Aggregated Vertical Web Search Results Research Framework

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<u>DECLARATION</u>

By affixing my signature, I affirm that this dissertation is a true representation of my original research. I have made diligent efforts to explicitly attribute contributions from other individuals, providing proper citations to relevant literature, and acknowledging collaborative investigations and discussions.

Supervised by Dr. Umer Rashid from the Department of Computer Sciences at Quaid-i-Azam University in Islamabad, this work has been conducted.

<u>Sumaira Ambreen</u>

<u>08-Sep-2023</u>

DEDICATION

I would like to dedicate my M.Phil dissertation to my parents, grandparents and brothers.

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First and foremost, I express my gratitude to Allah Almighty, for His abundant blessings that have supported and empowered me throughout this research.

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Abstract

Conventional search engines often present users with ranked lists of search results, necessitating manual sifting through documents to extract information. This approach restricts the exploration of web-based multimedia content, particularly when using vertical search engines. Interacting with results from various verticals can lead to a loss of exploration context, making it challenging to assemble relevant information and requiring extensive scrolling and clicking.

To address these limitations, we propose a concise framework for researching of aggregated vertical web search results, facilitating comprehensive exploration of aggregated multimedia documents. Our system employs advanced techniques such as clustering and summarization to efficiently organize search results and enhance user interaction. Non-linear representations, such as tree-map and pie-chart visualizations, offer an intuitive and interactive exploration experience. The proposed system's user-friendly interface enables seamless exploration across disjoint verticals, maximizing contextual understanding and cognitive engagement.

A comprehensive assessment of the proposed aggregated research framework, tool, and mechanism has been undertaken for the purpose of general usability research and empirical analysis. The collective findings vividly demonstrate the precision and feasibility of the aggregated research frame-

work. The user interface (SUI) of the proposed tool proves to be user-friendly, delivering a high level of satisfaction while minimizing the number of clicks required and seconds spent.

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Chapter 1

Introduction

1.1 Background

According to [Chinnasamy (2016)], humans possess an innate inclination for exploration. Through interactions with their surroundings, explorers endeavor to extend their knowledge beyond the immediate realm before them [Palagi et al. (2017)]. Humans strive to satisfy their social and psychological assimilation, as well as their world-learning needs. In the capacity of explorers, we amass data to refine our sophisticated cognitive capabilities [Palagi et al. (2017)]. These capabilities encompass evaluation, synthesis, analysis, and comprehension [Palagi et al. (2017)]. This progression evolves from a vague awareness of lacking something to discerning the particulars that contribute to comprehension and significance [Chinnasamy (2016)]. In the late 1989, Tim Berners-Lee conceived the World Wide Web to address the challenge of information exploration [Hiremath and Kenchakkanavar (2016)].

The potential of systems to interconnect and retrieve information across myriad computers via the internet constituted a novel notion made feasible by the web [Storsul (2019)]. During its nascent years, textual content predominated the web [Rashid and Bhatti (2017)]. Marking the 32nd anniversary of the internet, there has been an exponential surge in the number of web users. The colossal volume of internet data necessitates management with the assistance of millions of interconnected devices [Flores-Martin et al. (2019)]. The availability of audiovisual content has substantially expanded as a consequence of the internet's proliferation [Rashid and Bhatti (2017)]. Myriad travel blogs, sightseeing photos, films, and various other forms of multimedia content have been contributed by users [Vrochidis et al. (2018)]. Presently, a substantial volume of multimedia content encompassing audio, video, and imagery is generated daily on the internet [Gupta et al. (2016)]. Users are increasingly inclined to conduct internet searches for points of interest in order to locate requisite information [Vrochidis et al. (2018)].

Since its inception, the web has embarked on a remarkable journey of expansion, evolving in both scale and sophistication, thereby solidifying its status as the preeminent and widely embraced platform in contemporary times [Taheri et al. (2018)]. This extraordinary growth has not only manifested in sheer quantity but has been accompanied by a discernible enhancement in its inherent quality as well. The web's pervasive influence has transcended boundaries and seamlessly integrated itself into the fabric of modern society, shaping how we interact, learn, and communicate.

As the digital landscape continues its rapid evolution, a critical imperative emerges: the necessity to transcend the confines of traditional data organization and classification frameworks [Zhou et al. (2016)]. This imperative arises from the sheer magnitude of information coursing through the digital arteries of the web a torrent that defies conventional methodologies. To ensure the accessibility and coherence of this vast informational ecosystem, innovative paradigms of categorization and navigation must be forged. The dynamic interplay between the escalating volume of web-generated content and the human quest for knowledge underscores the urgency to sculpt novel methodologies for information dissemination. Only through this unyielding dedication to adaptability and progress can we truly unlock the boundless treasures concealed within the labyrinthine corridors of the digital universe.

1.2 Verticals Aggregation Exploration

In today's digital age, the internet has seamlessly integrated into virtually every aspect of people's lives, serving as a fundamental conduit for accessing information [Tan and Goonawardene (2017)]. The widespread accessibility of the internet has made it the go to resource for most individuals when they embark on quests for knowledge. This phenomenon is commonly referred to as information exploration, which involves the active pursuit of information to bridge gaps in understanding or achieve specific objectives [Lu and Hsiao (2017)]. This process unfolds in response to the recognition of a knowledge deficit that impedes the completion of tasks [Lu and Hsiao (2017)]. Notably, as a consequence of the rapid assimilation and extensive utilization of multimedia data encompassing images, audio, video, and text users' information exploration behaviors have evolved from a reliance on purely textual content [Gupta et al. (2016)].

The digital landscape continues to undergo dynamic shifts, and the internet's role as a gateway to information remains unwavering. The accessibility and interconnectedness facilitated by the internet have not only democratized information access but have also redefined the very essence of knowledge exploration. In an era where multimedia has become an integral part of communication, users are no longer confined to traditional textual sources; instead, they navigate a diverse array of mediums to satisfy their quest for understanding. This multidimensional information seeking paradigm underscores the need for tailored strategies that accommodate the evolving preferences and motivations of modern digital explorers.

The motivations driving users' engagement with multimedia artifacts have undergone a transformation in the twenty first century, reflecting the changing landscape of information consumption [Pantic (2020)]. In this era, users are increasingly drawn to multimedia information not merely for the acquisition of knowledge, but also to satiate their need for security, curiosity, and a deeper understanding of themselves, their communities, and the broader world [Pantic (2020)]. The quest for multimedia content, ranging from movies and photographs to hyperlinks and other forms of media, is fueled by users' intrinsic desire for gratification and enrichment [Pantic (2020)]. As the seeker's information void begins to dissolve, the information search process culminates, marking the conclusion of the journey [Lu and Hsiao (2017)]. As users traverse the digital realm in pursuit of knowledge, the transition from textual-centric approaches to multimedia driven exploration mirrors the shifting landscape of modern information consumption. Embracing this evolution requires a nuanced understanding of users' motivations, aspirations, and the ever expanding array of multimedia resources, ultimately fostering a more enriching and fulfilling information exploration experience.

1.3 Verticals Aggregation Search Engines

In the present age of information, our daily routines encompass a multitude of information processing tasks, prominently including the pursuit of electronic information [Vuong et al. (2019)]. With each passing day, billions of users embark on a plethora of web searches, progressively incorporating diverse applications and services beyond the web itself for their information quests [Vuong et al. (2019)]. This paradigm shift is an outcome of the internet's ability to furnish instantaneous, extensive, and continuously updated information [Dutta and Das (2017)]. The virtual expanse of this digital library, accessible through the modest screens of personal computers, encompasses an array of digital formats, ranging from entire manuscript collections and well worn printed documents to invaluable archival materials, photographic archives, and dispersed yet invaluable audio visual compilations [Nori et al. (2020)]. Additionally, this repository boasts a diverse assortment of electronic resources, spanning electronic books, journals, reports, and various other digital assets [Nori et al. (2020)]. In today's landscape, online searches have become almost ubiquitous, penetrating households, workplaces, and educational institutions alike [Yamamoto and Nah (2018)].

This ubiquity is attributable to the internet's global nature and its incessant accumulation of information [Yamamoto and Nah (2018)]. Remarkably, individuals can delve into and disseminate information on a nearly boundless array of subjects within this vast digital realm [Yamamoto and Nah (2018)]. Within the web's expansive confines resides an ever evolving and exceedingly heterogeneous collection of documents, reflecting the dynamic nature of the digital ecosystem [Pouyanfar et al. (2018)]. In tandem with this evolution, the internet is witnessing an unprecedented surge in multimedia assets, encompassing images, videos, and audio files [Pouyanfar et al. (2018)]. However, this abundance of highly diverse multimedia data has ushered in both novel opportunities and intricate challenges in the contemporary era of voluminous data.

Users have become adept at employing conventional web search engines, which typically necessitate the input of query phrases, to unearth multimedia content scattered across the digital expanse [Gäde et al. (2015)]. These search results are often presented in a diverse array of formats, comprising web pages, images, videos, and an assortment of files [Kathuria et al. (2016)]. Nevertheless, the sheer pace and extent of the transformations within online data are staggering [Batrinca and Treleaven (2015)]. The resultant information mosaic is an intricate, multifaceted virtual organism woven from blog fragments, publications, web services, photo galleries, and an assortment of other sources [Batrinca and Treleaven (2015)]. Addressing the diverse spectrum of user information needs necessitates the aggregation of indexes compiled through comprehensive web crawling by general web search engines, including but not limited to Baidu, Bing, Google, Yahoo!, and Yandex [Nguyen et al. (2012)]. These engines currently harness state-of-the-art technologies for information retrieval, embodying the cutting edge of internet-based search mechanisms [Kathuria et al. (2016)].

Beyond standardized information, these search engines often yield rich results spanning structured data, photographs, news, videos, and the broader web [Wang et al. (2016)]. As elucidated by [Wang et al. (2016)], each distinct corpus, termed a vertical, manifests with unique visual attributes, layouts, and dimensions, frequently spanning multiple columns on the page. In the face of this deluge of data, the imperative of transforming the web into a more potent and beneficial information repository is underscored [Pouyanfar et al. (2018)]. Facilitating this transformation is the role of information retrieval systems, colloquially referred to as search engines, empowering online users to navigate the vast expanses of the internet in pursuit of vital information [Kataria et al. (2015)]. This phenomenon encompasses a vast spectrum of topics, encompassing articles, news, sports, history, products, multimedia, and an array of other subjects [Kathuria et al. (2016)]. As research by[Kathuria et al. (2016)] attests, the employment of search engines ranks as the second most prevalent online activity among internet users, showcasing the pivotal role these engines play in shaping modern digital interactions.

1.4 Verticals Aggregation Search Paradigm

The process of conducting a search is typically characterized by several distinct steps, commencing from the initial encounter with an information demand and culminating in the generation and provision of a final response set. Upon registering an information requirement, searchers embark on the formulation of a search plan, which involves explicitly verbalizing the request. This phase also entails the strategic selection of which search engines and databases to engage with first and in what sequential order [Gäde et al. (2015)]. Subsequently, query formulations are devised to interrogate the chosen databases. Execution of the search strategy and the generation of an answer set that adequately addresses the information demand follow suit. A salient advantage of internet searching resides in the users' capability to adjust and refine their search approach at any juncture [Ruotsalo et al. (2018)].

Furthermore, throughout the entirety of the search process, individuals retain the ability to modify the phrasing of their queries. However, succinct and narrowly formulated search queries struggle to keep pace with the escalating expectations of contemporary online user services [Athukorala et al. (2016)]. As [Ruotsalo et al. (2018)] posit, human information demands are evolving to encompass increasingly intricate and inquisitive pursuits. One particular manifestation of information-seeking behavior is characterized as exploratory search [Palagi et al. (2017)]. In contrast to solely seeking definitive answers to queries, exploratory search encompasses instances where users engage with the search process to enhance their comprehension, expand their knowledge, explore novel concepts, and more.

Exploratory search, as an integral facet of this endeavor, not only fosters intellectual growth but also nurtures curiosity and a deepened understanding of diverse subjects. By empowering users to traverse an intricate network of ideas, insights, and data, the process of exploratory search has evolved into a pivotal mechanism for holistic learning and cognitive expansion. As users increasingly demand more from their online interactions, the concept of exploratory search continues to evolve, enriching the digital experience and promoting a more profound exploration of the boundless realms of information. The primary objective of exploratory search is to facilitate users in accomplishing more intricate tasks, often necessitating the evolution and transformation of search intentions, in addition to delivering relevant outcomes for specific queries [Ruotsalo et al. (2018)]. These tasks are principally categorized into convergent and divergent pursuits.

1.4.1 Convergent

Convergent search tasks are oriented toward generating discrete and meticulously structured outcomes [Russell-Rose and Tate, 2012]. In the realm of convergent search, an issue is presented with a high degree of specificity and clarity, leaving no room for ambiguity regarding the prerequisites of the sought after solution. This is exemplified by elements such as names, numbers, and concise sentences. Convergent searches predominantly focus on the dimensions of who, when, and where [Russell-Rose and Tate, 2012]. These distinct search tasks are occasionally referred to as "known item" searches.

A prevailing perception among users labels these endeavors as "fact retrieval" or "question answering" exercises [Russell-Rose and Tate, 2012]. As elucidated by [Ruotsalo et al. (2018)], convergent search tasks are frequently analytical in nature, characterized by meticulously crafted queries designed to yield precise outcomes, thereby minimizing the need for extensive result evaluation. However, in the era of the internet's ascendancy as the primary source of information, users are increasingly seeking enhanced support for tasks that exhibit a dual nature of comprehensiveness and complexity [Ruotsalo et al. (2018)]. In the swiftly evolving landscape of digital information retrieval, the role of convergent search tasks remains pivotal, providing swift and precise solutions to well-defined queries. However, the expanding horizons of user expectations and the intricate interplay between technology and information-seeking behavior demand a broader perspective. Users no longer solely engage in fact retrieval; they seek to extract insights from vast and multifaceted information repositories. In response, search engines and digital platforms must adapt, evolving to cater not only to discrete inquiries but also to accommodate the spectrum of users' exploratory quests. This shift towards comprehensive and nuanced support acknowledges the diverse dimensions of modern information needs and positions technology as a facilitator of not just answers, but deeper understanding and insight.

1.4.2 Divergent

In contrast to inquiries centered around who, when, and where, diverse search activities are intricately tied to the realms of what, how, and why [Russell-Rose and Tate (2012)]. These multifaceted responsibilities necessitate the amalgamation of knowledge derived from diverse sources, encompassing a broad spectrum of valid solutions [Russell-Rose and Tate (2012)].

Given their limited pre-existing subject expertise, individuals engaged in such tasks often approach essential documents within the collection, meticulously exploring their contextual surroundings [Russell-Rose and Tate (2012)]. The evolution of search activities mirrors the ever-changing nature of information needs in an interconnected world. Modern search tasks transcend mere retrieval, encompassing a synergy of learning and investigation that empowers users to engage with information in a multifaceted manner. As individuals seek to decipher complex phenomena, address intricate queries, and glean insights from an expansive digital landscape, the potency of search engines becomes increasingly pronounced. These assignments harmoniously blend the realms of learning and investigation [Ruotsalo et al. (2018)].

