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EXPLORING THE ROLE OF DATA LITERACY FRAMEWORKS IN WORKFORCE SKILL ASSESSMENT, EDUCATION, AND TRAINING

Systematic Literature Review

Master's Thesis
Faculty of Management and Business
Examiner: University Lecturer Anu Suominen
Examiner: Professor Marko Seppänen
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ABSTRACT

Paula Mäkinen: Exploring the Role of Data Literacy Frameworks in Workforce Skill Assessment, Education, and Training: Systematic Literature Review
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In today's fast-paced digital work environments, data has become an indispensable component of various business professions. Being data literate is now an essential skill, as the rapid expansion of digital technologies and the generation of large amounts of data have transformed the required skill set of employees and the educational objectives of organisations. Additionally, the impact of AI transforming working environments is evident but still emerging.

This thesis explores Data Literacy (DL) as a phenomenon, the reasons for its emergence, evolution, and proliferation, and its relevance in European policy, academic research, and business operations. It also examines how DL is being operationalised in educational and organisational settings. This thesis provides a holistic view of the DL-related frameworks for enhancing workforce skills assessment, education, and training to better understand the concept of DL and its relevance in organisational and business contexts.

Through semi-structured interviews and a rigorous systematic literature review, the thesis explores the alignment between DL-related frameworks and organisational needs for a data-literate workforce. The study identifies key principles inherent in these frameworks – such as multifaceted skill set, tailored training programmes, empowerment through DL, and the relevance of AI literacy – that align with organisational needs and priorities. These principles are valuable in guiding the development of robust DL programmes to reskill and upskill employees, emphasising technical knowledge, critical thinking, ethical awareness, and agility.

The thesis recognises a gap in current DL frameworks' ability to capture the nuanced skill sets required in professional settings, particularly in estimating the emerging needs of AI-technology integration in working environments. The thesis proposes the conceptualisation of Workplace Data Literacy (WDL), focusing on the specific empowerment experience from mastering data-related tasks and addressing the skill gap prevalent in the business domain. The anticipated influence of AI on workforce dynamics underscores the need to re-evaluate and expand current DL frameworks to include AI literacy. By integrating AI literacy into the development of WDL, the thesis aims to bridge the gap between existing theoretical concepts and practical applications, ensuring DL frameworks remain relevant and robust amidst technological advancements.

This research contributes to the knowledge management and organisational management literature by proposing a forward-looking perspective on DL in organisational contexts. It advocates for a comprehensive approach to cultivating a data-literate workforce capable of navigating the complexities of data and human-machine interaction.

Keywords: Data literacy, information literacy, AI literacy, framework, business, organisation, review, systematic literature review

The originality of this thesis has been checked using the Turnitin OriginalityCheck service.

TIIVISTELMÄ

Paula Mäkinen: Datalukutaidon viitekehysten merkitys työntekijöiden taitojen arvioinnissa ja kouluttamisessa: Systemaattinen kirjallisuuskatsaus
Diplomityö
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Nykyisissä nopeasti kehittyvissä digitaalisissa työympäristöissä, data on välttämätön osa monien yritysten työntekijöiden työnkuvia. Datalukutaito on olennaista, koska digitaalisten teknologioiden nopea leviäminen ja suurten datamäärien tuottaminen ovat muuttaneet työntekijöiltä edellytettäviä työskentelytaitoja ja organisaatioiden koulutustavoitteita. Lisäksi tekoälyn vaikutus työskentely-ympäristöjen muuttumiseen on ilmeinen, vaikkakin vasta kehittymässä.

Tämä työ tutkii datalukutaitoa ilmiönä, käsitteen syntymistä, kehittymistä ja leviämistä sekä sen merkityksellisyyttä eurooppalaisessa koulutuspolitiikassa, akateemisessa tutkimuksessa ja yritysten liiketoiminnassa yleisesti. Se tarkastelee myös, miten datalukutaidon käsitettä on sovellettu koulutussektorilla ja liiketoiminnassa. Työ muodostaa kokonaisvaltaisen näkemyksen sellaisista datalukutaitoläheisistä viitekehyksistä, jotka liittyvät työntekijöiden taitojen määrittämiseen, arviointiin tai kouluttamiseen yrityksissä. Työn tavoitteena on luoda kokonaisvaltainen ymmärrys datalukutaidosta käsitteenä ja sen merkityksestä yrityskontekstissa.

Puolistrukturoitujen haastattelujen ja kattavan systemaattisen kirjallisuuskatsauksen avulla diplomityö selvittää, miten datalukutaitoon läheisesti liittyvät viitekehykset vastaavat organisaatioiden tarpeisiin datalukutaitoisen työvoiman kouluttamiseksi. Tutkimus tunnistaa viitekehyksistä keskeisiä periaatteita – kuten monipuoliset taidot, räätälöidyt koulutusohjelmat, voimaantuminen ja tekoälyn lukutaidon merkitys – jotka ovat yhteneväisiä organisaatioiden tarpeiden ja prioriteettien kanssa. Nämä periaatteet ovat arvokkaita ohjenuoria kehitettäessä kattavia työntekijöiden taitoja päivittäviä ja lisääviä datalukutaidon koulutusohjelmia, jotka painottavat teknistä osaamista, kriittistä ajattelua, eettisiä periaatteita ja ketteryyttä.

Diplomityö tunnistaa nykyisissä datalukutaitoon liittyvissä viitekehyksissä puutteita niiden kyvyssä kattaa työympäristöille oleelliset monipuoliset taidot ja erityisesti tekoälyteknologioiden omaksumisesta nousevat tarpeet. Työssä ehdotetaan uuden käsitteen, työpaikan datalukutaito, käyttöönottoa. Sen tulisi keskittyä työntekijöiden voimaannuttamiskokemuksen synnyttämiseen auttamalla työntekijöitä suorittamaan dataliitännäisiä työtehtäviä sekä kuromaan umpeen vallitsevia taitovajeita. Myös tekoälyn käytön yleistymisellä on työntekijöihin vaikutuksia, jotka korostavat tarvetta arvioida uudelleen datalukutaidon käsitettä ja siihen liittyviä viitekehyksiä. Tekoälylukutaidon yhdistäminen datalukutaitoon uuden, työpaikan datalukutaito -käsitteen alle, pyrkii kaventamaan teoreettisten käsitteiden ja käytännön tarpeiden välistä kuilua, varmistaen datalukutaitokäsitteen pysyvän teknologioiden kehittyessä tulevaisuudessakin merkityksellisenä ja sisällöltään oikeanlaisena.

Tämä diplomityö edistää tietojohtamisen ja organisaatioiden johtamisen tutkimusta tarjoamalla proaktiivisen näkökulman datalukutaidon kehittämiseen yrityksissä. Työ kannustaa kokonaisvaltaiseen lähestymistapaan, joka auttaa kasvattamaan datalukutaitoisia työntekijöitä, jotka kykenevät työskentelemään monimutkaisissa dataan liittyvissä työympäristöissä ja hallitsevat vuorovaikutuksen koneiden kanssa.

Avainsanat: Datalukutaito, informaatiolukutaito, tekoälylukutaito, viitekehys, liiketoiminta, organisaatio, yritys, kirjallisuuskatsaus, systemaattinen kirjallisuuskatsaus

Tämän julkaisun alkuperäisyys on tarkastettu Turnitin OriginalityCheck –ohjelmalla.

PREFACE

As I present this thesis, I reflect with deep gratitude on the journey that brought me here. Dreams, as they say, are made to be fulfilled, and this work is a testament to that timeless truth.

First and foremost, I would like to express my deepest gratitude to my thesis supervisors. Anu Suominen, your guidance and support have been excellent during the writing process. Your advice has made the learning process really enjoyable and fruitful. Professor Marko Seppänen, I am grateful for all your comments and thoughts.

Secondly, I want to thank Professor Juho Hamari for his patience and great support, being always ready to answer my basic questions when conducting the systematic literature review. You have inspired me to pursue excellence with integrity and passion.

I am also grateful to my employer for granting me the opportunity to take a study leave, which has been invaluable in completing this thesis.

To my dear husband and children, who have made this journey much smoother – this thesis is as much yours as it is mine. Your belief in my dreams and encouragement allowed me to pursue this goal with a clear mind and a full heart. I am thankful for both the quiet moments and the loud cheers you shared with me along the way.

I would also like to honour the memory of my parents. Though you are no longer with me, Your values and dreams continue to live on through me. This is especially for you, Mom, who hoped to educate yourself but could not due to post-war poverty.

To everyone who supported me – siblings, peers and friends – who have provided their advice, lent an ear, and celebrated each small victory. I am profoundly thankful. Your support and encouragement have helped me achieve this dream and taught me the value of community and collaboration.

Thank you for being part of my dream and making this possible.

Ulvila, 15 April 2024

Paula Mäkinen

USE OF ARTIFICIAL INTELLIGENCE IN THE THESIS

My thesis has utilised artificial intelligence applications:

☐ No
☒ Yes

According to my declaration, I have used the following artificial intelligence applications during the thesis process:

ChatGPT 3.5 and 4.0

Grammarly v1.2.72.1368

Purpose of use:

I have utilised ChatGPT as a personal mentor throughout the thesis process. This involved engaging in discussions about the content and structure of my thesis and seeking ideas on how to enhance my work. ChatGPT served as an interactive tool to brainstorm, refine ideas, and clarify complex concepts, which greatly assisted in shaping the final output. I also created a custom GPT model using Open AI’s GPT builder, specifically designed to assist with conducting the literature review with PRISMA methodology.

I used ChatGPT to extract specific information directly from documents, such as methodologies, key findings, and specific content relevant to my study. Despite extracting this information, I consistently undertook thorough checks of all extracted data myself to ensure its relevance and accuracy.

I employed Grammarly to ensure the text's clarity, correctness, and coherence throughout my thesis. This tool helped to refine the grammar, punctuation, and style of my writing, which enhanced the readability of the thesis.

Sections where AI has been used:

ChatGPT and Grammarly were employed throughout the thesis.

I am aware that I am fully responsible for the entire content of my thesis, including parts produced with artificial intelligence, and I accept responsibility for any violations of publication ethical standards.

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LIST OF SYMBOLS AND ABBREVIATIONS

AI	Artificial Intelligence
AIL	Artificial Intelligence Literacy
BI	Business Intelligence
DGL	Digital Literacy
DigComp	Digital Competence Framework for Citizens
DIKW	Data-Information-Knowledge-Wisdom
DL	Data literacy
ICT	Information and Communication Technology
IL	Information Literacy
MLL	Machine Learning Literacy
NU	Numeracy
ODI	Open Data Institute
PPADC	Problem Plan Data Analysis Conclusion
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SL	Statistical Literacy
SLR	Systematic Literature Review
UNESCO	The Constitution of the United Nations Educational, Scientific and Cultural Organisation

1. INTRODUCTION AND MOTIVATION

This chapter serves as the foundation of the thesis, providing an essential background of the chosen topic and its context. The focus is on how data literacy has growing importance in today’s data-intensive business world. Giving background is crucial for understanding the research that follows. This chapter introduces the gap in knowledge about how data literacy frameworks align with workforce education and assessment. The reason for studying this topic and the key research questions guiding this inquiry are also presented. This sets the groundwork for the following chapters, each building upon the understanding established here.

1.1 Background of the Research

For centuries, good reading and writing skills have formed the foundation of all learning, enabled individuals to participate in societal activities, and given opportunities to the literate far exceeding those available to the illiterate (Frank et al., 2016). Without literacy skills, it is nearly impossible to navigate the modern world, making it a fundamental necessity that provides individuals and societies with the opportunity to succeed. It is an essential prerequisite for acquiring new knowledge. Across academic disciplines, extensive research has been conducted for decades to explore different aspects of literacy education (Tierney & Pearson, 2021). One literacy dimension that's gaining importance is Data Literacy (DL) (Koltay, 2015). DL is crucial for decision-making in data-reliant businesses and requires skills to understand, analyse, and interpret data. It is essential for organisations to educate their workforce in these skills.

The concept of DL is a relatively recent development compared to the broader notion of literacy. Scholarly articles in the early 2000s, such as those by Gray (2005), Hunt (2005), and Schield (2005), first introduced the concept within the field of knowledge management. This was particularly relevant to topics such as information literacy and statistical literacy. DL has become more popular in the last decade due to the rapid increase in data availability and lower data management costs. A literature review conducted by Ghodoosi et al. (2023) on DL education argues that focusing on organisations and their need for support in strategic decision-making helped distinguish the concept of DL from statistical literacy and information literacy.

There is no unequivocal and universally accepted definition of DL, as definitions vary across different sources (Frank et al., 2016; Sternkopf & Mueller, 2018; Wolff et al., 2016). With DL still needing to be more settled, researchers and business developers use slightly different definitions depending on the discipline. However, DL can generally be understood as a learning process enabling the ability to read, recognise, understand, and communicate data as meaningful information. In the absence of DL, data is reduced to a collection of structural or non-structural information that lacks any significant meaning. That is why it is essential for individuals to possess the skills and knowledge required to interpret and analyse data in order to draw meaningful insights and make informed decisions. Organisations cannot use data effectively to achieve their goals or improve performance if the workforce lacks these skills. Therefore, a focus on developing DL is essential in today's business environments.

A recent literature review on the evaluation of DL (Cui et al., 2023) found that the domains of DL education and assessment are constantly evolving, and a pressing need exists for effective and reliable tools to assess DL. Furthermore, Wolf et al. (2016) argue in their study that current definitions of DL are not entirely appropriate as they do not consider the various roles individuals need to apply their DL skills. Without a clear definition, assessing DL is also challenging.

In the literature review conducted by Cui et al.(2023), studies related to the assessment of DL are categorised into two main groups focusing on different target populations. The first category includes studies that assess the DL of students and citizens. These studies predominantly emphasise various educational contexts, mainly due to the growing recognition of DL as an essential general skill in a data-driven society. The second category includes studies assessing the DL of knowledge workers and, more broadly, all workforces. Most studies in the second category focused on assessing the DL of knowledge workers. In the literature review, researchers (Cui et al., 2023) identified 25 documents between 2012 and 2021 that belonged to either of the abovementioned categories, with most of the documents falling into the first category. The limited studies found on DL assessment indicate that this research area is still emerging and developing. Furthermore, based on Cui et al.'s (2023) review, it can be noted that most of the examined assessment tools did not focus on tool development or validation, which may hinder the utilisation of DL assessment tools.

The work of Gummer et al. (2015) sheds light on a crucial aspect to consider in achieving a comprehensive understanding of DL. The authors place particular emphasis on an individual's values, identity, and epistemology in relation to data usage for teaching. This highlights the need also to assess the behavioural component of DL. The evolution and transformation of literacy and numeracy necessitate the development of DL in the workforce. DL skills are increasingly becoming a fundamental requirement for success in today's business landscape. Considering the limited studies on assessing DL in workforce contexts despite its growing recognition, it is imperative to cultivate DL among the workforce. This indicates a research area that requires further exploration.

1.2 Problem Description

With an understanding of DL's evolution and increasing significance, it is possible to turn to a critical gap in the field: the alignment of DL-related frameworks with the workforce and their needs. The purpose of this study is to provide a linkage between DL-related frameworks and skills assessment and education, a crucial step toward developing appropriate assessment models or training methods for the business workforce. The research journey ahead involves a twofold approach.

Firstly, to better understand the specific challenges and opportunities related to the research focus, semi-structured interviews will be conducted. These interviews aim to capture in-depth insights from practitioners in the field. Secondly, a Systematic Literature Review (SLR) will be conducted to critically analyse existing frameworks. This will help identify the necessary features to consider when evaluating DL skills, specifically in the context of workforce competence development. This dual approach provides a path toward a more data-literate workforce, blending academic rigour with practical relevance.

1.3 Motivation

To achieve the objective presented, it is crucial to explore the motivation driving the study, which will focus on understanding the components needed for advancing workforce skills in the data-rich digital environment. Enhancing DL skills in the workforce is probably a crucial part of the future competence development programmes in organisations, where data and its added value usage are vital for operational and strategic business success. The trend of DL becoming a requisite for all domains is increasingly apparent.

This SLR thesis, which includes empirical interviews, aims to explore the role of DL frameworks in assessing and educating workforce skills. To successfully incorporate DL programmes into development plans, organisations must understand and identify the necessary requirements to establish a culture of DL. This involves understanding both technical skills and human behaviour when working with data. It is essential for employees to possess the skills and knowledge needed to manage and utilise data effectively for any organisation. Promoting a culture of DL empowers the workforce and creates a more efficient and productive workplace. This ultimately allows organisations to achieve optimal value from their data assets and remain competitive. This study aims to present research findings that provide a comprehensive and informative foundation for organisations to understand how to enhance DL in the workforce.

1.4 Research Question and Limitations

This study aims to answer the following research question: "How can existing frameworks assist in developing workforce DL programmes and evaluating DL?" This overarching question is further dissected into five sub-questions to facilitate a comprehensive exploration of the research topic:

1. Which principles are most frequently emphasised in academic frameworks related to DL, and how do they align with organisational priorities in workforce development?
2. In what ways can these principles be operationalised into training practices and assessment methodologies within organisations?
3. What reported outcomes have these education and assessment programmes achieved in meeting organisational objectives?
4. How effectively do metrics from these frameworks address the identified skill gaps in the business domain?
5. How might the widespread integration of AI transform DL frameworks and their role in workforce reskilling initiatives?

Although this research has set out to provide a comprehensive overview of its subject, it is important to acknowledge that there are limitations that need to be considered. This thesis presents the following limitations:

- To maintain a manageable volume of literature, the thesis' theory section focuses mainly on literature published between 2010 and 2023. After completing the theoretical part, the SLR will be conducted without any time limitations.
- Throughout the research, the thesis will rely on DL-related studies that are accessible at the time. It's noticeable that as DL is a broad and evolving concept, new frameworks, models, or modifications to existing ones may become accessible. It's possible that the conclusions of this study may not remain applicable in the future if these advancements aren't considered. Additionally, limitations related to databases accessed, keywords used, or language constraints can affect

the comprehensiveness of this thesis. Missing key publications or relying on a limited set of databases can mean that this thesis is not fully representative or comprehensive, leading to gaps in knowledge or understanding.

- As DL is an interdisciplinary concept that is still emerging, the significance of certain aspects of it may shift over time. Changes in technology, pedagogy, or societal needs can shift the focus or understanding of the term DL over time. One example is the development of artificial intelligence (AI), which can impact DL dimensions related to workforce needs. It is crucial for organisations to continuously monitor and adapt to changes to ensure their workforce is reskilled with data fluency through continuous education.
- The results of some studies explored in this thesis may only be applicable in specific contexts and may not be generalisable to other situations or populations. Therefore, it is important to understand the context in which a study is conducted and to be cautious in applying its results to other situations without further investigation.
- Although the author aims to maintain objectivity when evaluating literature and findings, personal biases or interpretations can unintentionally influence the process.

The thesis is a combination of a SLR and semi-structured qualitative interviews. The empirical interviews provide insights from the real world and facilitate a more in-depth exploration of the topic. The thesis explores the concept of DL, first in theory and subsequently by presenting a systematic review of existing literature following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) workflow. This methodology adopted for the thesis is designed to enable a thorough and comprehensive understanding of the field while identifying existing gaps in research. Having established the research questions and acknowledged the study’s limitations, it is possible to outline the structure of this thesis, guiding the reader through the forthcoming chapters and their respective focus areas.

1.5 Structure of the Thesis

The thesis follows a structured format consisting of several chapters. The opening chapter sets the foundation for exploring DL in the workforce. It introduces the research question and objectives of the study and outlines the motivation for investigating the chosen topic. In Chapter 2, the theoretical background of the topic is constructed in detail, examining historical developments and key definitions. This background provides the context necessary to understand the DL-related frameworks discussed later and their relevance to workforce development. Chapter 3 details the methodologies employed in the thesis, including semi-structured interviews and a systematic literature review. The methods chosen are integral to gathering the data needed to answer the research question, especially in understanding how DL-related frameworks can be applied in real-world settings. This chapter is valuable for comprehending research methodology and contributes to scientific credibility.

Chapter 4 presents, analyses, and synthesises the data collected from interviews and SLR. This chapter is central to answering the research questions set for the SLR, as it directly addresses how current DL-related frameworks are being, or could be, used to develop and assess DL skills in the workforce. This chapter is also crucial in synthesising the results gained from the SLR and interviews.

Chapter 5 concludes the thesis by presenting the main research results that answer the main research question and sub-questions. It also introduces the study's implications. In the subsequent section, the discussion focuses on what the research tells when considering the overall data in this thesis. Finally, the conclusion section summarises the key points of the study, providing readers with a clear understanding of what was achieved and why it is significant.

2. DATA LITERACY AS A CONCEPT

DL is crucial in today's world and involves both data culture creation and individual willingness and ability to understand and utilise data in the organisational context. The subject has gained growing attention across various sectors, including academia, the policy sector, and business. This chapter explores the meaning of data, information, and literacies and the multifaceted nature of DL, including its emergence, its relationship to the digital revolution, its evolution as a phenomenon through research articles and European policy, and its relevance in a business setting. The primary objective of this chapter is to extract literature that directly addresses the concept of DL. By using precise terminology, the search ensures that the retrieved articles are closely related to the topic, thereby maintaining the relevance and specificity of the literature. Narrowing the search string also ensures a manageable volume of articles and a replicable review process. It helps to trace the historical evolution of the term and understand how its definition, application, and significance have changed over time.

2.1 Data and Literacies

The concept of DL consists of two distinct terms, namely 'data' and 'literacy'. To gain a comprehensive understanding of these terms, it is beneficial first to examine them separately and gain insight into their respective meanings and how they interconnect within the context of DL.

The Data-Information-Knowledge-Wisdom (DIKW) hierarchy (Ackoff, 1989; Rowley, 2007) represents a commonly adopted approach for describing levels of abstraction in information processing. This hierarchy outlines the progression of data from its raw, unprocessed state to useful knowledge that can be leveraged for decision-making purposes. Information is built upon the foundation of data. Data consists of raw and unprocessed facts and figures that act as the fundamental building blocks of knowledge. Typically, data lacks context or meaning and appears as isolated pieces of information, such as numbers, words, or symbols, that do not convey any message on their own. Examples of data include individual temperature readings, fluctuating stock prices, or individual words in a book.

Information is a crucial component of our daily lives. It is the result of processing and organising data, which gives it context and meaning. Data on its own can be overwhelming and difficult to comprehend. However, when data is transformed into information, it becomes more understandable and provides answers to questions like “who”, “what”, “where”, and “when” (Ackoff, 1989). Information conveys a message or knowledge about a particular topic, such as trends and patterns. It adds context to data, making it useful for decision-making and understanding the world around us. (Rowley, 2007, pp. 171–172)

Weather forecasts, news articles, and graphs depicting stock price trends over time are all examples of information. Weather forecasts provide us with information about the expected weather conditions in a particular area at a specific time. News articles provide us with information about current events and happenings around the world. Graphs depicting stock price trends can help us understand market patterns and make informed investment decisions. In summary, information is a processed form of data that is organised and structured to provide context and meaning. It is an essential tool for decision-making and understanding the world in which we live (Rowley, 2007, pp. 171–172).

Knowledge represents a sophisticated level of comprehension and discernment that goes beyond the mere acquisition of information. It is the fruit of a further process in which information is organised, contextualised, and synthesized in such a way that it leads to insights and a deeper understanding. Knowledge not only informs the individual about a given topic but also provides guidance on how to effectively use that insight to attain specific goals or address problems. It can involve the integration of information from various sources, the identification of patterns, and the ability to draw meaningful conclusions. For example, knowledge can be illustrated by the ability to diagnose and repair a technical issue on a mobile phone based on a comprehensive understanding of error messages and system behaviour. With knowledge, one can make sound decisions and take decisive action. (Rowley, 2007, pp. 172–174)

Wisdom lies at the highest level of the DIKW hierarchy. It denotes the ability to make informed judgments and decisions based on experience and knowledge while taking into consideration moral values, ethical considerations, and a deep understanding of the broader context. Wisdom goes beyond mere knowledge by answering the ‘why’ question and discerning the long-term implications of actions. It involves making informed choices that are not only beneficial but also considerate of the greater good. Wisdom is often acquired through reflection, experience, and a holistic view of complex situations. For example, wise decisions benefit both an organisation's short-term profitability and long-term sustainability. (Ackoff, 1989; Rowley, 2007, p. 174)

It can be concluded that the DIKW model is a representation of the progression from raw data to information, knowledge, and, finally, wisdom. Each level of the model is built upon the previous one, with wisdom being the highest level of cognitive and ethical development in the pursuit of better decision-making and understanding of various aspects of life and knowledge domains. The DIKW model is a well-known framework that finds its application in diverse fields such as business, academia, and technology. It is usually illustrated in the form of a diagram, as shown in Figure 1, which helps to understand the hierarchy of information processing, from raw data to valuable insights. (Rowley, 2007)

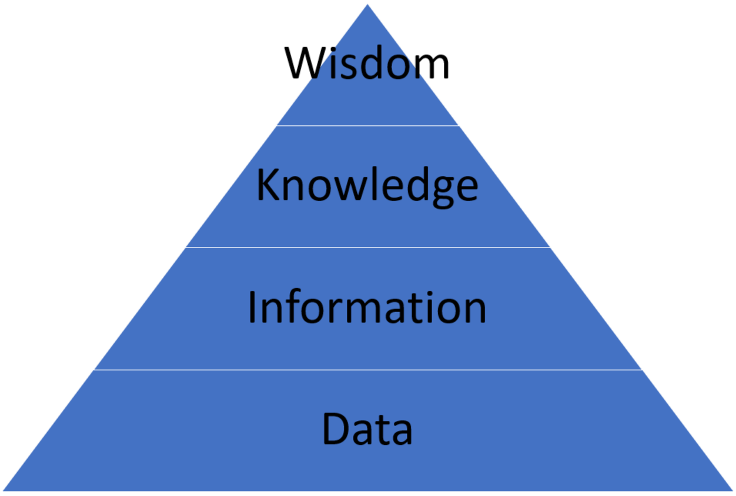


Figure 1. *DIKW hierarchy (Rowley, 2007)*

In today's world, comprehending data is crucial. The DIKW model is a useful tool for understanding the various levels of knowledge one can attain. It is a hierarchical framework that describes the transformation of raw data into wisdom. It is more about the conceptual progression of understanding. In this way, the model is closely linked to the concept of DL, which is a skill set or competency enabling individuals to effectively work with data and derive valuable insights from it. DL is about an individual's ability to work effectively with data at various levels. While the DIKW model provides a theoretical structure for understanding the relationship between data, information, knowledge, and wisdom, DL is about practical abilities in handling and making sense of data. Both concepts can be stated as being integral to academia and research, especially in fields that heavily rely on data.

Understanding and being able to utilise data to gain information and knowledge is crucial in the current digital era. However, it's equally important to recognise the significant role of literacy and numeracy in this process. Peters et al. (2006) elucidate the term **numeracy** as "the ability to process basic probability and numerical concepts". Their series of four studies demonstrated that an individual's numerical proficiency affects their ability to make well-informed decisions, whereas decision-makers with low numeracy skills are left with incomplete and poorly understood information. The scope of numeracy typically includes understanding numerical data, performing calculations, interpreting mathematical information, and applying mathematical techniques to solve problems in everyday life. Numeracy can be seen as a foundational component of DL. In work, this means, for example, the ability to do budgeting or measuring.

The term **literacy** has evolved over time. Historically, it was linked to literature and meant the ability to read. Later, it began to signify the possession of general necessary skills, competencies, and knowledge (Livingstone et al., 2014, p. 2). In the past, literacy was a well-defined concept often associated with the implications of its opposite, illiteracy. Illiteracy was connected to poverty, lack of access to knowledge, and economic stagnancy (Buschman, 2009). Over time, libraries and librarians have played a pivotal role in promoting good reading material to the public. However, the digital era has challenged traditional notions of literacy, expanding and diversifying the concept with new literacies and changing their meaning (Livingstone et al., 2014). Next, new and some older forms of literacy will be introduced and briefly explained.

With the advent of new communication and information technologies, people need to develop a set of skills and knowledge to operate them effectively. These skills and knowledge are often referred to as literacy. **Information literacy** means “the ability to identify, locate, evaluate, organise and effectively create, use and communicate information to address issues and problems at hand” (Livingstone et al., 2014, p. 4). With the rise of social media and collaborative online communities, Mackey and Jacobson (2011) argued that information should encompass not only finding and evaluating information but also producing and sharing it in participatory digital environments.

Statistical literacy is a key component in understanding a vast amount of information (Schield, 2005). The ability to interpret and analyse statistical data is crucial in numerous business and academic settings. Therefore, comprehending statistical concepts is essential for developing a strong foundation, for example, in data analysis. According to Wallman (1993, p. 1), statistical literacy is “the ability to understand and critically evaluate statistical results that permeate our daily lives – coupled with the ability to appreciate the contributions that statistical thinking can make in public and private, professional and personal decisions.”

Defined by the Center for Media Literacy, **media literacy** involves the ability “to access, analyse, evaluate, create and participate using messages in a variety of forms”. This definition highlights the importance of understanding, comprehending, critiquing, and creating media materials. In today's rapidly evolving technological landscape, it is crucial for individuals to possess lifelong learning skills that enable them to adapt to changes in the information environment. (Livingstone et al., 2014)

The Council of the European Union officially adopted the key competencies for lifelong learning in May 2018. These competencies were first identified in 2006 and have since been revised. The Digital Competence Framework is a set of skills that enables individuals to confidently, critically, and responsibly engage with digital technologies for learning, work, and society. (Council of the European Union, 2018) This framework can be considered as the definition of **digital literacy**. Paul Gilster defines digital literacy as the ability to access networked computer resources and use them. It encompasses both accessing and using digital resources, with an emphasis on making informed judgments about online content (Mackey & Jacobson, 2011). According to UNESCO (2018) digital literacy is “the ability to access, manage, understand, integrate, communicate, evaluate and create information safely and appropriately through digital technologies for employment, decent jobs and entrepreneurship. It includes competencies that are variously referred to as computer literacy, ICT literacy, information literacy and media literacy.”

Our world is increasingly saturated with visual content, making **visual literacy** a crucial skill. It involves not only the ability to understand and analyse visual information but also the capability to create and communicate ideas through various digital media. Visual literacy enables us to appreciate the significance of visual communication and its impact on our daily lives.(Mackey & Jacobson, 2011)

Computational literacy and computational thinking are two phrases that are often used interchangeably and are often seen as technical literacy. Computational literacy is a crucial skill in the modern world, encompassing the ability to use computational thinking to solve problems and make informed decisions. It involves an understanding of the various computational techniques available, as well as their limitations and potential uses. This skill set goes beyond the ability to perform mathematical calculations manually, recognising that computers are now the primary tool for such tasks. Being computationally literate means being able to leverage technology to its fullest potential in order to achieve desired outcomes. (Grover & Pea, 2013; Wikipedia, 2023)

The concept of DL is also linked with that of **scientific literacy**, a term that has been in use since the pre-1950s. At the time, the focus was on inductive reasoning, observing natural phenomena, and drawing conclusions based on empirical evidence. Over time, this concept has evolved to encompass not only a basic understanding of scientific concepts but also a broader comprehension of how scientific knowledge can be applied in everyday life and the ability to make informed decisions based on that understanding. (DeBoer, 2000)

The proliferation of generative AI and large language models has, in a very short time, demonstrated the need for **AI literacy** in a variety of contexts. This need has stemmed from the fact that AI is now being used in various applications across different industries, and it is essential for individuals to possess proficiency to interact effectively with and understand AI-driven technology. Long and Magerko (2020) define AI literacy as “a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace.” A robust understanding of its foundational principles, with a particular emphasis on aspects related to data quality and machine learning issues, is invaluable in this thesis context. Therefore, the importance of AI literacy and its competencies overlapping with DL competencies in today’s world cannot be overstated in this thesis. (Long & Magerko, 2020; Ng et al., 2021; Olari & Romeike, 2021)

Based on the contents explained in this subchapter, the DIKW hierarchy is a useful tool that helps us understand how raw data can be turned into meaningful insights. In today's digital age, literacy has expanded to include a wide range of essential skills that are necessary to navigate the information landscape effectively. Each type of literacy emphasises the importance of comprehending, interpreting, and utilising data, resources, or information in a meaningful way. The combination of ‘data literacy’ provides us with the ability to make informed decisions in our increasingly data-driven world. The close connection between data and literacy highlights the importance of DL as a crucial skill for anyone who wants to succeed in an information-rich environment.

2.2 Data Literacy as a Trending Topic

To gain a comprehensive understanding of the term ‘data literacy’, it is useful to first explore its prevalence as a potentially popular topic on a global scale, as well as its frequency within relevant academic literature and subject areas. According to Google Trends data from the past decade, with worldwide, all categories and web search parameters, there has been a significant increase in the use of this term. The most substantial growth has occurred in the last five years, as shown in Figure 2 on the following page. This development course suggests promising opportunities for continued growth and positive advancement in this area of study.

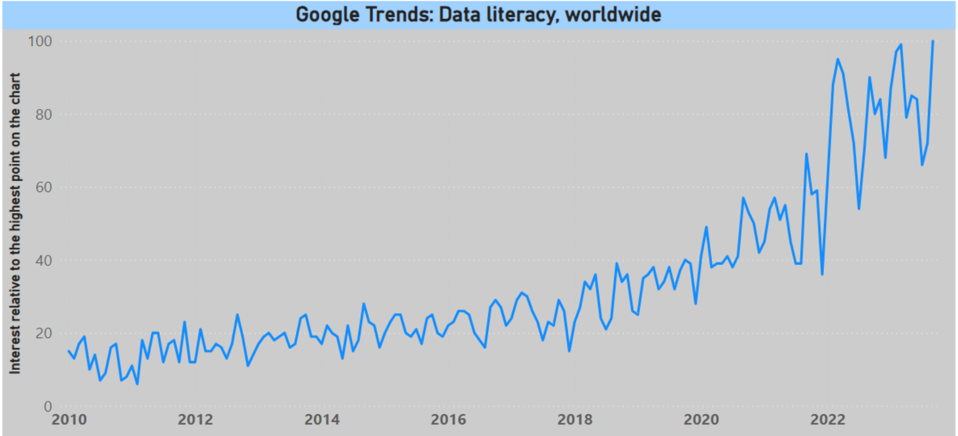


Figure 2. *The popularity of the term 'data literacy' in Google Trends from 2010 onwards*

To ensure an unbiased analysis, the timeline is extended to the year when Google Trends data first became available. The inspection Figure 3 displays the Google Trends data on DL over an expanded timeline starting from the year 2004, when Google Trends was introduced. Figure 3 indicates varying levels of interest in DL over time. In the early 2000s, there was a growing awareness regarding the importance of data. The initial spikes in interest could be attributed to the early recognition of the potential of data-driven insights by academics, researchers, and businesses. This could include experts in computer science, information technology, and business analytics, and coincide with key conferences or seminal publications that brought attention to the importance of DL.

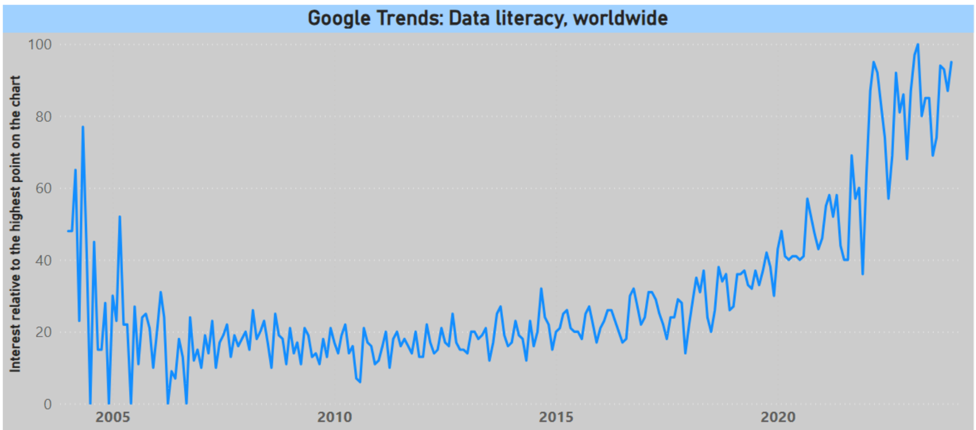
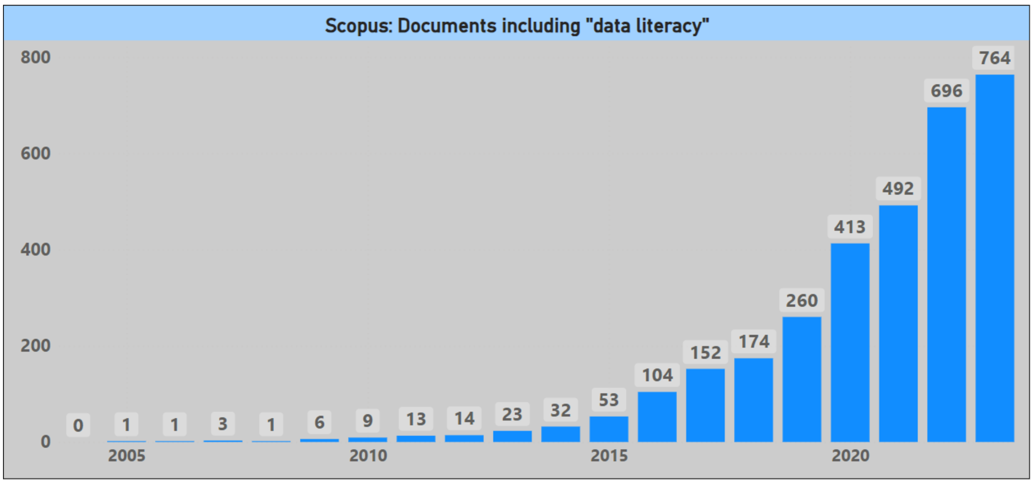
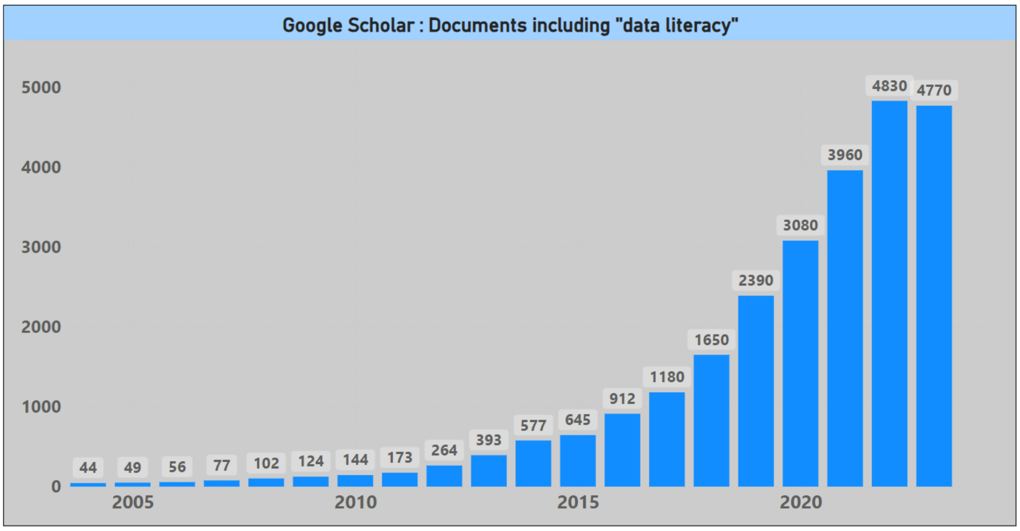


Figure 3. *The popularity of the term 'data literacy' in Google Trends from 2004 onwards*

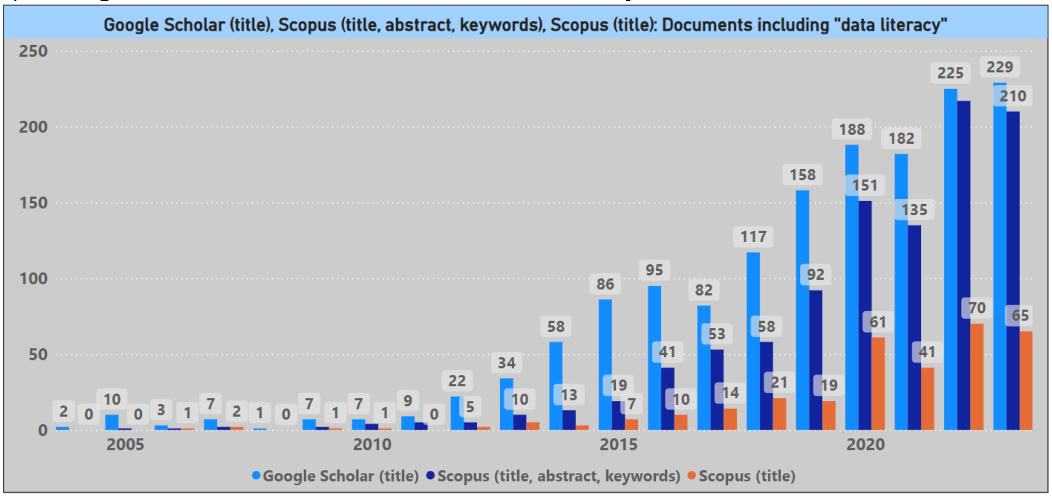
Conducting a thorough analysis of the term 'data literacy' across Elsevier's abstract and citation databases Scopus and Google Scholar with the timeline of 2004-2023 shows an increasing trend of DL as an interesting future topic in the search results for both broad and specific searches in Figure 4 on the next page. The figure includes three graphs that showcase the number of document outcomes of various searches.



a) *Scopus search with the term "data literacy"*



b) *Google Scholar search with the term "data literacy"*



c) *Narrow searches of document titles in Scopus and Google Scholar and title-abstract-keywords in Scopus*

Figure 4. *Documents in Google Scholar and Scopus, including the term "data literacy" between 2004-2023 (a-c)*

Taking a broader look at the Scopus search results for ‘data literacy’ with no time limitation achieves a total of 3215 unique documents. Out of all the documents, only one is from 1956, while all the others were published in 2005 or later. Limiting the term’s search string to title-abstract-key and having no time limitation, the total number of documents is diminished to 1020, but replicating the same as with a broader search, one document from 1956 and all the rest from 2005 or thereafter. Based on the analysis, it can be concluded that the figure presented earlier, i.e. Figure 4, provides an accurate representation of the evolution of the term 'data literacy' in academic research. Furthermore, the assumptions established when examining Figure 3 can also be confirmed, indicating that the term's evolution and first recognitions emerged in the mid-2000s.

Figure 5 illustrates the distribution of 1020 documents across different subject areas. Several documents can be categorised under multiple subject areas, leading to a cumulative count that exceeds the actual number of unique documents. Therefore, while the figure provides valuable insights into the distribution across disciplines, overlaps exist in categorisation. Findings reveal that social sciences and computer sciences comprise slightly over 60% of the total documents discovered. The subsequent 20% of documents, making up nearly a total of 80%, consist of engineering; business, management, and accounting; mathematics and arts and humanities, with each subject area comprising between 4 to 7 % of the total share. The remaining 20% is attributed to various subject areas, each representing less than 4% of the total document count. These results demonstrate that the term ‘data literacy’ possesses a solid multidisciplinary character, potentially leading to a wide-ranging proliferation in its definition.

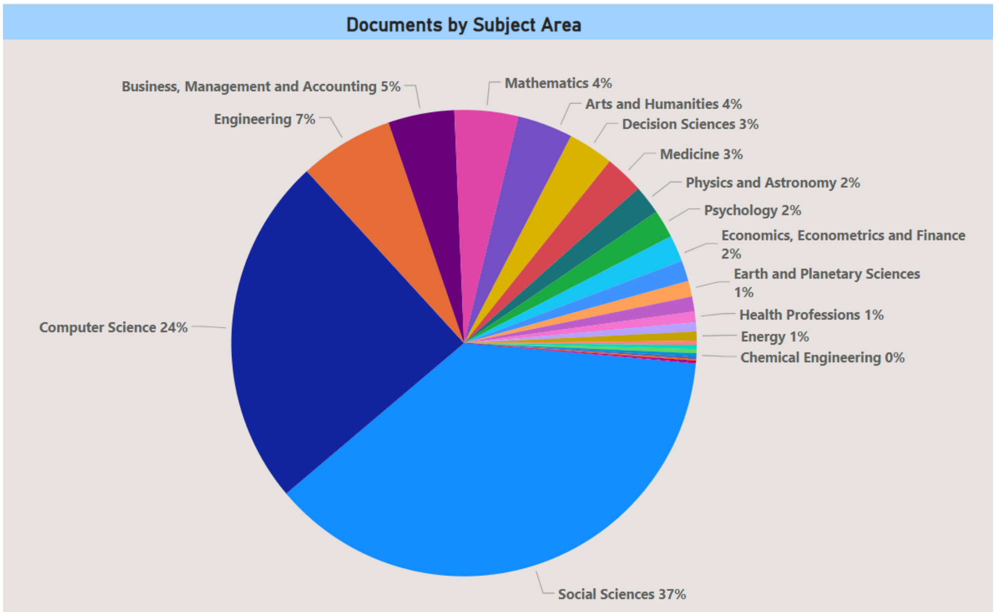


Figure 5. *Data literacy documents by subject area in Scopus*

In order to meet the future needs of the business, management, and accounting field, Figure 5 highlights the importance of further academic research. In the past, accessing and understanding data has posed a challenge for employees requiring experts to capture, model, visualise and interpret it. As a result, computer science and social sciences have led the way in research, with educators and researchers integrating DL concepts into curricula and pedagogical practices. However, the emergence of generative AI tools means that organisations and individuals will be able to easily ask questions, for example, about data patterns or anomalies, transforming every level of the workforce into a ‘data person’. This rapid shift in the data and analytics workflow also incentivises organisations to reskill their workforce with DL and adapt to new ways of working and managing business.

