudes are not believed to be the most significant hindrance to AI implementation, according to Cox (2022), who argues that it is the large resource investment it requires. In contrast, results from a study by Andrews et al. (2021), conducted in both academic and public libraries, indicate that ‘attitude towards use’ and ‘performance expectancy’ are two significant factors in the decision of adoption. Concurrently, statistics from SCB (2023) indicate that for both businesses and the public sector in Sweden, ‘knowledge of technologies’ and ‘employee expertise’ are the biggest hindrances to AI implementation. Thereby, one could assume that a lack of technological knowledge could lead to a distrust of new developments and negative attitudes, which, in turn, can impact an institution’s decision to adopt (AI) technologies. Consequently, the situation is at risk of becoming circular, where a lack of adoption thereafter hinders learning and exploration of AI. It is clear that the relationship between ICTs and the library profession is complex, as suggested by Cox (2022), where attitudes towards implementation among CH professionals can lean negatively, whilst research instead highlights technological solutionism. This reflects the AI debate at large, where professionals seem to take a more cautious stance towards technological solutionism, whereas researchers argue for opportunities with limited practical implementation for support. Moreover, Wang et al. (2022) found that the goals of introducing new technology do not always align with the employees’ understanding or use of it. This might increase the risk of negative attitudes developing. Instead, Summanen (2021) proposes that the institutions draw on employees’ expertise and involve them in the construction of models to ensure that CH remains the primary focus instead of becoming techno-centric.

3.3. Ethics and Sustainability

The ethical implementation of AI is hindered by two primary issues: bias and lack of transparency. This is reflected in statistics by SCB (2023), where the public sector in Sweden rated ‘legal or ethical issues’ and ‘integrity issues’ highly when asked about hindrances to AI adoption. In order to ensure integrity, implementation into CH should strive to be non-discriminatory. These concerns are discussed by Cushing and Osti (2021), who argue that perpetuated bias and inappropriate use are problems for both users of the service and
employees, which can be mitigated with training and supervision. Likewise, personal information and sensitive data are at risk of being openly distributed for malicious purposes, for instance, hacker attacks. To combat breaches of privacy and copyright during, for example, data leaks, Jaillant and Caputo (2022) state that CHIs tend to close their collections, in part due to resource constraints, which consequently leads to less transparency and accessibility. This is unfortunate since, as Colavizza et al. (2021) argue, the use of algorithms increases the need for transparency and accountability. Interdisciplinary work is thus vital to find suitable and ethical solutions for AI in recordkeeping and archives to avoid breaches of privacy and improve security (Colavizza et al., 2021).

3.3.1. Explainability and Transparency

Another aspect of transparency follows the discussion on XAI, where Maclure (2020) argues that when it is problematic to identify how AI algorithms work and generate outcomes, it complicates adoption in professional settings. It is argued that as ML plays an increasingly integral part in libraries and archives, it is also important to incorporate XAI to safeguard both internal and public interests (e.g. Ridley, 2022; Davet et al., 2023; Cordell, 2020). Additionally, LIS should strive to be involved in the progression of XAI and ML, as AI is imperative to both the field and information systems (Ridley, 2022). This ensures that the voice and interests of CHIs are part of the discussion and development, advocating for systems built with core values like transparency in mind. The implementation process must guarantee these values in favour of progressing at the pace of technology (Cordell, 2020). Systems that are opaque and use training data that have been collected in vast amounts without consent and taken out of context, as argued by Crawford (2021), become harder to implement. This is because training data and its classification truth are the foundation for representational sensemaking in the systems (Crawford, 2021; Cordell, 2020); in other words, ethical issues with the training data cause ethical issues with the output.

To mitigate uncertainties attributable to murky systems, documentation becomes a vital part of the practices and decision-making of CH professionals. One suggested way to introduce documentation is described by Davet et al. (2023) as paradata, the information of tools, procedures and the people performing them. This could include information about training data, performance and versioning and could potentially reduce and automate time-consuming tasks for CH professionals and uphold standards for automated archival functions. This is expressed as especially necessary for fields with increased use of technological assistance, like automated data collection. Proper documentation supports
individual search and retrieval by being more responsive to the needs of users, and additionally, it aids in collecting and preserving more data about documents previously deprioritised by institutions (Davet et al., 2023). Currently, Davet et al. (2023) discuss the theoretical uses of paradata but state that technology has advanced enough to enable implementation.

Furthermore, alongside proper documentation, transparency in CHIs when utilising AI and ML relies on explainable models. Li (2022) reasons that there are benefits to a cooperative process between humans and algorithms as it could drive creativity. In such cases, AI is to be considered ‘a tool rather than a co-worker’, and restorations that use algorithmic models could, for clarity, be labelled ‘AI-assisted content’ (Li, 2022, p. 12). This example is closely tied to the aforementioned discussion of paradata by Davet et al. (2023). AI, particularly DL, is exemplified as a useful tool in the restoration of fragmentary works, prolonging their lifecycles and revealing an author’s original intent (Li, 2022). When AI is used for restoration, additional ethical aspects must be considered; for instance, the copyright entitlement to works as originality, quality and authenticity can become questioned (e.g. Li, 2022; Davet et al., 2023). Additional critique toward using algorithms for restoration include their lack of perception and emotions associated with human restorative interventions (e.g. Li, 2022). With this insight, CHIs should reflect on whether the benefits of a cooperative process outweigh the disadvantages. Furthermore, digital preservation can be regarded as continuous practices entwined with all phases of information creation, management and storage, as well as technology development (Xie & Matusiak, 2016). It is, therefore, important that policy development is built on expertise (Bryson, 2016) and adheres to the real needs, experiences and concerns of those affected by it in their work practices. This is part of the larger debate on XAI, concluding that a concurrent methodology of ethical decisions and thorough documentation needs to be in place to mitigate issues and support the work of CH professionals.

3.3.2. Guidelines and Regulations

There is an ongoing discussion on how principles and guidelines within CH remain largely conceptual and focus on the theoretical implementation phase without considering the long-term effects or analysing practical cases (e.g. Seppälä et al., 2021; Crawford, 2021). Guidelines that are developed parallel with technological advancement are at risk of becoming fragmentary and reactive rather than proactive (see Section 2.4.1), which could lead to a muddled view of current standards among staff. Seppälä et al. (2021) found that even when
guidelines were in place, staff did not have consistent knowledge of them throughout the organisations. Therefore, to ensure that ethical AI guidelines are instituted and upheld in professional settings, Eitel-Porter (2021) argues that strong mandated governance is required.

AI and LLMs could prove difficult to predict and, thus, regulate as they gain popularity; however, systems are likely to grow more sophisticated and thus assist in diminishing their shortcomings (Eloundou et al., 2023; Floridi & Chiriatti, 2020). Ethical uncertainties about LLMs and training data could also, to some extent, be mitigated with fine-tuning, such as avoiding bias and offensive responses while ensuring factual accuracy (Sejnowski, 2022). However, even with fine-tuning and advancements, if models are opaque, the understanding of how algorithms produce their output will remain unclear. The datasets themself and their application can still be problematic. To this point, Crawford (2021, p. 114–115) argues that the extensive, continuous data harvest where individuals are thought of as ‘data subjects’ without subjectivity or defined rights should not be blindly accepted. Instead, it must be questioned and understood, not least in terms of who is best served by this process, as described in the following quote:

> Artificial intelligence is not an objective, universal, or neutral computational technique that makes determinations without human direction. Its systems are embedded in social, political, cultural, and economic worlds, shaped by humans, institutions, and imperatives that determine what they do and how they do it. They are designed to discriminate, to amplify hierarchies, and to encode narrow classifications. When applied in social contexts such as policing, the court system, health care, and education, they can reproduce, optimise, and amplify existing structural inequalities. (Crawford, 2021, p.211)

This quote also illustrates the need to mitigate the risks of a computational divide, which could disproportionately benefit large universities and tech companies while limiting or completely pushing out smaller research institutions from the arena, as discussed by Luitse and Denkena (2021). In addition, Luitse and Denkena (2021) argue that independent research is continuously influenced by big tech corporations acting as gatekeepers with collaborations, funding of scholars, study programmes, and conferences to control the discussion in favour of their interests. As such, there is a need for financial efforts focused on independent AI research (Luitse & Denkena, 2021). This also stretches beyond the research sphere, where a computational divide would subsequently affect values and decision-making when proprietary tools and methods are built into software solutions and social institutions (as discussed by Crawford, 2021).
The ongoing debate on how to best regulate these concerns considers many facets. One suggestion by Jaillant and Caputo (2022) is that the implementation of AI into CH should be guided by cross-disciplinary collaborations and a framework based on ethical principles and practices of archivists, historians, anthropologists and social science combined. Kansteiner (2022, p. 133) makes a similar proposition, referring to Luitse and Denkena's (2021) concept of the political economy of AI, by suggesting a specifically designed, publicly controlled ML system that is academia-compatible and that could “advance the cause of environmental protection”. This conclusion is drawn after the possibilities and current limitations of LLMs are discussed from a historical theorist perspective. Regarding Swedish CHIs, Griffin et al. (2023) argue that a national strategy for implementing AI would be beneficial, concluding that, while institutional processes tend to work slower than technological changes, as previously suggested by Taormina and Bonini Baraldi (2022), CHIs will have to find ways to make use of advances in AI.

3.4. Concluding Section

AI technologies are increasingly adopted into CHIs, with a variety of potential benefits being identified. As for LLMs, Colavizza et al. (2021) emphasise their potential for automation of internal processes and work tasks, the innovative forms of digital archives, alongside increased accessibility, to name a few. Researchers also conclude that implementation might be mutually beneficial to AI research (Colavizza et al., 2021; Davet et al., 2023). Whilst concerns about occupations and work tasks becoming replaced by AI exist, it should rather be discussed from the point of view that new professions will emerge and existing ones will evolve to accommodate the technological advances. Researchers remark upon the current lack of expertise among staff as employees do not have the up-to-date knowledge required due to their long-term positions within their institution (Griffin et al., 2023). Additionally, successful implementation requires employees' trust in AI, as suggested by Wang et al. (2022). Ethical considerations should be present during this process, as reflected in the discussion regarding XAI (e.g. Davet et al., 2023; Colavizza et al., 2021; Cushing & Osti, 2021). It concluded that AI can be the source of transgressions, such as inappropriate use of technologies and perpetuated bias, but it can also help mitigate these issues by enforcing transparency and ethical standards. Therefore, it is imperative to debate the ethical issues surrounding AI and develop regulations grounded in realistic applications and expertise.
4. Method

This thesis aims to explore and gain an understanding of the current AI landscape within Swedish CH by identifying and discussing selected projects. It does so using a qualitative approach of interviews and a bricolage of analytic tactics. Interviews are commonly used in exploratory studies (Salmons, 2014), and semi-structured interviews are particularly suitable when mapping out phenomena (Kvale & Brinkman, 2014). Qualitative methods, like interviews, are established within LIS research.