As outlined by [Russell-Rose and Tate (2012)], learning activities encompass the acquisition of novel knowledge, entailing cognitive processing and iterative search endeavors. Conversely, investigative tasks revolve around identifying gaps in knowledge, frequently in service of strategic planning and prognostication, or the transformation of existing data into innovative insights [Russell-Rose and Tate (2012)]. The overarching objective, as posited by [Russell-Rose and Tate (2012)], revolves around the acquisition of information through a holistic process that involves comprehension, interpretation, comparisons, and the organization of concepts and data. Contemporary users increasingly harness the power of search engines to navigate the vast expanse of online information and fulfill their search undertakings [Hassan Awadallah et al. (2014)]. The digital era has witnessed a paradigm shift in how individuals interact with information, leveraging technology to facilitate their exploration and comprehension of various subjects. As users embark on these dynamic information-seeking journeys, search engines play an integral role, not only as gateways to data but also as tools that empower users to uncover insights, derive meaning, and satiate their intellectual curiosity.

1.5 Deficiencies in Verticals Aggregation Exploration

In order to navigate the information space effectively, the users' complicated information-seeking behavior is treated as a non-linear journey [Ruotsalo et al. (2018)]. The information is sought for by the users [Bates, 1989]. The existing concept of giving the most exact information in answer to the given queries does not satisfy their complicated information needs [Russell-Rose and Tate (2012)]. Instead, users select the most intriguing items from different information patches, giving more information for the same amount of work [Russell-Rose and Tate (2012)]. Users develop a non-linear pattern of information searching as a result [Russell-Rose and Tate, 2012]. The search engines, on the other hand, are more geared for straightforward lookup queries that favor precision over recall [Tablan et al. (2015)]. Internet users frequently come across a lot of irrelevant material because many web search engines rank their search results according to link popularity or methods other than relevance [Swar et al. (2017)]. As a result, it might be challenging to find the most desirable results. The search engines have begun to incorporate some vertically-specific results compiled from the other data sources as a result of their recognition of the consumers' needs for multimedia information [Bakrola and Gandhi (2016)]. Information exploration is nonetheless limited by the widespread practices of information presentation in the form of a linear sorted list of predetermined findings [Rashid and Bhatti (2017)]. Additionally, the integration of the verticals is primarily partial-blended [Rashid and Bhatti (2017)], which may be suitable for straightforward lookup searches if a user knows what to look for, but is in-sufficient for complicated information exploration and discovery jobs [Tablan et al. (2015)]. [Ruotsalo et al. (2014)] These tasks go beyond straightforward keyword-based queries. Users frequently struggle to describe their information demands, which are typically dynamic [Ruotsalo et al. (2014)]. These tasks call for a variety of information sources, greater recall than precision, and [Tablan et al. (2015)]. It questions the conventional wisdom of grouping search results from various verticals into separate collections [Rashid and Bhatti (2017)]. It demands that users be able to search for and retrieve multimedia information [Gupta et al. (2016)]. In comparison, search engines are still essentially the same as they were a decade ago. According to empirical studies, people struggle with exploratory search sessions in between 40% and 65% of web search sessions [Ruotsalo et al. (2018)]. The present search engines have a lot of issues. As separate components, the verticals are integrated [Rashid and Bhatti (2017)]. According to [Rashid and Bhatti (2017)], the connections between multimedia objects are disregarded. Linear lists continue to be used to display the information [Ruotsalo et al. (2018)]. For straightforward lookup activities, this presentation of the information from conventional search engines might be adequate, but it falls short for difficult exploration tasks [Klouche et al. (2015)]. Increased recall is preferred over precision, information fragrance, and sensemaking are all required for these tasks [Tablan et al. (2015)]. A new method to encode and show multimedia information for research is required due to the shortcomings of the current exploration methodologies [Rashid and Bhatti (2017)], [Gäde et al. (2015)], [Russell-Rose and Tate (2012)], [Ruotsalo et al. (2018)]. The existing web search engines have the following shortcomings:

- The existing search engines continue to treat exploratory search as a lookup activity and limit the study of multimedia content by displaying search results as a linear list.

- The search engine result page still combines the multimedia verticals as separate elements.
- Because the relationship between the retrieved multimedia search results is frequently disregarded, pertinent information is dispersed throughout the results.
- Unlike exploratory searches, which are conducted before retrieving all relevant results, traditional searches are more inclined towards precision than recall.
- The purpose of an exploratory search is frequently to obtain an overview of the available information, although traditional presentation of the search results lacks search space understanding.
- The non-linear navigation pattern of exploratory searches is constrained by the non-linear nature of the search results.
- A lack of research and exploratory tools that assist both information search and exploration activities.

1.5.1 Motivation

In this research, we proposed a formal "Aggregated Vertical Web Search Results Research Framework" to address the browsing, reachability, scrolling and navigational issues of vertical web search results. In our presented solution to explore vertical web search results:

1. Browsing is supported via a well structured Search User Interface (SUI), where users exploratory tasks non-linearly by utilizing a variety of interaction options, including as overview, grid and tree-map, and pie-chart visualizations.

2. Reachability enables quick access to vertical web search results by requiring travelers to pass through the fewest possible intermediate hubs.

3. Scrolling the tee-map and pie-chart representations of vertical web search results provide no scrolling to save the user time and effort.

4. Navigation, allows for non-linear exploration of a graph of image results.

5. Use of real dataset to avoid the lack of generic exploration mechanism using Semantics.

1.5.2 Research Questions

To carry out this research study, the following research questions have been formulated:

1. Are web users interested in researching aggregated vertical web search results to fulfill their information needs?

2. How can a framework be codified to provide the research and exploration of aggregated vertical web search results nonlinearly and efficiently?

3. How can a Search User Interface (SUI) be designed to provide the research and exploration of aggregated vertical web search results in a useful way?

4. Do clusters and graphs accurately represent precise results, and does the reachability of exploratory activities improve through intra-cluster result connectivity via multimodal links?

5. Do the SUI design, connected exploration mechanism, and aggregated vertical web search results research tool enable a usable exploration of vertical web search results?

1.6 Thesis Organization

Chapter 1 begins the discussion from the textual to shift of multimedia background with respect to user information need. Based on user's information seeking journey, the information searching paradigms were identified and for research paradigm is briefly discussed. We deficiencies in the existing exploration approaches are identified and the relevant research questions were took into consideration and set forth our motivation and problem statement. In the concluding remarks, we identified in the existing discovery approaches and set forth our problem statement.

Chapter 2 elaborate the theoretical background as well as in the domain of information exploration related work done is provided. The dissertation's "Research Question 1" is addressed in this chapter. With the help of literature,the critical analysis is provided and with respect to most recent state-of-the-art approaches and techniques the discussion is combined. The benchmarks, evaluation strategies and measure are employed in existing literature with closing remarks to conclude this chapter.

Chapter 3 provides our formalized aggregated vertical web search result research framework. We presents proposed framework's theoretical foundation and our our approach's instantiation details. A comparison of our proposed approach is briefly provided with the existing state-of-the-art approaches and techniques to determine the effectiveness of our proposed approach in comparison with existing approaches. The dissertation's "Research Question 2" is addressed in this chapter.

Chapter 4 presents a discussion on the research framework & user behavior. We are concerned here precisely demonstrating the information exploration by user perspective with the help of a case study, and existing techniques and literature. We explain our research design and a discussion is provided on how the information exploration is provided. The dissertation's "Research Question 3" is addressed in this chapter.

Chapter 5 provides evaluation methodology we used to evaluate our research framework, it presenting evaluation measures such as apparatus, instruments and procedures as well as tasks. The dissertation's "Research Question 4" is addressed in this chapter and explains the obtained results from the substantial evaluations and an in-depth discussion is provided about the findings.

Chapter 6 conclude the dissertation overall taken into consideration our research contributions and in brief summary the detailed concluding remarks in this dissertation on everything are discussed. The dissertation's "Research Question 5" is addressed in this chapter

Chapter 2

Literature Review

The representation of multimedia content across multiple verticals has gained significant importance in the realm of vertical web search. Within the context of aggregated search processes, the selection of verticals assumes a pivotal role. This selection procedure furnishes a list of relevant verticals, subsequently refining the pool of candidate verticals by eliminating those that are deemed non-relevant [[Achsas et al. (2018)]]. This dynamic scenario encompasses two distinct but interconnected dimensions: lookup searches, geared towards retrieving precise responses to questions involving who, when, and where [White and Roth (2009)], and exploratory searches, delving into broader questions of what, when, and how, demanding versatile strategies to navigate their intricate terrain [White and Roth (2009)]. In the context of research, the notion of exploratory searches intertwines organically with the concept of aggregated vertical web search results. The propose to explore the literature is to address the first Research Question ("Do web users show an interest in researching the outcomes of vertical web searches to fulfill their informational needs?") Central to the philosophy of exploratory searches is the proactive expansion of knowledge, underpinned by the study and immersion in subjects. Navigational strategies are pivotal to this process, mirroring the active involvement of users in the search journey [Gäde et al. (2015)]. The research framework embraces this essence, emphasizing the design of search systems that not only involve users but empower them through intuitive visual interfaces enriched with semantic insights, inherent structures, and meaningful categorizations [Gäde et al. (2015)].

This chapter on Literature Review is organized into several coherent sections. Section 2.1 embarks on a comprehensive exploration of web search mechanisms. Proceeding to Section 2.2, an elucidation of vertical web searches ensues. In Section 2.3, the focus shifts to the outcomes of vertical web searches, namely, the vertical web search results. Building upon this, Section 2.4 delves into an overview of existing state-of-the-art methodologies. Undertaking a discerning perspective, Section 2.5 engages in a critical analysis of the existing paradigms. Subsequently, Section 2.6 delves into the subject of benchmark datasets and the strategies employed for evaluation purposes. Concluding this review with synthesis, Section 2.7 encapsulates the essence of the discourse presented throughout this chapter.

2.1 Web Search

Due to the widespread accessibility of computers and the internet, users find themselves conducting information searches on a daily basis [Pouyanfar et al. (2018)]. According to researchers, this searching is primarily divided into lookup and exploratory searches. The most basic form of searching is considered to be lookup. The terms "known item" and "fact retrieval" are also used to describe it [White and Roth (2009)]. The main goal is to find a precise response to the "who," "when," and "where" questions. In exploratory searches, the "what," "when," and "how" questions are sought after. There are various ways to answer these open-ended, complex questions [White and Roth (2009)]. Exploratory search has been described as a process of studying and researching the subject matter to broaden one's knowledge base. Support for browsing strategies is necessary for this knowledge-gaining browsing journey. To describe this procedure and the user's active participation in the search process, the term "Human-Computer Information Retrieval" is also used [Gäde et al. (2015)]. To achieve this, researchers must leverage their knowledge and expertise to create search systems that actively engage users by organizing intuitive visual workspaces using semantics, inherent structure, and meaningful categorization [Gäde et al. (2015)].

Web applications are now using exploration techniques to better understand and meet user needs. The world has entered a massive multimedia era with the rise of handheld devices and internet services [Pouyanfar et al. (2018)]. The number of multimedia objects, such as image, video, and audio files, is increasing online, and users can access this virtual library on the small screen of a personal computer. According to [Summers and Punzalan (2017)], this library's digital collection includes a variety of electronic resources, including electronic books, electronic reports, electronic journals, printed documents, the complete manuscript collection, photographic collections, materials with significant archival value, oral history recordings, and other helpful dispersed audio-visual collections.

While using a relevant document search engine like Google, the PageRank algorithm is employed. However, the PageRank algorithm has certain drawbacks. For instance, sometimes the relevant hidden pages are not retrieved by the focused crawlers [Pavani and Sajeev (2017)]. These hidden pages may contain important information similar to the displayed page. To address this, these hidden pages can be retrieved by combining semantic similarity information and page ranks to retrieve the relevant pages. This approach ensures that all relevant information is displayed accurately. For vertical web search engines, an important algorithm used is the link selection algorithm such as HITS. This algorithm performs better for vertical searches, enhancing exploration across multiple verticals [Zheng et al. (2009)]. Many research activities on the web are performed actively. A flexible facility is provided for measuring the performance of web search servers and generating HTTP workloads [Xi et al. (2011)]. Therefore, all web search engines are required to satisfy these types of information needs based on the user query. The multimedia and textual content is integrated and represented, which is accessible by using a web search engine [Vrochidis et al. (2018)]. There exist differences between adults and school-going children in the perception of SERPs on web search [Gossen et al. (2014)]. Children pay more attention to attractive things during searches, such as thumbnails and embedded media. Additionally, children prefer navigational menu categories. On the other hand, adults pay more attention to textual summaries and less attention to navigational menu categories [Gossen et al. (2014)]. Different search engines designed especially for adults and children explain that Google, as a benchmark, provides more effective results than Yahoo Kids [Bilal and Ellis (2011)].

To check the performance of different search engines in the Arabic language, [Tawileh et al. (2010)] explore five search engines: Google, Yahoo, Arby, Ayana, and MSN in Arabic language and evaluate that Google outperforms other search engines. They also reveal that although both Arabic web search engines perform better in the native language, neither of them has the ability to compete internationally. Web search is required in every area of life. Architectural knowledge retrieved from the web is explored and utilized by software engineers, who require up-to-date knowledge about architectures to make informed design decisions [Soliman et al. (2021)]. With the passage of time, the behavior of web search engines has changed, and search interfaces have improved as users now perform mobile searches as well as desktop searches. This improvement in web search engines provides more feasibility for users to fulfill their information needs [Strzelecki (2020)]. On the web, there are many web search engines, and these search engines require appropriate searching methods for retrieving relevant topic information. Using the right search engine at the right time will provide the best relevant results [Seymour et al. (2011)].

Behind every user query in web search, the goal might be a transactional search, a navigational search, or an informational search. Navigational search is one where the user seeks to find a specific website based on their information needs. Some mediated activity is performed during transactional searches, while informational searches are about finding specific information on a topic [Broder (2002)]. Web search engines on the web contain websites that consist of multimedia content, which can be displayed as search results [Seymour et al. (2011)]. When a document is displayed as a result of a user query, its ranking is important. This document ranking can be improved by combining two different approaches instead of relying on a single approach. One approach matches the query with the local representation of documents, and the other uses learned distributed representation. This approach results in more effective and favorable displayed results [Mitra et al. (2017)]. User queries are efficiently processed when search engines are based on cache hierarchy, which is more useful compared to simple queries as cached data leads to faster search results [Marin et al. (2010)].

2.2 Vertical Web Search

Multimedia content representation from various verticals has gained significance in vertical web search [Liu et al. (2015)]. Diverse approaches are employed to represent pertinent documents, which are centered around document judgment to attain relevant verticals. Consequently, this approach aligns vertical relevance—predicated on collections—with vertical intent [Liu et al. (2015)].

During a vertical web search, users browse to acquire requisite information, a process that inevitably consumes time. Search engines furnish users with copious amounts of information, which at times only partially satisfies their informational needs. This situation arises mainly due to the non-specific nature of most search engines. Users, understandably, are not content with sifting through vast amounts of data to find the information they require. To address this, a domain-specific model has been developed and implemented. This model streamlines the process of obtaining precise and easily accessible information [Sriramoju and Gadde (2014)].

A vertical search engine tailored for disaster situation reporting within a specific domain offers navigational and presentation tools for both disaster-related and geographical information. Furthermore, this disaster situation reporting platform incorporates information monitoring and analytical tools essential for facilitating decision-making during the recovery phase of a disaster [Zheng et al. (2012)].

The PageRank algorithm encounters certain limitations, such as the "rich get richer" phenomenon. Often, pertinent but concealed web pages are not retrieved by focused crawlers. In such scenarios, vertical search tools emerge as pivotal solutions. By employing web query interfaces, users can effortlessly access domain-specific information [Castro et al. (2018)].

