UNIVERSITY OF TURKU
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Telling business tales with data: A systematic literature review on data storytelling in business analytics

Information Systems Science
Master's thesis

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This thesis presents a systematic literature review on data storytelling in business analytics based on PRISMA guidelines. Data storytelling refers to using narratives and visualizations when communicating insights from data. The purpose of this thesis is to outline the academic literature around this subject and report the key findings on the impacts of data storytelling in business analytics, the practices of data storytelling used by business analytics professionals as well as the enablers of data storytelling in business analytics. The systematic literature review includes 19 articles on the impacts, practices, and enablers of data storytelling in the context of business analytics.

Based on the findings, leveraging data storytelling in business analytics can have a positive effect on business performance. One likely reason for this is the improvement of decision-making quality. It was also found that leveraging data storytelling in their work can improve the performance of business analysts.

The findings implicate that the leveraging of data storytelling in business analytics is inhibited by insufficient support from visual analytics tools as well as the lack of data storytelling competency and training. The findings highlighted that in order to leverage data storytelling in business analytics, business analysts should understand their target audience as well as business themes and communicate and collaborate with their colleagues and the audience. The findings also discussed suitable data story genres and design principles for the business analytics context.

Key words: data storytelling, data stories, business analytics, systematic literature review.

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Tässä Pro gradu -tutkielmassa esitellään PRISMA-ohjeistuksiin perustuva systemaattinen kirjallisuuskatsaus datan tarinankerronnasta bisnesanalytiikassa. Datan tarinankerronnalla tarkoitetaan narratiivien ja visualisointien hyödyntämistä datasta tehtävien havaintojen kommunikoinnissa. Tutkielman tarkoituksena on koota yhteen aiheen akateemista kirjallisuutta sekä esittää keskeisimmät löydökset vaikutuksista, joita datan tarinankerronnan hyödyntäminen bisnesanalytiikassa tuo sekä mitä datan tarinankerronnan käytäntöjä bisnesanalytiikan ammattilaiset työssään käyttävät ja miten datan tarinankerrontaa voidaan hyödyntää bisnesanalytiikassa. Kirjallisuuskatsaukseen sisältyi 19 artikkelia, joissa käsiteltiin datan tarinankerronnan vaikutuksia, käytäntöjä ja hyödyntämistä bisnesanalytiikan kontekstissa.

Tutkielman löydösten perusteella datan tarinankerronnan hyödyntäminen bisnesanalytiikassa voi vaikuttaa positiivisesti liiketoiminnan menestykseen. Todennäköisesti yhtenä syynä tähän on päätöksenteon laadun paraneminen. Datan tarinankerronnan hyödyntämisen todettiin myös voivan parantaa bisnesanalyytikkojen suorituskykyä.

Löydökset osoittavat myös sen, että datan tarinankerronnan hyödyntämistä bisnesanalytiikassa rajoittavat riittämätön tuki visuaalisilta analytiikkatyökaluilta sekä datan tarinankerronnan taitojen ja koulutuksen puute. Tuloksissa korostui myös se, että datan tarinankerronnan hyödyntämisen mahdollistamiseksi bisnesanalyytikoiden on tärkeää ymmärtää yleisöään sekä liiketoiminnan edellytyksiä ja kommunikoida sekä tehdä yhteistyötä kollegoiden ja yleisön kanssa. Löydöksissä tuli myös esiin bisnesanalytiikan kontekstiin sopivia datatarinoiden genrejä sekä periaatteita datatarinoiden suunnitteluun.

Avainsanat: datan tarinankerronta, datatarinat, bisnesanalytiikka, systemaattinen kirjallisuuskatsaus.

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1 Introduction

1.1 Research background and motivation

In order to motivate people to take action, you have to engage their emotions. The key to people's hearts is through stories. In the business world it's common to try to persuade people by appealing to their intellectual side. You make a PowerPoint presentation with numbers and facts and expect people to be inspired and take action by reason alone. A more effective way to persuade and inspire people is to combine an idea with an emotion. This can be done by creating and presenting data as a memorable, compelling story that actually gets the audience behind you and your ideas. (McKee & Fryer, 2003.)

Companies have understood that there lies a lot of business value in utilizing data effectively in decision making and thus many strive to become data-driven. Wavestone reported in their 2024 survey with Fortune 1000 and leading global organizations' data executives on Data and AI leadership that, although the percentage has increased since the past years, only roughly half (48.1%) of the companies have succeeded in becoming data-driven. Considering that these are the leading organizations, an even bigger percentage of all organizations struggle with becoming data-driven. In the 2024 Data and AI survey, it was also found that the challenges of becoming a data-driven organization are not due to technology limitations. It's the culture, people, process change and organizational alignment that make it difficult.

A common misinterpretation is that just recruiting data analysts with data preparation and analysis skills allows companies to tap into the full potential of data. This is not the case. What data analysts often struggle with is communicating their insights effectively to others so that their insights would convert into actions. This is the "last mile" of actually deriving value from data and it can be achieved with data storytelling. By turning the data into a story, the numbers receive a voice. (Dykes, 2016.)

Tales aren't only for children. Sharing stories is a hardwired, ancient instinct of ours and even to this day it works as a key mechanism for communication and learning (Yang, 2013). Using stories to convey information has been found effective in the learning process of adults (Caminotti & Gray, 2012). Matei & Hunter (2021) explained that "*The best stories excel because they induce a change in the audience through learning*". However, telling compelling data stories that effectively convey information is not as easy as writing a bit of narrative to showcase key data findings and putting that onto a PowerPoint. Data storytelling takes skill.

With the rise of self-service analytics it's not just professional data analysts that need data storytelling competencies but also people across business functions. Regular business users have less data literacy and skills than analysts working regularly with data. The number of insights generated will continue to rise but the conversion rate of insight-to-value will decrease. Insights won't drive action and change unless the insights are compelling and understood. (Dykes, 2016.) How to facilitate the learning of data storytelling competencies for professional analysts as well as business users should therefore interest organizations.

There is a lot of ambiguity around the terms business analytics (BA), business intelligence (BI) and big data analytics (BDA). Sometimes a combined term of business intelligence and analytics (BI&A) is used. Business intelligence and analytics is often referred to as "*the techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make timely business decisions*". The technologies on which BI&A are based are called big data analytics. (Chen et al., 2012.) Due to the ambiguity of these terms, the terms business analytics, business intelligence, and business intelligence and analytics are used interchangeably in this study.

Data storytelling is a key element in the area of data journalism and thus there are many studies on it. For example, Ojo & Heravi (2018) studied the data storytelling practices of award-winning data stories, Matei & Hunter (2021) developed a framework for storytelling in data journalism, and Showkat & Baumer (2021) examined how reporters come up with interesting story ideas when working with data. In the business analytics context, less has been studied in terms of data storytelling. Boldosova & Luoto (2019) studied storytelling in business analytics and big data interpretation, Gunklach et al. (2023) developed and tested design principles for data stories in BI&A, and Ramm et al. (2021) explored storytelling in business intelligence and the use and acceptance of storytelling features in business intelligence tools, for example.

This thesis will focus on the practices of data storytelling, their impacts and how they can be enabled in the context of business analytics. In chapter two, I will present a definition for data storytelling and explain some background for data stories. In chapter three I will present the methodology of the thesis as well as the execution of the systematic literature review. In chapter four I will present the results and then discuss them in chapter five along with limitations of this study and directions for future research. The conclusions of this thesis are presented in chapter six.

1.2 Research questions

The goal of this thesis is to conduct a systematic literature review to answer the research question:

1. How is data storytelling discussed in the academic business analytics literature?

Additional research questions for this thesis are:

2. What impacts does data storytelling in business analytics have?
3. What data storytelling practices are used by business analytics professionals?
4. What are the enablers of data storytelling in business analytics?

2 Data storytelling

2.1 Purpose of storytelling

Storytelling is rooted in the evolution of our brain so it's not surprising that storytelling is an effective form of communication when it comes to the retention of information and the amount of information that can be delivered. Sharing stories has been a strategy for humans to understand and manage struggles as well as enhance the collective wisdom of communities. Stories are probably the most natural way for us to communicate and learn. (Yang, 2013.) But not all stories are good stories for exchanging information.

> "*If the dog bites the mail carrier, it is not a story; if the mailman bites the dog, THAT is a story!*" (Matei & Hunter, 2021.)

Interesting stories are good stories. Violating people's expectations is what makes stories intriguing; it triggers our curiosity and makes us search for solutions. This is also why stories can't reveal everything from the beginning. That would kill the suspense and inhibit a deeper engagement from the audience. When you are telling a rosy story of how results meet expectations you are just stating the obvious which is not rhetorically effective. (Matei & Hunter, 2021; McKee & Fryer, 2003.) "*An excellent story connects an unexpected cause to a known effect or a known cause with an unexpected effect"* (Matei & Hunter, 2021).

Stories can be discovered by asking the right questions (McKee & Fryer, 2003). Nowadays, there is a vast amount of data that can be used for this purpose. Some stories would be difficult to find without data analysis and visualization. The process can start with a question, a problem, an idea, or a dataset. Starting with the right dataset is easier but not always the case. The relationships, patterns, outliers, correlations, or differences found in data play a crucial role in the formation of data stories. (Weber et al., 2018.)

2.2 Data stories

The purpose of data stories is to inform, persuade, and explain. In data journalism, data stories are commonly used to explain a phenomena for deeper understanding, reveal anomalies and deficiencies in a system, or reveal information of personal interest. (Ojo & Heravi, 2018.) Quantitative analysis and data can persuade people but they aren't admitted to our hearts and inspire us like stories do (Monarth, 2014).