4.1. Interviews as Method

Qualitative interviews inflict a level of subjectivity to the data and its interpretation. As such, Bryman (2016) points out a critique of the limit of generalisability and the difficulty of replicating such studies. It is, however, not the intention of qualitative research to be representative of a population but rather to generalise theories (Bryman, 2016). Pertaining to this study, the modest scope of participants neither can nor should be generalised to the Swedish CH sector at large but rather present an image of some of the ongoing work with AI. The purpose of this type of study is, according to Kvale and Brinkman (2014) and Bryman (2016), to be descriptive and provide a contextual understanding of what is studied. Subsequently, questions are often more general and open not to restrict the study or the respondents too much (Bryman, 2016). This tends to yield richer data and a more in-depth understanding of a topic.

Interviews can vary within a range of structures on both the questions and the interaction, from strict to informal. Typically, three levels of formality are discussed concerning interviews: structured, semi-structured, and unstructured (Wildemuth, 2017). For this exploratory thesis, semi-structured was deemed most suitable due to the flexibility it provides. Semi-structured interviews are less rigid than structured ones, allowing the researcher to modify along the way and follow the respondent’s train of thought with follow-up questions (Wildemuth, 2017; Salmons, 2014). This supports a certain level of natural conversation to take place whilst using a thematic framework or loosely formulated questions rather than a strict order of pre-formulated questions. This was the approach used when formulating the interview guide, which, in accordance with Wildemuth (2017) and Bryman (2016), can be an outline of topics used as a loose basis during the interview, meaning that neither order nor wording needs to be strictly adhered to. The overarching themes in the interview guide (see Appendix A) were derived from the research questions and its sub-themes
from the research presented in chapter 3 (e.g. Jaillant & Caputo, 2022; Terras et al., 2021; Summanen, 2021). This flexibility provides a more conversational style, which could lead to both unexpected insights and build trust between both parties. In fact, follow-up questions and allowing respondents to go on tangents are recommended as they often provide rich answers about what is relevant from the interviewees' perspective (Bryman, 2016). Tangents can also provide information not inquired by the interview guide; for example, ethical issues became more prevalent than estimated. In contrast, environmental topics were moderately discussed. As the interviews did not follow a concise structure, different questions or wordings were used and formulated in the moment, which is in agreement with Bryman (2016) and Salmons (2014), who suggest that an open structure can yield the most relevant information.

4.1.1. Online Interviews

There are several ways in which to conduct interviews. This study provided all participants with the option of in-person or online interviews over Zoom or email, resulting in six online interviews - four over Zoom and two over email. Offering the choice may result in a higher participation rate due to comfort and convenience, allowing respondents to be geographically dispersed (Bryman, 2016; Salmons, 2014). University guidelines necessitated Zoom as the platform for interviews, which requires familiarisation with the software, in addition to a backup plan, should technical issues arise. A utilised benefit of Zoom is that interviews can be recorded and securely downloaded when an interview is completed. Caution should be taken when using online technology as it is not always clear how the data is stored, who owns it, or if it is possible to delete the files afterwards (Salmons, 2014). The recordings are stored for the duration of the thesis process and deleted thereafter. Recording an interview is beneficial as it allows the interviewer to focus on what is being said and steer the conversation rather than taking ample notes (Bryman, 2016). Additionally, it minimises the risk of distorted memory of the conversation.

The recordings were instantly transcribed after each interview, providing an opportunity to reflect upon the collected data to identify the need for follow-up questions and annotate it in preparation for the analysis. Follow-up questions are helpful to ensure similar results to the flexible and open nature of face-to-face interviews. Regarding emails, one of the main consequences is that it may affect the depth of responses (Kvale & Brinkman, 2014) and risk more misunderstandings as clarifications can not be made instantaneously. Two respondents were contacted with additional questions. After the analysis had been compiled, all respondents were given the chance to provide feedback and clarify any misinterpretations.
This is an important step as valuable corrections and elaborations could be provided by the participants, which helps strengthen a study (Salmons, 2014).

As technology and online platforms are ever-changing, ethical concerns differ for online interviews (Wildemuth, 2017). To ensure an ethical practice, every measure was taken to grant privacy and security of recorded material. This is one of the main challenges with online software (Wildemuth, 2017; Salmons, 2014; Kvale & Brinkman, 2014). Each participant signed a consent form beforehand, per Salmons’ (2014) recommendation, thus agreeing to be recorded. Informed consent acts as an agreement, setting the framework surrounding the collected information, ethical concerns and rights of the participant (Kvale & Brinkman, 2014). A degree of anonymisation was decided upon to allow for open reflections and critiques to be shared. Moreover, the respondents were selected based on insight into specific projects and institutions, assuring a certain degree of knowledge of the relevant topics. When referring to respondents in the results and analysis, the choice is to use the institution's name rather than personal names. In select cases where responses have felt sensitive or especially critical, additional anonymisation was applied by omitting the institution's name.

4.2. Respondents

This research is situated within the context of Swedish CHIs and their AI/ML implementation. For this study, a purposive sampling was conducted. This is a non-probability sampling, used strategically and with the intent to find relevant cases that meet the research questions (Bryman, 2016; Salmons, 2014). Selection for this study was made purposefully and considered ongoing or completed projects across archives, libraries and museums in Sweden. This limitation was chosen to gain knowledge into practices rather than theoretical applications, which may not have yielded as much insight. Cases are often chosen to represent variety (Bryman, 2016), and this was particularly relevant in this study as practices, experiences, and regulations can vary across the CH sector. The purposive sampling led to a select number of initiated projects that mainly used AI for textual materials like HTR and NLP.

Furthermore, when contacting potential candidates, the question of other projects or organisations suitable for the study was posed based on the contacts’ expertise, insights and professional networks. This technique is often referred to as snowball or chain sampling (Bryman, 2016; Salmons, 2014). It opens up possible contacts that otherwise would have been hard to find or less inclined to participate without a contact reference. Ongoing or planned projects within the CH sector can be difficult to locate without a professional network, resulting in some interesting cases being overlooked. This contingent approach is, according to
Bryman (2016), guided by the research questions yet flexible enough to allow for adjustments should the criteria or needs change along the way.

This study consists of six interviews with five institutions. There are no set rules for how many participants a study should strive for to be deemed valid. Instead, it is situational and dependent on each study's specific parameters and purposes. Such as a study's time frame and available resources (Kvale & Brinkman, 2014). One guideline is to use a large enough sample to support the conclusions with credibility (Bryman, 2016). When using purposive sampling, Salmons (2014) argues that how cases are chosen, and the data it yields are more important than the number of participants. This has been the foundation upon which the sampling and selection are justified.

4.2.1. KBLab
KBLab at the National Library of Sweden started in 2019 after a pilot study had been conducted the year before. In the pilot study, some mentioned benefits of a lab were new value-making of existing collections, ‘cutting-edge data-driven research’ from various disciplines and support of the library staff’s digital knowledge (Snickars, 2018). KBLab describes itself as “a national research infrastructure for digital humanities and social science”, making new use of KB’s collections to build models and testing for ways to utilise AI within the library (KBLab, 2022). This opens up the collections for quantitative research on a large scale and provides accessibility to the vast collections that might unveil innovative uses and analysis. Textual analysis methods that can be applied to these datasets are, for example, NER, topic modelling and word embedding models (Snickars, 2018). KBLab collaborates with researchers and actors nationally and internationally (KBLab, 2022).

Among the various models KBLab creates is KB-BERT, a monolingual Swedish LLM trained on a large selection of cleaned textual resources from the KB collections. It has been proven to outperform M-BERT and other Swedish models when used for NLP tasks (Malmsten et al., 2020). KBLab emphasises three valuable conclusions drawn from this: the significance of large datasets for model performance, providing an extensive range of language types for robustness and inadequate Swedish testbeds (Malmsten et al., 2020).

4.2.2. Digitisation Project at the University of Lund
Lund University Library (UB) is one of Sweden’s largest depository and research libraries. One of its long-term goals as an institution is to make the library’s collections accessible by
increasing digitising efforts and working with AI technology to streamline selected projects (UB, 2022a). Among its collections are large sets of cards that are yet to be digitised. Out of the card collections, Catalogue-57 alone has about 800,000 documents, of which a large part are written by hand (UB, 2022b). Prior to Catalogue-57, a pilot project concerning the library’s catalogue of portraits was used to test technologies. Where Transkribus was considered and tested, the digitisation project is processed using HTR-Flor, in addition to E-scriptorium and Kraken, for final touches. The purpose of the project digitising all of Catalogue-57 is for the requested information to be made available for the public in a legible and accessible way and possible use for citizen research (UB, 2022b).

4.2.3. The Swedish National Archives

The Swedish National Archives FoU, in Swedish: Riksarkivet FoU, is a research infrastructure within the Swedish National Archives that, as a mission, initiates projects and collaborates with researchers at Universities. It keeps separate reports and budgets. While the Swedish National Archives also houses research and AI efforts in other departments, the respondent mainly provides information specific to The Swedish National Archives FoU in the interview.