In their work, [Gil-Costa et al. (2012)] introduced the CPN (Colored Petri Net) model for predicting the behavior and performance of vertical search engines. The CPN model's principal objective lies in evaluating diverse service configurations, including workload distribution across resources below 40%, maintaining consistent query throughput, and ensuring query response time remains below specified upper limits. Query throughput, denoting the number of processed queries per unit time, is a key metric. Notably, the modular design of CPN enables the incorporation of alternative vertical search engine components. Performance evaluations of this model underscore CPN's efficacy in exploring various scenarios and determining optimal search engine configurations.

2.3 Aggregated Web Search

By seamlessly amalgamating essential web outcomes with specialized niche search providers, the concept of aggregated search yields a harmonious and dependable user interface. This innovative approach not only integrates diverse search sources but also ensures a uniform and intuitive experience for users. The seamless fusion of primary web findings and distinct niche resources culminates in an aggregated search that delivers a unified and seamless browsing encounter. This synergy of core and specialized search elements results in an aggregated approach that fosters a cohesive and user-centric interface. The aggregated search is further broken down into federated search and media specific search with detail discussion as below:

2.3.1 Federated Search

Federated web search stands out as a pivotal technology for information retrieval, enabling exhaustive database and multi-search engine exploration to cater to every user inquiry. This method culminates in an amalgamation of results for user presentation. Across diverse domains such as Shopping, Health, and Recipe, researchers, as exemplified in [Sardar et al. (2019)], evaluate the efficacy of different techniques based on resource selection. A pioneering endeavor, as showcased in [Arya et al. (2015)], employs personalized federated search to mine LinkedIn users' intent through recent activities and profile data. This data-driven approach optimizes the LinkedIn Homepage, thereby substantially enhancing member engagement.

An innovative contribution by researchers, detailed in [Collarana et al. (2016)], introduces FuhSen—a hybrid, RDF-based, federated search platform that harnesses LinkedIn data for searching, summarizing, and integrating information from diverse sources. FuhSen exhibits a federated architecture wherein a single user query triggers multiple searches across information sources, followed by aggregation for user-friendly presentation. This hybrid vocabulary-centric federated search embodies a semantic integration pattern, encompassing universal search and multimodal retrieval. Exploring beyond traditional boundaries, Tanium Reveal emerges as a trailblazing federated search engine, as presented in [Stoddard et al. (2021)]. Leveraging the Tanium platform, Reveal orchestrates network communication, facilitating asynchronous indexing and parsing at network endpoints. Deployed on enterprise networks, this design demonstrates swift data query execution across billions of files.

In a recent advancement [Tian et al. (2021)], FALIoTSE, an IoT search engine underpinned by federated adversarial learning, is introduced. The proposed approach leverages shared federated model parameters, as exemplified in smart parking garage real-world dataset experiments. Impressively, the results exhibit effective increase in training error from gradient noise. The realm of federated search continues to evolve, with innovative solutions revolutionizing information aggregation from diverse web sources and internal databases. These advancements hold promise in diverse domains, including crime investigation, user engagement optimization, and IoT exploration.

2.3.2 Media Specific Search

In [Sejal et al. (2016)], a pioneering image recommendation framework seamlessly integrates visual features with user relevance feedback sessions. This innovative IR_URFS_VF framework adeptly sifts through image repositories, precisely extracting images that resonate with user preferences. By analyzing both clicked and un-clicked images from the user's search history, valuable insights are gleaned to enhance the recommendation process. The intricate web of image relevance is meticulously woven through the computation of image features, culminating in a ranking mechanism that employs cosine similarity and click frequency. This dynamic interplay results in an intelligently curated image selection that captivates user engagement.

Breaking new ground in image retrieval, [Xie et al. (2015)] introduces a paradigm-shifting framework bolstered by a newly curated database. This innovative approach injects semantic attributes into the very fabric of the inverted index, ushering in a new era of efficient search engine results at scale. The framework's modular design beckons to be paired with complementary retrieval algorithms, promising a customizable and adaptable image search experience that evolves with user needs.

The landscape of news search engines unfolds with a symphony of relevance as users are greeted by tailored news pages sourced from a multitude of online outlets. Renowned platforms like NewsLookup, Google News, and Bing News set the stage for an evaluation of retrieval effectiveness that reverberates through the industry. [Bokhari et al. (2021)] orchestrates a meticulous performance analysis, enlisting stalwart retrieval models, including latent semantic indexing, VSM, and Okapi BM25. Among the contenders, Google News emerges as the crescendo, leading the ensemble of news search engines with its superior performance.

Elevating video content indexing, [Hamroun et al. (2019)] introduces a visionary semantic indexing model, amplifying content discovery through the precision of the DCM classification method and innovative relevance feedback loops. This model's prowess finds its showcase in VISEN, a video retrieval system that seamlessly harmonizes with the proposed semantic model, affording users effortless access to their desired videos. The semantic tapestry of video content, intricately woven with concepts like planes, cars, people, and roads, achieves remarkable fidelity and precision, as underscored by [Hauptmann et al. (2008)]. An exploration into bridging the semantic divide through intermediate concepts adds a layer of sophistication, further enriching the understanding of video content by melding visual and textual cues. In the dynamic landscape of media-specific search, these advancements forge new frontiers in recommendation, fine-grained search, news retrieval, and video content indexing, ultimately shaping more efficient and user-centric information access.

2.4 Web Search Results Research

The OrgBox is a tool developed by researchers in [Ward and Capra (2021)] that engage users in cognitive and metacognitive activities during monitoring their information, planning next step, and evaluating so far found information. The users are allowed to create as well as label boxes during a search to organize information. The OrgBox is integrated based on custom-built search in which users are allowed to synthesize, save and organized information by using drag and drop. For exploratory search task it also provides users with a substantial support.

A novel system SearchLense is introduced by researchers in [Chang et al. (2019)] where a 'Lenses' collection is built up by searchers that reflect latent interests of searchers and across different contexts to find relevant items the Lenses are composed. The personalized interfaces are generated by SearchLense with visual explanations based on Lenses that enables deeper exploration and transparency. The SearchLens is tested across a field study as well as in a lab and results indicates that with more query terms the interests of the participants are expressed more significantly and SearchLense is found beneficiary for the participants.

The researchers in [Klouche et al. (2015)] presented an Exploration Wall having a touch-based UI by which incremental exploration and large information spaces for sense-making are allowed by entity search combination, as a query parameter result entities flexible use and search stream spatial configuration for interaction that are visualized. Entities are reused flexibly for modification and new search stream creation and with other entities to inspect their relationships entities are manipulated. For exploratory search in [Ma and Zhang (2018)] the query recommendation method is presented. Based on searchers behavioral characteristics in the goal shift processes of search, all the submitted queries in goal shift processes from logs of search engine are extracted using machine learning.

A Nutch and Solr based Vertical search engine is proposed by researchers in [Ma et al. (2019)] use for information retrieval for tourism. The authors have presented the solution to achieve web crawling. Dictionary based segmentation algorithm is used for Chinese segmentation, Vector space model is employed in the proposed framework based on keywords for topic relevance implementation. The word library for tourism domain and user search module is extended to collect and filter information. A user-friendly interface with related and popular word recommendation is provided for exploratory search with better user experience. The experimental results show that the proposed approach is convenient for users in tourism domain for information search. The tourism information retrieval precision is improved by the proposed approach.

The researchers in [Müller et al. (2017)] described LIVIVO developed by ZB MED having a usability-tested and user-friendly interface with 55 million citations data that is derived from multiple databases. For high throughput data retrieval and data export a standardized programming application interface is available. On life science entities basis, the semantic retrieval is allowed with filtering options by search functions. Required task is taken by LIVIVO to vertically integrating information in the life sciences from divergent research areas. The search services are delivered with the help of service-oriented architecture of LIVIVO having four implementation layers. Heterogeneity of data is managed by ZB MED by developing Knowledge Environment. This knowledge environment provides heterogeneous information core linking.

The researchers in [Seo et al. (2011)] introduced a technique for click counts smoothness. The proposed approach uses spectral graph analysis to address rank cut (sparseness). The authors use clickthrough data recorded in an aggregated search from verticals. The question answer community-based snapshot data set is used in the proposed technique. This data set is from a commercial search portal namely vertical of Naver in Korea. Experimental results show that vertical search is improved by proposed technique effectively as well as the clickthrough data's smoothness compared to baseline.

The researcher in [Zheng et al. (2012)] developed and implemented Disaster SitRep (Disaster Situation Reporting) framework which is an information analysis tool that collect, integrate, and present particularly disaster information. The Disaster SitRep is a domain specific vertical search engine that address disaster related critical tasks by utilizing domain knowledge as well as provide geographical information navigation platform. Information retrieval and data mining techniques are used in the proposed system for disaster preparedness and recovery for the current disaster situation's better understanding. It is lightweight and comprehensive web-based application that is fully implemented in java. The evaluation is taken in a table-top form exercise where the current disaster situation potential details are provided by the information injection.

In [Wang et al. (2020)] a Meta-Search framework is proposed with product feature extractor based on multi-pooling to extract discriminative features. To obtain few-shot features a meta-learning feature extractor and to adapt incremental search a batch weight combiner is proposed. These modules allow novel categories recognition in consolidated way. The proposed framework is evaluated on Mini-ImageNet and RPC product datasets under incremental conditions and few-shot, the results shows that the framework achieve robust feature extraction through meta-learning from novel categories.

In [Chen et al. (2012)] the researchers presented image vertical search engine namely iLike that integrate visual features with textual to improve the performance of information retrieval. The iLike system consists of mainly three components namely crawler, processor, and search& User Interface components. The semantic gap is bridged by capturing from visual feature space each text term's meaning and then reweight the feature in accordance with their query term's significance. The visual meanings are also inferred behind textual queries, so the user intention gap is also bridged. The experimental results indicates that the iLike system performance is effective and it perform outstanding in large descriptive terms. While for some keywords especially non-adjective and many of them have abstract meaning the iLike framework does not perform well for such keywords. The overall performance of iLike for vertical search is effective.

The researcher in [Sejal et al. (2017)] proposed a vertical image search framework namely ANOVA ACSIR (Cosine Sim Image Recommendation). To fill the semantic gap visual and textual features are integrated in the proposed framework. By considering visual features of images with the help of ANOVA p value each term's visual synonyms are computed on text-based search. The initial results set is obtained by performing text-based search and user input queries are obtained from the generation of expanded queries. In the proposed model cosine similarity is computed for pairwise image to make images recommendation. Experiments are performed on crawled myntra.com website's images data and with iLike method comparison of obtained results is made. The ACSIR framework accuracy for relevance score is increases for top recommended images by 15.26% with iLike comparison.

The researchers in [Lin and Yajie (2016)] developed HVSE (Hadoop vertical search engine) to overcome the problem of centralized search engine.

The proposed framework is designed on traditional search engine's basic principles. Lucene and MapReduce programming model is used for data processing and web crawler's current algorithms are improved. Distributed cluster environment is provided for HVSE working. The HVSE's efficiency is tested and compared with centralized search engine. HVSE outperformed than that of centralized search engines with high precision and efficiency when dealing with huge information on web. The accuracy of HVSE is also greater than general search engines.

The ensemble of approaches is presented in [Arguello et al. (2010)] which improve new target vertical predictions by using training data from source verticals only. The portable model is adapted in the proposed approach by using portable model's target vertical predictions. The proposed approach outperforms for base model as well as alternatives that require no adaption. The results show that human annotations and given available resources on new target verticals are the best alternatives. It also revealed that more focused required on different features is when maximizing probability and adaptability.

The researchers in [Sheng et al. (2021)] developed a domain specific semantic vertical search engine for electric power metering to collect, exploit and manage huge data efficiently. The authors use knowledge units extracted for semantic search from knowledge graph. The lack of specialization and targeting like shortcomings of the traditional general search engine has been overcome by the proposed approach. The proposed approach has stable recall and higher accuracy as well as enabling relational analysis and semantic understanding as compared to general search engines. The experimental results show that the proposed approach can improve timeliness and accuracy for retrieval of power metering knowledge.

2.5 State-of-the-Art

A significant amount of research has been dedicated to vertical search over the past few decades in order to address research challenges. This underscores the importance of exploring vertical search results. Research has delved into information and knowledge discovery within various contexts. This involves the unexpected encounter of unanticipated information, leading to positive outcomes. It also encompasses the identification and extraction of valuable patterns and meaningful information from large web-based datasets [Kosala and Blockeel (2000)]. Additionally, information visualization is a key component, utilizing users' natural perceptual, analytical, exploratory, and comprehension abilities through visualizations [Alhenshiri et al. (2010)]. The semantic web, on the other hand, focuses on uncovering information through ontological reasoning and inferences [Tablan et al. (2015)]. Moreover, exploratory searching aids users in learning and investigative tasks by providing appropriate tools and resources [Ruotsalo et al. (2014)]. This quest for information discovery is explored within the context of diverse content aggregations [Rashid and Bhatti (2017)]. The facets of information aggregation and exploration can be categorized into two main aspects: (i) Frameworks & Interfaces and (ii) Data Models. Detailed explanations of these aspects are provided in the respective sections below:

2.5.1 Frameworks & Interfaces

The researchers in [Rashid and Bhatti (2017)] proposed a framework to provide the research through relational aggregation of multimedia assets. The aggregation is performed based on the textual, visual, and acoustic similarity measures of the multimedia objects belonging to disjoint verticals. The proposed approach follows a layered based architecture. The graph-based data model is used that is built by performing the containment relationship and cosine similarity to link the multimedia objects and the link is established based on a predefined threshold. This graph-based approach results in a non-linear representation of the results which provide exploration. During instantiating the semantic relationship between the multimedia objects is ignored.

The researchers in [Rashid and Bhatti (2015)] proposed a framework that addressed the multi modal information retrieval core issues. The authors provided a mechanism for search results for blending integration and query formulation as well as within search space a navigation of multiple media objects. The initial search is allowed by the proposed framework by providing query terms and later user navigation within search space. It also allows query formulation by media objects combination along with their corresponding information modalities. The presented framework's user interface consists of three panels namely query formulation panel, result panel and navigation panel. By textual terms query formulation is possible and media objects relationship is established by considering acoustic, visual, and textual similarities by the search system for the multiple media information. On a real-world scenario, the proposed framework is validated.

The researchers in [Rashid et al. (2016a)] proposed a framework for the aggregation of multimedia objects from different verticals. This aggregation is performed based on the textual, visual, and acoustic similarity measures of the multimedia objects belonging to disjoint verticals. The graph-based data model is used that is built by performing the containment relationship and media objects are accessed and then based on their modality Jaccard index is computed to link the multimedia objects and this link is established based on a predefined threshold. The multimedia documents and multimedia objects are the nodes, and it is displayed as the search space result. This graph-based approach results in a non-linear representation of the results which provide exploration to the users.

The researchers in [Achsas et al. (2018)] proposed a framework for relational aggregation of multimedia assets from various verticals using deep neural network. The framework consists of three main components such as query dispatching component, relational retrieval, and relational aggregation component. The query dispatching component consist of three types of queries namely relational, instance and class query. They used stack auto-encoder technique to encode and decode the information for relational aggregation to form the clusters of multimedia documents. The clustering of multimedia documents results in non-linear representation of the search results which provide exploration activities precisely.