Dykes (2016) describes data storytelling as using a combination of data, visuals, and narrative in order to communicate insights from data. Data together with narrative explains what is happening and why. Combining visuals with data helps the audience to discover ideas they wouldn't pick up on without, for example, charts and graphs. Narrative coupled with visuals are what engages the audience. Merging all these three elements together, data, visuals, and narrative, you can make a data story that drives change. Just creating visually pleasing charts is still commonly misinterpreted as data storytelling although this is not the case.

Lee et al. (2015) relate data storytelling as a process of exploring data, making a story, and telling a story, as represented in figure 1. The exploration phase involves data acquisition, tinkering with data and coming up with an interesting story idea (Showkat & Baumer, 2021). The exploration phase results in a set of data excerpts from which a storyline is constructed. The process of crafting a compelling storyline involves, for example, making logical connections and formulating a message. This iterative process may require revisiting the data exploration phase for additional insights. After this stage, you have a plot that describes the relation of the story pieces and their significance for the overall context. Once the story has been constructed, it has to be delivered to an audience. To form a presentation, story material is made from the plot and story pieces. Story material can be visualizations, animations, interactive systems, or narrations, for example. When delivered to an audience, the story material becomes a shared story which is then perceived by the audience. There can be multiple people involved in the storytelling process playing different roles. For example, an analyst can explore and analyze the data and then pass it onto a scripter that builds the plot. One person can also play multiple roles in the process.

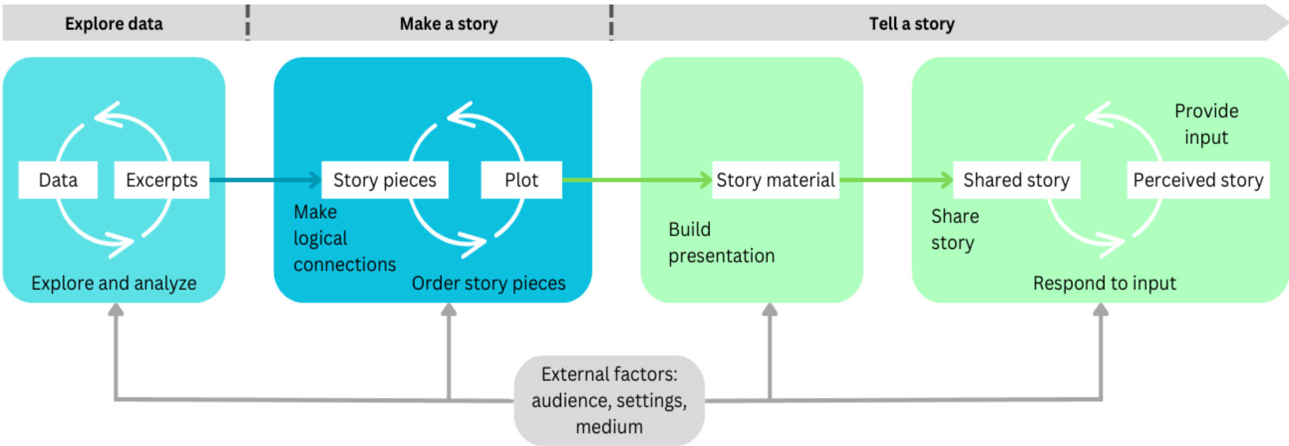


Figure 1 Storytelling process, modified from Lee et al. (2015)

2.2.1 Audience and interactivity

The target audience, the settings as well as the medium through which the story is presented are external factors that should be considered throughout the storytelling process. Typical storytelling settings vary by time, place, and audience participation level. (Lee et al., 2015.) These are presented in table 1.

Table 1 Common storytelling settings (Lee et al., 2015)

Example scenario	Time	Place	Audience participation level
Live presentations	Synchronous	Colocated	Low
Dynamic discussions	Synchronous	Colocated	High
Recorded videos, static infographics	Asynchronous	Distributed	Low
Guided tours, interactive infographics	Asynchronous	Distributed	High

Interactivity refers to the level of user engagement with the story as well as interaction with the data visualization. Users could, for example, have the option to explore the data visualization on their own to find further stories on their own or the data story designers could embed quizzes into the visualizations. (Weber et al., 2018.)

Interactive elements are an intriguing but tricky element in data storytelling. They can interfere with the story arc or take away from the focus of the story. Business presentations are often live presentations where the presenter can respond to the audience's questions although the interaction level is usually on the lower side if there is a bigger audience. Annotation and highlighting can be useful tools to get the story better across if the interaction between the presenter and audience is limited. (Kosara & Mackinlay, 2013.) Interactivity directly affects the story experience and is widely used in journalistic data storytelling. The most utilized interactive elements are annotated graphics and maps. (Ojo & Heravi, 2018.)

2.2.2 Narrative tactics

Segel & Heer (2010) identified visual narrative tactics and narrative structure tactics which can be used to assist and facilitate a narrative. Visual structuring, highlighting and transition guidance are forms of visual narrative tactics. Visual structuring helps the viewer to grasp the overall structure of the narrative and lets the viewer track their progress through the visualization. For example, a checklist of the content that is about to be covered can be used to help the viewer comprehend the overall structure. Then a progress bar on the screen can be used to show the stage of progress they are viewing at the moment. Highlighting using colour, motion, or framing, for example, is used to draw attention to elements of particular interest. Transition guidance, like animated transitions, is used for progressing through or between scenes.

Narrative structure tactics observed by Segel & Heer (2010) included ordering, interactivity and messaging. Ordering means the arranging of scenes and it can be done linearly (by the author), randomly (with no suggested order), or by letting the user select the order among alternatives made by the author. Interactivity refers to elements that let the user explore the visualization by filtering, selecting, searching, or navigating the data. Messaging is used to provide observations about the visualization in the form of text or audio.

2.2.3 Data story arc

A classical storytelling structure is Freytag's Pyramid. A modified version of it suitable for data stories is presented in figure 1. Setting refers to the context of the data story and it should be made interesting so that the audience's attention is captured from the get-go. Elements to utilize in this stage include introducing visualizations or numbers to grab the audiences' attention, raising a question, and giving a preview of what is to come. The rising action builds tension and presents supporting information that continues to the climax which showcases the data story's key insights. Elements to include in this stage involve showing contrasting data, similar data facts, changes over time, and showing rankings of data. Conclusions and take-away messages are provided in the resolution stage. In this stage, you can make a recap of the main insights, predict the future, provide next steps to encourage action taking, and revisit the beginning of the story. (Yang et al., 2022.)

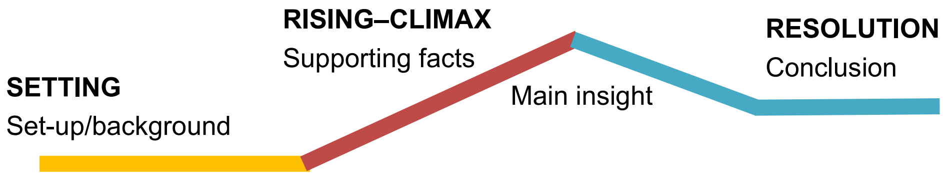


Figure 2 Freytag's Pyramid for data stories (Yang et al., 2022)

2.2.4 Tools in data storytelling

There are many tools and frameworks that can be used in crafting data stories: over 130, to be exact. Data visualisation (e.g. Tableau, R), web development and publishing (e.g. HTML, Python) as well as data analysis tools (e.g. Excel, SAS) are the technologies most commonly used in data journalism. Supporting technologies include map visualisation, databases (e.g. SQL, MongoDB), social media, data preparation and wrangling (pre-processing data for analysis), and data scraping (collecting data). (Ojo & Heravi, 2018.)

Which tools to use depends on the complexity of data, methodology, the amount of time there is, the competence of the stakeholder, and whether static or dynamic data is utilized. Dashboards are great for dynamic data that may need updating frequently whereas a presentation does the job with static data. Dashboards are more suitable for complex data and analysis, pdfs and Excel for briefer analyses and simpler data. Excel is also an example of a tool that is easier to handle than some more advanced tools that are more time-consuming. (Oberascher et al., 2023.)

3 Methodology

3.1 Research design

In this thesis, a systematic literature review was conducted to review literature of data storytelling in business analytics. A systematic review "*seeks to systematically search for, appraise and synthesis research evidence…*" (Grant & Booth, 2009). Reviewing prior literature provides a foundation on which knowledge on that matter can be further advanced, as well as shines light on new areas that could be researched (Webster & Watson, 2002). The concept of data storytelling is not new but there aren't too many studies focusing on it in the context of business analytics. Systematic literature review was therefore chosen as the best method in order to systematically map the current literature of leveraging data storytelling in business analytics.

For this systematic literature review, I chose to follow the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-analyses) guidelines and PRISMA 2009 checklist (Moher et al., 2009). Using checklists like PRISMA in systematic reviews "*is likely to improve the reporting quality of a systematic review and provides substantial transparency in the selection process of papers in a systematic review*" (Knobloch et al., 2011.)

The systematic literature review in this thesis was a three-step process. To develop a review plan, the research objectives were defined, inclusion and exclusion criteria developed, and relevant digital databases were searched. The databases selected for this review were Scopus, IEEE Xplore, Web of Science Core Collection, and ACM Digital Libraries of conference proceedings and journal publications. In executing the review, keywords were selected and formed into search strings that also included the developed criteria for this study. The articles were reviewed in three phases to form the final sample of articles. Backward citation chaining was conducted on the sample articles. Finally, the data was organized and discussed. The search process is demonstrated in figure 3.

