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Master Thesis - MSc Data Science and Marketing Analytics

# Automating the Voice of Customer: Enhancing Efficiency and Accuracy of Qualitative Research using Text Analytics

Author: Alexander Inshin
Student ID number: 502756

Supervisor: Dr. N.M. (Nuno) Almeida Camacho

Second Assessor: Dr. (Michel) M. van de Velden

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# Abstract

This master thesis introduces an automated framework to the existing procedures of phenomenological analysis of consumer and expert opinion-derived textual data, replacing labour-intensive manual coding with the more current methods of topic modeling and sentiment analysis. The methodological mechanism explores essential patterns in the context of Web3 technology and addresses the research question of how automated text analysis can replace traditional qualitative research methods by producing similar output. The automation apparatus incorporates Latent Dirichlet Allocation (LDA) for topic modeling. and sentiment analysis, enabling efficient analysis of large volumes of textual data. The research contributes to social relevance by stimulating a deeper understanding of societal issues and human experiences, thereby empowering evidence-based exploration of unveiled topics and advancing text analysis techniques in academia. The literature review pinpoints the relevancy of automation in exploratory research, showcasing notable tools and studies in automation. The results from Studies I and II provide valuable insights into the industry wide Web3 domains, and the evaluation of the automated model's validity shows high convergence and substantial agreement between human raters. Approximately 75% of topics labeled by human coders match the LDA-derived topics within the framework. This indicates that the model effectively captures the essential themes discussed in expert interviews. Cohen's Kappa coefficient 0.79 demonstrates substantial agreement between LDA-generated and human-coded topics. The proposed automated text analysis methodology represents a significant advancement in qualitative research (i.e., phenomenological review), empowering academics and market researchers to gain deeper insights into social phenomena and human behavior.

**Keywords** NLP, Machine Learning, Sentiment Analysis, Text Analysis, LDA, Phenomenology.

*Scan the QR code to access the code repository used in this master thesis.*

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## 1. Introduction

In the current digital age, where expansive information is available for immediate use, one might question the continued relevance of exploratory research and qualitative methods. Yet, these methodologies' ongoing academic and business usefulness indicates their ability to withdraw meaningful information from unique human experiences. While the widely known concept of big data offers vast amounts of quantitative information derived from large-scale datasets, it needs more depth and human context qualitative methods provide. Such was exemplified by the downfall of Nokia, which over-relied on quantitative data and failed to recognise the valuable insights uncovered by ethnographic research (Wang, 2016). Implementing automated methodologies further enhances the implementation of exploratory research by reflecting on potential weaknesses (Ma & Sun, 2020).

Exploratory techniques offer characteristic benefits, even as quantitative methods growingly dominate data-driven research. They help uncover hidden patterns and themes in data beyond just surface-level observations or what quantitative solutions may present (Alantari et al., 2022). There exist a plethora of qualitative methods, interviews and group discussions included, which allow those who use them to explore subjective human experiences. Still, many of these techniques suffer from comparable drawbacks, such as the need for human involvement in coding, which can be subjective and time-consuming (Davis et al., 2011). This paper presents an efficient method to analyse consumer opinions using an automated framework. I compare the results of this framework to those of standard qualitative research techniques that require added human labour. A proposed framework can minimise research process costs and, at the same time, can apply to any relevant subject matter.

The market research field has dramatically evolved in the new data generation. With advancements in technology and the increasing importance of data, analysts began to weigh the advantages of "thick" and "big" data (Wang, 2016). "Thick" data refers to rich, qualitative information that provides detailed insights into a particular phenomenon's context, meaning, and emotional aspects of the parties involved (Grove & Fisk, 1992). In contrast, big data refers to the vast quantities of quantitative data that can be analysed using computational techniques to identify classification and correlations (Rust, 2020). In recent research, incorporating "thick" data in analysis has become a notable trend in exploratory research. Including qualitative techniques ensures that rich contextual details and subjective experience are noticed.

Furthermore, technological advancements like topic modelling and sentiment analysis have encouraged the implementation of exploratory research, often done with qualitative methods

(Vargo & Lusch, 2017). Digital platforms, social media, and online forum communities (e.g., Twitter or Reddit) have created new opportunities to engage with the main stakeholders and gather their qualitative data, composed of their diverse perspectives. At length, this progress in analysis has changed how exploratory research is carried today.

One of the fundamental elements of exploratory and qualitative techniques is the emphasis on capturing participants' subjective experiences (Kwortnik & Ross, 2007). Methods like in-depth interviews on a topic and surveys are standard ways of gathering opinion data and understanding participants' views about particular phenomena.

Despite having many benefits, both exploratory and qualitative techniques should also be closely analysed for their common flaws. While they provide invaluable insights into people's thoughts, the process of obtaining these results is where the challenge lies in performing the techniques. This process is notably resource-intensive, stemming from three key factors. First and foremost, traditional face-to-face interviews demand substantial resources to cover expenses associated with the participants and researchers alike. This includes compensating interviewees for their time and participation and accounting for the human coding work that follows the interview, which is a labour-intensive task (Timoshenko & Hauser, 2019). Secondly, labelling topics within the content of the interview requires the human coder's familiarity with the subject at hand. Transcribing the discussions from their recorded raw format is time-consuming and necessitates keen attention to detail to ensure accuracy. Moreover, the subsequent analysis of this transcribed data is a subjective process that involves identifying and elucidating patterns amidst the qualitative information gathered (Huang et al., 2016). Finally, there exists an innate subjectivity within the post-analysis which can influence the interpretation of findings.

For the reasons above, developing a novel methodology capable of processing easily accessible expert interview data available online while also automating the extraction of qualitative insights from this data holds significant potential and relevance. Bearing in mind the absence of existing literature exploring a connected framework, it is crucial to establish this methodology to simplify extracting valuable insights while demonstrating that its outcomes align with those of human coders. An exemplary framework should be subject to various metrics that ensure the validity of the proposed approach. Using two common tests, convergent validity and Cohen's Kappa coefficient, is highly preferred as these tools assure the researchers of the framework's credibility. On the occasion of the appropriate mark given by the two tests, the proposed approach is proven to be relevant in the analysis of qualitative data obtained from stakeholder interviews.

Text analysis and automation have emerged as valuable instruments offering new ways for extracting insights and simplifying the research process (Kopalle et al., 2022). While traditional exploratory techniques have delivered rich understandings of different phenomena, they often face human power-related costly challenges. One key reason for considering text analysis on top of existing qualitative methods is that it allows processing the most extensive amounts of textual data. Established analytical practices such as natural language processing (NLP) and machine learning algorithms such as Latent Dirichlet Allocation (LDA) provide an automated fashion to processing textual information in large volumes and translating it into straightforward representations. To uncover topics and latest trends, a streamlined process allows marketeers to comfortably analyse various sources, including sentiment-holding social network posts and interview data.

Existing literature covering the fusion of text analysis in qualitative research demonstrated its derived benefits. For instance, Moon and Kamakura (2017) employ an ontology learning technique to analyse online hotel and wine product reviews. The authors of this technique make a product positioning map by blending together NLP and psychometric mapping - a way to visualise and connect different behavioural variables. The product positioning map shows the clients' views of different wine and hotel brands by extracting the main terms communicated via customer reviews. In this way, their approach eliminates human bias from the final output by only using textual information derived from consumer reviews rather than predefined rating scales set by the research designers in a survey.

Likewise, Vermeer et al. (2020) identify relevant electronic word-of-mouth (eWOM) on social media by focusing on the content of reviews rather than their associated sentiment. They find that machine learning methods like Support Vector Machines (SVM) display high accuracy in identifying relevant eWOM on social media along with sentiment analysis.

Based on these results, machine learning automation in text analysis offers various ways to enhance objectivity i n findings and reduce researcher and manager bias. Besides being costly, human interpretation and coding of qualitative data can introduce subjectivity and potential biases. Automating certain parts of the analysis process can minimise the effects or altogether remove these issues by providing a consistent approach. Even as the interpretation of results nevertheless requires human judgment, automated techniques come in help by reducing the innate biases associated with manual coding.

Regarding the derived insights, text analysis, with the power of automation, introduces new and advanced formats of data exploration to reveal previously overlooked topics in a given text corpus. In an exploratory study by Tirunillai and Tellis (2014), the authors successfully implemented the LDA framework to a pre-processed chunk of review data from the mobile phone market. They end up with six distinct Motorola phone quality dimensions, backed up by unique words for each topic, which helps them in labelling and rating based on overall sentiment (e.g., Portability [Positive], Discomfort [Negative]).

In this analysis, I propose an automated approach for extracting topics from stakeholder and consumer opinion-derived textual data. Ideally, this should eliminate the manual coding effort and promote a streamlined and unbiased analysis process. The main objective is to analyse patterns within a recently introduced technology ecosystem discussed in Section 5. Using topic modelling and sentiment analysis techniques, I identify and explore domain (topic)-specific areas for discussion. Additionally, I measure the "importance" of each domain and investigate whether it is perceived positively or negatively within its respective sphere, utilising sentiment analysis. To achieve this, the following research question is addressed:

*How can automated text analysis methods yield comparable conclusions as human coding to explore and analyse consumer opinion-derived textual data, thereby replacing subjective methods and reducing human effort in qualitative research?*

As proven with research, putting an automated method within text analytics into use makes it possible to simplify the process of analysing large volumes of textual data and achieve more in-depth learning of social phenomena.

Equipping automation within exploratory research can stimulate researchers to combine their expertise through an accessible workflow to analyse their textual corpus and encourage discussion of their ideas.

The results and discussion sections of the thesis infer that the proposed automates approach efficiently extracts valuable topics from a selected research subject (Section 6), suggesting new windows for exploration. The content of the automated approach benefits business growth for established and emerging firms while attracting necessary stakeholders. The study uses an automated methodology using Latent Dirichlet Allocation (LDA), a machine learning method designed for essential topic extraction, web-scraping as a way to collect textual input from social media, vectorisation of the obtained text for computation, and sentiment analyses for quantifying opinions about the derived topics. This framework applies to any phenomena that are appropriate for qualitative investigation.

The results of Study I and Study II demonstate two approaches that forward-looking marketeers and academics may benefit from.  Both studies, which pertain to the framework introduced in Section 5, are applicable to any subject study, but in the context of this research paper, domains of Web3 development are studies industry-wide. In Study I, the analysis of expert interviews revealed prominent topics: 35% focused on new technology and data, 22% on the metaverse, 15% on privacy and security concerns, 12% on risks and regulations, and 16% on identity, decentralization, and digital verification. In Study II, AI-generated interviews tailored for specific industries led to 45% of topics related to immersive consumer gadgets, 28% to NFTs, and 27% to smart contracts. Moreover, the sentiment analysis demonstrated, on average for both studies, that 72% of the topics are perceived positively, while 28% are perceived negatively. Most importantly, the validity assessment shows the proposed research solution successfully determines prevalent domains in the text corpus with the help of convergent validity and intra-rater tests.

## 2. Theoretical Framework

### *2.1 Exploratory and Qualitative Research: Foundations*

Both exploratory research and qualitative methods have gained recognition for their capacity to explore emerging phenomena and uncover underlying topics; they are related but are distinct approaches. An exploratory approach is one that performs preliminary investigation to gain general information within a research question and formulate more concrete research objectives. This research is undertaken when current knowledge is limited, or the research topic is still in the early stages of exploration (Blazevic & Lievens, 2008). Qualitative techniques act as instruments within exploratory work to dissect the essential domains derived from human experiences. They involve studying real-life contexts and collecting non-numerical data from the study participants, such as words, actions and simple observations which help in generating a nicely shaped aggregate analysis (Bhandari, 2023). The theoretical framework examines the definitions of both exploratory research and qualitative techniques, their main characteristics as well as drawbacks. At the end, it emphasises the significance of introducing text analysis as a powerful approach for analysing text data, resulting in comprehensive interpretation of essential domains.

According to Janiszewski & Osselaer (2021), the "flexibility" of exploratory research methods allows researchers to adapt and refine research questions and methods during the investigation, enabling a better understanding and analysis of the research topic. Such adaptive nature increases the value of exploration - it lets researchers present their findings and arguments more convincingly while reducing the temptation to engage in less-than-ideal research practices.

Exploratory research uses open-ended questions and flexible data collection methods, such as verbal measurement or visual attention procedures, enabling researchers to uncover unusual insights and patterns typically not discovered by numerical analyses (Pieters & Warlop, 1999). As the name implies, exploratory research primarily focuses on exploring a research problem or question rather than proposing and testing explicit hypotheses. Instead, it strives to develop a steady space for hypothesis development and ideas for further examination (Steenkamp & Burgess, 2002). The popularity of exploratory research has also been on the rise once again. As the world becomes more interconnected and multidisciplinary approaches are sought, exploratory research is critical in the researcher's toolkit (Meskus & Tikka, 2022). Exploratory research adds on to the existing knowledge by sparking curiosity about newly discovered domains (Sheppard, 2020).

As already established, qualitative research is made up of a range of methods that help explore non-quantitative data. Interviews involve direct engagement with participants (experts) through structured, semi-structured, or unstructured interviews. They can be performed in person or through digital platforms such as YouTube, Vimeo or (Apple) podcasts. Similarly, Zeithaml et al. (2020) propose a qualitative research method called the "theories-in-use" (TIU) approach for making marketing research more personal. The TIU approach consists of collaborating with research participants to explore marketing theories that are directly linked to marketing topics, rather than borrowing notions from other fields. It highlights the role of active listening to create reasonable and innovative theoretical recommendations.

This thesis scavenges expert, as well as AI-generated interviews as primary mediums of textual data. However, qualitative research is more expansive than this. Observational methods involve systematically recording and transcribing behaviours of subjects in real-life settings. Observations can be participant or non-participant, naturalistic or controlled, depending on the research goals. Case studies entail thoroughly examining a specific entity (individual or organisation) which offers contextual knowledge of the subject. The field of case studies uses different techniques, possibly with a combination, such as interviews, documents as well as simple observation to gain necessary information within a given context.

### *2.2 Exploratory and Qualitative Research: Advantages*

As mentioned earlier, there are many scenarios why exploratory research may be superior when analyzing certain (emerging) phenomena.Its methods offer an unequalled benefit, making exploring ideas as detailed as possible. Investigators can engage with participants meaningfully and flexibly by employing qualitative techniques, allowing for a rich and thorough exploration of the research topic (Tenny et al., 2023).

This rigorous analysis approach can motivate future research to pinpoint unusual topics hidden between the lines of transcripted text and help gain familiarity with a phenomenon under the loop. Complex phenomena, by nature, are hard to categorize. They require a more careful analysis which can easily zoom in to a substance of a domain, which quantitative studies cannot offer in their strict system. Therefore, qualitative research excels in unravelling complex and multifaceted phenomena by capturing the richness and complexity of social, cultural, and psychological contexts (Burgess & Steenkamp, 2006). Through ethnography, grounded theory, or phenomenology, it becomes possible to explore the various dimensions of a phenomenon by studying its underlying complexities, contradictions, and interrelationships (Goulding, 2005).

One strength of qualitative methods is their flexibility and adaptability as the research is taken place. Unlike strict quantitative frameworks, qualitative approaches allow us to refine the initially proposed research questions, modify data collection methods, and adapt our focus as new information emerges at the moment of writing. This dynamic nature of qualitative research enables embracing all the unexpected turns of exploration, and making modifications when necessary, leading to more organic and contextually levelled results (Fischer & Guzel, 2022).