The researchers in [Khan and Rashid (2021)] proposed a relational aggregation framework to provide the exploration. This aggregation is performed based on the semantic relationship between the multimedia objects. For semantic analysis the sentence embedding technique is used which refer to extract the data semantics. The pairwise similarity (cosine similarity) between the user query and multimedia snippets is performed. Then the results are re-ranked in non-ascending order to present the relevant multimedia snippet at the top. A quickly lookup of relevant information is provided from Wiki based on entities identified in the user's query. This is aimed to improve the user's understanding of the search results space.

The researchers in [Khan et al. (2021)] proposed a framework to provide the exploration through relational aggregation of multimedia assets. The aggregation is performed based on the semantic relationship between the multimedia objects. The proposed approach follows a layered based architecture.

After the creation of multimedia objects, the clusters are constructed. Then the graph-based data model is used that is built by performing the containment relationship and Jaccard index to link the nodes and the vertical snippets, multimedia documents and clusters are the nodes, and it is displayed as the search space result. This graph-based approach results in a non-linear representation of the results which provide exploration.

The researchers in [Rashid et al. (2021)] proposed a framework to provide the research through relational aggregation of multimedia assets. The aggregation is performed based on multi-modal similarity and the semantic relationship between the multi-modal objects. The graph-based data model is used that is built by performing the containment relationship and media objects are accessed and then based on their modality Jaccard index is computed to link the multimedia objects and this link is established based on a predefined threshold. The multimedia documents and multimedia objects are the nodes, and it is displayed as the search space result. This graph-based approach results in a non-linear representation of the results which provide exploration to the users based on the semantic relationship.

The researchers in [Khan et al. (2023)] presented a well-defined search user interface to provide exploratory as well as simple lookup search. The interface consists of different panels such as discovery, exploratory, look-up panel and visualization. The graph-based approach is used where the edges of the graph are based on containment and similarity relationships. By default, when a user visits the AMED software, the discovery interface is displayed, which gives a comprehensive view of the search results space. In exploratory interface, users have the option to explore the search results through non-linear browsing using paths based on containment and similarity. The lookup interface offers comprehensive semantic aggregation, in contrast to the current search engine method of merging a limited set of disconnected verticals that lacks coherence in the search results. The exploratory search is provided more precisely through a visualization panel where a graph-based representation displays the multimedia documents, multimedia snippets and multimedia group of documents. The interface enables the user to enter full text query in query formulation panel and latterly the user can enhance the query from advance query filtration panel based on OR, AND or NOT.

The researchers in [Rashid et al. (2016b)] proposed a relational aggregation framework to provide the explorations. The relational aggregation is performed based on the graph data model by performing the part of link relationship that a multimedia object belongs to the identical multimedia document and media objects and similarity relationship among them. The multimedia documents and multimedia objects are the nodes, and it is displayed as the search space result. This graph-based approach results in a non-linear representation of the results which provide navigation and exploration of the searched results. The proposed approach have precise search user interface through which user can perform multi-modal query, this interface provide visualization tool to the user based on graph.

2.5.2 Data Models

Etymo exploration engine was created by researchers for artificial intelligence (AI) research in [Zhang et al. (2018a)]. Their web-crawling architecture downloads research papers from different journal websites and by cosine similarity measure full-text indexing is performed. Based on user clicks, stars, and Twitter4 mentions, it creates a similarity-based network linking related papers. The graph's significant connections are then reinforced using this data. In addition to providing a visualization of each paper in the list and a graph visualization with nodes, Etymo's web interface also displays a list of search results ranked by importance. Node sizes vary according to importance, and color corresponds to the journal. By historical significance markers, the system evaluation demonstrates improved search results.

In [Khan et al. (2023)] provide the exploration and visualization of search results by using a graph data model. The vertices of the graph are multimedia clusters, documents, and sippets. A generic search user interface provides, and the visualization of the search results represented by tree like graph model. They represent the graph in three-layer format such an initially when user click on presented clusters the multimedia documents and snippets as well as other clusters that are like the selected cluster are presented to the user. The user can select and navigate to the desired document or snippet. The exploratory view of the search results also enables the user to explore the relevant documents. Their approach is more recall oriented rather than precision oriented.

Researchers used information visualizing approaches to provide the Visualization of Semantic Data Representation (VSDR) exploration and discovery framework in [Kanjanakuha et al. (2019)]. Their framework makes use of semantic information contained in a modal with three layers of hyperbolic trees. With this method, the user's keyword-based input is used to generate a graph that displays the data. Each layer reduces the information's scope from a large to a small one. The three-layer technique improves navigation and engagement while lessening confusion brought on by information overload. Moreover, the graph has functions for node description, highlighting, panning, zooming, and linking. Improvements in user information exploration and discovery skills were seen in the evaluation of VSDR.

The researcher in [Rashid and Bhatti (2017)] developed a method for exploration and visualization of multimedia search result in generic data-models. Among the multimedia elements their approach establishes containment and similarity-based relationships and connects these multimedia elements using a graph data model. Deconstructing a rich multimedia entity, such a video, into its component modalities such as text, audio, and image they provide a containment relationship. Generic textual, acoustic, and visual, and similarity measures are used to provide for similarity relationship. A general search user interface is offered to enable the user to build a query, set restriction constraints in the form of (AND, OR, NOT) Boolean text input field , in the form of checkboxes the media mode, and similarity relationship is provided.

For accidental discovery in connected open data, authors of [Khalili et al. (2017)] developed Faceted & Serendipity catalyzer (FERASAT) browser. They have faceted navigation, menu-driven, hypermedia provided by the presented architecture. Moreover, multiple data representations are offered, making it easier to get data overview. Serendipitous discovery and information exploration are encouraged by the adaptable user interface elements and interactive visualizations, which assist both convergent and divergent information-seeking tasks. The lack of user evaluation makes it impossible to determine whether their strategy is beneficial.The researchers in [Rashid et al. (2016b)] uses graph data model for the visualization of the searched space results. The edges of the graph are multimedia documents and multimedia objects while the edges are established based on the containment and similarity relationship.

2.6 Critical Analysis

2.6.1 Comparison Mechanism

In the current landscape of research, significant efforts have been dedicated to the investigation of search result exploration. Numerous researchers have focused on enhancing user experiences by providing visualizations that facilitate exploratory searches, catering to distinct information-seeking behaviors. In this realm, a distinction emerges between "look-up" and "exploratory" search activities. The former entails a precise and well-defined information need, while the latter involves a more open-ended or loosely formulated query.

To enhance the efficiency of exploratory search endeavors, the researchers in [Khan and Rashid (2021)], [Khan et al. (2023)], and [Khan et al. (2021)] have introduced innovative mechanisms that facilitate information exploration through both visual and textual modalities. One notable strength of their approach is the elimination of the need for users to explicitly specify their preferred query modality in advance. By seamlessly integrating semantic analysis, containment, and similarity relations, these studies successfully aggregate multimedia objects, streamlining the search process.

Further advancements in the field are exemplified by the contributions of [Rashid and Bhatti (2015)] and [Rashid and Bhatti (2017)], who propose exploration mechanisms rooted in semantic analysis. Notably, these studies offer visualizations using a graph data structure and provide users with the capability to predefined their query modality, which indeed presents a promising step forward. However, a noteworthy limitation persists—a notable gap arises due to their concentrated focus on semantic analysis, which could potentially lead to an oversight of the diverse information concealed within other facets of search results. This limitation has the potential to constrain the scope of a comprehensive exploration strategy, warranting further consideration for a more holistic approach. A detailed comparison of the state-of-the art literature is given in the Table 2.1.

Table 2.1: Critical Analysis

Analysis Parameter	**Analysis Parameter Value**	**Publication & Year**									
		[Rashid and Bhatti (2015)]	**[Rashid and Bhatti (2017)]**	**[Khan et al. (2021)]**	**[Paul et al. (2019)]**	**[Rashid et al. (2016a)]**	**[Khan and Rashid (2021)]**	**[Rashid et al. (2021)]**	**[Khan et al. (2023)]**	**[Kanjanakuha et al. (2019)]**	**[Zhang et al. (2018b)]**
Query formulation	Simple	✗	✗	✓	✓	✗	✓	✗	✓	✓	✓
	Boolean	✓	✓	✓	✗	✓	✓	✓	✗	✗	✗
Data-set	Real	✓	✓	✗	✗	✗	✗	✓	✗	✗	✗
	API	✗	✗	✓	✗	✗	✓	✗	✓	✗	✗
	Domain Specific	✗	✗	✗	✓	✓	✗	✗	✗	✓	✓
Search Type	Full text	✗	✓	✓	✓	✗	✓	✗	✓	✓	✗
	Federated	✓	✓	✗	✗	✓	✓	✗	✗	✗	✗
	Fielded	✗	✗	✓	✗	✗	✗	✓	✗	✗	✗
	semantic	✓	✓	✓	✗	✓	✓	✓	✓	✗	✓
Query Modality	Textual	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓
	Acoustic	✓	✓	✗	✗	✓	✗	✓	✗	✗	✗
	Video	✓	✓	✗	✗	✓	✗	✓	✗	✗	✗
	Image	✓	✓	✗	✗	✓	✗	✓	✗	✗	✗
Data Model	Linear	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
	Non-Linear	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Retrieval Modal	Mono-modal	✗	✗	✗	✓	✗	✗	✗	✗	✓	✓
	Cross-modal	✓	✓	✓	✗	✓	✓	✓	✓	✗	✗
Search Result	Document Snippet	✗	✗	✓	✓	✗	✓	✗	✓	✗	✓
	Document Clusters	✗	✗	✓	✗	✗	✓	✗	✓	✗	✗
	Multimedia Document	✓	✓	✗	✗	✓	✗	✓	✗	✓	✗
Media Type	Text	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗
	Image	✓	✓	✓	✗	✓	✓	✓	✓	✗	✗
	Video	✓	✓	✓	✗	✓	✓	✓	✓	✗	✗
	Audio	✓	✓	✓	✗	✓	✓	✓	✓	✗	✗
SUI Search Activity	Look-up	✗	✗	✓	✗	✗	✓	✓	✓	✓	✗
	Exploratory	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗
	Visualization	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓
Data Relationship	Semantic	✗	✓	✓	✗	✗	✓	✓	✓	✓	✗
	Containment	✗	✗	✓	✗	✓	✓	✗	✓	✗	✓
	Similarity	✓	✗	✓	✓	✓	✓	✗	✓	✗	✗
Data Architecture	Layered Based	✗	✓	✓	✗	✗	✓	✗	✓	✗	✗
	Component Based	✓	✗	✗	✗	✓	✗	✗	✗	✗	✗
Results Representation	Linear	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓
	Tree-map	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
	Pie-chart	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
	Grid-view	✓	✓	✓	✗	✓	✓	✓	✓	✓	✗
Evaluation Parameter	Precision	✗	✓	✗	✗	✗	✓	✗	✗	✗	✗
	Usability Test	✓	✗	✗	✓	✓	✓	✓	✓	✗	✗
	Accuracy	✗	✗	✓	✗	✗	✗	✗	✗	✗	✗
	CRT	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗

2.7 Motivation

The state-of-the art provides crucial observations regarding the current utilization of information exploration techniques. The limited non-linear behavior exhibited by these established approaches raises substantial concerns, impeding their ability to comprehensively capture the intricate relationships and complexities inherent in contemporary datasets. Furthermore, a discernible trend is emerging wherein a considerable portion of these strategies predominantly relies on graph visualization approaches, often disregarding alternative and potentially more illuminating modes of representation, such as pie charts or tree maps. This skewed emphasis on graphs overlooks the diverse ways through which data can be effectively conveyed, potentially hindering a complete grasp of intricate patterns and connections. Our motivation for this research intends to close these gaps by proposing a state-of-the-art framework that makes use of the strength of non-linear modelling to better capture complex data relationships. In addition, we propose an investigation of the untapped potential of pie charts and tree maps, outside of the conventional graph-centric approaches. By embracing these innovations, offering more nuanced insights, and encouraging a deeper understanding of complex information, we seek to enhance the exploration experience. In the end, our research aims to herald in a new era of information exploration that overcomes the limitations of partial non-linearity and limiting visualisation possibilities, thereby developing a more complete and intuitive method for exploration.

2.8 Benchmarks

2.8.1 Data Set

The researchers in [Khan et al. (2023)], [Khan and Rashid (2021)] used Google APIs for the extraction of image, web, audio, and video objects. They collected 100 media objects of each media type in response to predefined queries. These APIs were used to collect data from the mentioned verticals of Google, after which the extracted data was pre-processed and utilized for aggregation. In [Rashid and Bhatti (2017)], the authors employed a dataset consisting of 10,305 content objects, namely Rich Unified Content Description, encompassing 36,389,567 instances. The researchers in [Rashid and Bhatti (2015)] utilized a real dataset for implementing and validating the proposed model. This collection of multimedia documents was generated by the I-Search Project2, totaling 10,305 content objects in the form of XML documents. From this dataset, they extracted 13,084 multimedia assets, comprising 467 acoustic objects, 1954 textual objects, 1553 video objects, and 9110 image objects.

From eight retailers, the researchers in [Chen et al. (2012)] crawled 22,292 items. These online retailers include Nordstrom, Pipelime, Gap, Bluefly, Banana Republic, Athleta, Macy's, and Old Navy. They extracted a popular set of 401 visual features from product images. An experiment involving query logs was conducted by the authors in [Gil-Costa et al. (2012)], where the query log was submitted to the AOL search service. The proposed framework by the researchers was deployed on a small cluster comprising 30 processing nodes, each with 4 cores. The researchers in [Seo et al. (2011)] employed a dataset of snapshots taken from a Korean commercial search portal. The dataset, containing around 30 million documents, was directly downloaded from service databases and includes Community Based Question Answering (CQA) data from Naver.

In [Pavani and Sajeev (2017)], the researchers used a URL dataset and web content. The URL dataset was formed by extracting URLs from web pages. The rank of each extracted page was calculated and the dataset includes the id, URL, and rank of each page. The web content data was extracted by parsing web pages. The researchers in [Sejal et al. (2017)] utilized a customized crawler to crawl 5582 images from myntra.com, an e-commerce website. The website provided annotated images with price, categories, image names, and product descriptions. Visual features of each image were extracted during crawling using an image processor, and these features were stored in an offline database for experimentation. The researchers in [Arguello et al. (2010)] used a dataset containing 25,195 unique queries, randomly sampled from web traffic.

In [Müller et al. (2017)], the authors employed meta records consisting of 55 million bibliographic data, forming the basis for the search services of the proposed framework LIVIVO. These records were collected from original heterogeneous data formats from over 50 databases, including Medline, Dublin Core, relatively detailed Marc, MAB, and proprietary formats. The researchers in [Sheng et al. (2021)] used over 2 million records of electricity consumption, including information on grid lines, grid plant stations, circuit fault records, and grid staff for three months. These records were used to test the proposed vertical search engine in the domain of electric power metering.