The project Transkriberingsnod Sverige is a collaboration between Gothenburg University and the Swedish National Archives to combine social research with AI technology (The Swedish National Archives, n.d.-a) in order to make way for a national node enabling vast amounts of handwritten sources to be machine-read (University of Gothenburg, 2023). Collaborations are essential to these types of projects as CHIs lack the necessary competencies and resources to do it independently (The Swedish National Archives, n.d.-b). The project aims to develop training datasets and HTR models to read hand-written text, making it possible to conduct large-scale text analysis while streamlining internal archival processes (The Swedish National Archives, n.d.-b). Making their CH data publicly accessible is argued to be a matter of democratisation (The Swedish National Heritage Board, 2022). The project builds on a previous project that ran between 2020-2021 (The Swedish National Archives, n.d.-b).

4.2.4. The National Museum of Science and Technology

The National Museum of Science and Technology, in Swedish: Tekniska Museet, is an infrastructure that utilised AI in their project ‘Digitala Modeller’. It was a collaborative effort with Umeå University that ended in 2020. The project aimed to research the role and the possibilities of digitisation within CH and present the findings in an exhibition. Three larger
collections were chosen for digitisation, and each collection got its own specialised digitisation method; Carl Sahlin’s collection of drawings and maps were digitised, indexed, and provided with metadata, whereas Christopher Polhem’s mechanical alphabet was 3D modelled and parts of it CT-scanned and displayed in VR (Attemark–Gillgren & Snickars, 2023).

The museum currently houses an exhibition named ‘Hyper Human’ about the symbiosis between human life and modern technological developments (The National Museum of Science and Technology, 2023). Some themes include AI, gene modification, and surveillance, and it explores the implications and ethical issues that AI brings (The National Museum of Science and Technology, 2023). The exhibition was in part designed by and in co-creation with AI algorithms (The National Museum of Science and Technology, 2023), testing new ways to implement AI into the museum's practices. The exhibition room’s spatial elements, as well as the chairs for visitors, were designed by AI, which was previously untested at Swedish museums.

4.2.5. The National Language Bank of Sweden

The National Language Bank of Sweden, in Swedish: Språkbanken, is a research infrastructure funded by Swedish libraries and government agencies (Språkbanken Text, 2022a). The infrastructure started as a supplier of large amounts of text for people within language studies in Swedish, and over time, has changed into a unit that focuses on language technologies. Its goal is to develop a national e-infrastructure for research within areas like linguistics, language technology, and AI (The National Language Bank of Sweden, n.d.). There are three divisions within Språkbanken: Text, Tal, and SAM. Språkbanken Text provides a large backlog of historical and modern text for the purpose of research and develops text-based digital tools and applications using language technology and AI. Some of their tools that use AI include KORP, which enables search in extensive collections of digital texts, and LÄRKA, a language-learning tool that evaluates the quality of written text based on the European frame of reference for language learning (Språkbanken Text, 2022b).

4.3. Analytic Approach

Inductive reasoning allows patterns and relationships in collected data to emerge and provide meaningful explanations (Salmons, 2014). A flexible, study-specific way to analyse qualitative research is to use what is described as bricolage (e.g. Pratt et al., 2022; Kvale & Brinkman, 2014). This approach entails tailoring various analytic tactics to solve the specific research
purpose, highlighting an interactive process to identify and understand data patterns (Pratt et al., 2022). It, therefore, puts high demands on the researchers to be knowledgeable and sensible in its application (Pratt et al., 2022). A primary benefit is customisation to the study, allowing a deep relationship between the researcher and the data to form whilst combining qualitative methods in ways that can be innovative and valuable (Pratt et al., 2022).

Miles et al. (2020) present twenty-six analytic tactics from which a minimum of three to five is recommended to combine for a bricolage approach. For this thesis, eight tactics were chosen to best suit the analysis of collected data, as presented in Table 1 below.

Table 1

<table>
<thead>
<tr>
<th>Bricolage choices of Analytic Tactics</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Noting patterns, themes</td>
<td>Identifying how the data goes together</td>
</tr>
<tr>
<td>Clustering</td>
<td>Forming and iteratively sorting data into categories</td>
</tr>
<tr>
<td>Comparison</td>
<td>Contrasting sets of data</td>
</tr>
<tr>
<td>Partitioning variables</td>
<td>Dividing data to avoid blurring and incoherent relationships</td>
</tr>
<tr>
<td>Subsuming particulars into the general</td>
<td>Categorising data into overarching, abstract classes</td>
</tr>
<tr>
<td>Factoring</td>
<td>Condensing data by communality</td>
</tr>
<tr>
<td>Making conceptual/theoretical coherence</td>
<td>Divulging larger contexts between data with other studies</td>
</tr>
<tr>
<td>Getting Feedback From Participants</td>
<td>Verifying the analysis with the respondents</td>
</tr>
</tbody>
</table>

Note. This table is presented with information modified from Miles et al. (2020).

In accordance with the first two tactics, the collected data was initially reviewed with an open mind to discern both overarching and smaller groupings based on themes. This allowed for patterns that were both easily discerned and more unexpected to emerge. At this stage, clusters can overlap and are not necessarily mutually exclusive; according to Miles et al. (2020), this could, therefore, be considered a broader categorisation suitable for early analysis. From these groupings and patterns, comparisons were drawn between cases, subsequently highlighting interesting points of discussion. By comparing data between cases, similarities and differences can surface, and previously chosen categories can be adjusted if necessary. To
ensure that the data is neither muddled nor too broadly classified for correct relationships to be identified, it was further partitioned until each variable represented a smaller but clearly defined value to ascertain coherent explanations (Miles et al., 2020). This was then reconstructed into abstract classes using an iterative process of working through the data until categories were ‘saturated’, as described by Miles et al. (2020). At this stage, the collected data became more clearly comprehensible and the abstract categories were condensed into fewer, clearly defined categories used as the framework when presenting the analysis. The findings were correlated with other studies to empirically ground the data in the larger research field (Miles et al., 2020). The final tactic allows for participants to present feedback. As previously mentioned, this was conducted after a draft of the analysis was completed and opened up for both scrutiny and potential corrections where misunderstandings may have occurred.

The analysis is structured around six defined categories, derived from the discussed tactics:

1. Practical Applications
2. Resources
3. Early Tests and Insights
4. Collaborations and Networks
5. Ethical Considerations
6. What is Next?

These categories follow a thematic arrangement, presented under subheadings. Firstly, practical applications and identified purposes of AI within the CH sector, which emerged from the interviews, are presented. The second category discusses needs and hindrances regarding necessary resources. Following this, pilot projects and their outcomes discussed by respondents are addressed. The fourth chapter presents existing collaborations and the value of networks. Aspects of ethical AI make up chapter five, and the last chapter provides insights into what the respondents predict will eventuate in the near future.

As the interviews were conducted in Swedish, the collected data were interpreted and translated by the authors. Quotes are often directly translated, but in a few cases, to keep the contextual coherence, certain words may have been adapted. A downside of translating data is that some nuances may be lost. Any misinterpretations are thus the fault of the authors.
5. Results and Analysis

5.1. Practical Applications

It was clear after the interviews that while AI is, to some extent, discussed and used within Swedish CHIs, it is in a very early stage of adoption. This aligns with the aforementioned research stating that implementation across the CH sector is currently low (e.g. Andrews et al., 2021; Grönkvist, 2018). However, all the interviews highlighted that AI can have several practical applications for CHIs, from textual and language purposes to image recognition, 3D digitisation and works with moving images. One primary use that emerged was in terms of increasing the accessibility of collections, which reflects the statement of Borowiecki and Navarrete (2017) regarding improved ‘availability, usability and functionality’ being the primary goal of digitising CH collections. As KBLab put it: “more people can access more material in an easy way”.

The respondents discussed digitising collections as an ongoing process, in terms of getting through the entirety of materials but more so due to technological advances and resource allocations. This supports what Evens and Hauttekeete (2011) state of the rapid pace of technology being both an opportunity and a challenge to digital preservation. The need to make decisions during the process and make master files available to utilise in the future in case of new features and advances was highlighted in the interviews. Both in terms of how meticulous the digitisation should be to meet the needs of accessibility with the resources at hand but also to avoid having to redo parts of the work later on. This is something UB had to do with previous scans of a collection where quality was lacking.

5.1.1. Metadata and Linked Data

An essential aspect of making collections accessible is metadata, as discussed by Bountouri (2017). During the interviews, the possibility of using AI for both search and a new way for metadata enrichment came up as a way to automate work tasks that are too much for any individual to achieve. Online collections are described as challenging to navigate due to meagre metadata. The fact that collections are often structured from the internal needs of the institution makes it harder to intuitively understand which search terms are relevant for each collection. AI could, therefore, be a tool to make collections ‘more comprehensible’. It was further exemplified with the pilot study at KBLab, where the image library of postcards had some issues with certain search terms not yielding results even though the search term might
be part of some postcards. The respondent pointed out that while a person “cannot write down every detail that exists on a postcard”, the use of AI could assist with more advanced search techniques that minimise the need for traditional metadata enrichment, thus saving both time and resources while generating better results. The collections are, therefore, made searchable in new ways, opening up possibilities to, for example, both deeper and wider searches that become easier in turn. Moreover, the respondent highlighted that the vastness of many collections often results in only superficial metadata as it would be impossible for any individual to transcribe all of the materials, which in turn means that considerable parts of collections remain hidden. Transcriptions, or indexing and cataloguing, is a vital first step to understanding what collections hold in order to make them searchable. At The National Museum of Science and Technology, early tests are ongoing to increase accessibility using AI for purposes such as generated summaries, image recognition and keyword identification. This is one of the interesting potentials that AI technology brings with it. In one interview, LLMs and NER were described as a compelling way forward, particularly to correct transcriptions. This could indicate that the increased advances in NLP have made it integral to CHI practices, especially since it is being understood and discussed by individuals within organisations rather than built-in opaque parts of a system.