A second key benefit of qualitative research methods is that they comprehensively understand *the context* in which a phenomenon develops. By immersing themselves in the natural settings of the interview participants, researchers can capture the social, cultural, and environmental factors that influence the phenomenon (Lilien, 2016). This contextual understanding enables a more accurate interpretation of data and supports identifying underlying patterns, topics, and connections between the elements that make up an idea (Nowell et al., 2017). Themes are identified by combining components or fragments of ideas and experiences through respective topic modelling frameworks, often meaningless when viewed alone. The significance of a theme is not always determined by measurable criteria but rather by its ability to encompass something essential to the research inquiry by using a set of keywords.

Finally, qualitative methods allow the marginalised participants under examination to voice their concerns and suggestions, which can be of tremendous social value. By actively involving the marginalised groups in the research process (interviews or participatory methods), researchers can bring forth their subjective realities and identify the areas of improvement.

To summarise, both exploratory and qualitative research methods offer their own respective benefits for studying cultural events. They both capture contextual information that statistical analysis may not put enough emphasis on. Qualitative methods give weight to underrepresented participants' opinions, promoting inclusivity and putting diminished themes to the forefront.

### *2.3 Exploratory and Qualitative Research: Disadvantages*

While exploratory and qualitative research methods have numerous advantages, it is essential also to recognise their limitations and potential drawbacks.

One primary problem in exploratory and qualitative research methods is the inherent *subjectivity* in data collection, analysis, and later interpretation (Calder, 1977). Since the latter often relies on human understanding and judgment, the research conductor may display biases, preconceptions, and personal experiences that can inadvertently influence the findings. It can be challenging to attain objectivity due to the challenge of human's subjectivity, which can result in doubts about the reliability and credibility of the conclusions.

Since research designers engaging in exploratory research and qualitative methods are actively involved in the research process, this may introduce research bias (Douglas & Craig, 1997). Researchers' opinions and prior expertise can warp the outcomes by influencing the research development.  Hence, the researchers must acknowledge the immutable possibility of a bias without external observers and reflect on the level of their judgements from their previous experiences. Implementing customized techniques can potentially minimise the risks of investigator biases. Also, it is possible to minimise the limitations of a given method by combining it with other methods with complementary strengths. This is important when combining multiple strategies to gain information about a given problem (Davis et al., 2012).

Next, while it was expressed that exploratory research, through qualitative methods, prioritises in-depth insights, this can lead to *limited generalizability* of findings. Due to the small sample size and precise environments typically studied, it is challenging to extend the findings to a larger population or generalise them beyond the specific context in which the research was run. This limitation needs caution attention applying exploratory research findings to broader contexts.

Additionally, the research often involves *complex* and *time-consuming data collection* techniques: interviews, observations, and document analysis (Grove & Fisk, 1992). These procedures need significant researcher labor and careful planning with interviewees to ensure the collection of high-quality and meaningful data.

Finally and notably, in almost every relevant study, *analyzing and interpreting* data can be labour-intensive and intricate (Steve et al., 2011). Investigators must navigate large volumes of the textual corpus of data, identify patterns and make educated interpretations based on them. Research designers can improve the accuracy of exploratory findings by using strict, but not data penalizing, methodologies that reduce potential biases, being transparent, and reflecting on their work. These conditions can set a seal on the fact that the contributions made to knowledge creation are trustworthy for the readers.

## 3. Automating Exploratory and Qualitative Research: Text Analysis

Studying the quick development of text analysis in exploratory research can aid in extracting valuable cases from "thick" data.

Text analysis involves systematically analyzing and decrypting textual data to derive meaningful topics (Ma & Sun, 2020). It is crucial in exploratory research to capture and analyse data from interviews, surveys, observations, and documents, uncover hidden meanings, identify emerging themes, and understand phenomena under investigation through human coding (Davis et al., 2011). Delving into textual data reveals valuable insights not apparent solely through other qualitative research methods.

Text analysis supports data collection and main analysis by organizing large volumes of textual information through transcription and representation based on meaning. Different frameworks of data analytical instruments aid data management, enabling the identification of important topics (Alantari et al., 2022).

*Content analysis* categorizes and quantifies textual data based on predefined codes, providing a quantitative lens to qualitative data analysis (Moon et al., 2021). The thematic analysis identifies and interprets patterns of meaning and recurring themes within the data, allowing topics to emerge organically (Mogaji et al., 2020). Discourse analysis examines how language shapes social opinions towards phenomena, revealing insights into identity construction (Fitchett & Caruana, 2014).

All around, implementing text analysis in exploratory research can improve the thoroughness of data analysis. Using text analysis, academics and marketers can fully use qualitative data's potential to reveal hidden information which strict analyses can overlook.

## 4. Literature Review

Automation is increasingly relevant in exploratory research, as it has become reputable for showing benefits of efficiency and unbiasedness. This literature review outlines automation's state of the art in exploratory research. It explores how automation has been applied in various research domains, including data collection, data analysis, and knowledge discovery. Furthermore, it highlights the advancements and impact of introducing text analytics in the effort to improve research efficiency and quality. Table 1 summarises the most relevant papers, their research topics and results.

***Table 1.*** *Literature overview.*

| **Study** | **Journal / Book** | **Research Topic** | **Main Findings / Result** |
|---|---|---|---|
| Shankar & Parsana (2022) | *Journal of the Academy of Marketing Science* | NLP models in marketing research | Description of NLP models application and how they can be applied / what insights can be derived. |
| Boegershausen et al. (2022) | *Journal of Marketing* | Web scraping in marketing research | Directions for future research to identify promising web data sources and embrace novel approaches for using web data. |
| Cunningham (2002) | *Proceedings of the 40th Annual Meeting on Association for Computational Linguistics* | Introduction of framework and graphical development program in language engineering - GATE | The GATE framework is widely used in exploratory research |
| Tirunillai (2014) | *Journal of Marketing Research* | Using LDA and NMF with online chatter output | This analysis helps marketers track how important different aspects are over time and map how competitive brands stand on those aspects as time goes on. |
| Hartmann et al. (2019) | *International Journal of Research in Marketing* | Social media data in research | Research in marketing has gravitated towards text classification, primarily through online user comments |
| Fitchett & Caruana (2014) | *Journal of Consumer Behaviour* | Role of discourse in marketing research | Text analytics draws inspiration from ethnography and anthropology. |
| Moon et al. (2021) | *International Journal of Research in Marketing* | Using NLP for fake consumer reviews | Studied the word patterns from each product category. |
| Rutz et al. (2011). | *Marketing Science* | Computational linguistics in paid search advertising | Keywords display a notable indirect effect of paid search, which varies significantly. |
| Berger et al. (2020) | *Journal of Marketing* | Using text for marketing insight | Text analysis can unify market research by providing a shared set of tools and approaches. |

### *4.1 Automation in Exploratory Research*

Natural Language Processing (NLP) and machine learning, with their power to host detailed data discovery, are the core in automating research. These approaches leverage algorithms that can learn patterns and relationships from data, enabling researchers to automate data classification, clustering, and prediction (Shankar & Parsana, 2022).

Automated data collection and processing have become rudimentary in research automation. Technologies such as web scraping, data APIs, and data integration platforms have made it easier for researchers to gather diverse datasets from various sources (Boegershausen et al., 2022). Additionally, automated data pre-processing techniques, including data cleaning, normalization, and feature extraction, have simplified the initial stages of research by handling the laborious tasks associated with data preparation (Singh et al., 2022).

#### *4.1.1 Notable Studies, Projects, and Tools in Research Automation*

Several inventions within research automation are known to have transformed the field. One such prominent tool is the General Architecture for Text Engineering (GATE), an open-source software framework designed to revolutionize text analytics and research automation (Cunningham, 2002). GATE software allows its affiliated researchers to automate their work development by offering a myriad of solution including but not limited to data extraction, text classification and sentiment analysis.

Topic modelling techniques, namely Latent Dirichlet Allocation (LDA), an unsupervised learning algorithm that probabilistically identifies hidden topics within a corpus of documents, have gained prominence in research automation (Tirunillai, 2014). This method enables analysts to dismantle topics within collections of text and make knowledge discovery possible in blind areas, most likely due to their hindrance by quantitative reviews. For example, topic modeling's versatility makes it a perfect instrument social science domain, or even biomedical research. Particularly in the social sciences area, LDA analysis of subject's voices lets us delve into human behaviour and its intricacies, identifying prevalent themes in this textual information. Moreover, convenient information retrieval is exponentially altered by automated document categorization and content recommendation, enabling users to navigate vast information repositories with ease.

As social media becomes the primary medium for consumer data, managers are continuously delving into it to derive customer sentiment towards products or services. These methods employ machine learning and NLP algorithms to classify the sentiment expressed in social media posts and comments (Hartmann et al., 2019). Automation in sentiment analysis is useful in many managerial areas, from discovering customer opinions of products for marketing purposes or running brand perception studies to encourage smarter decision making.

### *4.2 Recent Advancements in Text Analytics for Automation*

There are many know research efforts that highlight the power of automated text analysis to reveal hidden domains behind data. These methods include the established NLP (Moon et al., 2021), machine learning (Ma & Sun, 2020), and computational linguistics (Rutz et al., 2011) approaches. One potential benefit of automated text analysis is extracting information and depicting patterns within extensive text collections of "thick" data. Berger et al. (2020) have contributed to text analysis by introducing automated approaches to analyse qualitative data at scale and emphasizing text impact on research receivers.

Despite the recent popularity within implementing text analysis, there is a common speculation about its lack of a strong basis in human sciences. Researchers in this area have spent considerable amount of time building valid models that capture human insights as efficiently and as detailed as possible. Relying on existing clear-cut automated techniques results in a loss of nuanced understanding and interpretive insights that can only come from close engagement with human data (Ezzy, 2013). The unstructured nature of automated text analysis methods can create difficulties in ensuring the results' accuracy as well as its 'contextual significance. Therefore, there exists a need for a careful automated framework that guides the development of automated text analysis approaches for exploratory research using qualitative data-gathering techniques. Such a framework should include social scientists' principles and proposed methods while leveraging the advantages of computational machine learning techniques. This framework would require a deep understanding of context, self-awareness, and interpretive analysis, effectively connecting the strengths of qualitative research with the possibilities offered by automated text analysis (Ravitch & Carl, 2020).

An exponential use of text analysis has opened up new frontiers for implementing exploratory research questions via human interaction. The work of Berger et al. (2020) covering the correct procedure for text synthesis to date, Ma & Sun (2020), with machine learning integration in the research process, and other related studies have demonstrated promising insights into applying automated text methods. However, there persists a gap in developing a structured and valid approach that combines the strengths of automated techniques with the ability to maintain deep human insights. Connecting this divide is crucial for ensuring automated text analysis's meaningfulness in qualitative and exploratory domains. Blending computational techniques with the fundamentals of qualitative research will lead to a more refined and comprehensive model for text analysis in the coming years.

Advancements in machine learning methods and data acquisition have automated research processes allowing for interesting findings. Tools like GATE and topic modeling aid text analytics by offering a myriad of tools that researcher can use as during the run of their work. With that, there is a demand for an aligned approach that merges the best existing automated techniques to a singular (customized) workflow to inspect human insights. Bridging this gap will lead to more refined and unbiased text analysis frameworks.

# 5. Methodology

With the gathered knowledge on research automation and text analysis emergence, it is now time now establish the mechanism of my research. The primary focus will be on automating the process of gathering essential topics via the exploration of "thick" data - the textual output - on the basis of phenomenological expert interviews. Throughout the automated analysis strategy funnel, I conduct sentiment analysis based on tweets to harness a view into the attitudes and opinions of users about the derived domains.

Interviews as qualitative methods in research play a vital role in achieving concept familiarity, especially when emerging phenomena are under the loop - they provide first-hand experience from professionals and knowledgeable individuals. The transcribed textual information from these interviews is fed into the automated analysis based on phenomenology, where it is categorised to garner key themes and patterns and rated using real human insights. This process should display how different individuals perceive and react to specific aspects of a research subject introduced in the following sections.

## *5.1 Ensuring Quality of Interviews*

When analyzing interviews, it is essential to follow a structured approach to ensure that the collected data is reliable. One of the main steps is to identify interviews that host individuals with relevant knowledge and expertise in the chosen phenomenon, preferably participating in its development. This may entail interviewing experts, academics, or other individuals who have experience in the subject matter and its impact on the respective industries they operate. Some of the available interviews are hosted by two interviewers, which increases the efficiency with which interviews can be conducted. The respondent always has the complete attention of one of the interviewers, thus freeing the interviews of breaks in continuity (Kincaid & Bright, 1957).

Implementing exploratory interviews rather than ones involving leading questions designed to prompt or guide the interviewee to give a particular answer or response is also essential. As leading discussions are planned to elicit specific responses, they may lead to partial or incomplete data. Therefore, the interviews I collect should remain open-ended, allowing interviewees to express their perspectives and experiences freely. After the interviews have been collected, it is necessary to analyse them and identify themes and topics that emerge from the responses. Such involves categorising the data and identifying commonalities and differences between the answers. Also, it is vital to note that the sample size of participants is less critical than the quality of the data collected. Therefore, the focus should be on obtaining rich and detailed data rather than the number of participants.

By gaining insights into the experiences and perspectives of industry experts and other individuals with relevant knowledge, I develop a deeper understanding of how Web3 is transforming industries and the challenges and opportunities that this presents.

### *5.2 Proposed Framework*

To build my framework, I first leverage work in phenomenology that makes up the initial qualitative analysis of interviews.

Phenomenology is a study endeavour aimed at learning how people respond to events happening around them and their perceptions at the moment in time. Fornier (1998) explains that understanding the larger context of people's life experiences is important for brand management. Their research data illustrates that the phenomenology of relationships in the consumer-brand domain is more of a perceived compatibility of goals between the two parties than an agreement between the product's attributes and personality trait images. Brands cohere into systems that consumers create to aid in living and give meaning to their lives. Phenomenological interviewing comes in help with discovery-oriented project goals of establishing consumer validity of the brand relationship offer.

Figure 1 summarizes the five steps of a traditional (human-driven) interview analysis and insight extraction according to phenomenologists such as Creely (2018).

Creely’s interpretation of a phenomenological study approach is that it focuses on unseen human experiential and thought states and their external material - their performative and cognitive outcomes.

By using it in exploratory research, participants' underlying meanings and existential experiences are accounted for, as well as their strategic thinking and hands-on techniques.

Phenomenological analysis of interview transcripts should be consistent with the gathering and the circumstances of its collection and focus on consciousness and experience.

The phenomenological textual analysis funnel begins with *identifying and transcribing specific experiential content*, such as interviews, which is then categorized into a proper format. This categorisation provides the sense and thus the meaning that is directed from internality to learning in the external world.