2.3 Digital Revolution: Proliferation and Technological Catalysts

To understand the pivotal role of DL, it is important to explore its historical evolution and how it has become a cornerstone in modern information education and business. This will be achieved by first discussing the proliferation of data and the technological catalysts behind it in this subchapter and then by conducting a detailed analysis of the historical evolution of DL in European policy in subchapter 2.4. and in academics in subchapter 2.5.

The emergence of Web 2.0 in the early 2000s marked a novel moment in the development and utilisation of the World Wide Web. Its impact on the formation of new literacies cannot be overstated. It offered users totally new possibilities to communicate, share information, interact, and collaborate, and it took only a little time for researchers to acknowledge the possibilities of education through technology and, for example, games. New literacies are tied to new technologies and to culture, which means that dimensions of literacy have broadened, and the ability to become and remain literate requires long-term commitment, usually identified as lifelong learning. (Koltay et al., 2015, p. 70)

Social media platforms and mobile technology have revolutionised the way people interact and communicate with each other. These advancements have given rise to new and innovative forms of engagement and collaboration that were previously unimaginable. As a result, businesses and organisations have had to adapt to these changes to remain competitive and relevant in today's digital landscape. The impact of these changes has been profound and will continue to shape the need for DL skills among students, professionals, and citizens. According to Pangrazio and Sefton-Green (2022, p. 1), datafication is the process of transforming personal actions and behaviours into data that can be organised, analysed, and monetised by both private companies and governments. The effects of datafication are far-reaching, ranging from positive outcomes such as increased efficiency and valuable insights to more concerning issues surrounding privacy, ethics, and fairness. Data has become a valuable commodity in the digital age. (Rydenfelt, 2024, pp. 18–19)

In recent years, there has been a growing recognition of the need to enhance citizens' digital competence, especially regarding datafication and exploring its various components. It is now widely acknowledged that DL, being a part of digital competence, is not exclusive to scientists alone but rather an essential skill for everyone to possess (Degbelo et al., 2016; Gould, 2017). This shift in mindset has also highlighted the significance of personal DL. Individuals must be equipped to approach their personal data critically, comprehend it, and feel confident while handling it. This approach, known as critical literacies, intends to empower individuals to take charge within the data framework (Pangrazio & Selwyn, 2019). Additionally, more attention is being given to what digital and DL signifies to citizens in the era of information manipulation and what factors should be considered while designing literacy programmes (Carmi et al., 2020).

In Slavkovic's (2023) research, two key factors were examined in relation to digital citizenship: information and DL, as well as information security management. The study aimed to explore how digital capabilities and digital citizenship impact digital transformation. A conceptual model was proposed and tested, which included the mediating role of digital citizenship. The analysis revealed that digital capabilities have a vital role in promoting information and DL alongside information security management. More specifically, the study highlights that digital competencies have a positive and significant impact on the aforementioned domains. These results underscore the importance of equipping individuals and organisations with the necessary digital skills and knowledge to navigate the digital landscape.

The advancement of technology has had significant implications for data science and for the attempts to define DL. With the capability to store vast amounts of information in condensed digital formats, data has become more easily accessible and shareable. Additionally, the definition of data has broadened to encompass not only structured but also unstructured data, which presents new challenges but also opportunities for utilisation in diverse fields. Phrases such as open data, public data, and big data have been deployed (Christozov & Toleva-Stoimenova, 2015; Lee, 2019; Okamoto, 2017; Sander, 2020; Tang et al., 2019) in many domains. Also, citizen or customer-generated data and citizens and customers themselves are recognised as valuable resources for different stakeholders, as discussed earlier, and it is important to understand and make use of such data (Chan et al., 2016).

In recent years, there has been remarkable progress in technology that has transformed the way devices communicate with each other. This has led to the development of automation and data exchange in manufacturing technologies, known as Industrial Revolution 4.0. To work with these digital technologies, the workforce needs to possess the ability to understand, interpret, and use data produced by these devices to make informed decisions. The Internet of Things (IoT) has simplified the interaction and data storage of different devices on a massive scale (Collin & Saarelainen, 2016). As a result, there is now an increased demand for technical development in data analysis, machine learning, and visualisation. This has led to the creation of more user-friendly data analytics platforms (Batt et al., 2020) that make data accessible even to non-technical users.

Businesses have confronted the continuous need to leverage new technologies and be able to scale their operations effectively, making various decisions concerning on-premises hardware and infrastructure, cloud migration, and platform solutions. Numerous organisations are grappling with technical indebtedness and data silos that have arisen from their initial digital transformation initiatives. Considering this, these organisations are now realising the need to modify their data collection methods to take advantage of the disruptive potential of AI. This recognition comes in the wake of the realisation that traditional data collection methods are no longer adequate to support the demands of modern businesses and organisations. As such, organisations are exploring innovative solutions to capitalise on the potential benefits of AI while minimising the risks associated with this transformative technology. (Vashishta, 2023, pp. 15–24)

As automation and digital technologies, together with AI disruption, become increasingly prevalent, it is crucial for the workforce to be reskilled in order to be comfortable with data. With advancements such as 5G connectivity, secure blockchain transactions, biotechnology, cybersecurity, quantum computing, and sustainable technology, it is essential for working professionals to stay up-to-date with the latest capabilities of transforming data into profit in order to remain competitive in their respective fields. (Dufva, 2020)

As data is now seen as a novel asset in organisations, the ability to effectively work with data is a noticeable divide, particularly in non-technical fields. To bridge this gap, D'Ignazio (2017) has introduced the concept of creative DL and outlined five tactics to cultivate it. These tactics include working with community-centred data, writing data biographies, embracing messy data, creating learner-centred tools, and prioritising creative, community-centred outputs. By applying these tactics, individuals can lay the foundation for a data-driven mindset and become proficient in articulating information through data. The article's tactics, collectively referred to as creative DL, emphasise a more humanistic and holistic approach to data skills, highlighting the importance of understanding the human stories and contexts behind the numbers. This is crucial, as there has been a lack of focus on developing the humanistic skills necessary to interpret, analyse data, verbalise, and solve problems with data (Saddiqa et al., 2019).

The challenges of teaching data to new learners, especially those from non-technical backgrounds, need to be considered more profoundly. D'Ignazio and Bhargava (2018) propose novel approaches for teaching data visualisation, emphasising the need for creative DL and suggesting design principles and activities that embody the concept of creative DL. This approach aims to democratise DL and make it accessible to a broader audience, thereby bridging the gap between technical experts and the general population in the understanding and use of data for storytelling and social change.

In a world of technology and data, it's important to be able to manage the amount of information we receive. Information overload can make it difficult to process information effectively. This is also an important part of being literate in data and understanding how it affects us as humans (Koltay, 2017b). While DL equips individuals with the skills to navigate and make sense of vast amounts of data, the sheer volume and complexity of data in today's business environment can lead to perceived data overload. This overload, in turn, can result in cognitive challenges, potentially impacting individual performance. Giudice and Macada (2021) found in their research that DL can act as a buffer, helping individuals manage and make sense of the data, thereby reducing the negative impacts of data overload.

To summarise, in the digital age, the rise of Web 2.0 has transformed the way we interact with each other online and how much data is possible to store and analyse. This shift has given rise to datafication, where machines and our everyday actions are turned into data, and the need to understand, analyse, and get actionable information has rapidly increased. As a result, DL has become a critical skill for success in the modern digital era. With the Internet of Things (IoT) and other technological advancements, the amount of data available will only continue to grow. In today's fast-paced world of technology, the ability to effectively process and utilise data is crucial. Understanding and interpreting data related to these environments is vital for making informed decisions. DL goes beyond just technical skills; it's also about skills related to comprehending the stories, origins, and implications behind the data, critical thinking, ethical considerations, open and innovative mindset, and lifelong learning. However, the abundance of information also presents challenges, such as information overload, which can cloud judgment and decision-making. A more human-centric approach to understanding data is necessary to ensure that individuals become informed participants in the digital age. As our world has become more data-driven, DL is an essential tool for navigating, interpreting, and thriving in this digital ecosystem where data and AI are leading a wave of new solutions.

2.4 Data Literacy in European Policy

The aim of this chapter is to explore the origins and evolution of the European digital competence framework with the intention of understanding the connection how it relates to DL. It also examines the significance of information and data literacy within this framework, to gain a better understanding of their prevalence in the digital world.

In 2006, the European Parliament and Council identified key skills for lifelong learning, such as communication, math and science knowledge, digital literacy, social and civic skills, entrepreneurship, and cultural awareness. In 2010, the 10-year digital agenda for Europe recognised the importance of information and communication technology (ICT) in helping Europe achieve its objectives. The European Commission has since maintained its focus on digital competence through several policies, actions, and communications.(European Commission, 2010a; European Commission, 2010b; European Parliament and the Council, 2006)

The key competencies for lifelong learning, initially identified in 2006 and subsequently revised, were officially adopted by the Council of the European Union in May 2018. Those competencies emphasised the importance of a combination of knowledge (i.e., concepts and facts), skills (the ability to carry out processes), and attitudes (e.g., a disposition, a mindset to act) to meet the demands of the contemporary world. Specifically, there are eight key competencies that have been identified as crucial for success today: literacy competence, multilingual competence, mathematical competence and competence in science, technology, and engineering, digital competence, personal, social and learning to learn competence, citizenship competence, entrepreneurship competence, cultural awareness, and expression competence.(Council of the European Union, 2018)

The ability to engage with digital technologies confidently, critically, and responsibly for learning, work, and society is known as the digital competence framework. This encompasses several areas such as information and **DL**, communication and collaboration, media literacy, digital content creation (including programming), safety (including digital well-being and cybersecurity), intellectual property, problem-solving, and critical thinking.(Council of the European Union, 2018)

2.4.1 Policy Evolution of Digital Competence Framework

The Digital Competence Framework for Citizens, also known by its acronym DigComp, is a crucial tool for promoting a common understanding of digital competence in the European Union. It has played a significant role in shaping digital skills policy, providing a framework for development, and enabling the evaluation of digital competence. DigComp is widely recognised across the EU as the primary standard for digital competence development and assessment. DigComp was established in December 2010 by the Joint Research Centre on behalf of the Directorate General for Education and Culture. DigComp 1.0 was published in 2013, and it identified digital competence as a blend of 21 competencies that fall under five primary categories: information, communication and collaboration, content creation, safety, and problem-solving.(Ferrari, 2013)

Ferrari and colleagues (2013) provided a comprehensive explanation of the DigComp 1.0 framework. Though Table 1 presents a condensed view of dimensions 1 and 2, which suffice for the purpose of this thesis, the official report provides further insights into these domains.

Table 1. *Overview of dimensions 1 and 2 (Ferrari, 2013)*

Dimension 1 Competence areas	**Dimension 2** Competences
1. Information	1.1 Browsing, searching and filtering information 1.2 Evaluating information 1.3 Storing and retrieving information
2. Communication	2.1 Interacting through technologies 2.2 Sharing information and content 2.3 Engaging in online citizenship 2.4 Collaborating through digital channels 2.5 Netiquette 2.6 Managing digital identity
3. Content creation	3.1 Developing content 3.2 Integrating and re-elaborating 3.3 Copyright and licences 3.4 Programming
4. Safety	4.1 Protecting devices 4.2 Protecting personal data 4.3 Protecting health 4.4 Protecting the environment
5. Problem solving	5.1 Solving technical problems 5.2 Identifying needs and technological responses 5.3 Innovating and creatively using technology 5.4 Identifying digital competence gaps

The report's principal aim was to propose a strategy that facilitates the effective utilisation and advancement of the DigComp framework and its descriptors for learners at all levels. Moreover, it established a shared vocabulary for identifying and detailing the key areas of digital competence, hence providing a consistent benchmark on a European level.

From the beginning, DigComp was utilised for various purposes, with a particular focus on employment, education, training, and lifelong learning. However, as society continued to rapidly digitise, new demands emerged, leading to the development of DigComp. In 2016, phase 1 of the updated conceptual reference model, DigComp 2.0, was introduced (Vuorikari et al., 2016). Although the overall structure of the five competence areas remained the same, improvements were made to the terminology and competence descriptors used. Notably, as illustrated in Table 2, the competence area of 'information' was expanded to include 'data literacy', reflecting the increasing importance of this skillset in light of new information visualisation tools and the growing availability of data. By doing so, DigComp made the connection between information literacy and its framework more visible and explicit, encompassing the main components of Information Literacy and part of Media Literacy from UNESCO's (2011, 2013) work.

Table 2. *Comparison of competence areas and competencies in versions 1 and 2 (Vuorikari et al., 2016)*

	Competence areas version 1.0	Competence areas version 2.0
Inter-related areas with overlapping points and cross-references	1. Information	1. Information and data literacy
	2. Communication	2. Communication and collaboration
	3. Content creation	3. Digital content creation
Cross-cutting across all areas	4. Safety	4. Safety
	5. Problem solving	5. Problem solving

Version 1.0	
Dimension 1 Competence areas	Dimension 2 Competences
1. Information	1.1 Browsing, searching and filtering information 1.2 Evaluating information 1.3 Storing and retrieving information

Version 2.0	
Dimension 1 Competence areas	Dimension 2 Competences
1. Information and data literacy	1.1 Browsing, searching and filtering data, information and digital content 1.2 Evaluating data, information and digital content 1.3 Managing data, information and digital content

In summary, Table 2 outlines the model development and modifications of competence areas conducted by Vuorikari et al. (2016) and changes in dimensions 1 and 2 in more detail. It's essential to recognise that the division of areas and competencies is somewhat arbitrary, resulting in numerous overlaps and cross-references across areas. Furthermore, it's worth highlighting that the DigComp framework is descriptive in nature rather than prescriptive.

After completing phase 1, the implementation of DigComp 2.1 began, which aimed to further develop the initial three proficiency levels in dimension 3 (foundation, intermediate, and advanced) by providing a more detailed eight-level description and practical examples of their use. This phase's objective was to assist stakeholders in further implementing DigComp (Carretero et al., 2017), developing learning and training materials, designing instruments to assess citizens' competence, and promoting career guidance and growth. To gain competence, the process is divided into three areas in Table 3 on the next page: the complexity of tasks, the level of guidance needed for completing them, and the cognitive domain indicated by action verbs.

To demonstrate the development of competency, one can characterise a level 2 citizen as capable of remembering and completing basic tasks related to the competency with the assistance of a digitally competent individual only when guidance is needed. Conversely, a level 5 citizen can proficiently apply their knowledge to tackle diverse tasks and solve complex problems. Furthermore, they can provide support to others in the completion of such tasks. Each level descriptor encompasses a comprehensive set of knowledge, skills, and attitudes, culminating in a total of 168 descriptors. This equates to 8 levels, with each level comprising 21 learning outcomes.

The most recent update of DigComp 2.2 was released in 2022, with a focus on over 250 new examples (dimension 4 and 5) of knowledge, skills, and attitudes that are relevant to each proficiency level, enabling individuals to confidently, critically, and safely engage with digital technologies, including those powered by artificial intelligence (Vuorikari et al., 2022). These examples do not represent a definitive list of learning outcomes that every citizen should achieve. However, they can serve as a starting point for creating clear and specific learning objectives, content, and assessment criteria. The DigComp framework aims to establish a shared comprehension of the skills required to tackle digitalisation challenges. It likewise promotes mutual understanding by utilising universally accepted terms that can be utilised consistently.

Table 3. *Main keywords that feature the proficiency levels (Vuorikari et al., 2022)*

Main keywords that feature the proficiency levels								
4 overall levels	**Foundation**		**Intermediate**		**Advanced**		**Highly specialised**	
8 granular levels	1	2	3	4	5	6	7	8
Complexity of tasks	Simple task	Simple task	Well-defined and routine tasks and straightfor-ward prob-lems	Tasks and well-defined and non-routine problems	Different tasks and problems	Most ap-propriate tasks	Resolve complex problems with limited solutions	Resolve complex problems with many interacting factors
Autonomy	With guidance	Autonomy and guid-ance when needed	On my own	Independent and accord-ing to my needs	Guiding others	Able to adapt to others in a complex context	Integrate to contribute to the pro-fessional practice and guide others	Propose new ideas and pro-cesses to the field
Cognitive domain	Remem-bering	Remem-bering	Understand-ing	Understand-ing	Applying	Applying	Creating	Creating

Figure 6 shows the different areas included in the digital competence framework for citizens related to dimension 1. The model helps people understand the digital skills they need to navigate the digital world effectively.

Figure 6. *The digital competence framework for citizens (Vuorikari et al., 2022, p. 67)*

In the most recent version of DigComp 2.2 (Vuorikari et al., 2022) , the definition of information and DL is outlined as follows:

Competence 1.1 of browsing, searching, and filtering data, information, and digital content:

- Competence to articulate information needs, to search for data, information, and content in digital environments, to access them, and to navigate between them. It is also the ability to create and update personal search strategies.

Competence 1.2 of evaluating data, information, and digital content:

- Competence to analyse, compare, and critically evaluate the credibility and reliability of sources of data, information, and digital content. To analyse, interpret, and critically evaluate the data, information, and digital content.

Competence 1.3. of managing data, information, and digital content:

- Competence to organise, store and retrieve data, information, and content in digital environments. Organise and process them in a structured environment.

The DigComp 2.2 update also shifts its focus towards citizens' interactions with AI systems rather than solely on knowledge about artificial intelligence. During the update process, the requirements gathering identified the following aspects related to citizens interacting with AI systems.:

KNOWLEDGE: To understand the benefits, limitations, and challenges of AI systems, it's important to know what they can and cannot do.

SKILLS: To interact with and provide feedback to AI systems as an end-user and to configure, supervise, and adapt AI systems by overwriting or tweaking them.

ATTITUDES: It is important to prioritise human agency and control, maintain a critical yet open attitude, and consider ethical implications when utilising technology.

To summarise, the DigComp 2.2 framework is a comprehensive approach to digital competence, and its first dimension emphasises the importance of both information literacy and DL in today's interconnected world. By integrating these two literacies, the framework recognises that mastering information navigation and data analytics is crucial for enhancing digital proficiency. This approach provides a comprehensive framework for developing digital skills alongside other dimensions. By promoting these literacy competencies across educational and professional settings, it is possible to create digital communities that are informed, skilled, and capable of making responsible decisions in a complex, data-rich environment. The DigComp 2.2. clearly outlines DL and its relevance, making the concept easily accessible and understandable.

2.4.2 The Adoption of DigComp in the Research Field

Academics have adopted the use of DigComp in their research, particularly in the assessment of digital competencies among teachers (Çebi et al., 2022; Fraile et al., 2018; Mannila et al., 2018) and students (Aruvee & Vintere, 2022; Heuling et al., 2021; López-Meneses et al., 2020; Martínez-Piñeiro et al., 2019; Muñoz-Repiso et al., 2019; Silva-Quiroz & Morales-Morgado, 2022; Zhao, Sánchez Gómez, et al., 2021) and monitoring progress in this field (Reisoğlu & Çebi, 2020). Additionally, there is a growing interest in measuring digital literacy across various age groups (Hernández-Martín et al., 2021; Jin et al., 2020; Oh et al., 2021) and studying its impact on professionals (Evangelinos & Holley, 2014; Kateryna et al., 2020; Zhu & Andersen, 2022). Some systematic reviews have also been conducted, including one focusing on digital literacy measurement among older adults (Oh et al., 2021), another comparing assessment instruments based on DigComp-related frameworks (Mattar et al., 2022), and one on empirical research regarding primary school students’ digital competencies (Godaert et al., 2022).

One interesting instance of DigComp being applied beyond Europe is Zhao et al.'s (2021) empirical investigation. The study sought to explore how in-service teachers in higher education perceive their own digital competence and how gender and years of teaching experience influence these perceptions. The researchers used the DigComp framework as a reference for assessing digital competence and found that the teachers generally viewed themselves positively in such areas as information and DL, communication and collaboration, security, and problem-solving. However, they rated less confident with their digital content creation skills. Male college teachers tended to rate their digital competence more highly than their female peers, and those with less teaching experience reported feeling more competent in areas such as communication and collaboration, digital content creation, security, and problem-solving.

The literature review conducted by Mattar et al.(2022) is of significant value to this thesis, which aims to explore the effects of DL frameworks on workforce education and the assessment of DL. Their research, which examines similar inquiries from a DigComp perspective, proves to be enlightening and informative, aiding in the planning of the systematic review process of this thesis. The article proposes a typology for designing and creating questionnaires to assess digital competences, consisting of four main categories that are not mutually exclusive: direct knowledge, self-assessment, scenarios, and performance. Direct knowledge involves straightforward questions that measure the level of digital competence based on answers. The self-assessment method is the most used and typically includes statements that request a self-assessment of digital competences (knowledge, skills, and attitudes) through Likert agreement scales. Scenarios involve presenting a case or scenario, followed by questions or statements used to self-assess the level of digital competence. Finally, performance involves assessing digital competence in a creative way for every competence measured.

Mattar and colleagues' 2022 article also discusses how to create effective digital competence assessment tools. Two types of validity are important: internal and external. The psychometric approach (focusing on internal validity) refers to how accurate and logical the tool is, while the pragmatic approach (focusing on external validity) refers to how useful it is for a larger audience. A pragmatic approach, which focuses on practicality and ease of use, may result in weaker internal validity but is more accessible to users who lack math or statistics training. On the other hand, the psychometric approach prioritises internal validity and scientific reliability but may be less user-friendly. According to Mattar et al., it is reasonable to expect an assessment tool for digital competence to strike a balance between these two approaches. Finally, the instruments analysed in their article served a dual purpose of assessing and providing feedback to professionals about their digital competencies, as well as collecting information for research. As a result, the collected data have been utilised for various outcomes, indicating a diverse range of frameworks referenced in their literature review.

2.4.3 Summary of the Policy Landscape of Data Literacy

The DigComp has played a crucial role in establishing a standardised understanding and evaluation of digital competence throughout the European Union. Introduced in 2010, this framework has evolved over time and now identifies five core areas of digital competencies: information and DL, communication and collaboration, digital content creation, safety, and problem-solving. The ongoing development of DigComp, culminating in the latest version, DigComp 2.2, demonstrates a flexible response to the rapidly evolving digital landscape, highlighting the growing importance of DL. In particular, the incorporation of ‘data literacy’ into the information competence area of DigComp 2.0 highlights the increasing significance of data-focused skills. This integration aligns with the international discourse on the development of information literacy and digital literacy led by organisations like UNESCO and the World Bank (Bashir & Miyamoto, 2020; UNESCO, 2011, 2013, 2018, 2023).

Knowing how to obtain, evaluate, and manage digital data and information is an important skill in today's world. The DigComp framework describes this skill as ‘information and data literacy.’ It involves expressing information needs, finding digital data and information, and assessing the accuracy and relevance of the source. It also includes the ability to handle digital data and information. DL is a wide-ranging skill that involves understanding, using, and creating content with digital tools. It is crucial for active participation in the digital world and helps people to identify reliable information and avoid misinformation.

Understanding different levels of digital proficiency, as outlined by DigComp, is imperative for both academic and real-world purposes. The DigComp framework outlines these levels and helps individuals improve their skills. Moreover, the framework is appropriate for professionals who are not specialists in information and communication technology. The latest update to DigComp includes examples of individual competencies in working with various AI systems and stresses new and increased literacy requirements, which are rapidly evolving with emerging technologies. DigComp provides a clear path toward digital literacy and proficiency, and ongoing improvement and use of such frameworks may be crucial. This shows how academic research, policy creation, and practical implementation can work together to create a digitally competent society.

2.5 Data Literacy in Academic Research

This chapter aims to explore the essence of DL and its existence in various fields by examining academic research related to DL from 2000 onwards. To establish a scholarly-based theoretical framework for this thesis, three aspects of DL will be examined. These include the evolution of DL and its definitions in educational contexts, DL in practice, and the exploration of organisational aspects and future implications, thereby broadening the horizon.

In Chapter 2.2, an analysis was conducted to explore the relevance of DL by analysing the search results obtained from Scopus and Google Scholar databases. The Scopus database yielded a total of 1020 results, which were exported to Zotero by subject area for the purpose of this chapter. The search results were sorted based on the highest number of citations and by subject area. Finally, they were thematically and chronologically grouped to be able to write this chapter in a meaningful way and with respect to timespan. Google Scholar search results were also used to supplement the findings by exploring the most frequently cited sources that were not found in Scopus but were cited in articles found in Scopus search.

2.5.1 Evolution and Definitions of Data Literacy

In the digital landscape, new terms and concepts can emerge faster than their comprehensive understanding. ‘Data literacy’ is one such that has gained prominence in recent years. To truly grasp its significance and application in contemporary contexts, it is crucial to delve into its definition and origin. By understanding where the term originates and how it has been defined, one can better appreciate its relevance and implication in today’s data-driven world.

The search conducted in the Scopus database revealed that the study of DL was initially focused on educational settings, leading to definitions, descriptions, or education efforts that were specific to those environments by the end of the first decade of the 2000s (Corti, 2005; Humphrey, 2005; Hunt, 2005; Jacobs et al., 2009; Qin & D’ignazio, 2010; Schield, 2005; Stephenson & Caravello, 2007). The proliferation of digital data, accessible first only to statistical professionals and librarians but later to a broader audience through websites and new technologies, has served as a catalyst for the emergence of DL as a broader phenomenon.

Early discussion and research on DL originated in the middle of the 2000s and are connected to other forms of literacy. Gray (2005) described statistical literacy as the primary focus when discussing an individual’s ability to think critically, interpret and evaluate data and statistics, and communicate insights about data. Schield (2005) argued that DL is an essential component of both information and statistical literacy and stated that evaluating information is crucial for data, statistical, and information literacy as they are interrelated and deal with similar problems. Schield further noted that students engaged in data analysis or statistics coursework need DL skills, but students in any major would benefit from having these skills. Schield defined DL as a student's ability "to access, manipulate, summarise and present data". Hunt (2005) noted that statistical literacy, quantitative reasoning or quantitative literacy, numeracy, and DL roughly mean the same thing and advocated for consistent language to persuade stakeholders. Also, questions about the baseline of competency and levels of competence required for statistical and DL were already being raised by Gray (2005) and Humphrey (2005).

Corti (2005) saw in her teaching DL project that adequate technical skills were important for students to reach the learning objects created. Gunter (2007) emphasised critical thinking and problem-solving skills together with technical skills when enhancing students' DL. Gunter noted that information literacy includes the concept of DL, whereas Stephenson and Caravello's research (2007) stated it is known as statistical literacy, quantitative literacy, or numeracy. Multifaceted DL lacked a comprehensive framework for several years until Mandinach and Gummer (2012) made an effort to address this issue in their white paper project. However, they encountered difficulties in formulating a formal and clear definition. Nevertheless, they were able to identify several knowledge and skill-based components that constitute DL in the educational context.

Mandinach and Gummer (2013) saw the urgent need for DL skills development to enhance data-driven decision-making skills in the education field and continued studying the subject and defined DL as the "ability to understand and use data effectively to inform decisions". Through continued research, Gummer and Mandinach (2015) introduced the initial conceptual framework for DL. This framework was based on a series of qualitative studies, including a cognitive approach identifying the fundamental knowledge and skills required for DL in teaching. The framework established a foundational structure consisting of six key components within the inquiry cycle. These components encompass "the identification of problems, the framing of questions, the utilisation of data, the transformation of data into information, the transformation of information into decisions, and the evaluation of outcomes".

A study conducted by Prado and Marzal (2013) explored definitions and competencies of DL and its integration into information literacy programmes. Their research identified two predominant trends: one highlights the correlation between DL and statistical literacy in the critical use of data, while the other emphasises the association between DL and data management. However, the researchers also noted that a common reference framework adaptable to the varied contexts and objectives associated with these competencies was absent, even though DL was seen as an essential competency in information literacy. As a result, they suggested a framework and formulated it under five instructional topics: “understanding data, finding and/or obtaining data, reading, interpreting, and evaluating data, managing data and using data”.

Throughout the 2010s, various definitions and terms have been introduced within academic discussions surrounding DL. However, the focus shifted away from information literacy, and the term DL started to establish its position alongside information literacy. Additionally, researchers have linked it to science data literacy (Qin & D’ignazio, 2010), research data literacy (Schneider, 2013), and data information literacy (Carlson et al., 2011). Koltay (2015) also examined the significance of DL in relation to other literacies and proposed the adoption of a definition by Prado and Marzal (2013) and suggested supplementing that with the viewpoint of Mandinach and Gummer (2013, p. 30) about DL as “the ability to understand and use data effectively to inform decisions”. Koltay argued that DL is a dynamic concept that requires a standardised language, given its developing nature. Koltay further highlighted that DL is comparable to information literacy in the need for unified terminology used and shares commonalities with various other literacies like statistical literacy, visual literacy, scientific literacy, media literacy, digital literacy, and metaliteracy.

In a comprehensive study conducted by Ridsdale et al., (2015, p. 2) researchers resulted in a more precise and hierarchical definition for DL: “Data literacy is the ability to collect, manage, evaluate, and apply data in a critical manner”. Experts emphasised adapting the definition of DL based on stakeholder input and that it is crucial to recognise DL as an essential civic skill. Bhargava and D’Ignazio (2015) also presented an extended definition of DL that builds upon earlier conceptualisations: “Ability to read, work with, analyse and argue with data. Reading data involves understanding what data is and what aspects of the world it represents. Working with data involves creating, acquiring, cleaning, and managing it. Analysing data involves filtering, sorting, aggregating, comparing, and performing other such analytic operations on it. Arguing with data involves using data to support a larger narrative intended to communicate some message to a particular audience.” The authors proposed that DL tools, available for work with data, should adopt a more pedagogical design approach. The tools should be focused, guided, inviting, and expandable, with an emphasis on being learner-centric instead of just user-centric.

According to Frank et al. (2016), “data literacy is a recent addition to a growing band of literacies such as numerical literacy, statistical literacy, and IT literacy”. The authors also noted research on DL has mainly focused on education and training, but this is changing due to the growing importance of open data. Although many countries have included basic statistics in their school curricula for decades, the challenge is to connect statistical literacy with DL and use these skills in a broader context. Crusoe (2016) had this kind of broader and holistic approach that underscored the importance of empowering individuals with the tools and knowledge to navigate the complex data-driven world, ensuring that they are not just passive consumers but active participants in the data discourse. Crusoe defined DL as “the knowledge of what data are, how they are collected, analysed, visualised and shared, and is the understanding of how data are applied for benefit or detriment, within the cultural context of security and privacy.”

Maybee and Zilinski (2015) aimed to advance the concept of DL and proposed a framework for data-informed learning in higher education. This framework highlights the use of data for learning and communication within disciplinary contexts. By combining elements of informed learning and generic DL models, the authors outlined principles and characteristics of data-informed learning and suggested future directions for investigating its real-world applications. Similarly, Bhargava et al. (2015) argued in a white paper that the concept of DL needed to be expanded upon. They suggested that the term ‘data literacy’ was insufficient, perpetuating pre-existing inequalities, and should instead be replaced by the broader concept of inclusion, which they conceptualised as “literacy in the age of data”. The authors argued that DL is intertwined with and builds upon all six fields of literacy, necessitating a blend of technical, critical, quantitative, and conceptual skills, as illustrated in Figure 7.

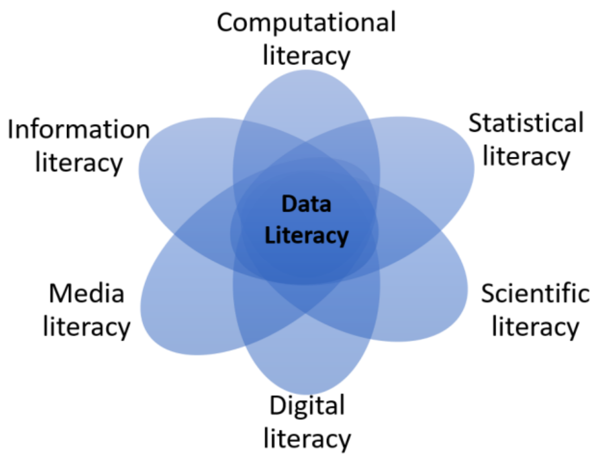


Figure 7. *Elaboration based on secondary sources (Bhargava, 2015, p. 9)*

In addition, Wolff et al. (2016) conducted an analysis of DL research literature with the aim of identifying shared characteristics among definitions and distinguishing it from the more explicitly defined field of statistical literacy. The authors argued that while there is some overlap with statistical literacy, DL encompasses a broader set of competencies.

They argued that it is essential to equip citizens with these competencies, starting with education in schools. Based on their research, they proposed a definition of DL that emphasises using an inquiry-based approach to understand real-world phenomena: “Data literacy is the ability to ask and answer real-world questions from large and small data sets through an inquiry process, with consideration of ethical use of data. It is based on core practical and creative skills, with the ability to extend knowledge of specialist data handling skills according to goals. These include the abilities to select, clean, analyse, visualise, critique, and interpret data, as well as to communicate stories from data and to use data as part of a design process”.

Frank et al. (2016) stated that Wolff (2016) and his team's research on DL has limitations. They suggested that instead of trying to create a comprehensive approach, it may be better to recognise that different situations require different kinds of DL. This means that one should think about different types of DL for different groups of people, like data producers, specialists, and regular users, rather than assuming that DL is a single concept. Also, Gray et al. (2018) argued that the definition of DL should be broadened to encompass more than just proficiency in reading and manipulating datasets. It should also include the capacity to comprehend, manage, and engage with the larger socio-technical frameworks that facilitate data creation, storage, and analysis. They called this more technical expanded concept ‘data infrastructure literacy’.

According to scholars Pangrazio and Sefton-Green (2020), DL should be considered separately from digital and media literacy. By acquiring these skill sets, individuals can better navigate a world that is heavily reliant on data. These scholars also argued that DL can serve as a safeguard against manipulation through datafication processes. Five years earlier, D'Ignazio and Bhargava (2015) discussed the emergence of the big data phenomenon, laying out their own definition of big DL, as discussed earlier. They stressed that big data is not just about mastering technical skills but also about gaining empowerment through the process of literacy. This includes proficiency in comprehending and operating machine-assisted algorithms. Francois et al. (2020) posited that big DL “is a wider concept than both statistical and mathematical literacy”, as it demands interdisciplinary abilities and competencies to enable critical and reflective citizenship.

Sander (2020) emphasised that DL should encompass more than just the ability to use data and proposed that the concept of extended critical big DL is at the core of this understanding, combining approaches from a variety of research fields like critical data studies, critical media literacy, critical digital literacy, and DL. According to Sander (2020), developing critical big DL aims to help users understand how their data is handled. This knowledge empowers individuals to analyse the practices of big data, assess evidence, form informed opinions on data analytics, and make informed decisions about sharing personal data and using services.

One can state and widely acknowledge that the academic community has devoted significant attention to exploring the educational aspects of DL, as discussed in this chapter. However, there remains a pressing need to implement this concept effectively across various domains. Sternkopf and Mueller (2018), for instance, emphasised that while DL is becoming increasingly important for various sectors, non-profit organisations lag behind in integrating data practices due to limited resources, capability, or opportunities. To address this, the authors introduced a DL maturity model outlining eleven DL competencies across four competence levels, aiming to enhance the understanding of the required skills for initiating data projects. They defined DL as ”a continuous learning journey that creates the ability to identify, understand, interpret, create, communicate, and compute pieces of information (data) to develop knowledge and the ability to participate fully in our society.”

To summarise, in the last decade, DL has gained growing attention, but there is currently no widely accepted description for the term. This is evident in Table 4 on the next three pages, where sixteen distinct definitions of DL are presented and identified. The table also consists of seven distinct expressions which elaborate on the “names” of DL.

The primary objective of this section was to clarify and identify the context of DL as a phenomenon while also examining its evolution, various definitions, and elaborations over the last two decades. This has helped the author of this thesis gain a deeper understanding of the relevance and importance of DL in the world of digital transformation and datafication. This has also enlightened the reasons why there have been difficulties in elaborating a definition comprehensive enough to cover all the dimensions attached to DL over the years. The subsequent sections explore the practical applications of the foundations elucidated in this section. These implementations have been developed over the past decade. The author of this thesis has chosen to focus on certain domains that are relevant to the thesis objective, namely educational practice and organisations. The forthcoming sections will provide an overview of these domains.

Table 4. *Definitions of data literacy in academic research*

Source	Year	Literacy	Definition	Audience
Love (p. 22)	2004	Data Literacy	Ability to examine multiple measures and multiple levels of data, to consider the research and to draw sound inferences	Educators
Schield (p. 8)	2005	Data literacy	Ability to access, manipulate, summarise and present data	College students
Qin and D'Ignazio (p. 189)	2010	Science data literacy	Set of skills to collect, process, manipulate, evaluate and use data for scientific inquiry	Educators, researchers
Carlson et al. (p. 652-653)	2011	Data information literacy	Encompasses both the production and consumption aspect of data inability to understand, read, use and manage science data in e-research environment	Students, educators, librarians
Mandinach and Gummer (p.30)	2013	Data literacy	Ability to understand and use data effectively to inform decisions meaning skills to identify, collect, organize, analyze, summarize and prioritize data	Educators
Prado and Marzal (p. 130)	2013	Data literacy	Understanding data, finding and/or obtaining data, reading, interpreting and evaluating data, managing data, using data	Librarians, educators, researcher
Schneider (p.3)	2013	Research data literacy	Understanding databases and data formats, discovering and acquiring data, managing and organizing data, conversion and interoperating data, assuring quality	Students, educators, researchers

Source	Year	Literacy	Definition	Audience
Bhargava and D'Ignazio (p.1)	2015	Data Literacy	Ability to read, work with, analyze and argue with data. Reading data involves understanding what data is, and what aspects of the world it represents. Working with data involves creating, acquiring, cleaning, and managing it. Analyzing data involves filtering, sorting, aggregating, comparing, and performing other such analytic operations on it. Arguing with data involves using data to support a larger narrative intended to communicate some message to a particular audience.	Educators
D'Ignazio and Bhargava (p. 2-3)	2015	Big data literacy	Reading data, working with data, analyzing data, arguing with data + three big data dimensions: 1. identifying data collection 2. understanding algorithmic manipulation 3. weighing ethical impacts	Nonprofits in the social sector
Ridsdale et el. (p. 2)	2015	Data literacy	Ability to collect, manage, evaluate, and apply data, in a critical manner	Educators
Maybee and Zilinski (p. 3)	2015	Data informed learning	Emphasises how data are used to learn and communicate within disciplinary learning contexts. Principles of data informed learning: 1. New ways of using data must build on students' prior experiences 2. Learning to use data should occur at the same time as learning about a disciplinary subject 3. Learning should result in students becoming aware of new ways of using data as well as developing new understandings of the subject being studied	Educators

Source	Year	Literacy	Definition	Audience
Wolff et al. (p. 23)	2016	Data literacy	Ability to answer real-world questions from large and small data sets through an inquiry process, with consideration of ethical use of data. It is based on core practical and creative skills, with the ability to extend knowledge of specialist data handling skills according to goals. These include the abilities to select, clean, analyse, visualise, critique and interpret data, as well as to communicate stories from data and to use data as part of a design process.	Educators
Crusoe (p. 38)	2016	Data Literacy	The knowledge of what data are, how they are collected, analyzed, visualized and shared, and is the understanding of how data are applied for benefit or detriment, within the cultural context of security and privacy	General public
Gray (p.1)	2018	Data infrastructure literacy	Competencies to read and work with datasets and also the ability to account for, intervene around and participate in the wider socio-technical infrastructures through which data is created, stored and analysed	Researchers, policy makers, public institutions
Sternkopf and Mueller (p.5046)	2018	Data Literacy	Data literacy is a continuous learning journey that creates the ability to identify, understand, interpret, create, communicate, and compute pieces of information (data) to develop knowledge and the ability to participate fully in our society	Non-governmental organizations
Sander (p. 3)	2020	Critical big data literacy	An awareness, understanding and ability to critically reflect upon big data collection practices, data uses and the possible risks and implications that come with these practices, as well as the ability to implement this knowledge for a more empowered internet usage	Educators, researchers

2.5.2 Data Literacy in Educational Practice

Alongside efforts to clarify the concept of DL and establish a framework for it, there has been a rising curiosity about how school leaders and educators can harness diverse data sources to elevate the standard of education. It is crucial for these individuals to possess DL skills and undergo sufficient training to proficiently leverage data for educational enhancement. (Cowie & Cooper, 2017; Kippers et al., 2018; Ndukwe & Daniel, 2020; Raffaghelli & Stewart, 2020; Reisoğlu & Çebi, 2020; Schildkamp, 2019; Sergis & Sampson, 2017)

As the research landscape continues to evolve, academic librarians must also adapt by incorporating DL into their instruction sessions. By doing so, they can effectively support researchers and prepare the next generations of scientists to manage and utilise data in their research workflows. DL is crucial not only for researchers but also for those pursuing careers in data management. (Koltay, 2017a; MacMillan, 2014; Macmillan, 2015)

In addition, today's educators are recognising the importance of equipping students with DL competencies. Across various levels of education, educators have explored different methods to help students develop fundamental DL skills, such as data science, analytical abilities, and critical DL. These methods include hackathons (Anslow et al., 2016), gamification to increase user engagement (Chin et al., 2016; Legaki et al., 2022; Legaki & Hamari, 2020; Wolff et al., 2015), online courses (Chen et al., 2018), the use of authentic data in the classrooms (Kjelvik & Schultheis, 2019), data visualisations (Shreiner, 2018; Shreiner & Dykes, 2021), mobile applications (Giese, Anderl, et al., 2020), and introductory courses to data-scientific thinking (Gould, 2021). Moreover, a competency model suitable for computer science education in schools has been developed that aligns well with the existing models, providing valuable insight into DL and structuring this topic more effectively (Grillenberger & Romeike, 2018).

The article by Giese et al. (2020) highlights the crucial role of DL in today's digital landscape and proposes a learning framework for undergraduate engineering students. This framework not only covers the technical aspects of data, but also places importance on transparency, awareness, and ethical considerations. This approach distinguishes it from many other educational initiatives that mainly concentrate on the technical aspects of DL.

According to Taibi (2021), it is important to provide DL courses to all university students, not just those studying computer science or technological fields, as data is relevant in almost every area of study. In their paper, they discuss the EU-funded project DEDALUS, which aims to develop DL courses for university students by identifying five key competencies: handling digital information formats in professional higher education contexts, data collection and interpretation in research, development, and teaching in higher education, critical thinking, specialist data processing in information technology study fields, and data management.

In recent studies concerning DL, there has been an increasing trend of efforts to try to expand the concept of DL, not just technical skills and understanding but also competencies that cover an individual's whole life environment. This seems to have a special impact in educational contexts, and it is also calling for education that goes beyond classrooms and academic activities. Raffaghelli et al. (2020) conducted a systematic literature review in which the findings were that the majority of the DL discourse is centred on data in learning, particularly its role in technical skill enhancement, with less attention given to discussions on data ethics, privacy, and empowerment in today's data-centric society and education. In his study, Gebre (2022) advocates for a new perspective on DL that emphasises the importance of meeting the literacy needs of students in today's data-driven world. Through a literature analysis, Gebre discovered that although there are recommendations for promoting DL in different fields, most explanations and interventions concentrate on equipping students with skills to handle data in an academic setting from a data-deterministic standpoint rather than a holistic approach to DL education.

Yousef and colleagues (2021) employed text-mining techniques to analyse DL communities. Their findings demonstrate that DL garners interest from diverse communities of practice, each approaching the topic from unique perspectives with little overlap. Based on their analysis, the communities can be classified into three categories: education, fields and professions, and citizenship. It was apparent that DL is approached differently within each community of practice. The researchers focused on three primary areas of DL education: assessment strategies, classroom impact, and communication modelling. Findings indicated that the education community emphasises the use of data and the creation of a conducive learning environment. Additionally, the theme of learning analytics emerged as a prevalent way to understand student performance.