Moreover, this accessibility is closely linked to the need for researchers to have access to high-quality data, which is identified as a key area where AI, LLMs and CHIs intersect (Cox, 2022; Colavizza et al., 2021; Cushing & Osti, 2022; Wittman et al., 2019; Borowiecki & Navarrete, 2017). The interest in doing research and large-scale analysis on the vast collections in Swedish CHIs is high, as reflected in the number of research applications KBLab gets, indicating the need for accessibility to digital materials and models that make the collections searchable, what Wittman et al. (2019) describe as ‘collections as data’. The interviews highlighted the amounts of valuable data and information that remains hidden in the collections due to lack of digitisation and quality of metadata, emphasising the new, additional meaning digital humanities can provide to the collections, as previously discussed (Gregory et al., 2019; Wittman et al., 2019; Borowiecki & Navarrete, 2017). This type of data-driven research is on the rise, increasing the demand for CHIs to digitise and utilise AI and LLMs for usability. New technology brings new issues to resolve so as to find how to collaborate with data-driven research efficiently. As the Swedish National Archives put it: “It will become a new landscape where one has to consider what is what”.

Furthermore, AI was discussed as a beneficial help in creating linked data between collections and other resources to bridge the different disciplines of the CH sector. Museums,
archives and libraries do not always work in tandem, and their existing systems may vary vastly in function. The need for systems to catch up to be able to link data and advance further was suggested. So, while CHIs might not yet be working with linked data to any significant degree, most respondents mentioned it as a potential goal going forward. Overall, a positive outlook of what opportunities these advances in ML and AI might bring seeps through every interview, exemplified by the statement from The National Language Bank of Sweden: “We welcome new and better language tools. They emerge today from the work with these LLMs”.

5.1.2. Textual Purposes

According to one of the respondents, the neural models play an important part in CHIs in that they improve OCR, concurring with Terras (2022) and Summanen (2021). OCR is a long-standing, practical application in CH practices with transcriptions. That HTR is one of the primary technologies to be adopted this early on in Swedish CHIs collaborates with conclusions drawn by Grönkvist (2018) and Griffin et al. (2023). As HTR has improved, it has opened up for CHIs to utilise the technology on handwritten materials with similar, high performance as OCR. HTR shows good results on a variety of collections, and it was highlighted that it can yield as good results as OCR on machine-written texts and, with training, increase results further, therefore being suitable for mixed collections as well. For example, when digitising the card collections at UB, HTR was used for text segmentation and transcriptions due to the combination of machine-written and handwritten texts in the collection. Depending on the materials in a collection, the performance of OCR and HTR differ; the Swedish National Archives exemplified that sources with tables tend to have worse results than plain text. At Riksarkivet FoU, the work with HTR allows for large amounts of new data from handwritten sources to be made accessible, which enriches the archives and is used to create training data.

Training data is, in turn, essential for modern AI systems, and as the National Language Bank of Sweden pointed out, should therefore make use of expertise and experience within closely related fields, such as language technology, to create training data that is not only high quality but meets the user needs and expectations. This conclusion concurs with Kansteiner (2022) and could be argued to be closely related to the discussion on sector convergence (Kann-Rasmussen et al., 2019; Summanen, 2021). To some extent, training of LLMs, primarily on collections of older text materials, has recently begun as part of pilot projects and testing, according to three of the interviews. As the National Language Bank of Sweden said: “Commercial actors have no economic reasons for developing LLMs for older Swedish [...]”, which is important when working with CH materials”. Continuing, the respondent argues that
as the need for these models exists, the task of training them falls to Swedish institutions that both want to do it and are well suited to do so. While KBLab builds and trains models, the other respondents primarily make use of existing LLMs, fine-tuning them to meet their particular needs and tasks. According to the interviews, this is mainly due to LLMs being resource-heavy but also partly because it is not necessary to build everything from scratch to fulfil institutional goals at the moment. This is an argument reflected by Cox (2022). The National Language Bank presented two projects where validation datasets in Swedish able to handle a variety of language problems were created, as well as a project with automatic pseudonymisation of identifiers. This is similar to what Colavizza et al. (2021) describe, where sensitive content could be identified using ML algorithms.

5.1.3. Tailored Cultural Experiences

As discussed in related research, personalised methods may improve and change how CH is interacted with (Pisoni et al., 2021; Agostino et al., 2020; Not & Petrelli, 2019). This was pointed out in one of the interviews regarding data-driven research and in terms of tailored experiences in physical visits to collections, such as museums, echoing what Terras et al. (2021) discussed regarding new forms of value being added. Regarding tailoring to individuals, the National Museum of Science and Technology said:

“AI/LLMs could find relevant information from a user’s needs and questions. It would be wrong [for us] to completely tailor collection data since the choice of a target group most likely excludes more than it includes”.

The respondent also pointed to the fact that there might be a large age gap or knowledge gap between those who access the collection. This opens up an interesting aspect of generative AI and the possibility of adapting the language used to describe collections. The National Museum of Science and Technology began incorporating AI into an exhibition in 2017. Three years later, a second exhibition, Hyper Human, opened where AI-generated spatial elements were designed and produced, resulting in exhibition spaces that felt both organic and practical in the sense that intuitive seating areas occurred. Whilst “letting go and allowing the shapes AI suggested be the final design” was challenging, it was more so fascinating and has encouraged more entanglement of AI and exhibitions to come. This concurs with and exemplifies Terras et al. (2021) argument that human–AI co–creative processes could be a valuable new practice in CH.
5.2. Resources

A major concern for AI implementation is internal considerations of CHIs, for example, an institution’s access to resources such as sustainable funding, computational power, a technological infrastructure, and staff with the required expertise. When asked about the current situation, there was consensus that resources were limited, and several respondents indicated that it is not enough to fix one aspect, as exemplified by: “I think, even if we suddenly received 10 million, we would still have these issues”. Instead, to enable sustainable AI adoption, a holistic approach is important as itfacilitates scaling up as necessary. One imperative step forward is to boost the general digitalisation process of CH in Sweden. KBLab raised the issue of its IT department’s large backlog, which problematises the transition from early testing to full implementation. Furthermore, several interviews highlighted the fact that the process is too slow. The National Language Bank of Sweden, in particular, pointed out the CH sectors’ call for increased investments into CH digitalisation, not only to turn collections into data, the term previously mentioned by Wittman et al. (2019) but for the purpose of preservation. Overall, as interpreted by the interviews, clear outlines of how to sustainably implement AI methods seem to be lacking. One respondent called for concise governmental guidelines as a means to become bolder with investments leading to AI adoption, as decisions would not be unfounded. This is indicative of the differences between museums, archives and libraries, as the National Museum of Science and Technology mentioned that the Swedish National Heritage Board aids Swedish museums with advice and guidelines concerning their digital transformation. The general consensus is that the institutions would benefit from more of every resource: man–hours, economic support, computational access and expertise. These assessments support Cox’s (2022) findings of AI as a promising application to CHIs but also a resource–demanding transformation to existing practices.

5.2.1. Technical

One of the larger investments stressed was the need for an overhaul of the entire technological infrastructure; however, a renewed IT infrastructure would be both costly and require a lot of man–hours. KBLab described a fragmented IT environment for the organisation at large, where systems lack cohesion, as well as a ‘technological debt’, indicating that the need for development “increases in a way where you cannot keep up or have the resources to scale up”. In other words, technology keeps advancing while resources remain insufficient. KBLab says:
The sentiment was echoed by other respondents, not least in terms of data storage. For example, the Swedish National Archives implied that using models that prove effective on large amounts of data was tempting but that “we need to think through the entire pipeline and be able to handle all the data”. Continuing, the respondent spoke of the requirement for information to be stored in perpetuity; hence, any additional data HTR and LLMs would extract from the physical collections is considered related to the original data and should be archived as such. Digital materials, both digitised and born-digital, thus increase the need and resources required for sustainable storage. The National Museum of Science and Technology argued that AI is not intended to completely take over tasks such as organising and indexing for preservation, highlighting that “we have primarily physical archives today and lack an infrastructure for storing digital collections”.

The organisational structure of KBLab was referred to by one respondent as a “complete, isolated IT environment”, consequently enabling more work with AI and ML to be conducted in-house. As such, the lab is a long-term investment, indicating that these technologies are imperative going forward. Important to note is that the focus of KBLab, as a national research infrastructure, is not exclusively to bring value to CHIs but rather to contribute to the overall AI infrastructure of Sweden with open-sourced models for anyone to use. “These types of models in Swedish, in view of our collections, can be of use to many organisations, and we have both governments, businesses and CHIs as a target demographic”, the respondent continued, highlighting a hopefulness that their models will be utilised to facilitate the accessibility of CH collections. One benefit of gaining access to transparent models trained on quality data is to limit the resources spent on building and training. The National Language Bank of Sweden explained that “to be able to create these large models, such as ChatGPT or even KBs BERT-model, requires enormous computational resources”. The computational power necessary when applying LLMs is exponentially more than for existing, everyday tasks due to the complexity of neural networks and the vast amounts of data. Because of this resource need, institutions have not yet been able to utilise it much. Moreover, access to supercomputers is limited and requires institutions to apply in advance. The application process can become an issue for projects, as one respondent illustrated:

“It is hard to meet the demands of development; it takes time to produce interfaces for accessibility, and it is not just accessibility, it is data storage that must keep up and simultaneously maintain existing systems and build up an infrastructure that can handle this type of demands. So resources are limited.”
“We need to constantly apply for different periods, and that is a whole process. We need to sit down and write a new application and gain access to another supercomputer in another country. It takes time and is tiresome, and it forces us to suddenly stop because we cannot do anything since we lost the access point”.

While CHIs could invest in procuring a supercomputer for the in-house infrastructure, that would be a waste since it would entail a lot of maintenance. The cost is also a primary hindrance for CHIs to build and manage their own infrastructure, as discussed by Cox (2022).

The argument whether to develop in-house or utilise external resources extends to software solutions and platforms. In-house systems that are tailored to specific needs and collections can be beneficial in terms of the adaptability of available features; moreover, you retain control of the data. However, some downsides are cost, the need for expertise and continuous maintenance. In-house development would require resources and focus that are needed for other projects. For HTR, there are several platforms and services to utilise. During the interviews, Transkribus was highlighted in particular. The Swedish National Archives describes usability, the interface and cooperative aspects as advantageous, especially for projects with citizen science: “It is easy to get started and is suitable for citizen science as anyone can access and start annotating, transcribing and creating training data this way”. It does not require a lot of technical knowledge to work with. In contrast, for UB, while Transkribus yielded good results, other issues with the system arose. “We opted out of Transkribus because we felt it was not particularly suited for our needs with the payment model they use”, the respondents say, continuing to describe the need for transparency and flexibility to meet the unique needs of specific tasks and collections. Instead, this has been solved using a source code system from Github, called HTR-Flor, combined with other complementary tools. Whilst it requires more programming skills, it has allowed for a more tailored system that works well within current practices. The National Museum of Science and Technology pointed to the limitations of their licensed systems, saying:

“There are several different AIs that together could be used for CH materials, but the systems we use today lack the technology that facilitates AI use. We will probably see more applications in a few years. Currently, we are dependent on how the suppliers of our software solutions plan”.