2.8.2 Evaluation Measures

Three main methods are used as evaluation measures which are in the literature for the exploratory search systems. The performance measures are related with assessing the system's performance based on recall and precision. The qualitative measures aim to assess the quality of the proposed tool's performance with the help of standardized scales. Data produced because of user interaction is another way to gauge the effectiveness of exploratory search systems. The evaluation measures are describe with diagrammatic view in Figure 2.1

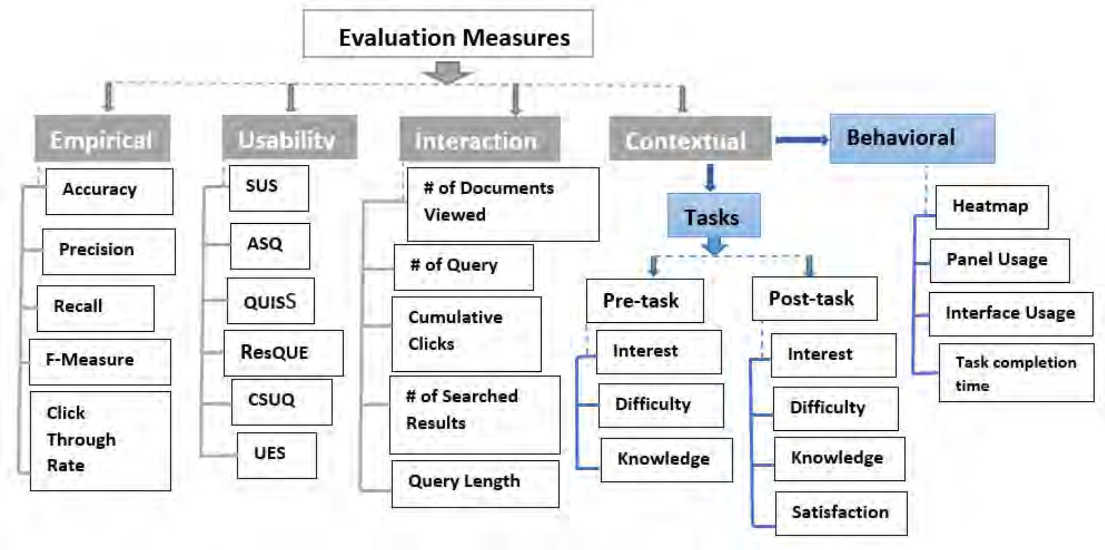


Figure 2.1: Evaluation Measure

- Empirical

  The system's performance is assessed by the performance measures. The goal of retrieval systems is to provide users with performance that is adequate. Although there are many different performance indicators, some of them are listed below. In the case of information retrieval systems, the performance metric in Table 2.2 assists in identifying the relevant and irrelevant results that are retrieved and not retrieved.

  The precision calculates the proportion of the total number of docu-

Table 2.2: Contingency Metric

	Relevant	**Irrelevant**
Retrieved	True Positive (TP)	False Positive (FP)
Not Retrieved	True Negative (TN)	False Negative (FN)

ments returned by a search that are relevant.This metric is primarily used in the evaluation of web searches.

$$\text{Precision} = \frac{\text{relevant items retrieved}}{\text{retrieved items}} = \frac{TP}{TP + FP} \tag{2.1}$$

The recall is calculated by dividing the total number of relevant documents that were found by a search by the number of relevant documents that were actually found.It is typically used for analyst tasks and deadline identification.

$$\text{Recall} = \frac{\text{relevant items retrieved}}{\text{relevant items}} = \frac{TP}{TP + FN} \tag{2.2}$$

When using the information retrieval system as a two-class classifier, accuracy is a metric that verifies the accuracy of the classifications. This demonstrates the efficacy of a system that is primarily used for machine learning classification issues.

$$\text{Accuracy} = \frac{\text{TP + TN}}{\text{TP + FP + FN + TN}} \tag{2.3}$$

F-measure is a measurement that compromises recall and precision. It is the recall and precision weighted harmonic mean.

$$F1 = \frac{2 * precision * recall}{precision + recall} \tag{2.4}$$

The click-through rate (CTR) is the calculation of the proportion of users who click on a given link or panel to the total users who view it. It evaluates a system's efficiency. This measure determines the quality of the imagery, positioning, and keywords.

$$CTR = \frac{\text{Number of clickthroughs}}{\text{Number of impressions} \times 100} \tag{2.5}$$

- **Usability**

  The majority of the qualitative measurements come from [Brooke et al. (1996)]'s System Usability Scale (SUS), [O'Brien et al. (2018)]'s User Engagement Scale (UES), [Lewis (1995)]'s Computer System Usability Questionnaire (CSUQ), and [Chin et al. (1988)]'s Questionnaire for User Interaction Satisfaction [QUIS]). Additionally, some researchers make the assumption that a visualisation system is comparable to a recommender system in that both suggest potential interactions to the user during system interaction and, as a result, use the Quality of User Experience (ResQUE) [Paninski (2003)] questionnaire for recommender systems.

  A few researchers use After Scenario Questionnaire (ASQ) [Lewis (1995)] for user satisfaction with the task. The major purpose of SUS is to measure the overall system usability, on a 5-points Likert scale consisting of 10 questions with a sliding scale from 1-5 with 1 being strongly disagree and 5 strongly agree. The QUIS evaluates screen terminology & system information, learning, system capabilities and usability aspects of the system on a 10-point Likert scale. The CSUQ is used for the general usability assessment of interactive systems on a 7-point Likert scale. The user engagement is a more recent scale, used to measure aesthetics, focused attention, felt involvement, perceived usability, novelty, and endurability aspects of the system on a 5-points

Likert scale.

- **Interaction**

  The engaging activities of a subject are treated as interaction, and interaction measures are used to quantify these activities. These measurements essentially consist of low-level behavioural data that may be started by the subject or system. The quantity of queries, the number of search results viewed, the quantity of documents viewed, or the length of the query are frequently used metrics. In addition to being system-specific, some interactions—like frequency counts—are also interface- or functionality-specific. These metrics include total queries [Taramigkou et al. (2017)], average query length [Arguello et al. (2010)], average query time [Tablan et al. (2015)].

- **Contextual**

  This metric is used to describe the topics and information requirements. Age and gender can be used to categorise the subject, whereas task type and domain knowledge can be used to categorise information needs. Because each person's subjective characterization is unique, it is typically kept apart from the search process and evaluated using different questionnaires that include demographic or personal information. The contextual metric include pre-task and post-task measure activities as well as behavioural measures such as average task completion rate , user interface panel usage ratio [Rashid and Bhatti (2017)].

2.8.3 Evaluation Strategies

[Zhang et al. (2018a)], the researchers proposed a recommender vertical search engine named PASO-WPR that focuses on semantic information. To enhance the outcomes of web page recommendations, a particle agent is exploited. This approach improves the response time of the system, resulting in enhanced framework scalability. The results indicate that the proposed PASO-WPR framework demonstrates improvements in accuracy measures, including aspects like coverage, accuracy, and the M-Metric, when compared to collaborative item-based systems used in filtering recommendation systems. The outcomes are utilized for generating recommendations to users. In their work [Lee et al., Bae et al., 2020], the authors presented a combined approach for information indexing maintained by Google. They generate target URL lists through a query generator, and subsequently utilize this information for file downloading and URL extraction. The authors employ SlideCrawler as a focused crawler in their proposed CourseShare vertical search engine since fall 2011. The capability of SlideCrawler is verified against the top 500 universities worldwide. SlideCrawler collects one million files from these universities, outperforming Nutch in terms of file collection. The researchers' proposed framework proves to be highly effective and cost-efficient.

In [Wu et al. (2022)], researchers introduced a power knowledge graph-based ISE (intelligent search engine) that autonomously identifies users' search intentions and interests with high accuracy. The framework provides fast relevance retrieval ranking of associated search results and intelligently filters and delivers information to users. The framework's accuracy is evaluated, and the ISE semantic search achieves an accuracy of 99.2%. The authors analyzed search queries to identify the main reasons for errors in search results with incorrect answers and found that parsed query nodes in the power knowledge graph are responsible for these errors.

The researchers in [Zhang et al. (2018b)] proposed the Joint Relevance Estimation framework. The model learns visual patterns from search result screenshots, explores the presentation structure from Hypertext Markup

Language source code, and adopts semantic information from textual content. The framework's performance is evaluated by constructing an SRR (Search Results Relevance) dataset, containing over 60,000 relevance scores, snippets, titles, and multiple information sources. The proposed Joint Relevance Estimation demonstrates superior performance and significantly improves the original ranking of the search engine by 2.54%, 8.60%, and 6.42% in terms of NDCG@3, NDCG@5, and NDCG@10, respectively.

For obtaining metadata from rich text documents, the researchers in [Chan et al. (2021)] utilized the Apache Tika framework. The framework implements word segmentation based on semantics and rich text content, calculating the weight of each keyword. The text index is established, and search keywords are input. The BM25 algorithm is employed to calculate similarity between text and keywords. Based on the calculated similarity output, rich text search results are provided. Experimental results demonstrate that the proposed framework outperforms traditional search engines, improving recall by 3.2% and maintaining a rich text content search accuracy of 95%. The index throughput is increased, leading to improved search effectiveness and efficiency.

2.9 Summary

This chapter offers a comprehensive synthesis that delves into a multifaceted exploration of critical dimensions in web search research. The discourse commences with a broad perspective on web searches, encompassing both general and multimedia considerations, subsequently progressing into the realm of vertical web search context. Building upon this foundation, a meticulous and comprehensive overview unfolds, navigating the intricate landscape of web search results research, elegantly weaving insights from the existing literature. Within this discourse, the chapter unfurls a panoramic canvas of the practices that currently shape the domain, meticulously dissecting the state-of-the-art frameworks, interface designs, and data models that have emerged from the scholarly efforts of dedicated researchers. These presentations provide an intricate tapestry of the evolving landscape of web search result paradigms. However, beneath the surface of these advancements lies a critical analysis that unearths the existing state-of-the-art's inherent limitations and deficiencies. This thoughtful examination unveils the gaps that persist in the current practices, creating a compelling segue into the overarching motivation that underpins this research endeavor. At its core, this chapter is fueled by a potent undercurrent of motivation, inspired by the need to transcend these limitations and usher in a new era of innovation. The seeds of aspiration are sown, cultivating a fertile ground for the novel framework that is poised to emerge. Concluding this tapestry of exploration, the chapter turns its gaze towards the horizons of benchmarks, shedding light on the pivotal role played by datasets, evaluation measures, and strategies within the research landscape. This nuanced discussion navigates the various facets of evaluating the efficacy and potency of novel paradigms, solidifying the groundwork for the chapters that lie ahead.

Chapter 3

Aggregated Web Search Research Framework

3.1 Proposed Approach Overview

In accordance with [Tablan et al. (2015)], search engines are primarily designed for quick, targeted queries that prioritize precision over recall. Consequently, they may fall short in offering extensive research opportunities to users. The most widely used commercial web search engines, including Bing2, Yahoo!4, Baidu1, Google3, and Yandex5, incorporate specific vertical-specific results gathered from other data sources. These results are integrated into the linear ranked list of standard outcomes to enhance the effectiveness of information retrieval behaviors. However, as stated in [Rashid and Bhatti (2017)], this vertical integration is often only partially integrated. While sufficient for straightforward targeted searches where the user knows precisely what they seek, this approach proves inadequate in supporting complex information exploration tasks.

Users exhibit dynamic behavior and often struggle to articulate their information requirements, surpassing the scope of conventional keyword searches [Gäde et al. (2015)]. These tasks demand greater emphasis on recall over accuracy and necessitate access to a variety of information sources. While existing approaches enable instant discovery of multimedia search outcomes, they often lack mechanisms for comprehensive research within the retrieved results space.

In the proposed framework, essential components for information exploration and research are incorporated to facilitate the user's information-seeking journey. This framework supports the user's nonlinear information-seeking behavior and offers flexibility in information presentation, addressing a gap in the existing literature. A sophisticated non-linear data model encompassing various representations of search results underpins the journey's non-linearity.

To initiate the process, a user submits a query, depicted in Figure 3.1 (a). The search result verticals, such as web, images, news, and videos, are retrieved and aggregated in response to the user's query, as illustrated in Figure 3.1 (b). After aggregation, the obtained results undergo transformation into different information representations, as depicted in Figure 3.1 (c). These representations encompass multimedia clusters and multimedia snippets. The multimedia document groups semantically similar multimedia snippets, enabling users to conceptually explore the search results space. Users can dynamically fulfill their information needs by conducting research on the retrieved results dynamically. These multimedia documents and multimedia snippets are then transformed to a non-linear graph data structure to obtain fully blended non-linear search results shown in Figure 3.1 (d). To enhance user experience, an appealing pie-chart and tree-map visualizations are presented, with each segment of the pie-chart and tree-map representing a multimedia document cluster. This visualization empowers users to visually delve into the searched results as presented in Figure 3.1 (e). The overview of proposed approach is presented by a schematic diagram in Figure 3.1.

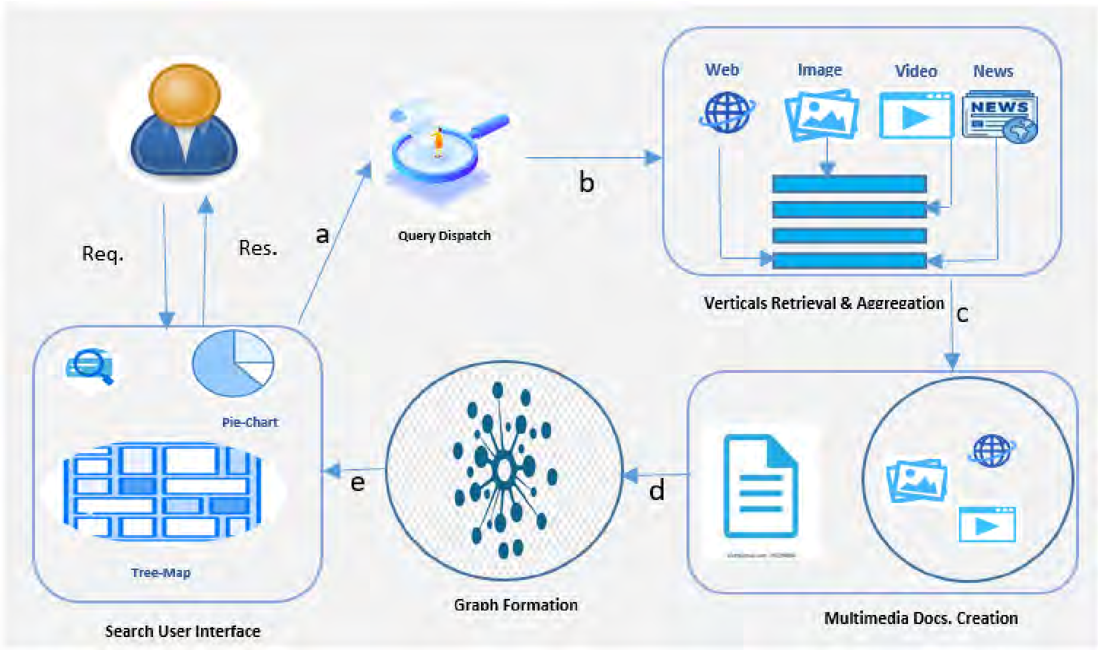


Figure 3.1: Searched Results Research Anatomy (a) Query Originate from User (b) Aggregation of Vertical Results (c) Formation of Multimedia Document's Clusters (d) Non-linear Representation Data (e) Non-linear Representation of Searched Results