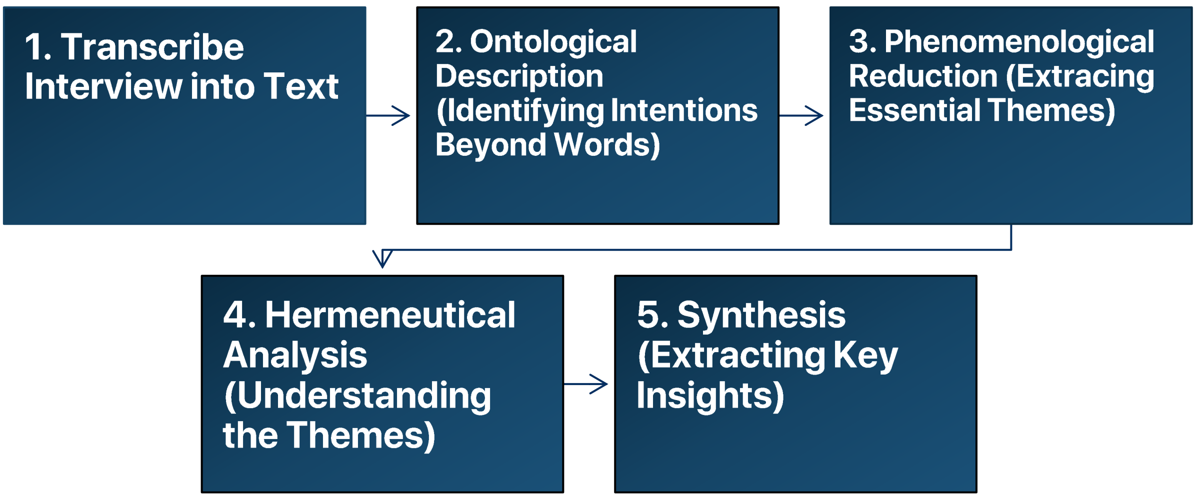
The next step, *ontological description*, focuses on the specifics of the subject's experience and includes sensory perception and capturing emotions, expectations and thoughts.

A *Husserlian reduction* is performed to identify the nature of participants' perceptions. These perceptions are the frameworks on which knowledge and consciousness are based. The act of reduction does not mean excluding experiences but determining the ground of such incidents.

*Hermeneutics* follows up as a field of textual analysis that deals with the meanings of texts about human study participants after whom such texts are formed. It is linked to the notion of how humans know about their relating to the world.

*Synthesis* then assembles findings from the steps in the funnel above. It describes critical structural elements in consciousness and a recap of hermeneutical views.

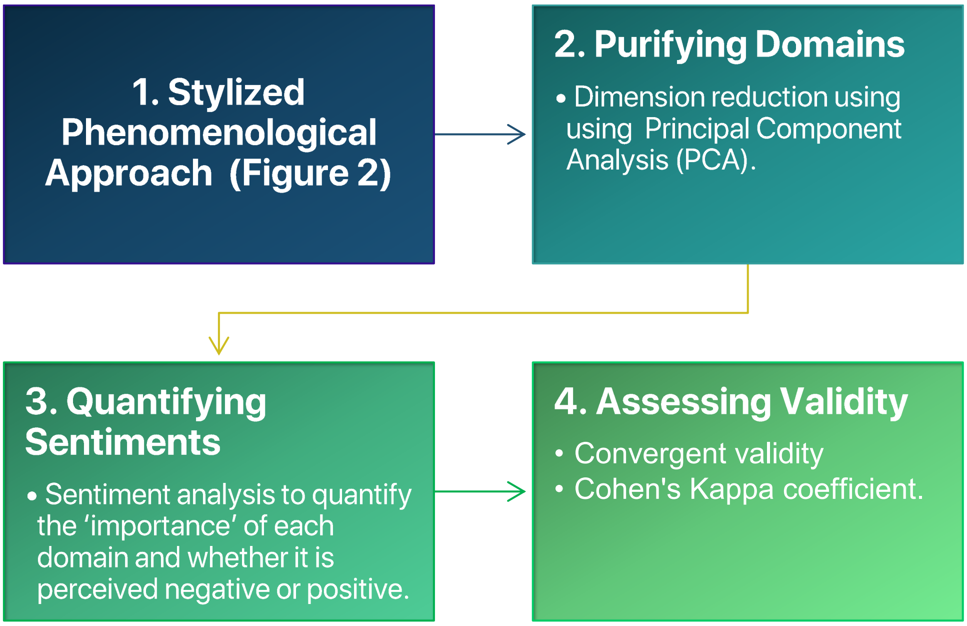
***Figure 1.*** *A Stylized Phenomenological Approach to Insight Extraction from Interviews.*




*Note: Adapted from Creely (2018).*

To automate steps 2 to 5 in Figure 1, I make use of the powerful toolbox of text analysis. Berger et al. (2020) provide an overview of automated text analysis for marketing research; this includes methods for analyzing individual words and expressions, linguistic relationships within and across documents, and topical topics discussed in the text. To automate the process of phenomenological extraction, topic modeling can be used to identify the essential topics discussed in a body of text, increasing understanding of the review content, and making it easier to assess how discussion changes over time. Similarly, to aid the synthesis part of the qualitative study, sentiment dictionaries such as AFINN, specialised in gathering social media sentiment, are used to extract user reviews' opinions on the obtained domains. For this purpose, Word2vec or word embedding allows me to extract user review words while understanding the context in which they were mentioned in the review. This approach preserves the context in which the words appear. I propose a unique methodological funnel (Figure 2) for topic modeling and sentiment review of Web3 tendencies.

***Figure 2.*** *An Automated Framework for Insight Extraction from Interviews (Study Methodology).*




In Figure 3, the first essential step is to get familiarity with the main procedures of phenomenological interviewing approach and performing its automation. This involves acquiring relevant interviews and transcribing them using applicable software (in case the transcripts are not already provided by the video hosting platforms), extracting general information behind the words, which can be achieved by multidimensional scaling (MDS), and specifying domains (topics) within the text corpus, which can be achieved through LDA analysis. Once the primary qualitative analysis is performed, the next step involves purifying the obtained domains to enhance their quality and relevance, which can be accomplished by using a dimension reduction technique like the Principal Component Analysis (PCA), which also operates with textual information. This dimension reduction will help "prune" the domains and ensure they effectively capture the essential aspects of the construct under consideration by maintaining the most relevant terms (words) regarding it. In the subsequent stage, I need to quantify the sentiments associated with each domain. Employing sentiment analysis will allow me to assess the 'importance' of each domain and determine whether the respondents perceive it as negative or positive. Quantifying the sentiments of the derived topics provides valuable insights into the overall perception of each domain among its users or adopters. The last step of an automated machine learning framework is essentially its validity assessment, for which two fundamental approaches can be applied to evaluate the validity of the measures. Firstly, I assess convergent validity, which involves comparing the derived output of the framework with manually derived topics using the help of real human coders, to ensure the work is aligned appropriately. This step helps establish the credibility of the developed automated funnel. Secondly, I then calculate Cohen's Kappa to determine the level of agreement between the two independent different raters. A high Cohen's Kappa value closer to indicates strong agreement and supports the validity of the measures.

Adapting this automated framework to the qualitative phenomenological analysis allows to construct a rigorous approach to developing measurement tools of textual, qualitative input, that can lead to more insightful and reliable exploratory research outcomes.

### 5.2.1 Stylized Phenomenological Approach

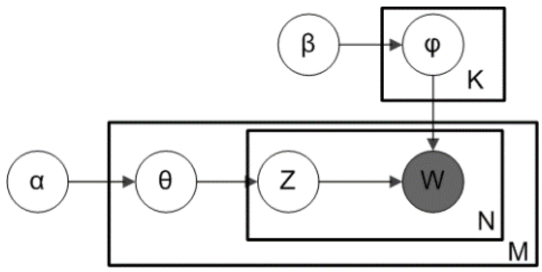
At the beginning of the framework funnel, I cover the use of Latent Dirichlet Allocation (LDA) as a topic modeling technique to specify industry-specific domains and automate the phenomenological extraction of themes.

LDA is a reputable topic modeling method used in various research branches. In an exploratory study by Tirunillai and Tellis (2014), the authors successfully implemented the LDA framework to a preprocessed chunk of review data from the mobile phone market. The main points of their analysis include introducing a word distribution metric that shows the occurrence percentage of top words throughout all text items to highlight main features, as well as the creation of latent topics with these features for different mobile phone functions and specifications. The authors end up with six distinct Motorola phone quality dimensions, backed up by unique words for each topic, which helps them in labeling and rating based on overall sentiment (e.g., Portability [Positive], Discomfort [Negative]).

The initial stage of implementing LDA for topic modeling involves collecting transcribed interview data related to a specific phenomenon or subject matter. Once the text data is assembled, the next step is to preprocess it by removing stop words, punctuations, capitalization, and other redundancies that might disrupt the analysis. After this preprocessing step, the data is ready for LDA topic modeling.

LDA works by assuming that each interview in the collected data is a mixture of various topics, and each topic is a mixture of multiple words. The goal is to identify these topics and the unique keywords associated with them. LDA does this by modelling the probability distribution of words within each document and the probability distribution of topics within each corpus. The hierarchical structure of LDA can be represented by the plate notation shown in Figure 3, created by Blei et al. (2003) and consisting of three levels: document level, word level, and global level.

***Figure 3.*** *Plate notation representing Latent Dirichlet Allocation (LDA).*




*Note: Here, M – is the number of documents (interviews), N – is the number of words in a given document, α – is the parameter of the Dirichlet prior on the per-document topic distribution, β - is the parameter of the Dirichlet prior on the per-topic word distribution, θi - topic distribution for document I, Ψk - word distribution for topic k, Zij - topic for the j-th word in document I and Wij - specific word.*

W being filled in means that words are the only observable variables, and the others are latent variables. Blei et al. suggests using a sparse Dirichlet before modeling the topic-word distribution, which means that only a few words have a high probability in a topic. θ represents the distributions over topics for each document, while Ψ represents the distributions over words for each topic. Ψ1,..., Ψk are sets of distributions over words, and θ1,..., θk are sets of distributions over topics.

Before applying the LDA technique, it is crucial to determine the appropriate number of topics to generate. To track this number down, I turn two two metrics: perplexity and coherence scores. Perplexity measures the predictive capability of a topic model on unseen data, with lower values indicating better performance. By training and testing the LDA model with various topic numbers (5, 10, 15, 20), also named Gibbs Sampling, it is possible to calculate perplexity scores and choose the model with adequately low perplexity, indicating a better fit to the data. Furthermore, the coherence measure assesses how coherent and buildable the generated terms are. Higher coherence scores indicate the topics outlined for synthesis are more meaningful. By checking coherence scores across different topic numbers, I determine the point at which scores plateau or reach their peak, indicating the optimal number of topics for the study. It is considered best to use coherence with a separate validation set rather than perplexity on the training or test set, as it considers topic quality in unseen circumstances and aids in achieving more interpretable results. Taking the two results together, I ensure selecting a suitable number of topics for the LDA topic extraction analysis that will enable me to comprehensively interpret the domains later.

These topics and associated terms can be interpreted and labelled to identify the main topics in the chosen context of research. Once the topics and associated words are identified for each industry, it is possible to visualise them in a manner of importance for each topic to help with interpretation. This involves clustering similar topics, identifying the most prevalent topics, and comparing the topics and associated words across industries to identify commonalities and differences. To ensure the quality of obtained results, I consider incorporating a further topic purification strategy as a preprocessing step for topic analysis to enhance the accuracy and interpretability of the topic modelling process.

### 5.2.2 Purifying Domains

After performing LDA topic modeling I attempt to reduce the dimensionality of the output data and identify the most influential features that contribute to the underlying topics.

One practical approach to achieve this is by employing dimensionality reduction techniques to simplify the topic-word matrix. By doing so, we aim to condense the information while preserving its essential characteristics. This technique involves taking the topic-word matrix generated by LDA and applying a dimensionality reduction algorithm to it, such as the standard PCA (Principal Component Analysis). PCA is a dimensionality reduction framework that can reduce the number of topics generated by LDA while preserving the variance in the interview data. This can help to identify the most critical topics for each industry and remove noise and unrelated topics. Once the dimensionality reduction technique is applied, I interpret the final result further. The process of domain purification is showcased through the following steps:

$$\mu = (1/T) * \sum Xi \tag{1}$$

$$X\_centered_{\mathrm{i}} = X_{\mathrm{i}} - \mu \tag{2}$$

$$Cov = (1/T) * (X\_centered_{\mathrm{i}})^{\mathrm{T}} * (X\_centered_{\mathrm{i}}) \tag{3}$$

$$(V, D) = eig(Cov) \tag{4}$$

$$Purified\_topic\_vectors_{\mathrm{i}} = X\_centered_{\mathrm{i}} * k\_eigenvectors \tag{5}$$

In step 1, I calculate the mean vector μ given T - the number of topics derived from the LDA model and $X_i = [x_{i1}, x_{i2}, \ldots, x_iN]$ in which each topic i can be represented as an N-dimensional vector where $x_{ij}$ is the probability of word j in topic i. In step 2, I center the data; a process where the mean of each feature is subtracted from its values to make the data have a mean of zero. In step 3 I compute the covariance matrix Cov. In the following step, I compute the eigenvectors V and eigenvalues D of the covariance matrix. Before commencing with the final step, I select the top k eigenvectors corresponding to the k highest eigenvalues from V. To simplify this process and make it visual, I construct a scree plot, which plots the eigenvalues against the number of clusters. I look for the point where the eigenvalues level off or start to decrease significantly, which indicates a suitable number of clusters.The resulting purified topics ($Purified\_topic\_vectors_i$) can be used as the basis for my domain analysis and further steps in the framework. In order to choose the correct value of clusters when running PCA,

By applying PCA to the topic-word matrix generated by LDA, it is possible to identify the most critical topics in a chosen subject matter and remove any irrelevant domains that the topic modeling framework may have generated.

Kunz and Hogreve (2011) use PCA as a method of dimension purification in their study of understanding service marketing. They perform the principal component analysis to identify the most relevant topics in the citation data gathered. Using the PCA, they recognise the components that account for most of the variation in the analysed variables, such as citations for specific articles.

### 5.2.3 Quantifying Sentiments

After purifying the domains of a phenomenon and its tendencies using LDA and PCA, the next step is to quantify the sentiment separately between the derived and purified domains. Sentiment analysis of public tweets comes in as a way to facilitate this and retrieve information about what people perceive of the domains.

*Sentiment analysis* is a natural language processing procedure that analyses text data to determine its sentiment (negative, neutral, or positive). In the context of the research question, sentiment analysis can quantify the 'importance' of each domain and whether it is perceived as positive or negative by individuals on Twitter as a social platform.

An adequate sample of 200 tweets per derived topic is collected using relevant hashtags or keywords to perform sentiment analysis. The text data from these posts can then be pre-processed to remove stop words but include capitalization for deepened analysis based on emotion.

A relevant paper by Hennig-Thurau et al. (2015) investigates the Twitter effect, which says that microblogging word of mouth (MWOM) on Twitter affects early product adoption rates. The authors run a multistage sentiment analysis on all tweets mentioning a movie to identify MWOM reviews. As examined in their research, MWOM influences consumers' early adoption decisions - more than half of respondents planned to see the film during the opening weekend, indicating that MWOM is most influential for early adoption decisions. Such a framework is easily implementable for Web3 evaluation in this thesis.