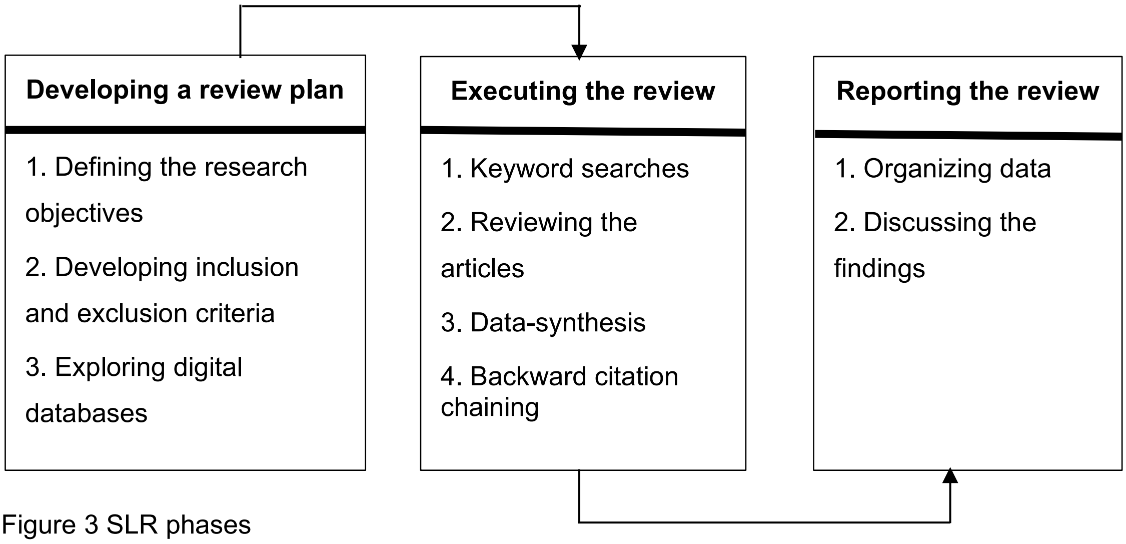


Figure 3 SLR phases

These steps are described more thoroughly in the next sections. The full search process of defining search terms, executing the database searches, screening and reviewing the results, conducting the backward citation chaining, and the criteria for selecting articles is provided in section 3.2. How the data was extracted for analysis is presented in section 3.3.

With this systematic literature review, the aim was to conceptualize the literature around data storytelling in business analytics. The research objectives presented in table 2 are formed around the research questions stated earlier. The impacts of leveraging data storytelling in business analytics, what data storytelling practices are be used in business analytics as well as what are the enablers of data storytelling in business analytics were also key objectives for this thesis. Overall, the possible impacts, practices and enablers are reviewed based on existing academic literature.

Table 2 Research objectives

#1	Conceptualize the literature of leveraging data storytelling in business analytics
#2	Impacts of data storytelling in business analytics
#3	Data storytelling practices in business analytics
#4	Enablers of data storytelling in business analytics

3.2 Data collection

In this section, I will go through step by step the search process and how the sample articles were chosen for this study. This process resulted in 19 articles from the searched databases and backward citation chaining.

The order for reviewing the databases was: 1) Scopus, 2) IEE Xplore, 3) Web of Science Core Collection, 4) ACM conference proceedings and ACM journal publications. The ACM searches had to be done separately to be able to include both conference papers as well as journal articles. All the search results were exported to Zotero where also all the duplicates were removed in the same order as the searches were conducted. In the first phase, IC#1, IC#2, EC#1 and EC#2 were taken into account when executing the database searches. In the second phase, I removed duplicates and screened the papers based on titles, abstracts, and keywords according to the inclusion and exclusion criteria. Finally, the full texts of the articles were reviewed. If reading through the article it became clear that the subject wasn't relevant to this thesis according to the inclusion and exclusion criteria, the article was scrapped. This resulted in the final database sample of only 10 articles. Given that data storytelling has been a much more popular theme in other academic literature areas like data journalism, this wasn't a big surprise. But it was expected that more articles suitable for this study would be found through backward citation.

The inclusion and exclusion criteria is presented in table 3. For this systematic literature search, only peer-reviewed journal articles and conference papers were included. The studies also had to be published in English. The exclusion criteria, therefore, were studies other than journal articles and conference papers. Also studies in other languages than English were excluded. According to the objective of this thesis, only papers that focused on data storytelling in the context of business data were taken into account. As stated earlier, data storytelling has been a popular research theme for other areas of academic literature, but this time the focus was strictly on business analytics. However, it was taken into consideration that business analytics, business intelligence, and visual analytics are very closely related and commonly discussed together. For example, BI&A is a pretty established term, and visual analytics tools are also used to analyse business data. This is why studies that didn't explicitly discuss "business analytics" but discussed similar topics under the terms of business intelligence and visual analytics, were not scrapped without further examination. These kinds of studies were examined by their closeness and possible relevance to business analytics, and if deemed relevant, they were included in the sample.

Table 3 Inclusion and exclusion criteria

Inclusion criteria (IC)		**Exclusion criteria (EC)**	
IC#1	Journal articles and conference papers only	**EC#1**	Other than journal articles and conference papers
IC#2	Studies published in English	**EC#2**	Studies in other languages than English
IC#3	Studies focusing on data storytelling in the context of business data	**EC#3**	Studies focusing on something else than data storytelling in the context of business data

The search strings used for the database searches had to include the term "business analytics" and either "data storytelling", "data-driven storytelling", "data stories", "data story", "narrative visualization", "data journalism", "storytelling", "narrative" or "interactive". The searches for Scopus and Web of Science Core Collection only included title, abstract, and keywords. For IEEE Xplore and ACM Digital Libraries searches, full texts were included.

Data collection began with Scopus. The first search resulted in 51 articles. IEEE Xplore resulted in 361 articles, Web of Science Core Collections in 38, and ACM Digital Library 134 as of conference proceedings and 43 as of journal publications. It was clear that the full text searches resulted in more hits, expect for ACM journal publications. The database searches included EC#1 and EC#2, so papers written in other languages than English and other than journal articles and conference proceedings were excluded. At this phase, the total number of articles was 627.

In the second phase, the articles were screened based on titles, abstracts, and keywords. IC#3 was considered in this phase so the articles had to focus on data storytelling in the context of business data. Duplicates were also removed in the same order as the searches were executed; Scopus, IEEE Xplore, Web of Science Core Collection, ACM conference proceedings, and ACM journal publications. A total of 578 articles were excluded according to these steps. So the total number of articles left after the second phase was

49. 15 from Scopus, 17 from IEEE Xplore, 1 from Web of Science Core Collection, 10 from ACM conference proceedings and 6 from ACM journal proceedings.

The final phase was to screen the full text of the remaining articles. So the 49 articles left were read in their entirety. Unless, like stated earlier, reading through the text it became clear that it didn't match the inclusion and exclusion criteria. Unfortunately, potential articles had to be scrapped if the abstract was in English but the full text was in another language or if the full text couldn't be accessed without paying. The third and final phase resulted in just 10 articles. 4 from Scopus, 4 from IEEE Xlpore, 1 from Web of Science Core Collection and 1 from ACM conference proceedings. None from ACM journal publications passed the final phase. The numbers of articles by database according to each phase is presented in table 4.

Table 4 Number of articles per searched database

Data Source	Phase 1	Phase 2	Phase 3
Scopus	51	15	4
IEEE Xplore	361	17	4
Web of Science Core Collection	38	1	1
ACM Digital Library conference proceedings	134	10	1
ACM Digital Library journal publications	43	6	0
Total	627	49	10

The majority of the articles collected in phase one were from IEE Xplore, followed by ACM conference proceedings. These databases were searched based on full texts, so this was quite expected. Many of those articles had to scrapped because they were irrelevant to this thesis. Especially the terms "narrative" and "interactive" were commonly used outside of data storytelling context.

The selected keywords were data storytelling, data-driven storytelling, data stories, data story, narrative visualization, data journalism, storytelling, narrative and interactive. These were combined with the term business analytics. Although data visualizations are a part of data storytelling, it was not used as a keyword because data visualization doesn't encompass the whole concept of data storytelling. The terms "narrative" and "interactive" were included in an attempt to encompass all articles that examined data storytelling without using any "storytelling" term in their titles, abstracts, and keywords. This was done because the concept of data storytelling is still quite unfamiliar in business analytics. Search strings are shown in table 5:

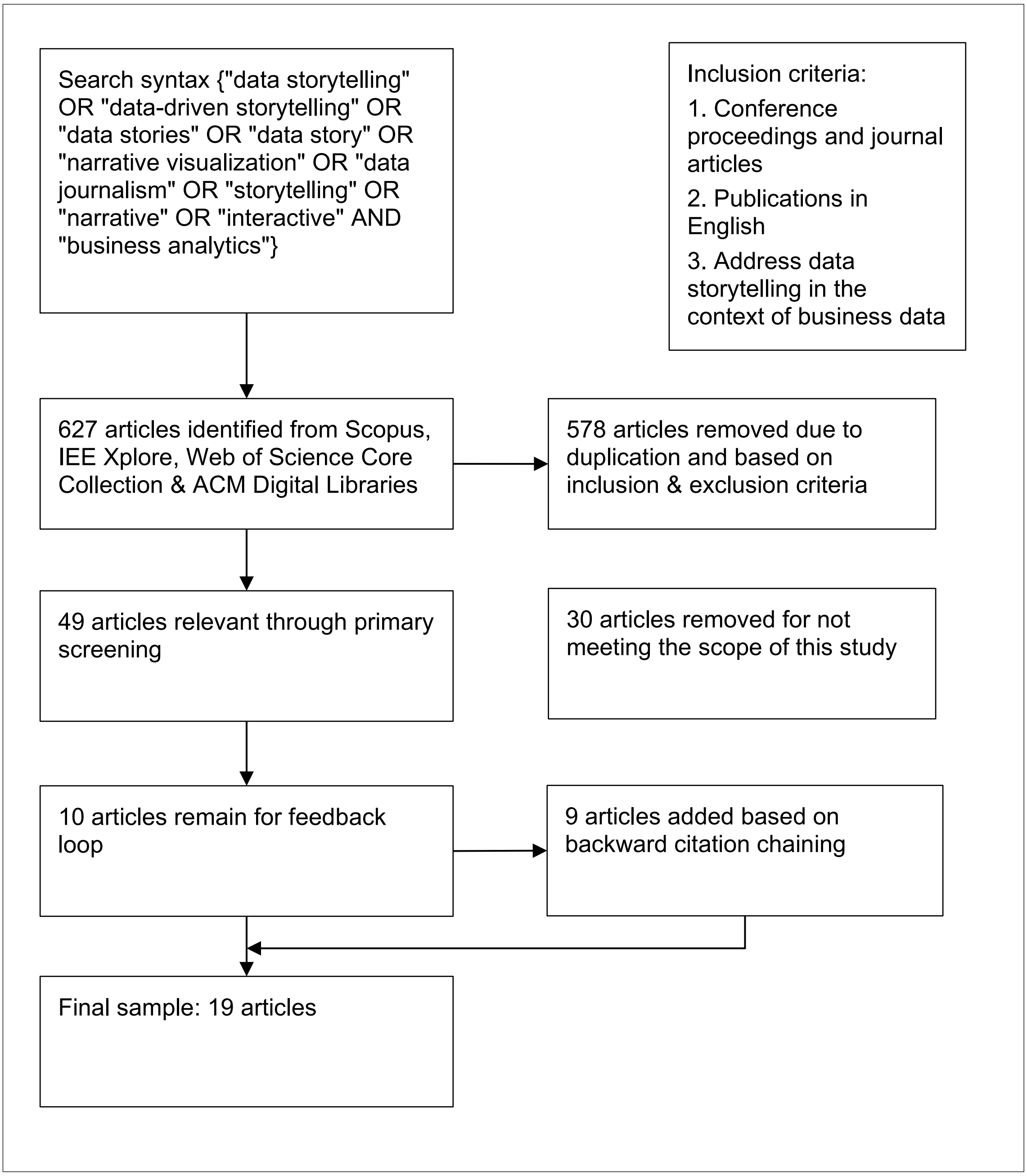
Table 5 Database search syntax

Data Source	Search Syntax
Scopus	TITLE-ABS-KEY ("data storytelling" OR "data-driven storytelling" OR "data stories" OR "data story" OR "narrative visualization" OR "data journalism" OR "storytelling" OR "narrative" OR "interactive" AND "business analytics") AND (LIMIT-TO (SRCTYPE , "p") OR LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (LANGUAGE , "English"))
IEEE Xplore	("Full Text & Metadata": data storytelling AND business analytics OR data-driven storytelling AND business analytics OR data stories AND business analytics OR data story AND business analytics OR narrative visualization AND business analytics OR data journalism AND business analytics OR storytelling AND business analytics OR narrative AND business analytics OR interactive AND business analytics) Filters Applied: Conferences Journals Magazines Early Access Articles
Web of Science Core Collection	(TS=("data storytelling" AND "business analytics") OR TS=("data-driven storytelling" AND "business analytics") OR TS=("data stories" AND "business analytics") OR TS=("data story" AND "business analytics") OR TS=("narrative visualization" AND "business analytics") OR TS=("data journalism" AND "business analytics") OR TS=("storytelling" AND "business analytics") OR TS=("narrative" AND "business analytics") OR TS=("interactive" AND "business analytics")) AND LANGUAGE: (English) AND DOCUMENT TYPES: (Proceeding Paper OR Article OR Review Article OR Early Access OR Editorial Material)
ACM Digital Library conference proceedings	"query": { "data storytelling" AND "business analytics" OR "data-driven storytelling" AND "business analytics" OR "data stories" AND "business analytics" OR "data story" AND "business analytics" OR "narrative visualization" AND "business analytics" OR "data journalism" AND "business analytics" OR "storytelling" AND "business analytics" OR "narrative" AND "business analytics" OR "interactive" AND "business analytics" } "filter": { ACM Pub type: Proceedings, Article Type: Research Article }

ACM Digital Library journal publications	"query": { "data storytelling" AND "business analytics" OR "data-driven storytelling" AND "business analytics" OR "data stories" AND "business analytics" OR "data story" AND "business analytics" OR "narrative visualization" AND "business analytics" OR "data journalism" AND "business analytics" OR "storytelling" AND "business analytics" OR "narrative" AND "business analytics" OR "interactive" AND "business analytics" } "filter": { ACM Pub type: Journals }

The total number of articles after the database searches was only 10. Through backward citation chaining, however, this number was expected to increase. Backward citation refers to searching through the citations of an article. Backward citation can be used to trace what led to the article and make sure any relevant articles are not missing (Hu et al., 2011). For each sample article, the reference list was screened for relevant articles. If the title seemed interesting for this thesis, I examined that citation article in more detail. Same exclusion and inclusion criteria was applied in the backward citation chaining process as in the database article screening. 9 relevant articles were identified in the backward citation chaining and included in the final sample. This increases the number of articles in the final dataset to a total of 19 articles. The process of database screening and backward citation chaining to get to the final sample is shown in table 6.

Table 6 Flowchart of the search process



3.3 Data extraction

The final dataset that was used in this analysis consisted of 19 articles. I collected the descriptive details of each article. These included the publication years, whether the article was published on a journal or a conference, the research methods used as well as some relevant details about the articles. The research objectives were used to help grasp the overview of the sample articles and identify categories of the trends that emerged in the articles. The impacts of leveraging data storytelling in business analytics and data storytelling practices and enablers were identified as the two main categories that the sample articles discussed. The data storytelling practices and enablers were then grouped into five subcategories: storytelling practices and visual analytics tools, user training, understanding the target audience and business themes, communication & collaboration & shared understanding, story genres, and story design choices.

4 Findings

In this section, I present the findings of the systematic literature review. The descriptive details of the samples are presented in section 4.1. The results are discussed in sections 4.2 and 4.3.

4.1 Descriptive details

The total sample of articles from the database searches is presented in table 7. The research method and topic are shown for these 10 articles.

Table 7 Sample from the databases

STUDY	ARTICLE	METHOD	TOPIC
P1	Daradkeh, 2021	Empirical (survey)	Data storytelling competency and business performance relationship
P2	Zhang et al. 2022	Empirical (case study)	CODAS: a report authoring tool for business analysts
P3	Camm et al. 2023	Conceptual	Teaching data visualization in business analytics courses
P4	Zhang et al. 2022	Empirical (interviews)	Guidelines for data reporting tools
P5	Sarikaya et al. 2019	Conceptual	Dashboard design
P6	Marjanovic, 2016	Action design research	Using visual stories as boundary objects
P7	Alspaugh et al. 2019	Empirical (interviews)	Data analysts' exploration practices
P8	Walchshofer et al. 2024	Empirical (interviews)	Socio-technical challenges of employees using Power BI
P9	Boldosova & Luoto, 2019	Conceptual	BA data-driven storytelling for improved decision-making
P10	Gunklach et al. 2023	Design science research	Designing data stories in BI&A

Table 8 presents the results of articles found through backward citation chaining. The research methods and topics are provided also for these 9 articles.

Table 8 Sample from the backward citation chaining

STUDY	ARTICLE	METHOD	TOPIC
P11	Segel & Heer, 2010	Empirical (case studies)	Design space framework for narrative visualization
P12	Kandogan et al. 2014	Empirical (interviews)	Business analysts' work practices
P13	Gershon & Page, 2001	Conceptual	Storytelling in information visualization
P14	Gagnon & Caya, 2020	Conceptual	The role of data-driven storytelling in driving insights into action
P15	Namvar et al. 2021	Empirical (interviews)	A model for analytical sensegiving in organizations
P16	Tory et al. 2021	Empirical (interviews)	Dashboard users' barriers in data conversations
P17	Watson, 2017	Conceptual	Data interpretation and storytelling in BI to ensure comprehension of visualizations
P18	Ramm et al. 2021	Conceptual & empirical	A morphological box for storytelling & the use and acceptance of a storytelling feature in BI tools
P19	Elias et al. 2013	Empirical (interviews)	A storytelling prototype tool

From the 19 articles, 12 were journal articles and 7 were conference papers. The earliest study was published in 2001 but the majority of the articles were from 2019 to date. Figure 4 shows the number of journal articles and conference proceedings by year.