One such limitation became evident during the project Digitala Modeller with the use of DigitaltMuseum, when a large collection of archival objects was digitised: “Availability of 47,000 objects in the form of images at DigitaltMuseum is not satisfactory when it is not
possible to conduct searches in the material or even display objects in a certain order”. This is, according to the respondent, not the purpose or current direction of the platform but alternative platforms with better functions are instead limited by language barriers and the fact that foreign companies do not tend to engage as many Swedish-speaking users. In summary, software solutions can be both useful tools when adopting AI in CH and hinder the process by, for example, lack of features or incompatibility. It might come down to using what is available or waiting for new, more suitable solutions. This leads to the question of when to settle, as exemplified by: “Should we be content with reproductions that are ‘good enough’ and that use fewer resources without having wasted the work in case a new and improved technology comes around?”.

5.2.2. Financial

Long-term financial security is an aspect that affects both projects and CHIs at large. One respondent argued that institutions are limited to modest budgets. Additionally, research projects are often, at least in part, dependent on grants. The National Language Bank of Sweden exemplified this, stating that the allotted grant restricted the scale of their projects Superlim 1 and 2, which aim to provide quality evaluation datasets. The Swedish National Archives pointed out the continuous applications needed for external funding to scale up AI-related projects: “AI is a field which has not been part of our ordinary work, so right now we need to scale up to be able to eventually transition”. The need for and structure of external funding can be interpreted as a stress factor necessary to supplement internal funds that impact the opportunities and limitations of CHIs. The empirical data reflects the aforementioned need for flexible funding with both short-term and long-term strategies (e.g. Karasti et al., 2010; Eschenfelder, 2021). In particular, since pilot studies related to AI, one respondent said, are not assigned any significant resources at the institution. This corresponds with the opinion of Summanen (2021; see Section 3.1.2). The argument was raised that project financing and perimeters could become clearer with changes to existing practices and management. For instance, KBLab started as a project and described that long-term financial security was one important aspect when striving to become an established unit within KB. Moreover, already strained budgets can be negatively impacted by unforeseen circumstances. One respondent spoke of the consequences of the Covid-19 pandemic, which resulted in economic difficulties and, in turn, led to cutbacks at the institution and a loss of skilled staff.
5.2.3. Expertise

When asked, the consensus was that the most pressing need in terms of resources is personnel, as exemplified by: “We have scarce resources of personnel working with digitalisation and have only just started to look ahead. Personnel and expertise are probably the first aspects we need to solve”. Respondents highlighted that while existing in-house competence is considered high, specific expertise is often limited to a handful of employees, described by Griffin et al. (2023) as a collective understaffing. Subsequently, this leads to tough prioritisations. “There are many people involved, and it is obvious that time is the most limiting factor”, the Swedish National Archives said regarding time management of projects, indicating the need for further recruitment. As argued by Nyberg Åkerström and Andersdotter (2020), an increase in competence development is essential for Swedish CHIs to keep up with the rapid technological changes. Additionally, this must be a continuous effort, as Griffin et al. (2023) conclude. Two suggestions are to invest in retraining parts of the current staff or to recruit new competencies. “There is a reason for us and our colleagues to work with this to build that competence [internally]”, UB said, highlighting competence development as a way forward when further implementing AI. Since Griffin et al. (2023) state that staff at Swedish CHIs tend to remain in one workplace long-term, the need for employees to stay up-to-date with technological advances and new practices is vital, as is the need to develop new skills. The Swedish National Archives identifies the need to do both: “We believe we will have to retrain some developers to a more AI focus, and we will probably have to recruit as well”. KBLab recognises that while they have personnel with expanded skill sets, there is a considerable need to recruit more data scientists and “developers in general to meet the demands regarding accessibility, storage and data collection”. However, as AI is a topical subject, expertise in the field is highly sought after, according to the respondents. For one, the Swedish National Archives argues it is “difficult to recruit when you cannot afford the high salaries that appeal to and are expected”. Institutions and governments are hard-pressed to compete with big tech companies that offer higher salaries, thus gaining a monopoly of the expertise, which relates to the discussion about power disparities (Luitse & Denkena, 2021; Crawford, 2021).

Among some of the respondents, educating in-house staff and recruiting new expertise is discussed as a long-term operation, while collaboration is suggested as a more plausible next step. For example, the Swedish National Archives suggests that collaborating with researchers and students could benefit both parties, saying: “It is better to collaborate with those who have new, up-to-date knowledge”. This collaborates with the suggestions by Summanen (2021). Especially concerning AI, where models advance swiftly, new needs and
skills arise continuously. As discussed by Taormina and Bonini Baraldi (2022) and Cox (2022), technological development is bound to impact existing roles or possibly necessitate new professions altogether, although the details of how remain unclear. Due to Swedish CHIs and the CH sector in general still being in the early stages of AI adoption, none of the respondents felt it had significantly impacted internal practices. However, the National Museum of Science and Technology argued that while the “limited implementation has not changed our practices yet, it can become part of how we build new practices”. It should, therefore, not be considered a threat to the current staff; instead, adopting AI could be considered an addition, as suggested by the Swedish National Archives: “It does not replace any existing work practices but rather adds a new dimension”. An opinion that concurs with the research of Taormina and Bonini Baraldi (2022), Rothman and Gulli (2022) and Sejnowski (2022). One interview discussed the duality of scepticism and curiosity among the staff. This was speculated to be partly due to the AI debate in the media.

5.3. Early Tests and Insights

As respondents were chosen partly due to available information on their work with AI, all respondents spoke of pilot projects and early tests that were either ongoing or recently completed. A common denominator that emerged was limitations to the scope of these projects, either financial, technological or in terms of man-hours. Each employee can only allocate a certain amount of time to a project as they tend to be involved in several projects at once or have other necessary tasks to complete. Thus, this creates a sense of internal struggle over existing staff, not least since some specific competencies might be restricted to one or a few employees. Additionally, it limits the number of projects that can be ongoing, as illustrated by the Swedish National Archives: “Since we are a small group working with this, a handful of people, we have to keep a clear focus and try to do one thing at a time. We cannot jump at everything at once”. As previously mentioned regarding Superlim 1 and 2, one essential reason for project limitations is how funding tends to work. Several respondents argued that more could be done and faster if funding, personnel and technical infrastructure were in place. “We have limited resources, simply put, and that is what is putting a stop to us moving forward faster”, KBLab said. Initial projects have, to some degree, been considered ‘trial and error’, not least in order to yield results that can justify initiating further projects, which is in line with the argument by Summanen (2021). This was discussed by two of the respondents, saying, “we need to make the applications first and get the point across that it actually works and then get feedback from the users saying ‘damn, this is good, we want this’, then that becomes
confirmation, and everyone says OK, and so we must offer it” and “we have so to speak sold this project to management as applicable outside of the project; otherwise it probably would not be worth the time to develop our own competence”. Pilot projects can thus be interpreted as a way to initiate work with AI with limited resources to test the technologies, gain internal knowledge and get a tangible result to be able to scale up the work later on. Using processes like this also allocates time after each project ends to reflect on how it fell out and how to move on.

5.3.1. Instituting New Practices

Iterative processes like these, with testing, feedback and adjustments, were argued to be a good way to work where continuous evaluations move the internal practices forward. The benefits of establishing projects internally are both a shared investment in the outcomes and the individual knowledge gained from project members naturally gets adopted into their other work tasks. With limited resources at hand, CHIs might be cautious and not prioritise projects regarding new technologies; instead, they let other institutions lead the way and consequently bear the cost. It was highlighted by two respondents stating, “we do not do the heavy work because we do not really have the resources to”, and that they are “awaiting developments” from other CHIs' work with 3D digitisation due to the systems being both expensive investments and the fact that advances in the field are rapid. Another aspect is the general slow pacing that tends to be present in these institutions, as exemplified by KBLab:

“It is one thing to do pilot studies and examples where you test things out, but to get it into production is harder. Both technically, but also how you need to change the way people work, and that takes time”.

Implementations in organisations like CHIs are inclined to take time, as suggested by Griffin et al. (2023). Something the respondents were all well aware of and that is described by Taormina and Bonini Baraldi (2022) as gradual and less disruptive to the institution.

Mapping out internal needs and exploring possibilities has been a first step for the institutions, in large part to calculate effectiveness and financial gains. In addition, internal surveys tend to focus on improving practices in some way. KBLab described an internal pilot project looking at LLMs as a tool to make practices more efficient with better results, stating: “A part of the project has been to increase the knowledge of these models, so learning, since our staff must get competence development and understand the possibilities”. Internal projects within CHIs, in particular, according to a respondent, tend to focus on case management. Examples of how to utilise LLMs and AI for internal practices that emerged were
the automatisation of routine, everyday tasks, which in turn would free up existing personnel for more qualified tasks. Another example, similar to the discussion on collection accessibility, is the potential to make internal documents and materials more accessible with increased searchability. This corresponds to the suggestions by Cushing and Osti (2022), as well as Andrews et al. (2021), of AI as a managerial tool assisting with everyday tasks. Moreover, it is consistent with the themes presented by Colavizza et al. (2021) of automation in processes, organising and accessibility. After internal surveys are completed and reviewed, applications that have been deemed valuable can be implemented. One institution stated that they had recently entered the implementation phase, indicating that changes or additions to work practices might be in the near future.

Overall, the interviews indicated that positive results from the pilot projects subsequently resulted in discussions or initiations of new projects or extending the implementations to other collections. The early stages of AI adoption in Swedish CHIs are consistent with the conclusion of Griffin et al. (2023). Among the respondents, there was consensus on the range of interesting projects being done by other CHIs globally, implying that there is both a need and a will to adopt AI if it proves beneficial, as well as actual investments being made to make it happen. “There is considerable potential”, as KBLab put it.