In this research, I quantify the sentiment of posts, explicitly using the AFINN dictionary, which has a particular purpose in social media research by helping determine the sentiment or emotional tone of a piece of a post, typically by assigning a sentiment score to individual words. The sentiment score of each tweet is calculated by considering the total number of AFINN terms (from -5 to +5) present in each word of the tweet and considering the character size of the tweet. The equation for calculating the initial sentiment score is expressed as:

$$Sentiment\ Score = \frac{Sum\ of\ AFINN\ Scores\ of\ all\ Tweets}{Total\ Character\ Length\ of\ all\ Tweets} \quad (6)$$

To achieve a sentiment score on a 0 to 1 ratio, which is easy for comparison between topics, I use the Min-Max normalization method as follows:

$$Normalized\ Sentiment\ Score = \frac{Sentiment\ Score - Min.Score}{Max.Score - Min.Score} \quad (7)$$

Where *Sentiment Score* is calculated as described in the previous equation, *Min Score* is the minimum possible sentiment score among all topics, and *Max Score* is the maximum possible sentiment score. By applying this normalised equation, I obtain a normalised sentiment score with limits from 0 to 1, where higher values indicate a more positive sentiment and lower values indicate a more negative sentiment. This formula allows for a quantitative review of stakeholder sentiment within each domain.

### 5.2.4 Assessing Validity

Ensuring the validity of any customized machine learning research is crucial to its methodology, because it is necessary to guarantee the readers of its real-world applicability, and that the conclusions are cleared of bias or noise (Berger et al., 2020).

In the context of text analytics applied to the interview data at hand, validity plays a pivotal role in establishing the accuracy and reliability of the newly proposed method. Specifically, when applying Latent Dirichlet Allocation (LDA) to transcribed interview text, the focus is on identifying latent topics within the text corpus that genuinely represent the underlying concepts or ideas in the interview responses.

To handle the validity concerns of the framework's findings, the concepts of content and construct validity are essential to consider. Content (construct) validity ensures that the topics extracted from the text accurately represent the phenomenon or constructs under investigation (Hulland et al., 1996). In the context of LDA, content validity is crucial to ensure that the identified topics are relevant, meaningful, and representative of the interview content. Additionally, it is essential to establish whether these identified topics align with the theoretical constructs or concepts of interest and convey the information effectively from the interview responses. By evaluating content validity, I ensure that the identified topics align with the research questions and the underlying information in the interview data.

As an integral part of content validity, convergent validity plays a vital role in establishing the accuracy of the proposed framework applied to interview text data and the derived topics by LDA. The convergent validity test involves recruiting two human coders who independently label the topics the automated LDA approach identifies. By comparing the labeled domains by human raters with the main results and receiving a high result of identicality of topics, I demonstrate the effectiveness of the automated framework in accurately capturing the intended hidden content within the interview text data. Aligning machine-identified topics with a real human check enhances the construct validity of the framework and its results in a chosen subject.

In addition to convergent validity, a Cohen's Kappa coefficient is adopted to establish the reliability of the framework. This statistical measure assesses the agreement and consistency among multiple onboarded coders/raters who independently assess the same interview transcripts. By using Cohen's Kappa in the context of a topic outlining analysis, I evaluate the reliability of the identified topics by examining the degree of agreement between the two coders. The coefficient value ranges from -1.0 to 1.0, with negative values indicating less agreement than would be expected by chance, 0 indicating agreement equivalent to chance, and positive values indicating agreement beyond what would be expected by chance. Cohen's Kappa operates with the following equation:

$$\kappa = \frac{Po - Pe}{1 - Pe} \tag{8}$$

Where Po is the observed agreement between the two human coders, i.e., the proportion of data points where both coders agreed on the same topic, Pe is the expected agreement between the two human coders by chance, i.e., the proportion of data points that both coders would be expected to agree on due to chance. To calculate Po, one needs to count the number of data points both coders agreed on and divide it by the total number of data points. This effort confirms the reliability of the topic modeling framework, verifying that the identified topics are consistent between the raters and are reproducible. Cohen's Kappa coefficient also serves as a quantitative inter-rater reliability measure, ensuring that individual coder biases or subjective interpretations do not influence the LDA analysis. By demonstrating a high Cohen's Kappa, I establish the robustness of the newly proposed method, independent of the individual perspectives of coders. Additionally, Cohen's Kappa helps assess the stability and generalizability of the analysis. Examining the agreement among coders across different subsets of interview transcripts translates whether the automated method produces consistent results across various parts of the data.

Two studies are conducted, both following the proposed framework, but differing in data collection methodologies to facilitate fair comparison of existing data sources up to date. An overview of the studies is displayed below (Table 2).

*Table 2. Overview of Studies and Summary of Key Results.*

| Study | Methodology and data | Details on Study Design | Summary of Key Results |
|---|---|---|---|
| **1** | Proposed automated methodology with existing expert interviews. | Latent Dirichlet Allocation (LDA) + sentiment analysis. Data collected from interviews with experts in the Web3 technology domain. | Interviews of Web3 enthusiasts and experts from various industries are retrieved and transcripts are made. LDA was applied to extract key topics and sentiments from the interviews. The main results shed light on the most recent importance of new technology in Web3 development. |
| **2** | Proposed automated methodology with AI-generated expert interviews using ChatGPT. | Latent Dirichlet Allocation (LDA) + sentiment analysis. Data collected from AI-generated expert interviews. Validation tests are conducted based on the results of this study. | The AI-generated expert interviews are prompted for specific industries, providing main industry insights. The input information is coherent and precise. However, the data was limited to information available up until the AI model's knowledge cutoff date, restricting the analysis to developments only up to that point. |

## 6. Research Background and Data

This section introduces an exemplary subject of the study for which expert interview data is retrieved and is fed into the automated framework. The main definitions of the subject are also left for readers' general understanding of interpretation of findings.

Namely, the concept of Web3 technology acts as a suitable research subject for several reasons. Firstly, Web3 is an emerging phenomenon with many unexplored domains within multiple industries. This new generation is backed up by first-hand data control by the users who own it, including their digital assets. This is an upgrade and slight deviation from the established principles of Web2 and requires a thorough breakdown as it encourages greater user autonomy and confidentiality online. Secondly, expert interviews provide direct knowledge from stakeholders responsible for Web3's development, offering first-hand perspective on the growth of this technology. Analysing these interviews using the automated framework can uncover emerging trends in the landscape of Web3 over the last five years. in four major affected spheres such as finance, entertainment, healthcare and education.

The concept of Web3 was first coined by computer scientists and Ethereum co-founder Gavin Wood in 2014 and emerged as a response to the limitations of Web2, which is the current version of the internet that we use up until today. The new internet system uses blockchain technology - a ledger system that enables secure and transparent transactions without requiring intermediaries (Davis, 2023), smart contracts - digital contracts that execute themselves, containing the terms agreed upon by the buyer and seller, written directly into lines of code (Lipton and Levi. 2018), and decentralised storage to create trustless and secure transactions without the need for intermediaries. Web3 is built on a concept of decentralisation, which eliminates the need for a controlling party in almost any data transaction. It is a significant shift from existing Web2 protocols, which rely on intermediaries that often have transparent information about users.

On a cellular level, Web3 works through an individual user's decentralised identity (DID). A unique DID is appointed to a user when they register on a platform, and it acts as a right for the user to perform transactions without intermediaries. The data ownership enabled by a unique DID increases user privacy in a world where personal data is increasingly vulnerable to hacking and misuse.

The *DeFi ecosystem* is similarly built by decentralisation and blockchain technology concepts. Transactions are processed without intermediaries, using a system, such as digital Web3 wallets, that reduces traditional financial institutions' necessity. DeFi applications are currently built on Ethereum, a blockchain platform and cryptocurrency that enables the creation of smart contracts. OECD (2022) proposes that DeFi markets operate as community-based networks that aim to automate the trust factors typically associated with centralised institutions. Instead of relying on centralised parties, DeFi markets operate globally orderless. DeFi transitions from the conventional financial systems we know today, which rely on controlling authorities (i.e. governments and banks). At the same time, a decentralised is operated by a network of users who work the system without intermediaries.
Non-fungible tokens (NFTs) are digital assets using blockchain tech to verify ownership and authenticity. NFTs have recently and very quickly become popular in the entertainment and finance industres alike as they provide a new way for creators and users to monetise their work and engage with their audience. NFTs use blockchain technology to create a decentralised system of ownership, where ownership of an NFT is verified by the blockchain (it is fixed) and

cannot be altered by any individual or entity. Another critical aspect of NFTs in decentralised entertainment is monetisation and revenue sharing. Linda Dounia (2022), one of the most prominent NFT artists to date, states the importance of art ownership: “One of the most attractive features of NFTs is the ability to retain ownership over my work and continue to profit from secondary sales through the smart contract.” NFTs also enable creators to create revenue-sharing streams with their audience, where they can receive a percentage of revenue generated from the sale or use (interaction) of their NFTs (Hahn, 2021). NFTs can enable new content distribution and monetisation forms, such as creating unique digital collectables, limited edition content, and directly selling digital assets to fans. For instance, the Canadian musician Grimes released a 10-piece collection of NFTs, including a music video, allowing fans to purchase an assemblage of unique digital collectables with exclusive content and access (Nifty Gateway, 2021).

To provide an overview of important concepts, I present a table of the essential Web3 definitions below (Table 3).

***Table 3.*** Types of *Web3 technologies* and their definition.

| | |
|---|---|
| Blockchain | A decentralised ledger technology that allows for secure and transparent secure and transparent transactions without the need for intermediaries (eg. Bitcoin, Ethereum). |
| Smart Contracts | Self-executing contracts that automatically execute when certain conditions are met (eg. protecting sensitive data, reducing costs). |
| Cryptocurrencies | Digital assets that use cryptographic techniques to secure transactions and control the creation of new units (eg. Bitcoin, Ethereum). |
| Decentralised applications (dApps) | Applications run on a decentralised network, giving users more control over their data and interactions (eg. OpenSea, the metaverse). |
| Interoperability protocols | Technologies that allow different blockchain networks to communicate with each other, enabling cross-chain transactions and interoperability between different dApps. |
| Web3 wallets | Cryptocurrency wallets that allow users to securely store and manage their digital assets and interact with dApps (eg. Coinbase, Rainbow). |
| Identity solutions | Decentralised identity solutions allowing users to own their digital assets, enabling more secure online interactions. |

With the research context defined, I pursue my analysis with the proposed model using the following steps. First, I intend to use topic modelling to discover and identify key topics and themes related to Web3 in four prevalent industries adopting the new technology - finance, healthcare, entertainment, and education. By analysing textual data from available expert and AI-generated interviews, I will retrieve important terms of the domains where Web3 technologies are making an impact. Namely, but not limited to, "dApps" in finance, "Blockchain clinical trials" in healthcare, "NFTs" in entertainment, and "Decentralised Learning Management

Systems" in education. Next, I plan to use Principal Component Analysis (PCA) to refine and purify the identified domains of Web3 of LDA algorithm. This approach reduces the dimensionality (noise) of the text corpus data and extracts the most relevant terms to help construct separate domains behind Web3 development industry-wide. Thirdly, I perform sentiment analysis on tweets and other online discourse related to the outlined Web3 themes. By analysing these discussions' overall sentiment or tone, I seek to quantify the public's perception and attitudes towards Web3 introduction and utilisation and their implications for the four industries. Finally, I perform two validation checks to guarantee the credibility of my findings. This requires help from independent interview data coders who are also briefed about the topic of Web3 before being presented with the texts.

# 7. Study I: Using Available Expert Interviews

### *7.1 Overview and Procedure*

First, I introduce my primary text study of available expert interviews focused on Web3 technology in four industries: healthcare, finance, education, and entertainment. The procedure begins with collecting high-quality expert interviews in these spheres, followed by transcription and conversion into a Document-Term Matrix (DTM) for further analysis. A word cloud is generated based on word distance to gain initial insights. LDA analysis is then applied to identify ten distinct topics within the text corpus of interviews. PCA method is employed to refine the derived topics. Furthermore, user sentiment from Twitter is collected by associating AFINN values with each domain (topic). To ensure the validity of the findings, convergent validity and Cohen's Kappa coefficient tests are performed.

### *7.2 Data*

The primary data sources used for transcription in this study comprise accessible interviews, which have been retrieved from an array of quality sources. They are conveniently obtainable in three distinct formats: video, audio, and text. Specific keywords like "Web3", "DeFi", "blockchain", "metaverse", and the name of the industry (healthcare, finance, education, entertainment) are used to identify relevant content throughout all platforms. For each industry, I discovered 30 individual interviews, which are equally divided between the three mentioned formats (10 interviews per format) – a total of 120 interviews ready for analysis.

The two leading video-sharing platforms used are YouTube and Vimeo. These sources are home to a vast array of interviews related to Web3 and involved topics, the latter serving as an open archive for videos that may have once been removed from YouTube. I evaluate the content based on the speakers' expertise, depth of discussion, clarity of explanations, and overall production value, especially with not many high-quality interviews available due to the novelty of the subject matter. Another source of openly available audial interviews is podcasts. These are increasingly becoming popular for information and insights, and many podcasts, such as "Fearless Media", "web3 with a16z crypto" and "Welcome to the Metaverse", focus on Web3 and related topics. I access relevant podcasts using platforms like Spotify, Apple Podcasts, and Google Podcasts, which contain dozens of applicable podcast names. Still, I again choose the most reputable for analysis (based on author expertise and stream numbers). For podcasts specifically, I use software *Trint* that transcribes the audial information into text on a sentence level, while video platforms like YouTube already incorporate live transcription under the videos. Online text publications such as digital-oriented news websites, blogs, and magazines also contain interviews with experts in Web3.

When obtaining the interviews, I ensure they are of length of at least 10 minutes and no more than 60 minutes. This allows for maintaining the richness of the content, as extended interviews provide a broader context for analysis and allow to delve into the experts' perspectives, and their thought processes in greater focus.

As for the sources to mine text data from for the sentimental analysis section, I turn to Twitter. Social media networks like Twitter have a mix of expert, enthusiast, and user reviews on Web3 for all industries. These opinions represent the sentiment towards Web3 technologies to respective sectors. For example, for the entertainment industry, I gather data on the sentiment towards Web3-based streaming platforms such as Audius and Emanate.

I follow several standard steps when cleaning and preparing the data for analysis. First, I convert all text to a consistent format by applying normalization techniques such as lowercasing, removing punctuation and stop words (they do not carry significant meaning, such as articles or pronouns), and handling special characters, as well as stemming (not performed for sentimental analysis of tweets and reviews). Additionally, I remove any remaining noise or unwanted elements, such as URLs, numbers, non-alphabetical characters, or specific domain-related terms irrelevant to analysis. Next, I split the text corpus into individual tokens or words to create an appropriate matrix for topic modelling commands, namely a document-term matrix (DTM), where rows correspond to individual documents (interviews) and columns represent unique terms (words) in the corpus.