The conclusions drawn by Yousef and his colleagues agree with the findings of Raffaghelli et al. (2020) and Gebre (2022) above, thus highlighting the pressing need to enhance DL in the field of education. The implications underscore the importance of expanding the collective understanding of DL and its potential applications in educational settings. It is imperative that educators and professionals alike prioritise this issue to ensure that students are equipped with the necessary skills to thrive in an increasingly data-driven world. Moreover, according to Ghodoosi et al.'s (2023) literature review on DL education, there is a lack of consensus within the education community on the specific competencies that comprise DL. Therefore, there is a pressing need for a well-established foundation on what to teach and how to best do so. Their analysis reveals that DL education is still a developing area of research, and it is evident that more effective teaching strategies need to be evolved, especially in the business sector.

In conclusion, as the field of DL is constantly evolving, it is crucial for the education sector to adapt accordingly. It is important to recognise the significance of a well-rounded approach to DL, one that combines technical proficiency with a broader understanding of data's role in society. The conversation surrounding DL has expanded to include topics such as data ethics, privacy, and empowerment, which reflect the complexities of today's data-driven society. Moreover, DL is viewed from diverse perspectives, which makes it challenging to reach a consensus on the required competencies and how they should be taught. By promoting a comprehensive understanding of DL, educators can arm students with the tools and knowledge they need to navigate the modern world.

2.5.3 Broadening the Horizon: Organisations and Future Implications

The contemporary organisational landscape is vastly dissimilar from its state two decades ago, with a significant emphasis on data. As entities such as businesses, governments, and institutions navigate this data-rich world, the significance of DL is increasingly apparent. DL has now started to integrate itself into the fundamental workings of organisational structures and strategies. This section delves into how the academic research field is adapting to meet the needs of organisations and their workforce in response to this evolution. (Jones, 2022, pp. 4–7)

In the world of business, making informed decisions is critical at every level of an organisation. Achieving this requires two essential components: a resilient technological infrastructure capable of managing data and ensuring that employees possess the necessary skills to work with it and make informed decisions based on that data. Nowadays, data is not solely the responsibility of data professionals; it comes in various forms and is encountered by individuals in different positions on a regular basis. This begs the question of what DL looks like from an organisational standpoint and how organisations can reskill and upskill their workforce to become data literate in an environment that differs from that of educational institutions. (Jones, 2022, pp. 4–7)

To gain a full understanding of the value and significance of DL in the workforce and within organisations, it is crucial to conduct a detailed examination of the existing academic research on the topic. Even though there are a limited number of studies available on this subject, such exploration is vital in successfully addressing the thesis' purpose.

Over the past ten years, digital transformation has had a profound impact on many industries, as discussed earlier. However, some sectors have undergone more significant changes than others. The COVID-19 pandemic and the Ukrainian war have expedited and transformed the rate and nature of digital transformation in multiple domains. Considering this, organisations have been compelled to adapt to remote work, online services, changes in consumer behaviour, rising inflation, and disruptions in supply networks, usually by developing their digital capabilities. The sectors most affected by these changes have probably been finance, education, retail, healthcare, manufacturing, and energy. The swift rate of digital transformation has brought both opportunities and challenges to businesses in all sectors. Organisations have been forced to adopt new technologies and business models to remain competitive and relevant while also navigating the challenges. (Klidas & Hanegan, 2022, pp. 52–53)

In the finance sector, digital transformation has led to the development of innovative and efficient financial services, such as mobile banking. The education sector has been transformed by e-learning platforms and digital classrooms, which have led to better access to education and training opportunities. The retail sector has experienced a significant shift towards e-commerce as consumers have increasingly turned to online shopping. The healthcare sector has been revolutionised by telemedicine and digital health applications, which have improved access to medical services. The manufacturing and energy sectors have also benefited from digital transformation, with the integration of automation and data analytics leading to improved efficiency and productivity. (Slavković et al., 2023)

The study conducted by Pothier and Condon (2020) delves into the increasing significance of DL in the modern business landscape as companies face challenges in recruiting data-literate professionals, particularly those skilled in analytics related to data modelling, segmentation, and attribution. The article highlights the crucial necessity of DL skills for businesses that are shifting toward data-centric operations. While the article addresses the educational actions required, it emphasises the importance of equipping business students with the essential DL competencies to thrive in today's business world. Such competencies are crucial not only for specialised roles like data scientists but also for various departments, ranging from HR to marketing.

It appears that the banking industry requires a workforce that possesses excellent DL skills. According to Maja and Letaba (2022), DL is becoming increasingly crucial in the banking sector, particularly considering the rapid digital and data-driven shifts that are transforming the industry. The future of banking is dependent on banks' ability to leverage the power of big data analytics, highlighting the importance of DL governance and a data-centric corporate culture. Arsal et al. (2022) also conducted a study in the banking industry that emphasises the strategic priority of digital transformation in enabling organisations to improve their business performance through data-driven decision-making. They argue that top management support, collaboration, and data skills are among the three critical organisational enablers. They suggest that employees should possess both DL (the ability to read, write, and communicate data in context) and digital literacy (the ability to use big data technologies and tools).

Algorithms-based software (Leicht-Deobald et al., 2019) used in organisations can present challenges that emphasise the importance of critical DL competencies. Navigating the complexities of algorithm-based decision-making requires a thorough understanding of the implementation process, which is not merely technical but also social in nature. The widespread use of such technologies can have a profound effect on employees, potentially impacting their personal integrity and sense of autonomy. The authors encourage a more critical and informed approach to utilising these tools. They highlight the importance of a holistic approach integrating technology, data, processes, and organisational change.

In addition, DL skills are crucially intertwined with various professions that rely on data analysis. Burn and Matthew's (2018) research emphasises the growing importance of DL in journalism as data increasingly becomes a primary source of information. As a result, journalists must possess the ability to efficiently interpret, analyse, and present it. This shift in journalism education necessitates a departure from traditional methods and an integration of data journalism as a fundamental skill. Bhargava and D'Ignazio's (2021) study further emphasises the significance of adapting pedagogical methods to keep pace with the technological advancements in the field of data journalism, causing a systemic disruption in journalism education.

The increasing need for a data-literate workforce has prompted the academic community to also focus on the development of DL assessment models from the perspective of workforce needs (Smolnikova, 2020, 2022; Smolníková et al., 2021). These models are often designed to quantitatively measure the level of DL maturity in individuals and organisations. The implementation of such models can provide valuable insights into the strengths and weaknesses of DL within an organisation, allowing for targeted interventions to improve DL skills where necessary. As such, these assessment models have the potential to play a significant role in shaping a data-driven future as organisations seek to leverage the power of data to gain a competitive edge.

A recent study conducted by Smolnikova et al. (2021) aimed to assess the competencies of business students and employees in economic fields. The study identified five key areas of DL: Data concepts, ethics and protection, Analytical principles and methods, Data collection and preparation, Data analysis and evaluation, and Data interpretation, communication, and decision-making. The researchers utilised Wolff et al.'s (2016) PPDAC approach, which involves problem identification, planning, data collection, analysis, and conclusion, in their prototype. Participants were divided into two categories: common business users and power users, and their proficiency levels were measured accordingly. They emphasise that their model is a synthesis of several existing models of DL competencies, like Prado and Marzal (2013), Ridsdale et al. (2015), and Grillenberger and Romeike (2018). Researchers argue that the model can be a valuable tool for both individuals and organisations looking to improve their DL, as it provides a clear assessment of current strengths and weaknesses.

Miloradov et al. (2022) stated that DL is not just a requirement for specialised roles, but it is essential for all workers. Organisations aiming for digital transformation need to prioritise DL training to ensure their workforce is equipped to handle the challenges of the digital age. They conducted desk research across 14 European countries to understand how DL is addressed in higher education and made a list of five groups of competencies based on that. These competencies are Data protection and security, Data selection and critical assessment, Data processing, Data analysis, and Data visualisation. The second part was an online survey conducted across 20 countries in Europe and North Africa focusing on employees' understanding of data skills. Online survey indicated that the most valuable DL competence for an employee is the ability to evaluate or reflect on data and skills related to reading or creating data classifications.

Accordingly, Inverarity and colleagues (2022a) argued that upskilling data practitioners alone is insufficient and advocates for a more comprehensive approach encompassing entire teams and departments. To address this, they developed the ODI Data Skills Framework within the ODI (Open Data Institute), a non-profit organisation founded in 2012 that is committed to promoting and advancing trust in data, including open data, shared data, and closed or private data (ODI, 2023).

The framework is illustrated in Figure 8 on the next page as a tool that effectively communicates the range of areas that necessitate some degree of DL, broadly divided into two categories. The left-hand side focuses on the softer skills related to decision-making, which involve delivering benefits while safeguarding people and data. The right-hand side, on the other hand, places greater emphasis on the practical side, which involves comprehending how data is utilised to inform decision-making. The framework seeks to integrate the more human element of data, from establishing communities to managing change and working ethically. The authors underscore the interconnectedness of different aspects, such as the close relationship between governance and data platforms or analytics and ethics. In summary, their framework represents a commendable effort to provide a holistic perspective on DL by combining both soft and practical skills related to data, highlighting the importance of a balanced approach that integrates both human and technical elements.

Figure 8. *The ODI Data skills framework (Inverarity et al., 2022b)*[1]

The emergence of AI solutions and the need for AI literacy will undoubtedly impact the field of DL and its education. According to Long and Magerko (2020), AI literacy refers to a set of skills that allow individuals to assess AI technologies critically, communicate and cooperate efficiently with AI, and use AI as a tool both online and in the workplace. The authors note that DL competencies and AI literacy competencies are closely

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intertwined, particularly in the subfield of machine learning, where recognising personal data used to train models and interpreting the outcomes in the context of data are critical DL concerns in AI.

When considering the implications of AI literacy and AI tools on DL in educational settings, it becomes apparent that such solutions will not leave this field unaffected. It is, therefore, important to consider the potential impact of AI on DL and to develop strategies for integrating these solutions into educational contexts in a way that maximises their benefits while minimising any negative effects. Ultimately, this will require a careful balancing of the advantages and limitations of AI, as well as a deep understanding of the needs and priorities of educators and learners alike.

2.5.4 Summary of Academic Perspectives on Data Literacy

The development of DL can be traced back to its connection with other forms of literacy. One can state that the emerging research around DL, being in its infancy, often considered DL as a subset of information literacy, was mainly explored for educational purposes. It discussed how to integrate DL into the curriculum and how to enhance data use in education. The focus was derived from statistical and information literacy, highlighting the importance of critical thinking, interpretation, and evaluation of data. Also, efforts to try to define what it means to be data literate were included. DL has emerged as a response to the increasing amount of data in our society as researchers and policymakers seek to comprehend its implications.

Early discussions centred around the need for consistency in terminology and basic competencies. As time has passed, the idea of DL has progressed from being an extension of other literacies to a separate concept. However, there is no universally accepted definition of DL, and it is often described as a combination of other relevant literacies. This has led to the proposal of initial frameworks emphasising problem-solving through inquiry. As the concept develops, efforts are made to expand and refine it beyond technical skills to encompass an individual's entire life environment. In today's world, having the ability to understand and work with data is no longer a luxury but a necessity. It has become widely acknowledged that DL is an essential skill set that spans across various communities, including education, professions, and citizenship. Being able to understand, read, analyse, and interpret data has become a fundamental aspect of being an informed and active member of society. In the most recent phase, the rise of AI solutions has necessitated the development of AI literacy, which is closely intertwined with DL. There's an emphasis on understanding the implications of AI on DL, especially in educational settings.

After analysing the available literature, it is evident that DL is a multifaceted phenomenon that demands further investigation. This raises important questions about the education sector's capacity to accommodate the diverse DL demands required by individuals and employers in training and workplace environments and keep up with its rapid development. This evolution highlights the growing significance of DL and AI literacy in our data-driven world, emphasising the necessity for continuous adaptation and integration of new technologies and methodologies. It can be asserted that DL represents the fundamental literacy of the 21st century, encompassing many other forms of literacy.

2.6 Data Literacy in Business Operations

In the theory section of this thesis, a lot of importance has been placed on the analysis of academic discourse and European policies. However, considering the primary objective of the thesis to explore DL in connection with workforce skill assessment and education, it is vital to broaden the perspective by including the insights and opinions of professionals in the industry and business operations. In the current dynamic business landscape, the continuous drive towards innovation and the strategic application of data have become imperative in maintaining a competitive edge. As a result, it is essential to cultivate a skilled workforce that is data literate. This chapter aims to explore DL in the public domain to determine if there is a gap between academia and the business world. Firstly, the definitions that exist in the public domain are examined. This is followed by a discussion of the aspects of training needs, organisational culture, and strategic perspectives. By adopting this approach, a more nuanced and sophisticated understanding can be achieved, which will enhance the overall quality of the theory construction.

2.6.1 Data Literacy Definitions in the Public Domain

In section 2.5.1., the definitions of DL in an academic research context were examined and presented. In this section, exploration is broadened to include publicly available definitions. To achieve this goal, a comprehensive Google search was performed using the keywords ‘data literacy’ and ‘definition’, carefully selecting results that were deemed to be representative. Some books related to DL that were accessed through the university library were also found. Furthermore, access to Gartner’s research reports database through the university library served as a valuable supplement to the abovementioned exploration. Gartner is a well-known research and advisory firm that is widely recognised for its analytical insights.

According to Gartner (2024), DL is the “ability to read, write and communicate data in context, including an understanding of data sources and constructs, analytical methods and techniques applied, and the ability to describe the use-case application and resulting value." Gartner stresses that organisations need to recognise the role of employees' DL in reaching digital business success. This is illustrated in Figure 9 in the form of DL capabilities and competencies, which are not only technical abilities but also business-oriented knowledge, effectiveness competence, and data and analytics process disciplines. It is also important to note that, in 2021, Gartner considered data science, machine learning, and artificial intelligence to be a part of data literacy. (Duncan et al., 2021)

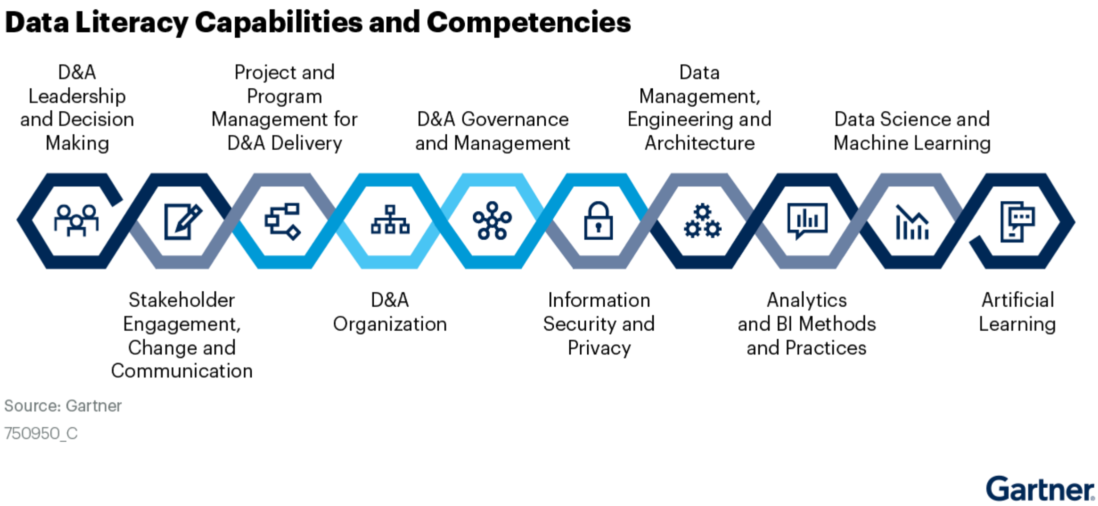


Figure 9. *Data literacy capabilities and competencies (Duncan et al., 2021)*

According to Gartner, it is essential for the workforce to possess both DL and AI literacy competencies. The two literacies are interconnected and share data and analytics as foundational components. It is necessary for organisational leaders to have a clear understanding of the significance of these literacies for enterprise and society. AI literacy, as defined by Gartner, refers to "the ability to effectively and responsibly utilise AI in context, business and societal, with competence to identify relevant use cases as well as implement and operate corresponding AI applications."(Medeiros & Duncan, 2023)

Various definitions of DL were found by Google search. Ghosh from Dataversity (2023), a producer of educational resources for business and information technology professionals, defines DL based on Gartner's explanation: "an individual's ability to identify and understand data sources, analyse data to derive insights, and use these insights to make value-added decisions". Ghosh proposes that success in DL programmes is measured by evaluating how many workers are asking the right questions, making informed decisions based on data, and effectively communicating data-driven findings. Business leaders and managers play a crucial role in fostering a data culture by using data to inform daily business decisions and encouraging employees to engage in DL programmes.

Ghosh underscores the need for comprehensive training programmes and a supportive data culture to enhance DL across all levels of an organisation.

Jones (2022, p. 6) defines DL as “the skill to extract meaning from data” in his book More Judgment Than Data. He emphasises that accurate predictions alone are insufficient for making good decisions; understanding how and why the prediction was made is equally important. Extracting meaning from the data is crucial for this understanding. A data-literate person is someone who knows what data to collect, what questions to ask about it, and how to extract meaning from it. Developing DL does not require mastering the latest statistical techniques or programming languages. Rather, it involves understanding the data-generating process and the larger context in which it operates. This big-picture view is essential for effective data-driven decision-making. (Jones, 2022)

In 2019, Bonikowska et al. (2019) published a report that focuses on the definition of DL and also emphasises its significance in interpreting data. According to the authors, DL is “the ability to understand information extracted from data and summarised into simple statistics, make further calculations using those statistics, and use the statistics to inform decisions. However, this definition is context-dependent.” Their report primarily focuses on the public service sector, where DL plays a vital role in improving service delivery, managing workforces, and deriving insights from data. The authors highlight the complexity of assessing DL, considering both specialists and non-specialists. They discuss the reliability of self-assessment tools for measuring DL, noting that these may not accurately reflect actual skill levels, as people tend to overestimate or underestimate their abilities. The report suggests that tracking the evolution of DL skills over time through self-assessments could be more viable despite inherent biases.

To summarise, beyond technical data skills, there is an obvious and growing emphasis on soft skills related to data. These skills include asking the right questions, understanding data relevance, interpreting data, creating visualisations, and storytelling to support decision-making. This area is also underscored by Bersin and Zao-Sanders (2020) as they argue for the critical need to enhance DL skills in the modern workforce, shifting the responsibility from educational institutions to employers. They highlight the evolving nature of these skills and define DL as the “ability to interpret data, to draw insights, and to ask the right questions in the first place”.

A complementary perspective to DL is introduced by Stobierski (2021), who defines DL as “an individual’s ability to read, understand, and utilise data in different ways.” The author clarifies that it requires a solid understanding of the basics rather than specialised knowledge, meaning that DL is a fundamental skill that allows non-data professionals to interpret and comprehend data, which in turn enhances their ability to make informed decisions. From Stobierski's perspective, DL encompasses the following skills and concepts: data analysis, data wrangling, data visualisation, the data ecosystem, data governance, and the data team. In essence, DL represents a holistic approach to data management that equips individuals with the essential knowledge and skills necessary to maximise the value of data in a business setting.

Tableau, a software company established in 2003, has emerged as a prominent in the field of business intelligence and data visualisation. Their webpage (Tableau, 2023) offers a definition of DL as "the ability to explore, understand, and communicate with data in a meaningful way". Tableau positions itself as a resource for organisations seeking to enhance their DL, offering tools and expert support to build a data-literate workforce. They describe DL as a combination of technical and non-technical skills. Technical skills range from data analysis and visualisation to more complex skills like mathematics and programming languages, whereas non-technical skills include critical thinking, research, communication, and domain knowledge.

Halper's (2021) report, sponsored by Amazon Web Services, Collibra, and Tableau, emphasises the importance of a holistic approach to building DL within an organisation. The author states that "different groups in an organisation often define data literacy differently. For instance, on the IT side, data literacy might include understanding the data, providing metadata, and defining data elements. For an analytics team, it may include the ability to understand the data and analyse it and communicate the results so different groups can understand them." The report, titled 'Building a Data-Literate Organisation', provides valuable insights into the critical role of data fluency in achieving organisational success. Best practices like training through external experts, in-house experts, and technology vendors are proposed in the report with the aim of building DL skills like critical thinking, interpreting data, and effective communication. Halper's holistic approach encompasses training, governance, and cultural change to build and maintain DL. The report states that data-literate organisations are more analytically mature and better able to measure value in terms of top or bottom-line impact.

Forrester Consulting (2022) defines DL in their Tableau commissioned paper as an individual "possessing the skills necessary to understand, explore, use, make decisions with, and communicate using data". They state that basic data skills include DL and basic data analysis abilities, and advanced skills include data science, AI, machine learning, and advanced analysis techniques. The report underscores the importance of DL training for enhancing organisational performance and competitiveness, highlighting the benefits of mature DL programmes and providing strategic recommendations for implementing effective training initiatives across organisations. Recommendations include company-wide data skills training programmes and strategic partnerships for training.

When considering the advantages of implementing widespread DL training and programmes aimed at improving organisational performance, it is important to consider why consulting organisations are recommending them. While these recommendations are made with good intentions and are meant to benefit the organisation, they may also align with the consulting organisations' business interests. This raises the possibility that the recommendations may be influenced by the organisations' desire to promote their own services. Therefore, it is crucial to carefully evaluate these strategies to ensure that they genuinely meet the needs and objectives of the organisation rather than primarily serving the interests of the consulting organisations.

Klidas and Hanegan (2022, p. 1) define DL as "a combination of skills and mindsets that allows individuals to find insights and meaning within their data to enable effective, efficient data-informed decision-making" in their book called Data Literacy in Practice. They stress that DL is highly context-dependent and differs from person to person, incorporating a human element. Consequently, organisations must ensure that all workers are reskilled for the future, given that everyone has distinct levels of data experience. The authors propose that the development of DL should be initiated in an organisation through a top-down approach, with leaders setting an example. Additionally, they explore the potential of machine learning, AI, and natural language processing in terms of cloud-based solutions, cost-effectiveness, and scalability, highlighting their close relationship to data, analytics, and informed decision-making.

The ODI, which was introduced earlier under section 2.5.3, is a unique entity that bridges the gap between academia, industry, and public policy. While it is not a traditional academic institution, the ODI has a foundation in scholarly principles, given its commitment to research and education. Simultaneously, the ODI engages actively with businesses and collaborates with government bodies. This is why Tarrant and Gráinne's (2023) blog post's definition of DL in the ODI's webpage is introduced in this section. They define DL as "the ability to think critically about data in different contexts and examine the impact of different approaches when collecting, using, and sharing data and information."

Lastly, the World Bank, established in 1944 and primarily known for its financial support to developing countries, plays a critical role in knowledge dissemination and policy advice. Recognising that data can transform lives through informed decision-making, the World Bank's World Development Report (2021) underscores the value of data in various sectors. It highlights data's role in government decision-making, civil society's monitoring policies, and the private sector's creation of business opportunities. The World Bank defines DL as "an individual's capacity to find, access, read, work with, and analyse data to responsibly inform decisions". It also sees DL as a critical skill for civic engagement and public sector innovation. (Kumar, 2023)

In summary, after exploring various definitions of DL available in the public domain from relevant sources and gathering these definitions into Table 5 on the next two pages, it is evident that both converging and diverging viewpoints exist. Although there is a consensus on the fundamental skills of understanding, analysing, evaluating, and communicating data, there is a distinction in the emphasis placed on technical versus non-technical proficiencies. Certain sources, such as Gartner, give importance to analytical techniques, and others, like the ODI, concentrate more on wider implementations and critical thinking. Additionally, there is variability in the target audience of these definitions, ranging from universal applicability across all sectors, as seen in the World Bank's inclusive approach, to more role-specific competencies highlighted by sources like Harvard Business School. This diversity in definitions reflects the multifaceted nature of DL and suggests that tailored approaches are necessary to cultivate these skills across different organisational contexts. It is also imperative to recognise the emerging intersection and symbiotic relationship between DL and AI literacy. In an era of AI disruption, possessing proficiency in both data and AI literacy seems to be crucial in this decade. However, this is not yet noticeable in definitions.

Reviewing these business domain definitions, they closely align with the upper levels of the DIKW model, which are knowledge and wisdom. These definitions go beyond basic data comprehension and processing and instead focus on critical thinking and problem-solving, which are necessary to obtain meaningful insights. They also emphasise the importance of making ethical and wise use of data for decision-making, often with a long-term view and the greater good in mind, referring to strategy aspects. Collectively, these definitions serve as a guiding mosaic for understanding and fostering DL.

Table 5. *Definitions of data literacy in the public domain*

Source	Year	Literacy	Definition	Organisation/ Source
Bonikowska, Sanmartin, Frenette	2019	Data Literacy	Ability to understand information extracted from data and summarized into simple statistics, make further calculations using those statistics, and use the statistics to inform decisions. However, this definition is context-dependent	Statistics Canada
Bersin and Zao-Sanders	2020	Data Literacy	The ability to interpret data, to draw insights, and to ask the right questions in the first place	Harvard Business Review
Stobierski	2021	Data Literacy	Ability to read, understand, and utilize data in different ways. It doesn't require an individual to be an expert - as a data scientist or analyst might be considered - but rather, to show an understanding of basic concepts, such as: Different types of data Common data sources Types of analysis Data hygiene Tools, techniques, and frameworks	Harvard Business School
Halper	2021	Data Literacy	Different groups in an organization often define data literacy differently. For instance, on the IT side, data literacy might include understanding the data, providing metadata, and defining data elements. For an analytics team, it may include the ability to understand the data and analyze it and communicate the results so different groups can understand them.	TDWI Research
Jones (p. 6)	2022	Data Literacy	The skill to extract meaning from data	Book
Klidas and Hanegan (p. 1)	2022	Data Literacy	The combination of skills and mindsets that allows individuals to find insights and meaning within their data to enable effective, efficient data-informed decision-making	Book

Source	Year	Literacy	Definition	Organisation/ Source
Blackborow	2022	Data Literacy	Possessing the skills necessary to understand, explore, use, make decisions with, and communicate using data	Forrester Consulting
Ghosh	2023	Data Literacy	An individual's ability to identify and understand data sources, analyze data to derive insights, and use these insights to make value-added decisions	Dataversity
	2023	Data Literacy	Data literacy is the ability to read, write and communicate data in context, including an understanding of data sources and constructs, analytical methods and techniques applied, and the ability to describe the use-case application and resulting value.	Gartner
	2023	Data Literacy	Ability to explore, understand, and communicate with data in a meaningful way. This can be on different levels: technically and advanced, or on a much more basic level	Tableau
Tarrant and O'Neil	2023	Data Literacy	Ability to think critically about data in different contexts and examine the impact of different approaches when collecting, using and sharing data and information	ODI (Open Data Institute)
Kumar	2023	Data Literacy	An individual’s capacity to find, access, read, work with, and analyze data to responsibly inform decisions	The World Bank

2.6.2 Need for Training, Organisational Culture and Strategy

This section examines empirical research from consulting organisations and governmental bodies, focusing on the vital interplay between training, organisational culture, and strategic planning, especially as they relate to DL. These studies can reveal the necessity of aligning DL training programmes with an organisation's cultural and strategic objectives.

The success or failure of a business depends on how well it manages its employees. Technical skills are no longer enough with the increasing importance of human-machine interaction. In the Industry 4.0 revolution, employees must have various skills, such as creativity, inventiveness, competence, and a willingness to take on challenges in the digital world. Digital transformation has had a huge impact on society and organisations by changing how we interact, communicate, and live our lives. This shift has caused businesses to rethink their practices and strategies to stay competitive in a constantly changing world. It can be described as a dramatic change because of how much it affects both businesses and people. Digitalisation has brought about many differences and obstacles that have been studied. These include customer expectations, competition strategies, new uses for ICT, and the knowledge needed to navigate this landscape. To succeed in this environment, employees must have a "digital mindset" that includes creativity, adaptability, and teamwork. Companies should be able to create an environment and culture that encourages taking advantage of digital transformation at a personal level. (Slavković et al., 2023; Solberg et al., 2020)

A survey conducted by Forrester Consulting (2022) on behalf of Tableau sheds light on the state of DL and culture in organisations. The investigation involved two online surveys administered globally in November 2021 to 1036 employees and 1032 decision-makers from large companies with 500 or more employees. The findings revealed a disparity between the need for data skills and the availability of training programmes. While 82 % of decision-makers expect all employees to possess basic DL, only 47 % of employees have received such training.

This discrepancy poses a challenge as the demand for data skills is projected to increase. By 2025, approximately 70 % of workers will need to use data extensively, compared to 40 % in 2018. To bridge this gap and ensure organisational success, the report recommends the democratisation of data training across all departments. Companies with high-maturity DL programmes that provide extensive training across various competencies and to all employees will likely reach the most significant benefits, including enhanced innovation, customer satisfaction, and employee experience. Forrester also underscores the importance of knowledge sharing and the crucial role of management in creating a thriving data culture. The report suggests that management should not only utilise data in decision-making but also transparently communicate the data's role in these processes. (Forrester Consulting, 2022)

This is also encouraged by Gartner (2021), which stresses the importance of linking the need for data-driven decision-making to specific business benefits and measurable outcomes. Assessing the extent to which data is being utilised is crucial in achieving these objectives. Finland's state-of-the-art can be evaluated by the latest Digibarometer report written by Ali-Yrkkö et al. (2023), which provides a comprehensive assessment of digitalisation capabilities across countries and their potential to benefit from technological advancements. Finland stands out as a leader in this field, ranking highly across a range of nine indicators. The report's focus for 2023 is on big data analytics and the impact of generative AI technologies on business operations and the broader economy.

One significant finding of the report is the low rate of big data integration into Finnish companies' business models. Although many Finnish companies work with data, only about one per cent have fully integrated big data into their operations. This indicates that while there is initial interest in these practices, they are still in their early stages. Furthermore, the adoption rate of big data techniques among Finnish companies has not kept pace with the global increase in data generation and availability. This slow uptake underscores a potential gap between recognising the value of big data and its practical application in the business sector.

The Digibarometer's insights indicate that Finnish companies and businesses globally need to strengthen their foundation in DL. Improving DL entails more than just technical handling of data; it involves creating an organisational culture and strategic mindset that recognises the potential of data-informed decision-making. In an era where data volumes are on the rise, the ability of businesses to extract actionable insights from big data and leverage AI tools will be a significant differentiator. Thus, enhancing DL at all levels of an organisation is essential to bridge the gap between data availability and its strategic use, enabling companies to effectively compete in a data-driven economy. Overall, the Digibarometer report provides valuable insights into the current status of digitalisation efforts and highlights the need for continued improvement in DL.

An Australia-based company, Data to the People, offers access to the Global Data Literacy Benchmark report (2022) to gain a more international perspective on the issue. This report provides an updated view of DL at a competency level of more than 5000 employees from around the world, like Australia, Canada, India, the United Kingdom and the United States of America. The company has developed an evidence-based DL competency framework and assessment tool for individual DL, which is based on the study of Ridsdale et al. (2015). The company's CEO, Jane Crofts, states in their study report that "over the past two years, there has been a noticeable increase in the attention and efforts of individuals and organisations across the globe to understand and address levels of data literacy". Crofts underscores that the need for job-relevant, contextualised development programmes is obvious to be able to build sustainable DL competencies across the workforce. The company's framework consists of 6 levels and 18 core competencies across the domains of data concepts and culture, reading, writing, and comprehension. They also have a publicly available tool called myDatabilities, which is a free, 10-minute DL assessment with personalised results and recommendations.

Girs et al. (2023) provide a fresh perspective on the role of data in decision-making in their article published by the International Institute for Analytics. They argue that data initiatives often fail to deliver the expected value because of a focus on technology over understanding business, human, or environmental problems. According to the authors, culture becomes manageable when addressed with cultural methods and skills, which is often seen as an obstacle when approached from a technological perspective. The authors highlight that humans base their actions primarily on intuition, with reasoning often only serving as post-hoc justification. This insight challenges the traditional emphasis on data-driven decision-making, suggesting that understanding human behaviour and social dynamics is crucial. They advocate for integrating social science and design thinking into data projects to truly influence behaviours and outcomes rather than just providing data for decision-making. The authors propose a shift from solely facilitating decision-making to designing interventions that influence behaviours in their social context, emphasising the importance of behavioural change over mere data provision. Measuring behavioural changes should be included in the success criteria of data projects, according to the authors.

2.6.3 Summary of Business Operations Perspectives

The concept of DL is gaining increasing importance in the business world, as it is crucial for organisations to have a workforce that is proficient in DL to maintain their competitive edge in today's technologically advanced and data-centric environment. This topic has attracted attention from various academic, industrial, and consulting circles, resulting in a range of perspectives on DL. This section of the thesis has explored these views, highlighting the multifaceted nature of DL in contemporary business operations.

Throughout the course of the conversation, numerous interpretations and definitions of DL were also approved to exist in the business domain, most of them derived more or less from academic definitions. Through this exploration, it is evident that technical proficiency in data management alone is not enough in a work-life setting. Rather, the ability to engage in critical analysis, interpretation, and articulate data-driven insights is essential to effectively harnessing the full potential of data for strategic decision-making and innovation.

Insights gleaned from industry reports emphasise the growing need for data proficiency across organisational levels. Such proficiency is deemed necessary at all levels of an organisation, from front-line employees to top executives. Despite existing training and development efforts, there remain significant gaps that must be addressed. The reports suggest a holistic approach to training that democratises data skills and cultivates a strong data culture, ultimately resulting in improved organisational performance. These insights highlight the importance of data as a key driver of business success and emphasise the need for organisations to invest in the development of data-related skills and knowledge across their entire workforce.

This section has explored the practical application and strategic integration of DL in business contexts. International studies and reports have been instrumental in revealing how DL aligns with and is influenced by organisational culture and strategic objectives. The discussion has underscored the transformative impact of digital evolution on businesses, emphasising the importance of a ‘digital mindset’ among employees and the pivotal role of leadership in cultivating a data-centric organisational ethos.

In conclusion, this section has acknowledged the various perspectives shared by the business domain and underscores the dynamic and context-dependent nature of DL. It emphasises the shift from a traditional focus on data comprehension to a more holistic approach that integrates technical acumen with the soft skills essential for ethical and strategic data utilisation. This narrative lays the groundwork for the next chapter, 2.7, which aims to unify all the discussion from this and previous subchapters into a cohesive synthesis of the theoretical background, providing a comprehensive analysis of DL’s role and significance in the current decade.

2.7 Synthesis of Theoretical Background

This subchapter is dedicated to consolidating and reflecting upon the extensive discussion presented in the previous subchapters regarding the dynamic concept of DL. The thesis started by addressing the fundamental interplay between data and various literacies, also introducing the DIKW hierarchy. Then, it explored DL as an emerging and significant topic in digital transformation. It has examined the role of DL in the context of European policy in the form of digital competence framework development and its adoption in the research field. The journey through the theoretical background was further extended, including academic research, scrutinising the evolution, definitions, and practical implications of DL, and expanding the discussion to encompass organisational perspectives and future implications.

After conducting theoretical research, the author has realised that the topic of DL has gained attention within academic circles and among a broader and more diverse audience. Scholars have produced an increasing number of articles on the subject, as evidenced by the growing number of entries in databases such as Scopus and Google Scholar. This indicates an increasing realisation that DL has evolved from being a specialised academic concept to a necessary lifelong learning skill that is required across various professional domains in the 2020s. The increasing scholarly attention underscores the importance of DL in the future, emphasising a human-centric approach to comprehending data. This phenomenon signifies a paradigm shift. As such, it is essential to acknowledge the complex nature of DL and its indispensable role in shaping the future of numerous industries. Additionally, it is vital to consider the transformative impact of AI solutions in redefining future DL needs.

Upon closely examining the definitions presented within this chapter, it has become increasingly evident that DL is a multifaceted concept involving diverse skills. These skills include, on a rough level, the ability to understand and utilise data based on the DIKW hierarchy and other sub-skills like mathematical aptitude, programming expertise, and critical thinking, also represented by other literacies. First and foremost, as demonstrated by the evolution of the definition in academic discourse and proof from DigComp, DL requires proficiency in information literacy. This entails the ability to effectively locate, evaluate, and utilise information. While conducting the study, it became clear that DL and information literacy are closely intertwined. In addition, numeracy, statistical literacy, digital literacy, and other literacy types include many overlapping fields with DL. Therefore, a data-literate workforce must possess a combination of skills based on them. Lastly, AI literacy is becoming increasingly important as AI integrations become more common in user interfaces. As the number of people working with AI algorithms increases, it is crucial to recognise that AI literacy and DL have overlapping skill areas. In the coming years, appreciating this overlap will be essential to ensure responsible and ethical collaboration between the workforce and AI algorithms.

To truly understand the core of DL and address the question of “What is data literacy?” presented in this chapter, it was necessary to examine a variety of definitions systematically organised in definition tables. Upon review, it can be stated that academic definitions primarily describe DL as an "ability", while public domain definitions use both "ability" and "skills" to define this concept.

The subsequent focus was on an examination of the different verbs included in DL definitions. Early definitions of DL in academics have emphasised the technical capabilities of working with data. However, the most frequent term and a kind of first key theme used across various definitions over the years is "understanding" what the data is. This suggests that a fundamental requirement for being proficient in DL is clearly comprehending the data. When the word "understanding" is absent, "reading" is often used instead, although the two terms are also used together, indicating that they have distinct meanings. “Reading” data implies basic recognition and identification, while “understanding” is more about contextualising and making sense of data.

Another key theme in DL definitions was “working” with data and related actions. Diverse actions were defined by specific verbs describing the nature of data interaction. These actions included identifying relevant data sources, creating new data sets, acquiring data from various sources, collecting data from different channels, refining or cleaning data by removing inaccuracies or redundancies and organising and managing data effectively. The term ‘working’ with data is quite broad. Still, in the field of DL definitions, it seemed to primarily refer to the process of handling and processing data to gain information or to extract meaningful insights.

This process is not just a mechanical task; it necessitates a blend of technical skills and competencies. These technical abilities include proficiency in data software tools, understanding data structures and formats, and the ability to transform raw data into a coherent and insightful narrative. “Working” with data is a critical skill in DL that highlights the need for technical expertise and a strategic approach to leverage data for meaningful outcomes effectively. Given the extensive range and depth of these technical tasks, it is no wonder that early definitions of DL heavily underscored these technical capabilities. This emphasis reflects an understanding that the foundation of DL is deeply rooted in one’s ability to engage with and manipulate data proficiently at a technical level.

The third central theme in various definitions of DL is the critical role of “analysing” data. This theme is articulated through multiple verbs, each highlighting aspects of the analytical process. Interpreting data involves the ability to recognise and comprehend the underlying meaning or patterns within a dataset. Calculating entails utilising mathematical or statistical methods to process data for more accurate insights. Summarising data is the act of condensing large and complex data sets into more understandable and manageable forms, often emphasising key takeaways or trends. Visualising data involves creating graphical representations, such as charts or graphs, which make the data more accessible and easier to understand at a glance.

Understanding and working with data is insufficient to draw meaningful insights from it. To make sense of data, it is necessary to have an analytical mindset that can connect disparate pieces of information to form coherent and actionable conclusions. This is why the theme of “analysing” data is essential because it involves interpreting the data and strategically utilising it to draw insights.

The fourth and final key theme identified in the DL definition tables was the ability to “communicate” the findings from data through various methods of communication. “Arguing with data” means to use data effectively as evidence to support or challenge an argument, requiring a good understanding of the data and the ability to present it convincingly. “Storytelling with data” is the art of weaving data into a compelling narrative that makes complex information understandable to a broader audience. “Sharing data” involves distributing data and insights thoughtfully and effectively to ensure clarity, impact, and ethical integrity. Effective communication in DL requires bridging the gap between complex data sets and diverse audiences. It is about conveying information and transforming data into a meaningful tool. This means combining technical data proficiency with storytelling and persuasive presentation skills. The emphasis on communication skills in DL definitions highlights the importance of a nuanced approach to a data-literate person.

To summarise, the author identified four fundamental pillars of DL definitions: understanding, working with, analysing, and communicating data. While each of these themes is essential, their complete potential can only be realised when combined with other relevant components found among definitions. One of these enriching elements found was critical thinking, which enables individuals to evaluate and interpret data beyond surface-level information, identifying underlying patterns, biases, and possible misinterpretations. An equally important finding was the responsible and ethical use of data, which ensures that data handling and dissemination are conducted with integrity, respect for privacy, and adherence to ethical standards.

A noteworthy finding from examining different definitions was the noticeable distinction in priorities between academic and public perspectives. Academic definitions tend to emphasise the first two fundamental pillars of DL – understanding and working with data.

This emphasis aligns with the academic approach to DL, which stresses the significance of mastering data management's foundational principles and complexities.

On the other hand, definitions that stem from the public domain tend to data analysis, effective communication of findings, and revealing insights within business contexts. This emphasis on deriving value or outcomes and making value-added decisions is especially noticeable. The reason for this divergence can be traced back to the pragmatic and application-based nature of the public domain, where the value of DL is frequently assessed based on its ability to derive business insights and produce tangible results.

Another viewpoint is that DL can mean different things depending on the context in which it is used. This difference in emphasis underscores the multifaceted nature of DL and how other sectors and professions have varying priorities and needs regarding understanding and using data. When dealing with data, it is crucial to recognise the significance of context dependency. Data cannot be viewed in isolation; its relevance and interpretation are frequently shaped by the circumstances or industry context in which it is utilised. Finally, the capacity to make value-driven judgments is the ultimate objective of a data-literate person. These DL features described in this synthesis section make up a framework for DL that encapsulates its essence.

Through extensive study and analysis of diverse definitions and key themes of DL, the author has formulated an interpretation of DL. This interpretation has been visually synthesised into a detailed Figure 10 on the next page, which showcases the key characteristics of DL and its intricate relationship with the DIKW hierarchy. This figure is a graphical illustration that clearly outlines the foundational features of DL discovered and their respective placements within the DIKW framework. It represents the culmination of the author's in-depth exploration, capturing DL's multifaceted nature in enhancing data understanding, cultivating DL skills, and facilitating reskilling possibilities. This visual representation offers insights into how DL's various elements interconnect and contribute to the broader data comprehension and application context, providing a clear and consolidated view of DL. The figure also stresses the vital aspect of human-machine interaction in this sphere.

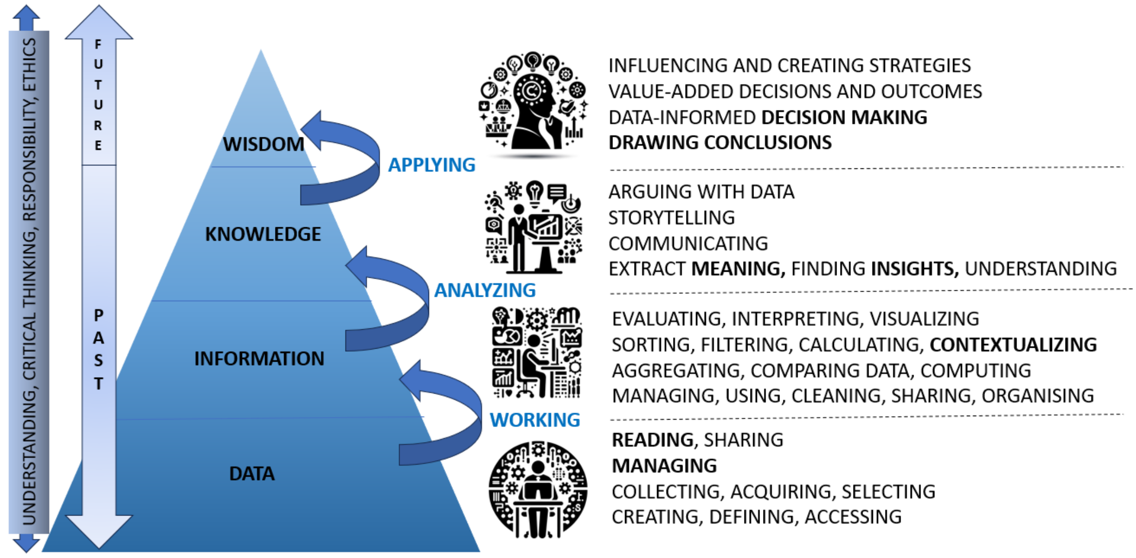


Figure 10. *The relationship of data literacy characteristics to the DIKW hierarchy*

DL is like being able to read and understand the language of data, and it focuses on the individual level. It differs from knowledge management maturity, which is more about the organisation and how well it manages all the knowledge, including data, to improve and grow (Dalkir & Liebowitz, 2011, pp. 5–7). DL is also more technical, involving skills like managing data, data analysis, interpretation, and critical thinking. Knowledge management maturity is broader than DL. It consists of managing data and information and the experiences and insights of people in the organisation. The main goal of DL is to empower individuals to make better decisions based on data. Knowledge management maturity aims to enhance an organisation's overall efficiency, innovation, and competitiveness by effectively managing knowledge resources.