3.2 Architecture

The proposed framework employs a hybrid architecture, combining layered and component-based approaches. This innovative design involves the integration of multiple layers, each comprising a distinct set of components. Within this architecture, there are four primary layers, each housing a diverse array of components. The foremost layer, known as the "Interface Layer," encompasses essential components such as query formulation, exploration, visualization, and alternative query suggestions. Moving onwards, the second layer is designated as the "Data Retrieval Layer," housing components exclusively dedicated to data retrieval. Progressing further, the third layer assumes the role of the "Retrieved Data Representation Layer," responsible for encoding and structuring the data retrieved from the preceding layer. Finally, the last layer, referred to as the "Data Organizer Layer," takes charge of efficiently arranging the data emanating from the third layer. Each layer plays a pivotal role in the framework's overall functionality and effectiveness. The component-based architecture of the proposed framework is displayed in Figure 3.2, which illustrates the flow of information and how each component is interconnected across each layer. In-depth discussions concerning each layer and its associated components follow below:

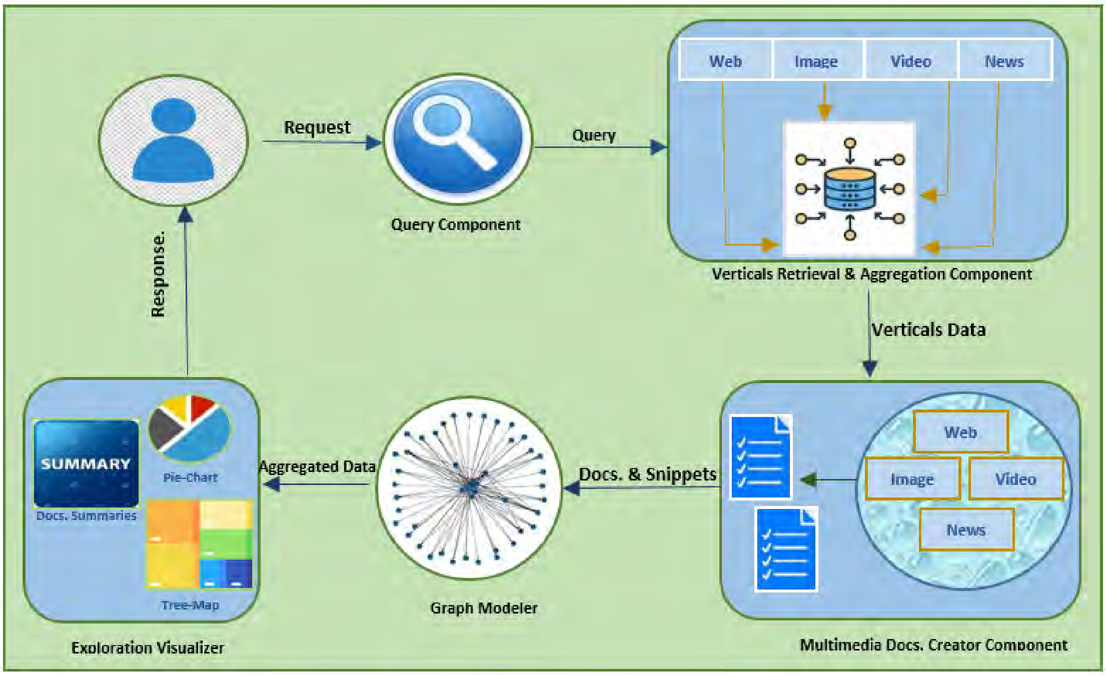


Figure 3.2: Component Based Architectural of Proposed Framework

3.2.1 Interface Layer

Four distinct interfaces constitute the interface layer, each serving a unique purpose. The initial interface focuses on query formulation, providing users with the flexibility to craft both simple and advanced queries. Once the query is formulated, users seamlessly transition to the subsequent interface.

The second interface is tailored for exploratory tasks. Within this interface, a non-linear representation of topical search results is presented, enabling users to thoroughly and efficiently examine their search outcomes. An exploration panel, positioned on the top of the screen, offers an array of informational snippets, facilitating swift exploration of selected multimedia clusters. Directly beneath, the dynamic query suggestions panel provides an additional non-linear representation, allowing users to promptly select and investigate suggested queries. Should users opt to create entirely new queries for novel search endeavors, a query formulation panel is readily accessible within this interface. Furthermore, the second interface provides users with the option to select the desired multimedia content, thereby granting them the ability to explore snippets of their desired modality.

The third interface is dedicated to visualizing the search results. Through this interactive visualization interface, users gain rapid insights into the overall context, explore relevant items, and navigate related traversal paths. This interface proves invaluable for analytically delving into multimedia search results, enhancing the user's understanding and decision-making.

Collectively, these interfaces within the interface layer establish a comprehensive framework that empowers users to seamlessly navigate, explore, and comprehend the vast realm of multimedia search outcomes. The thoughtful integration of these interfaces facilitates efficient interaction and extraction of meaningful insights from the wealth of searched results. Figure 3.3 shows the prototype overflow of the interface layer.

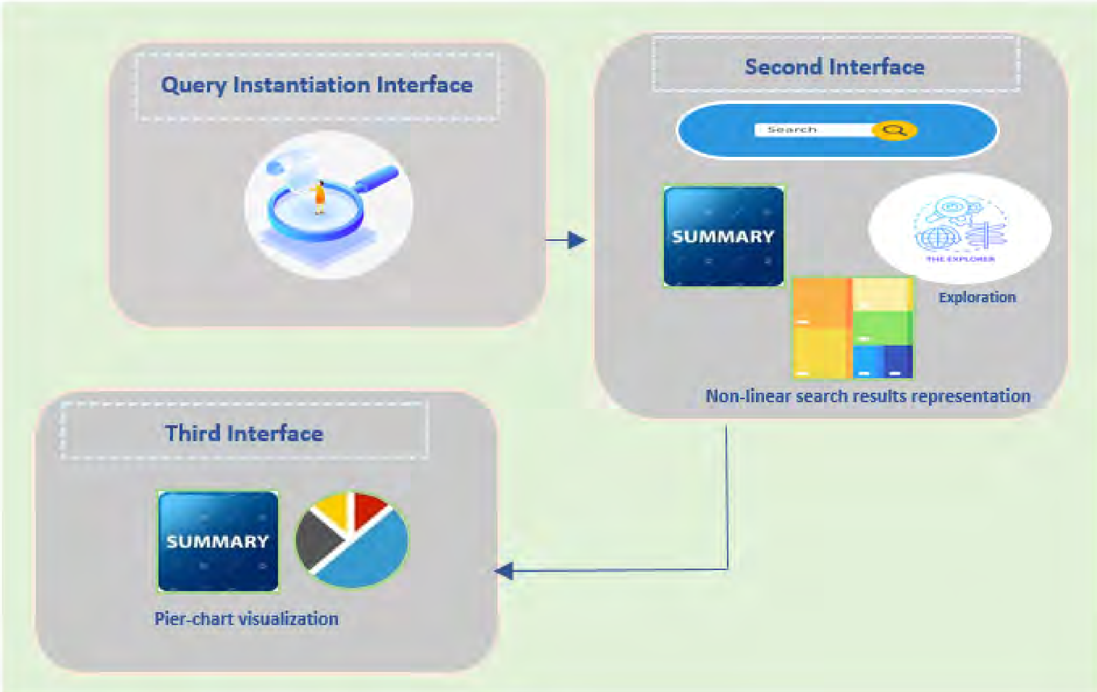


Figure 3.3: Prototype of Interface Layer

3.2.2 Data Retrieval Layer

The user query is dispatched to this layer once a search activity is initiated by the user. The retrieval layer efficiently directs the user's query request to external information sources, also known as verticals. In this context, our focus encompasses a range of verticals including news, web, images, and videos. To fulfill the user's request, direct queries are made to publicly accessible APIs on behalf of the user, yielding a response that comprises the relevant verticals. Each vertical comprises search results of a similar nature, accompanied by their pertinent details.

For the image vertical, the associated metadata comprises a thumbnail, URL, and title, as indicated in Table 3.1. Correspondingly, the web vertical's metadata encompasses URL, description, and title, demonstrated in Table 3.2. Similar metadata arrangements are applicable to the News and Video objects, detailed in Table 3.3, encompassing URL, description, title, and upload date.

Following the retrieval process, preprocessing is executed on the acquired vertical data. The de-noising (cleaning) component undertakes the task of removing punctuation, numerals, inline dates, and special characters. These elements are expunged as they do not contribute significant semantic value to the data. In addition to the original metadata and user query, the aggregation component incorporates the entirety of the cleaned content, encompassing textual descriptions and titles. This aggregated dataset is subsequently transmitted to the third layer, which orchestrates a meticulously organized representation of the retrieved data.

Table 3.1: Structure & Metadata of Retrieved Web Object

Web Index	**Web Metadata**
W_1	Title , Description , URL
W_2	Title , Description , URL
W_3	Title , Description , URL
W_4	Title , Description , URL
W_5	Title , Description , URL
$\vdots$	$\vdots$
W_n	Title , Description , URL

Table 3.2: Structure & Metadata of Retrieved Image Object

Image Index	**Image Metadata**
I_1	Title , Thumbnail, URL
I_2	Title , Thumbnail , URL
I_3	Title , Thumbnail , URL
I_4	Title , Thumbnail , URL
I_5	Title , Thumbnail , URL
$\vdots$	$\vdots$
I_n	Title , Thumbnail , URL

Table 3.3: Structure & Metadata of Retrieved News & Video Objects

News & Video Index	**News & Video Metadata**
N_1, V_1	Title, Description, URL, Description, Date
N_2, V_2	Title, Description, URL, Description, Date
N_3, V_3	Title, Description, URL, Description, Date
N_4, V_4	Title, Description, URL, Description, Date
N_5, V_5	Title, Description, URL, Description, Date
N_6, V_6	Title, Description, URL, Description, Date
$\vdots$	$\vdots$
N_n, V_n	Title, Description, URL, Description, Date

3.2.3 Clustering Layer

Within this layer, the semantic analyzer receives an aggregated list of searched results, excluding the query itself. The clustering process organizes multimedia search outcomes into cohesive clusters, characterized by shared semantic attributes. Each of these clusters is termed a "multimedia document," housing semantically akin multimedia snippets. These multimedia documents are subsequently stored within a hash table, indexed using alphanumeric identifiers.

A text summarizer is employed to encapsulate the essence of each multimedia cluster, with the resulting summary text being associated with the index of its respective multimedia cluster. Moreover, to facilitate the dynamic generation of alternative queries from the search results, the semantic analyzer extracts pertinent keywords and concepts from the multimedia documents. These extracted elements serve as the foundation for generating novel queries, enhancing the ability to refine or expand the original search scope.

The generated queries find their place within a query pool, offering a dynamic repository that evolves alongside the user's exploration of the search results. As new multimedia documents are incorporated into the search results and the user delves deeper into exploration, the query pool is continuously updated. Subsequently, the hash tables, enriched with these summarized multimedia documents and query-related information, are seamlessly transferred to the subsequent layer – the Non-linear layer – for further intricate processing.

This intricate interplay of processes within the layer not only enhances the efficiency of query refinement and result exploration but also contributes to a more comprehensive understanding of the searched content. By meticulously structuring multimedia data this layer sets the stage for a more nuanced and fruitful interaction between the user and the search results. The prototype of the Clustering Layer is shown in Figure 3.4

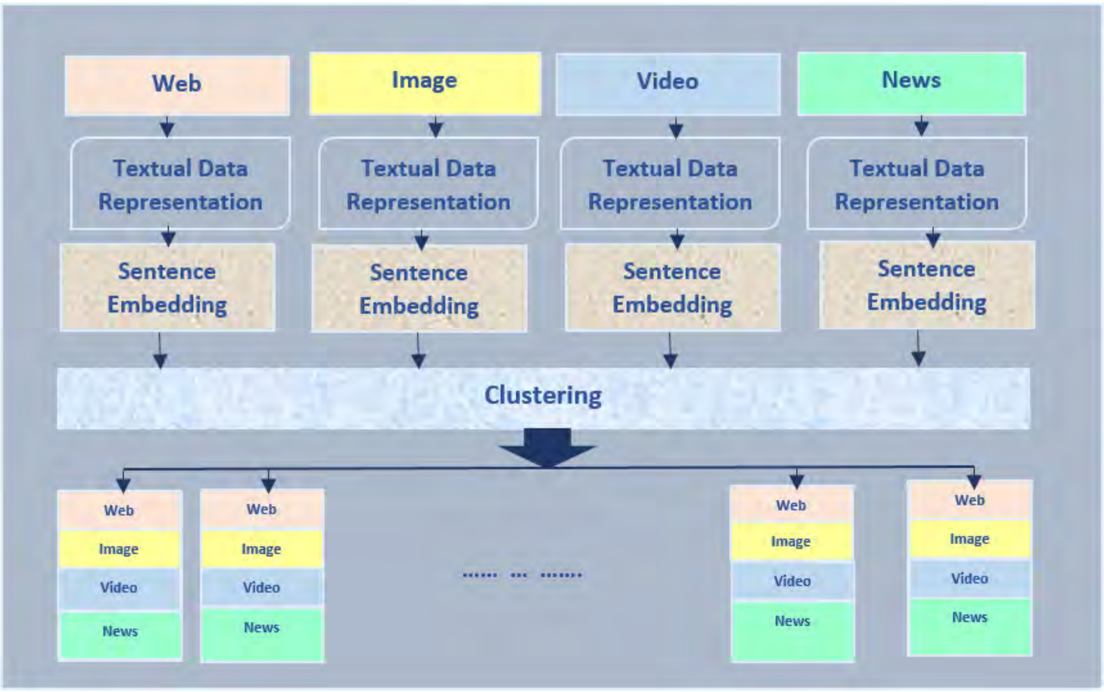


Figure 3.4: Aggregated (Clustering) Search Process Framework

3.2.4 Non-linear Data Model Layer

In this layer, the hash table undergoes a transformation into a meticulously organized data structure. Each entry within the hash table is assigned a corresponding vertex, facilitating a non-linear arrangement of information. The attributes of these vertices are imbued with the metadata linked to each index in the hash table, as visually depicted in Figure 3.5 c (Solid gray lines). Notably, each item within the postings list, situated adjacent to a given key, forms an integral part of it. As a result, links are established between the constituent elements of the postings and the key entity itself, a concept visualized in Figure 3.5 c (Solid green lines), and these links are referred to as containment edges.

Within the context of each posting, depicted in Figure 3.5 a (dotted lines), the items of multimedia documents are meticulously compared for their similarity based on summary data. To manage the density of the graph and ensure its clarity, the normalizer selectively establishes similarity links only when the similarity score surpasses a predetermined threshold. Conversely, similarity edges falling below this threshold are pruned. Figure 3.5 a aptly illustrates this process.

The outcome of this intricate process is stored in the form of an adjacency list. Meanwhile, the multimedia search results, representing clusters, are maintained as a linear list, thoughtfully organized by similarity scores for the sake of linear arrangement, as delineated in Figure 3.5.

Subsequent to the cluster formation, the summary of each cluster undergoes further refinement, aimed at identifying the most closely aligned multimedia document with the user query. This refinement entails the application of the vector space model, ultimately culminating in a more efficient and precise array of search results that aptly address the user's query. This intelligent refinement process contributes significantly to enhancing the relevance and accuracy of search outcomes, thus elevating the user experience.