### *7.2.1 Basic Descriptives*

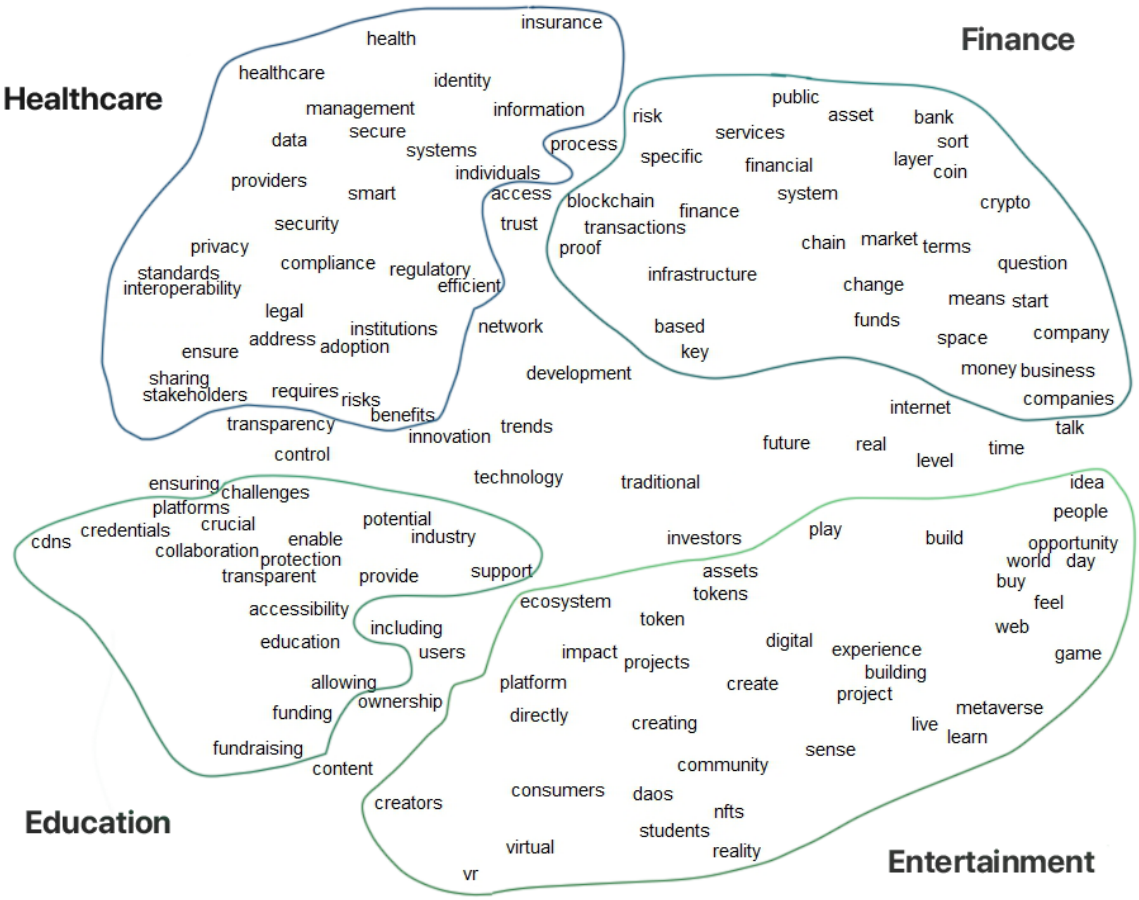
The dataset consists of a substantial corpus of transcribed interviews, encompassing various topics related to Web3 technologies. The dataset is approximately 432,000 words, offering a rich and comprehensive collection of textual data for analysis in all four mentioned industries. When considering the page length of the verbatim transcripts, on average, each interview transcript spans around 14-15 pages of text (considering it is a 30-minute interview). The collected data undergoes a preprocessing phase to ensure consistency and compatibility for text analysis. This phase involves removing non-verbal elements, standardizing formatting, and correcting transcription errors to enhance the quality and reliability of the dataset. The data was carefully sourced from reputable platforms, ensuring a representative sample of insights and perspectives within the Web3 ecosystem.

### *7.3 Results*

For the quality of results, I use the 200 most frequently occurring words based on the counts in the DTM.

To gain a first look at the data, I generate the top words into the word cloud, which are visualised based on their spatial distribution within the text corpus. A similarity matrix is calculated based on the co-occurrence matrix. The distances between words are computed using the sim2diss function. Next, Multidimensional Scaling (MDS) is performed on the similarity matrix to obtain a low-dimensional representation of the words in a two-dimensional space. This representation aims to preserve the distances between words as much as possible. Finally, I use the MDS coordinates to create a word cloud depicted in Figure 4. The closer the words are in the cloud, the higher their co-occurrence and similarity. Bottom of Form

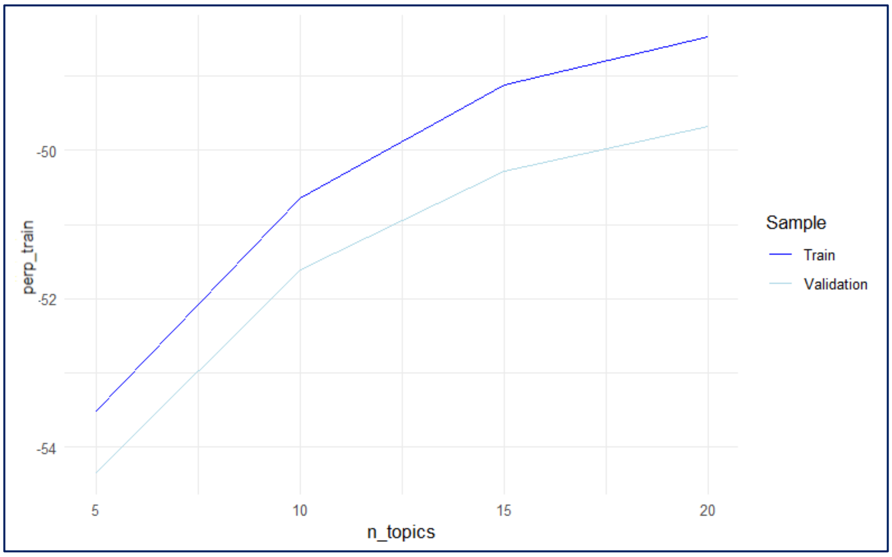
***Figure 4.*** *Word similarity cloud for Study I.*

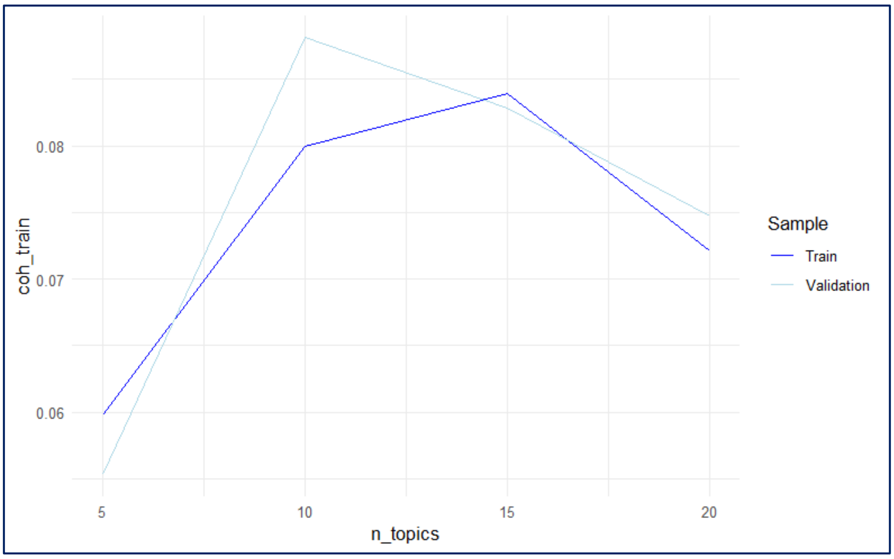



By looking at the word cloud, I observe various terms related to the four industries under investigation (healthcare – “insurance”, “providers”, finance - “transactions”, “services”, entertainment – “metaverse”, “game”, and education – “credentials”, “accessibility”, among others) as well as broader concepts related to Web3 development at the centre of the figure.

The next step involved is extracting topics from the interviews. One common approach to selecting the number of topics mentioned earlier is by analyzing perplexity and coherence values for different topic models. As shown in the first plot (Figure 5), the perplexity all around increases as the number of topics increases. There is a point of diminishing returns, and the perplexity improvement becomes less significant with more topics. In this case, the model with 5 topics has the lowest perplexity value, prompting to focus on the number of topics on the left side. The second plot (Figure 6) shows that in the validation sample, coherence increases as the number of topics increases at first, then slowly drops after this point. There is no point of diminishing returns. In this case, the model with 10 topics has the highest coherence value, indicating that the topics generated by this model are more coherent and better-defined.

***Figure 5 & 6.*** *Perplexity and coherence values over number of topics (5, 10, 15, 20) – Study I*

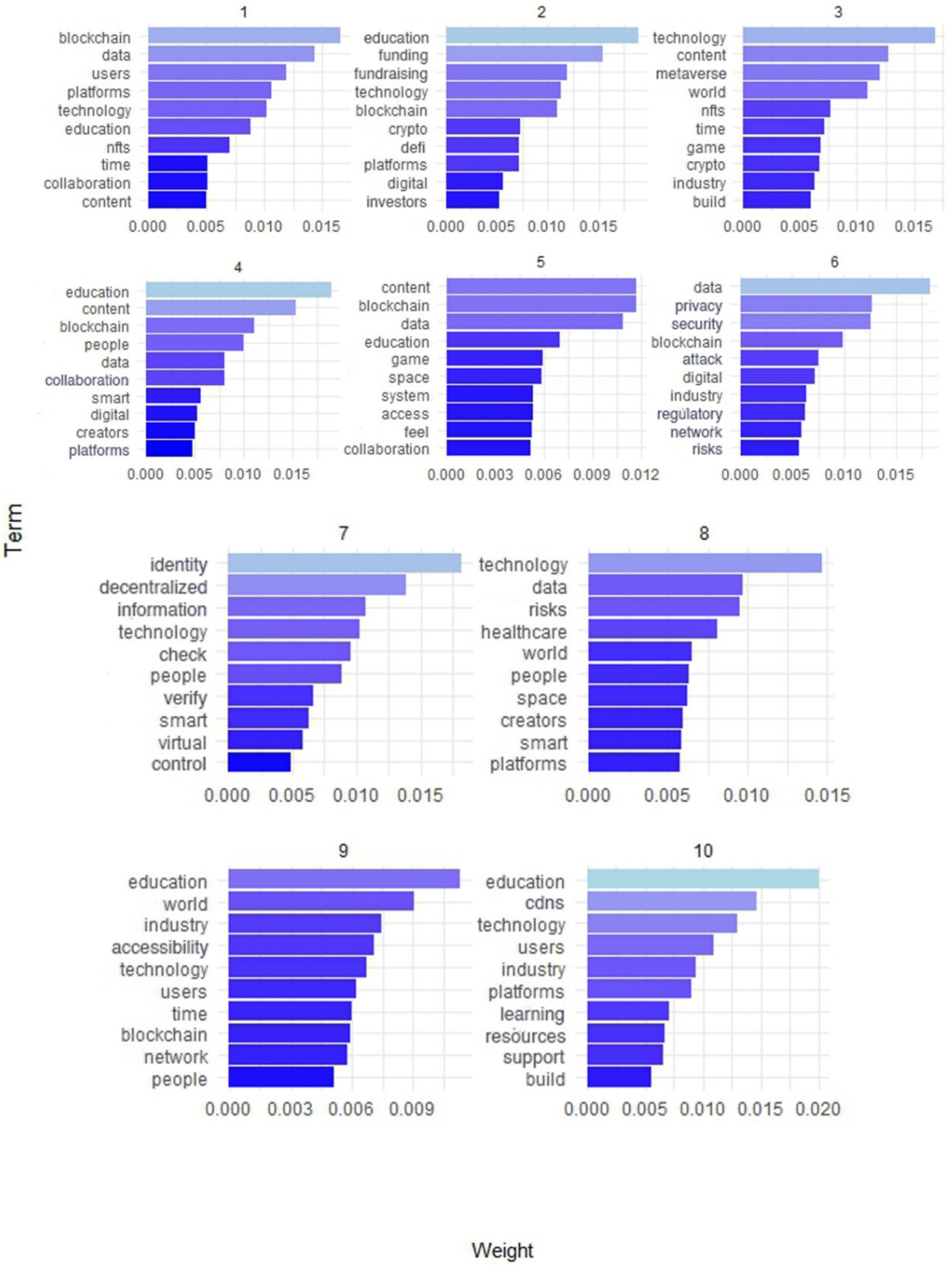



Considering both perplexity and coherence, the model with 10 topics appears to strike a good balance between a reasonably low perplexity value and higher coherence, suggesting that it may be the most appropriate choice for the first LDA study analysis. Exact coherence and perplexity values over number of topics can be found in Appendix (Table B.3).

Finally, after fitting the information into the LDA model, I obtain 10 topics, each represented by 10 keywords, depicted in Figure 7 after being purified using PCA. To determine the optimal number of components , I construct a scree plot, which displays the eigenvalues of the principal components. The scree plot helps identify the correct number of components that explain a significant amount of variance in the data (Figure B.1 in Appendix). The topic formations below (Figure 7) provide insights into the emerging aspects of Web3 development across various industries within the most recent and prevalent interviews, after being purified using PCA.

***Figure 7****. Purified domains from retrieved interviews.*




*Note: Numbers represent latent topics identified by the topic modeling algorithm. Term (located left of bar charts) represents individual word that makes up a latent topic. Weight represents the importance of the word in the formation of the topic. Light blue – higher contribution of word to the topic, blue - weaker contribution of word to the topic.*

The derived topics by LDA display suggestions that may significantly shape the Web3 technology across different industries. When skimming through these topics, it is possible to detect am emphasis on the importance of new technology and data, as well as the emerging metaverse concept. Privacy, security, risks, and regulations are critical concerns in the Web3 space, as mentioned in the topic background section. The existence of digital identity, decentralization, and digital verification are also pinpointed, suggesting that there is a potential of developing such digital identities. Also, education stands out as a prominent area, with terms focusing on its global impact, accessibility, technological infrastructure, and support systems.

All of the above provides valuable comprehension into the Web3 landscape, its emerging trends, and the diverse topics that contribute to the evolution of the phenomenon.

With the main domains uncovered, I continue obtaining user and stakeholder sentiment of these domains through user tweets. The sentiment scores to the titled domains based on keywords provided in Table 4 indicate general sentiment towards various topics related to Web3 development.

***Table 4.*** *Sentiment retrieved for domains from tweets using AFINN lexicon – Study I.*

| Latent Topic / Domain | Normalised Sentiment Score |
|---|---|
| *1. Blockchain Data Platforms* | *0.69* |
| *2. Decentralised Education Funding* | *0.82* |
| *3. Metaverse* | *0.90* |
| *4. Student Data Platforms* | *0.48* |
| *5. Simulation of Education* | *0.74* |
| *6. Privacy and Security* | *0.51* |
| *7. Education Content Platforms* | *0.75* |
| *8. Identity Verification* | *0.43* |
| *9. Accessibility in Education* | *0.60* |
| *10. Content Delivery Networks (CDNs)* | *0.76* |

Out of the more prominent areas, blockchain data platforms received a moderately positive sentiment score of 0.69. Decentralised education funding received a positive sentiment score of 0.82, suggesting increased accessibility within virtual education. On the other hand, the privacy and security domain received a neutral sentiment score of 0.51, potentially due to concerns regarding implementation and scalability. The metaverse garnered a highly positive sentiment score of 0.9, driven by the excitement surrounding the creation of immersive digital experiences and virtual economies. However, Web3 identity verification received a lower sentiment score of 0.43, likely due to scepticism and uncertainty surrounding implementation and acceptance. Lastly, decentralised content delivery networks (CDNs) received a positive value of 0.76, which displays that Web3 tech stimulates content availability and discourages censorship of content.

Obtaining these sentimental scores allows us to rank the relevance of the most recent developments of Web3 in the present time based on active users'opinions.