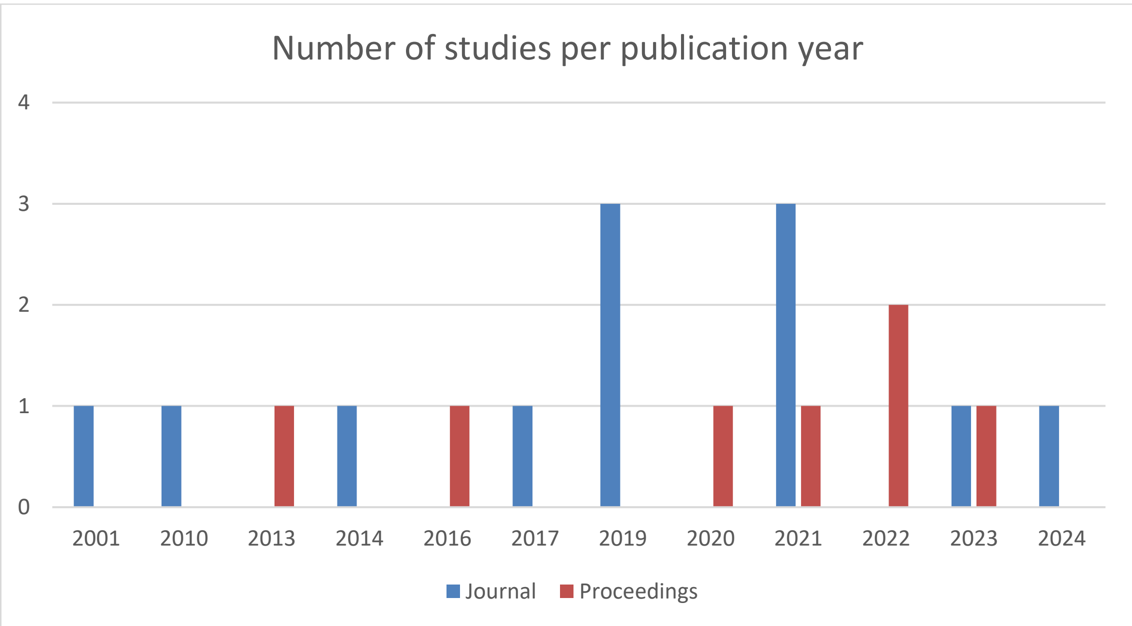


Figure 4 Number of studies per publication year

The journals and conferences where the sample articles were published in are presented in figure 5. IEE Transactions on Visualization and Computer Graphics was the most popular one with four of the sample articles published in that journal. Hawaii International Conference on System Sciences and International Workshop on Visual Analytics were the only conferences where at least two sample articles were published. IEE Computer Graphics and Applications journal had two hits as well. The rest of the journals and conferences only had one mention.

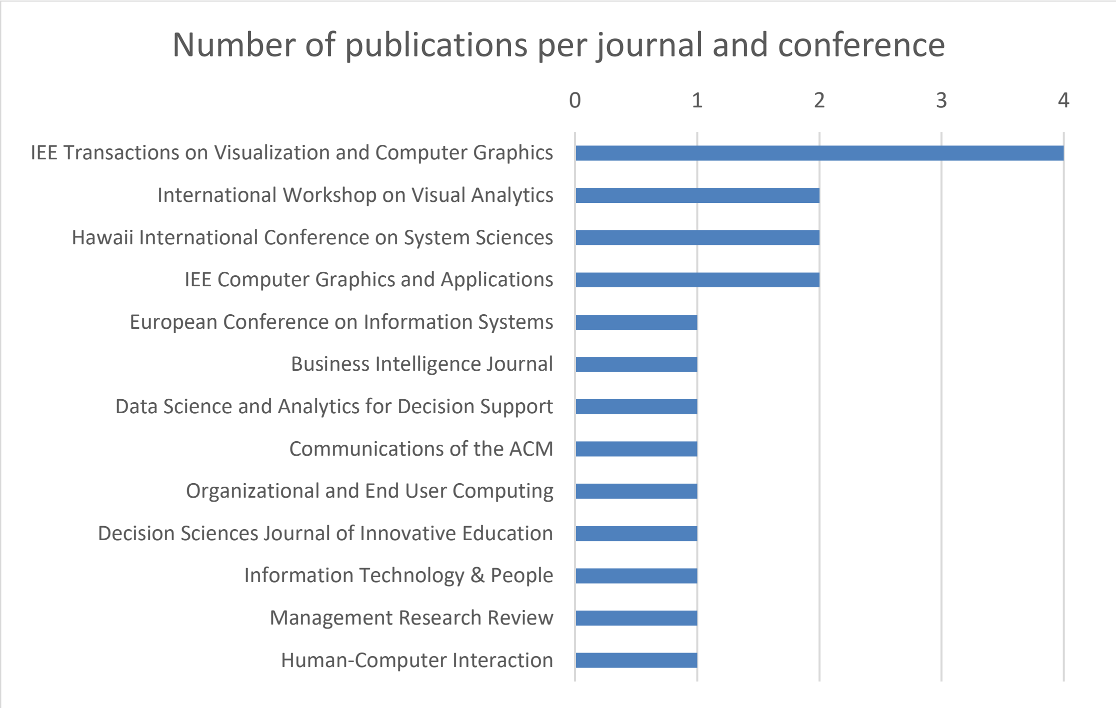


Figure 5 Journals and conferences

The research methods of the articles were quite even between empirical and conceptual. 10 of the studies were empirical, mostly interviews, and 6 were conceptual studies. One study used both empirical and conceptual methods.

The empirical studies were mostly interviews. The sample sizes of the interview studies are shown in figure 5. Two studies were case studies and one study was based on a survey.

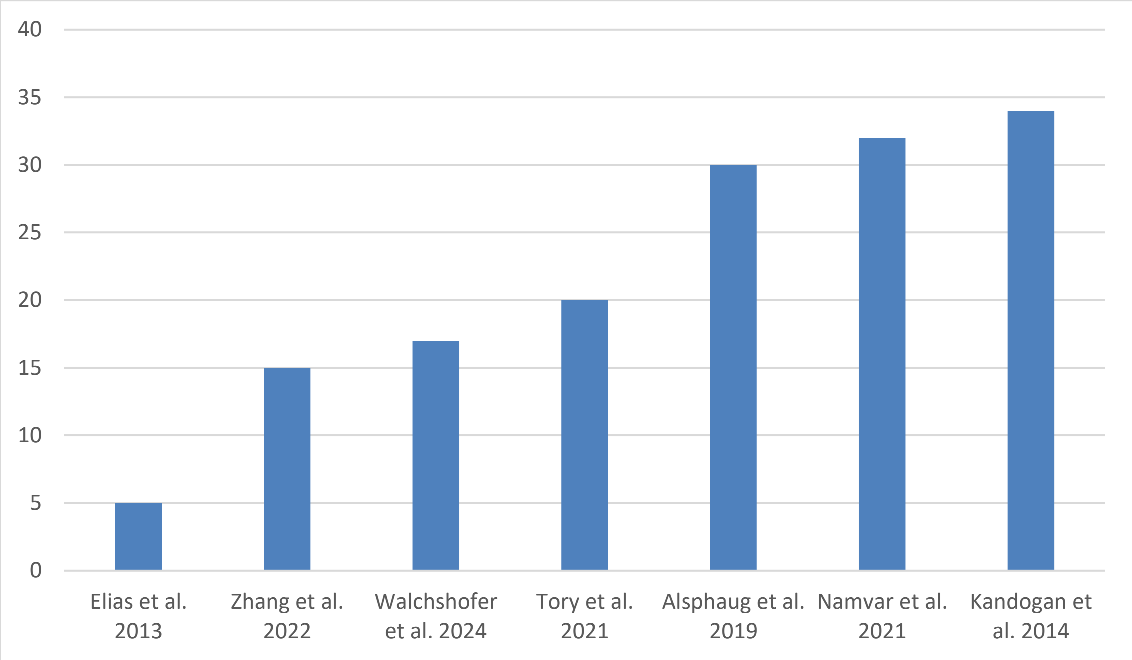


Figure 6 Sample sizes of the interview studies

Kandogan et al. (2014) interviewed 34 business analysts to examine an overview of the analytic work in a Fortune 100 IT company. Namvar et al. (2021) interviewed 34 data analysts conducting business analytics reports in order to understand how they generate insights for decision makers. Tory et al. (2021) interviewed 20 data workers who use dashboards in their work about their data practices and difficulties in data interaction. Elias et al. (2013) interviewed five business intelligence experts on their practices in creating and sharing business intelligence stories and designed a storytelling prototype tool. Zhang et al. (2022b) interviewed 15 professional analysts that use visualization tools about data-driven report authoring and then developed design guidelines for authoring tools for business analysts. Alspaugh et al. (2019) interviewed 30 professional data analysts about their data exploration habits. Walchshofer et al. (2024) interviewed 17 participants in various data analysis and IT roles about their work practices in an organization that was transitioning to Power BI.

Daradkeh (2021) studied the impact of data storytelling for business performance in the context of business analytics practices. A total of 182 business analytics practitioners in Jordan were surveyed.

Zhang et al. (2022a) developed an authoring tool called CODAS to support business analysts in the creation of data-driven reports and then evaluate it with two case studies that include business analysts. Segel & Heer (2010) examined the designs of narrative visualizations and identified data graphics techniques for telling stories from data.

Ramm et al. (2021) proposed a morphological box for storytelling in business intelligence and analysed the use and acceptance of the storytelling feature in BI tools. For the empirical part of the study, they surveyed 113 business intelligence users on their experience or expectations of storytelling in business intelligence.

Two studies used design science research methods. Gunklach et al. (2023) proposed design principles for data stories in business intelligence and analytics. In the research process, they interviewed 12 business users who work with data about their experiences on dashboards for exploring data and deriving decisions. Marjanovic (2016) combined design science with action research to find out how business users could be empowered to develop their visual data exploration skills.