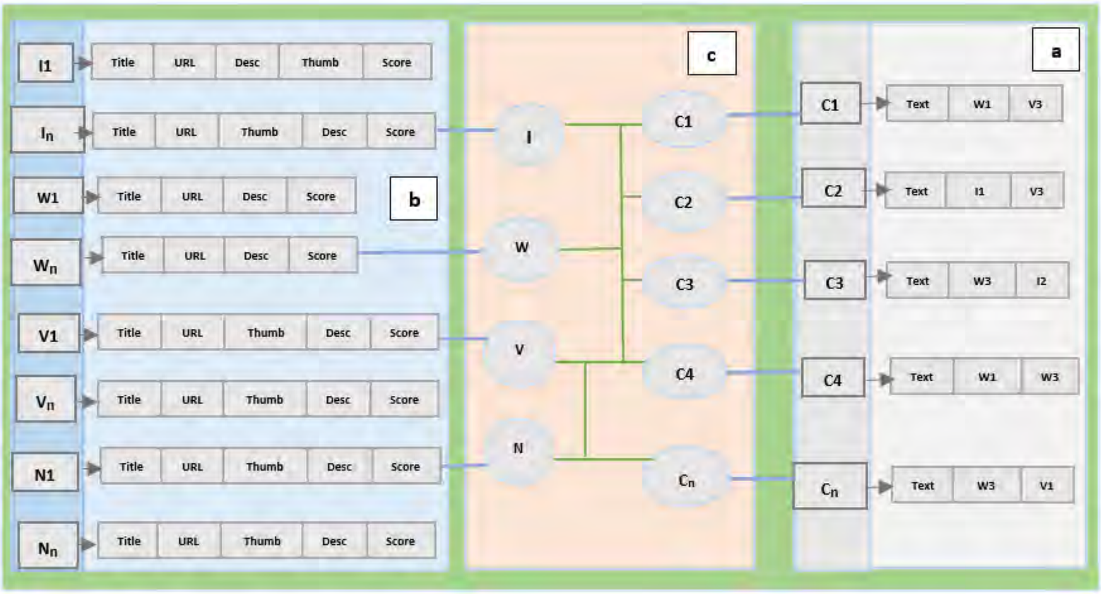


Figure 3.5: Non-linear Data Model Structure

3.3 Proposed Approach Formalization

The proposed approach for formalizing overflow consists of six distinct parts, each dedicated to illustrating a specific process. In the initial segment, we delve into the formalization of vertical aggregation, intricately describing the meticulous process through which various verticals are aggregated cohesively. This foundational step sets the stage for a comprehensive understanding of the subsequent components. Advancing to the second part, we intricately expound upon the formalization of multimedia document creation. This facet delves into the intricate steps involved in crafting multimedia documents, encapsulating the entire journey from inception to completion. Through meticulous detailing, this part sheds light on the intricate interplay of elements necessary to weave together a cohesive multimedia narrative. Transitioning seamlessly to the third segment provide the description of graph instantiation formalization, unraveling the process of translating abstract concepts into tangible graphical representations. As we culminate this comprehensive journey through the overflow formalization, the final part unveils the intricate design principles behind the formalization of the search user interface. This ultimate layer harmoniously merges aesthetics and functionality, offering users an intuitive and seamless interaction with the overflow framework.

3.3.1 Verticals Aggregation

The process of encapsulating all of the media objects inside of each vertical in a single composite container is what we refer to as verticals aggregation. Figure 3.6 shows the features presented in a media object, and Table 3.2 displays the vertical retrieval parameters from the Google.

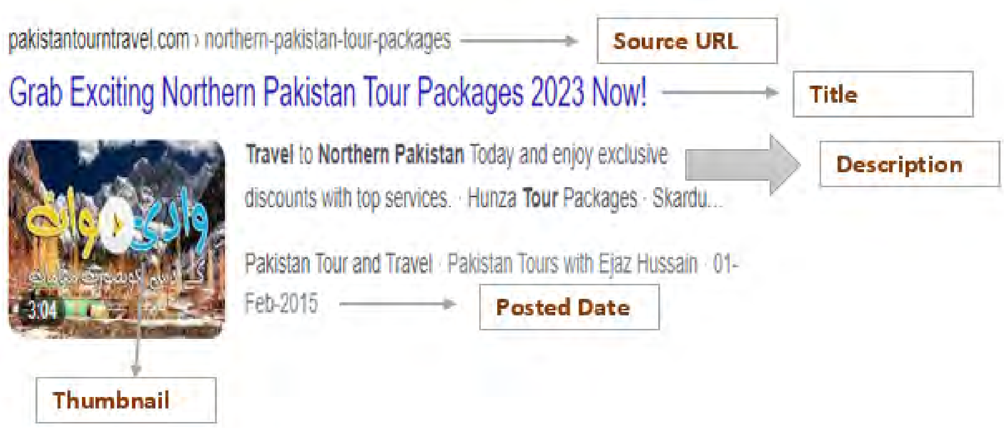


Figure 3.6: Anatomy of Searched Result Media Object

Let ω, ρ, σ, and τ signify the acquired verticals, forming a set denoted by V as follows: $V = \omega, \rho, \sigma, \tau$. Here, each vertical is described as: ω represents a collection of web entities, denoted by: $\omega = W_1, W_2, W_3, \ldots, W_m$ ρ signifies an assembly of video entities, denoted by:

Table 3.4: Parameters of Retrieved Vertical

Vertical	**Source**	**Modality**	**No.of results**	**Features**
Web	Google	Textual	≤ 100	URL, Title, Description
Video	Google	Visual + Textual	≤ 100	URL,Title, Description, Date, Thumbnail
Images	Google	Visual + Textual	≤ 100	URL, Title, Thumbnail
News	Google	Visual + Textual	≤ 100	URL, Title, Description, Date, Thumbnail

$\rho = V_1, V_2, V_3, \ldots, V_m, V_{m+1}, V_{m+2}, V_{m+3}, \ldots, V_{2m}$ σ indicates a compilation of image entities, denoted by:

$\sigma = I_1, I_2, I_3, \ldots, I_m, I_{m+1}, I_{m+2}, I_{m+3}, \ldots, I_{2m}$ τ denotes an assortment of news entities, denoted by: $\tau = N_1, N_2, N_3, \ldots, N_m, N_{m+1}, N_{m+2}, N_{m+3}, \ldots, N_{2m}$

In the above definitions, ψ represents the textual aspect, while ϕ represents the visual aspect associated with each media entity. Now, let A represent the subset of V that consolidates all elements containing solely textual information, given by the equation: $A = \bigcup_{i=1}^{m} V_i^{\psi}$, where V_i^{ψ} signifies the textual components (such as title and description) of the i-th media entity.

3.3.2 Multimedia Document Formation

For each vertical $v \in V$, let E_v represent the set of element embeddings, denoted as $E_v = e_1, e_2, e_3, \ldots, e_n$. Here, each embedding e is a multi-dimensional vector in space R^d, where d represents the embedding dimensionality. The multimedia elements in E_v are clustered based on their semantic relationships. This results in the formation of clusters: $E_v = \bigcup_{i=1}^{n} c_i$, where c_i represents the i-th cluster. The clusters are formed using agglomerative hierarchical clustering, employing Ward's method and utilizing a dissimilarity measure such as Euclidean distance. The formation of clusters is guided by a predefined threshold. Table 3.5 shows the clustering parameters.

Text Summarization within Clusters:

Each cluster c_i contains a coherent set of textual content $T_i = t_1, t_2, t_3, \ldots, t_m$, where $t \in T_i$ represents an individual text fragment. To summarize the textual information within each cluster, a text extractive summarization algorithm is employed. This algorithm produces a sequence of words, denoted as $S_i = s_1, s_2, s_3, \ldots, s_k$, where $s \in S_i$ represents a word in the summary.

Multimedia Vertical Synthesis:

The summarized text sequences S_i from each cluster c_i collectively contribute to the generation of a multimedia vertical synthesis. Let S denote the set of summarized sequences, such that $S = S_1, S_2, S_3, \ldots, S_n$.

Mapping and Multimedia Document Formation: A mapping function $M_d : S \rightarrow V$ establishes a relationship between the synthesized multimedia verticals and the summarized text sequences. For every vertical $v \in V$, there exists a corresponding text sequence $\kappa \in S$ such that $M_d(\kappa) = v$. The formalization describes a systematic process of aggregating multimedia verticals by embedding, clustering, summarizing, and mapping, resulting in the synthesis of multimedia documents with enhanced coherence and information representation.

Table 3.5: Clustering Parameters

Parameters	**Parameter Description**	**Parameter Value**
$n_clusters$	No. of clusters to find	None
Affinity	Metric to compute the linkage	Euclidean Distance
$distance_threshold$	The lineage distance threshold for merging clusters	θ
Linkage	Distance method between set of observation	Ward

3.3.3 Dynamic Query Generation

The dynamic query suggestions is the key process when the user wants to research the searched results. Let R be the set of multimedia search results obtained from a query q. Each search result $r \in R$ consists of a set of features f such as $r = \{f_1, f_2, f_3, \ldots, f_n\}$, where each feature f_i consists of both textual and visual modalities. Let Q be the set of dynamically generated queries based on the multimedia search result space R. Each query $q \in Q$ is represented as a set of keywords k given as $q = \{k_1, k_2, k_3, \ldots, km\}$. The process of dynamically generating queries from the multimedia search result space R involves the following steps: Extract the top-ranked search results from R based on a ranking metric that takes into account both textual and visual modalities. For each search result $r \in R$, extract the most relevant keywords k from both the textual and visual modalities of the features f. Aggregate all the extracted keywords from all the search results to generate the set of dynamically generated queries Q. Formally, the set of dynamically generated queries Q can be defined as follows: $Q = \{q \mid q = k_1, k_2, k_3, \ldots, k_m, k_i \in F, r \in R, r = f_1, f_2, f_3, \ldots, f_n, k_i = argmax_{j=1,n}(sim(k_i, f_j, T) + sim(k_i, f_j, V))\}$, where $sim(k_i, f_j, T)$ is the similarity measure between the keyword k_i and the textual modality of the feature f_j, $sim(k_i, f_j, V)$ is the similarity measure between the keyword k_i and the visual modality of the feature $f_2zqa1\ Q!\ j$, and **argmax** returns the feature f_j with the highest combined similarity score to keyword k_i.

3.3.4 Graph Data Model Formation

Graph-Based Exploration of Multimedia Search Results:

The exploration of multimedia search results is facilitated through a dynamic graph data structure. This structure is composed of interconnected vertices and edges, denoted by $G = (V, E)$, where V encompasses vertical multimedia clusters (M_c) and multimedia documents (M_d), represented as $V = M_d, M_c$.

Part-of & Similarity Relationships:

The relationship between multimedia documents (M_d) and multimedia clusters (M_c) is captured by the edge (δ), signifying a part-of (containment) association. Specifically, δ is defined as follows: For every multimedia document $m \in M_d$, there exists a corresponding multimedia cluster $c \in M_c$ such that $f(M_c) = M_d$.

Similarity Relationship within Clusters: The graph incorporates edges (δ) to represent similarity relationships within each multimedia cluster (M_c) and among the multimedia documents (M_d) within that cluster. This is defined as follows:

a. Similarity among multimedia clusters (M_c):

The edge (δ) is established between pairs of clusters M_c based on their Cartesian product. This similarity is quantified using the Jaccard similarity coefficient (J), resulting in the formation of the edge δ only if the similarity exceeds a threshold (θ).

b. Similarity among multimedia documents (M_d) within Clusters:

Edges (δ) are established among multimedia documents (M_d) within each cluster (M_c). For each cluster, denoted as M_k^c, the similarity among the multimedia documents is calculated using the Jaccard similarity coefficient (J). An edge δ is created if the similarity surpasses the threshold (θ).

The Jaccard similarity coefficient is defined as:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \tag{3.1}$$

Threshold-based Edge Formation:

Edges (δ) are formed based on a threshold J for both inter-cluster and intra-cluster similarity relationships. The threshold θ represents the average similarity score for all selected pairs of vertices in the graph.

The proposed formalization outlines a graph-based approach to explore and represent multimedia search results, leveraging part-of and similarity relationships between multimedia documents and clusters. This allows for non-linear exploration and insightful navigation through multimedia data.

3.3.5 User Interface

We have meticulously crafted three Search User Interfaces (SUIs) tailored to facilitate distinct research activities: query formulation, tree-map exploration, and pie-chart exploration. These interfaces are collectively denoted as SUI = SUIq, SUIt, SUIp. Within this framework, SUIt and SUIp are ingeniously composed of a set of panels, defined as C = Pq, Pg, Ps, Pu. To delve into the specifics, Pg represents the versatile grid view panel, Pq stands as the query formulation panel, Ps embodies the search results summaries panel, and lastly, Pu assumes the role of the user guidance panel. This thoughtfully designed ensemble of panels synergistically works to empower users with a comprehensive and interactive visualization interface, enriching their research experiences.

3.4 Implementation

3.4.1 Software Specifications

The proposed framework is implemented in Python3, leveraging openly accessible libraries. Real-time extraction of verticals from search engines is achieved through the utilization of free APIs to access search results. The search results for Web, Image, News, and Video verticals are obtained using the Google3 search engine. Given Google's preeminent status as a search engine [Ali and Gul (2016)], it was a natural choice to adopt it as our primary retrieval source. Whenever available, associated metadata such as title, thumbnail, URL, date, and description of each snippet are retained.

For text summarization, the LexRank[1] extractive algorithm is employed. Semantic analysis utilizes the ward's linkage method from the sklearn[2] Python package, incorporating SBERT[3] sentence embedding on the pre-optimized bertbasenlimeantokens[4] pre-trained model. Agglomerative clustering is then

[1] https://gist.github.com/rodricios/fee45381356c8fb36004
[2] https://scikit-learn.org/stable/
[3] https://pypi.org/project/sentence-transformers/
[4] https://github.com/UKPLab/sentence-transformers/blob/master/docs/pretrained-models/nli-models.md

employed to generate clusters. The Networkx[5] Python module constructs an undirected network, serving as the foundation for the graph. Each node in the graph represents a web snippet, multimedia document, or cluster of multimedia documents. The relevant metadata is encapsulated within the snippet node attribute, while the content of multimedia document nodes and multimedia document snippets nodes is encompassed within their respective attributes.

The User Interface (UI) front end is developed using HTML, CSS, and JavaScript. To ensure a systematic presentation of data and enhance the overall aesthetics of the HTML, the front-end employs the Bootstrap[6] toolkit. The UI creatively presents the search results in a non-linear and interactive manner, fostering cognitive engagement through tree-map charts[7] and pie-charts[8].

Facilitating communication between the UI and the data model, the back-end server relies on the Django[9] Python library. Django is specifically employed to process user input from the interface, retrieve processed data from the data model, and seamlessly display the obtained information on the user interface. The web based architecture of the proposed framework is presented in figure 3.7

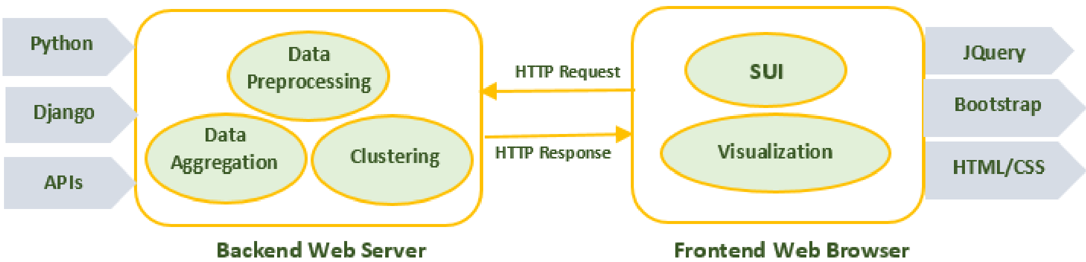


Figure 3.7: Proposed Framework Web Based Architecture

[5] https://networkx.github.io/
[6] https://getbootstrap.com/
[7] https://www.anychart.com/products/anychart/gallery/Tree_Map_Charts/
[8] https://developers.google.com/chart/interactive/docs/gallery/piechart
[9] https://www.djangoproject.com/

3.4.2 System Specifications

The system designed for proposed system development and execution consists of a HP laptop with cutting-edge 64-bit operating system, seamlessly integrated with an advanced x64-based processor. This dynamic pairing not only empowers the system with enhanced computing capabilities but also facilitates seamless multitasking on a whole new level. Boasting a substantial 12.0 GB of RAM, the system demonstrates exceptional proficiency in managing memory-intensive tasks and resource-demanding applications.