To critically evaluate the theory part of this thesis on DL, it is essential to acknowledge its strengths, limitations, and potential biases. The theory part's strengths are evident in its comprehensive coverage, thoroughly exploring various aspects of DL. It uses scholarly articles, a widely known European policy framework, and recognised public actors in the private sector, enhancing its academic rigour and practical relevance. Additionally, the theory part is well-researched and cited, demonstrating scholarly depth, and it maintains a clear structure that makes it easy to understand and follow the logical progression of the text and the author's thinking process.

However, it is essential to note that the theory part has certain limitations. Although comprehensive, it may not cover certain niche aspects of DL, which could result in an overemphasis on some areas while neglecting others. This imbalance could reduce the overall usefulness of the thesis theory section. Furthermore, some of the data or references may be specific to a certain time period, making them less relevant over time.

Regarding possible biases, the theory part may reflect the author's personal or professional background, which could affect the perspective and analysis presented. Another potential issue is selection bias, which could result in favouring specific sources or viewpoints over others. A tendency towards technological optimism could lead to an overestimation of the positive impact of technology in DL, potentially overshadowing the important role of a human-centric perspective, which emphasises the importance of understanding and addressing human needs, behaviours, and interactions in the effective implementation and utilisation of technological solutions in DL. Lastly, the theory section focuses on academic research, which may have resulted in less attention to practical industry insights.

3. RESEARCH DESIGN AND METHODS

This chapter outlines the methodological framework for this thesis, starting with an overview of the chosen research design. The data collection methods are then described in detail, explaining why they were chosen and how they will assist in answering the research questions. The analytical procedures are also presented systematically, demonstrating a methodical approach to interpreting the collected data. This narrative describes the methodological decisions and explains the reasoning behind them, ensuring transparency and a well-reasoned explanation of their contribution to the field.

3.1 Overview of Research Design

The methodological framework of the thesis follows Saunders et al.'s (2019) 'research onion' model, which encompasses research philosophy, approach to theory development, methodological choice, research strategy, time horizon, and data collection and analysis. This thesis employs a double-phase research design, which involves a qualitative method followed by a quantitative method, creating a sequential exploratory study (Saunders et al., 2019, p. 182). Data is collected through interviews during the qualitative phase, and the quantitative phase involves collecting data through SLR. The author combines two methods to obtain a more comprehensive understanding of a complex research problem. The SLR is used as the primary investigative tool to ensure that the research is based on a rigorous and systematic analysis of the existing literature. Meanwhile, the semi-structured background interviews play a complementary role and provide an opportunity to gather additional insights and perspectives from experts in the field, which can help to enrich this mixed-methods study's findings.

This thesis integrates positivism and pragmatism (Saunders et al., 2019, pp. 144–145) as the guiding research philosophies, each playing a distinctive role in shaping the research approach. Pragmatism guides the operational and application aspects of the study and emphasises the practical implications of research findings obtained from background interviews. It values actionable knowledge and solutions that are applicable in real-world scenarios, ensuring that the findings of this thesis are not only theoretically sound but also practically relevant and implementable. Positivism, which underpins the SLR, is grounded in the principle that knowledge is derived from observable and measurable facts uninfluenced by human interpretation or bias. It relies on quantifiable data from existing research to systematically answer the overarching research question. This approach is characterised by its focus on objectivity, testing hypotheses, and validating existing theories through empirical evidence. The aim of these research philosophies is to comprehensively explore existing DL-related frameworks and their application in workforce development, aligning with the primary research question and related sub-questions.

The semi-structured interviews are conducted using an inductive approach and serve as an initial exploratory step in the research process. These interviews aim to capture the practical experiences, challenges, and perceptions of professionals who regularly engage with data and education or leadership questions. This will provide a preliminary contextual understanding of DL issues in the real world. The qualitative data collected from these discussions serves as a lens through which the subsequent SLR is constructed. Their primary function is to inform and enhance the depth of the SLR. They ensure the SLR is rooted in empirical evidence and sensitive to the nuances and gaps identified by those who work with DL issues.

The centrepiece of this thesis is the SLR, which uses a deductive approach to systematically review the existing academic literature on DL and related literacy-type frameworks. This approach involves critically examining the literature to explore the established frameworks within the context of business and organisations. The SLR seeks to investigate the state of the art of DL-related frameworks and aims to identify how scholars have studied DL and related literacies in a business or organisational setting. This methodological choice ensures rigorous, evidence-based literature evaluation, forming the foundation for answering the primary research question and sub-questions.

The thesis combines inductive insights from interviews with the deductive analysis of a systematic literature review using an abductive methodology (Saunders et al., 2019, pp. 152–153). Combining inductive and deductive elements enables the study to test existing theories against empirical findings and incorporate new interview perspectives and insights. However, the SLR remains the primary driver of the study, as it provides a comprehensive exploration and synthesis of DL and related literacies frameworks.

The scope of this thesis is limited to a cross-sectional time horizon (Saunders et al., 2019, p. 212), focusing on collecting and analysing data at a specific point in time. This approach is suitable for capturing a snapshot of current practices, opinions, and trends in studied frameworks and their application in workforce development. The subsequent sections will detail this thesis's specific data collection and analysis techniques and procedures. This includes thoroughly explaining the methodologies used in the SLR and the semi-structured interviews, ensuring a clear understanding of how data is gathered, analysed, and synthesised to address the research questions effectively.

Figure 11 visually summarises the methodological decisions and research trajectory of this thesis. The figure is based on Saunders et al.'s (2019) research onion model and outlines the different layers of methodology used in this thesis. It covers research philosophies, approaches to theory development, methodological choices, research strategies, and the time horizon. This illustration briefly summarises the research design, which follows a sequential exploratory approach and serves as a visual testament to the study's methodology.

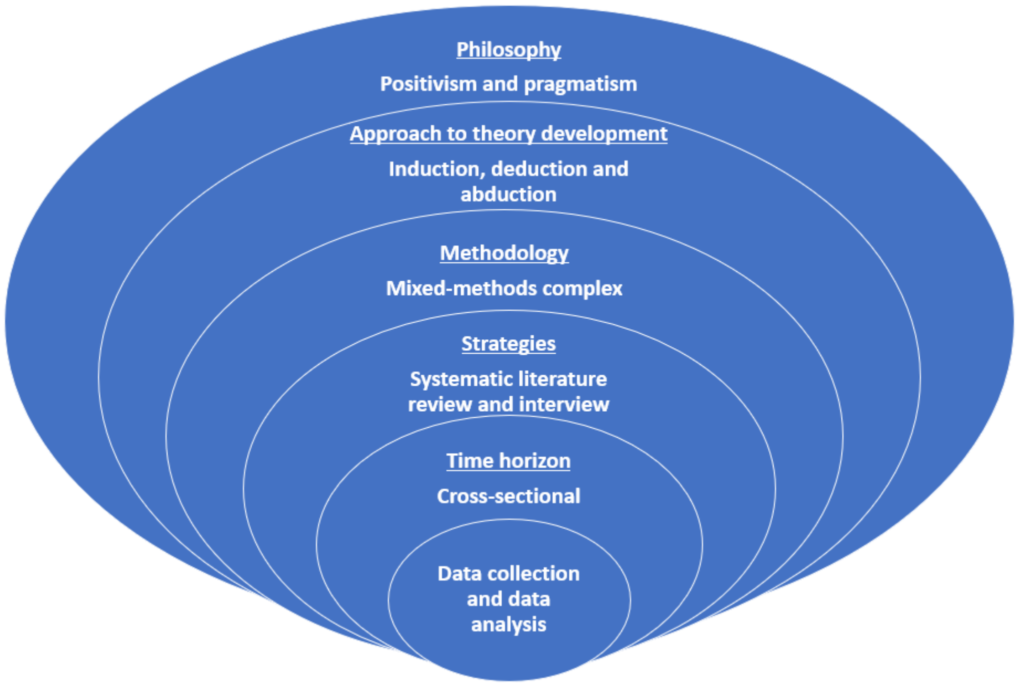


Figure 11. *The 'research onion' choices made in this thesis*

3.2 Interview Method

To better understand the DL and its surroundings in the business domain, a series of qualitative semi-structured interviews (Saunders et al., 2019, pp. 437–438) is conducted prior to the SLR. The following subsections describe the methodology used to select knowledgeable participants, the interview structure, the development of guiding questions, and the management of the collected information to preserve the integrity and depth of the insights obtained.

The choice to employ interviews is driven by the need to capture the lived experiences and expert opinions that exist beyond the reach of published literature. This approach allows for the exploration of nuanced views and tacit knowledge, which are seldom articulated in academic texts or formal documents. By engaging directly with professionals who deal with DL in various capacities, this thesis aims to identify and understand the challenges, opportunities, and practical applications that can only be conveyed through personal narratives. Interviews aim not only to determine the current state of understanding DL as a skill that the workforce needs but also how to update it for future workforce needs.

Participant selection

The selection process for participants was designed to ensure a diverse representation of individuals who engage with data in their workplace. To achieve this, the inclusion criteria were based on the participants' job responsibilities related to data management, analysis, decision-making, or educational expertise. Five individuals were selected to participate, each offering a unique and valuable perspective on DL within their professional context.

Interview format

The interviews followed a semi-structured format, allowing for the exploration of predetermined topics while providing the flexibility to delve into emergent themes. Each session lasted approximately one hour and was carried out via a secure video conferencing platform, Teams, to accommodate participants' schedules and locations. Although the conversations were not recorded, detailed notes were taken to ensure accurate capture of the discussions.

Guiding questions

The guiding questions were developed after an initial exploration of the topic area to facilitate a deeper conversation about how interviewees experience DL in their professional roles. These questions were designed to explore core themes, thereby providing a rich and nuanced understanding of the subject matter. The questions were as follows:

1. Definition and understanding of DL: How do participants define and understand the term 'data literacy', and how do they interpret its significance in their work?
2. Impact of data democratisation: How does the widespread availability of data within an organisation affect processes, decision-making, and culture in terms of DL?
3. Assessment practices: How is DL evaluated practically, and what tools or metrics are utilised?

4. Personal beliefs and identities: How do individual beliefs and self-perception influence the use of data in general?
5. AI and the future of DL: What are their perceptions of artificial intelligence's role in the evolution of data literacy requirements and practices?

These structured questions aim to reveal each participant's multifaceted relationship with DL to uncover the subjective experiences that shape their interaction with data in a work environment.

Data collection and management

A systematic note-taking (Fasick, 1977) approach was employed to manage the interview data properly. This involved using pen and paper for real-time notes of key points. Following each interview, the notes were reviewed to maintain the integrity of the data collected. The interviews were designed to prioritise rich conversation and authentic experiences, laying the groundwork for the systematic literature review.

Thematic analysis

The analysis utilises a thematic approach (Saunders et al., 2019, pp. 651–660). This involves an iterative process of reading through interview notes multiple times to identify emerging themes. These themes are categorised deductively and aligned with predefined research questions and theoretical frameworks. This ensures an audit trail from the raw data to the analytical conclusions.

3.3 Systematic Literature Review

This section aims to provide a clear and concise explanation of the research methodology used in the SLR and give the reader a comprehensive understanding of the process. The methodology presentation covers the definition of SLR, the introduction of the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method, and the presentation of goals and process steps like search strategy, search keywords, data collection, evaluation, analysis, and synthesis.

3.3.1 Introduction to Systematic Literature Review

A systematic literature review is a methodical and comprehensive approach that follows a structured and systematic process. Its purpose is to identify, evaluate, and integrate all existing and available research relevant to a specific research question, topic area, or phenomenon. This rigorous methodology aims to collect and synthesise findings from various studies. Using replicable methods, an SLR meticulously examines existing literature, ensuring that all relevant information is captured and evaluated accurately and objectively. The quantitative nature of an SLR lies in its ability to aggregate and analyse data from multiple studies, providing a more quantifiable, accurate, and holistic view of the research area. (Page, McKenzie, et al., 2021; Pollock & Berge, 2018)

The implementation of a predefined protocol is important in SLRs, as it aids in producing research that is reliable, transparent, and free from bias. This approach is vital for establishing a solid foundation for future studies and enhancing the credibility of the findings. SLRs are a valuable tool that can help identify research areas lacking sufficient evidence. It is particularly useful in guiding future studies to fill these gaps and produce more robust and comprehensive research outcomes. By leveraging the strengths of this methodology, researchers can make well-informed decisions and significantly contribute to the advancement of knowledge in their respective fields. SLRs play a crucial role in academic research as they provide a standard for current knowledge and help researchers and practitioners better understand the extent of research on a specific topic, including any agreement or disagreement in the findings. (Page, McKenzie, et al., 2021; Pollock & Berge, 2018)

SLRs are a unique type of review that stands out from other types of reviews through its rigorous and structured methodology. SLRs are a highly regarded research method in many fields. This methodology results in a more objective and quantitative synthesis of research findings. Other reviews often rely on the author's expertise and perspective, which can lead to a more subjective interpretation of the literature. In contrast, SLRs follow a predefined and systematic process, ensuring that the review is comprehensive, reproducible, and less prone to bias.(Pollock & Berge, 2018)

3.3.2 PRISMA Methodology Overview

In 2009, The PRISMA statement was published to assist researchers in reporting their systematic reviews in a transparent manner (Moher et al., 2009). It offered direction on the purpose of the review, the steps taken by the author, and the outcomes obtained. The PRISMA framework is a protocol for conducting and reporting SLRs. It provides a comprehensive workflow that ensures the integrity and quality of the review process. PRISMA guidelines are not merely a set of recommendations but a widely accepted approach to conducting and reporting systematic reviews. Adhering to the PRISMA framework ensures that the literature review is conducted thoroughly and transparently, and readers can evaluate the credibility and applicability of the results. By following the PRISMA protocol, research findings can be effectively communicated and contributed to advancing knowledge in respective fields. (Page, McKenzie, et al., 2021)

Moher et al.’s (2009) first version of the original PRISMA statement consisted of a flow diagram with four phases and a checklist of 27 essential items. As illustrated in Figure 12, this diagram serves as a visual representation of the selection and screening process used in systematic reviews.

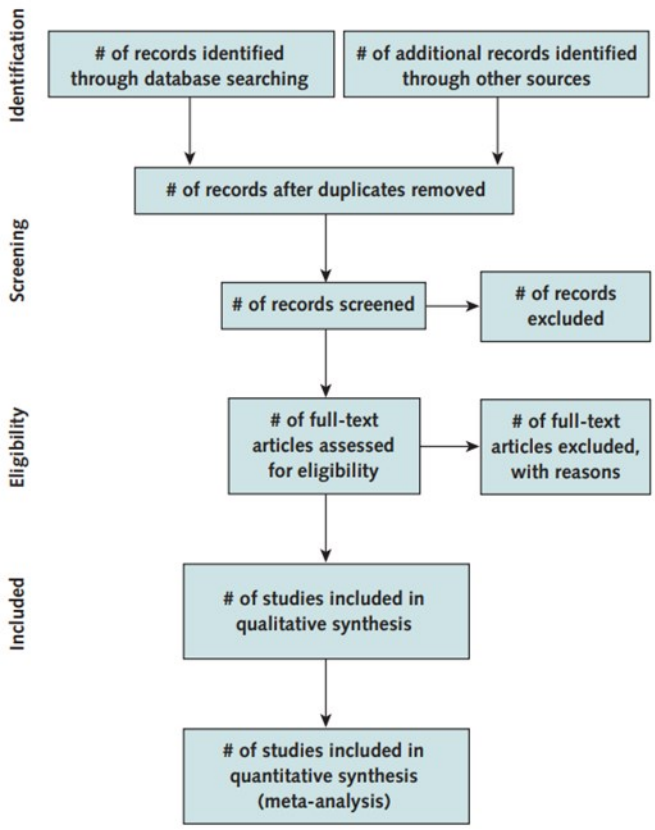


Figure 12. *Flow of information through the different phases of a systematic review (Moher et al., 2009)*

The phases in the workflow diagram include:

1. Identification: This initial phase involves a broad search of databases and sources to identify relevant studies
2. Screening: Following identification, this phase entails a detailed examination of the identified records to eliminate irrelevant or non-qualifying studies based on predefined criteria
3. Eligibility: In this stage, closer scrutiny of the remaining studies is conducted, assessing them for their direct relevance and compliance with the review criteria
4. Included: The final phase culminates in the selection of studies that meet all the specified criteria and are included in the systematic review

The reporting of SLR is guided by a 27-item checklist that is designed to ensure comprehensive and transparent reporting. These items encompass aspects from the title and abstract to the methodology, results, discussion, and funding. Furthermore, a companion document called “Explanation and Elaboration” was created by Liberati et al. (2009) to provide further guidance on reporting for each item. This document is essential in offering authors detailed explanations and examples for each item, which ensures that the reporting in SLRs is clear and consistent. This approach not only guarantees that the reviews are thorough but also that they conform to standardised reporting practices, which makes it easier for the research findings to be replicated and verified.

However, the systematic review methodology and terminology have progressed over the last decade. As a result, The PRISMA 2020 statement has been introduced to replace the previous version introduced in 2009. This updated guideline incorporates reporting guidance that reflects advances in techniques for identifying, selecting, evaluating, and synthesising studies. PRISMA 2020 statement is primarily meant to conduct systematic reviews of health intervention studies. Still, it is suitable for various systematic reviews, and checklist items can be applied to other types of interventions, such as social or educational. The PRISMA 2020 checklist comprises 27 items grouped into seven sections, some of which have sub-items. (Page, McKenzie, et al., 2021)

Key differences and updates in the PRISMA 2020 flow diagram are:

1. A greater emphasis on the use of automation tools by acknowledging their role in the screening process and distinguishing between records excluded by these tools and those that were manually screened. This provides a clearer understanding of the impact of technology on SLR.
2. Distinct reporting of databases and registers: PRISMA 2020 advises reporting the number of records identified from each database or register searched rather than the total number across all sources.
3. Refined screening and eligibility phases: The screening process is more detailed, with separate counts for records screened, records excluded, reports sought for retrieval, and reports not retrieved. This enhances transparency in the review process.
4. During the eligibility phase, the update recommends listing the reasons for excluding reports and a count for each reason. This will provide a clearer rationale for exclusion, which in turn will help in replicating and evaluating the review’s rigour.
5. In the final phase of reporting included studies, there is a clear differentiation between the number of studies included in the review and the number of reports of each of these studies. This distinction is essential because a single study can

have multiple reports, and the 2020 update ensures that this aspect is not overlooked, providing greater clarity in the reporting of included studies.

Figure 13 shows the updated PRISMA 2020 diagram. This update enhances the SLR's clarity, transparency, and detail. It aligns with contemporary practices in data handling and technology use, ensuring that the SLR remains a robust tool for synthesising research evidence.

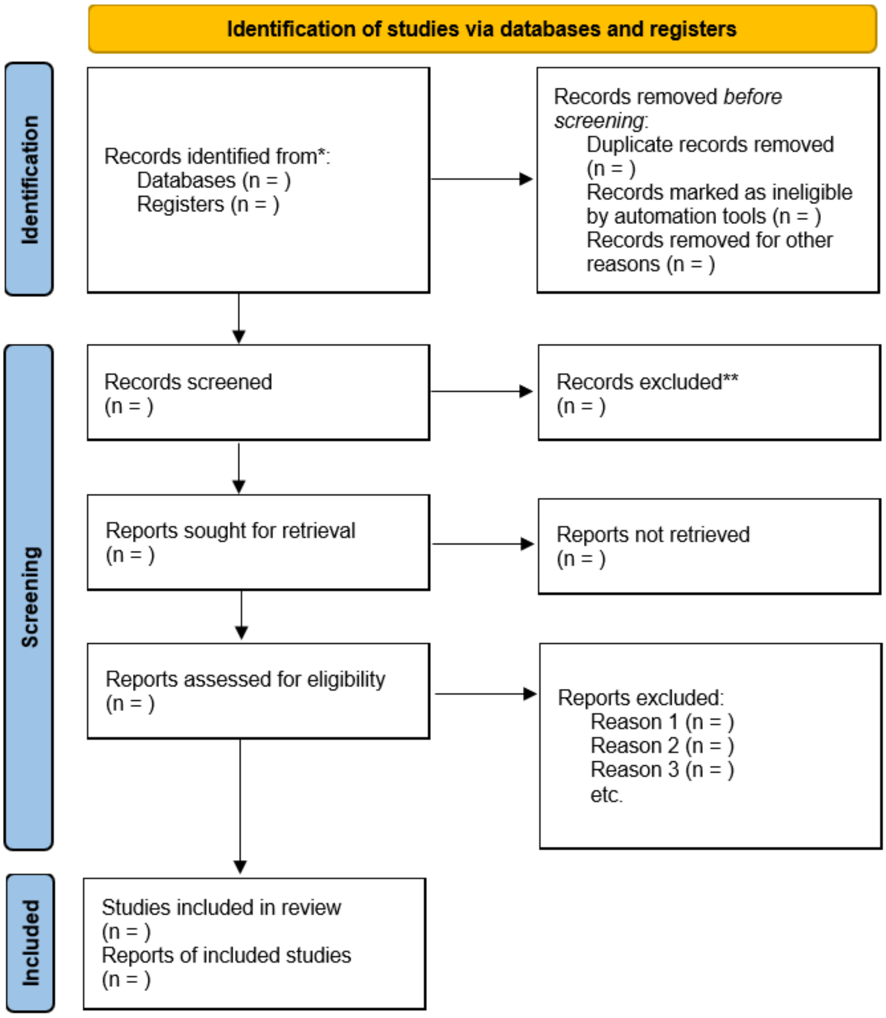


Figure 13. *The updated PRISMA 2020 flow diagram (Page, McKenzie, et al., 2021)*

In this thesis, the PRISMA 2020 statement has been chosen as the framework for the SLR. This decision was based on the well-known, comprehensive, adaptable, and up-to-date guidelines provided by PRISMA 2020, which ensure the rigour, transparency, and reproducibility of SLR. Although PRISMA is typically used for health interventions, it was deemed suitable for the research objectives in this thesis as it offers a review methodology that can accommodate diverse types of studies, ranging from empirical research to conceptual analyses. PRISMA 2020's flexibility allows for the inclusion of various study designs relevant to DL and related literacies, ensuring a comprehensive review of the literature. In conclusion, adopting the PRISMA 2020 statement for the SLR in this thesis is a strategic choice underpinning the study's commitment to academic rigour and methodological excellence. Its alignment with the objectives of exploring DL and related literacy frameworks ensures that the findings of this research are credible and comprehensive and contribute meaningfully to the field of DL.

3.3.3 Research Question and Review Objectives

This section aims to align the review process with the primary research question introduced in the thesis: "How can existing frameworks assist in developing workforce DL programmes and evaluating DL?". To achieve this, appropriate sub-questions for the review are formulated. This alignment is crucial, given the focus is on exploring DL-related frameworks existing in academia, their empirical applications in scholarly literature, and the outcomes of these implementations. Ensuring the review process aligns with this objective is important to achieve the intended outcome. The sub-questions designed explicitly for the literature review are presented in Table 6:

Table 6. *Literature review research questions*

Number	Research question
RQ1	What are the existing frameworks used in business or organisational settings to define, evaluate, or enhance DL-related competencies?
RQ2	What key principles are emphasised in these studies?
RQ3	What are the reported outcomes of these studies?
RQ4	How are the outcomes validated, and what methodologies are employed?

The main goal of the SLR is to systematically address these questions by focusing on the application and effectiveness of frameworks as presented and utilised within academic literature. This will involve a detailed analysis of how these frameworks are proposed in theory, their practical implementation in academic settings, and the resulting educational outcomes reported in scholarly studies.

Considering the challenge of gaining access to practical, real-world workforce environments, each sub-question is designed to examine the applications and outcomes of established frameworks. Through this academic lens, the SLR aims to provide a comprehensive and evidence-based response to each sub-question. The goal is to contribute to a nuanced understanding of how these frameworks can guide the development of workforce DL programmes and DL competence evaluation.

When exploring the frameworks of DL and related literacies, it is important to understand that the term “framework” encompasses various terminologies that reflect the interdisciplinary nature of these literacies. Framework terminologies (Nilsen, 2015) can include models, theories (Wacker, 1998), guidelines, approaches, protocols, and systems, each providing unique perspectives on DL and related literacies. For instance, a model may outline the stages of literacy development, while a theory provides a conceptual understanding. Guidelines can suggest practical education standards and approaches that focus on specific methodologies. Protocols can describe systematic procedures, while systems may refer to integrated tools and processes. Acknowledging this range of terms is essential to the SLR, as it enables capturing the full scope of academic discourse on DL and related literacies, including its diverse structures, methodologies, and applications.

3.3.4 Research Protocol and Process

The cornerstone of any reliable research study is a well-designed protocol and process. This subchapter aims to explain the comprehensive methodology used to conduct this systematic review, highlighting the rigour and precision inherent in the research approach. It starts by describing the search strategy and keywords, detailing the systematic method and terminology used to find relevant literature. This is to ensure the reproducibility and transparency of the research. Subsequently, the inclusion and exclusion criteria section outlines the parameters used to select studies, thereby defining the scope of the review. These criteria maintain focus and relevance and reduce bias.

In the data collection and extraction phase, the systematic approach used to collect and summarise information from the chosen studies will be explained, highlighting the methods and tools employed to ensure consistency and reliability in data handling. The quality assessment section explains the criteria and tools used to assess the methodology and risk of bias in the included studies. Finally, the data analysis and synthesis section outlines the analytical frameworks and synthesis methodologies applied to interpret the data. This includes a detailed explanation of the thematic analysis techniques, offering insights into how the data converge to inform the research questions.

Search strategy and keywords

The systematic search strategy deployed for the SLR focuses on utilising the Elsevier’s Scopus database. The choice of Scopus is supported by its extensive coverage of peer-reviewed literature across diverse fields, offering a comprehensive repository of academic articles relevant to DL and its frameworks. This database is selected for its robust indexing, relevance to the research field, and accessibility to high-quality scholarly works.

The search strategy is designed to capture the breadth and depth of the literature on DL-related frameworks and DL development or evaluation among the workforce. It incorporates a combination of specific keywords and phrases, systematically structured to ensure an exhaustive retrieval of relevant studies. These keywords are chosen based on their relevance to the research questions and objectives outlined earlier, ensuring alignment with the thematic focus of the thesis.

Furthermore, the synthesis of this thesis theory section has influenced the search strategy, as numeracy and literacies such as DL, information literacy, statistical literacy, and AI literacy are interconnected. Workers often need a blend of these skills to effectively interpret and use information and data in decision-making. Understanding the overlap and how these literacies complement each other in organisational settings strengthens the rationale for a broad search string.

Organisations operate in complex environments that require employees to possess a range of literacies to navigate data, statistical information, AI outputs, and general information. By including various literacies in the search string, the author aims to capture a comprehensive picture of the literacies that contribute to organisational effectiveness, innovation, and competitiveness. Understanding the broader landscape can provide insights into how organisations can prepare their workforce for future challenges. Broadening the scope to include DL-related literacies can also help identify gaps in the literature more effectively, especially regarding how these literacies intersect and support each other in organisational settings. This approach enriches the current understanding and highlights areas for future research.

A targeted approach is adopted to refine the search results. The search is narrowed to encompass only specific types of documents to ensure the inclusion of the most relevant and credible sources. These include journal articles, book chapters, and conference publications. Journal articles have been chosen due to their rigorous peer-review process, which typically ensures a high standard of research quality and academic rigour. Book chapters are included as they often provide comprehensive overviews of a topic and can offer in-depth theoretical perspectives and research findings. Conference publications are also considered, as they often present cutting-edge research and innovative ideas. By focusing on these types of documents, the review aims to capture a breadth of academic discourse, encompassing established and emerging research in the field of DL and related literacies. This selection criteria aligns with the objective of the thesis to develop a thorough understanding of frameworks applied within the workforce and grounded in academically rigorous and professionally recognised sources.

The initial search strategy in the Scopus database aimed to identify research studies around data literacy, numeracy, and statistical literacy. The approach incorporated relevant application words like manage, organise, and company. This search resulted in 1195 studies. However, after several rounds of iterations and test searches, the author became convinced that the search string would benefit from including the terms AI literacy and information literacy. The findings of the theoretical part of his thesis also supported this type of modification. To ensure coherence with the application words, the search string was modified to consist of words that are synonyms with the word “organisation”. The conclusion was that the words “business”, “corporate,” and “firm” were added to the search string, and “manage” was deleted. This search doubled the amount of studies, resulting in 2567 records.

To enhance the clarity and methodological transparency of the search strategy, Table 7 illustrates the final key search terms and their combinations when the search applies to the title, abstract, and keyword in the Scopus database:

Table 7. *Table of key search terms and their combinations*

Keyword Category	Keywords	Combination (TITLE-ABS-KEY)
Core Concept	data literacy numeracy statistical literacy information literacy AI literacy	“data liter*” OR numeracy OR “statistical liter*” OR “information liter*” OR “AI liter*
Application	organisation organization company corporate corporation firm business	organis* OR organiz* OR compan* OR corporat* OR firm* OR business*
Language	English	English

Keyword Category	Keywords	Combination (TITLE-ABS-KEY)
Document type	article book chapter conference publication	ar OR cp OR ch

Inclusion and exclusion criteria

This section forms a critical part of the SLR review, establishing the parameters that govern the selection for inclusion. These criteria are designed to ensure that the literature review remains focused on the research questions while maintaining selected studies' relevance and academic integrity. Inclusion criteria are listed in the following Table 8.

Table 8. *Inclusion criteria*

Criterion number	Criterion name	Criterion explanation
1	Date range	No restriction
2	Language	English-language publications, ensuring that the content is accessible and comprehensible
3	Type of publication	Journal article, book chapter, or conference publication
4	Frame-work identifica-tion	A solid theoretical basis and a clear structure that is applica-ble to defining, evaluating, or enhancing competencies re-lated to DL in business or organisational contexts
5	Study rele-vance	Articles focusing on frameworks related to DL or related liter-acies (information literacy, numeracy, statistical literacy, AI literacy), including their application in organisational or busi-ness contexts. This encompasses studies discussing DL-re-lated principles, instructional methods, assessment tech-niques, and impacts on educational practices.

Exclusion criteria are listed in the following table (Table 9).

Table 9. *Exclusion criteria*

Criterion number	Criterion name	Criterion explanation
1	Non-peer-reviewed materials	While Scopus primarily indexes peer-reviewed literature, conference papers that do not demonstrate clear evidence of peer-review processes will be excluded to maintain a focus on scholarly, peer-reviewed work.
2	Studies outside scope	Documents that do not directly investigate frameworks that align with DL or related literacies or competencies' evaluation or enhancement in business or organisational contexts, even if they discuss DL in a broader sense. For the purpose of this review, 'business contexts' refer to environments where commercial activities are conducted, including but not limited to private sector companies, corporations, small and medium-sized enterprises, or startups. Studies that explore DL or related literacies within other contexts outside the business sector (e.g., educational teachers, scientific researchers, governmental bodies, library professionals, healthcare settings, and non-profit organisations) will be included only if they provide valuable insights from the aspect of the workforce.
3	Studies outside scope	Journal article, book chapter, or conference publication
4	Redundant publications	Documents offering duplicate findings will be excluded
5	Accessibility issues	Articles that are either incomplete or not fully accessible will be excluded to maintain the integrity and completeness of the review.

By establishing these criteria, the review aims to be exhaustive in its scope and precise in its focus, aligning closely with the research objectives and questions outlined previously. The final search string in the Scopus database using Boolean logic combining key aspects from the review's RQ1 is:

TITLE-ABS-KEY ("data liter*") OR TITLE-ABS-KEY (numeracy) OR TITLE-ABS-KEY ("statistical liter*") OR TITLE-ABS-KEY ("AI liter*") OR TITLE-ABS-KEY ("information liter*") AND TITLE-ABS-KEY (corporat*) OR TITLE-ABS-KEY (firm*) OR TITLE-ABS-KEY (business*) OR TITLE-ABS-KEY (organiz*) OR TITLE-ABS-KEY (organis*) OR TITLE-ABS-KEY (compan*) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp") OR LIMIT-TO (DOCTYPE , "ch")) AND (LIMIT-TO (LANGUAGE , "English"))

Addressing potential weaknesses in the search strategy

Despite the design of the search strategy to encompass a broad spectrum of relevant literature on DL and related literacies, the inherent limitations associated with any keyword-based search are recognised. The specificity and variability of terminology, especially in an emerging and interdisciplinary field of DL, may inadvertently lead to the exclusion of pertinent studies not to be captured by the initial search string index.

To mitigate this potential weakness and ensure the comprehensiveness of systematic review, both forward and backward citation searches will be employed as supplementary methods. By following the trail of research that has subsequently referenced the core article, additional studies can be uncovered contributing to the dialogue on DL in the organisational and business settings. Conversely, a backward citation search entails the reference lists of the studies included in the initial searches. This historical perspective is important for understanding the evolution of frameworks or models and their application in business settings.

Utilising Scopus, the author of this thesis examines the reference lists and citations of all studies selected for review after the eligibility phase. The total flow of the identification process can be traced back through the comprehensive Excel file that will be created for this purpose. By incorporating this additional step, the author aims to reduce the risk of publication bias and to ensure a more exhaustive survey of the available literature. This step also provides a broader perspective on the evolution of research within the thesis area of study, offering an up-to-date synthesis of the evidence and reflecting the current state of knowledge on the topic.

Data collection and extraction

Data from each included study will be systematically collected utilising the Scopus database to ensure literature retrieval. A standardised data extraction form will be used to gather, organise, and analyse essential information from each study. The extracted data is organised into distinct tables, each serving a specific analytical purpose aligned with the research questions.

In order to categorise the findings in a systematic way, the author will utilise the framework categorisation proposed by Stephen Downes (2023). Downes suggests a three-part structure for understanding DL, which includes a competency framework that outlines the necessary skills and knowledge required for DL, an assessment framework that provides methods for evaluating DL competencies, and a teaching framework that offers strategies for enhancing DL skills. This approach helps the author analyse studies in a more detailed way, differentiating between those focusing on defining competencies, developing assessment methods, and ensuring skills through educational strategies. This results in a clearer understanding of the current state of DL and DL-related research in organisational and business settings.

The first table, Table 10, provides an overview of all studies, offering a snapshot of their fundamental characteristics and helping in navigating the results section of this thesis. This table is located in Appendix A.

Table 10. *Overview of studies*

Study ID	Author(s)	Title	Year

The second table, Table 11, details the primary literacies studied and the corresponding research year. Inside this table, all selected studies are categorised by literacy type and indicated with brackets [ ] to better illustrate the whole corpus of the studies.

Table 11. *Primary literacy studied*

Year	Number of studies	Primary literacy studied by literacy type	Other literacies mentioned

The third table, Table 12, provides a summary of the research methodologies employed in the studies selected.

Table 12. *Research methods*

Research method	Number of studies	Study ID

The purpose of the fourth table, Table 13, is to detail the features discussed in the results section by listing the number of studies, percentage of total studies, and study IDs.

Table 13. *Features discussed*

Nature of the study	N	%	Study IDs
Type of framework	**N**	%	**Study IDs**
Validation methods	**N**	%	**Study IDs**

The purpose of the Table 14, is to summarise framework characteristics discussed in the results section. This table will be located in Appendix B.

Table 14. Summary of framework characteristics

StudyID	Theoretical /conceptual	Empirical	Competency framework	Assessment framework	Teaching framework	Other	Sample / Settings	Aim of the study	Business/organisational setting	Target Audience

Table 15 aims to summarise the target group of the studies, first by literacy type and then by framework type.

Table 15. *The target group of the studies*

Literacy type	Framework type	Specific target group	Broader target group

The purpose of Table 16 is to summarise the key findings related to the reported outcomes and studies' validation methods. This table will be located in Appendix C.

Study ID	Description of framework	Outcomes	Validation method	Key principles

All collected data will be securely stored and organised in an Excel file to ensure transparency. Discrepancies in data extraction will be resolved through discussion or consultation with examiners.

Through this data collection and extraction process, the review aims to gather comprehensive and relevant data that directly contribute to answering the main research question of this thesis. This phase is crucial in establishing a strong foundation for the quality assessment and analysis of the literature, ultimately aiming to synthesise insightful findings aligned with study objectives.

Data analysis and synthesis

After conducting the SLR the last phase is to describe how the systematically collected data is translated into meaningful insights that respond to the SLR's research questions. Following the PRISMA methodology, this process includes an analysis of identified frameworks or models related to DL in organisational or business settings within the collected literature. The focus is on providing a comprehensive understanding of existing DL-related frameworks or models, the principles emphasised in these studies, and the outcomes reported.

3.4 Synthesis of Qualitative and Quantitative Methods

In this thesis, the fusion of qualitative and quantitative methods through abductive reasoning is crucial in developing a nuanced understanding of DL in the workforce. A holistic perspective on studying DL can be attained by utilising a sequential exploratory mixed-methods approach that integrates insights from qualitative interviews with the findings of an SLR.

The qualitative interviews conducted at the beginning provide valuable and contextual insights into DL professionals' practical experiences and perspectives. These narratives form the foundation, informing the formulation of research questions and areas of focus for the subsequent SLR. The qualitative data not only guide the direction of the SLR but also ensure its alignment with existing gaps and real-world challenges in DL, thereby enhancing the relevance of the research.

Following the qualitative phase, in accordance with the PRISMA statement, the thesis presents a rigorously conducted SLR that thoroughly gathers and examines empirical evidence related to DL frameworks in organisational settings. This methodical approach ensures a comprehensive analysis of the existing literature. The PRISMA-guided SLR, which focuses on methodological transparency and replicability, complements the qualitative interviews' exploratory nature.

The synthesis of findings in this thesis is characterised by abductive reasoning, a method that allows for the iterative development of new theoretical insights. It involves an ongoing process of hypothesis generation, refinement, and re-evaluation based on the interplay of qualitative interviews and the SLR data. This approach facilitates the identification of both convergent and divergent themes, integrating grounded, practical insights from the qualitative data with broader empirical evidence from the literature. This integrative analysis bridges the theoretical and practical dimensions of DL and fosters the generation of new theoretical understandings that contribute to advancing the field.

Through this sequential exploratory mixed-methods approach, the thesis emphasises the collaboration between qualitative and quantitative research methods. The abductive synthesis of these methods enriches the comprehension of DL within the workforce. It demonstrates the effectiveness of mixed-methods research in navigating complicated and multi-dimensional phenomena in the field of knowledge management and education. This approach aligns with the research philosophies of positivism and pragmatism, which encourage intellectual exploration and innovation in the field of DL.

3.5 Criteria for Methodological Evaluation

Evaluating the methodologies employed in any research is fundamental to validating its conclusions and enhancing the credibility of its outcomes. Such an evaluation scrutinises the consistency and integrity of the research methods and ensures that the processes are transparent and can be independently verified. This is important in academic research, where the reliability of results underpins the entire scholarly contribution. (Glinka & Hensel, 2018; Qu & Dumay, 2011; Seale, 1999, pp. 2–8; Stasik & Gendźwiłł, 2018)

This subsection establishes the criteria against with the methodological choices of this thesis will be evaluated. The evaluation framework aims to ensure that the methodologies are rigorously assessed in terms of their suitability, effectiveness, and contribution to the research objectives. The criteria set forth here will guide the subsequent analysis in the results section of this thesis.

3.5.1 Criteria for Evaluating Semi-Structured Interviews

In assessing the quality and relevance of the information gleaned from the semi-structured interviews, a set of evaluation criteria is established based on theoretical underpinnings and methodological rigour (Qu & Dumay, 2011; Seale, 1999). These criteria serve to ensure that the insights obtained contribute meaningfully to understanding DL within the business domain, providing a foundation for the subsequent SLR. The evaluation criteria encompass the following aspects:

1. Relevance of interview questions (Qu & Dumay, 2011, p. 251; Stasik & Gendźwiłł, 2018, pp. 226–233): The questions must directly relate to the research objectives,

facilitating the extraction of information about DL in professional settings. The clarity and focus of each question will be evaluated to ensure that they are conducive to gathering meaningful and actionable insights.

2. Participant representation (Stasik & Gendźwiłł, 2018, pp. 237–238): The selection and the amount of interview participants are crucial. The criteria will assess whether the sample is diverse and representative of the target population in relation to the timetable and resources available to the author. This includes considering the variety of professional backgrounds, levels of experience, and roles in data management and decision-making in organisations.
3. Clarity and coherence of responses (Qu & Dumay, 2011, pp. 246–247): The degree to which participants' responses are clear, coherent, and logically connected to the questions posed. This criterion assesses the quality of communication and the ability of the interview process to facilitate meaningful discourse.
4. Depth and quality of data (Glinka & Hensel, 2018, pp. 254–255): The richness of the data collected from the interviews will be evaluated. This includes the level of detail and the range of perspectives captured, which are essential for a nuanced understanding of the subject matter. The ability of the interview format to encourage open, reflective responses from participants will also be considered.
5. Consistency and reliability of information (Glinka & Hensel, 2018, pp. 249–250): The consistency of information across different interviews and reliability of the insights obtained. This criterion examines the extent to which similar themes or viewpoints emerge from different participants, providing a measure of validation for the findings.
6. Ethical considerations and data integrity (Qu & Dumay, 2011, pp. 252–253): the adherence to ethical guidelines in the conduct of interviews and the management of collected data. This includes ensuring participants freely volunteer, knowing the reasons for interviewing, obtaining informed consent, and informing about the interview process and how the data will be used.

3.5.2 Criteria for Evaluating Systematic Literature Review

Systematic literature is particularly valuable in addressing the uncertainties surrounding evidence on a specific topic as it comprehensively synthesises and evaluates existing studies to clarify the current state of knowledge. The systematic review must be structured around a clear research question, employ methods to minimise selection bias, rigorously assess the quality of included studies, and report findings objectively to ensure reliable and unbiased conclusions.(Dixon-Woods et al., 2007, pp. 375–376; Petticrew, 2001, pp. 99–101; Petticrew & Roberts, 2008, p. 28)

To ensure the SLR in this thesis adheres to the standards of methodological rigour and relevance, the evaluation of its process and outcomes is based on criteria derived from the PRISMA statement (Page, McKenzie, et al., 2021; Page, Moher, et al., 2021). These criteria are designed to facilitate the transparent and comprehensive synthesis of research findings related to DL in the business and organisational domain. The evaluation of the SLR in the form of a checklist encompasses the following aspects:

1. Comprehensiveness of search strategy: Evaluating the breadth and depth of the search strategy employed to identify relevant studies. This includes the use of appropriate database(s), keywords, and search terms. The aim is to ensure a comprehensive capture of the relevant literature, minimising the risk of publication bias.
2. Selection and inclusion criteria: Assessing the clarity, relevance, and consistency of the criteria used for including or excluding studies. This criterion reviews the process of screening titles, abstracts, and full texts to ensure that only studies pertinent to the research questions and theoretical framework are included. It also involves evaluating the rationale behind inclusion and exclusion decisions.
3. Objectivity and rigour of analysis: Examining the systematic nature of the literature review process, the accuracy of data extraction using predefined fields, and the methods used to synthesise and interpret findings. This ensures findings are free from bias and adhere to the predefined PRISMA protocol, focusing on integrating findings in a way that addresses the research objectives and contributes to a deeper understanding of the workforce's DL in business and organisational contexts.
4. Reporting and transparency: Reviewing the clarity, completeness, and transparency of the SLR report, adhering to the PRISMA guidelines. This involves providing a detailed description of the methodology, including the search strategy, selection process, quality assessment, data extraction, and synthesis of findings, as well as the disclosure of any limitations and potential biases.
5. Contribution to knowledge and practice: Evaluating the extent to which the SLR advances understanding of DL in the business domain and offers practical implications. This criterion evaluates the SLR's capacity to fill knowledge gaps, confirm existing theories or reveal new insights, and determine its relevance to practitioners and policymakers.

6. Relevance and application of findings: Assessing the extent to which the literature reviewed contributes to answering the research questions of SLR and how it informs the development of DL frameworks within business contexts.

By applying these evaluation criteria, the SLR not only adheres to the methodological standards set by the PRISMA statement but also ensures that its findings are robust, relevant, and capable of informing both theory and practice in the field of DL.

3.5.3 Criteria for Evaluating the Synthesis of Results

In synthesizing the results of this thesis, a systematic approach is utilised to merge the qualitative and quantitative findings through abductive reasoning. This subsection delineates the criteria against which this synthesis will be evaluated, ensuring the integration is methodologically sound and intellectually enriching.