Sarikaya et al. (2019) studied dashboards and their use, characterized dashboards, and built a design space for dashboards. Boldosova & Luoto (2019) explored the role of storytelling in business analytics and created a conceptual framework for BA data-driven storytelling. Gagnon & Caya (2020) studied the role of data-driven storytelling in maximizing the likelihood of taking action based on insights. Camm et al. (2023) studied data visualization and storytelling in the context of teaching data visualization courses in business analytics. Watson (2017) studied data visualization, data interpreters, and storytelling in BI to ensure data visualization comprehension. Gershon & Page (2001) studied the use of storytelling for information visualization.

4.2 Impact of data storytelling in business analytics

The first additional research question concerned the possible impacts of data storytelling in business analytics. Two studies covered impacts on business performance and business value creation. The impacts on discovering insights from data and improved decision-making were presented in two studies as well. One study focused on the impacts on individual business analytics user’s performance when leveraging data storytelling in their work.

Table 9 Impacts of data storytelling in business analytics

Category	Article
Business performance & business value	Daradkeh (2021) Gagnon & Caya (2020)
Discovering insights & improved decision-making	Daradkeh (2021) Boldosova & Luoto (2019)
User performance	Ramm et al. (2021)

Daradkeh (2021) found that data storytelling competency is strongly linked to business performance. This relationship is probably at least partially mediated by decision-making quality. The size of the organization or the industry type were not found to have a significant impact on business performance. The study suggests that effectively utilizing data storytelling in business analytics practices helps in discovering insights from the data. This would not be possible to the same degree with only visual or numerical communication.

Gagnon & Caya (2020) studied the insight to action phase of the analytics process in order to tell a well-constructed narrative that maximizes the likelihood of taking action based on the insights. They proposed a conceptual framework linking analytical storytelling to the business value creation of big data analytics. They argued that the level of big data analytics literacy of the target audience and the level of complexity of the big data analytics task influence analytical storytelling. Daradkeh (2021) suggests that data storytelling competency improves the communication of data insights to reach a wider audience and helps in guiding the audience to comprehend the main insights better.

In the study by Ramm et al. (2021), business intelligence users expected or noticed an increase in their performance by using storytelling. Ramm et al. (2021) assumed that the increase in performance is due to faster and more effective analysis and presentation and easily accessible results. Time is saved when they can work more efficiently and don’t have to spend as much time trying to understand their data. The participants in this study also argued that through fostering storytelling in their work and increasing their performance, there would be reasonable grounds for a salary increase. These findings support the conceptual suggestion made by Boldosova & Luoto (2019), that business analytics data-driven storytelling results in improved data interpretation and decision-making. Boldosova & Luoto (2019) also argued that these improvements increase the level of daily business analytics use by contributing positively to the organization's data-driven decision-making culture.

4.3 Data storytelling practices and enablers in business analytics

In this chapter, I present the findings concerning data storytelling practices and enablers in business analytics. Several studies focused on the work practices of experts in the business analytics field as well as the utilization and design of visual analytics tools. Some studies emphasized user training to improve data storytelling competencies. Knowing the target audience and the business requirements were highlighted as important softer skills for people working in business analytics. Communication, collaboration, and the creation of a shared understanding among analysts and business users was also found important by several studies. Lastly, data storytelling techniques were discussed in some studies in the context of data story creation. I categorized these into Table 10.

Table 10 Data storytelling practices and enablers in business analytics

Category	Articles
Storytelling practices and visual analytics tools	Kandogan et al. (2014) Tory et al. (2021) Ramm et al. (2021) Elias et al. (2013) Zhang et al. (2022a) Zhang et al. (2022b) Sarikaya et al. (2019) Walchshofer et al. (2024)
User training	Marjanovic (2016) Walchshofer et al. (2024) Boldosova & Luoto (2019) Sarikaya et al. (2019) Gunklach et al. (2023) Camm et al. (2023)
Understanding the target audience and business themes	Cagnon & Caya (2020) Namvar et al. (2021) Camm et al. (2023) Boldosova & Luoto (2019) Watson (2017) Gershon & Page (2001)
Communication, collaboration, and shared understanding	Namvar et al. (2021) Elias et al. (2013) Tory et al. (2021) Kandogan et al. (2014) Alspaugh et al. (2019)

	Walchshofer et al. (2024)
Story genres	Segel & Heer (2010) Gershon & Page (2001) Zhang et al. (2022b) Elias et al. (2013) Gagnon & Caya (2020)
Story design choices	Segel & Heer (2010) Namvar et al. (2021) Gunklach et al. (2023)

4.3.1 Storytelling practices and visual analytics tools

Business analysts face difficulties trying to create stories of their findings using common visual analytics tools. Kandogan et al. (2014) found that business analysts try to create a cohesive story for decision makers but still force their insights into a linear narrative and reduce their ideas to simple bullet points in a PowerPoint slideshow. These do the job but a lot of nuance and context is lost in this process. Similar issues were highlighted by Tory et al. (2021). They stated that current dashboards, even the “interactive” ones, don’t really support personal expression but rather work as a one-way street from the data to the data worker. Dashboards that would better provide data shaping and creation of new data artifacts and narratives could help organizations covert from data-driven to data conversant.

Elias et al. (2013) found that business intelligence story creators struggle with the limited interactivity features of current reporting tools when sharing stories outside of the organization. The participants would want to make more interactive reports but due to the problems with reporting tools, they limit more advanced interactions. Same problems were identified by Zhang et al. (2022b) in their interview. The existing visual analytics tools don’t meet the needs of business analysts for combining narratives with interactive charts or designing narrative-based layouts. These would be possible with additional programming expertise but since business analysts are not usually professional coders, relying on them to improve their programming skills is unrealistic. Zhang et al. (2022b) and Sarikaya et al. (2019) also came across the interactivity preservation issues as mentioned earlier. The interactive features of visualization charts were often lost in transition from dashboard to external data reporting tools. Business analysts often screenshot dashboards and incorporate the screenshots into slideshows to preserve the contextual information annotations (Sarikaya et al., 2019).

In the study by Kandogan et al. (2014), the participants didn't use any advanced qualitative-analysis tools, mostly just PowerPoint, MS Word, or a file system to put together their findings. Communication of the findings was typically done by preparing and presenting a PowerPoint in teleconferences with decision makers. This was also the case in the study by Walchshofer et al. (2024), where the employees still relied heavily on static reports like PowerPoint or PDF form although they had had access to Power BI for 6-12 months. The employees just didn't know how to structure data into a clear linear story as easily as with static reports. And as these kind of static reports can grow to be hundreds of pages long, keeping them updated becomes very challenging. (Walchshofer et al., 2024.)

Tory et al. (2021) highlighted in their study the pain that dashboard users go through when they try to create appealing data stories within their current tool ecosystem. The tools the participants used in this study were mainly Excel and business intelligence tools. Since conversations around data and with data were equally important, analytics tools that don't cover both of these won't fully support dashboard users' engagement with data. Tory et al. (2021) suggested the exploration of new mashup tools that dashboard users could utilize in organizing and restructuring their data contents: *"Imagine if a dashboard user could easily snag content from different dashboards, arrange it in a new layout, customize the formatting, add new narratives to construct their own data story, and share their new data artifact with others, all without leaving the dashboarding ecosystem"*. Tory et al. (2021) noted that the holistic data journey and network of actors should be considered when designing tools for data workers.

In contrast to the difficulties stated earlier about using visual analytics tools for storytelling, Ramm et al. (2021) found that the usability of business intelligence tools didn't have an effect on the use of storytelling by the users. They suggested that business intelligence tools may already be pretty user-friendly that there might not be any need for improvements for storytelling features in business intelligence tools. Ramm et al. (2021) did note that some of their participants were sharing their expectations of storytelling as they didn't have a lot of experience in storytelling. But the majority of their participants did use storytelling intensively.

To overcome the lack of storytelling support of most visual analytics tools, Zhang et al. (2022a) developed and tested the CODAS system which would help users combine storytelling elements, author various levels of interaction and order story elements to generate the final data story artifact. The idea of CODAS is not to take existing visual analytics tools' place but complement the existing tools and business analysts' workflow. Business analysts already struggle with having to interrupt their workflow by switching between different tools in order to create reports on visualizations (Zhang et al., 2022b). The feedback Zhang et al. (2022a) received for CODAS from two experts was positive. Adding story pieces was easy, they could automatically refresh the data of visualizations, the layout was useful and overall it was a pretty convenient system for many use cases. The lack of automatic data updating in reports as well as the lack of support for a narrative layout was identified as an issue for business analysts by Zhang et al. (2022b). What CODAS still lacked was more diverse exporting options, templatized annotations and more design control over the system page, for example.

Sarikaya et al. (2019) noted in their study that there are different categories of dashboards and probably no one set of design principles fits every type of dashboard. The layout decisions of communication dashboards that include effective narrative functionalities may not be the best fit for operational decision-making dashboards that call for the ability to glance at the key metrics easily, for example.

4.3.2 User training

Proper training is often necessary to improve users' storytelling competencies (Gunklach et al., 2023). Sarikaya et al. (2019) reminded that the visual, analytic and data literacy of the dashboard users themselves needs to be regarded when designing dashboards and training for their use. This was also supported by Gunklach et al. (2023), who found that dashboards don't sufficiently accommodate different users and they need more guidance about the utilization of the dashboard. The importance of proper training when transitioning to a new dashboard system was also highlighted in the study by Walchshofer et al. (2024). The training included in the purchase of Power BI was not sufficient for the employees to embrace the use of dashboards. Without proper training for dashboard creation, the employees were intimidated by filtering features, interactive features, and layout design. Thus, they weren't able to bring their data stories to life. The management had to arrange additional training and the employees spent non-working hours learning the system by themselves. Camm et al. (2023) argued that when teaching a course on data visualization and influencing, the training should include data visualization best practices, skills for effective storytelling as well as written and oral presentation. This content goes beyond just teaching users how to make charts and graphs.