5.4. Collaborations and Networks

Collaborations are, as previously mentioned, discussed as a solution to the issue of resources and collaborations with the intent of sharing the output as the end goal with the development of technologies within many CHIs. The respondents are all larger CHIs who are, to varying degrees, involved in formal or informal collaborations that engage AI. The referenced AI networks and national research infrastructures can be considered formal collaborations. These infrastructures are often externally financed by Vinnova, the Swedish National Heritage Board, or the Swedish Research Council. The Swedish National Archives describes these as “a consortium with researchers from different universities in Sweden”. Many of the highlighted collaborations are between research infrastructures and universities rather than between CHI’s. This indicates that projects and collaborations tend to be exploratory in nature rather than practically implemented, with the exception of the exhibitions at the National Museum of Science and Technology. Within the museum sector, there are specific collaborations. The National Museum of Science and Technology mentions the Swedish National Heritage Board and the Council of the Swedish National Museums, where the latter has only just initiated work within AI. Formal collaborations regarding advanced technologies are, as discussed in Section
3.1.2., seen as imperative for their success (e.g. Taormina & Bonini Baraldi, 2022), and expansion to suit collaborations can be costly in resources. The respondents mention collaborations in national research infrastructures, for example, Swe-Clarin and Huminfra. It is suggested that collaborations can be challenging to navigate within such a fast-moving field; “A great deal of coordination is needed in these areas […] there are many initiatives right now, it is so much. There are so many different groups that do different things that you can no longer survey the situation”, one respondent says. Both of these infrastructures and several other collaborations work with questions regarding AI.

The respondents view collaborations within AI initiatives positively but recognise that not all collaborations need to result in a larger project. Respondents repeatedly mention having informal channels where they communicate and work together with other CHIs. “It is always good to learn from one another”, and “we are always interested in exchanging experiences. Because of the challenging subject matter, all information is good information, and we are trying to pick up every piece of advice”, UB says. Informal networks have, in some instances, led to collaborations organically forming and expanding beyond what was first planned as researchers and institutions volunteer to participate. These networks expand past national collaborations. The American Library of Congress and the National Library of Norway were mentioned as valuable sources of information about technologies and AI implementation by KBLab. Similarly, the Swedish National Archives is collaborating with the National Archives of Finland as they also possess older material in Swedish that can be used for training data. Even though some respondents do not work together directly, they affirm the usefulness of open source data. KBLab uploads its models to open source platforms like Hugging Face, making the models accessible and free for everyone. Open source software is a practice being used by several CHIs. Respondents also present a level of knowledge of what other institutions, some among the interviewees, are working on. The Swedish National Archives explains that, with this insight, their institution can make decisions that avoid redundant work. The Swedish National Archives cites KBLab’s focus on the twentieth century in their training datasets as one of the reasons to specialise in historical texts: “It would be foolish of us if we tried to go in and create data for AI models on the same type of data as they do right now, so we complement each other better if we work with historical data". Elaborating on this point, they argue that working together with universities and organisations and sharing their data is beneficial for processing historical text with LLMs and the CH sector at large.
5.5. Ethical Considerations

“The aim of KBLab is to have an open and transparent development of methods that is open for all to use”, KBLab explains. The emphasis on transparency and openness is reflective of the wishes of respondents who construct or use AI models and tools for professional purposes. All respondents showed interest in various ethical concerns throughout the interviews, transparency issues with datasets, tools, and models, the benchmarks of ethical preservation of material and their limitations, and the plausible environmental effects of AI implementation. The notion of “democratising AI” is important among the larger research infrastructures, along with researching and ultimately choosing systems that are built on transparent and, thus, ethical practices, according to KBLab. Crawford (2021) similarly cites AI as important for shaping modern communication and collective knowledge. UB initially used and ultimately chose to withdraw from using Transkribus for their Catalogue-57 project. They cited the tool’s issues of transparency as one of the reasons. The respondent named issues with uncertainty of free versus paid services and documentation regarding the processed end result as “eye-opening” drawbacks. “We do not know how it [Transkribus] works; we have discovered things afterwards, but it is fairly non-transparent”, they conclude. The National Language Bank of Sweden remarks on the growing interest in what happens inside AI models and LLMS – as part of the XAI field. “It is rather important that [...] one understands why they [AI systems, including language models] do as they do, especially if they are primary decision makers [...] or put in as support for decision making”, they say. In positions of decision-making, any existing biases present in the training data are at risk of being perpetuated; research into the inner workings of the models is therefore imperative for preventative methods of bias, the respondent concludes. The necessity of transparent systems and models is similarly highlighted by Davet et al. (2023).

In line with ethical systems, respondents who use KBLab’s open source software appreciate the institution’s attention to transparency regarding their training data and feel secure in their decision to use it, which falls in line with Maclure’s (2020) notion of how ‘black box’ can lead to increased mistrust and rejection of AI adoption. “One should support research that practises normal accounting and discloses from where they get their results”, the National Language Bank of Sweden says. While there are reasons why large companies do not disclose specific training data pertaining to copyright and ethical concerns, some respondents cite the highly competitive nature of private organisations’ development of AI models as a main reason why they remain non-transparent. “Google is better than the others, I would say, but they also
have a limit to when their revenues are threatened”, one respondent says regarding openness. Respondents also deem open source beneficial as it facilitates testing and experimentation. However, the National Museum of Science and Technology points out that instead of building the required competence necessary to develop open source systems, those resources will, at the moment, be utilised in tasks such as enriching metadata and integrating collections into linked open data. This indicates that prioritisations are being made in regard to current resources.

5.5.1. Copyright Concerns

Although KBLab can disclose what datasets they train their models on, they cannot always share material with other CHIs for copyright reasons. Respondents name copyright and GDPR as tricky ethical concerns that restrict accessibility to CH material out-of-house. One institution cites this issue of legal complexity in conjunction with inadequate digital resources as something they do not believe AI can do. Keeping up with standards of ethics for CHIs can be difficult, one respondent says. “We try to keep à jour with it, but we are not good at it, and it is something that changes quickly”. They highlight the changing review practice of ethics as an example of how Swedish practices can come to change in line with the European where what was in the past considered open data can be put behind a paywall for researchers. The reason is that personal details are to be treated as sensitive data, and researchers need approval to be able to use it for research, the respondent says. “It costs 5000kr just to get a preliminary dictum, and it is also the case with ethics reviews that you can only apply for a specific purpose. One cannot re-use the material for different research”. Ethical accessibility to research material is thus affected by the CHIs’ economic well-being. “It is interesting and very, very complicated”, the respondent concludes.

5.5.2. Censorship

One aspect not covered in the related research but highlighted in the interviews is censorship within CHIs. The censorship relates to both physical and digital material, in addition to the data used for language or other AI models. As digital documents are used as training data for AI models, the language used is important for ‘appropriate’ content. Respondents remark upon handling sensitive information regarding historical language not in use today as an ethical concern within CHI. “Whether one should exhibit it [historical language] or not, it is not completely risk-free, but still pretty safe. We felt secure in using and sending this type of data
in between one another and partly use Transkribus as a cloud service”, a respondent says about storing historical data. KBs textual and visual content is not censored, their respondent says:

“In collections, there are things that now are completely crazy to write and are absolutely not politically correct, but then it was okay, and we do not want to tidy that up. That was the past, exactly as you want to preserve the contemporary for what it is and what people really say and think”.

However, they choose to annotate any sensitive material that is shared publicly and explain their decision not to censor material. The dilemma of including sensitive material in AI models is raised in the interviews and in research. While Sejnowski (2022) proposes that offensive responses from AI models can be prevented with fine-tuning, the question is being processed.

5.5.3. Environmental Issues

The National Language Bank of Sweden spoke of the demanding effort of utilising AI models, “LLMs are not exactly climate friendly [...] to apply basic training they can use as much electricity as a small city”. This sentiment is shared by DIGG (2023), who claim that digitalisation is a multi-faceted issue with negative and positive environmental effects. The responses vary as to how much environmental concerns play into the implementation of AI models in CHIs. Important to note is that insight into these issues could be influenced by the respondent’s role in their respective institution. One respondent discloses that AI technology is not part of the institution’s environmental goals, and another presents limiting services to primarily virtual servers as a way to combat the overuse of energy, which concurs with DIGG’s (2023) notion of cloud services as a more resource effective choice of storage than private solutions however, the cloud is, to a large extent, fueled by coal energy. “It is not in our future to expand on this type of server; we have this server, and we will use it”, the respondent concludes. Other respondents cite inaccessibility to computational resources as the reason for refraining from creating LLMs, aware of their environmental impact. With newer, larger models in sight, there is a difficult balance between expansion and environmental concerns; “you have to strive towards finding more effective ways, perhaps, of training models that do not use as much power, but that goes against the increasing need for data to make these super-models, so it is difficult to get away from”, one respondent says in regards to energy consumption. Furthermore, the respondent pointed to earlier studies indicating a vast energy consumption of LLMs, whereas, in comparison, internal calculations suggested a lower
consumption than reported and concluded that “you have to look at and try to weigh the benefits, and we believe the benefits outweigh [the consumption]”.

5.6. What is Next?

While AI in CH is in its early stages, CH practices have been entangled with technology for a long time, not least regarding collection management and digitisation. This interdependency is highlighted in related research (e.g. Huizing & Cavanagh, 2011; Griffin et al., 2023) and reflected in the interviews. When discussing the possibilities of AI adoption, several of the respondents were of the opinion that it is inevitably becoming integrated into CHIs; it might just take some time. As the Swedish National Archives pointed out: “It will take some time, but it is absolutely going to happen, and there is such an awareness, I would say, that something is underway”. In agreement with this, KBLab stated: “It cannot be stopped in any way, I think. It takes some time; you have to have some patience, but I absolutely think we are on our way forward”. Therefore, as suggested by Taormina and Bonini Baraldi (2022), it could be that the change will be gradual and less disruptive.