1. Integration of methodological insights: this criterion assesses the effectiveness of combining qualitative and quantitative findings. The synthesis should demonstrate how insights from the semi-structured interviews and the SLR are integrated to address the research questions comprehensively. The evaluation will focus on the clarity and logic of how these distinct methodological insights are brought to form a cohesive understanding
2. Abductive reasoning process: The use of abductive reasoning in synthesising results is central to the development of new theoretical insights. This criterion evaluates how well the abductive process is articulated and executed within the thesis. Specifically, it examines the iterative hypothesis generation, testing, and refinement process based on the interplay between empirical evidence and theoretical frameworks. The effectiveness of this reasoning in leading to logically substantiated conclusions that advance the field will be critically assessed.
3. Theoretical contribution and innovation: The evaluation will consider the extent to which the synthesis of findings contributes to existing knowledge and theoretical development in the field of DL. This includes assessing the originality of the theoretical insights derived and their potential to impact future research and practice. The synthesis should bridge theoretical concepts with practical applications, demonstrating how new understandings can inform DL workforce development and educational strategies.
4. Coherence and logical consistency: This criterion examines the synthesised results' overall coherence and logical consistency. The thesis's final conclusions should logically follow from the combined qualitative and quantitative data,

ensuring that the results are not only integrated but also align with the established research objectives and questions.

By incorporating these criteria, the evaluation framework will provide a comprehensive basis for assessing the thesis's methodological rigour and intellectual merit. This approach ensures that the final synthesis of results is sound and advances the understanding of DL within the workforce.

4. RESULTS

This chapter presents and synthesises the findings from the dual-phase research methodology used in this thesis, following Saunders et al.'s (2019) "research onion" model. The approach began with qualitative research to gather contextual insights, followed by quantitative methods. This sequential exploratory framework combined the depth of qualitative analysis with the empirical breadth of quantitative data, ensuring comprehensive and well-rounded research outcomes. The methodology effectively balanced detailed exploration and broader generalisation, providing a robust and nuanced understanding of the research topic.

4.1 Introduction to Results

Firstly, the qualitative results from semi-structured interviews with professionals are presented. These interviews provided insights into the practical experiences and perspectives of interviewees. In this phase, pragmatism was employed as the guiding research philosophy, emphasising the practical implications of the findings and their relevance in real-world contexts.

After completing the qualitative analysis, the next step was to move on to the quantitative phase. This involved conducting an SLR, which utilised a deductive approach grounded in the positivist philosophy. The main goal of this phase was to critically examine academic literature on DL-related frameworks, focusing on systematically analysing existing frameworks concerning workforce development and competence evaluation.

The chapter then progresses to synthesising the findings from the qualitative and quantitative phases. This synthesis used abductive methodology, integrating inductive insights from the interviews with the deductive analysis from the SLR. This approach facilitated the exploration of frameworks against empirical findings and the incorporation of new perspectives revealed through the interviews. Although the SLR served as the primary driver of the study, providing a comprehensive exploration of DL-related frameworks, the insights from the interviews enriched this exploration, contributing to a more nuanced understanding.

This chapter offers insight into current knowledge and trends regarding DL-related frameworks and their application in workforce development. The study was conducted through a cross-sectional time horizon to answer the primary research question and its sub-questions utilising dual philosophies and a sequential exploratory approach.

4.2 Results from Interviews

This section plays a vital role in connecting the theoretical exploration of DL with the practical realities individuals and organisations face. By synthesising the findings from the interviews through a pragmatic lens, this analysis focuses on the practical implications and real-world utility of DL. This approach allows for a grounded understanding of how DL manifests in the experiences of individuals and organisations, highlighting its role and potential evolution in response to technological advancements.

Subsequent sections systematically uncover the layers of understanding and perception surrounding DL, as expressed by the interviewees. The discussion is intentionally structured to address DL's real-world impact at an individual and organisational level. The pragmatic approach here emphasises the practical, actionable aspects of DL, ensuring that the theoretical aspects of DL are firmly rooted in everyday experiences and challenges.

The theoretical framework outlined earlier in this thesis is the key to interpreting the interview findings. At its core, an enhanced DIKW model is broadened to include essential DL components. This model enables a nuanced analysis of the interviews, drawing connections between the theoretical constructs of DL and the practical experiences and insights shared by interviewees. By applying this model pragmatically, the analysis bridges the gap between theory and practice, enabling a deeper understanding of how DL theories translate into practical actions and strategies.

Through this pragmatic analysis, the various stages of interaction with data, from its initial collection to the derivation of actionable insights, are examined in the context of real-world settings. This approach provides a structured method to analyse the interviews and helps identify key challenges and opportunities in the field of DL. Consequently, the findings from the interviews are not just isolated responses, but they are contextualised within a broader landscape, offering a pragmatic understanding of DL that is directly applicable to current and future challenges and opportunities in the field.

4.2.1 Personal Level Challenges and Opportunities

In a series of engaging interviews with professionals, the concept of DL was explored, revealing a spectrum of interpretations and understandings. Each interviewee brought a unique perspective, reflecting the nature of DL in their contemporary professional context, resonating with the different levels of the DIKW model.

One interviewee presented a specific and comprehensive understanding of DL. This person described it not merely as a set of technical abilities but as a confluence of attributes emphasising DL as a holistic skill set, blending cognitive, ethical, and interpersonal competencies. Another interviewee approached DL through the lens of skills, knowledge, and attitudes assumingly due to the person's professional background as one developer of DigComp but underscoring the need for a balanced approach that integrates technical prowess with a broader understanding and data-favourable mindset.

Other interviewees had a more functional perception of DL. For them, it either represented a cultural phenomenon or a technical acumen. The diversity in understanding highlights the complexity of DL and the importance of adopting a comprehensive approach to cultivating these skills within organisations.

During the interviews, participants disclosed various challenges and opportunities associated with DL at the individual level, with a strong focus on practical implications. A key insight that emerged is the essential role of an individual's awareness in leveraging data effectively. This encompasses not only knowing what data is accessible but also understanding how to locate and capitalise on this resource. Such awareness and skill in identifying and harnessing data resources are essential in optimising the use of data for personal advancement in data-informed decision-making. This more profound understanding of data's potential and how to exploit it underpins the successful application of data at a personal level.

Additionally, two interviewees highlighted three key components in their own words, aligning with the DigComp framework: knowledge, skills, and attitudes. Professionals expressed that these elements collectively establish the foundation for an individual's proficiency in DL. One professional explained that attitudes towards data involve not just the curiosity and eagerness of an individual to engage with and apply data in decision-making processes but also the element of trust in data. This includes evaluating the reliability of the data and assessing whether it can be confidently relied upon for accurate insights and guidance in decision-making scenarios.

One notable challenge raised by interviewees is the data utility issue. Participants shared the struggles that the workforce can have in utilising data for practical decision-making without being data specialists. During discussions about working with data, it became clear that finding the correct data can be a daunting task. It is about accessing data and identifying which data is valuable and pertinent in real-world situations. This challenge poses a significant obstacle and requires developing data-finding and evaluating approaches.

This challenge is also faced when transitioning raw data to actionable wisdom, as described in the DIKW model. These can include challenges such as difficulty in making sense of complex raw data (data stage) into understandable information (information stage) that falls outside their regular area of expertise, challenges in combining and using data from various business departments (knowledge stage), and uncertainty about how to derive actionable insights from the data to inform daily business actions (wisdom state). These experiences underline the gap between theoretical knowledge of data and its real-world application. They emphasise the importance of pragmatic skills training approaches that can effectively bridge this disconnect and facilitate each stage of the DIKW model, making data more accessible and valuable for practical decision-making in a business context.

One interviewee particularly emphasised the significance of Business Intelligence (BI) solutions, like dashboards, in addressing data utility challenges from the perspective of the workforce. The expert highlighted that dashboards are instrumental in rendering complex data more accessible and in democratising data, aligning with the information stage of the DIKW model. However, he noted that the efficacy of these dashboards is mainly contingent on their design and user-friendliness. He also stressed the importance of observing how the workforce interacts with these dashboards. The interviewee argued that regular training and ongoing support are vital to ensuring staff access and accurately interpret the data.

Moreover, the interviewee pointed out that dashboards' effectiveness does not depend on the volume of reports and data they display but rather on the pertinence and necessity of the information provided. This perspective underscores the need for a strategic approach to implementing BI tools, aiming to strike a balance that boosts efficiency and fosters individual DL among the workforce at the personal level.

Additionally, the same interviewee commented on the extensive use of Microsoft Excel in handling data within the workforce. The interviewee pointed out that, for many non-specialist staff, Excel remains the go-to tool for data-related tasks, primarily due to its widespread availability and familiar interface. Excel's flexibility in managing and manipulating data makes it a popular choice, especially for those who may find more advanced BI tools intimidating. The interviewee suggested that while Excel is a valuable tool for specific tasks, there is a growing need for workforce training in more advanced BI tools and solutions. Such training can broaden the data handling capabilities of the workforce, enabling them to leverage data more effectively and make more informed decisions.

In the interviews, several participants also delved into the prospective impact of AI solutions on DL and workforce dynamics. They envisaged a future where AI tools could significantly alter the current data handling landscape, introducing new levels of efficiency and insight. According to the interviewees, these AI solutions could automate routine data processing tasks (data and information stages), freeing up staff to focus on more complex and strategic aspects of data utilisation (knowledge and wisdom stages). One interviewee predicted that this would be only an intermediate phase, leading to a future where machines make decisions without human interference. This raises an intriguing question about the extent to which human-machine interactions will transform in the upcoming years. The implications for the workforce at large cannot be overstated.

On the other hand, a few participants also raised the growing need for effective human-machine interaction. The interviewees expressed that as AI becomes more integrated into data analysis processes, there will be an increased demand for skills centred around interpreting AI-generated insights and collaborating with these systems. They saw this as an opportunity to elevate DL, moving beyond basic data manipulation to a more nuanced understanding of AI outputs. Participants believed that embracing AI in data processes would necessitate a shift in DL training, focusing more on understanding AI algorithms, assessing the credibility of AI-generated insights, and making decisions based on this advanced analysis.

Additionally, the impact of biases on data interpretation was seen as significant by interviewed professionals. The recognition and understanding of biases, both within data and AI solutions, as well as those inherent in human judgment, is essential. Experts noted that while AI can significantly improve data processing, it may also inherit biases from its training data or algorithmic design, potentially leading to skewed results. Also, workers can bring their biases and favour data supporting their preconceptions, overlooking contradictory information. Therefore, a comprehensive approach to DL must involve awareness of these dual aspects of bias: a critical evaluation of data inputs and algorithmic logic and self-awareness of one's cognitive biases. Enhancing DL within the DIKW framework involves developing skills and awareness to identify and address biases at each stage. This means technical skills in data handling and understanding the psychological and algorithmic factors that can distort data interpretation. This underscores the requirement for cultivating critical thinking capabilities, empowering individuals to engage with data through an objective and well-informed lens.

Furthering the exploration of DL within the DIKW framework, the ability to effectively translate data into coherent narratives and communicate findings emerged as a crucial skill expressed by interviewees. This aspect of DL becomes particularly significant in the latter stages of the DIKW model – knowledge and wisdom. Professionals commented that the art of storytelling is the skill to weave data into narratives that are meaningful and engaging and transform the value of figures and analyses into stories that resonate with value-added outcomes like profits and lead to actionable and impactful insights. This confirmed the author’s perception about DL as a holistic skill set, enabling individuals to not only interpret data but also to share and apply its wisdom effectively across diverse contexts.

This analysis of interview responses examined the aspects of DL at an individual level. The findings underscore the challenges in data utility, the importance of awareness in leveraging data, and the need to recognise biases when working with data. The interviews confirmed the understanding that knowledge, skills, and attitudes are three essential components of DL. Discovered insights align well with the thesis's theoretical DIKW model, which shows the journey from raw data to actionable wisdom.

The interviews also revealed the significant role of tools such as BI dashboards in democratising data access. However, findings highlight the importance of strategic implementation and advanced training. Moreover, results point to a future where DL transcends basic data manipulation. It demands a nuanced understanding of AI and acute awareness of biases at every stage. The potential transformation of the data landscape by AI solutions and the imperative for effective human-machine interaction underscores the importance of DL.

The findings also emphasise the importance of storytelling and communication skills in the knowledge and wisdom stages of the DIKW model. They reinforce the notion of DL as a holistic skill set. This is crucial for interpreting data and sharing and applying its insights effectively across diverse scenarios.

4.2.2 Organisational Level Challenges and Opportunities

At the organisational level, interviewees identified the lack of data governance as hindering effective data management and overall DL. This absence points towards a need for implementable governance frameworks that align with organisational goals and culture, resonating with the foundational layer of the DIKW model, where accurate and well-governed data form the base for further information processing. For example, the overwhelming volume of reports suggests a requirement for strategic data management, advocating for pragmatic approaches to manage data effectively and focus on relevant and actionable information.

One interviewee expressed that there is a need for business-critical data governance. Business-critical data governance is aligned with DL, ensuring that employees across the organisation understand the importance of this data and how it impacts their roles and decision-making processes. This alignment reflects the progression in the DIKW model from information to knowledge, where understanding and contextualising information becomes crucial. It also ensures employees understand business-critical data management policies, standards, and procedures. It provides the framework to ensure their data is reliable, accurate, and available. Three interviewees stated that data governance and cultivating DL require a cultural shift within an organisation. Data governance was seen as setting the formal framework, while DL ensures that employees at all levels are equipped to adopt and adhere to these governance structures.

The critical role of executive leadership in shaping a data-centric culture became evident through interviews. It also aligns with the upper tiers of the DIKW model, particularly the wisdom aspect. Executives advocating for data democratisation ensure that data is accessible and used ethically and effectively, guiding the organisation toward wise decision-making. This involves providing access to data across all levels of the organisation and promoting transparency regarding how data is collected, processed, and utilised. By doing so, executives empower every organisation member to engage with and effectively utilise data in their respective roles. “If executives are not engaged, nothing will happen”, stated one expert.

Furthermore, two experts mentioned that building data-driven communities within an organisation is not just a theoretical concept but a practical approach to fostering a collaborative environment for data usage, integral to creating a sustainable and pragmatic data culture. Such communities can break down silos, fostering open communication and encouraging the sharing of insights and best practices. They mentioned that this openness enhances operational efficiency and nurtures a sense of collective responsibility and trust in data-informed decision-making. Experts saw the active involvement of executive leadership in advocating for a culture of data democratisation and transparency as integral to creating a sustainable, pragmatic, and ethical data culture.

Two interviewees also commented that data democratisation or evolution could be facilitated by providing all employees with a fundamental data catalogue and a data glossary. This helps to share the understanding of “the truth of data” at the organisational level, diminish misunderstanding of definitions, and operate as a mediating force. Collaboration between departments and business areas in data utilisation was also seen as a key to success.

One interviewee emphasised that creating a data culture is not a project initiative but an enduring process of developing skills, nurturing curiosity, and fostering an environment where data-driven insights are part of the everyday decision-making process. It is about building a foundation where data is valued and understood and an integral part of the organisational mindset and approach to problem-solving, innovation, and growth.

One expert mentioned AI solutions' predictive capabilities, indicating a new dimension to DL. Rather than solely relying on historical data, organisations can leverage AI to forecast future trends, anticipate customer needs, and address potential challenges. This transition from retrospective analysis to predictive foresight can offer a competitive edge for organisations to be more proactive, customer-centric, and efficient. At the organisational level, this shift in DL underscores the need for a more forward-thinking approach to transforming how organisations think about and use data for decision-making, customer engagement, and long-term growth. It also reflects a move towards the apex of the DIKW model, where wisdom is derived from knowledge and driven by predictive insights.

In conclusion, the insights from interviews underscore the interplay between effective data governance, DL, and the role of executive leadership in fostering a data-centric culture within organisations. The necessity for a business-critical data governance framework is clear, aligning with developing comprehensive DL across all organisational levels. This alignment is about managing and understanding data and embedding a culture of data democratisation and transparency driven by executive engagement and advocacy.

Forming communities and providing resources like data catalogues and glossaries are practical steps toward this goal. They enhance collaboration and reduce misunderstandings. They represent tangible efforts to democratise data, making it a shared and understood resource across organisations.

Furthermore, the emergence of AI solutions and their predictive capabilities signals a transformative shift in DL. Moving from a retrospective to a predictive outlook, AI encourages organisations to adopt a more proactive stance. Overall, these insights paint a picture of DL as more than a procedural requirement. They are foundational elements of a dynamic, data-informed organisational culture. This culture is characterised by continuous learning, adaptability, and a forward-looking approach that leverages data for strategic advantage.

Table 16 on the next page presents a synthesised overview of the key findings from the interviews introduced in this section. It reveals a spectrum of key insights, challenges, and opportunities concerning DL at the personal and organizational levels. The table highlights the nuanced understanding of DL as it manifests in real-world contexts and illustrates its complex landscape. It also maps out the practical implications and strategic approaches identified by interviewees.

Table 16. Summary of interview findings

Category	Personal level	Organisational level
IN-SIGHTS	**Understanding and application:** DL involves a blend of cognitive, ethical, and interpersonal competencies. Individual awareness is crucial for leveraging data effectively. Skills, knowledge, and attitudes influence DL, highlighting a balanced approach integrating technical prowess with a broader, data-favourable mindset.	**Implementation and impact:** Data governance plays a critical role in effective DL management. Executive leadership is essential for fostering a data-centric culture. DL requires a cultural shift within organisations for sustainable practice.
CHAL-LENGES	**Difficulties in utilising data:** Accessing relevant data and evaluating its utility are major hurdles. Non-specialists find it challenging to make sense of complex data. Difficulty in data interpretation and application in decision-making. Recognising and addressing biases within data and AI solutions is crucial. Awareness of personal cognitive biases is necessary for effective DL. Training should focus on understanding algorithmic logic and data inputs to manage biases effectively.	**Structural and governance issues:** Lack of data governance hinders effective data management. Organisational silos impact efficient data utilisation. The overwhelming volume of data and reports necessitates strategic data management to focus on relevant and actionable information.
OPPOR-TUNITIES	**Enhancing personal DL:** BI tools like dashboards enhance data-driven decision-making. Training in advanced BI tools and embracing AI can automate routine tasks and focus on strategic data use. Increased need for training in DL to handle data effectively and make informed decisions. Continuous training in data handling and interpretation enhances DL. Storytelling and communication skills are crucial in transforming data into actionable insights. Critical thinking capabilities empower individuals to engage with data through an objective and well-informed lens.	**Strategic advancements in DL:** Building data-driven communities enhances collaboration and DL. Implementing business-critical data governance aligns with DL's needs. Leveraging AI for predictive insights aids proactive decision-making. Providing data catalogues and glossaries helps share the understanding of data truths. AI tools are predicted to significantly alter data handling, introducing new efficiencies. BI dashboards democratise data access and make complex data more accessible. Regular training and support are vital for the effective use of technological tools in DL.

4.3 Results from Systematic Literature Review

This section describes the study selection process of the review in detail. It also provides a comprehensive overview of the chosen articles and answers the research questions presented for the literature review in section 3.3.3. The results are presented through tables that categorise each article's content, providing a clear understanding of the studies' design, methods, key themes, and topics covered. Basic information about the selected articles, such as author(s), title, and year, are covered in Appendix A to facilitate readers' navigation through the results presented in this section. The numbers marked with [ ] in this section refer to the article numbers presented in Appendix A. The primary goal is to provide a clear and concise summary of the process and results.

4.3.1 Study Selection Process

The initial search constructed the foundation of the review and consisted of 2567 studies from the Scopus database. Before any screening, records were refined by removing duplicates (26 records), additional instances of the same item (3 records), non-English language publications (115 records), and documents not categorised as journal articles, book chapters, or conference publications (287 records). This pre-screening step was conducted to streamline the focus towards the most relevant sources of information. The remaining 2136 records were extracted on 21.1.2024 from the Scopus database into the Excel file. In this phase, the information extracted from the Scopus included title, year, publication stage, and www-link to the study. These 2136 records were screened based on their titles and abstracts after the identification phase.

This phase was instrumental in distinguishing studies specifically addressing DL or related literacies (information literacy, statistical literacy, numeracy, AI literacy) frameworks within business or organisational contexts. The process resulted in the exclusion of 1982 records for not aligning with the review's criteria. Excluded were studies that, while possibly discussing DL or related literacies, did not centre on defining its competencies or enhancing or evaluating these competencies in business or organisational settings. Excluded were studies that offered insights outside the specified scope, such as educational, governmental, healthcare, or non-profit environments. However, exceptions were made for studies from these excluded sectors if they provided valuable perspectives on DL or related literacies operationalisation to meet workforce needs in organisational or business contexts. This phase was critical for narrowing down the vast pool of literature to a manageable and focused collection of reports for detailed evaluation.

To uphold the integrity and transparency of the review process, it is important to provide an overview of the nature of the 1982 records excluded during the screening phase. This reflection demonstrates the author's commitment to the PRISMA workflow and offers insights into the existing landscape of related research and its multifaceted applications across various contexts. During the screening phase of the records, it became evident that the primary literacy type among records was information literacy. This is understandable, as the term was coined already in 1974 by P. Zurkowski (Badke, 2010), who thought that information literacy is a crucial element in developing organisations. Since then, scholars have discussed and developed information literacy in various contexts, and this was observable among screened records.

These records in question placed emphasis on exploring the role of information literacy in education and among librarians, instructors, and scientists. This is likely due to the widespread recognition among educators and researchers that information literacy is crucial in determining student outcomes in this domain and needs to be measured and conceptualised from this perspective. Beyond the education field, information literacy was related to themes like lifelong learning, digitalisation, and other domains such as politics, information science, and the healthcare sector. The omitted studies in other literacy types reflected a similar distribution, although the number of studies is significantly smaller and has only increased after the terms became more common. Specifically, statistical literacy and numeracy records have grown from 2000 onwards, data literacy from 2010, and AI literacy from 2020 onwards.

The evolution of screened literacy types reflects the broader societal shift towards the digital and information-driven age. Information literacy has a significant role in shaping organisational development and influencing diverse sectors. Records analysis shows a progression of literacy types from the initial focus on information literacy to the inclusion of emerging literacies. The increasing relevance of these literacies indicates the expanding digital landscape and emphasises the need for continuous adaptation and integration into educational frameworks, professional development, and policy-making. These trends affirm the importance of comprehensive research reviews in mapping the contours of this dynamic field.

In the detailed phase of the review workflow, 126 full-text reports were assessed for eligibility. At this phase, the authors of the chosen 126 studies were added to the Excel file. After fully reading the studies, 103 reports were excluded for various reasons, including misalignment with the study's focus (78 reports), inappropriate contextual focus (16 reports), being a review (5 reports), and no recognisable framework (4 studies). The intensive screening and eligibility assessment culminated in including 23 reports before enrichment through forward and backward search. These 23 reports served as the foundation for the systematic review. However, recognising the importance of capturing the most comprehensive array of relevant studies, the forward and backward search strategies were employed in February – March 2024 to uncover additional reports that might have been missed in the initial database search. The forward search involved reviewing the citations of the initially included reports to identify subsequent studies that cited them and were relevant to this review. Conversely, the backward search entailed examining the references within the initially included reports to find earlier studies that had contributed to their research but had not been captured in the initial search. The whole workflow is illustrated in Figure 14 below.

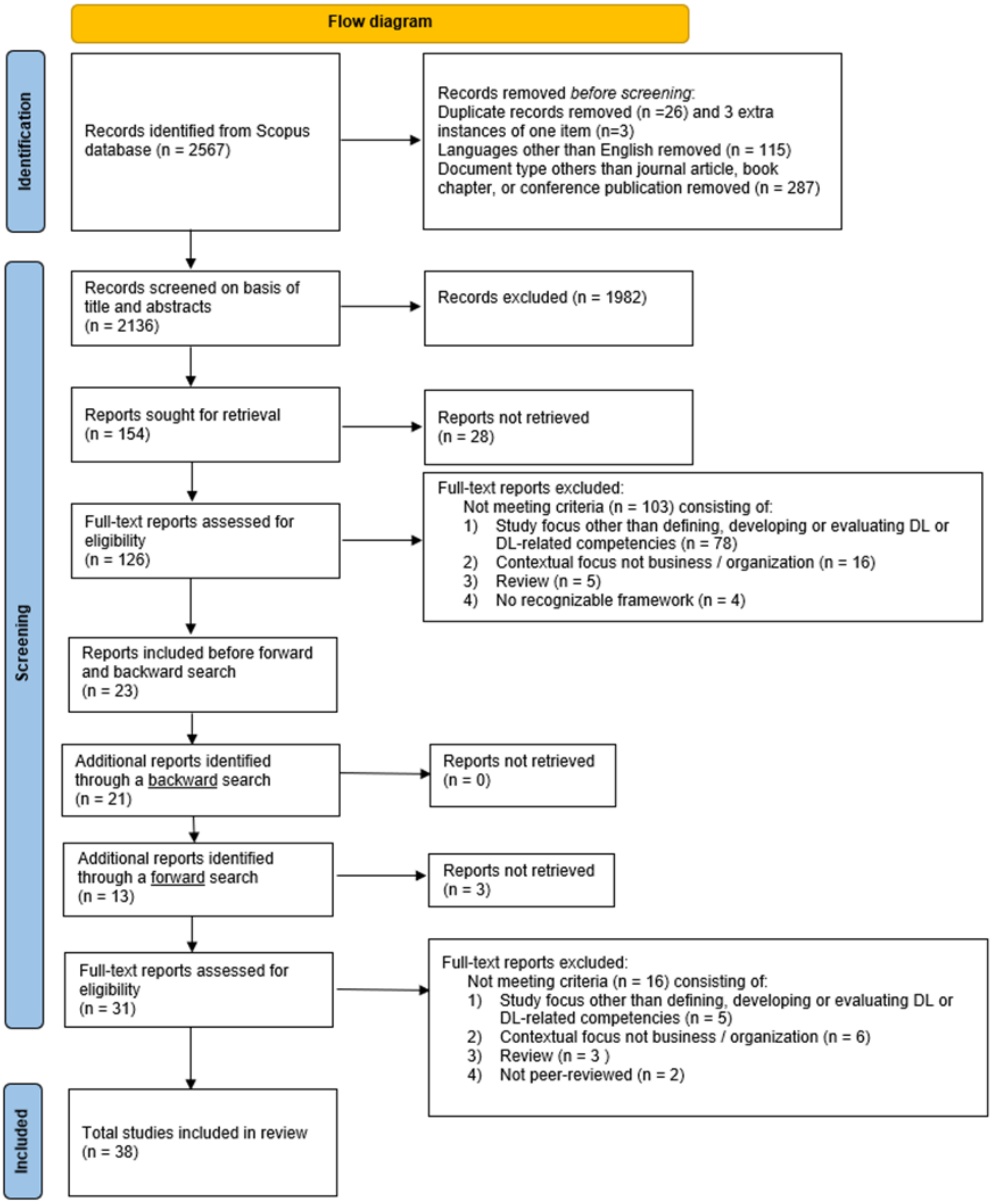


Figure 14. *Overview of the search protocol based on the PRISMA statement*

The dual search approach enriched the pool of potential studies. Through the backward search, 21 additional retrievable reports were identified. The forward search yielded 13 additional reports, although three could not be retrieved. This process brought the number of new reports to 31 for eligibility checks. After fully reading the studies, 16 reports were excluded for various reasons, including misalignment with the study's focus (5 reports), inappropriate contextual focus (6 reports), being a review (3 reports), and being no peer-reviewed (2 studies). Combining the initially included 23 reports with the 15 newly identified and eligible reports from the forward and backward searches resulted in a total of 38 studies being included in the systematic review. This selection process ensured the review was grounded in relevant, high-quality, and up-to-date research evidence. Including the reports from backward and forward searches enriched the quality and diversity of the studies included. In case of any uncertainty during this process, the author consulted with Juho Hamari, a professor at Tampere University. The information extracted and added to the Excel spreadsheet from the selected studies is listed in Table 17.

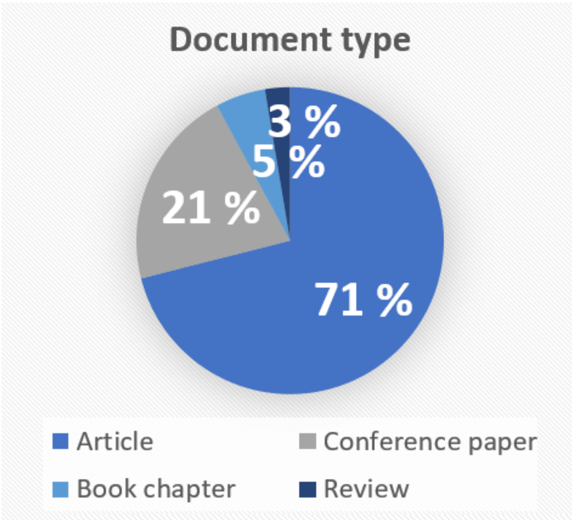
Table 17. *Information extracted from studies for analysis*

1	Author(s)
2	Title
3	Year
4	Www-link
5	Publication stage
6	Information on whether the study includes a framework and/or empirical
7	Type of framework (competency, assessment, teaching)
8	Description of framework/model
9	Type of study design and method
10	Sample/settings
11	Validation method
12	Literacies mentioned
13	Business / organisational setting
14	Target audience
15	Key principles emphasised
16	Aim of the study
17	Outcomes of the study

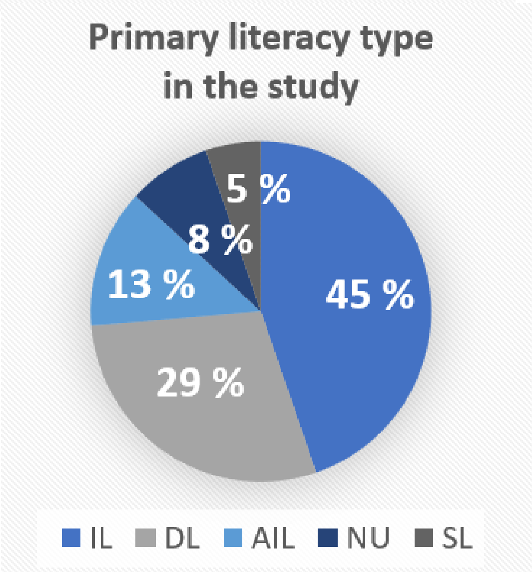
4.3.2 Overview of Reviewed Articles

In the analysis sections, abbreviations are employed to denote literacy types. The following abbreviations are utilised: N for the total number of studies, IL for Information literacy, SL for Statistical literacy, DL for Data literacy, AIL for AI literacy, Nu for Numeracy, DGL for Digital literacy, and MLL for Machine learning literacy.

Figure 15 illustrates the document type of papers and the distribution of the studies where the primary literacy type was recognised. It showcases that 71 % of papers were published in journals, 21 % were conference articles and the rest totaling for 8 % consists of book chapters (5 %), and reviews (3%).



Document type	N	%
Article	27	71 %
Conference paper	8	21 %
Book chapter	2	5 %
Review	1	3 %
	38	



Primary literacy type	N	%
IL	17	45 %
DL	11	29 %
AIL	5	13 %
NU	3	8 %
SL	2	5 %
	38	

Figure 15. *Document type and primary literacy type*

The presence of conference papers points to an exchange of ideas in professional circles, showcasing preliminary results that may lead to further investigation, whereas the predominance of journal articles underscores the engagement with current research questions suggesting a dynamic community of practice.

Additionally, the findings indicate that among the full set of papers, the majority of studies focus on IL (45 %) and DL (29 %); next comes AIL (13 %), NU (8 %), and SL (5%). This finding is aligned with the previous observation conducted from the records' screening phase, IL being the most researched area, DL and AIL following with an increasing amount of research. One study [11] was excluded from the figure due to its lack of primary literacy focus.

Table 18 on the next page showcases that the final set of selected papers was published between 1999-2024. Remarkably, the publication years of these articles were more evenly distributed among information literacy studies. In contrast, data literacy studies have appeared since 2015 within the specified organisational or business context, and studies on AI literacy have only recently been conducted, with the first studies appearing in 2020. The number of studies dealing primarily with statistical literacy, numeracy, or combined literacies is insignificant and does not indicate a growing trend, unlike studies with primary literacy being information literacy, data literacy, and AI literacy.

Six of the 38 articles [5,6,7,11,14,24] also discussed other literacy types in addition to the primary literacy type, which reflects the multidisciplinary nature of these studies. Other literacies that emerged were computer literacy, digital literacy, risk literacy, statistical numeracy, scientific literacy, machine learning literacy, AI-specific literacies, and technological literacy. One study [7] also discussed literacy and numeracy.

Research conducted on the development of competencies related to literacies in the workforce suggests that while there has been a primary focus on domains such as information, data, and AI literacy, the number of papers in these areas remains somewhat restricted. Further research in these domains is crucial to ensure that the workforce is well-equipped with the necessary skills in the near future. As organisations increasingly operate in data-rich environments with human-AI collaborative systems, the role of DL and AIL will continue to increase.

The analysis reveals that information literacy emerges as the most prevalent, underscoring its foundational role in identifying, understanding, and using information effectively. These are skills that underpin critical thinking and decision-making also in business operations. DL follows, reflecting the growing importance of data-driven insights in optimising business processes and enhancing customer experiences.

Table 18. *Characteristics of the articles*

		Primary literacy studied						
Year	**N**	IL	SL	NU	DL	AIL	Com-bined	*** = Other literacies mentioned**
1999	1	[10]						
2002	2	[5*]	[18]					DGL
2007	1	[23]						
2008	1	[13]						
2010	1		[26]					
2012	3	[6*,17,38]						Computer literacy (one article)
2013	1			[14*]				Primary term in the study: statistical numeracy; Other: risk literacy
2014	2	[20]		[7*]				Literacy
2015	1				[33]			
2016	1				[16]			
2017	1				[15]			
2018	3	[8,28]			[36]			
2020	4	[2]		[9]	[32]	[24*]		DL, scientific literacy, DGL, computational literacy, MLL
2021	3	[37]			[3,35]			
2022	5	[19,27]			[1,34]	[25]		
2023	7	[4,29,30]			[21,31]	[22]	[11*]	AI-specific digital literacies, DL, technological literacy
2024	1					[12]		
Total	38	17	2	3	11	4	1	

(N = number of articles, IL = information literacy, SL = statistical literacy, DL = data literacy, AIL = AI literacy, DGL = digital literacy, MLL = machine learning literacy)

While less represented in current literature, AIL is quickly becoming essential as AI systems become more integrated into business operations and are, to organisations, a way to maintain their edge in a technological landscape. Employees with AIL can collaborate effectively with AI technologies. While current research provides an initial understanding of the importance of these literacies, it is clear that there is a need for more research in this domain. The mastery of these literacies enables employees to function effectively in a digital-first environment. Developing frameworks for the systematic enhancement of these literacies is crucial.

The research methods of these studies are provided in Table 19. One action research, 9 conceptual papers, and 28 empirical studies were conducted on the topic. Among the empirical studies, the majority of researchers employed quantitative methods, namely surveys [2,9,11,22,26,27,28,29,30,31,35,37] and one validation study [14] to gauge the participants' level of literacy in question or to develop a competency framework. Some researchers used qualitative (7) methods, such as phenomenographic study [10], case study [1,5,7,13,25], and observations coupled with semi-structured interviews [23], to propose practical suggestions for developing and improving training programmes, an education framework, or to describe how workers become literate in their workplace.

Table 19. Research methods

Research method	N	Studies
Quantitative	14	[2,9,11,12,14,22,26,27,28,29,30,31,35,37]
Qualitative	7	[1,5,7,10,13,23,25]
Mix-Method	7	[4,6,8,16,19,21,34]
Conceptual paper	9	[3,15,17,18,20,24,32,33,38]
Action research	1	[36]
	38	

The remaining researchers took a mixed-method approach to propose a competency framework [21,34], assessment framework [4,19], or teaching model [6,8,16]. They gathered data from diverse sources, such as surveys, the Analytic Hierarchy Process and Fuzzy Comprehensive evaluation, skill level tests, gap analysis, expert reviews, observations, feedback collection, and literature review. In addition to these methods, one action research was conducted to enhance the understanding of DL within non-governmental organisations.

Table 20 on the next page elucidates the apparent distribution of studies within the research corpus. Among the 38 studies reviewed, 15 papers, representing 39 % of all studies, are theoretical. These studies primarily focus on conceptual examinations, developing a nuanced understanding of DL and related literacies without immediate practical application. They serve as a foundation for the framework, offering insights and principles that inform DL and related literacies.

Table 20. *Nature of the study*

Nature of the study	N	%	Studies
Theoretical	15	39 %	[1,3,6,12,15,17,18,20,21,24,31,32,33,36,38]
Empirical	11	29 %	[5,7,9,14,16,25,26,27,28,29,30]
Both	12	32 %	[2,4,8,10,11,13,19,22,23,34,35,37]
	38		

In contrast, 11 studies, approximately 29 % of all studies, are empirical. These investigations apply concepts of DL or related literacies within real-world contexts, testing hypotheses and contributing tangible evidence to the field. They validate and challenge theoretical assumptions through hands-on data collection analysis, thereby enhancing the empirical grounding of research in this domain.

12 studies, constituting 32 % of the sample, integrate theoretical and empirical approaches to bridge the gap between theory and practice. These studies enrich the corpus by discussing concepts and demonstrating their application within various settings, thus providing a comprehensive view of the field. The balance among these categories reflects a varied diversification within the field. This combination of theoretical analysis and empirical evidence is essential for advancing the field and informing future practice.

Next, the research findings are organised in alignment with the research questions and are discussed in greater detail. This approach ensures a thorough exploration of each question, delving into the nuances and implications of the findings.

4.3.3 Answering the Research Questions of SLR

RQ1: What are the existing frameworks used in business or organisational settings to define, evaluate, or enhance DL-related competencies?

To address the complexity inherent in this research and systematically categorise the findings, the author adopted the framework taxonomy proposed by Stephen Downes (2023). Downes suggests a three-part structure for elucidating DL frameworks or models: an evaluation or assessment framework outlining methodologies for gauging competencies, a competency framework delineating requisite skills and knowledge for proficiency, and a teaching framework presenting strategies and learning methods for enhancing skills.

This paradigm in this thesis is instrumental for this reason: it facilitates the author's structured analysis of the corpus, enabling differentiation among studies based on their primary focus: defining competencies within the competency framework, developing evaluative methods within the assessment framework, or enhancing skills through educational tactics or practices within the teaching framework. This systematic approach ensures a thorough and organised review of studies found. The studies are also classified based on their inherent nature, whether theoretical or conceptual, apply one in an empirical setting, or integrate both approaches. This nuanced categorisation underscores the multifaceted application of frameworks in DL-related research and promotes a deeper understanding of how theoretical models translate into practical applications and empirical investigations. Thus, Downes' three-part structure is an important tool for facilitating a comprehensive synthesis of existing knowledge and identifying avenues for future research in this thesis.

Table 21 categorises the papers into three main frameworks, as described earlier, with the addition of an 'other' category for studies that do not fit neatly into the three proposed categories. The distribution of papers across these frameworks is as follows. The competency framework category encompasses 11 studies (29 %), signifying efforts to define requisite competencies and knowledge for the proficiency of specific literacy. The assessment framework category contains 15 studies (39 %), indicating a considerable interest in developing methodologies for evaluating competencies and reflecting a diverse range of approaches to assessment methods. The teaching framework category includes 11 (29 %) studies showcasing strategies and methods for enhancing skills through educational practices. These studies demonstrate a commitment to advancing the education field in business and organisational contexts. A single study falls outside these categories because it consists of two types of frameworks.

Table 21. *Type of framework*

Type of framework	N	%	Studies
Competency	11	29 %	[3,11,12,18,20,21,24,32,33,34,36*]
Assessment	15	39 %	[2,4,8*,9,14,19,22,26,27,28,29,30,31,35,(36*),37]
Teaching	11	29 %	[1,5,6,7(8*),10,13,15,16,17,23,25]
Other	1	3 %	[38]
	38		(* = study includes two types of framework)

This categorisation underscores the importance of a multifaceted approach to understanding and enhancing investigated literacies in organisational and business contexts. It reflects the complex interplay between development, assessment methodologies, and educational strategies in the field.

When delving deeper into frameworks' characteristics, Table 22 provides a comprehensive breakdown of the target groups for studies focusing on various literacy types and frameworks.

Table 22. *The target group of the studies by literacy and framework type*

Primary literacy type	Framework type	Specific target group (e.g., profession)	Broader target group (e.g. organisations)
IL	Competency		[20]
	Assessment	[19]=safety officers, [27]=investigation officers, [28]=scientists, [29]=journalists, [30]=lawyers	[2,4,8*,[37]
	Teaching	[5]=research workers, [23]=firefighters	[6,10,13,17,8*]
	Other	[38]=safety management	
DL	Competency	[3]=auditor, [21]=goverment officers	[32,33,34,36*]
	Assessment		[31,35,36*]
	Teaching		[1,15,16]
AIL	Competency		[12,24]
	Assessment		[22]
	Teaching	[25]=construction workers	
SL	Competency		[18]
	Assessment	[26]=MBA students	
	Teaching		
NU	Competency		
	Assessment	[9] = loan officers	[14]
	Teaching	[7]=production workforce	
Combined	Competency		[11]

The field of IL frameworks encompasses 17 studies in the context of business and organisation. Surprisingly, only one study was categorised as a competency framework among these studies. This study sought to understand IL in the workplace, especially in developing countries like Nigeria [20]. The framework's absence of specified target professions indicates broad applicability across a wide range of organisational roles. This suggests the basic IL skills necessary for effective workplace functioning and decision-making.

Assessment framework studies examine a range of professionals, including safety officers [19], investigation officers [27], scientists [28], journalists [29], and lawyers [30], with an expansion into broader settings such as SMEs, public and private sectors, and various organisational leaders [2,4,8,37]. This diversity reflects the universality of IL's application in professions where accurate information processing is critical.

The IL teaching frameworks found address the specific needs of research workers [5] and firefighters [23] and are extended to wider target groups, including adult learners [6], professionals in higher education [10], business professionals [13], and workplace leaders [17]. This approach is characterised by the development and implementation of training programmes tailored to the unique information needs and contexts of the target groups.

The field of DL frameworks comprises 12 studies. Among these, competency framework studies are more dominantly focused on broader target groups like librarians and workforce needs [32,33], various business roles [34], and non-governmental organisations. Two studies are targeted at specific professional groups like auditors [3] and government officers in Thailand [21]. Three frameworks are categorised as assessment frameworks targeted to the broader target groups, and one of these studies [36] includes both a competency framework and an assessment framework. The other two frameworks are corner groups like governmental organisations [31] and employees in general together with university students [35]. This indicates a general push to assess DL in various settings, suggesting a universal application in the digital era. DL teaching frameworks target a broad range of audiences like employees [1], people in non-technical fields [15], and DL learners, including journalists and non-profit organisations [16]. The emphasis on broader target groups underscores the need for data skills across the field of business and organisations.

AIL frameworks, which are just emerging, consist of 4 studies in the specified context. Two frameworks were categorised as competency frameworks, and both were linked to broader categories, such as employees within digital workplaces [12] and education and public understanding of AI technologies [24]. One assessment framework was recognised, which led to the development of a measurement tool for non-experts [22]. One teaching framework found had a specific target group of construction workers [25] in an Australian company. These few papers indicate the early developmental stage of AIL in the workplace.

SL frameworks consisted of two papers, one competency framework with a general target group of adults in information-laden societies [18] and one assessment framework with MBA students [26], suggesting that SL is particularly relevant for those in managerial positions. No teaching framework was recognised belonging to the field of SL.

The field of numeracy covers three frameworks. One assessment framework targeted the specific professions of loan officers [9], and another assessment framework introduced a numeracy validation test [14] designed to assess statistical numeracy and risk comprehension among educated individuals, including professionals in medical and business fields. No specific competency framework was found. Additionally, one combined competency framework paper was found outside all primary literacy type frameworks. That paper [11] aimed to explore the impacts of generative AI on the business skill sets valued among business practitioners, focusing on the perceptions of these practitioners regarding the evolving importance of various competencies. That implies an understanding that modern business practices require a blend of various literacies.

Across all competency frameworks found in various literacy types, there is an emphasis (9 papers out of 11) towards a framework that is targeted to a broader audience, which can indicate a pursuit toward a more holistic view of skills needed in various organisational roles. On the contrary, assessment frameworks are more evenly distributed among specific (7 papers) and broader target groups (9 papers). This can be interpreted in that assessment varies greatly among the specific professions, reflecting the tailored needs of different roles. On the other hand, more generalisable assessment tools are also being pursued.

Overall, the representation of different literacy types and consecutive frameworks and their application in business and organisational contexts indicates a landscape where different literacies are not a one-size-fits-all concept but instead tailored to the unique requirements of each dimension or job role and the broader organisational goals. The emphasis on dominating assessment frameworks (40 %) highlights the effort to evaluate skills adequately and perhaps also the need for employers to get factual information on skill levels to plan training activities aligned with these needs.