# 8. Study II: Using AI-Generated Expert Interviews

### *8.1 Overview and Procedure*

The objective of the second study within the thesis is to add another layer to the proposed text analysis framework and investigate the effectiveness of utilizing AI-generated expert interviews, specifically through Chat-GPT, compared to using actual existing interviews. The study involves the collection of AI-generated expert interviews using Chat-GPT, focusing on Web3 technology in the same four industries: healthcare, finance, education, and entertainment. Through using AI-generating software, I am aiming to validate the truth that was expounded by the actual interviews from Study I. By comparing the results obtained from the AI-generated interviews with those derived from gathered and transcribed interviews in the previous study, this investigation aims to highlight the advantages and limitations of employing AI-generated interviews as a viable alternative. Through this comparative analysis, a deeper understanding can be gained regarding the potential of AI-generated interviews in capturing insights on a chosen topic. This study is crucial for assessing the practicality and implications of using AI-generated interviews, offering valuable insights that can inform future research methodologies and guide the integration of AI in qualitative research practices.8.2 Data

### *8.2 Data*

The primary data source for this study comes essentially from Chat GPT-generated interview text to conduct text analysis for topic modeling on Web3 developments and, perhaps, new undiscovered domains in different industries. To collect interview data, I prompted Chat GPT to create expert interviews specifically tailored for each industry. These interviews serve as the primary source of transcribable data for the second main analysis. An example of a prompt fed into the generative AI software is as follows:

*"Create an extensive expert interview that will be used for analysis a master thesis doing topic modeling on web3 developments and trends in the (name of industry) industry using industry expert interview text data"*

As seen above, I ensure a diverse range of perspectives by requesting interviews with experts in the four industries separately. Each industry consists of 30 individual interviews. This, like the previous study, amounts to a total of 120 interviews available for analysis. This time, I did not use any Web3-related keywords apart from the phenomenon's name to eliminate any specifications of domains in dialogue. By incorporating the industry name into the prompts, I obtained relevant content for each sector.

During the data collection process, due to output capacity of the Chat GPT service, the interviews are generated with duration of about 10 minutes duration, which still allows for the inclusion of rich content and contextual understanding.

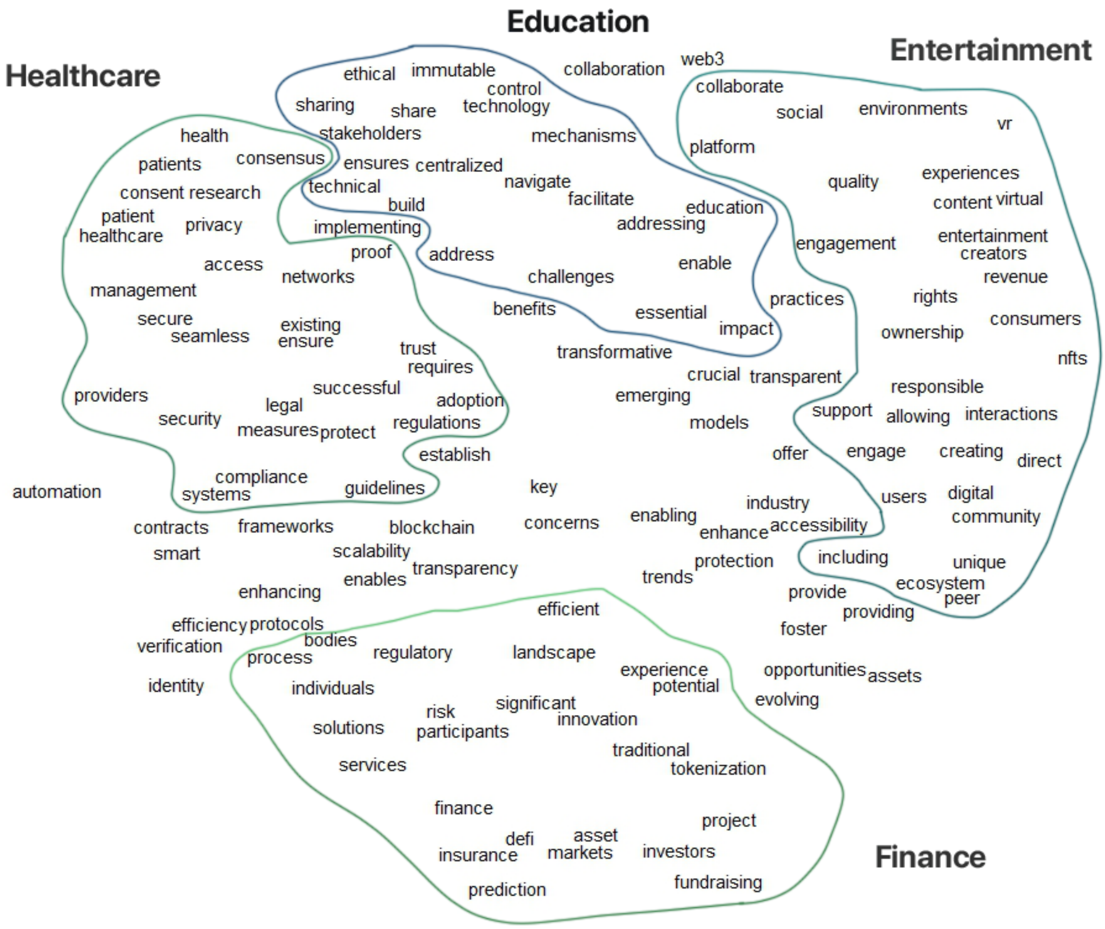
Like the first study, Twitter retrieves user and stakeholder sentiment towards the newly generated topics, allowing for a fair comparison.

Standard cleaning and preparation steps are followed to prepare the data for analysis. The text was converted to a consistent format through techniques such as lowercasing, removal of punctuation and stop words (insignificant words like articles and pronouns), handling special characters, and stemming (excluding sentimental analysis of tweets and reviews). The resulting text corpus was split into individual tokens or words, creating a document-term matrix (DTM) for topic modeling commands. In this matrix, each row represented an individual document (interview), and each column represented a unique term (word) within the corpus.

### *8.3 Results*

Figure 8 reveals essential insights into Web3 developments in the four industries. This map manages to highlight similar significant groupings of sectors in the same manner as Figure X.

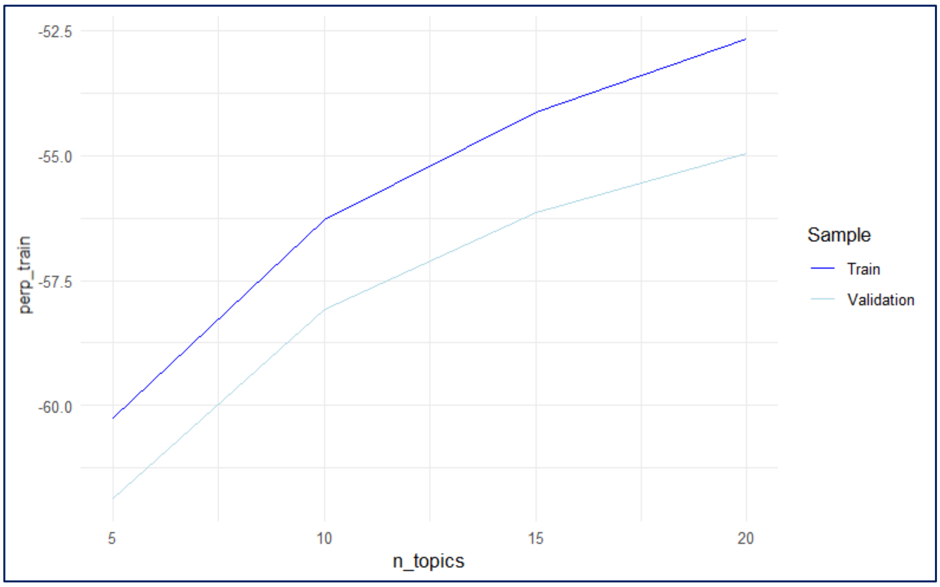
***Figure 8.*** *Word similarity cloud for Study II.*

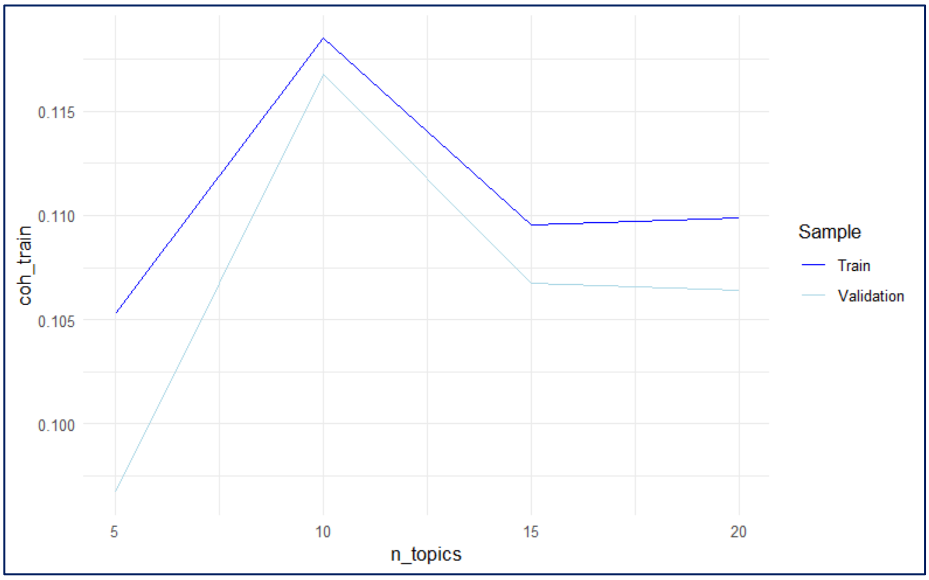



The cloud indicates the significance of trust, security measures, and immutable records in Web3. It emphasises the importance of collaboration, consent, and decentralised control. Web3 can transform healthcare, finance, entertainment, and education industries, offering improved experiences and privacy. It requires ethical considerations and regulatory frameworks for responsible adoption. Web3 addresses privacy concerns, compliance with regulations and promotes transparency. It introduces tokenization, scalability and fosters innovation in these industries. Also, Web3 enables enhanced accessibility, efficiency, ownership, and consumer benefits. It opens up new opportunities and challenges traditional practices. Interestingly, the AI-generated interviews seem to highlight the more technical and ethical terms compared to original interviews ("protocols," "automation," "compliance"). Additionally, this word cloud includes terms like "vr," "nfts," "blockchain," and "defi", stressing the exact technologies involved in the development of Web3.

I compare perplexity and coherence values to determine the optimal number of domains. In Figure 9, the perplexity generally increases as the number of topics increases, but the improvement becomes less significant with more topics. The model with 20 topics has the lowest perplexity value, indicating that it performs best in predicting the held-out data. However, it is essential to consider other factors, such as interpretability and coherence, to make an informed decision. The coherence values, shown in Figure 10, generally increase as the number of topics increases. The model with 10 topics has the highest coherence value, indicating that the topics generated by this model are more coherent and better defined.

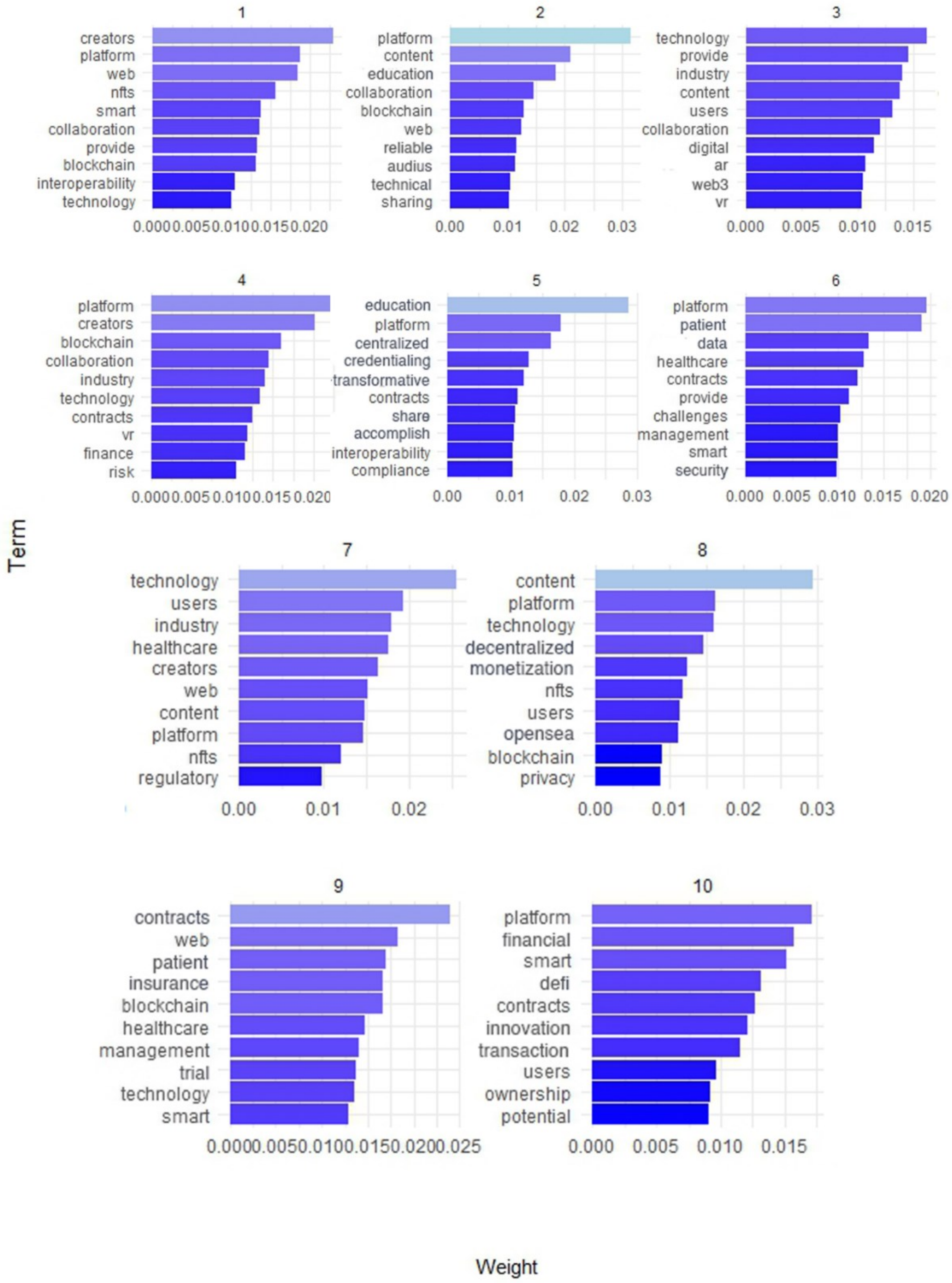
***Figure 9 & 10.*** *Perplexity and coherence values over number of topics (5, 10, 15, 20) – Study II*




Therefore, based on the perplexity and coherence values, I conclude with 10 domains that best balance predictive performance and interpretability. This is similar to the number of topics conducted in Study I, which makes it convenient for comparison later in my research context. Precise coherence and perplexity values over number of topics can be found in Appendix (Table B.4). Next, I apply PCA with the correct number of components (Figure B.2 in Appendix) to purify the topics further and end up with results displayed in Figure 11.