One of the aspects that emerged most clearly from the interviews was the need to set up in-house competence, either through the development of existing staff, new recruitments, or a combination of both. One example was to not only have AI experts but to establish a common, internal knowledge of AI, its possibilities and limitations. Regarding one pilot project, KBLab described that it has been important to educate staff to “increase knowledge of the possibilities with these models, [...] what methods you could use and also try to find the competence needs within the organisation”. Having a common foundation could positively impact attitudes toward the adoption of new technologies and changes in practices, as suggested by Andrews et al. (2021). It could, therefore, be considered essential for the success of AI adoption.

During the interviews, respondents agreed that a lot will happen in the near future. One highlighted aspect was a new legal deposit act for digital materials, which could provide improved conditions to handle born-digital materials. In conjunction with the act, AI could come to be valuable for such materials, as indicated by Colavizza et al. (2021), suggesting that the utilisation of ML algorithms for born-digital data is beneficial. Another aspect is the potential of a Nordic or Swedish supercomputer that CHIs can utilise. This would hopefully provide more permanent access to the necessary computational power, which will become increasingly important in the coming years, according to the Swedish National Archives. For the institutions, continuing initiated work with the pilot projects and developing this further is prioritised. In addition, as advances in AI are being made, KBLab is continuously developing
new models and variants of developed models. The respondent pointed to the need to stay up to date with the development of models, saying: “You look at new models being released and consider ‘how can we make them?’, and we compare our models between themselves, which ones are suited for what data and what types of questions”.

5.6.1. Increased Digitisation

Moving forward, it is fundamental to increase the pace of Sweden’s digitisation of CH. Only a small part of collections have been digitised; this issue was unanimously raised during the interviews as a hindrance, with the National Museum of Science and Technology saying: “We need to get to a higher degree of digitising and digitalising before we can assess the greater good of AI”. Whilst some exceptions were highlighted, such as KBs database of newspapers and Litteraturbanken, overall digitalisation in Sweden was described as slow and “words but no action”, especially regarding older text sources. “It is not like in France or Norway where they have invested in extensive digitisation initiatives for older materials. This is a larger hindrance than eventual lack of collaborations”, one respondent argued, continuing: “It is the general opinion amongst those involved that Sweden has done very, very little when it comes to digitising historical text materials, so it is really required”. In addition, there is a need for standards and standardised digital formats, correlating with the argument by Xie and Matusiak (2016) regarding long-term implications for quality and maintenance. Choices made early on tend to affect the effort and resources required later; as exemplified by Huizing and Cavanagh (2011), the management of CH materials is continuously adjusted to suit technological advances. One argument raised was that some people consider existing standards to be lacking, and some simply do not adhere to them. This is problematic, as concurred by Gregory et al. (2019), arguing that a lack of standards negatively impacts collection discoverability.

New ways to conduct searches to improve accessibility to collections that require users to visit KB was pointed out as a feature to develop: “We keep the collection in its entirety at the institution, but you can query towards it, the vast amounts of data, and receive only the answer to the question in particular without getting access to the material in itself”. This was also discussed by the Swedish National Archives, saying: “To combine [large amounts of data] with language models to be used like ChatGPT to query large archives, and be able to ask all sorts of questions and receive data to present in different ways, it will become interesting for researchers”. In theory, this is possible with existing models, however, as the respondent concluded: “It is mostly just a question of how we should do it”. This is indicative of just how entangled technology, CH and IPs are.
6. Concluding Discussion

It is unmistakable that cultural heritage is intrinsically socio-materialistic and to such a degree that it should be considered and viewed interdependently. CHIs can, in a way, be described as IP organisations taking part in all aspects of the information lifecycle. They maintain and make available vast amounts of information and valuable CH; consequently, technological developments undoubtedly impact both management of and practices regarding information. The theoretical lens of IP and socio-material entanglement has, therefore, been valuable through which to view advances in AI adoption.

This study aimed to explore and gain an understanding of the current AI landscape within Swedish CHIs. The insights will be structured around the two research questions proposed in this thesis. In addition, at the end of the chapter, the trustworthiness of the thesis and suggestions for future research are presented.

6.1. First Research Question

RQ1. In what ways have AI technologies been implemented into the work of cultural heritage in Sweden, and what prospective work practices can be identified?

It has been stated, in both related research (e.g. Griffin et al., 2023) and the interviews, that AI is in an early phase when it comes to utilisation in CHIs. The consensus is that internal practices have not yet been affected in any distinct way by AI due to its limited use. It is clear that the discussion and, to an extent, implementation of AI is increasing, and as such, it may affect and reshape practices and work roles going forward. From the interviews, it is concluded that institutions in Sweden primarily adopt AI through pilot projects. This can be indicative of CHIs often being institutions with a long history and thus rather lived-in ways of doing things; changes do not always come easy and can be met by hesitation or discontent amongst employees. In addition, current low implementation is to be expected as the necessary advances in computational power, LLMs, and investments into AI by tech companies are recent. This supports the statement by Taormina and Bonini Baraldi (2022) that for CHIs, processes take time, and changes often come gradually. One benefit of this is that technologies have time to mature, and early issues can be handled before implementation, mitigating the risk of teething problems.
Overall, there seems to be both optimism and a will to explore the possibilities and opportunities of AI. Some of the reasons why the implementation process is slow, which emerged from the interviews, are the current degree of collection digitisation of heritage materials, a general lack of resources and a cautiousness to take the leap. This was exemplified in that guidelines were not specified, and that decision-making within an institution requires testing and pilot projects before commitments are made. As such, it would seem that there is not necessarily a coherent view of or understanding of AI in institutions, which in turn could be dependent on how technical work practices are structured internally. This reflects the statistics presented in Section 3.1 and the discussion in Section 3.3 (e.g. Wang et al., 2022; Summanen, 2021). Knowledge and technical responsibilities can be shared between departments or centred on an IT department, or cross-expertise groups might be composed for specific projects and tasks. While this thesis has not specifically studied how to optimise organisational structures when working with AI, one conclusion is that in order to successfully adopt AI, it should be well established internally with clearly laid out needs and a long-term strategy in place.

A primary focus in the pilot projects was textual sources and, to a lesser extent, ongoing projects with, for example, photographs and images. This might be due to the long-standing work with OCR within CH and the newer HTR application expanding the utilisation to handwritten materials. This is a benefit for researchers both gaining access to more source materials and because of technological advances, the vast amounts of digitised materials can, in turn, be utilised to improve LLMs, as mentioned above. Some exceptions to the text-based projects that emerged were the postcard project and a future project of content managing videos, such as news programs stored at KB, in addition to the exhibitions at the National Museum of Science and Technology. This highlights both the usefulness and the broader benefit of image and audio recognition for metadata extraction and advanced searchability imperative to CH. Moreover, it points to the width of potential applications across collections and material types stored at CHIs. It would, therefore, be interesting to study more projects within CH that make use of AI in these contexts, one example being the recently presented porcelain identification project at Rörstands Museum, which aims to be in place in early 2024.

6.1.1. Prospective Implementations

In terms of prospective ways to utilise AI in Swedish CHIs, the analysis (see Section 5.1.) highlighted various objectives that can be grouped together as ‘automated tasks’. Examples included indexing, metadata extraction and enrichment, summaries and keyword extraction. Implementing AI to assist with automated tasks might make work more effective in terms of
time and qualified staff being freed up for other tasks. Tasks like these are often
time-consuming, not least due to the sheer amount of materials that are to be processed, and
affected by subjective interpretations of individuals that may change over time. As such, AI
might provide more long-term consistency for indexing and keyword extraction. AI is also
suitable for finding patterns that can be hard for humans to perceive, further expanding upon
the value of the collections, not least for digital humanities research (see Section 3.1.1.). It is,
however, important to consider transparency in algorithmic processes. We conclude that the
suggestion of incorporating paradata early in the practice could be a significant step towards
achieving this transparency. Thus, institutions would not be reactive to advances but would
have proper documentation throughout the process.

Additionally, AI as a tool can be part of a solution for some of the ethical issues in CH,
for example, sensitive content and personal information, as suggested by Colavizza et al.
(2021). One project of automated pseudonymisation presented by the National Language Bank
of Sweden supports this notion and suggests that some potential uses of AI in this regard are
being explored. AI and NLP could assist in identifying sensitive content and possible breaches
of GDPR in the vast amounts of collections more efficiently than any human could. Content
warnings could be automatically added to these materials and flagged for manual assessment
before publication. Pseudonymisation, for example, replacements of names and text
redactions, would be a possible action for AI to pursue. This has the potential to free up staff; in
addition, it could speed up digitisation and publication of sensitive materials as well as act as a
safety net catching data that might otherwise have been hard to identify.

As accessibility of collections is identified as a prioritised argument for AI adoption,
linked data emerges as an adjacent concept. For internal purposes, an issue that surfaced is a
disconnect between current systems, which can be problematic with respect to linked data.
Consequently, to achieve this, a comprehensive approach must be taken. It would be
reasonable to assume that future projects and practices will aim at linking not only internal
collections but external resources as well, as discussed in Section 5.1.1. Furthermore, it seems
logical that it would transcend the different institutional boundaries (addressed in Section 3.1.)
and assume a more holistic approach to the Swedish CH at large. From the analysis, the
benefits of linked data were primarily highlighted from the perspective of digital humanities
research, but it could also be utilised for preservation purposes and public access. It should,
thus, be argued that libraries, archives, museums and other CH institutions come together to
collectively face future challenges and potentials that technological advances, and AI in
particular, bring.
In the context of experiencing CH, for example, in exhibitions or interface design, AI provides the possibility to personalise how people interact with collections and information (see Section 5.1.3.). This can have multiple meanings, meeting the range of user preferences to user needs. It may allow people to experience CH on their own terms, making it a valuable addition for individuals with special needs and disabilities. In conclusion, it could add new value to the CH and change current IPs in unexpected ways.

6.2. Second Research Question

RQ2. What implications for long-term sustainability and relevance for said technologies can be discerned regarding socio-technological entanglement and cultural heritage materials?