In the study by Marjanovic (2016), visual data stories created by primary designers (application developers) were used to help develop the visualization skills of secondary designers (business users without prior experience in data visualization). Marjanovic (2016) proposed a method to use visual stories first as syntactic objects designed to present and inform the secondary users, then as semantic objects to engage the sharing of both technical and contextual knowledge, and lastly as pragmatic objects to empower the secondary users to create stories independently. Marjanovic (2016) found that the development of data visualization skills (of business users without prior experience) is best facilitated through this kind of design-in-use instead of skill-based training focusing on technology. Boldosova & Luoto (2019) also agreed that employees shouldn't be overburdened by complex descriptions of business analytics functionalities, but instead leverage storytelling to help business analytics users remember the key takeaways. It's best to implement any training processes gradually over time instead of within one training session (Marjanovic, 2016) like in the scenario studied by Walchshofer et al. (2024) where the employees attended only a half-day workshop when transitioning into Power BI.

4.3.3 Understanding the target audience and business themes

Having a deep understanding of the target audience is important for business analysts so that they can create a well-suited story that captures the audience's attention and facilitates turning data into insights and insights into action (Gagnon & Caya, 2020; Gershon & Page, 2001; Watson, 2017). Visualizations and data stories in business analytics are often presented to users with varying types and levels of skills and knowledge (Gershon & Page, 2001). The stories should be tailored to the audience members through, for example, visual features that emphasize or deemphasize aspects in the data (Camm et al., 2023). Namvar et al. (2021) found in their study that data analysts consider the background of their audience when deciding what type of visualizations to use. They found that the data analysts believed that visualizations are a medium to bridge the gap between a technical and non-technical person. The data analysts also suggested starting with simpler graphs and reports, and then as the audience's understanding built, progressing to more complex analytics presentations. Watson (2017) also stated in his study that familiar visualizations may be easier for senior managers to understand; so business analysts shouldn't go too crazy with visualizations that they forget the audience's capabilities. Which information to include in and exclude from the visualization is important to consider when preparing the presentation. What makes this difficult is the fact that the information and stories in business analytics are more complicated than traditional entertainment media. (Gershon & Page, 2001.)

Kandogan et al. (2014) found that data analysts used a very limited number of visualizations because only top-level managers cared about them; mid-level and below focused on almost strictly numbers. Namvar et al. (2021) had similar findings; the data analysts stated that they provided more straightforward comparisons of data for other than strategic level management. Detecting the level of big data analytics literacy of the audience is important for the storyteller so that they can create a compelling story that matches the target audiences' characteristics and needs. There is no one best way to tell a story that would suit every audience; business analysts should have a deep understanding of their often nontechnical audience. (Gagnon & Caya, 2020.)

Comprehending business themes is also important when leveraging data storytelling in business analytics. Identifying the business issues and challenges and setting the data story into a business context facilitates the translation of the data into business insights. Contextualizing the story in a business setting explains more deeply how the data can solve the business problem and what decisions the story triggers. (Boldosova & Luoto, 2019; Watson, 2017.)

4.3.4 Communication, collaboration, and shared understanding

Communication with decision makers as a part of the story creation process in business intelligence was also highlighted by Elias et al. (2013). Story tellers' stories evolve through communication and collaboration with story readers (decision makers). The story tellers create the story to answer to specific questions but these answers then lead to more detailed questions from the story readers which results in the need for new stories. So there is an open communication loop with data stories. (Elias et al., 2013). Sometimes, the questions can be very open-ended. The decision makers don't always know exactly what they want and leave it to the analyst to find interesting stories in the data. Analysts don't always like to engage in ad hoc exploration if the goal and analysis plan isn't well defined; exploring data is a lot of work and there is a chance you don't find anything interesting. (Alspaugh et al., 2019.)

Namvar et al. (2021) identified enactment as a sensemaking property that data analysts leverage to improve end users' sensemaking of the analytical outcomes. Enactment means that the end users give feedback to data analysts about their actions and impacts after acting on the business analytics outcomes. This creates an environment of shared understanding of data, business, and their relationships. This kind of shared understanding between data analysts and end users is important for effective use of data in decision making.

Tory et al. (2021) examined dashboard users' data activities and found that conversations through and around data were equally critical as conversations with data. Conversation through data means reshaping data to deliver information or a story to others. Conversation around data concern interactions that arise from data and its artifacts and may lead to further questions, insights, and actions. The interactions directly between the data worker and their data is defined as conversation with data. Tory et al. (2021) reported in their study that in preparing for conversations through and around data, dashboard users created visualization content, data presentations, and narratives of data. Giving an explanation or context to the data enabled discussions and interactions better than just reporting the numbers.

Kandogan et al. (2014) found that the end product of the analytical work was result of multiple people's effort before reaching the decision maker. The business intelligence experts in the study by Elias et al. (2013) explained that designing a new report requires plenty of effort and experience and thus the business intelligence experts often used a senior creator's template which they modified to fit their needs. This kind of peer support is especially useful if dashboard users struggle with data visualization skills like in Walchshofer et al. (2024) study, where only one of the employees had enough knowledge and skills to construct an interactive dashboard.

4.3.5 Story genres

According to Segel & Heer (2010), there are different genres of narrative visualizations, such as annotated chart, flow chart, slide show, and animation, and some of them work better for different story types. The genres of narrative visualization are presented in

Figure 7. A good choice of genre depends on, for example, the complexity of the data and the story, and the target audience. Slide shows are a typical genre for business-related presentations. Messaging (text or audio) and interactivity can be used on top of these genres but the appropriate use of these again depends on various factors. There are certain trade-offs; lots of annotations could clarify the message but also produce clutter. Gershon & Page (2001) also argued that the choice of presentation genre and medium can have either a positive or negative impact on the effectiveness of the audience's learning process.

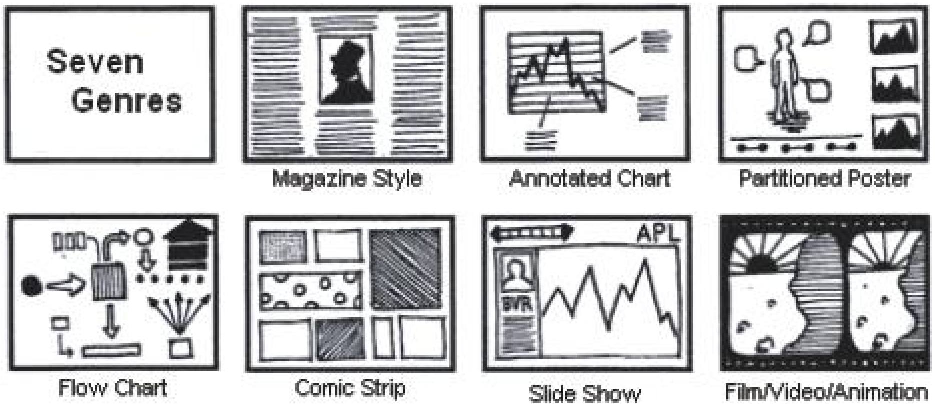


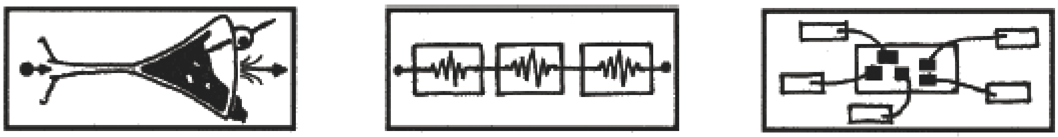
Figure 7 Genres of narrative visualization by Segel & Heer (2010)

Zhang et al. (2022b) found that professional analysts prefer shorter narratives with customized explanations and captions to provide additional context for the decision makers. Heavy narratives are used only seldomly. In the study by Elias et al. (2013), the business intelligence experts ranked annotated chart as the preferred template, followed by slide show, flow chart and comic strip with added annotations. Partitioned poster was regarded as a potential template for business intelligence stories. Elias et al. (2013) argued that an annotated dashboard would be a useful new template for business intelligence story creators. Gagnon & Caya (2020) argued that the level of big data analytics task impacts the suitable analytical storytelling approach. Utilizing only visual representations of data for more complex analytics methods, such as predictive and prescriptive analytics, may not be appropriate. For simpler methods like descriptive and diagnostic analytics, less elaboration may be needed in order to get the audience to identify the patterns and relationships in data.

4.3.6 Story design choices

Segel & Heer (2010) argue that narrative visualizations lie somewhere along a spectrum of author-driven and reader-driven stories. Towards the author-driven story extreme, the scenes are in linear order with a lot of messaging but no interactivity. On the other side of the spectrum, reader-driven stories do not have a prescribed order of scenes, does not involve messaging but relies heavily on interactivity. For the purpose of storytelling or efficient communication, the author-driven approach is more suitable. This is also typically used in business presentations and any non-interactive slideshows. The reader-driven approach is better for pattern discovery or data diagnostics with visual analysis tools like Tableau. Leveraging interactive features for decision makers is something business analysts could utilize in making their data insights understood: *"It is risky to give decision makers something to explore themselves unless you have supplemented that with something else. The danger is that they cannot figure out the actual reason. If you can give them something interactive, which heads them in the right direction, I would feel a lot more confident walking away from that they will understand"*, elaborated a data analyst in the study by Namvar et al. (2021).