In the following text, the components of the frameworks will be briefly discussed. The information related to these findings is available in Appendix C under the column "Description of framework". Some common themes can be identified among these frameworks. One of the most important aspects of these frameworks is their tailored nature and applicability to various fields such as auditing, management, vocational training, safety management, and governmental performance. This wide-ranging application highlights the importance and relevance of these literacies across different disciplines.

Competency levels or categories are featured across various frameworks, revealing the importance of measuring competencies and progressing them from basic to advanced levels. Some studies [3,8,14,19,25,29,30,31,35,36,37] showcase this level progression, while others focus on different dimensions of competencies [2,4,10,11,12,18,20,21,22,24,28,32,33,34,36,38]. When it comes to assessment, frameworks detail various tools and scales. Under competency, some frameworks are explicitly designed to delineate competencies, and the acknowledgement of skill differentiation further enhances this focus, as frameworks categorise competencies to cater to the diverse skill levels within professional hierarchies. Multidimensionality is a recurrent concept; integration with work practices is also a common thread.

Regarding teaching methodologies, frameworks such as the study [16] propose pedagogical principles highlighting the significance of focused, guided, inviting, and expandable learning experiences, which contribute to a well-structured educational journey. A systemic approach is recommended in the study [17], which includes aspects such as needs assessment and technology integration to create a comprehensive teaching strategy. The frameworks can be distinguished based on their specificity, learning approaches, and level of integration.

In summary, these frameworks provide valuable insights into designing and implementing different literacies in various settings. They reflect a strategic focus on developing a literate workforce capable of navigating the complexities of the modern information landscape. Thanks to their multidimensional, progressive, and integrated approaches, these frameworks serve as pivotal references when aiming to foster robust literacy skills.

RQ2: What key principles are emphasised in these studies?

All the subsequent research questions (RQ2, RQ3, and RQ4) are answered mainly based on the information compiled in Appendix C, which gathers the studies' key principles, outcomes, and validation methods.

Emphasis on practicality

Across all papers, there is a clear emphasis on the practical application of diverse literacy skills. The principles across the studies underscore the need for education to be contextual and applicable to real-world scenarios, ensuring that learners can effectively apply their knowledge in their work.

The findings suggest that literacy across different literacies is not merely about theoretical understanding. Paper [1], for example, discusses DL education strategies that include experiential data training and autonomous experimentation. It points to a learning process involving direct engagement with data and self-guided exploration, which are practical approaches to applying knowledge in tangible settings.

Similarly, paper [21] focuses on developing DL skills that are directly relevant to the diverse roles within government agencies, highlighting the importance of tailoring DL education to the specific tasks and challenges employees face. This indicates that DL education is most effective when closely aligned with the learners' professional contexts.

The practical application is also emphasised in the paper [5], which includes practical application and evaluation as part of a broad scope of IL. It suggests that learning interventions should result in demonstrable skills that can be assessed in practical, possibly organisational settings rather than just understood in the abstract. Study [15] further illustrates this point by advocating for creative DL for empowerment, which includes engaging with community-centred data and building learner-centred tools. These principles are geared towards enabling learners to interact with data in a manner that is directly connected to their communities and environments, ensuring that the skills learned are immediately applicable.

A study [33] also identifies a need for a systematic and formal approach to DL education. It emphasises hands-on practical learning and the integration of real-world data into the learning process. This reflects a recognition that for DL to be truly beneficial, it must incorporate actual data scenarios that learners are likely to encounter outside the classroom.

In summary, the findings showcase a recurring theme of integrating various literacy skills with hands-on, experiential learning methods that resonate with the learners' everyday experiences and professional duties. This practical orientation is essential to ensure that literacy skills are acquired, retained, refined, and readily utilised.

Interconnectedness of literacies

While categorised into different types, the literacies share common traits such as the necessity for critical thinking, the ability to evaluate information, and the importance of ethical considerations. These traits can also be categorised as meta-skills, which apply across various fields and are crucial for adapting to and managing complex, multifaceted problems and environments. These skills enable individuals to use more specific skills across different contexts effectively and are foundational for lifelong learning and adaptability. Therefore, the convergence of literacies around these competencies underpins meta-skills role in empowering the workforce to navigate and synthesise across multiple literacy domains effectively.

For instance, the multidimensional nature of IL, as described in the study [2], reflects a comprehensive approach that spans information acquisition, evaluation and use, and information ethics. This illustrates how IL is not a single skill but a composite of critical thinking, ethical understanding, and practical use of information, which are applicable across various literacy forms.

Study [5] further supports this interconnectedness by stressing IL's interdisciplinary nature and critical thinking as a central element, underscoring the necessity for literacy that transcends disciplinary boundaries and hinges on evaluative thinking. Likewise, a study [18] describes SL in terms of interrelated knowledge bases and enabling beliefs, indicating that SL is not just about understanding statistics but also about integrating this understanding within a broader context of information evaluation and decision-making.

Moreover, the AIL study [11] speaks to evolving competency needs and the importance of soft skills and character traits, which aligns with the recognised need for critical evaluation and ethical considerations for deploying AI technologies. This reveals the relevance of these competencies beyond traditional literacy domains, extending into emerging areas like AI.

These examples showcase how critical thinking, information evaluation, and ethical considerations are not confined to a single literacy but are interwoven through various domains. They are the threads that connect DL, IL, SL, AIL, and other relevant literacies, demonstrating a convergence of core competencies essential for understanding and operating effectively. This interconnectedness suggests that while the specific content of each literacy may differ, the foundational skills remain consistent, creating a tapestry of relevant and transferable competencies across different fields and work settings.

Evolving nature of literacies

The papers reflect an understanding that literacy demands are not static. The mention of AI, machine learning, and data analytics indicates that as technology advances, literacies must evolve to keep pace with new information and communication modalities.

The study [11] discusses, for example, the integration of general AI in business practices and the evolving competency needs accompanying such integration. The mention of soft skills and character traits, alongside the role of education and training in addressing AI's impact, illustrated the dynamic nature of AIL, which must account for both the technical aspects of AI and the soft skills necessary to interface with it effectively.

Further, the study [16] addresses designing tools and activities to support DL among learners, indicating a need to make DL accessible and engaging for novices. The study's emphasis on hands-on activities and incremental learning acknowledges that as data analysis and visualisation tools evolve, so must the methods we teach and learn these skills. The concept of MLL is implicit in the competencies required for engaging with AI and advanced data analytics, as noted in the study [3], which discusses proficiency in advanced data analysis techniques and proposes dividing them into basic, median, and high levels. This segmentation showcases the depth and breadth of skills needed to remain literate in a rapidly developing field, implying that literacy is a spectrum of competencies rather than a fixed set of abilities. Moreover, the study [31] expresses the necessity for up-to-date metrics that reflect current technological capabilities and the impact these have on performance.

Each of these examples underscores the fluid nature of researched literacies shaped by technological advancements. AI, machine learning, and data analytics are not static fields; as they expand and become more sophisticated, the literacies associated with them must concurrently progress. This reflects a recognition that literacy in the modern era is a continual process of growth and adaptation.

Cultural and societal relevance

The key principles in selected studies reflect an acute awareness of the cultural and societal dimensions of various literacies. This suggests that literacy must resonate with the cultural and societal fabric within which individuals operate to be effective and relevant. Study [10] underscores IL as a significant component of learning organisations and a key characteristic of their employees. It implies that IL is not just an individual competency but also a collective attribute that can define an organisation's learning culture and, by extension, its societal impact.

In a study [7], the reframing of literacy and numeracy within lean production principles points to an understanding that these skills must align with the current economic and organisational paradigms, indicating their socio-economic relevance. Similarly, a study [20] talks about contact sensitivity and sociocultural awareness, highlighting that literacy is most effective when it is aware of and responsive to the social and cultural contexts in which it is applied.

Furthermore, the study [23] stresses the social construction of knowledge and the contextual nature of learning, reinforcing the idea that literacies are deeply intertwined with social interactions and the contexts in which individuals live and work. It recognises that literacy is not merely a function of individual abilities but also a product of social engagement and cultural practices.

The principles extracted from the studies emphasise the need to understand literacies within cultural and societal contexts. They point to the necessity for literacy education to be adaptable to the norms, values, and expectations of the society in which it exists. This broader perspective ensures that literacy is not only about personal empowerment but also about contributing to and enhancing the cultural and social systems that individuals are part of.

Importance of empowerment and inclusivity

The findings underscore the importance of empowerment and inclusivity in the context of various literacies, signifying that these literacies serve as critical enablers for broader participation in society and the workplace.

Inclusivity is explicitly mentioned in the study [6], which highlights accessibility and inclusivity as key principles, advocating for IL education that is accessible to all learners, thereby enabling a wide range of individuals to benefit from dorm literacy skills. This principle is about providing access and designing IL education to account for diverse learning needs and backgrounds, thus supporting full participation from all workforce segments. Study [22] reinforces this notion by emphasising the inclusivity of non-experts in the field of AI. The aim is to enhance individuals' abilities to interact responsibly with AI technologies, which implies breaking down complex concepts into understandable and manageable components for a broader audience.

Empowerment through literacy is also a core theme in several studies. For instance, a study [15] talks about cultivating creative DL for empowerment, suggesting that DL can be a force that enables individuals and communities to achieve greater control over their environment and data narratives. Similarly, the study [20] focuses on empowerment through IL, indicating that IL is a functional skill and a means for individuals to gain greater agency in their personal lives. Additionally, the principle of lifelong learning mentioned in the study [6] and the call for continuous adaptation in the study [11] reflect a view of literacy as a journey rather than a destination that empowers individuals to keep pace with the developing demands on their environment.

The principles laid out across these studies clarify that these literacies are envisioned as tools for social equity. They aim to provide all individuals with the skills necessary to contribute meaningfully to their societies and workplaces. This approach also positions these literacies as a fundamental right and essential component of an inclusive work culture, where everyone has the opportunity to grow, learn, and participate fully in digital surroundings.

In summary, all the key principles from the studies described above point towards a dynamic, practical, and socially grounded approach to these literacies, which prepare the workforce for the increasing demands of the modern information society. These findings are essential for designing literacy programmes that are effective, inclusive, and responsive.

RQ3: What are the reported outcomes of these studies?

Importance of tailored training programmes

The importance of tailored training programmes is a recurring theme throughout the studies, underscoring the recognition that literacy training cannot be one-size-fits-all. Instead, it should be customised to the learners' needs, existing skill levels, and professional context. For example, a study [1] highlights the development of DL training programmes that accommodate three levels of DL competency: basic, medium, and advanced. This differentiation suggests that training must start where the learners currently are regarding their DL skills and build from them. It also points to the barriers within organisations that could affect the rollout of such programmes, emphasising that the context within which these skills are to be applied plays a role in how the training should be designed.

Furthermore, the study [5] shows that IL skills were improved in two case studies where the training content and delivery methods were adapted to the specific needs of different audiences. This could mean modifying the complexity of the information presented, the language used, or the examples and case studies that are relevant to the learners' professional tasks and environments. The study also mentions the recognition of the need for contextualised training, which alludes to the idea that IL does not operate in a vacuum but is applied within a particular context that should be mirrored in training for maximum effectiveness.

The study [7] also provides insight into how literacy and numeracy are integrated into lean production training within different organisational settings. The benefits discussed, as well as possible alternatives, suggest that integrating these literacies into training programmes must be aligned with organisational goals and practices. The implication here is that training should not only teach the generic principles of literacies but also show how these principles can be applied within specific workflows, cultural norms, and operational needs of an organisation. Also, a study [20] acknowledges that different cultural and economic environments require customised approaches to IL training, and a study [25] discusses the need for tailored AIL programmes that consider the specific learning needs and work context of construction workers.

Additionally, Study [10] professional IL education and training programmes should expose learners to a broad spectrum of IL experiences, emphasising social and collaborative aspects. This recognition of varied experiences necessitates that training programmes should be designed to cover multiple facets of IL that are pertinent to the learners' professional lives. A study [30] showcases that lawyers felt competent in basic IL skills but noted a need for more advanced skills. This finding suggests that training should be designed to bridge the gap between their current proficiency levels and the more advanced competencies required in their legal practices.

The above-mentioned studies support the notion that literacy training should be specialised, addressing the varying demands of different learner groups and ensuring that the content directly applies to the learners' daily tasks and long-term professional requirements. The effective transfer of training to workplace performance is a critical measure of success for such programmes, and this is more likely to be achieved through customised training approaches.

Role of literacies in decision-making and performance

Literacies' role in decision-making and performance is central to the understanding that literacy skills contribute significantly to the quality of decisions made within an organisation and its overall performance. The explored studies demonstrate that enhanced literacy is not merely an academic asset but a practical tool that drives better outcomes in the workplace. Study [31] addresses the impact of DL on performance by providing empirical support for a positive relationship between DL and internal organisational performance. This suggests that when employees can effectively collect, manage, evaluate, and apply data, they can improve internal processes, leading to higher efficiency and productivity. The study also notes that while DL may not directly enhance external performance, it does so indirectly by positively affecting internal performance, subsequently influencing customer satisfaction. That signifies that DL is instrumental in fostering an environment where data-driven decisions are leading to improvements that customers can perceive.

The study [2] illustrates how a CEO's IL positively impacts exploratory and exploitative innovations within small and medium-sized enterprises. Opportunity recognition, facilitated by IL, acts as a mediator in this process, demonstrating that IL empowers leaders to identify and leverage new opportunities, thereby driving innovation and competitive advantage in their businesses. Furthermore, the study [10] delves into IL's role, suggesting that it is vital in processes such as environmental scanning, information management, research, and development. These activities are crucial for strategic decision-making and long-term planning, indicating that well-developed IL skills contribute to an organisation's ability to adapt, grow, and remain relevant in its market.

Finally, the study [9] connects numeracy to the accuracy of credit assessments made by loan officers, particularly during economic booms. This implies that strong numeracy skills enable professionals to make more informed and reliable financial decisions, which is crucial for risk management and economic stability within financial institutions.

These notions convey that literacies transcend the foundational ability to read, write, and perform arithmetic. It encompasses a deeper skill set that includes the critical evaluation of information, strategic application of knowledge, and data-driven decision-making. In the modern workplace, where information is abundant and data is a critical asset, the ability to interpret and use this information correctly is a key determinant of individual and organisational success. Literacies form the backbone of a competent workforce, driving innovations, productivity, and informed decision-making that align with and promote an organisation's strategic goals.

Need for precise frameworks.

After exploring the selected studies, it was found that assessment and framework development in business and organisational contexts have unique features. The frameworks are varied and appear to be tailored to address specific literacies. These studies emphasise the importance of having structured approaches to define, measure, or enhance various literacies. Having precise tools and frameworks to evaluate literacy levels within different professional settings is crucial. According to the studies, various levels of literacy are not uniform and may progress from basic to advanced. This implies that individuals or organisations can follow a pathway that leads to developing different kinds of literacies at different stages. Tools help benchmark current competencies, identify skill gaps, and guide the design of targeted educational interventions. They also enable organisations to move from a general awareness of the need for literacy to actionable insights and strategies that can directly improve the effectiveness and efficiency of their workforce.

In summary, across the studies, there is a clear intent to define, measure, and improve various literacies. Many studies seek to create tools or scales for assessment, emphasising the multifaceted nature of these literacies. There is also a common recognition of the need for tailored training that acknowledges the specific needs of different learner groups or professionals. These studies reflect a growing recognition of these literacies' critical role in personal and organisational effectiveness, particularly within innovation, technology adoption, and data-driven decision-making. The significance of these findings lies in their potential to guide employers, HR professionals, trainers, and consultants in business and organisations in developing increasingly crucial competencies. These studies collectively and in a multidisciplinary way advance the understanding of the modern information landscape. They provide insights into how different literacies can be conceptualised, assessed, and developed to meet current and future challenges. The reported outcomes highlight a progression toward more sophisticated and nuanced approaches to explored literacies education and training, emphasising practical and contextual application.

RQ4: How are the outcomes validated, and what methodologies are employed?

A recurring theme in the content validation methods is the use of expert assessment. This is evident in studies [2,27,28,30] and [34] where a panel of experts reviewed content for validity. Another common approach is statistical analysis to establish reliability and validity, as seen in studies [4,8,9,14,22,26,26,29,31] and [37], which employ techniques like Cronbach's Alpha, regression analysis, ANOVA, and Exploratory Factor Analysis (EFA). Studies [8] and [9] also stratify samples, such as by numeracy level, to enhance the specificity of their validation.

Table 23 illustrates the different validation methods used. The methodologies used to validate outcomes in these studies are diverse, with a notable reliance on statistical analysis and expert assessment. However, the presence of multiple studies (37 %) without formal validation methods raises questions about the rigour and reliability of findings in those cases. The table clearly demonstrates the methodological diversity and rigour in research validation.

Table 23. *Validation methods used*

Validation methods	N	%	Studies
Expert assessment	5	13 %	[2,27,28,30,34] ([19*])
Statistical analysis	9	24 %	[4,8,9,14,22,26,29,31,37]
Qualitative analysis	3	8 %	[1,7,25] ([5*,16*,19*,21*])
Formative assessments	1	3 %	[6] ([5*,16*])
Empirical validation	2	5 %	[35,36] ([5*,16*])
Comparative analysis		0 %	([21*])
Mix-Method	4	11 %	[5*,16*,19*,21*]
No formal method	14	37 %	[3,10,11,12,13,15,17,18,20,23,24,32,33,38]
	38		(* = study incorporates two or more types of validation methods)

Some validation methodologies have distinctive features. For example, studies [1,7,25] and [5,16,19,21] use qualitative methods, such as interviews and thematic coding, which differ from the quantitative methods seen in other studies. Formative assessment appears in studies [5,6,16]. The ethnographic method in the study [7] stands out as it includes observations and field notes, providing a rich contextual understanding of findings. The study [36] employs Action Design Research, an iterative evaluation involving various stakeholders, which is uncommon in other studies. Empirical validation is used in studies [35,36] and [5,16]. A combination of various validation methods is used in studies [5,16,19,21].

The study's [16] use of iterative design and real-world testing exemplifies a hands-on approach to validation, incorporating both qualitative and quantitative feedback. In contrast, the study [31]'s use of Confirmatory Factor Analysis (CFA) with Partial Least Squares Structural Equation Modeling (PLS-SEM) represents a robust statistical method.

Table 24 on the next page categorises validation methods by framework type to construct a more descriptive summary and analysis of the validation methods used. The results indicate that competency frameworks primarily had no formal validation method. Two studies utilised expert assessment [2,34] and one mixed method [21] consisting of comparative and qualitative analysis. The use of expert panels underlines the role of domain knowledge in assessing the validity of frameworks and tools and complements quantitative measures.

The assessment frameworks mainly use statistical validation methods, which is understandable given the need for objective measures to ensure the reliability and validity of assessment tools. This is integral to the psychometric approach, focusing on the accuracy and logical consistency of the assessment tool. The rigour of statistical validation ensures that the tools developed for assessing competencies are scientifically reliable, though this seemed to come at the cost of user-friendliness.

Teaching frameworks appear to have no formal validation method, or alternatively, qualitative methods, formative assessments or empirical validation methods are used. This suggests a focus on iterative development and contextual understanding, which is important in educational settings where the practical application of the framework is the priority. The differences in validation methods align with the goals of the frameworks; competency frameworks focus on establishing a foundation of skills and knowledge that experts validate. In contrast, assessment frameworks emphasise measurement reliability and validity through statistical methods. Teaching frameworks prioritise applicability and adaptability in educational settings, reflected in their use of qualitative methods and formative assessments. This nuanced use of different validation methods across framework types underscores the complexity of framework development and the need for methods tailored to each framework's specific goals and contexts.

Examining frameworks by literacy type is also beneficial, as different literacy types have been utilised throughout the results section. This kind of analysis allows for identifying whether any particular type of validation is duplicated within a literacy type or if the majority of them are without formal validation. Table 25 on the next page showcases this type of illustration.

Table 24. *Validation methods by framework type (*= study incorporates two or more types of validation methods)*

		Formal method						
Framework type	**No formal method**	Expert assessment	Statistical analysis	Qualitative analysis	Formative assessments	Empirical validation	Comparative analysis	Mix-Method
Competency framework	[3,12,18,20,24,32,33]	[2,34]		([21*])			([21*])	[21]
Assessment framework		[27,28,30] ([19*])	[4,9,14,22,26,29,31,37]	([19*])		[35]		[19]
Teaching framework	[10,13,15,17,23]			[1,7,25] ([5*,16*])	[6] ([5*,16*])	([5*,16*])		[5,16]
Combined	[11]		[8]			[36]		
Other	[38]							

Table 25. *Validation methods by literacy types (*=study incorporates two or more types of validation methods)*

		Formal method						
Framework type	**No formal method**	Expert assessment	Statistical analysis	Qualitative analysis	Formative assessments	Empirical validation	Comparative analysis	Mix-Method
Competency framework	DL,AIL,SL,IL,AIL,DL,DL	IL,DL		(DL*)			(DL*)	DL
Assessment framework		IL,IL,IL,(IL*)	IL,NU,NU,AIL,SL,IL,DL,IL	(IL*)		DL		IL
Teaching framework	IL,IL,DL,IL,IL			DL,NU,AIL (IL*,DL*)	IL,(IL*,DL*)	(IL*,DL*)		IL,DL
Combined	AIL+DL		IL			DL		
Other	IL							

It appears that all studies are quite evenly distributed when reviewed by literacy type. Among assessment frameworks, there is one DL framework with a statistical validation method and one with an empirical validation method. Three DL frameworks are categorised as teaching frameworks: one with no formal validation method, one with qualitative analysis, and one employing mixed-method validation. The analysis reveals that the number of DL frameworks is currently quite limited, which is understandable considering the emerging nature of the field. Most efforts have been primarily focused on defining the competencies associated with DL. This serves as a first step towards broader development and application of DL within organisational and business contexts. The number of competency frameworks for DL is quite low, and it is necessary to develop validated assessing frameworks for DL that are suitable for organisational and business contexts. Teaching frameworks existing for DL are also surprisingly scarce.

4.4 Synthesis of Results

Based on the detailed insights from the interviews and SLR, this synthesis aims to integrate interview findings and the systematic literature review. This effort combines findings and generates insights that best explain the observed phenomena using an abductive reasoning approach. This synthesis navigates through the depth and breadth of the research findings, highlighting key points, divergences, and common themes to construct a coherent understanding of DL's current landscape and future directions.

The current study has identified a research gap (Miles, 2017) in the field of DL within the examined context. The limited availability of DL frameworks evidences this. The scarcity of appropriate frameworks highlights the need for further research and development. Furthermore, the scarcity of frameworks also appears among other literacy types and their associated research with organisational and business contexts. Therefore, it is worthwhile to consider how the results from all these studies could be leveraged in the development of DL frameworks. This approach could provide valuable insights and methodologies that enrich the DL framework development process, ensuring a more comprehensive understanding and application of DL in professional settings.

Convergence on the holistic nature of DL

Both sets of findings underline that DL is a complex skill that includes technical abilities like skills to operate with data and information, knowledge, and individual attitudes towards information and data. The interviews conducted as part of the research revealed a broad spectrum of professional perceptions regarding DL, reflecting its multifaceted nature and the subjective experiences of different professionals. This diversity and complexity are also reflected in the various frameworks identified in the literature review. However, the SLR presents a more structured exploration of DL and related literacies, focusing on established frameworks and defined competencies. This underlines the contrast and divergence between the individual, experiential understanding of DL in practice and the academic conceptual frameworks that seek to standardise competencies and assessment criteria and conceptualise the best teaching methods.

Based on the results of this study, the concept of DL has two different perspectives: the view of industry professionals and the systematic literature view. The view of industry professionals is broad and lacks structure, while the SLR presents a more segmented view of DL. This approach is based on structured frameworks and theoretical models, such as Stephen Downes' (2023) framework, which divides DL into three distinct categories: competency, assessment, and teaching frameworks. This analytical approach facilitated the breakdown process of the broad concept of DL into manageable and assessable components and helped the systematic evaluation of DL-related dimensions in organisational settings.

How DL is treated in academic literature within an organisational context differs from how people experience it in real-world scenarios. This shows a gap between the two. The theoretical models used in academic analysis may oversimplify DL, a dynamic and interdependent concept. The focus on categorisation and structure in literature is a prerequisite for academic purposes. Still, it may not consider all the fluidity and cross-disciplinary aspects of DL in the contemporary workplace setting. Despite all this, findings indicate a convergence on the holistic nature of DL as both industry and academia acknowledge the complexity of DL, which combines technical skills with meta-skills like critical thinking, ethical considerations, and effective communication abilities.

The emphasis on DL as a complex skill set comprising technical abilities, knowledge, attitudes toward information and data, critical thinking, ethical considerations, and effective communication skills reflects the DIKW model's progression from data to wisdom. The findings suggest that industry professionals and academic frameworks recognise the importance of fully navigating these layers to leverage DL. However, the gap between practical experiences and structured academic models highlights the challenge of translating theoretical concepts like DIKW and various frameworks into actionable competencies.

Need for empowerment experience

The synthesis of interview and SLR results provides a nuanced understanding of DL and its related literacies. The interview results revealed a broad spectrum of perceptions surrounding DL, indicating its complexity and multifaceted nature. Respondents viewed DL not just as technical skills but as a holistic set of competencies encompassing technical skills, knowledge, communicational proficiency, and collaborative abilities. Many individuals recognise the value of data but struggle with effectively locating, evaluating, and utilising data in decision-making processes. This diversity reflects the varied contexts within which individuals encounter and engage with data, underscoring the need for a comprehensive approach to DL education that addresses these multiple facets. It also underscores the challenge of translating theoretical knowledge into practical application, a gap further highlighted by the emphasis on personal awareness and the practical skills necessary in various professions for leveraging data effectively.

During the interviews, participants described how the challenges in finding, using, and understanding data can prevent employees from experiencing the empowerment possible when working on data-related tasks. The SLR emphasised the importance of empowerment as a key principle across the studies. This points towards the role of DL as a tool for broader societal participation and engagement in workplaces. This indicates a shared recognition of the significance of DL beyond mere technical proficiency. It underscores the fact that an individual's ability to engage in a meaningful and productive manner in digital and data-driven work environments is a pivotal aspect of comprehending the value of DL.

The need for empowerment resonates with the transition from knowledge to wisdom in the DIKW model. Empowerment emerges when individuals access and understand data and also apply this understanding to make informed decisions and drive meaningful action. The recognition of empowerment as a principle underscores the transformative potential of DL, suggesting that beyond technical proficiency, the ultimate value of DL lies in enabling individuals to navigate the DIKW hierarchy effectively, thereby contributing to organisational advancements.

Need for adaptive and tailored training

The interviews revealed that individuals face challenges in using data, understanding its usefulness, and transforming it into actionable insights. These personal-level insights complement the findings of the SLR, which emphasises the need for customised training programmes and the important role of DL in improving individual decision-making and organisational performance. This suggests a direct connection between an individual’s

DL competency and organisational effectiveness, highlighting the importance of developing targeted DL programmes that cater to specific professional needs and contexts and recognise the level of expertise needed.

Findings from the literature review emphasise the practical application of DL skills, advocating for education deeply rooted in real-world scenarios. These could be, for example, project-based learning or case examples combined with collaborative and interactive working methods. This practicality, combined with understanding how DL intersects with informational, statistical, numerical, and AI literacies, suggests a holistic approach to education that prepares individuals for complex environments. On the other hand, the foundational role of information literacy could imply its inherent role in DL without distinct recognition, whereas AI literacy represents a new paradigm.

The significance of tailored training programmes emerges as a pivotal theme, highlighting the necessity of customising training to meet the learner's specific needs and contexts, thus enhancing literacies' role in informed decision-making and organisational performance. Tailoring DL training to fit individual roles as well as broader organisational culture and goals can enhance the relevance and impact of DL education. DL training programmes must be flexible and have strong executive support to be effective, as each organisation has unique values, objectives, and challenges. Results suggest that DL training should be grounded in real-world applications and adaptable to the fast-developing technological landscape, particularly in AI.

The future of work with the AI paradigm

Based on interviews and the literature review, DL is a constantly developing field, especially with regard to the advancement of AI technologies. The interview insights indicate that AI may significantly impact future DL and workforce trends. At the same time, the literature review recognises that technological progress is driving the continual evolution of literacy demands. Therefore, it is essential to develop DL frameworks, assessment methods, and training programmes that are adaptable, forward-thinking, and capable of keeping pace with technological advancements in the years to come.

The interviews touched on AI's transformative potential in DL and workforce dynamics. As AI tools become more integrated into data processes, there is a growing need for skills in interpreting AI-generated results and collaborating with AI systems. Looking forward, the anticipated integration of AI into workplace practices necessitates a re-evaluation of current frameworks to include AI literacy, preparing the workforce better for future AI-mediated workplaces where data and AI solutions play a central role in decision-making processes.

These insights underscore the complexity of cultivating DL and related literacies in the modern workplace. A comprehensive strategy that incorporates practical, real-world application, anticipates the future integration of AI, and tailors training to individual and organisational needs is paramount. Such an approach bridges the gap between theoretical knowledge and practical application and prepares individuals and organisations for AI-infused workplace environments. These insights call for an educational paradigm shift towards more experiential learning models integrating AI literacy. This approach facilitates the increasing integration of AI tools in various sectors, necessitating a workforce skilled not only in DL but also in understanding and collaborating with AI systems.

Theoretical implications and practical notions

The concept of DL has both theoretical and practical aspects, and a comprehensive understanding and development approach is required. The results demonstrate that DL is clearly interconnected with the expanded DIKW model presented in the theoretical section of this thesis, with all aspects under discussion reflected within the DIKW model. Most frameworks investigated focus on developing, evaluating, or defining skills related to the two lowest blocks of the DIKW model (data, information). Still, approaches that extend to the third (knowledge) and even the fourth block (wisdom) can be seen in teaching frameworks. This is understandable because the two lower blocks of the DIKW model form the fundamental competencies on which to build. Measuring more abstract aspects becomes increasingly difficult with the higher blocks of the model.

Results also underscored the importance of a holistic approach to DL. There are only a very limited number of frameworks in academia for DL in business and organisational contexts, which means that more research is needed to expand these frameworks in the future. While structured frameworks are important for educational purposes, it is equally essential to comprehend how DL can be applied in industry. This approach will help bridge the gap between theory and practice, ensuring that DL frameworks are comprehensive and adaptable to the specific demands of the workforce.

This analysis highlights the importance of integrating new competencies related to DL, specifically those that reflect advancements in AI technology, into current frameworks. In addition to technical skills like prompt engineering, there should be more focus on developing cognitive abilities, such as analytical thinking and problem-solving. It is also important to emphasise ethical considerations and transparency concerning digital interactions. Improving skills for effective human-machine interaction in a hyper-connected AI-infused working environment is highly relevant in workplaces.

It is important to emphasise the importance of enhancing both the fundamental frameworks and practical application of DL in organisations. By incorporating a range of skills in DL programmes, especially those related to AI, organisations can cultivate a proficient workforce capable of navigating digital tools and infrastructures and using these technologies ethically, socially, responsibly, and creatively.

In order to apply the theoretical models of DL in business contexts, organisations must implement flexible and adaptable DL initiatives that can keep up with the changing digital sphere. This is especially crucial due to the rapid advancements in AI technology. An effective approach would be acknowledging that the digital domain is inherently dynamic and constantly influenced by technological innovations. Therefore, organisations should develop a DL curriculum and training programmes responsive to emerging technologies and platforms.

In conclusion, this synthesis of findings reveals DL as a critical, multifaceted competency essential for employees in data-rich environments. The findings suggest a pathway toward developing more nuanced, adaptive, and effective DL frameworks to meet the challenges of enhancing the DL among the workforce. Future research could further explore the integration of DL and AI literacy and the impact of organisational culture on the effectiveness of DL programmes.

The role of abductive reasoning

Using abductive reasoning to synthesise the findings has highlighted the importance of looking beyond the data to generate insights that address observed gaps and discrepancies. This methodology has enriched the analysis and paved the way for innovative approaches to DL's development and implementation in organisational and business contexts.

5. DISCUSSION AND CONCLUSION

The final section of this thesis aims to answer the primary research question, “How can existing frameworks assist in developing workforce DL programmes and evaluating DL?” along with its sub-questions stated at the beginning of this interesting research journey. The author has conducted insightful interviews and an extensive literature review to gain a thorough understanding of the subject. This section presents the main research results and critically discusses how these results contribute to the existing body of knowledge and the practical implications for the development of DL in organisational and business contexts. It will also further discuss how the insights gained align with or diverge from the established theories and practices in the field of DL. Limitations of this study and suggestions for future research directions to address the identified gaps are also discussed. This chapter illustrates how the author's knowledge was enriched through this thesis.

5.1 Main Research Results

RQ1: Which principles are emphasised in academic frameworks, and how do they align with organisational priorities in workforce development?

1. Multifaceted and holistic skill set: DL emerges as a complex competency, encompassing a broad range of skills across the frameworks. Technical abilities, knowledge, attitudes toward information, critical thinking, ethical considerations, and communication skills are repeatedly highlighted through frameworks. This “spectrum of competencies” aligns with the earlier presented DIKW model, which illustrates the progression from basic data handling to wisdom in decision-making, suggesting that DL requires navigating through these layers. The findings from both industry professionals and academic perspectives reveal a nuanced understanding of DL, highlighting the importance of a holistic approach that transcends mere technical proficiency.

   This emphasis is in line with the organisation’s objectives, as in the context of organisational development, it is important to consider the complex environment in which employees operate. Development efforts are always a combination of hard and soft skills for which appropriate methods must be found, and the different requirements of job roles for individuals must be taken into account. From the organisation’s perspective, skill development involves a variety of objectives that are closely related to the implementation of strategy. Therefore, it is not merely about mastering technical skills often labelled as hard skills; it is equally about inspiring employees to recognise their personal need for learning and to participate in this journey with genuine enthusiasm. Organisations also prioritise the development of a workforce with a holistic set of competencies that extend beyond technical prowess to include meta-skills like problem-solving and critical thinking. This aligns well with the multifaceted nature of DL, which is emphasised in frameworks.

2. Tailored and adaptive training programmes: The call for adaptive and tailored programmes is loud and clear, emphasising the need to develop DL competencies that cater to specific professional needs and contexts. The integration of practical application scenarios, such as project-based learning and real-world data, underscores the importance of real-world relevance in workforce DL education. This approach facilitates the practical application of DL skills and addresses the cross-disciplinary aspects of DL in the contemporary workplace.

   From the perspective of organisations, this is important because it ensures that training programmes evolve and adapt to take into account technological advancements and the resulting workforce skill requirements. Organisations prioritise workforce development that fosters lifelong learning, and organisational priorities benefit from such customised training, as it ensures that employees are equipped with relevant competencies that directly contribute to organisational effectiveness and performance. This emphasis on practical application can also be seen as a principle that extends to the empowerment aspect, with the aim of enabling employees to make informed decisions and engage meaningfully with data in their professional roles.

3. Empowerment through DL: A common theme across the findings from frameworks was the necessity for employee empowerment experiences. The ability to effectively locate, evaluate, and utilise data is crucial for employees to feel empowered in their roles, contributing to meaningful engagement and productivity, but also encompasses the ability to navigate through the DIKW hierarchy, applying to understand to drive informed decisions and actions. Such empowerment aligns with organisational priorities by enhancing employee autonomy, satisfaction, and the capacity for innovation, thereby fostering a culture of continuous learning improvement and adaptability.

Organisations seek to empower employees to use data effectively, trying to make DL a strategic asset. This is in sync with the frameworks that highlight the practical application and the role of DL in enabling employees to make data-driven decisions. Public domain definitions investigated in the theory part of this thesis often emphasise analysis and communication skills to derive business insights, reflecting an organisational focus on outcome-based literacy that supports value-driven judgments. That is why there is a recognised need for DL training to be specific to the professional context and adaptable to individual roles within the organisation. This principle is crucial for organisations to develop competencies that directly contribute to organisational goals and performance.

4. The role of AI in future workforce development: DL can not be seen in isolation but rather as integrated with other related literacies such as numeracy, information, statistical, and AI literacy. So far, academic research has been conducted mostly on IL in the workplace in business and organisational settings. This is understandable because of its longer historical academic background, which is a key DL component. The anticipation of AI's growing influence on data analytics and workforce dynamics necessitates a re-evaluation of current frameworks to include AI literacy.

   With AI integrations becoming more common in the workplace, an organisational priority for literacy encompasses effective human-machine collaboration and understanding of algorithmic thinking. As AI technologies are expected to play an increasingly central role in the workplace, organisations will prioritise cultivating competencies that accelerate the wise utilisation of their data assets. This encompasses understanding the new technology-practical applications of data and the ethical considerations involved, thereby highlighting the growing importance of AI literacy.

To sum up, the DL principles emphasised in frameworks closely align with organisational priorities. The objective is to cultivate a data-literate workforce that is technically proficient, feels empowered, and is well-equipped to adapt, embrace, and innovate with technological advancements. This also reflects the important role of DL in enhancing organisations' competitiveness in the current data-rich, technology-driven environments.

RQ2: In what ways can these principles be operationalised into training practices and assessment methodologies within organisations?

Incorporating the discussed principles into training practices and assessment methodologies within organisations requires a strategy that addresses the multifaceted nature of DL, emphasises continuous learning, ensures practical application and empowerment, and integrates with other literacies. Developing a DL training programme for an organisation needs to cover the broad spectrum of DL competencies, including technical skills, critical thinking, and communication abilities relevant to different target groups and skill levels. By clearly defining what DL means within the context of their industry and organisation, companies can develop more specific, measurable competencies for assessment.

The skill level categories should be defined as few rather than many. For example, critical basic skills that everyone should possess in a particular position, advanced skills, and expert-level skills. It would also be useful to evaluate the basic level skills that everyone should possess or learn, regardless of the job role. Implementing modular training programmes that can be updated as technology evolves, particularly with advancements in AI, could be beneficial.

Competency-based assessments should be designed to cover technical proficiency, critical thinking, ethical decision-making, and the ability to communicate insights effectively. This could include digital tests, practical demonstrations, and colleague reviews to evaluate these competencies. It would be beneficial to assess DL competencies by engaging employees in solving real-world problems relevant to their roles and the organisation's objectives. This could be an easy way to evaluate, for example, their ability to integrate various data sources, apply ethical considerations, or communicate findings to different stakeholders.

Designing interdisciplinary training sessions that mix DL and AI literacy dimensions could be utterly beneficial. Collaboration with industry partners could further enrich these training modules by integrating current, industry-specific data sets and problems. Conducting need assessments to identify gaps and customise the training content to meet the needs facilitates training programme design.

Encouraging self-directed learning and access to resources for ongoing education works to some extent. Still, there should also be a cultural push created and continued by executives and supported by the human resources function, affecting the attitudes of the workforce in realising how the nature of one's work is changing and what is needed to keep oneself updated. Fostering an organisational culture that values and encourages

DL by recognising and rewarding data-driven decision-making and innovation would be beneficial.

RQ3: What reported outcomes have education and assessment programmes achieved in meeting organisational objectives?

The development of explored frameworks enables the identification of different levels of DL proficiency most suitable for an organisation. These frameworks provide metrics that can identify existing skill gaps in the business domain by categorising skill levels and offering targeted strategies for improvement. These metrics can also help quantify DL and its effects, enabling businesses to focus on areas needing development.

Several studies highlighted the need for frameworks to be customised to the unique requirements of different learner groups and work contexts. The effectiveness of these metrics lies in their adaptability and the recognition of the importance of contextualised training content. Outcomes related to the practical application of literacy, such as developing educational content and models and the need for empowerment experiences, suggest that some frameworks provide metrics that facilitate practical, hands-on learning and enhance employee empowerment.

The results obtained from various educational and assessment studies focused on enhancing or evaluating one literacy showed that implementing relevant metrics and tailored training methods leads to improvements in the workplace or the organisational setting. These outcomes are supported by reported enhancements in employee performance, efficiency in literacy-centric tasks, and the ability to make informed judgments, all of which are crucial for achieving strategic business objectives.

Outcomes pointing to the importance of soft skills and AI competencies indicate an expanding scope for future frameworks. These frameworks are set to include essential human-machine collaboration skills, meta-skills, and technical proficiency required by the workforce. This evolution also suggests an increase in complexity within DL frameworks, reflecting the intricate interplay between technological advancements and the essential human skills needed to leverage these technologies effectively.

RQ4: How effectively do metrics from frameworks address the identified skill gaps in the business domain?

Frameworks serve as structured methodologies to develop, assess, and refine the competencies necessary for effective engagement in digital and data-driven work environments. However, there is a notable discrepancy: while these frameworks aim to standardise competencies and provide metrics for assessment, they often fall short of fully addressing the multifaceted and dynamic skill sets required in real-world business scenarios. This gap primarily arises from the framework's tendency to focus on technical skills or foundational knowledge, sometimes neglecting the softer meta-skills such as critical thinking, problem-solving, ethical considerations, and effective communication, which are equally vital in the contemporary workplace.

The challenge in developing frameworks that can cover "everything" lies in the breadth of competencies that modern work environments demand but also in the depth and nuance of these skills. The various competency frameworks revealed this through SLR findings. Striking a balance between covering a broad array of skills and diving deep into the intricacies of each skill set is inherently complex. This complexity is compounded by the rapidly evolving nature of technology and work practices, which require comprehensive and adaptable frameworks.

Furthermore, the rapid advancement of AI technologies introduces new dimensions to the skill gaps in the business domain. This suggests that existing DL-related frameworks may not be fully equipped to address the emerging needs for AI literacy. The emphasis on AI and data literacy underscores a need for frameworks that adapt and anticipate technological shifts.

All these aspects together reveal the complex landscape of DL in the business domain, characterised by a dichotomy between the experiential understanding of DL by industry professionals and the structured exploration provided by academic literature review. This complex is probably the reason for the limited availability of DL frameworks so far tailored to the nuanced needs of the business world, suggesting that current frameworks may not fully capture the multifaceted nature of DL as required in professional settings.

The integration of empowerment and tailored training into frameworks emerges as a key theme from the results. Empowerment, a principle echoed across multiple studies, highlights the transformative potential of literacy beyond mere technical proficiency. It points towards the role of literacy in enabling meaningful engagement and informed decision-making in work environments. However, this aspect of empowerment is often underrepresented in current metrics, suggesting a gap in the holistic assessment of literacy's impact.

Tailored training programmes, highlighted as necessary, underscore the importance of customising learning experiences to fit individual roles, professional needs, and organisational contexts. While providing a baseline for skill development, the current frameworks' metrics may not adequately capture the nuances of personalised learning pathways critical for addressing specific skill gaps within diverse business environments.

In addressing the question, it is clear that while existing frameworks and their associated metrics provide a valuable foundation for understanding and developing data and related literacies, there is a pressing need to conduct more research on this topic. Frameworks in an organisational or business context should integrate holistic competencies, including meta-skills and AI literacy, more effectively and embrace the principles of empowerment and tailored training. Doing so will ensure they are relevant and sufficiently robust enough to bridge the existing and emerging skill gaps in the business domain. While current DL-related frameworks provide a valuable starting point, there is a call for future efforts to refine and expand current frameworks, ensuring they address the skill gaps in the business domain and enhance metrics accordingly.

RQ5: How might the widespread integration of AI transform DL frameworks and their role in workforce reskilling initiatives?

As technologies evolve, so will the information and skills required to work alongside them. AI integration may expand the competencies within DL frameworks to include understanding AI technologies and their implications in business and society. A greater focus will probably emerge on technical skills such as algorithmic understanding, prompt engineering, modelling, and data interpretation from AI outputs. Still, in the background, there is the same need for critical appraisal of AI systems, understanding biases, and recognising ethical considerations, as these are also inherent in DL. Both data and AI projects require collaboration across organisations and with stakeholders. There is also a human-machine collaboration skills area that needs to be covered in the workforce.

This indicates that AI literacy may become essential to DL frameworks, ensuring employees can use AI tools effectively, collaborate with them productively, and understand and critically assess their output. One innovative solution could be merging these into literacies. This combination could be called DAIta literacy. This interdisciplinary literacy framework empowers the workforce to participate effectively and ethically in data-rich and AI-infused environments and adapt to the changing nature of work.

Finally, future DL teaching frameworks and research agendas should evaluate AI's possibility to personalise learning experiences by analysing individual learning patterns and adapting content accordingly. This would facilitate individualised reskilling pathways, making workforce initiatives more effective.

5.2 Discussion

This thesis conducted a systematic literature review using the PRISMA method, alongside semi-structured interviews, to explore how frameworks related to DL can support the development of DL programmes and the evaluation of workforce DL skills. The systematic literature review showed an increasing interest in exploring IL, DL, and AIL in organisational and business contexts. Organisations are facing a growing need for an information-literate workforce proficient in data and AI utilisation skills. There is a lack of theoretical and empirical research to define DL in organisational and business contexts and investigate its development in the workforce. Thus as a contribution this study revealed a prominent knowledge gap in this area.