In the empirical data, respondents repeatedly highlight the need for sustainable access to resources to further their current ability to implement AI technologies. Successful implementation relies on financial support, expertise, and the infrastructure to do so, as discussed in Section 5.2. Digitisation is one of the primary hindrances to long-term strategies, which supports the conclusions by Griffin et al. (2023) that Sweden is lagging behind in comparison to other European countries and that there is a lack of understanding of the opportunities of AI on a governmental level. The analysis suggests a deep socio-technical relationship concerning CH, with digitisation providing additional values and opportunities for interaction with the materials. The CH sector seems in agreement that additional investments must be made from a governmental level to achieve this and that the matter is urgent. It might also be important from beyond a preservation standpoint to improve LLMs and AI, as suggested in the interviews. The vast collections at Swedish CHIs are a good source for high-quality datasets that span centuries and a range of text types that can be utilised, for example, as training data. Subsequently, improvements in the training of LLMs make for better performance in models, which leads to more potential applications (see Section 5.1.2.). It could also make the financial investments into AI more justifiable as higher performance would, in a way, pay for itself.

AI technologies are in a phase of primarily testing rather than implementation, focusing little on the aspect of long-term maintenance. Keeping a short-term perspective of pilot projects, exhibitions, and so forth might make it more difficult to integrate these into the current IT environment cohesively, subsequently causing further fragmentation. Even if it provides insights and experiences, internal competition for resources may arise without clear
visions and boundaries. It can, therefore, be argued that a steady supply of the necessary resources would increase productivity and enable institutions to do more than currently possible. This aligns with the arguments made regarding insufficient finances limiting progress by Evens and Hauttekeete (2011) and Summanen (2021). Three aspects of long-term sustainability are considered in this study: technical, financial and environmental. There is an emphasis on how AI changes the information infrastructures of CHIs and pushes the boundaries of their internal structures. AI places new demands on CHIs, which cannot be met with current infrastructures (see Section 5.2.1.). Instead, as the analysis highlights, there is a need for a complete overhaul and modernisation of the IT environments to become cohesive and enable the implementation of AI.

Additionally, a second issue is sustainable access to the necessary computational power, with LLMs, in particular, being resource-heavy (see the environmental discussion in Section 5.5.3.). Two suggested methods going forward are to either minimise energy use or find long-term, reliable ways of accessing power to sustain expansion. As deduced by the state of LLMs in the media and from our responses, the development going forward supports the latter. At the moment, the preferred way to sustain LLMs is through access to supercomputers. Some speculate that Sweden will, in the near future, have their own supercomputer, which could simplify access to consistent computational power. However, a Swedish supercomputer is not a ‘magic’ solution to staffing and monetary resource problems, and it would be purely speculative who would own it and grant access to it, influencing the accessibility for CHIs.

Moreover, as suggested in Section 5.2.2., current funding structures might not be sufficient for necessary long-term financial security. The demands of AI need to be met with adequate and diverse expertise, achieved by both continuous competence development and new recruitment (see Section 5.2.3.). One remedy that surfaced during the interviews was to include researchers and students who possess up-to-date knowledge of technologies, which was also discussed in Section 3.2 as both possible and problematic. Thus, it can be surmised that various internal approaches and collaborations must be employed to ensure expertise. Furthermore, implementing AI subsequently leads to an expansion of current practices and more work in general, which necessitates more in-house staff at hand. Lastly, to further accessibility and reduce the ‘cost’ of effort in upgrading the institution to suit the technological landscape, open source software is a suggested way to develop their practices. The nature of open source, as it is used, developed and modified, enables experimentation with AI technologies (Birkinbine, 2020) without having to invest in development or licensing costs, thus potentially lessening the financial strain. Open source, by its adaptability, could enable
iterative feedback processes between users and developers that support the active development of technological practices of CHIs. Investments in open source also reinforce the transparency of data, which is a long-term ethical goal of CHIs.

6.2.1. Networking

With a decentralised approach to software development, open source might facilitate collaborations across sectors. As it stands from the discussion in Section 5.4., we believe it is clear that larger institutions collaborate to an extent through formal and informal communications in an attempt to mitigate redundancy by complementing each other's work while striving for a common goal. Despite efforts at networking, the assembly of information and training data is dispersed on the level of counties, municipalities or even village records. This lack of synergy is expressed to exist for both institutions and their technological systems where old and new can conflict; see, for example, the discussion by Kann-Rasmussen et al. (2019) and Summanen (2021) in Section 3.1.2. To rectify this, some respondents call for clear standards to be enforced, which could also aid networking and convergence of organisations by providing set formats, storage solutions and AI strategies for long-term sustainability and relevance. We argue that without enforced standards, the goal of a national CH infrastructure is lofty and could further problematise the process.

The environmental cost of technology should be included in the institution’s guidelines and standards. Environmental concerns as a sustainability issue are seemingly more theoretical within research than practically pertained to within institutions. While literature (e.g. DIGG, 2023; Crawford, 2021) highlights the negative environmental impact, such as unsustainable energy consumption, there seems to be a lack of institutional discussions regarding this. Consequently, the benefits seem to outweigh the costs (see Section 5.5.3.). For example, cloud services seem to be the preferred storage solution without acknowledged reasoning behind this decision. We believe this is a disadvantage to the debate; not reflecting upon and acting towards more environmentally friendly systems and practices throughout the process can potentially lead to long-term consequences both financially and ethically.

The analysis suggests that there is a certain zeal around AI and a knowledge of the need for digitalisation due to rapid technological advancement. Ostensibly, several group formations that concern AI have been formed, but to cite one respondent, “there is much talk but little action”. We find this problematic as it could cause uncertainties regarding both guidelines and implementation. With somewhat unclear distinctions between the groups (as suggested in Section 5.4.), overlapping or contradicting aims may occur. In addition, with
staffing resources already limited, pressure to participate in these groups could challenge resources further and reduce the time allotted to experimentation.

In conclusion, AI can meet a range of needs within Swedish CH as well as create new opportunities. However, for implementation to be successful, a holistic approach should be taken and should be consolidated on a national level. First, institutions might benefit from internally establishing clear guidelines and practices with a long-term perspective in mind. Well-defined parameters could assist with consistency and lowering the threshold of experimentation. In addition, the CH sector should come together, as suggested by Kann-Rasmussen et al. (2019) and Summanen (2021), to work across institutional boundaries to mitigate conflicting expectations and practices, thus ensuring the benefits of linked data. Collaborations ensure a unified view of and joint work with the Swedish CH. This study suggests a national strategy for the Swedish CH, in accordance with Griffin et al. (2023), in terms of preservation, accessibility and the new dimensionality that comes with socio-technical entanglement, which could greatly benefit the sector. The strategy should consider and make use of advances in technology, not least AI, to best utilise the limited resources and area expertise.

6.3. Trustworthiness of this Study

The authors have been conscientious in obtaining the trustworthiness of this thesis, as it is crucial for its integrity. Trustworthiness is established through explanations of the performed process (Pratt et al., 2022). It is used as a means to impart validity while reflecting the choices made to mitigate bias and ensure credibility. In this thesis, every step of the process is presented and argued for, as well as ethical concerns such as confidentiality and informed consent, as described in Chapter 4. Moreover, reflexivity to assess any researcher bias was continuously performed by evaluating the methodological choices and the steps of the interview process. For example, personal relationships with and interests in the institutions were reflected upon. While one of the authors worked at a participating institution, they had no previous insight into either the project or familiarity with the respondents. This is important to disclose as it imparts credibility to the study, according to Salmons (2014). Due to the ‘berry-picking’ approach to finding relevant projects, keeping an open mind for what to find or the directions taken during the entire process was necessary. For example, regarding finding new respondents throughout the process, but also to be able to get back to early respondents with follow-up questions that emerged during later interviews to gain additional information and context.
Additionally, the analysis and concluding discussion are performed in accordance with the three criteria to establish trustworthiness presented by Pratt et al. (2022): competence, integrity, and benevolence. To ensure competence, the analytical tactics were assessed – in this instance, the bricolage method was adhered to in an effort to best interpret the results of the interviews. While some approaches could be instantly dismissed for lack of suitability, the remaining tactics were tested with the collected data to ensure competent implementation. To establish integrity, it is essential to be cohesive throughout the study. Therefore, it has been our best effort to remain consistent, from formulating research questions to choosing methodological approaches and analytical tactics so that they are compatible. Benevolence refers to fidelity to the collected data, which in this case concerns translations (Section 4.3.), feedback from respondents (Section 4.1.1.) and connecting theories and insights gained from the interviews (Chapter 6). The authors of this thesis have, as such, taken measures to ensure trustworthiness through transparency, mitigating bias and validating results.

6.4. Suggestions for Future Research

This study explores AI adoption in Swedish CHIs from a perspective of IP and socio-technical entanglement. The identified research gap, as presented in the problem statement, indicates a need for studies from various perspectives. As such, the following suggestions are made for future research. First, an in-depth comparison of work practices associated with their adoption and use of AI technologies could be performed in CHIs. It would require a higher degree of implementation in the sector or focus on initial changes during adoption. This would tie into the discussion on IPs and sociomateriality. Second, it could prove valuable to perform a systematic literature review on this topic’s current research landscape within Sweden and globally and compare what is being studied to what organisations are actually implementing. This could reveal discrepancies between the CH sector and the research community, which could prove informative. Lastly, a comparative study on work with AI technologies at the Nordic National Libraries could provide interesting insights into their respective approaches. Differences in practices could be mapped out, and potential collaborations across the libraries and participation in international networks could be explored in more detail. As the Nordic languages are all considered small, low-resource languages, the development and continuous management of their respective monolingual LLMs could be studied and tested. This might yield informative data for improvements and identify both hindrances and solutions.
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8. **Appendix A - Interview Guide**

- **Information Practices**
  - Internal Utilization
  - Identified Changes
  - Internal Discussions
  - Possibilities Going Forward

- **AI in Cultural Heritage**
  - Utilization
  - Hindrances
  - Collaborations
  - Ongoing Projects

- **Implications and Future Use**
  - Advances in LLMs/AI
  - Ethical Concerns and Guidelines
  - The Role of the Institution
  - Risks of AI Integration

- **Long-term Sustainability**
  - Technical
  - Financial
  - Resources
  - Guidelines and Laws
  - Environmental Impact