In their studied dataset of narrative visualization, Segel & Heer (2010) found that all of them used a mix of author-driven and reader-driven approaches. They also noticed three common schemas: the martini glass structure, the interactive slideshow structure, and the drill-down story structure. These are presented in figure 8. The martini glass visualization structure begins with an author-driven phase where the narrative is introduced. It then transitions to a reader-driven phase, allowing interactive data exploration. The structure resembles a martini glass, with the stem representing the author's narrative on the widening mouth enabling reader interaction. The interactive slideshow structure allows for interaction during the narrative but the individual slides work like in the martini glass structure. So the individual slides communicate the author-intended narrative before allowing for user interaction. The drill-down story structure lets the user decide what stories are told and when by presenting the general theme from which the user can then choose what additional details they want to see. The emphasis is on the reader-driven approach but the author still needs to decide the possible types of user interaction, which stories to include and with what details.



Martini glass structure Interactive slideshow Drill down story

Figure 8 Common narrative visualization structures (Segel and Heer, 2010)

In their study, Gunklach et al. (2023) came up with three design principles for data stories. First, the data story should display the key insights of data through a narrative structure using a sequence of separate visualizations. The narrative structure combined with the sequential ordering of visualizations prevents misinterpretation, makes the information easier to process, and helps to comprehend the purpose of the visualization. To facilitate the comparing of data with visualization sequences, an introduction or a conclusion view with a progress bar could be provided, as suggested earlier by Segel & Heer (2010) as well. The second design principle proposed by Gunklach et al. (2023) was to provide users more information at a single glance with annotations and other textual elements. This would help especially those users that have little to no prior experience working with data to understand the insights presented. To overcome the issue of too many annotations explained by Segel & Heer (2010), Gunklach et al. (2023) examined that more detailed explanations could be displayed on separate pages for those who need them. The third design principle Gunklach et al. (2023) proposed was to include different data perspectives that users of varying roles could choose from when accessing the data story. For each user role, the data story would be presented with only the relevant data for that user group. The potential data perspectives could be for different business domains like marketing or finance, or for specific user roles like HR manager or logistics controller. This could help users find relevant insights from the data story faster.

5 Discussion

In this section, the key findings of this systematic literature review are presented. Then, the limitations of this study are considered along with potential areas for future research.

5.1 Key findings

The largely conceptual suggestions on the positive impacts of leveraging data storytelling in business analytics (Boldosova & Luoto, 2019; Gagnon & Caya, 2020) was supported on an empirical level by Daradkeh (2021) on a business performance level and by Ramm et al. (2021) on a business analytics user level. The medium through which data storytelling can improve business performance is most likely decision-making quality (Daradkeh, 2021). Maximizing the likelihood that decision makers take action based on the insights might also be one medium that links data storytelling to improved business performance (Gagnon & Caya, 2020). Leveraging storytelling could result in increased performance on an individual level through faster and more effective analysis (Ramm et al., 2021).

Multiple studies examined the storytelling practices of professionals working with business data and found that many struggle to incorporate storytelling into their work due to the lack of storytelling support in visual analytics tools. The lack of interactivity features (Elias et al., 2013; Tory et al., 2021; Zhang et al., 2022b) and the inability to preserve interactive features when transferring visualizations to external reporting tools (Sarikaya et al., 2019; Zhang et al., 2022b) were identified as struggles for analysts. The lack of skills and training to use more advanced tools held back some professionals (Walchshofer et al., 2024; Kandogan et al., 2014) as well as insufficient support for engaging with data (Kandogan et al., 2014; Tory et al., 2021). Surprisingly, Ramm et al. (2021) reported that business intelligence tools may already be quite user-friendly and there may not be need to improve the storytelling features. But they also noted that some of their participants didn’t have a lot of storytelling experience.

Zhang et al. (2022a) developed their own system, CODAS, to overcome the lack of storytelling support most visual analytics tools were found to lack on some level. CODAS wouldn’t replace any existing tool but rather complement them and support business analysts’ workflow. The CODAS-system got a positive rating; it was easy to add story pieces, the layout was useful, and the data in the visualizations could be refreshed automatically. But it still lacked templatized annotations and design control among others.

The importance of training users' storytelling competencies and visualization skills came up in several studies. Users need different kind of guidance based (Gunklach et al., 2023) based on their skills (Sarikaya et al., 2019). Camm et al. (2023) highlighted that teaching data storytelling goes beyond just teaching people how to use visual analytics tools and make visualizations with them. Design-in-use was found an effective method over skill-based training that focuses on the technology and complex descriptions of business analytics tools functionalities (Boldosova & Luoto, 2019; Marjanovic, 2016). The training shouldn't be just one short workshop but rather a gradual process (Walchshofer et al., 2024; Marjanovic, 2016).

Professionals working with business data should understand business requirements as well as their often nontechnical audience. The data stories should be tailored to the audience in order to capture their attention, help them understand the insights and turn them into action (Camm et al., 2023; Gagnon & Caya, 2020; Gershon & Page, 2001; Watson, 2017). Business analytics experts should and do consider the audience's background when deciding what type of visualizations to use (Kandogan et al., 2014; Namvar et al., 2021; Watson, 2017). Senior managers tend to care more about complex visualizations and stories than mid-level and below employees who focus more on just the numbers (Kandogan et al., 2014; Namvar et al., 2021).

The communication and collaboration of business analytics professionals among their peers as well as with their audience is important in developing a shared understanding of data and business. The end product of the analytical work presented to the decision makers was found to be the result of multiple professionals' effort (Walchshofer et al., 2024; Elias et al., 2013; Kandogan et al., 2014). Communication and feedback between business analytics professionals and decision makers about the data story raises questions, triggers further analysis, and creates a shared understanding of data, business, and their relationship (Elias et al., 2013; Namvar et al., 2021; Alspaugh et al., 2019; Tory et al., 2021). This kind of shared understanding improves the effective use of data in decision-making (Namvar et al., 2021).

Lastly, story genres and design choices in business analytics were studied. The most suitable story genres for presenting business themes are slide shows and annotated charts as well as flow charts and comic strips with added annotations for more information (Elias et al., 2013; Segel & Heer, 2010). Business analytics professionals prefer shorter narratives with added textual elements over heavy narratives (Zhang et al., 2022b) but the complexity level of analytics should also be taken into account when choosing a suitable storytelling approach (Gagnon & Caya, 2020).

Segel & Heer (2010) argued that data stories can be placed on a spectrum between author-driven and reader-driven stories that differ in the amount of messaging and interactivity as well as scene order. Author-driven stories are better for storytelling purposes, but all of the narrative visualizations studied by Segel & Heer (2010) used a mix of them. For designing data stories, Gunklach et al. (2023) proposed design principles that included using narrative structure and a sequence of visualizations, using more textual elements, and including different data perspectives for users of varying roles. These principles were positively rated by the chosen focus groups.

5.2 Limitations

One of the main limitations of this thesis is the fact that I was the sole author of it. The data collection and reviewing process shaped the potential results of this study as personal bias can’t be excluded. It cannot be ruled out that the evaluation of the inclusion criteria #3 and exclusion criteria #3 could have altered the results of this study, especially since I was the only one doing the evaluation. There is also the possibility of humane errors in the collection and reviewing process. For example, I could have missed some relevant studies by mistake.

Another limitation is also the fact that only academic conference proceedings and journal publications that were in English and could be accessed by a student at the University of Turku were included in this thesis. As stated earlier in section 3.2, some potential articles had to be scrapped due to these criteria.

5.3 Future work

This study adds to the quite limited body of academic research of data storytelling in the context of business analytics. Several studies have looked into the work practices of experts working with business data and identified the difficulties they face. Suggestions for better leveraging data storytelling competencies are still limited and haven’t been empirically tested enough. It would also be interesting to study the cultural acceptance of data storytelling in business analytics. Do executives see the value of it and are they interested in working on improving the leveraging of data storytelling.

6 Conclusion

In this study, a systematic literature review was conducted to explore the literature of leveraging data storytelling in the context of business analytics. The following four databases were searched: Scopus, IEEE Xplore, Web of Science Core Collection, and ACM Digital Library for conference proceedings and journal publications. The review and search process was done following the PRISMA guidelines and checklist. After the database review and backward citation chaining, 19 relevant articles were analysed for this study. Based on these 19 articles, I examined the impacts of data storytelling in business analytics as well as the practices and enablers of data storytelling in the context of business analytics.

The results suggest that leveraging data storytelling can positively impact business performance as well as the performance of individual business analysts. The most likely medium for the link between data storytelling and business performance was found to be the quality of decision making.

The findings also highlighted different practices and enablers of data storytelling in business analytics. Professionals working with business data struggle with incorporating storytelling practices into their work due to various reasons. Visual analytics tools lack usable interactivity features and don't support their transferring to external reporting tools. Employees lack data storytelling skills and the training of them is insufficient. Understanding business themes and the target audience is crucial for business analysts who want to incorporate data storytelling. Communication and collaboration between business analysts and their audience is key in order to develop a shared understanding of data and business that improves the effective use of data in decision-making.

It was also found that there are common story genres that are suitable in a business context. Slide shows, annotated charts, flow charts and comic strips with additional annotations are effective for the purposes of business analysts. Data stories can also be put on a spectrum between author-driven and reader-driven. Design principles for data stories were also identified in the articles and positively rated by users.

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