***Figure 11.*** *Purified domains from AI-generated interviews.*




*Note: Numbers represent latent topics identified by the topic modeling algorithm. Term (located left of bar charts) represents individual word that makes up a latent topic. Weight represents the importance of the word in the formation of the topic. Light blue – higher contribution of word to the topic, blue - weaker contribution of word to the topic.*

The purified topics once again unconceal a myriad of interconnected topics which now delve into details about Web3 in collaboration, examples of its blockchain and content creation technology, and smart contracts across the four industries. The first set of topics (1, 2, and 3) mention that there is an intersection of creators, platforms, and web technologies that build up the idea of collaboration and interoperable content on the chain. This theme especially pertains to education (topic 2) and the transformative role of platforms in promoting this collaboration, as well as sharing educational content on hosting (digital) agents like Audius. Moreover, topics 3, 4, and 5 jump into other way of applying this technology in spaces such as virtual reality, augmented reality, and healthcare, where collaboration and the use of smart contracts are key in enhancing patient data management. Lastly, topic 10 draws attention to the innovative role of Web3 technologies in the financial sector, explicitly saying that is has the transformative power of smart contracts and DeFi. These topics collectively showcase the connectedness in collaboration on the blockchain technology, also saying that smart contracts have a potential to change how various industries operate within the Web3 ecosystem.

However, the analysis currently lacks in most up-to-date details of the phenomenon and has yet to identify any more recent trends within Web3 like in the analysis of Study I, which mentions identity verification and further feats in establishing privacy for users on the blockchain network.

Based on sentiment acquired for the outlined domains in Table 5, it appears that NFTs have received the highest normalised sentiment score of 0.92, indicating a largely positive sentiment. The positive sentiment could stem from the excitement around the potential for increased ownership rights, provenance, and value creation in the art world and other industries.

***Table 5.*** *Sentiment retrieved for domains from tweets using AFINN lexicon – Study II.*

| Latent Topic / Domain | Normalised Sentiment Score |
|---|---|
| *1. Collaboration in Web3* | *0.78* |
| *2. Creator Platforms* | *0.70* |
| *3. Content Creation Methods* | *0.37* |
| *4. Smart Contracts in Finance* | *0.81* |
| *5. Credentialing Platforms* | *0.70* |
| *6. Patient Data Platforms* | *0.46* |
| *7. Web3 Implementation (General)* | *0.79* |
| *8. NFTs* | *0.92* |
| *9. Medical Trials* | *0.25* |
| *10. DeFi innovations* | *0.74* |

Smart contracts in finance received a sentiment score of 0.81, indicating a relatively positive sentiment. This could be attributed to the perceived benefits of efficiency and transparency that smart contracts bring to the finance industry. DeFi (Decentralised Finance) innovations received a sentiment score of 0.74, indicating moderately positive sentiment. driven by the potential for financial inclusivity, reduced reliance on centralised institutions, and the ability to access various financial services permissionless. Creator platforms and decentralised credentialing platforms both received a sentiment score of 0.7. The positive sentiment for the first may be due to the potential for creators to have greater control over their content and to be fairly rewarded for their contributions, while for the second refers to the perceived advantages of tamper-resistant credentials and increased trust in the verification process. Patient data platforms received a sentiment score of 0.46, suggesting a more neutral sentiment. The relatively lower sentiment could be due to concerns around the initial privacy, security, and ethical considerations when handling sensitive patient data. On the more down side, Web3 medical trials received the lowest sentiment score of 0.25, suggesting a more negative sentiment. The doubts about blockchain's practicality, scalability, and overall impact in this domain could be an indicator of this.

### *8.4 Comparison and Summary of Studies I & II*

The automated output of both studies offers a critical look into the main aspects of the chosen topic and its industry-wide departments. In Study I, the topics strongly emphasise the importance of new technology and data as a whole and the emerging concept of the metaverse. Privacy, security, risks, and regulations are also identified as critical domains within the Web3 digital space, mainly in the financial field. The role of identity, decentralisation, and digital verification is also added upon, meaning there is a potential of digital identities and smart systems.

In Study II, AI-generated expert interviews are tailored for each industry. As a result, Study II reveals essential insights into specific corners of Web3 development, focusing more on the specifics of the phenomenon - its immersive consumer gadgets, NFTs, and smart contracts. Moreover, the analysis of this Study covers potential areas of transformation and innovation in healthcare, finance, education, and entertainment through the adoption of Web3 technologies. In contrast, the topical results from human interviews mainly cover state-of-the-art concepts and ideas.

Despite the efficiency and crispness of insights gained from AI-generated interviews, one significant limitation is evident—the data only encompassed interviews until September 2021, compared to the richness of insights garnered from Study I. As a result, the analysis might not have captured the latest developments and trends in the Web3 domain beyond that date, which means they are limited to the knowledge available until the model's training cutoff date.

In conclusion of the study comparison, it must be stated that Study I and Study II both offer valuable insights into the chosen phenomenon in various industries. Study I provides a nuanced analysis of existing expert interviews with first-hand expertise in emerging concepts, while Study II explored the potential of AI-generated interviews as an efficient alternative for research. Based on the rundown of the results, it is worthwhile to weigh and consider the limitations of each approach, with Study II holding perhaps inconclusive or inefficient information and Study I being constrained by the abundance of sometimes irrelevant textual information. To gain a broader and more current understanding of emerging phenomena, researchers may benefit from converging the depth of actual interviews in Study I with the efficiency of AI-generated interviews in Study II.

# 9. Measuring Validity

In this section, I evaluate the validity of the purified LDA output by examining the convergence validity and Cohen's Kappa agreement between the derived topics and the topics manually labelled by two human coders. This assessment is ensures the accuracy of the qualitative analysis in capturing the topics found in the interviews across different industries comparing with human-labelled topics.

### *9.1 Convergent Validity*

The convergence validity analysis determines the degree of similarity between the topics generated by the LDA model and those manually identified by human coders. To facilitate the coding process, I provided the human coders with equally balanced AI-generated interviews, which are more concise and efficient than actual interviews. Each coder independently labeled three topics for each interview, resulting in 180 topics provided by each human coder. This assumes each coder received 60 interviews from the total set, equally distributed per industry.

To ensure consistency in the evaluation, some of the topics derived by the human coders are renamed to match the exact labels derived by the LDA model. On the other hand, topics that are considerably different from any of the LDA-generated topics are left unchanged before proceeding with the analysis. For example, “Clinical Trials” was renamed to “Medical Trials”, and “Credentials” was renamed to “Credentialing Platforms”, while "NFTs Ads" and "Real Estate on Web3" where unchanged.

Roughly three-quarters (¾) of the topics from the human coders matched those derived from the LDA model after renaming. This is a high level of agreement, and it indicates a strong convergence validity, implying that the LDA model has effectively captured the main themes discussed during the expert interviews. The relatively high convergence rate suggests that the LDA algorithm performs well in representing the underlying structure of the data.

With that, it is vital to consider the remainder of the topics that did not align perfectly with the LDA-derived topics have been lost in the results, which means they are underrepresented in textual frequency when the algorithm derived the latent topics. Apart from the model's limitations in capturing nuanced concepts, these discrepancies might be attributed to other human factors, such as coder interpretation or differing levels of knowledge and expertise.

### *9.2. Cohen's Kappa Value*

To further evaluate the inter-rater reliability between the generated topics and the human-coded topics, I employ Cohen's Kappa coefficient. Using the formula (8), the Cohen's Kappa coefficient for comparing the generated and human-coded topics is 0.791, indicating substantial agreement between the LDA-generated and human-coded topics. While the obtained indicator value is considered appropriate and shows promising reliability, it is clear that the specific subject matter in my study context should be considered further. As the present topic is of emerging character, it is natural that some information may be misinterpreted by human coders, leading to a slightly decreased Kappa coefficient. In more commonly familiar topics under research, Cohen's Kappa value could be higher by default.

The validity of the framework is confirmed by the two credibility tests. The high convergence validity indicator suggests that the proposed qualitative framework does a good job at outlining important topics from textual data which resemble those derived by human coders. Meanwhile, a high Cohen's Kappa coefficient provides an overview into the consistency of the labeled topics, the familiarity with the topic among the human coders and dependability of the framework. Combining convergence validity and Cohen's Kappa analysis demonstrates that the topic modelling framework is a dependable and valid tool for extracting topics from Web3 expert interviews across the four major industries.

## 9. Discussion

The automated framework proposed in this work as an interim of phenomenological studies of interviews successfully positions itself as a valuable addition in the context of textual exploratory research. The automation mechanism offers an up-to-date scientific procedure for conducting text analysis within interviews and obtains unbiased derivation of the topics positioned within them. The premise of this research was to address the primary research question based on asking how automated text distillation methods are efficient in obtaining similar quality in results when exploring peoples' experience-derived textual data as human derived effort would. By incorporating a standard phenomenological approach for retrieving insights from interviews and extending with an automated text analytics framework, this study has effectively explored the depths of the chosen topic to fit the framework - Web3 technology ecosystem.

The extracted terms, which factually produce the emerging domains in within the subject, encourage the discussion about the trends intra-industry-wide.

The synthesised findings align with the modern relevance of automation in the exploratory research genre, in which previous literature has only touched upon the use of NLP and a few hand-picked machine learning methods to automate research processes. The curatorship of the machine learning methods that make up the automated mechanism enables more precise data analysis and allows research designers to uncover hidden insights behind the lines of vast "thick" data. The newly established automated further contributes to the field by incorporating NLP, machine learning solutions for topic modeling, dimensionality reduction and sentiment analysis into the existing efforts made to the knowledge of phenomenological studies, enabling efficient analysis of complex volumes of human-derived textual information. Automation allows for an enhanced outlook on social phenomena and the peculiarities within humans' behaviour associated with them.

The comparison of Study I and Study II delivers awareness of the strengths and limitations of each approach in the era of generative AI information. Study I, focusing on analysing traditional expert interviews, offers an all-encompassing run-through of the Web3 technology, covering all essential up-to-date topics associated with the term. In contrast, Study II capitalises on the potential of AI-generated expert interviews tailored for specific industries, streamlining the data collection process and providing efficient and targeted insights into more detailed information about Web3 possibly due to the coherence and particularity of the received text through careful prompting. However, the reliance on the AI model's knowledge cutoff date may restrict the analysis to information available until that point, potentially missing recent developments in the context of Web3.

To overcome the limitations of each approach, future researchers may consider combining the depth of available interviews from Study I with the efficiency of AI-generated interviews from Study II. A hybrid configuration of automation and information acquisition like this may provide a more well-rounded outlook of Web3 development, or any other applicable subject for review, offering a powerful way for exploring the rapidly growing landscape of phenomena.

Assessing the validity of framework applied to the interviews is crucial making sure the quality of the study's content is high. The high convergence validity, with approximately 75% of the topics from human coders matching the LDA-derived topics, indicates the effectiveness of the automated approach in capturing the main features discussed during the expert interviews. The substantial agreement demonstrated by Cohen's Kappa coefficient further fortifies the confidence in the automated model's performance. Nevertheless, the 25% of topics which did not ideally converge between human-coded and LDA-generated topics highlight the need to explore potential sources of coder biases or limitations of the LDA algorithm. Future research can try out fitting alternative research topics with the automated framework which line up with the concept of phenomenology or implement other machine learning models to enhance the framework's accuracy of outlining prevalent concepts in the corpus.

Despite the promising signs through easy interpretation of results and the validity of the proposed automated text analysis framework, it is essential to acknowledge its weaknesses. The reliance on the LDA model might only capture some intricate aspects of qualitative data. AI-powered interview text can entail expired consensus on the subject matter that researchers should consider carefully when interpreting the findings. To overcome the limitations of each approach and to enhance the accuracy and consistency of future works, research designers may consider combining the depth of actual interviews from Study I with the efficiency of AI-generated text from Study II.

The automated framework in text analytics based on phenomenology offers a few strengths that positively shape up future exploratory research. Such mechanism levels the research design effort by eradicating the common barrier of human coding of lengthy textual information, allowing its users to explore large "thick" samples on their own without worrying about recruiting additional human power. Furthermore, the inclusive manner of text analytics as a whole enables analyst of diverse backgrounds to make the very best out of the automation aspect of the framework, simultaneously promoting multidisciplinary teamwork.

To wrap things up, the automated framework proposed in this paper stands true with recent exploratory and phenomenology-centered research and lengthens the knowledge in both by empowering forward-looking adopters to effectively "skim" through consumer experience-derived textual input. The model's unbiased output suggests there are meaningful and unexplored (but merely speculated) ideas within Web3 technology across various industries, encouraging businesses and marketeers to think ahead of others in term of innovation and decision-making as a result of understanding this social behaviour. As researchers repose on the outlined strengths of the model prototype, the proposed automated mechanism can add on to the growing bank of apprehension within text analysis.

# 10. Conclusion

This master's project critically weighs an automated framework of inspecting textual representation derived from human experiences in the domain of Web3 development. Its content and elaboration of results successfully answer the established central research question and shows beyond doubt that the proposed automated text analysis technique can substitute manual coding effort in research development and capitalise on the analysis exactness by eradicating the noise of research bias.

The findings in both studies are socially pertinent, as the automated mechanism unlocks possibilities for researchers to grasp the concept of the meanings behind individual voices and human perspectives beyond explicit words. This endeavor brings together interdisciplinary cooperation of researchers and knowledge sharing thanks to its adaptive nature. By careful analysis of the phenomenology in expert interviews and AI-generated interviews tailored for specific industries, the study provides valuable insights into the importance of emerging trends within the Web3 domain. By comparing the performance of Study I and Study II, I present new paths for future research that can combine the depth of human interviews with the precision and clarity of AI-generated discussions. A check of validity of the automated model demonstrates its trustworthiness for adopters in capturing the essential themes discussed in the interviews, further crystallizing its credibility in research.

The offered text analysis framework contributes to the growing popularity of automation in exploratory science and the mechanisation of phenomenology, leveraging advanced techniques to modernise data processing and uncover hidden data inside vast text corpora. While the study concedes the challenges of automated methods, it emphasises the benefits of a structured and valid methodology that combines the latest computational techniques with the variation of qualitative research techniques.

As the advances in analyzing "thick" data evolve, academics and marketeers can learn from the, and from what is highlighted in this study to make evidence-based decisions and navigate the rapidly changing phenomena. The recommended automated framework is a valid methodological discovery in the text analysis bracket, promising an array of smart applications for future exploratory groundwork in areas that require more than basic speculation.

Altogether, this analysis opens new perspectives for data-based decision making, all the while encouraging further integrative collaboration of researchers in the exponentially enticing area of exploratory research.