This study revealed that DL in the context of workforce development is multifaceted and requires a holistic approach that integrates technical skills with critical thinking, ethical consideration, and effective communication. The author found an alignment between these competencies and organisational priorities, highlighting the need for customised training programmes that address immediate professional needs and anticipate the evolving interplay between human and AI capabilities.

Additionally, findings suggested that DL is key to empowering employees and fostering autonomy and innovation in the workplace. These insights provide a more refined understanding of DL's role in organisational resilience and competitive advantage, framing it as a skill set and a strategic asset crucial to navigating the complexities of today's data-rich environment. Next, specific results are discussed in more detail.

Multifaceted and holistic DL

This thesis's emphasis on a multifaceted and holistic approach to DL aligns well with the DigComp framework's (Vuorikari et al., 2022) focus on information and data literacy. That framework underscores the importance of equipping individuals with the ability to understand, evaluate, and use information and data effectively, which mirrors the author's identification of a broad spectrum of competencies beyond mere technical DL proficiency. This alignment is further supported by the conceptualisation of DL by Ridsdale et al. (2015), who defined DL as the ability to collect, manage, evaluate, and apply data critically. Findings echo this approach, highlighting the necessity of a comprehensive skill set that includes technical abilities, critical thinking, and ethical considerations in workforce development.

The principle of AI in future workforce development and the integration of AI literacy within DL frameworks represent an extension of existing theory. While the DigComp framework has begun to address the integration of AI systems (Vuorikari et al., 2022), this study suggests a more pronounced emphasis on AI literacy as essential for the future data-literate workforce. AI literacy is necessary for the future workforce, as AI technologies are becoming increasingly important in the digital landscape. Integrating AI in workplaces transforms work practices and the skills required for them (Margaryan, 2023). This forward-thinking approach is essential for adapting to these changes and illustrates the multifaceted aspect of DL in practice.

Alignment with organisational priorities

The rapidly changing digital work environment demands that organisational priorities align with the principles of DL. This alignment is vital for creating a competitive and adaptable workforce. This thesis showcases that DL is not limited to technical competencies but has become a strategic asset for organisations to navigate the complexities of the data-driven business environment. Nowadays, organisations understand the value of a skill set that covers technical proficiency, critical thinking, ethical considerations, and effective communication skills. Such competencies are essential for informed decision-making that drives organisational strategy and performance optimisation. The literature on DL in the public sector emphasises this importance in organisational development (Bersin & Zao-Sanders, 2020; Bonikowska et al., 2019; Jones, 2022, p. 6; Tableau, 2023).

Academic DL frameworks found through this study showed a tendency to try to be aligned with the organisational priorities in workforce development to prepare for the future, and these efforts must continue. The alignment should focus on the both the technical and soft skills to navigate future technological environments. Rowley's (2007) DIKW model illustrates the progression from basic data handling to wisdom in decision-making, demonstrating the depth and breadth of DL required within the workforce. Such alignment is particularly relevant, as it reflects the multifaceted nature of DL emphasised both in academic and industry discussions (D'Ignazio, 2017; Halper, 2021; Koltay, 2015; Medeiros & Duncan, 2023; Pangrazio & Sefton-Green, 2022).

The DL-related frameworks examined displayed a tendency for alignment, especially with technical skills and, to some extent, soft skills or meta-skills. It was observed that these frameworks did not demonstrate a tendency to incorporate the latest advancements in the field closely related to DL like AI literacy aspects, which are already interconnected by Gartner (Medeiros & Duncan, 2023) and DigComp (Vuorikari et al., 2022). The results of this study suggest that these kinds of frameworks integrating the two literacies could be valuable tools for businesses, as they offer a robust foundation for encountering the workforce needs.

Operationalising DL principles: tailored training programmes

The results of this study revealed that the principles promoted in academic frameworks and organisations' strategic objectives share a common goal: to create a technically skilled workforce with a wide range of competencies to solve complex problems. Tailored and adaptive programmes are necessary to meet the dynamic workforce requirements posed by technological advancements (Bhargava & D'Ignazio, 2015; Prado & Marzal, 2013).These programmes should have real-world applicability and connect directly to practical scenarios across various professional contexts. This approach addresses the cross-disciplinary aspects of DL in the workplace.

Tailored and adaptive training programmes are essential for operationalising DL principles within organisational settings. Developing DL competencies that cater to diverse professional needs and contexts is critical. This approach facilitates the practical application of DL skills and addresses the crucial cross-disciplinary aspects of DL in workplace settings. This study's findings on the need for adaptive and tailored programmes point to a divergence from the common one-size-fits-all approach often found in organisational practices. This reveals a gap between the theoretical ideal of customisable training (Frank et al., 2016), as suggested by the evolving nature of DL, and the actual implementation within organisations (Halper, 2021; ODI, 2023). The DigComp framework's inclusion of "problem-solving" as a core digital competency implicitly supports the need for adaptive learning paths (Carretero et al., 2017). However, the real-world application of such tailored programmes appears to lag, underscoring an area for organisational development and policy adjustment.

The evolving nature of technology and the workplace, as discussed by Long Magerko (2020), Ng et al. (2021), and Olari and Romeike (2021), further highlights the significance of adaptive training programmes. This indicates that DL training must continually adapt to incorporate new tools and methodologies. This is echoed in the DigComp framework's latest iteration, which integrates AI literacy to reflect technological advancements (Vuorikari et al., 2022). The framework can serve as a guiding model for designing DL training programmes that are comprehensive and forward-looking.

In light of these insights, it becomes evident that a multifaceted strategy is required. Training programmes must be tailored to the workforce's specific needs, incorporating hands-on, real-world projects that simulate actual data challenges encountered in professional settings. Such programmes should not only focus on the technical aspects of

DL but also emphasise critical thinking, ethical considerations, and the socio-technical dynamics of the data used in an organisational context. This is not an easy task.

Empowerment through DL

Empowering individuals through DL emerged as a central theme that aligns with organisational goals of enhancing employee autonomy, satisfaction, and innovation capacity, as Sander (2020), Bhargava (2015), Pangrazio & Selwyn (2019), and Crusoe (2016) pointed out. By providing employees with the necessary skills to locate, evaluate, and utilise data effectively, organisations can foster a culture of continuous improvement and adaptability, which is essential for maintaining competitiveness. This emphasis on empowerment was supported by academic frameworks found to prioritise real-world relevance in DL education, facilitating the hands-on application of DL skills. This aspect has also been recognised as important also when equipping students with DL competencies, as demonstrated by hackathons (Anslow et al., 2016), gamification to increase user engagement (Chin et al., 2016; Legaki et al., 2022; Legaki & Hamari, 2020; Wolff et al., 2015), online courses (Chen et al., 2018), the use of authentic data in the classrooms (Kjelvik & Schultheis, 2019), data visualisations (Shreiner, 2018; Shreiner & Dykes, 2021) and mobile applications (Giese, Anderl, et al., 2020).

Empowerment through DL also necessitates addressing the ethical dimensions of data use, as articulated by several authors (Bhargava & D'Ignazio, 2015; Giese, Anderl, et al., 2020; Wolff et al., 2016). These scholars emphasise the importance of embedding ethical considerations into the concept of DL, ensuring that individuals possess the technical skills to work with data and the moral compass to use it responsibly.

The role of AI in future workforce development

The lack of AI literacy within examined frameworks concerning DL was surprising for the author. According to Long and Magerko (2020), Olari (2023) and Gartner (Medeiros & Duncan, 2023) DL and AIL competencies are closely intertwined. Olari also hypothesises that "the effective development of AIL should include the development of DL".

Building on the insightful contributions of Long & Magerko, and Olari, which illustrate the profound interconnection between DL and AIL, it is compelling to explore the proposition of integrating AIL into DL frameworks. Olari's suggestion brings a hypothetical statement: the cultivation of AIL is most effectively achieved on the bedrock of robust DL. If this notion is true, it suggests the symbiotic relationship where the nuances of AI technologies are best understood and applied within the context of solid DL foundations.

The rationale for embedding AIL within DL frameworks rather than treating them as separate entities is again multifaceted and deeply rooted in the practical realities of the contemporary workforce. Firstly, DL encompasses the foundational skills required to navigate a data-rich environment, including understanding, analysing, and interpreting data. These competencies are prerequisites for meaningful engagement with AI technologies. As AI systems continue to be integrated into various business sectors, the ability to critically assess and apply these technologies becomes increasingly important. Integrating AIL into DL acknowledges the hierarchy of learning, where a deep understanding of data underpins the effective use of AI.

Moreover, the seamless integration of AIL into DL frameworks reflects the development, where AI is not a standalone phenomenon but a sophisticated tool for data analysis and application. The fundamental nature of working with AI lies in managing data. It is an acknowledgement of reality that the efficacy of AI systems is directly linked to the quality of data they are trained on. As such, the process of developing and training AI models necessitates the acquisition, cleaning, and manipulation of large datasets. Therefore, a comprehensive understanding of data management, from its acquisition to its analysis, is a crucial prerequisite for effectively working with AI.

Furthermore, integrating AIL into DL frameworks aligns with the pragmatic needs of organisations striving to adapt continuously. As businesses increasingly rely on AI for decision-making, analytics, and operational efficiencies, employees equipped with both DL and AIL are better positioned to contribute to organisational goals. The surprising observation of a gap of AIL in DL frameworks underscores a need to revisit these frameworks to encompass this ability.

In summary, including AI literacy in DL frameworks signals the expected increase in AI’s impact on data analytics and workforce dynamics. With the growing presence of AI integrations in the workplace, there is a noticeable shift towards developing competencies to enable effective human-machine collaboration. This shift highlights the changing nature of DL. It emphasises the need for organisations to adapt their priorities accordingly, ensuring that their workforce is proficient in leveraging AI technologies effectively.

Validation aspects

The diversity in validation methodologies—ranging from qualitative analysis, using interviews and thematic coding, to empirical validation and even a hands-on approach involving iterative design and real-world testing—illustrates the multifaceted nature of DL-related research. Each methodology brings its own strengths and caters to different aspects of framework development and assessment, from conceptual understanding to practical applicability. This highlights the need for tailored methods that address specific framework goals. The mixed methodologies used in validation point toward a scholar's understanding of these frameworks as a multifaceted domain requiring comprehensive and rigorous validation approaches.

Incorporating these insights into the broader discourse, as initiated by Mattar et al. (2022), reinforces the importance of a balanced approach to developing DL frameworks. On the other hand, Cui et al. (2023) argue that most of the assessment tools examined in their study did not focus on tool development or validation, which may hinder the utilisation of DL assessment tools.

Striking a balance between scientific rigour and practical accessibility emerges as a key consideration in the creation of these frameworks or tools. The insights from these validation methodologies provide a roadmap for future research and practice in developing effective, validated DL assessment tools that balance scientific reliability with practical usability.

5.3 Limitations

The studies included in this research's theory and literature review sections were selected with great care and attention. The selection process of SLR was thorough, ensuring that only studies of high relevance were considered for literature synthesis. Inclusion criteria were defined stringently, and results were expanded to include backward and forward results. This approach strengthened the validity of the SLR’s findings and enriched the analysis.

However, when conducting the SLR alone, there’s a risk of unintentionally narrowing the scope of literature due to individual biases or oversight. The author might have missed relevant studies outside her expertise or familiarity, leading to a less comprehensive review. The screening phase is particularly vulnerable to these limitations. Constructing a search string and manually selecting results also has limitations that impact the robustness and transferability of results.

The search string chosen for this study may have limited the scope of the literature examined since some studies used the word ‘workplace’ instead of all the specific terms defined in the search string for organisational and business contexts. To address this issue, the author conducted test searches in Scopus for each literacy term and found that adding the word ‘workplace’ to the search string resulted in about 500 new records for numeracy and IL together. In contrast, DL, AIL, and SL results increased by about 20 additional records. The author screened these additional 20 records for DL, AIL, and SL dimensions, but none met the inclusion criteria or were already found using the original search string. Therefore, the decision was made not to widen the scope of the search as it was already extensive. However, it is possible that some relevant studies were missed in the numeracy and IL dimensions due to this limitation.

This thesis combined theoretical frameworks with practical insights from the industry, offering a well-rounded understanding of DL in organisational contexts and enhancing the findings' relevance and applicability. While semi-structured interviews offered rich, qualitative insights, reliance on a note-taking approach may limit the precision and completeness of the data captured. Furthermore, the sample size of five interviewees poses limitations in terms of representativeness and generalizability, restricting the ability to draw broader conclusions. This underscores the importance of considering interview results as indicative rather than definitive.

Although this thesis's results lay a solid groundwork for understanding and developing DL in organisational and business settings, their wide applicability should be approached with an appreciation for the context-specific nature of the research conducted. Finally, this thesis's interdisciplinary complexity means that certain aspects or implications relevant to a specific literacy are less explored.

5.4 Evaluation of Research Methodologies

To ensure a comprehensive evaluation of the methodologies employed in this thesis, the author assesses their relevance, effectiveness, and integration based on established criteria outlined in Section 3. This section aims to validate the integrity and value of the research findings and explore how the qualitative and quantitative approaches complement each other. By examining the strengths and weaknesses of each methodology, the author substantiates the conclusions drawn and provides informed recommendations for future research in the field of DL. This reflective analysis is important as it identifies opportunities for methodological enhancements and deepens the theoretical integration of the findings.

5.4.1 Evaluation of Qualitative Interviews

The semi-structured interviews were designed to bridge theoretical knowledge of DL with practical experiences in organisational contexts. The choice of a semi-structured format intended to capture the nuanced perspectives of professionals allowed flexibility in response and fostered a dynamic exchange of ideas. While this approach enabled participants to express their views naturally, it also presented challenges in maintaining consistency across interviews. The variability in depth and focus of responses occasionally led to difficulties in achieving uniform data quality and comparability, underscoring the importance of balancing directive and open-ended questions to effectively steer discussions toward core research topics. (Criterion 1: Relevance of interview questions).

The decision to use a note-taking strategy during the interviews, instead of audio or video recordings, was driven by practical considerations and the interviews' pre-informative role. However, this method heavily relies on the interviewer's ability to accurately and comprehensively capture information in real time. A potential drawback of this approach included the possibility of missing nuanced details and compromising data integrity.

In the absence of a standardised template for note-taking, the data collection process in this study primarily depended on the structured interview questions. This setup presents challenges and opportunities in ensuring the reliability and consistency of the information gathered, as specified in Criterion 5 (Consistency and reliability of information). This meant that the note-taking approach was inherently subjective, influenced by the author's perspective and interpretation. This could lead to consistency issues across different interviews, affecting the comparability of responses and impacting the overall reliability of interview findings. Acknowledging this limitation is crucial for reflexivity, as it emphasises the potential gaps in data collection and the impact on the study's findings, thus addressing concerns related to Criterion 5.

The integrity of data may have also been compromised without a standardised approach to note-taking (Criterion 6: ethical considerations and data integrity). The integrity of the data would benefit from more structured documentation practices, such as employing a detailed note-taking framework, which could provide a more reliable and consistent data capture method (Criterion 4: depth and quality of data). The author, being the single interviewer, increases the vulnerability to biases and preconceptions, potentially skewing the data captured towards personal interpretations rather than objective recording. Future research could also benefit from incorporating video recordings to complement note-taking, ensuring a more complete and accurate dataset for analysis. Ethically, the process maintained good standards, with all participants informed about the nature of note-taking and their consent obtained, ensuring transparency and ethical compliance. Ongoing reflexivity was important throughout the research process, involving a critical examination of how personal biases might influence the data collected. (Criterion 6: Ethical considerations and data integrity)

The interviews revealed a diverse understanding of DL, emphasising its multifaceted nature, which spans technical abilities, cognitive competencies, and ethical considerations. This approach was particularly effective in uncovering the varied perceptions of DL across different professional backgrounds, enriching the research with a spectrum of insights that aligned well with the enhanced DIKW model used as the theoretical framework. However, the results also indicated that the alignment of interview questions could have been further refined to maintain a sharper focus on the research questions, suggesting an area for methodological refinement.

Conducting the interviews during a holiday period posed scheduling challenges, which restricted the availability of potential interviewees. Additionally, the nascent nature of the discourse on DL in Finland limited the pool of experts, leading to a relatively small and possibly less representative sample. These factors may have impacted the depth and breadth of the data collected, which impacts the generalizability of the findings (Criterion 2: Participant representation). Moreover, not all participants had reviewed the interview questions in advance, despite these being sent out ahead of time, which might have influenced the richness of the discussions (Criterion 4: Depth and quality of data). Despite these challenges and limitations, the use of a semi-structured format was appropriate as it provided sufficient flexibility to explore emergent themes while maintaining focus within the limited time of one hour per interview.

The selection of interviewees, while limited, managed to cover a range of perspectives within the field of DL. This diversity was important for understanding the multifaceted nature of DL (Criterion 3: Clarity and coherence of responses). Nevertheless, the inclusion of a more diverse set of voices, particularly those recently trained in DL, could provide deeper insights into the practical implications of such education on workplace efficiency and data handling (Criterion 2: Participant representation).

In conclusion, the non-recording, note-taking approach of semi-structured interviews served as a foundational component of the research, offering valuable perspectives and enabling a thematic analysis that enriched the subsequent SLR. This method presented unique challenges in terms of data capture and analysis, as well as raising questions about validity and reliability. Despite these challenges, the interviews captured a broad range of experiences and understandings related to DL. This evaluation highlights opportunities for enhancing the methodological design of this research phase. Addressing the identified limitations through improved scheduling, improved data collection methods, more focused interview preparation, and broader participant selection would strengthen the validity and applicability of the findings. This reflective consideration of these elements exemplifies the critical self-awareness essential for this kind of qualitative research.

5.4.2 Evaluation of Systematic Literature Review

PRISMA checklist and flow diagram

The author conducted the SLR following the PRISMA guidelines and PRISMA checklist, as these are globally recognised for increasing transparency, clarity, and reproducibility in reporting systematic reviews. Adhering to these guidelines was not just a procedural requirement but also a valuable learning experience that helped the author understand the intricacies of systematic inquiry and transparent reporting. Throughout the review process, the author was meticulous in adhering to the PRISMA checklist to maintain methodological rigour and reflect on my research process continuously. This approach helped critically evaluate each step of the process, from developing the research question to reporting the results. It ensured that every phase was carried out in accordance with established standards.

The author documented the study selection process using the PRISMA flow diagram, which was a valuable tool for managing and displaying the vast information flow through the different phases of the research. It provided a clear and structured overview of the number of studies screened and assessed for eligibility and the reasons for excluding studies at each stage. This enhanced the transparency of the research and allowed the author to evaluate and reflect on the decisions made at each junction. This ensured that research objectives and theoretical framework were aligned throughout the study.

By incorporating these tools into SLR, the author followed the methodological standards outlined in the PRISMA statement and integrated a continuous reflective practice throughout the process. This reflective practice was instrumental in the author's learning journey, enabling the identification of areas for improvement, comprehending the implications of methodological choices, and confirming the reliability and relevance of the findings. The process was a transformative experience that improved the author's skills in conducting systematic reviews and contributed significantly to the author's understanding of the field of DL and related literacies in business and organisational contexts.

Comprehensiveness of search strategy

Developing a comprehensive and high-quality search strategy for the author's first SLR presented some challenges, mainly due to the initial limited understanding of the systematic review process. The creation of an effective search string was demanding. It required preliminary searches and careful evaluation of the results to determine which terms were synonymous and essential for crafting a search string that was both comprehensive and relevant. This iterative process also involved guidance from Professor Juho Hamari, which enhanced the author's approach to formulating search queries.

In addition to the technical aspects of constructing a search string, aligning it with the main research question posed in this thesis and the specific research questions guiding this SLR was essential. This alignment was vital for ensuring that the results obtained were directly relevant and could contribute meaningful answers to these questions. The process involved refining SLR's research questions and evaluating the search terms and their correlation with the research objectives, requiring an understanding of the topic and the scope of the thesis. This alignment was essential for the integrity and relevance of the SLR, as it directly impacted the potential to draw valid conclusions and fulfil the research aim.

This learning process was crucial not only in developing a robust search strategy but also in understanding how to approach the subject without prematurely excluding documents. Utilising Scopus as the primary data ensured access to a broad array of peer-reviewed records. However, relying on one database may have introduced a selection bias, potentially omitting relevant studies indexed in other databases or published in formats not covered by Scopus. While the search strategy was designed to minimise publication bias, the exclusion of non-English articles might have limited the review's scope, potentially overlooking valuable insights from non-English publications that could enrich the understanding of DL.

The search, conducted through the Scopus database, initially yielded 2 567 studies, reflecting the broad scope of defined parameters. The subsequent title, keyword and abstract screening was particularly challenging due to the nuanced differences between closely related literacies and context interdependencies. The author's increasing understanding of the importance of defining the context strictly enough and having a clear understanding of that facilitated the screening process essentially.

This phase, and especially the next phase of assessing full-text reports for eligibility, required marking informed judgments on the pertinence of studies to the research questions and theoretical framework, which was a complex task given the author's initial unfamiliarity with conducting SLR. Due to the extensive initial retrieval, the process of refining the search to focus on the most relevant sources was at first very challenging. It was a continuous learning process trying to ensure the inclusion of pertinent studies related to specified contexts. As the objective of the study became clearer and the author's competence to evaluate documents increased, the joy of conducting the literature review grew at the same time. It presented a learning curve, as the flow diagram required the author to document each decision meticulously, a practice that was time-consuming and essential for the integrity of the review.

Additionally, the inclusion of forward and backward search methods significantly enhanced the comprehensiveness and depth of the review. These techniques allowed for the identification of additional studies that might not have been captured through database searches alone, thereby ensuring a more exhaustive coverage of the literature and strengthening the validity of the review's findings.

In conclusion, as the search strategy incorporated a carefully constructed combination of keywords to ensure an exhaustive retrieval of literature, the challenges encountered during the review process underscore the complexities of conducting an SLR. This approach aimed to minimise publication bias by capturing both widely recognised and less visible studies, thereby providing a comprehensive overview of the field. The search's breadth and depth, detailed in the research protocol, underscore its alignment with the research objectives, confirming the strategy's effectiveness in gathering pertinent literature and establishing a robust foundation for synthesising current knowledge in the field of DL in a specified context.

Selection and inclusion criteria

The clarity and relevance of the selection and inclusion criteria were critical in maintaining the focus and integrity of the SLR. By defining these criteria, the review ensured that only studies directly related to the research questions and theoretical framework were considered. This process was important for excluding irrelevant or tangential studies, enhancing the review's relevance and coherence. In defining the selection and inclusion criteria, the author faced the challenge of balancing the breadth of material with maintaining a focused view. The concentration on the specified context facilitated the defining process, ensuring the review remained targeted and coherent, capturing essential studies. The rationale behind each decision to include or exclude studies was clearly documented in the flow diagram, providing transparency and allowing the reproducibility of the review process.

The selection and inclusion criteria were crafted to ensure that only studies directly relevant to the SLR's objective were included. This succeeded well and helped maintain the review's focus and relevance. However, the stringent criteria may also have excluded studies that, while not directly focused on DL-related frameworks in organisational and business contexts, could offer indirect insights or complementary perspectives. This could potentially limit the richness of the review's findings. The transparency in documenting the rationale for inclusion and exclusion mitigates this concern but does not entirely eliminate the potential for subjective bias in study selection, especially considering the absence of the author's experience in conducting SLRs. Additionally, the author's know-how grew little by little as the review process progressed, which could have affected the final set of studies. The use of multiple reviewers would have mitigated this potential bias.

Objectivity and rigour of analysis

The objectivity and rigour of the analysis were maintained through systematic data extraction and the use of predefined fields. This structured approach facilitated the accurate and consistent collection of data across studies, which was crucial for ensuring that findings were robust and as free from bias as possible. The synthesis of the extracted studies adhered strictly to the PRISMA guidelines, which guided the integration of findings to address the research objectives comprehensively. This methodological rigour supported a deeper understanding of DL-related frameworks within the specified context, highlighting the review's contribution to theoretical knowledge and practical applications.

Nonetheless, the interpretation of findings could still be influenced by the author's perspectives, especially in synthesising data where subjective judgment plays a significant role. Acknowledging this, efforts were made to adhere strictly to the PRISMA protocol, aiming to mitigate these biases and enhance the objectivity of the conclusions drawn.

Reporting and transparency

The SLR report exemplifies clarity, completeness, and adherence to the PRISMA guidelines. Detailed descriptions of the methodology are provided, enhancing the report's transparency. The disclosure of potential biases and limitations further underscores the honesty and integrity of the review. This transparent reporting ensures that the review can serve as a reliable source for future research and practice, setting a benchmark for methodological excellence in the field.

To further enhance transparency and facilitate reproducibility, all data collected and analysed during the review are recorded in an Excel file. This file includes details about each study, ensuring that all necessary information is available for the review to be independently verified and replicated. This Excel file is available upon request, demonstrating the author's commitment to open and accessible scientific inquiry.

However, the inherent complexities of interpreting diverse studies and the possible underreporting of non-significant or negative findings within the reviewed articles could introduce reporting biases. These biases might affect the generalizability of the review's conclusions, suggesting a need for a cautious interpretation of the findings. Readers are encouraged to consider these factors when applying the conclusions drawn from this review.

Contribution to knowledge and practice

The SLR advances the understanding of DL-related frameworks within the business domain, filling existing knowledge gaps and offering practical implications. By systematically synthesising and analysing literature, the review identified competencies and strategies that are important in business environments. Its findings are highly relevant to practitioners and policymakers, offering actionable knowledge that can directly impact business practices and organisational strategies.

The review's capacity to bridge theoretical concepts with practical applications demonstrates its profound impact on both academic and practical realms, enriching the discourse on DL and related literacies. For instance, the review highlighted the importance of multifaceted skill sets that combine technical abilities with soft skills like critical thinking and ethical considerations, proposing a more holistic approach to employee development.

While these contributions are evident, it is important to acknowledge that the practical applications of these findings may vary based on organisational context, industry-specific challenges, and regional differences. This variability should be considered when applying the SLR's insights to practice, as the findings may not be universally applicable without adaptations.

Relevance and application of findings

The findings of the SLR are highly relevant and provide a robust foundation for the development of DL frameworks within business contexts. The review effectively answered the research questions, highlighting its success in addressing the set objectives and contiburing valuable insights. However, the dynamic nature of DL and the rapid evolution of technology mean that the review's findings must be continually updated to remain relevant. The field's fast-paced change could quickly outdate even the most thorough reviews, suggesting the need for ongoing research and periodic updates to the SLR.

5.4.3 Evaluation of the Synthesis of Results

Integration of methodological insights

The synthesis effectively integrates the qualitative insights from semi-structured interviews with the quantitative findings from the SLR. This integration effectively addresses the research questions comprehensively, providing a cohesive understanding that bridges the gap between experiential individual insights and systematic academic models.

The way qualitative and quantitative data interact in this thesis is important because it challenges and supports existing theories in the field of DL. For instance, the qualitative data brought up professional perceptions of DL that were nuanced and sometimes contradicted the more structured frameworks that were identified in the SLR. This contrast prompted a re-examination of existing models, suggesting that while structured frameworks are essential for understanding DL, they may not fully capture the dynamic and context-specific ways professionals encounter DL in real-world settings. These findings support a more flexible and contextually adaptive approach to DL frameworks that could lead to improvements in how DL is conceptualised and taught.

The integration of different research methods enriches the understanding of DL by combining qualitative insights with quantitative evidence. Through qualitative interviews with professionals, the author gained a deeper understanding of their complex experiences with DL, which could not be captured by an SLR alone. This melding of methodologies provided a more nuanced view of DL in professional settings, highlighting the required competencies and the personal and situational factors that influence DL.

This thesis elaborates on various aspects to demonstrate a clear and logical methodology. It combines distinct insights to form a more dynamic view of DL. The thesis showcases how different methodological approaches inform and enhance each other in the study of DL.

Abductive reasoning process

The application of abductive reasoning in synthesising the results has been articulated well. This reasoning effectively utilises the empirical evidence and theoretical frameworks to develop new insights into DL within business contexts. The synthesis navigates through various suggestions about DL’s application and integration in professional settings, which are tested against findings from both interviews and literature. While the reasoning led to substantiated conclusions, further details during the synthesis could provide deeper transparency and insight into the reasoning process.

The abductive process especially helped to uncover a broader, holistic view of DL that integrates technical skills with meta-skills like critical thinking and ethical considerations. This was evident when contrasting the structured nature of DL competencies in the SLR with the fluid, often improvisational skills discussed by professionals in interviews.

Theoretical contribution and innovation

The synthesis has made important theoretical contributions by linking DL with broader competencies and situational applications in the workforce. The innovative aspects of this synthesis lie in its ability to consolidate diverse views on DL from both industry professionals and academic sources into a holistic framework that appreciates the complexity of DL. This approach enriches the theoretical landscape of DL and suggests practical pathways for future framework development and workforce training. Synthesis could benefit from a more explicit discussion on how this new understanding challenges existing theories or introduces new paradigms in the field of DL. By pushing the boundaries of current theoretical models and suggesting practical implementations, this thesis contributes to a deeper, more actionable understanding of DL, setting the stage for advancements in theory and practice.

Coherence and logical consistency

The overall coherence and logical consistency of the synthesised results are creditable. The final conclusions drawn from the combined qualitative and quantitative data logically align with the established research objectives and questions. The synthesis navigates through complex data and diverse perspectives to present a unified view of DL that is both theoretically enriched and practically applicable. However, the transition from empirical findings to synthesised insights could be made more explicit by detailing the logical steps taken to merge different types of data. This would strengthen the narrative by clearly showing how each piece of evidence contributes to the overall conclusions.

To summarise, this thesis successfully addressed the initial research problem and questions outlined in the beginning. The utilisation of a mixed-methods approach was instrumental in developing a comprehensive basis for understanding the topic. Both semi-structured interviews and the SLR were crucial in responding to the research issues, each method reinforcing the other. The integration of results was effectively executed, allowing the generation of new knowledge and suggesting future research directions. This work's contribution extends beyond theoretical insights, offering practical recommendations that enrich the understanding and application of DL in organisational and business settings.

5.5 Conclusion and Future Work

This thesis has explored the field of DL and related literacies in organisational and business contexts. It illuminates the pivotal role of existing DL-related frameworks play in developing a data-literate workforce. This study, which draws on an extensive literature review and insightful interviews, reveals the multifaceted nature of DL and its alignment with organisational objectives and makes multiple contributions to the existing literature.

As a contribution to the literature of DL and AIL, this study revealed several principles inherent in academic frameworks that align with the needs of modern organisations.

These principles include a holistic skill set, customised training initiatives, empowerment through DL, and the growing importance of AI literacy. By applying these principles, organisations can, in practice, create robust DL programmes that reskill and upskill their workforce with the technical knowledge, critical thinking, ethical awareness, and agility needed to excel in the workplace.

The research's insights also made a contribution by revealing gaps in current DL-related frameworks applied in workplace settings, including the underrepresentation of AIL and the challenge of fully capturing the nuanced skill sets demanded in professional settings. Concentrating on the development of DL frameworks in the business sector is needed, and it holds potential for progress and advancement. Moreover, the anticipation of AI's growing influence on workforce dynamics necessitates re-evaluating and expanding current frameworks to encompass AI literacy, ensuring they remain relevant and robust in the face of technological shifts.

Based on the results of this study, for future research, the author proposes developing and conceptualising Workplace Data Literacy (WDL) as a distinct construct from Workplace Information Literacy (WIL). WDL should acknowledge the specific empowerment experience that comes from mastering data-related tasks and address the identified skill gap prevalent in the business domain, particularly those emerging from the integration of AI technologies and collaborating with them. Future frameworks would better align with organisational needs by focusing on DL within workplace contexts. Incorporating AI literacy into developing WDL as a formal term can help bridge the gap between theoretical concepts and practical applications. This doesn't mean narrowing the focus of DL but rather enriching it to reflect the nature of modern data work with AI technologies.

The author proposes first the conceptualisation of WDL, explicitly incorporating AI literacy to reflect the integral role of AI in contemporary data work. This initial phase of conceptualisation will identify and define the core components of WDL, distinguishing it from DL and WIL. Once WDL is conceptualised, incorporating theoretical and practical considerations, the research could proceed with a mixed-methods research design. This approach could explore the application of WDL in specific business domains like retail or banking sectors. The choice of outcome measures would be directly informed by the conceptual framework of WDL, focusing on data-related task proficiency, effective collaboration with AI technologies, and their influence on organisational decision-making and innovation.

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APPENDIX A: LIST OF ARTICLES

No.	Author(s)	Title	Year
1	Abhari, K., Brodskiy, R., Davis, D., Ness, H., Pagador, J., & Parsons, M.	Data Swagger: A Systemic Approach to Train, Motivate and Engage Data Savvy Employees [1]	2022
2	Ahmad, F., Widén, G., & Huvila, I.	The impact of workplace information literacy on organisational innovation: An empirical study [2]	2020
3	Appelbaum, D., Scott Showalter, D., Sun, T., & Vasarhelyi, M. A.	A framework for auditor data literacy: A normative position [3]	2021
4	Aslam, M., Batool, S. H., & Ameen, K.	Workplace information literacy in context: scale development and validation [4]	2023
5	Bawden, D., & Robinson, L.	Promoting literacy in a digital age: Approaches to training for information literacy [5]	2002
6	Birdsong, L., & Freitas, J.	Helping the non-scholar scholar: Information literacy for lifelong learners [6]	2012

7	Black, S., Yasukawa, K., & Brown, T.	Changing conceptualisations of literacy and numeracy in lean production training: Two case studies of manufacturing companies [7]	2014
8	Bolek, V., Kokles, M., Romanová, A., & Zelina, M.	Information literacy of managers: Models and factors [8]	2018
9	Brown, M., Kirschenmann, K., & Spycher, T.	NUMERACY AND ON-THE-JOB PERFORMANCE: EVIDENCE FROM LOAN OFFICERS [9]	2020
10	Bruce, C. S.	Workplace experiences of information literacy [10]	1999
11	Cardon, P., Fleischmann, C., Logemann, M., Heidewald, J., Aritz, J., & Swartz, S.	Competencies Needed by Business Professionals in the AI Age: Character and Communication Lead the Way [11]	2023
12	Cetindamar, D., Kitto, K., Wu, M., Zhang, Y., Abedin, B., & Knight, S.	Explicating AI Literacy of Employees at Digital Workplaces [12]	2024
13	Cheuk, B.	Delivering business value through information literacy in the workplace [13]	2008
14	Cokely, E. T., Ghazal, S., Galesic, M., Garcia-Retamero, R., & Schulz, E.	How to measure risk comprehension in educated samples [14]	2013
15	D’Ignazio, C.	Creative data literacy: Bridging the gap between the data-haves and data-have nots [15]	2017

16	D'Ignazio, C., & Bhargava, R.	DataBasic: Design principles, tools and activities for data literacy learners. [16]	2016
17	Farmer, L. S. J.	Technology aspects of information literacy in the workplace [17]	2012
18	Gal, I.	Adults' statistical literacy: Meanings, components, responsibilities [18]	2002
19	Guo, Y., Tao, J., Yang, F., Chen, C., & Reniers, G.	An evaluation of the information literacy of safety professionals [19]	2022
20	Jinadu, I., & Kaur, K.	Information literacy at the workplace: A suggested model for a developing country [20]	2014
21	Jirakitpaibool, C., Thammaboosadee, S., & Socharoentum, M.	Data Literacy Framework for Thailand Government Officers [21]	2023
22	Laupichler, M. C., Aster, A., Haverkamp, N., & Raupach, T.	Development of the "Scale for the assessment of non-experts' AI literacy" – An exploratory factor analysis [22]	2023
23	Lloyd, A.	Learning to put out the red stuff: Becoming information literate through discursive practice [23]	2007

24	Long, D., & Magerko, B.	What is AI Literacy? Competencies and Design Considerations [24]	2020
25	Maitz, K., Fessl, A., Pammer-Schindler, V., Kaiser, R., & Lindstaedt, S.	What do Construction Workers Know about Artificial Intelligence? An Exploratory Case Study in an Austrian SME [25]	2022
26	McAlevey, L., & Sullivan, C.	Statistical literacy and sample survey results [26]	2010
27	Naveed, M. A., & Kamran, M.	Workplace information literacy: a case of investigation officers from Punjab Police, Pakistan [27]	2022
28	Naveed, M. A., & Rafique, F.	Information literacy in the workplace: A case of scientists from Pakistan [28]	2018
29	Naveed, M. A., & Saadia, H.	Information literacy at journalists' workplace in Pakistan [29]	2023
30	Naveed, M. A., & Shah, N. A.	Information literacy in the legal workplace: Current state of lawyers' skills in Pakistan [30]	2023
31	Ongena, G.	Data literacy for improving governmental performance: A competence-based approach and multidimensional operationalization [31]	2023

32	Pothier, W. G., & Condon, P. B.	Towards data literacy competencies: Business students, workforce needs, and the role of the librarian [32]	2020
33	Ridsdale, C., Rothwell, J., Smit, M., Ali-Hassan, H., Bliemel, M., Irvine, D., Kelley, D., Matwin, S., & Wuetherick, B.	Strategies and best practices for data literacy education. Knowledge synthesis report. Strategies and Best Practices for Data Literacy Education: Knowledge Synthesis Report. [33]	2015
34	Smolnikova, M.	Building a Data Literate Business Workforce [34]	2022
35	Smolníková, M., Chalupová, H., Potančok, M., Novotný, O., & Puskas-Juhasz, R.	Building and testing a comprehensive data literacy model for business users [35]	2021
36	Sternkopf, H., & Mueller, R. M.	Doing good with data: Development of a maturity model for data literacy in non-governmental organisations [36]	2018
37	Widén, G., Ahmad, F., Nikou, S., Ryan, B., & Cruickshank, P.	Workplace information literacy: Measures and methodological challenges [37]	2021
38	Yang, F.	Exploring the information literacy of professionals in safety management [38]	2012

APPENDIX B: FRAMEWORK TYPES AND CHARACTERISTICS

No.	Theoretical /conceptual	Empirical	Competency framework	Assessment framework	Teaching framework	Other	Sample / Settings	Aim of the study	Business/organisational setting	Target Audience
1	X				X		Semi-structured interviews, 14 in-depth interviews, 2 teams within the U.S Department of Defense	This paper proposes a systematic data education framework for increasing data literacy across organisations	Training and engaging employees in DL. Study focuses on end-users = non-specialists who utilise extracted data to make informed decisions	Organisations looking to improve DL among their employees
2	X	X		X			An electronic survey distributed via email, with two reminders sent during the May–September 2018 period. CEOs of knowledge-intensive SMEs in Finland, identified through the Orbis database. The sample was refined to 1,960 potential respondents after removing duplicates and accounting for non-reply email addresses. A total of 184 complete responses were received, representing a net return ratio of 9 %. The respondents varied in age, with a significant proportion in the 50-59 age group (41.5%), and most having tertiary education (83%). The majority were male (80%), and they came from a diverse range of industries, including Telecommunications Technology, Internet & Electronics (15.6%), and Other (26.1%), indicating a diverse cross-section of the population that could be considered reasonably representative of Finnish SMEs	This paper aims to explore the impact of CEOs' information literacy on organisational innovation within small and medium-sized enterprises (SMEs), specifically examining how information literacy influences the development of both exploratory and exploitative innovations and the mediating role of opportunity recognition in these relationships.	The impact of CEO's IL on innovation in SMEs	SME managers, academics

No.	Theoretical /conceptual	Empirical	Competency framework	Assessment framework	Teaching framework	Other	Sample / Settings	Aim of the study	Business/organisa-tional setting	Target Audi-ence
3	X		X				Commentary/conceptual analysis	This paper aims to articulate the need for a framework of auditor data literacy, addressing the gap between cur-rent professional requirements and the evolving techno-logical landscape in auditing	The importance of DL for auditors within busi-ness and organisational contexts, focusing on enhancing audit quality through advanced data analytics	Auditors, ac-counting pro-fessionals, re-searchers
4	X	X		X			Administrative staff working in the Quality Enhancement Cell (QEC) of public and private sector universities in Pun-jab province, Pakistan. Total of 250 employees targeted, with 172 usable responses received and analysed. Major-ity of participants were male (63%, n=109), with the most common age group being 36–40 years (29%), followed by 31-35 years (23%)	This paper aims to develop a validated scale to measure the workplace information literacy (WIL) skills of Quality Enhancement Cell's staff based on the i-skills model	Workplace IL	Staff working in the public and private sector
5		X			X		Case study 1: Planning, implementation, and evaluation of a training programme in IL for research workers at a multinational pharmaceutical company; Case study 2: A summer school training course in information literacy for professionals from Central and Eastern Europe, the for-mer Soviet Union, and other countries, focusing on digital literacy	This paper aims to demonstrate the necessity for di-verse, broad, and context-aware training approaches in the field of information and digital literacy. Through the presentation of two case studies, it underscores the need to tailor information literacy training to the varied scopes of concepts, skills, and attitudes required for ef-fectively dealing with information in multiple formats and contexts.	Multinational pharma-ceutical research organ-isation (IL training)	Information professionals, educators, re-search staff

No.	Theoretical /conceptual	Empirical	Competency framework	Assessment framework	Teaching framework	Other	Sample / Settings	Aim of the study	Business/organisa-tional setting	Target Audi-ence
6	X				X		Adults outside traditional academic environments, specif-ically small to medium-sized business owners, adults over fifty, women without homes experiencing extreme pov-erty, and youth.The training began face-to-face in late 2007 in the Denver and Boulder metro areas of Colorado, United States, utilising public libraries, small business de-velopment centers, and computer labs of nonprofit or-ganisations	This paper aims to explore the effectiveness of the Infor-mation Literacy Initiative (ILI) at the University of Wash-ington Information School in providing information liter-acy training to populations outside of traditional aca-demic environments	Population including: lifelong learner, profes-sional development	Adult learners
7		X			X		Two medium-sized manufactuging companies with pro-duction workforces of between 45 and 60 workers, lo-cated on the outskirts of capital cities in different Austral-ian states. Companies are diverse in their products but similar in the composition of their production workforces, mainly comprising workers born overseas with English not being their first language	This paper aims to explore the changing conceptualiza-tions of literacy and numeracy within the framework of lean production training in two case studies of manufac-turing companies.	Lean production train-ing in manufacturing companies	Business profes-sionals, educa-tors, research-ers
8	X	X		X	X		The survey was conducted among Slovak Republic busi-ness managers across different sectors, data collection was conducted from September 2013 to June 2014 with 200 managers approached and 180 responses. Respond-ents were segmented into operational, tactical, and top managers, with the majority holding a Master's degree and distributed across various age groups and fields of education, primarily in economics, management, and business.	This paper seeks to design a quantitative and qualitative information literacy model for a specific group (manag-ers) by comparing and defining the concept of infor-mation literacy and selected information literacy models	Managers' IL	Business man-agers, research-ers, organisa-tional leaders

No.	Theoretical /conceptual	Empirical	Competency framework	Assessment framework	Teaching framework	Other	Sample / Settings	Aim of the study	Business/organisa-tional setting	Target Audi-ence
9		X		X			The study's sample consists of loan officers working in a retail bank in Romania, with a focus on small business lending. The data includes information on all loan applica-tions processed by these loan officers, along with their performance in a standardized numeracy test. The sam-ple period covers 2007 to 2010, allowing for the analysis of loan officers' performance across different economic conditions, including both pre-crisis and crisis periods. The study takes advantage of a unique dataset provided by the retail bank, linking loan officers' numeracy test scores with detailed loan-level data on the credit assess-ments and subsequent loan performance	This paper aims to empirically examine the relationship between employee numeracy and on-the-job perfor-mance, focusing on loan officers in a retail bank.	The impact of numeracy on loan officers' perfor-mance in a retail bank	Banking profes-sionals, aca-demics in fi-nance and eco-nomics
10	X	X			X		The participants were primarily professionals from Aus-tralian universities, encompassing librarians, IT profes-sionals, counseling services staff, staff developers, and ac-ademics in fields such as engineering, music, business, and architecture. These individuals, considered as 'knowledge workers', provided insights from their 'work-places', which were various organisational units within higher education institutions. Data were gathered from over 60 individuals, with 16 participating in semi-struc-tured interviews and the remainder contributing written data	This paper aims to summarise the outcomes of an inves-tigation into the experience of information literacy among various types of professionals. It explores the possible differences and interrelations between individ-ual and organisational information literacy suggested by these outcomes and discusses the implications for edu-cation and training.	Developing a compre-hensive picture of how IL is understood and en-acted in the workplace	Managers, trainers, educa-tors
11	X	X	X				Online survey: 692 business practitioners working in dif-ferent countries including United Stated, Germany, India, Finland, South Korea, China, the United Kingdom, Can-ada, and others	This paper aims to explore the impacts of generative AI on the skill sets valued among business practitioners, fo-cusing on the perceptions of these practitioners regard-ing the evolving importance of various competencies.	Business professionals	Business practi-tioners, educa-tors, curriculum developers, re-searchers

No.	Theoretical /conceptual	Empirical	Competency framework	Assessment framework	Teaching framework	Other	Sample / Settings	Aim of the study	Business/organisa-tional setting	Target Audi-ence
12	X		X				Analysis of 270 articles focused on AI literacy among em-ployees in digital workplaces. Collected from Scopus data-base, considering articles and conference papers in Eng-lish related to AI literacy, focusing on social sciences and business.	This paper seeks to explore and define the concept of AI literacy among employees within digital workplaces.	AI literacy capabilities within digital work-places	Researchers, managers
13	X	X			X		In-depth investigation over a 3-month period in late 2006. Participants: employees of ERM, over 3000 staff, in-cluding senior executives and consultants. Over 1000 nar-ratives (stories and experiences) gathered from col-leagues based in 40 different countries.	This paper aims to explore how Environmental Re-sources Management (ERM), recognised as the world's largest environmental consulting firm, leverages 'infor-mation literacy' as a pivotal component of its knowledge management programme to generate value for the com-pany	Exploring the imple-mentation of IL strate-gies within a real-world business context	Business profes-sionals
14		X		X			Initial validation study: A community sample of 300 par-ticipants, primarily current or former undergraduate or graduate students from universities in Berlin, Germany. Additional validation studies: 20 further studies involving 5036 participants across 15 countries, including diverse samples (community samples, Mechanical Turk web pan-els, medical professionals).	This paper aims to introduce and validate the Berlin Nu-meracy Test, a tool designed to rapidly and effectively assess statistical numeracy and risk comprehension among educated individuals, including college students and professionals in medical and business fields.	One goal for the Berlin Numeracy test is to of-fer an instrument that can quickly assess sta-tistical numeracy in working professionals	Researchers, educators, pro-fessionals

No.	Theoretical /conceptual	Empirical	Competency framework	Assessment framework	Teaching framework	Other	Sample / Settings	Aim of the study	Business/organisational setting	Target Audience
15	X				X		Conceptual analysis drawing from the author's experiences as a data literacy researcher, educator, and software developer, as well as broader issues affecting global populations regarding data literacy. The study's data comes from the author's extensive review of relevant literature, personal experiences in the field, and illustrative examples of projects and initiatives that align with the proposed tactics for cultivating creative data literacy	This paper seeks to bridge the growing gap between individuals who can work effectively with data ("data-haves") and those who cannot ("data-have nots"), particularly in the context of increasing control over data by state and corporate actors. By introducing the concept of "creative data literacy," the paper aims to highlight the importance of empowering people in non-technical fields with data literacy skills.	Addressing the broader issue of DL across various segments of the population, emphasising the importance of making data skills accessible and engaging for everyone	Educators, data creators, tool developers, visualisation designers
16		X			X		The population includes students, journalists, non-profit organisations, community activists, and educators. Primarily based in the United States, with tool accessibility online for broader use. Evaluation workshops were conducted with a mix of undergraduate students and adult learners from various sectors.	This paper proposes a novel approach to designing digital tools and activities to enhance data literacy among learners. Specifically, it aims to shift the focus from using data tools for mere utilisation to a more pedagogically grounded method that supports learning	Study targets DL learners, including journalists and non-profit organisations	DL learners, students, journalists, non-profit organisations, community activists
17	X				X		Conceptual analysis, review-based: synthesizing existing literature, theories, and best-practices related to IL and technology in the workplace	This paper seeks to address the need for information literate employees in modern workplaces, necessitated by the increasing volume and complexity of information affecting organisational operations. It aims to explore the symbiotic relationship between technology and information literacy in the workplace, concentrating on associated training issues and the imperative for organisations to systematically identify key information and technology literacy processes	Technology aspects of IL within workplace environments	Workplace leaders, educators, HR professionals
18	X		X				Conceptual analysis: a literature review + framework development	This paper seeks to enhance understanding of statistical literacy as a crucial skill for adults in information-laden societies	Adult's statistical literacy, also in workplaces	Educators, statisticians

No.	Theoretical /conceptual	Empirical	Competency framework	Assessment framework	Teaching framework	Other	Sample / Settings	Aim of the study	Business/organisa-tional setting	Target Audi-ence
19	X	X		X			Survey: 40 safety officers from 4 representative compa-nies	This paper aims to evaluate the information literacy level of safety management personnel for improving their ability to comprehend safety language/technology/infor-mation	Safety management sector	Safety profes-sionals, manag-ers, researchers
20	X		X				Conceptual analysis: literature review and conceptual modeling. Setting: Information literacy at the workplace, specifically focusing on developing countries like Nigeria	This paper aims to address the gap in existing infor-mation literacy models which do not adequately support the perspective and understanding of information liter-acy at the workplace, especially in developing countries like Nigeria	Specific needs of the workplace particulary in developing countires like Nigeria	Information professionals, organisational leaders and managers, aca-demics
21	X		X				Government officers across various departments in Thai-land, document does not specify the exact number of participants	This paper aims to develop a comprehensive data liter-acy framework for government officers in Thailand.	Government officers in Thailand	Government of-ficers
22	X	X		X			Heterogeneous group of non-experts (individuals without formal AI or computer science education). 479 initially re-cruited; final sample size was 415 after excluding non-at-tentive responses. The study involved collecting data through an online platform (Prolific) and analysing it us-ing statistical software.	This paper aims to present the development of the "Scale for the Assessment of Non-Experts' AI Literacy" (SNAIL). It seeks to offer a reliable and valid instrument for measuring AI literacy among non-experts.	General public, individu-als engaging with AI technologies in their daily lives and work en-vironments	General public, individuals en-gaging with AI technologies in their daily lives and work envi-ronments
23	X	X			X		Firefighters in regional New South Wales, Australia. 20 participants (14 in phase 1, including 7 experienced and 7 nocies; 6 in phase 2 fot thematic elaboration)	This paper aims to redefine information literacy by ex-ploring how firefighters become information literate through their engagement with a variety of information sources and practices within their workplace.	Firefighters	Information sci-ence profes-sionals, educa-tors, HR profes-sionals

No.	Theoretical /conceptual	Empirical	Competency framework	Assessment framework	Teaching framework	Other	Sample / Settings	Aim of the study	Business/organisa-tional setting	Target Audi-ence
24	X		X				Scoping study: Review of interdisciplinary literature re-lated to AI literacy	This paper aims to provide a concrete definition of AI lit-eracy based on existing research. It synthesizes interdis-ciplinary literature into a set of core competencies of AI literacy and suggests several design considerations to support AI developers and educators in creating learner-centered AI technologies.	AI literacy in a broad context, including edu-cation and public under-standing of AI technolo-gies	AI developers, educators, re-searchers
25		X			X		Construction workers in a small Austrian company. 20 semi-structured interviews: 19 male, 1 female.	This paper aims to explore the knowledge and attitudes of construction workers towards AI within a small Aus-trian company. By examining their associations with the AI term, sources of knowledge about AI, and their per-ceptions of changes, risks, and opportunities related to AI in their work environment, the study seeks to uncover the depth of AI understanding among these workers	Construction workers	Researchers, practitioner in the field of AI literacy
26		X		X			MBA students with managerial experience: 99 responses, location: University of Otago, New Zealand	This paper seeks to investigate the level of understand-ing of statistical literacy, particularly the interpretation of sample survey results, among MBA students with prior managerial experience.	The understanding of statistical concepts among managers/MAB students	Business educa-tors, statisti-cians
27		X		X			Investigation officers from Punjab Police, Sargodha Divi-sion, Pakistan. Total population 696 officers, sample size 234 officers, April-July 2020, response rate 200 out of 234 questionnaires, 85,47%	This paper seeks to investigate the current state of infor-mation literacy development among investigation offic-ers	Investigation officers	Investigation of-ficers
28		X		X			Scientists working at the Pakistan Council of Scientific and Industrial Research (PCSIR) Lahore, 121 responses out of 140. The questionnaire included both the adaptation of an existing instrument and the Information Literacy Self-Efficacy Scale (ILSES) with 28 items across seven sub-scales	This paper seeks to explore information literacy among scientists employed at the Pakistan Council of Scientific and Industrial Research (PCSIR) in Lahore, Pakistan	Scientists at the Paki-stan Council Scientific and Industrial Research in Lahore	Scientists and researchers

No.	Theoretical /conceptual	Empirical	Competency framework	Assessment framework	Teaching framework	Other	Sample / Settings	Aim of the study	Business/organisa-tional setting	Target Audi-ence
29		X		X			Four provinces and the Federal Capital of Pakistan. 1089 responses, Gender: 64.6% male, 35.4% female, Age range: Majority 31-40 years,Educational Background: Majority graduates (60.2%), Professional Experience: Majority with 11-15 years (76.9%), Work Medium: Mostly electronic media (81.3%), Job Nature: Mostly news reporters (69.6%), followed by anchors and desk editors, Regional Distribution: Sindh (32.3%), Punjab (32.0%), Federal Capital (31.3%), with fewer from Khyber Pakhtunkhwa and Baluchistan	This paper aims to investigate the development of information literacy skills and their self-perceived assessment among journalists in Pakistan	Journalists professions	Journalists, media organisations, educators, researchers
30		X		X			Lawyers practicing at the District Bar Association of Sargodha, Punjab, Pakistan. Questionnaire with 20 statements related to information literacy and demographic variables, 297 responses.	This paper aims to investigate the current state of information literacy (IL) skills among lawyers	Lawyers	Legal professionals and lawyers, law educators and academics
31	X			X			Dutch governmental agencies, the survey was conducted targeting team leaders within governmental agencies, the questionnaire was self-administered and online, 120 responses	This paper aims to develop data literacy as an organisational competency by identifying its dimensions and measurements and examining the relationship between data literacy and governmental performance (both internal and external).	Governmental organisations	Researchers and managers in public sector organisations
32	X		X				Literature review and conceptual analysis	This paper aims to establish a conversation about data literacy in business education, discusses the role of the librarian in this domain, and proposes a set of data literacy competencies that librarians could help incorporate into business school education. By doing so, it seeks to address the gap between current business students' data literacy skills and the workforce needs, highlighting the crucial role that librarians play in bridging this gap.	The study focuses on how business students can meet workforce needs through DL competencies	Business educators, academic librarians

No.	Theoretical /conceptual	Empirical	Competency framework	Assessment framework	Teaching framework	Other	Sample / Settings	Aim of the study	Business/organisational setting	Target Audience
33	X		X				Narrative Synthesis: systematic review, thematic analysis, annotated bibliography and synthesis. The study leverages a transdisciplinary team with expertise in multiple disciplines, including Science, Computer Science, Business Information Management, Arts and Social Sciences, and Education	This paper seeks to address the growing demand for data literacy in the knowledge-based economy by synthesizing current strategies and best practices for data literacy education. It aims to establish a shared understanding of data literacy, identify core competencies and skills necessary for effective data literacy education, and recommend best practices for integrating data literacy into undergraduate curricula across Canadian post-secondary institutions. Through its analysis, the study endeavors to contribute to the broader conversation on enhancing data literacy among graduates, thereby better preparing them for the demands of the 21st-century workforce.	The study acknowledges the importance of DL for the workforce. Researchers examined the context of DL in three main areas one being Canadian Employers and Economy	Educators, curriculum developers
34	X	X	X				Web-based survey from November to December 2021: to collect data on the data literacy objectives for different business roles, population: operational level employees and managers across various industries, aiming to cover a broad spectrum of business roles and their data-related task, 53 respondents, where 32 were operational level employees and 21 were managers at different levels, respondents wew primarily from the Czech Republic, with respondents also from Germany and the USA. Feedback from businesses.	This paper seeks to explore and improve the data literacy of various business roles by identifying their specific data-related work tasks and focusing on the competencies necessary to enhance their ability to work effectively with data.	DL in different business roles	Businessess and organisations seeking to enhance the DL of their workforce
35	X	X	X	X			The study focuses on employees and university students to enhance their data literacy skills. The prototype test of the data literacy assessment was answered by 50 respondents, including 44 freshman students at a business university with several IT programmes and 6 data professionals	This paper aims to create a measurement tool for data literacy that represents the initial step towards enhancing the data literacy of employees and university students	Aim to improve DL among employees and university students	Employees and university students

No.	Theoretical /conceptual	Empirical	Competency framework	Assessment framework	Teaching framework	Other	Sample / Settings	Aim of the study	Business/organisational setting	Target Audience
36	X		X	X			Non-governmental organisations (NGOs), specifically focusing on individuals and teams within these organisations who handle data, data collection is based around the Datenschule, a project of the Open Knowledge Foundation Germany in Berlin, number of participants was limited to 9 due to time constraints of the study, Semi-structured expert interviews and testing of a questionnaire and maturity grid with NGO representatives	This paper seeks to enhance the understanding of data literacy within non-governmental organisations (NGOs) by developing a Data Literacy Maturity Model (DLMM)	Non-governmental organisations (NGOs)	NGOs that want to evaluate their DL capabilities or plan future actions in this field
37	X	X		X			Survey instruments were used across three separate studies to measure workplace information literacy (WIL) and its impact within different organisational context. Context: Small and medium enterprises (SMEs), universities, and community councils. Number of Participants not specified across all studies, one study had 1036 usable responses from community council members	This paper aims to explore the role of workplace information literacy (WIL) in supporting work activities from a quantitative research perspective, addressing the gap in WIL measurement tools for evaluating its impact on organisational outcomes	Study investigates workplace IL (WIL) in various organisational contexts including small and medium enterprises (SMEs), universities and community councils	Information professionals, researchers
38	X					X	A literature review and conceptual analysis	This paper aims to propose and explore the concept of information literacy (IL) for professionals engaged in safety management	Professionals in safety management	Safety management professionals, researchers, educators

APPENDIX C: SUMMARY OF KEY PRINCIPLES, OUTCOMES AND VALIDATION METHOD

No.	Description of framework	Outcomes	Validation method	Key principles emphasised
1	Proposes a systematic data education framework based on Transformative Learning Theory (TLT) and Experiental Learning Thoery (ELT)	Practical suggestions for developing and improving DL training programmes and identifies barriers to DL in organisations. End-users consists of DL at 3 levels: basic DL, medium DL and advanced DL	Interviews and thematic coding	DL education strategies: experiental data training, critical incident reflection, rational open discourse, autonomous experimentation
2	Developed a new IL scale by selecting and modifying the survey items from the previous scales to measure information acquisition, evaluation and use (Bruce 1999, Cheuk 2008, De Meulemeester et al 2018, Gilbert 2017) Additionally, three more constructs were identified: learning form information experience, awareness of information environment and information ethics. Final IL scale comprised of thsee six dimensions.	A positive impact of CEO's IL on both exploratory and exploitative innovations in SMEs, with opportunity recognition acting as a mediator	1) Content validity assessment: two experts with extensive knowledge of IL research as well as scale development 2) Pilot study with a small group of 12 information professionals and academics 3) Confirmatory study (PLS-SEM). Testing the measurement model included an assessment of the construct's reliability and validity.	Multidimensional nature of IL, the study operationalizes IL through six dimensions: information acquisition, evaluation, use, awareness of the information environment, learning from information experience, and information ethics
3	A proposal for framework of ADA (Audit Data Analytics) knowledge and skills that future auditors would receive. Framework is based on AICPA's suggestions and standard audit objectives. This framework spans a range of data analytics technique and tools, including data visualisation, classification/regression, text mining. IT categorises ADA competencies into basic, median, and high levels based on the auditor's position and responsibilities	An ADA framework proposal for auditor DL, highlighting necessary skills and knowledge areas to improve audit practices through technology. The study showcases how ADA techniques can be applied within various audit contexts, such as risk assessment and audit testing. A set of recommendations for addressing the gaps in current auditor DL through changens in accounting education, CPA exam requirements, and professional standars	No formal method	Proficiency in advanced data analytical techniques, requirement level of knolwledge and skills for ADA techniques proposing dividing them into three levels: basic, median, high with specific competencies tailored to the auditos's role and responsibilities

No.	Description of framework	Outcomes	Validation method	Key principles emphasised
4	The framework developed is inteded to measure the WIL skills across various dimensions and it is based on i-skills model encompassing 8 key dimensions: Identify information need, assess information need, retrieving information, evaluate information critically, adapt information, organise information, communicate information, review the process	Development of a WIL scale, identification of key WIL dimensions, validation of the scale and developing a practical tool for assessment, framework for future research and application	Construct validity testing encompassing content validity and face validity at the initial stages, followed by Exploratory Factor Analysis (EFA) for further validation. Internal consistency reliability of the scale was teste using Cronbach's Alpha	Comprehensive assessment of IL, scale development and validation, interdisciplinary nature of IL, context-specific measurement, practical application in organisational settings, contribution to IL research
5	The examples provided show how training for IL and digital literacy can be contextualized and adapted to meet the needs of different learner groups, incorpocating elements of competency identification, teaching methodologies, and learner assessment withi their designs	Improved IL skills in both case studies. The study emphasises the importance of adapting training contect and delivery methods to suit specific needs of different audiences, positive participant feedback. Recognition of the need for contextualized training. Acknowledging the challenges in providing and assessing training on broader aspects of IL. Highlighting the role of critical thinking.	Formative and summative evaluation (interviews and self-assessments)	Broad scope of IL, contextualization of training, interdisciplinary nature of IL, critical thinking as a central element, practical application and evaluation, adaptive learning environments, collaborative learning and sharing
6	Model for IL, identified as IN PFAC using the concepts from the Big6 (Eisenberg & Berkowitz, n.d.). Model is developed for non-scholar scholars outside traditional academic environments	The succesful reach and engagement of diverse learner groups, development and deployment of educational content and models, and the identification of challenges that offer direction for future enhancements in IL training efforts	Formative assessment (need for more robust validation methods)	Accessibility and inclusivity, practical and applicable learning, lifelong learning, adaptability and flexibility, participant-centered feedback
7	The concept of 'embedded' (or intergrated) literacy and numeracy in workplace and vocational learning - social practice approach, worker's level of literacy and numeracy were reported according to the national standardised measure, the ACSF	Insights into how literacy and numeracy are conceptualized and integrated into lean production training in two different organisational settings. Benefits and possible alternatives are discussed.	Ethnographic method, including observations, interview and field notes to explore and validate findings	Reframing literacy and numeracy, lean production principles, diverse approaches to training, impact on workplace training programmes

No.	Description of framework	Outcomes	Validation method	Key principles emphasised
8	1) The construction of an Aggregate Information Literacy (AIL) index was developed based on 70 indicators segmented into four groups: hardware, software (application operational), communication, and information. Each manager's literacy level was quantitatively measured on a scale from 0 to 1, where the value reflects the level of literacy. 2) Proposes a model of IL in managers' education: The information literacy model presents 6 blocks: identification of need, searching for information, information processing, assessmetn, use of information, and evaluation. Managers' education in these blocks creates the synergy effect on managers' information literacy, which is affected by personal attributes and managers' surroundings	Study identifies factors affecting IL among managers and proposes models to enhance this literacy. It also quantifies the level of IL among managers in the Slovak Republic and discusses the implications fur business and management practices.	A mix of statistical tests and linear regression analysis to ensure to reliability and validity of the findings. Validation approach: Kolmogorov-Smirnov Test, regression analysis, ANOVA and hierarchical binary logistic regression	Adaptability to changing needs, integration of technical and operational skills, continual learning, balance between knowledge and practical skills
9	Numeracy test used in this study is a comprehensive measure of numeracy comparable to test discussed in Ginsburg, Manly and Schmitt (2006)	Findings show that higher numeracy levels among loan officers are associated with more accurate credit assessments, particularly during peridos of economic boom	Validation process: regression analysis, Chow test for comparison, Sample Splits by numeracy level	The critical role of numeracy in enhancing loan officer's job performance, particularly in accurately assessing credit risk. The study underscores the value of investing in the development of employees' quantitative skills within the banking sector to enhance organisational performance and risk management
10	The study provides a framework by identifying 7 distinct "faces" or ways in which IL is experiences in the workplace. The 7 faces of IL identified in the study are: Using information technology for information awareness and communication, Finding information from appropriate sources, Executing a process that includes problem-solving and decision-making based on information, Controlling information to bring it within one's personal or professional sphere for easy retrieval and use, Building up a personal knowledge base in a new area of interest through critical thinking and learning, Working with knowledge and personal perspectives to gain novel insights or understandings, Using information wisely for the benefit of others, reflecting a conscious application of personal values and professional ethics in information use	Identification of 7 experiences of IL and the recognition of the multifaceted nature of IL. The findings suggest that professional education and training programmes should aim to expose learners to the broad spectrum of IL experiences. Emphasis on social and collaborative aspects, suggesting that workplace learning and professional development inititatives should foster a culture of collaboration and mutual support. IL plays a vital role in processes such as environmental scanning, information management, and research and development. Call for organisational support.	No formal validation method	Study underlines the complextiy and multidimensionality of IL in the workplace. Seven different experiences of IL is proposed. IL is presented as a significant component of learning organisations and a key characteristic of the organisations' employees. The study suggests that both individual and organisational aspects of IL are important for professional education and continuous learning, emphasising the need for education and training programmes to incorporate these aspects. The study highlights the importance of collaboration, social interaction and reliance on information professionals and peers in experiencing IL.

No.	Description of framework	Outcomes	Validation method	Key principles emphasised
11	A competency framework from the Graduate Management Admissions Council (GMAC) is utilised to explore the evolving skills needed by business professionsl in the AI age. This framework categorises competencies into 3 main areas: communication, leadership, and technical skills	Increased importance of character-based traits and soft skills, evolving competency needs, empirical data on AI use in business, perception of AI's impact on work efficiency and creativity, insights for business education and training, guidance for organisationa talent development	No formal validation method	Integration of gen AI in business practices, evolving competency needs, importance of soft skills and characte traits, role of education and training in addressing AI's impact, perception of AI as a positive force, need for continuous learning and adaptation
12	Proposing a framework for AI literacy for employees, developed through iterative analysis between theory and the topics resulting from Hierarchical Topic Tree (HTT) analysis	A novel conceptualization of AI literacy, identifying key competencies needed for employees in digital workplaces	No formal validation method	Technology-related capabilites, Work-related capabilities, Human-Machine-Related capabilites, Learning-related capabilities
13	Adaptation of Bruce's framework (1997) to define IL in the workplace and bundle them into four dimensions according to ERM's unique context. These four dimensions provide a framework to drive cultural change: Strategic use of information, Organising information for retrievability, Skills in using information sources/systems, Consciousness in information seeking and use	Increased work productivity and on-the-job-larning, redefinition of the information overload problem, investment in information exchange programmes, empowerment of employees, improved information accessibility, enhanced learning and application	No formal validation method	Framework to drive cultural change and including 4 dimensions and 7 phases to experience information: Dimension 1: using information wisely on a strategic level. Dimension 2: Organising and controlling information for it to be retrievable. Dimension 3: The minimum IL requirement is to have acquired the skills to use existing information sources/systems. Dimension 4: To be more conscious of the information seeking and use process
14	Berlin numeracy test	The study validates the Berlin Numeracy Test as a reliable and valid instrument for assessing statistical numeracy and risk comprehension in educated samples. This means that the test scores are useful in predicting how well individuals can comprehend and make decisions on risk-related information. Cross-cultural and population generalizability. The development of a computer-adaptive test format is a key innovation, allowing for quick and accurate assessment of statistical numeracy with minimal questions.	Cross-cultural validation studies and application in different populations. Hierarchical regression analyses used to explore predictive validity and comparative studies with existing numeracy tests.	Psychometric soundness, Validity aspects, Cross-cultural and population generalizability, efficiency and accessibility of the test

No.	Description of framework	Outcomes	Validation method	Key principles emphasised
15	Five tactics to cultivate creative data literacy for empowerment	Introducing the concept of creative DL, along with five specific tactics to cultivate DL for empowerment, aiming to make data more accessible and meaningful for non-technical learners and communities	No formal validation method	Five tactics to cultivate creative DL for empowerment: work with community-centered data (developers, data creators and publishers, tutorial authors, educators), write data biographies (data creators and publishers, governmetn, educators, students and learners), make data messy (community and event organisers, educators, government seeking public participation), build learner-centered tools (developers and designers, tutorial authors), favour creative, community-centered outputs over Tuftean purity (designers and artists, educators, community and event organisers)
16	The study proposes a set of pedagogical design principles, which are intended to guiden the development of tools and activities that support DL learners. Principles outlined in the study are: 1)Focused: Tools shouls be focused to do one thing well, providing a clear and narrow scope to ensure ease of learning and use 2) Guided: Tools should include strong activities or guidance to help learners start and continue their learning journey, making the learning process explicit and structured 3) Inviting: Tools should be appealing and engaging learners, using relevant data, playful design, and accessible language to lower barriers to entry and encourage exploration 4) Expandable: Tools should allow for growth in learning, offering pathways for learners to deepen their understanding and skills beyond initial engagement	Development of DL tools: three tools WordCounter, WTFcsv and Samediff each designed to target specific aspetcs of DL. Pedagogical design principles for DL tools. Early results suggest that the tools developed can help learners build their DL skills. The study indicates that integrating storng pedagogical principles into toole design can make a significant difference in learning outcomes. Study offers a model for how digital tools can be designed and used to support learning in this area.	Iterative design and testing, evaluation in real-world settings, qualitative feedback (participant perceptions, engagement with the tools) and quantitative data (pre- and post-tests to measure learning gains)	The study emphasises key principles for designing tools and activities to support DL among learners. These principles aim to make DL accessible and engaging for novices in data analysis and visualisation, including students, journalists, non-profit organisations, and community activists. Key principles in this study are: focus on learning, multi-facted definition of DL, pedagogical design principles for tool development, emphasis on hans-on activities, incremental learning, community and context relevance
17	Suggesting systemic approach: needs assesment, content development, employing adult learning principles, technology integration, collaborative learning and communities of practice, knowledge management systems, leadership and support	Study outlines strategies for enhancing IL in the workplace through technology, highlighting the importance of continuous learning, the integration of technology in training programmes, and the role of leadership in promoting an information-literate culture	No formal method	Outlined principles and approaches to IL and technology integration: systematic approach to learning gaps (identifying and assessing), resource allocation for learning and development, fostering a culture of continuous learning, collaborative and authentic learning experiences, knowledge sharing and cooperative learning

No.	Description of framework	Outcomes	Validation method	Key principles emphasised
18	5 interrelated knowledge bases (literacy skills, statistical knowledge, mathematical knowledge, context/word knowledge, and critical skills). Supporting dispositions and enabling beliefs underpin the use and application of the knowledge bases in engaging with statistical information. They include a critical stance towards statistical messages, an awareness of the importance of data, and an understanding of the omnipresence of variability	A detailed conceptualization of SL, identifying its core components and the interplay between knowledge bases and dispositions necessary engaging with statistical information critically. The study identifies the responsibilities of stakeholders in fostering SL among adults. It highlights the importance of designing education and training programmes that not only focus on the knowledge components of SL but also promote critical thinking and questioning attitude towards statistical information. The outcomes aim to elevate the discourse on SL, stressing its significance for informed decision-making .	No formal validation method	Definition and importance of statistical literacy. Interrelated knowledge bases, dispositions and enabling beliefs. The study provides a framework for understanding SL emphaszing its multifaceted nature and the critical tole it plays in empowering individuals to navigate and make sense of the statistical information that permeates everyday life.
19	Proposing an IL evaluation index system of safety professionals using AHP (Analytical Hierarchical Process) and fuzzy comprehensive evaluation as the framework. The systems includes 5 first-level indicators and 25 second-level indicators	Identification of key factors affecting IL in safety professionals and recommendations for improving IL levels	Comparing the correlation between the results of qualitative and quantitative analyses	The study investigates factors affecting knowledge acquisition among adult workers in online informal learning activities. It highlights the importance of information querying, differentiation, online communication self-efficacy, and information evaluation and extraction in enhancing knowledge acquisition. The findings suggest that fostering information literacy and providing user-friendly online collaboration tools can significantly improve online informal learning experiences for employees.

No.	Description of framework	Outcomes	Validation method	Key principles emphasised
20	5 key competencies proposed in the model include: Ability to identify information needs: Recognising when information is needed for a specific job-related task. Efficient information seeking: Knowing how to locate relevant information using available resources, which may include both technological and traditional sources. Critical evaluation: Assessing the relevance, validity, and reliability of the information gathered to ensure it meets the required job task. Effective use and management of information: Applying the information appropriately to complete tasks, make decisions, or solve problems, and managing it in a way that is accessible and beneficial for future use. Knowledge sharing: The ability to communicate and share useful information with colleagues, enhancing collective knowledge and supporting organisational learning.	Identifying gaps in existing IL models when applied to the context of developing countires, especially in workplace settings. Proposing a framework designed to address the unique need of workplace in developing countries. The model focuses on enhancing and evaluating IL competencies crucial for prganizational success. The study outlines key competencies necessary for effective IL in the workplace	No formal validation method	Context sensitivity, sociocultural awareness, competency-based approach, collaboration and knowledge sharing, holistic view of IL, empowerment through IL
21	The framework outlines a set of core data literacy competencies, including data collection, data management, data governance, data assessment, and data utilisation. It divides officers into six categories (Executives, Managements, Academics, Services, Technologists, Others) to tailor training and development. Specifies the data literacy skills required for each officer level, including data analysis, visualisation, and ethical use.Emphasises the importance of data governance practices and ethical considerations in data use.	Development of DL framework tailored to the needs of Thailand government officers. Core components: Data collection, data management, data governance, data evaluation, data application. The framework categorises government officer job positions into 6 levels: Executives (E), Managements (M), Academics (A), Services (S), Technologists (T), and Others (O), framewrok emphasises DL skills like data analysis, interpretation and viusalization.	Combination of expert assessment and comparative analysis against existing frameworks (APS Data Capability Framework, EU DigComp, And Thailand's Office of the Civil Service Commission Digital Literacy)	Focus on addressing and enhancing DL skills across government agencies. The study focuses on developing DL skills that are directly relevant to the diverse roles within government agencies mapping out competencies across different job levels and ensuring that the framework addresses the unique challenges and requirements of each role. Emphasises the need for practical, hands-on training programmes that allow government officers to apply DL concepts in real-wolrd scenarios. The study underscores the necessity of periodically reviewing and updating DL Framework to ensure its continued relevance and effectiveness.
22	Assessing AI literacy among non-experts. The framework is desgined to capture a broad range of competencies related to understanding, evaluating, and applyin AI technologies by individuals without formal training in AI or computer science	The framework identifies 3 key areas of AI competencies: Technical understanding, critical appraisal, practical application	Exploratory Factor Analysis (EFA) in validating the scale (SNAIL questionnaire)	Inclusivity of non-experts, multidimensional competency framework, the goal is to enhance individuals' ability to interact knowledgeably and responsibly with AI technologies

No.	Description of framework	Outcomes	Validation method	Key principles emphasised
23	The proposed framework highlights 3 primary modalities through which IL is developed and enhanced in the workplace: 1) Textual modalities (technical manuals, administrative documents, policies, procedures, and forma training materials) 2) Corporeal (physical) modalities: knowledge and skills that are developed through physical practice and sensory experiences on the job 3) social modalities: learning through interactions within the community of practice including both formal and informal exchanges with experienced firefighters	New definition of IL, model of IL in the workplace, insights inot workplace learning and professional identity formation, practical implication for training and development	No formal validation method	Complexity of IL, embodied knowledge and practice, social construction of knowledge, integration on multiple information modalities, contextual nature of learning, transformational learning process
24	Conceptual framework for AI literacy, outlining core 17 competencies and 15 design considerations for developing AI literacy programmes from a survey of interdisciplinary literature	Outcomes include a concrete definition of AI literacy, a set of competencies necessary for AI literacy, and design considerations for educational content aimed at increasing AI literacy	No formal method	The key principles emphasised are centered around defining AI literacy and proposing a set of AI literacy competencies and design considerations.
25	Principles suggested in the study are aimed at guiding future research and practical applications to enhance AI literacy and address AI anxiety among workers in manual labor occupations, particularly in the construction industry	Study reveals that construction workers have a superficial understanding of AI, often associating it with physical devices like robots, and suggest the need for tailored AI literacy programmes that consider their specific learning needs and work context	Qualitative analysis of data gathered through interviews	Study focuses on understanding workers' knowledge of AI, which is found to be superficial, diffuse and vague. AI anxiety is significant concern of the study. The study suggests that building up AI literacy might help tackel these misconceptions and related anxieties. Based on findings, the researchers propose tentative implication for designing AI literacy support in this specific target group. These include focusing on the basics of digitalisation, automation, and AI; building on the learners' actual experiences and making learning opportunities accessible using tangible examples; designing to reduce AI anxiety by pointing out the limits of AI and emphasising the role of human agents

No.	Description of framework	Outcomes	Validation method	Key principles emphasised
26	A brief questionnaire was based on the results of a political opinion poll detailed in nation-wide newspapers	The study finds significant misunderstandings among managers/students regarding confidence intervals and the impact of population size on survey results, highlighting the need for improved statistical education	Statistical analysis: Chi-squared test and randomization t-tests	Importance of statistical literacy, the study highlights the common misunderstandings among MBA students, even those with previous statistical education. Need for effective statistical education to mitigate misunderstandings related to statistical concepts. Emphasis on practical understanding. Recommending that the teaching of sample surveys in MBA courses add some important but quick questions not requiring specific calculations that make explicit common failures in statistical thinking. The implication for consultant statisticians is that being involved in the planning, data collection and analysis phases of a survey may often be insufficient. Ideally, they need to be present with the client when the results are being interpreted and used for business decision-making purposes.
27	The survey instrument used in the study was developed based on previous research and included the Information Literacy Self-Efficacy Scale, which comprises 25 items. The scale was measured using a seven-point Likert-type scale with response categories ranging from 1 (almost never true) to 7 (almost always true), allowing respondents to indicate their level of agreement or self-efficacy regarding various aspects of information literacy	Lack of formal IL instructions, perceived importance of IL skills, investigation officers recognised the importance of IL skills in their workplace. The officers expressed confidence in their basec IL skills, however they felt less comfortable with advanced levels of IL such as evaluating online resources, using e-recources, and limiting search strategies. The study found that personal variables (age, professional experience, computer proficiency) influenced their self-efficacy for IL.	Content validity: The questionnaire was reviewed by a panel of experts	Critical need for IL instruction, importance of IL in the workplace, recognition of IL self-efficacy, relationship between IL and personal variables, urgency in addression IL needs

No.	Description of framework	Outcomes	Validation method	Key principles emphasised
28	The survey instrument used in the study was adapted from a suitable and directly related data collection instrument developed by Anwar (1981), modified in light of previous studies and considering the contemporary information environment. Additionally, the Information Literacy Self-Efficacy Scale (ILSES) developed by Kurbanoglu et al. (2006) was included to measure scientists' IL self-efficacy. This scale consists of 28 items divided into seven sub-scales, Likert scale, each designed to assess different aspects of information literacy self-efficacy: 1)Defining an information need 2)Initiating the search strategy 3)Locating and accessing the resources 4)Assessing and comprehending information 5)Interpreting, synthesizing, and using the information 6)Communicating information 7)Evaluating the product and process	A large majority of scientists never received any formal IL training, indicating a gap in IL skills development. Despite the skills gap, scientists generally perceive IL instructions as important for their work, emphasising the need for targeted IL training programmes. The study found positive correlations between IL self-efficacy and varibales such as age, research experience, and number of publications.	Content validity: The questionnaire was reviewed by a panel of experts	Importance of IL skills, gap in formal training, perceived value of IL instructions, relationship between IL self-efficay and demographic variables, need for IL instruction programmes
29	The questionnaire, which included statements relevant to IL in journalists' work environments was based on five information literacy standards developed by the Association of College and Research Libraries (ACRL) to measure journalists' self-perceived information literacy skills. The survey instrument based on a Likert scale. The questionnaire included a total of 30 statements designed to measure journalists' self-perceived information literacy skills.	Majority of journalists had received some form of IL instruction during their careers which indicates a recognition of the importance of these skills. Journalists perceive IL as invaluable in their work context, suggesting that these skills are considered essentila for effective journalism practice. Journalists reported high levels of self-perceived IL competencies. Impact of demographic and professional variables: age and job experience were found to positively predict journalists' IL skills. Findings underscore need for IL instruction programmes for journalists.	Reliability: Cronbach's alpha for the survey instrument	The importance of IL in journalism, comprehensive understanding of IL, need for formal IL education, role of experience and education in developing IL skills, perception and self-assessment on IL skills
30	Lawyers were requested to express their levels of agreement or disagreement for 20 statements manifesting the phenomena of IL on a five-point Likert scale	Lack of formal IL training, perceived importance of IL skills, lawyers felt more competent in basic IL skills, need for advanced skills. The study found that IL skills are associated with certain demographic and professional variables, including age, practical experience, practicing level, computer proficiency, and English language proficiency. The need for the development of formal IL instruction programmes tailored for legal professionals.	Content validity: The questionnaire was reviewed by a panel of experts	Importance of IL in legal practice, gap in formal IL training, need for improvement in advanced skills, association of IL skills with demographiv and professional variables, advocacy for IL instruction programmes

No.	Description of framework	Outcomes	Validation method	Key principles emphasised
31	Theoretical framework and measurement instrument for examining the relationship between DL and governmental performance. The survey included a developed a measurement instrument for assessing organisational DL. The framework is built upon the two frameworks on DL, from Sternkopf and Mueller(2018) and Ridsdale et al. (2015) and enriched by the framework of Pangrazio and Selwyn (2019). Eleven skills are proposed that jointly constitute DL: Data identification (find, get), data understanding (clean, analyse), data uses (embed, define, verify), data communication (visualise, present), data reflexivity (assess, ethicize)	Empirically supports the theoretical framework and demonstrates a positive effect of DL on internal performance. The study also explores the relationship between data literacy and external performance, revealing that while DL alone may not be sufficient to significantly enhance external performance, it indirectly improves it through its positive impact on internal performance. This nuanced understanding underscores the importance of considering both tangible and intangible resources alongside DL to develop services that improve customer satisfaction.	A confirmatory factor analysis (CFA) was conducted to validate the measurement model using PLS-SEM with the Sorftwate SmartPLS.	The development of a comprehesive theoretical framework for DL, based on a review of practice-based literature and scientific research evaluated by experts. Creation of a measurement instrument for DL to assess DL of organisations. Assessment of DL's impact on governmental performance. The study suggests that organisatiosn need to pay particular attentio to improving employees' DL, as without data-literate employees, the implementation of big data analytic technologies may not improve governmental performance.
32	Proposes a set of DL competencies, 'seven baseline DL competencies': Data organisation and storage, understanding ddata used in business contexts, evaluating the quality of data sources, interpreting data, data-driven decision making, communicationg and presentin effectively with data, data ethics and security	The seven key business data literacy competencies proposed in the study are: Data organisation and storage, Understanding data used in business context, Evaluating the quality of data sources, Interpreting data, Data-driven decision making, Communicating and presenting effectively with data, Data ethics and security	No formal method	The key principles emphasised for business students: data ethics, integrtaing DL into the curriculum, communication and presentation with data, DL competencies
33	Data literacy competencies matrix synthesizes a set of skills and abilities that together comprise various levels of DL. The matrix is structured around five core aspects of DL: data collection, management, evaluation, application, and the overarching concept of data itself. Each of these aspects is further broken down into specific competencies, totaling 23 competencies, along with associated tasks and skills, amounting to 64 in total. The matrix is intended to form the basis about standards for assessing and evaluating levels of DL and to inform the creation of learning outcomes in DL education.	A synthesized definition of DL as "the ability to collect, manage, evaluate, and apply data in a critical manner". DL competencies matrix. Identification of several best practices for teaching DL, including collaboration between educators, organisations, and institutions. Identification of research gaps: specific teching methods, assessment strategies and the integration of DL across different disciplines and levels of education	No formal validation method	Definition of DL. DL is framed as the ability to collect, manage, evaluate, and apply data in a critical manner. The study identifies a gap in the systematic and formal approach to DL education, particularly in Canada's post-secondary institutions and stresses need for systemati education. DL is described as a foundation for lifelong learning. The study highlights the importance of engaging teaching methods. Best practices include collaboration between educators, organisations, and institutions, diverse and creative teaching approaches, hand-on practical learning, and the intergration of real-world data into the learning process. A syntehsis of skills and avilities comprising various levels of DL is presented. Recognition of DL as a civic skill.

No.	Description of framework	Outcomes	Validation method	Key principles emphasised
34	Data literacy competency model. The theoretical framework consists of mapping of the distinct DL competencies and priority work objectives of the selected job roles. Model is a result of a synthesis of several existing models of DL competencies evaluated in the context of usefullness for target audience.	Outlining specific DL competencies required for different business roles. Five categories of competencies in which knowledge areas (A,B) represent ability to understand basic concepts necessary for data analysis and skills areas (C,D,E) cover ability to apply those concepts in real-case data scenarios. • A. Data Concepts, Ethics, and Protection • B. Analytical Principles and Methods • C. Data Collection and Preparation • D. Data Analysis and Evaluation • E. Data Interpretation, Communication and Decision-Making Two levels of mastery within these competencies: data analytics consumer needs and data analytics power user	Content validity: The validation method involves analysing job tasks and gathering feedback from relevant stakeholders via a preliminary web-based survey.	Defining necessary DL competencies, five main categories of competencies are identified, study assumes two levels of mastery within these competencies (data analytics consumers and power users), study emphasises the importance of tailoring DL training and competencies to spesific business roles and industries. The study advocates for a strategic approach to improving DL across organisation.
35	DL competency model divided into knowledge and skills-related areas. The questionnaire comprised 38 multiple-choice questions, designed to measure competencies across different areas of data literacy.	The development of a prototype of DL assessment tool	Empirical validation: A prototype test (questionnaire) with 50 respondents, the testing tool developed on the basis of this model served as another level of the model validation as the results from the DL assessment either confirmed or disproved the components of researchers' view on DL	Comprehensive understanding of DL, segmentation of competencies, two levels of proficiency (common users, power users), utilisation of PPDAC approac (Prolem, Plan, Data, Analysis, Conclusion) in employed in the development of the DL assessment tool, practical application and testing
36	Data literacy maturity model (DLMM) in non-governmental organisations. It oulines a framework that categorises 11 DL competencies across 4 levels of competence. The competencies cover areas: data culture, ethics, security, and various skills like asking questions, finding, verifying, cleaning, analysing, visualising, communicating, and interpreting data. Framewrok aims to enhance understanding of the necessary skills for initiatiating data projects, identifying strengths and gaps, and planning future data practices.	Development of a maturity model for individuals to assess and enhance DL within NGOs, including 11 DL competencies on 4 competence levels and complemented by a self-assessment tool	Iterative evaluation: Action Design methodology (ADR). This approach involved three iterative phases, creating common understanding, developing an alpha version of the model, and evaluatine the alpha version while defining a beta version. The validation method encompassed literature synthesis, expert interviews, model testing with practitioners, and evaluation with end-users, including NGOs.	The DLMM incorporates a wide range of DL competencies across 4 levels of competence. Focus on NGOs. THE DLMM is taiored to help NGOs assess their DL competencies, identify areas for improvement, and guide future data practices.

No.	Description of framework	Outcomes	Validation method	Key principles emphasised
37	Development of a new scale for measuring workplace IL based on multidimensional constructs of IL activities relevat to organisational outcomes	The development of quantitative measures for WIL, insights into the complexity of studying WIL in organisational contexts, and the relationship between information literacy and organisational outcomes such as innovation and digital technology use.	Reliability and validity: Statistical analyse: partial least squares structural equation modeling (PLS-SEM) and fuzzy-sets Qualitative Comparative Analysis (fsQCA). Methods were used to validate the developed scales for measuring WIL and to analyse the relationship between WIL and organisational outcomes	The multifaceted nature of workplace information literacy (WIL), recognising it as a crucial competency in organisational contexts. It underscores the importance of developing robust measures to evaluate WIL, highlighting its impact on organisational outcomes such as innovation and efficiency. The study advocates for a comprehensive approach to understanding and enhancing information literacy in the workplace, integrating it into organisational strategies for improving performance and competitiveness
38	Conceptual framework outlining the components and determinants that influence IL of professionals in the field of safety management. The interplay between knowledge, skills, and attitudes highlights the dynamic nature of IL, where each component is both influenced by and contirubtes to the effectiveness of safety management practices. 3 main areas: information knowledge (understanding of computers and networks, familiarity with informal networks, awareness of ethical issues), information skills (IT application skills, integration of IT into safety management, information communication skills), information attitudes (attitude toward IT cognition, IT learning willingness, application of IT in safety management).	Proposal of conceptual framework for IL in safety management, identification of determinants influencing IL, highlighting gap in existing research	No formal validation method	Multifaceted nature of IL, interdisciplinary approach, determinants of IL, role of organisational culture, importance of continuous learning, integration into safety management practices, need for further research, practical implications for training and education