# Appendix

## *Appendix A*

***Table A.1:*** *Methods overview.*

| Study | Journal | Method | Main Findings / Result |
|---|---|---|---|
| **Fournier et al., (2011)** | *Political Psychology* | Interviews of voting citizens. | A minimal contextualization in an interview can have a sizable effect on people's opinion quality. |
| **Kincaid & Bright (1957)** | *The Public Opinion Quarterly* | A tandem Interview: the interviews were conducted by a man-woman team, and the female team member recorded the notes. | Improved quality of information obtained in the personal interview. |
| **Churchill (1979)** | *Journal of Marketing Research* | An array of suggestions about approaches to assessing the quality of measuring marketing data. | N/A (review paper) |
| **Berger et al. (2020)** | *Journal of Marketing* | Automated text analysis for marketing insight. | Encourages researchers to think about how they can incorporate textual data into their research. |
| **Blei et al. (2003)** | *Journal of Machine Learning Research* | LDA plate notation | N/A (review paper) |
| **Tirunillai & Tellis (2014)** | *Journal of Marketing Research* | LDA (Latent Dirichlet Allocation). | Successful division into dimensions of phone model quality. |
| **Kunz & Hogreve (2011)** | *Journal of Research in Marketing* | PCA domain purification. | Identification of the most prominent research topics in service marketing. |
| **Hennig-Thurau & Feldhaus (2015)** | *Journal of the Academy of Marketing Science* | Sentimental Analysis on tweets. | Early reviews reduce the information asymmetry between producers and consumers. |
| **Hartmann et al. (2019)** | *International Journal of Research in Marketing* | Cross-validation tuning. | Performance spread across the five machine learning methods varies across data sources. |

***Appendix B***

***Table B.1.*** *Most Frequently Used Keywords in Web3 Development (real interviews), 2019 - 2023*

| Keyword | Frequency | Keyword | Frequency |
|---|---|---|---|
| Web3 | 803 | ■ Game | 197 |
| Decentralised | 745 | Privacy | 197 |
| Data | 707 | Collaboration | 193 |
| Blockchain | 670 | Contracts | 192 |
| Technology | 668 | Adoption | 183 |
| ▲Education | 617 | Ownership | 183 |
| People | 524 | Security | 180 |
| Content | 505 | Traditional | 179 |
| Platforms | 478 | Stakeholders | 177 |
| Users | 383 | Information | 176 |
| Industry | 351 | Community | 174 |
| ■ NFTs | 337 | ● Assets | 163 |
| World | 303 | ● Financial | 160 |
| ◆ Healthcare | 301 | Provide | 154 |
| Time | 291 | Sharing | 152 |
| Digital | 289 | Control | 152 |
| ◉ Crypto | 281 | Trust | 150 |
| Access | 247 | Management | 139 |
| Smart | 228 | Web | 138 |
| Potential | 211 | Institutions | 137 |
| ■ Creators | 206 | ■ Create | 135 |
| ● Regulatory | 203 | Network | 135 |
| ■ Build | 201 | Virtual | 134 |
| Space | 199 | System | 132 |
| Experience | 199 | ▲Credentials | 132 |

*Notes. Among the top 50 commonly used words, those associated closely with the educational sector are marked with a closed triangle (▲), those associated with entertainment sector with closed square (■), those associated with healthcare sector with closed diamond (◆),* and *those associated with financial sector with closed circle (●).*

***Table B.2*** *Most Frequently Used Keywords in Web3 Development (AI-generated interviews), 2019 – 2021*

| Keyword | Frequency | Keyword | Frequency |
|---|---|---|---|
| Data | 419 | Identity | 92 |
| Decentralised | 348 | Adoption | 90 |
| Platforms | 316 | Virtual | 86 |
| Content | 252 | Challenges | 86 |
| ■ Creators | 238 | ■ Entertainment | 84 |
| Technology | 236 | Risk | 82 |
| ◆ Healthcare | 224 | Control | 81 |
| Web3 | 207 | Transparency | 80 |
| Industry | 197 | ◆ Ensure | 78 |
| Users | 181 | Provide | 77 |
| Blockchain | 172 | Ensuring | 76 |
| Collaboration | 160 | ● Compliance | 76 |
| ■ NFTs | 149 | ● DeFi | 74 |
| Smart | 148 | Governance | 72 |
| Contracts | 137 | Enable | 72 |
| Regulatory | 131 | Interoperability | 71 |
| Stakeholders | 112 | Digital | 71 |
| Sharing | 111 | Processes | 66 |
| ■ VR | 108 | ◆ Patient | 58 |
| Ownership | 108 | Access | 58 |
| Privacy | 105 | Opportunities | 5 |
| ● Finance | 99 | Mechanisms | 58 |
| Potential | 96 | Access | 57 |
| Security | 95 | ● Assets | 56 |
| Management | 94 | Experiences | 55 |

*Notes. Among the top 50 commonly used words, those associated closely with the educational sector are marked with a closed triangle (▲), those associated with entertainment sector with closed square (■), those associated with healthcare sector with closed diamond (◆), and those associated with financial sector with closed circle (●).*

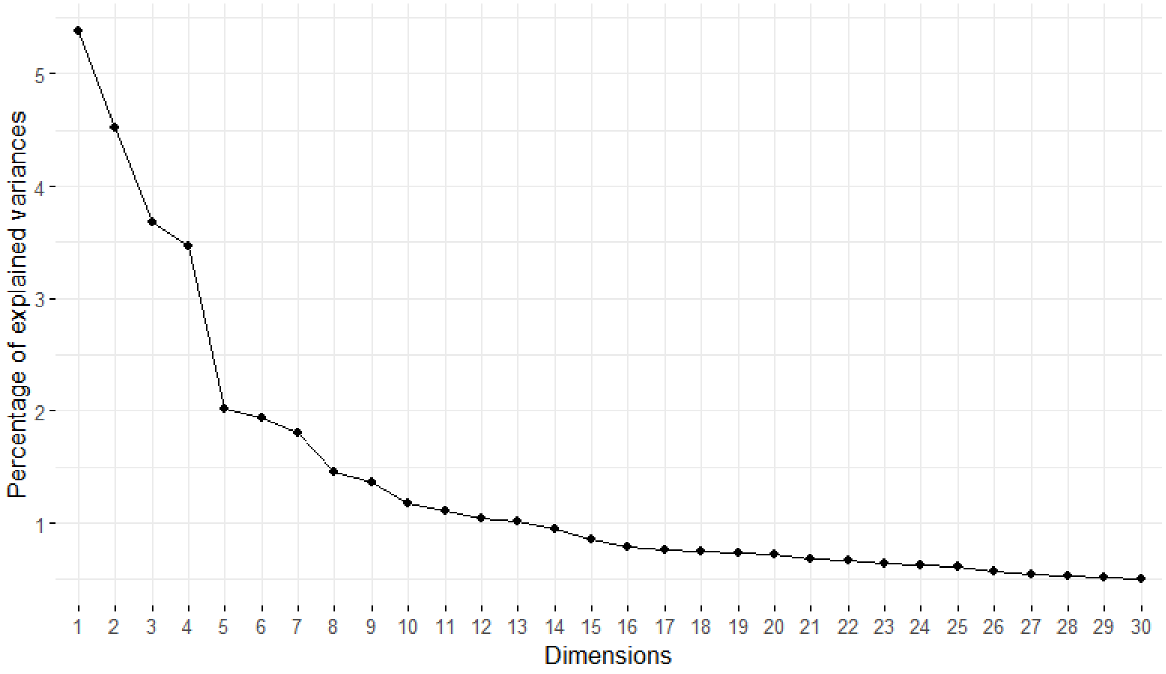
***Table B.3*** *Coherence and Perplexity values for training and validation datasets – Study I*

| n_topics <dbl> | perp_train <dbl> | perp_validation <dbl> | coh_train <dbl> | coh_val <dbl> |
|---|---|---|---|---|
| 5 | -53.50923 | -54.34846 | 0.05981952 | 0.05528902 |
| 10 | -50.64610 | -51.60953 | 0.07995933 | 0.08813336 |
| 15 | -49.11285 | -50.27970 | 0.08392785 | 0.08285764 |
| 20 | -48.47157 | -49.67558 | 0.07214091 | 0.07468643 |

***Table B.4*** *Coherence and Perplexity values for training and validation datasets – Study II*

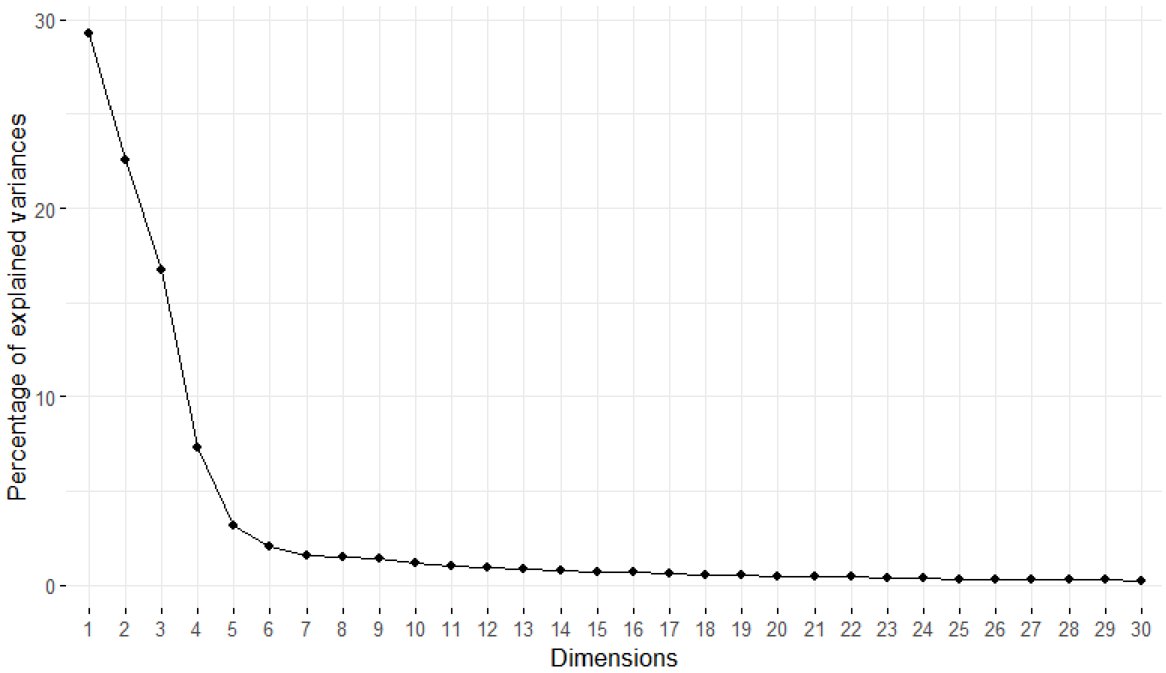
| n_topics <dbl> | perp_train <dbl> | perp_validation <dbl> | coh_train <dbl> | coh_val <dbl> |
|---|---|---|---|---|
| 5 | -60.24179 | -61.86277 | 0.1052994 | 0.09670311 |
| 10 | -56.29000 | -58.08462 | 0.1185053 | 0.11677810 |
| 15 | -54.14041 | -56.13404 | 0.1095722 | 0.10672743 |
| 20 | -52.67464 | -54.95511 | 0.1099001 | 0.10641586 |

***Figure B.1***. *Scree Plot of PCA Analysis – Study I.*




*Note: The scree plot shows the placement of explained variances across dimensions. The Y-axis represents the proportion of variance accounted for by each dimension, while the X-axis denotes the different components. The plot indicates an evident elbow point (5 dimensions), suggesting an optimal number of components for dimensionality reduction.*

***Figure B.2***. *Scree Plot of PCA Analysis – Study II.*




*Note: The scree plot shows the placement of explained variances across dimensions. The Y-axis represents the proportion of variance accounted for by each dimension, while the X-axis denotes the different components. The plot indicates an evident elbow point (5 dimensions), suggesting an optimal number of components for dimensionality reduction.*

***Table B.5.*** *List of Human Coder and LDA – Derived Topics with Frequencies – Study II*

| ***Human Coder- Derived Topics*** | |
|---|---|
| **Human Coder 1 (180 topics)** | **Human Coder 2 (180 topics)** |
| *"Blockchain Aid Distribution"* | *"Blockchain Data Privacy"* |
| *"Blockchain Voting"* | *"Blockchain Voting Systems"* |
| *"Carbon Credit Markets"* | *"Carbon Offset Tokens"* |
| *"Blockchain City Governance"* | *"Collectible Automobile Tokens"* |
| *"Cross-Border Payments with Web3"* | *"Combating Misinformation"* |
| *"DAOs for Creativity"* | *"Content Curation with TCRs"* |
| *"Data Monetization with Web3"* | *"Cross-Chain Interoperability"* |
| *"Decentralized Energy Grids"* | *"DAOs in Web3"* |
| *"Decentralized Philanthropy"* | *"Decentralized Crowdfunding" (4)* |
| *"Decentralized Social Media" (2)* | *"Decentralized Governance"* |
| *"IoT Identity on Blockchain"* | *"Decentralized Health Monitoring"* |
| *"IP Ownership Tokens"* | *"Decentralized Social Media" (3)* |
| *"Landmark Ownership Tokens"* | *"Decentralized Supply Chains"* |
| *"NFTs Ads"* | *"Decentralized Universities"* |
| *"Online Community Governance"* | *"Digital Collectibles Markets"* |
| *"P2P Lending on Blockchain"* | *"Disaster Response in Web3"* |
| *"Real Estate on Web3"* | *"Fair Music Royalties"* |
| *"Remote Work Verification"* | *"Fair Trade on Blockchain"* |
| *"Renewable Energy Trading"* | *"Global Remittances on Blockchain"* |
| *"Smart Contracts for Fair Trade"* | *"Impact Investment Crowdfunding"* |
| *"Smart Contracts in Trade"* | *"IP Management on Blockchain"* |
| *"Startup Funding on Blockchain" (5)* | *"Legacy Industry Challenges"* |
| *"Supply Chain Financing"* | *"Luxury Goods Provenance"* |
| *"Sustainable Agriculture"* | *"Microinsurance in Web3"* |
| *"Sustainable Development"* | *"Monetizing Content with NFTs"* |
| *"Sustainable Mobility"* | *"Music Collabs on Blockchain"* |
| *"Tokenized Health Records"* | *"Open-Source Governance"* |
| *"Transparent Charities with Blockchain"* | *"P2P Energy Trading"* |
| *"Transparent Supply Chains"* | *"Remote Work ID Verification"* |
| *"Virtual Concerts" (3)* | *"Renewable Energy Tokens"* |
| *"Web3 Climate Solutions"* | *"Supply Chain Financing"* |
| *"Web3 Gaming" (4)* | *"Sustainability Tracking"* |
| *"Web3 in Scientific Research"* | *"Tokenized Real Estate Rentals"* |
| *"Web3 Legal Contracts"* | *"Transparent Digital Advertising"* |
| | *"UBI on Blockchain"* |
| *(out of which from LDA output):* | *"Virtual Concerts" (2)* |
| | *"Web3 Gaming" (3)* |
| *“Collaboration in Web3” (15)* | *"Web3 in Agriculture"* |
| | *"Web3 in Legal Industry"* |
| *“Content Creation Methods” (10)* | *"Web3 in Transportation"* |
| *“Creator Platforms” (15)* | *(out of which from LDA output):* |
| *“Credentialing Platforms” (5)* | *“Collaboration in Web3” (18)* |

| | |
|---|---|
| *"DeFi Innovations" (20)*<br>*"Medical Trials" (7)*<br>*"NFTs" (21)*<br>*"Patient Data Platforms" (7)*<br>*"Smart Contracts in Finance" (23)*<br>*"Web3 Implementation (General)" (10)* | *"Content Creation Methods" (9)*<br>*"Creator Platforms" (13)*<br>*"Credentialing Platforms" (3)*<br>*"DeFi Innovations" (16)*<br>*"Medical Trials" (10)*<br>*"NFTs" (18)*<br>*"Patient Data Platforms" (5)*<br>*"Smart Contracts in Finance" (25)*<br>*"Web3 Implementation (General)" (14)* |

| ***LDA-Derived Topics (Study II)*** |
|---|
| *"Collaboration in Web3" "Content Creation Methods" "Creator Platforms" "Credentialing Platforms" "DeFi Innovations" "Medical Trials" "NFTs" "Patient Data Platforms" "Smart Contracts in Finance" "Web3 Implementation (General)"* |

## Resources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