The operating system of choice is the dependable and secure Windows 10 Pro, which serves as the robust foundation for this innovative setup. Its reliability ensures consistent and uninterrupted performance, while its security features provide a shield against potential vulnerabilities. In the context of the proposed approach, this meticulously crafted environment becomes a powerhouse of potential, offering a versatile playground for framework development and execution. From seamless coding to the execution of complex algorithms, this system guarantees smooth operations and optimal performance across a spectrum of computing tasks.

3.5 Comparison & Discussion

In this section, we undertake a comparative analysis between our proposed system and contemporary state-of-the-art research. Our aim is to facilitate information exploration and research, wherein each research endeavor utilizes a specific array of methods and mechanisms. We extract the core parameters along with their corresponding values. As illustrated in Table 3.6, these parameters are further categorized into groups based on their respective objectives, enhancing their interpretability. Functionalities provided are marked with a tick sign ("+"), while absent features are represented by with blank space.

The comparison analysis across a spectrum of parameters between the existing literature and the proposed system reveals a nuanced landscape of information retrieval methods. In terms of query formulation, it is evident that the proposed system aligns more closely with Boolean queries, a trend consistent with recent advancements [Khan et al. (2023)]. Notably, while the existing studies predominantly focus on real datasets, the proposed system introduces a paradigm shift by emphasizing API-based data sources [Paul et al. (2019)]. This transition is reflective of contemporary data access practices, enabling faster and more dynamic data retrieval [Khan et al. (2023)]. The data model aspect accentuates the significance of non-linear models, wherein the proposed system follows the trend set by many recent studies [Rashid and Bhatti (2017)]. This underlines the adaptability of the proposed system to handle complex relationships within data, enhancing its relevance for contemporary applications. Furthermore, the cross-modal retrieval modal employed in the proposed system, similar to the approach highlighted by [Khan et al. (2023)], underscores the growing need to bridge multimedia content gaps effectively [Rashid et al. (2016a)]. Conversely, the existing literature showcases a preference for mono-modal retrieval, indicative of an evolving need to cater to users' multimodal information needs.

In the realm of media type, the proposed system encompasses a comprehensive array of content types, including text, image, and video, aligning with the multi-format preferences observed in recent research [Khan et al. (2023)]. This incorporation is indicative of the evolving media consumption patterns, with users increasingly seeking diverse content types. Furthermore, the results representation dimension reveals a substantial emphasis on grid-view, contrasting with the literature's focus on linear representation [Rashid et al. (2021)]. This innovative representation approach may enhance user engagement and insight extraction in the proposed system. The comparison analysis brings to light the proposed system's alignment with contemporary trends, such as API-based data access, non-linear data models and result representation , and diverse media types. The cross-modal retrieval and innovative results representation in the proposed system signify its potential to offer enhanced user experiences and insights. The discussion underscores the proposed system's ability to adapt to evolving user needs and technological advancements, positioning it as a robust and forward-looking solution in the realm of research and exploration.

Table 3.6: Proposed Framework Comparative Analysis

Analysis Parameter	**Analysis Parameter Value**	**Publication & Year**										
		[Rashid and Bhatti (2015)]	**[Rashid and Bhatti (2017)]**	**[Khan et al. (2021)]**	**[Paul et al. (2019)]**	**[Rashid et al. (2016a)]**	**[Khan and Rashid (2021)]**	**[Rashid et al. (2021)]**	**[Khan et al. (2023)]**	**[Kanjanakuha et al. (2019)]**	**[Zhang et al. (2018b)]**	**Proposes System**
Query formulation	Simple			+	+		+		+	+	+	+
	Boolean	+	+	+		+	+	+				+
Data-set	Real	+	+					+				+
	API			+			+		+			+
	Domain Specific				+	+				+	+	
Data Model	Non-Linear	+	+	+	+	+	+	+	+	+	+	+
Retrieval Modal	Mono-modal				+					+	+	
	Cross-modal	+	+	+		+	+	+	+			+
Search Results	Document Snippet			+	+		+		+		+	+
	Document Clusters			+			+		+			
	Multimedia Document	+	+			+		+		+		+
Media Type	Text	+	+	+	+	+	+	+	+			+
	Image	+	+	+		+	+	+	+			
	Video	+	+	+		+	+	+	+			+
	Audio	+	+	+		+	+	+	+			
SUI Search Activity	Look-up			+			+	+	+	+		+
	Exploratory	+	+	+	+	+	+	+	+	+		+
	Visualization	+	+	+	+		+	+	+	+	+	+
Data Architecture	Layered Based		+	+			+		+			+
	Component Based	+		+	+	+				+		+
Results Representation	Linear			+			+		+		+	
	Non-linear		+	+		+	+	+	+	+		+
	Grid-view	+	+	+		+	+	+	+	+		+

3.6 Summary

In this chapter, we introduce the "Aggregated Web Search Research Framework," a novel approach designed to enhance information exploration and research capabilities. The chapter is structured into several sections, each contributing to the framework's development. The "Proposed Approach Overview" highlights the limitations of conventional search engines and presents the concept of aggregating results from diverse verticals, transforming them into various representations, and accommodating users' nonlinear exploration. The framework's architecture is detailed, featuring layers such as Interface, Data Retrieval, Retrieved Data Representation, and Data Organizer. The Interface Layer enables flexible query formulation, exploration, visualization, and dynamic query suggestions. The Data Retrieval Layer employs APIs to gather results, which are then preprocessed and aggregated. The Clustering Layer organizes multimedia search outcomes into coherent clusters, enabling concept-driven exploration. The Non-Linear Data Model Layer transforms data into an interconnected graph, fostering non-linear navigation. Lastly, the "Proposed Approach Formalization" presents a formal breakdown of the framework's processes, including vertical aggregation, multimedia document creation, dynamic query generation, graph data model formation, and user interface design.The chapter concludes with a comparison between the proposed framework and existing literature. The comparison highlights the unique features and innovations introduced by the proposed system, such as API-based data retrieval, non-linear data models, dynamic query generation, and innovative user interface elements.

Chapter 4

User Search Research Behaviour

This chapter discusses search user interfaces role in multimedia information research and exploration. Before the recently published paper, different methods for encouraging information exploration had been used. It included information presentation using visualizations interactively (charts, graphs, sliders , bars etc.), tabbed or spatially, grids, linear list [Kanjanakuha et al. (2019)], [Kerne et al. (2006)],[Ruotsalo et al. (2018)],[Di Sciascio et al. (2016)], [Dörk et al. (2008)], [Rashid and Bhatti (2017)],[Tablan et al. (2015)], [Krishnamurthy et al. (2016)]]. Each information display technique's function is briefly discussed. The proposed exploratory, research and lookup interface in detail is discussed below. Following is the organization of this chapter. The significance of the search user interface in terms of the user and information exploration is discussed in Section 4.1. A general suggested strategy to promote multimedia information discovery is presented in Section 4.2. Information on the suggested data model is provided in Section 4.3. In Section 4.4, a case study is discussed that explains the search process from the user's point of view, from the first search to the fulfilment of the information requirement that leads to researching. In a brief demonstration of our discovery user interface in Section 4.5, it is examined from every angle, a connection to well-defined theories and studies is made, and the lookup, exploratory, and researching search scenarios are presented. This chapter's executive summary is found in Section 4.6.

4.1 Search User Interface an Overview

An efficient SUI improves interaction and increase opportunities of information exploration [Ruotsalo et al. (2014)]. Information should be visualized on a system for information retrieval that can offer users a range of options in an appropriate manner [Kerne et al. (2006)]; [Tablan et al. (2015)]; [Khalili et al. (2017)] to show this effectiveness. The ultimate objective should be to engage people with multimedia content that enables quick information processing in response to changing information needs dynamically [Ruotsalo et al. (2014)], [Di Sciascio et al. (2016)], [Ruotsalo et al. (2018)]. By focusing on information relationships and fostering increased familiarity with information whenever possible, a user interface should enable users to view previously hidden aspects of the information space and assist sense making [Ruotsalo et al. (2014)]. The inability of standard web search engines to effectively present and visualize information might make it more difficult to assist information exploration and discovery [Ruotsalo et al. (2014)].

Finding information has grown increasingly difficult, particularly when the search is interdisciplinary and exploratory in nature [Conaway et al. (2010)]. We must comprehend these properties in order to enable exploration and research activities. In order to navigate the information space effectively, the users' complicated information-seeking behaviour is modelled as a non-linear journey [Ruotsalo et al. (2018)]. The information is sought for by the users [Bates (1989)]. The current practise of only providing the most accurate information in answer to supplied queries does not satisfy their complicated information needs [Russell-Rose and Tate (2012)]. Instead, users choose the most intriguing pieces of information from various informational patches [Russell-Rose and Tate, 2012]. In a perfect world, these informational patches would yield more information for the same amount of work [Ruotsalo et al. (2018)]. Users develop a non-linear pattern of information searching as a result [Russell-Rose and Tate (2012)].

Our research mechanism comprises of four essential panels, as illustrated in figure 4.1. The first and foundational panel is the query formulation interface, designed to empower users to articulate their information needs and dispatch queries seamlessly. By providing a user-friendly and intuitive platform for query input, this panel serves as the gateway to the entire research process. Moving on to the second panel, we introduce the tree-map interface, an innovative and visually engaging way to present multimedia documents in a summarized form. By leveraging the power of non-linear representation, this interface allows users to navigate through vast amounts of multimedia data with ease. The tree-map not only facilitates efficient exploration but also assists in recognizing patterns and relationships between different documents, enabling users to gain comprehensive insights into the data at hand.

The third panel, in our research mechanism, is dedicated to a pie-chart representation of multimedia documents. This cognitive engagement tool offers a unique perspective on the distribution of information categories within the dataset. Users can visually grasp the proportions and proportions of different multimedia content types, fostering a deeper understanding of the content's composition and significance. Lastly, the fourth panel embodies the grid view interface, which serves as a practical and versatile way for users to access their desired information efficiently. By presenting multimedia objects in an organized and structured manner, users can swiftly navigate through the dataset and locate specific content items. The grid view empowers users with an at-a-glance overview of available multimedia documents, streamlining the research process and enhancing overall user satisfaction.

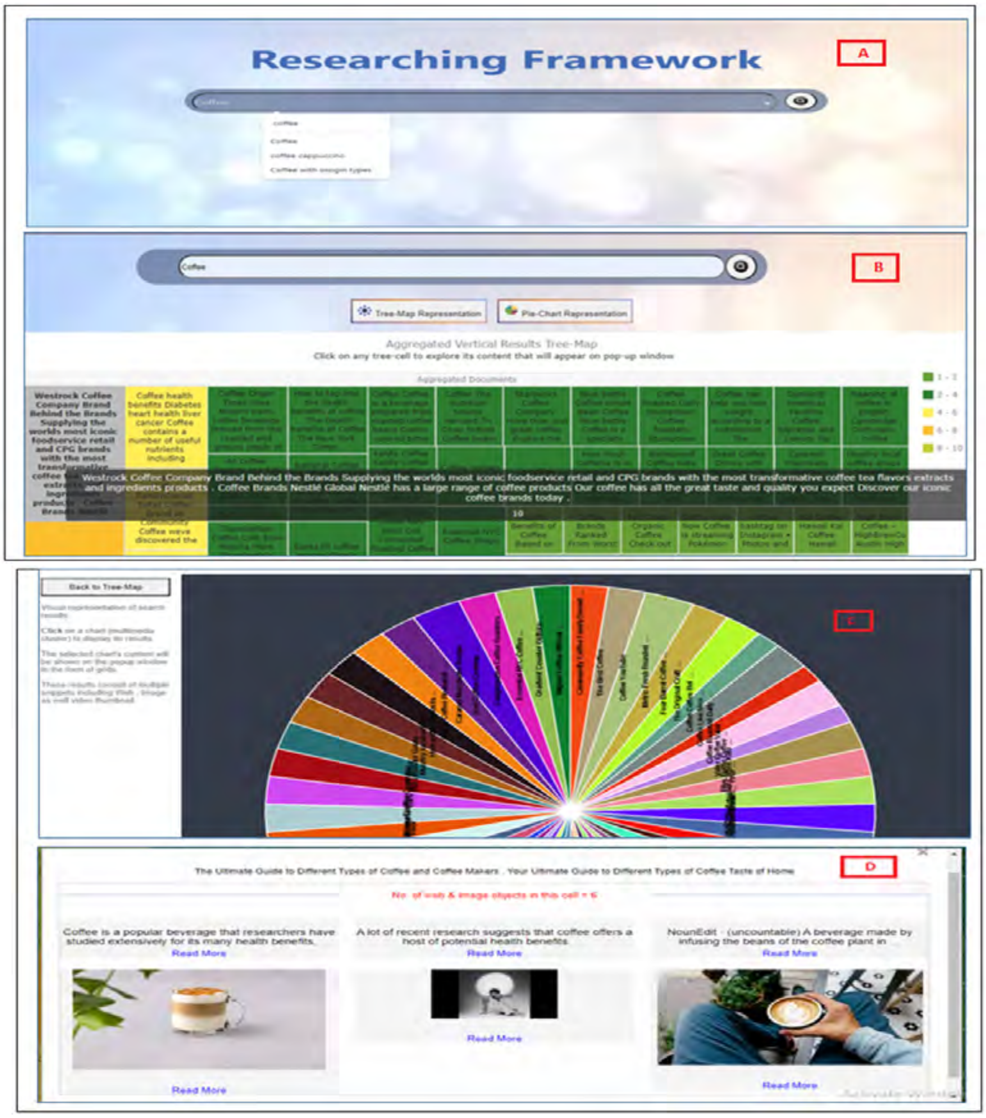


Figure 4.1: (a) Query Dispatching Panel, (b) Tree-map Representation of Searched Results,(c) Pie-chart Representation of Searched Results (d) Grid View of Multimedia Objects from Pie-chart as Well as Tree-map

4.2 SUI Design

The search user interface consists of six interfaces and below is the detailed discussion of each interface.

4.2.1 Query Formulation Panel

The query formulation panel offers a seamless and efficient platform for users to initiate their information search process. With its user-friendly interface, users can easily instantiate queries, allowing them to swiftly retrieve known items. However, when the information sought is more extensive or the user is exploring unfamiliar topics, the search process may take longer. This is particularly evident in exploratory search scenarios where users often opt for shorter and less well-articulated queries, as seen in lookup search contexts[Ruotsalo et al. (2018); Athukorala et al. (2016)]. In response to this challenge, our system intelligently assists users by providing relevant keywords and suggestions, thereby enhancing the search journey and guiding users towards more fruitful results. By offering interactive support, this panel facilitates the formulation of Boolean queries, enabling users to employ logical operators to refine their searches further.

This functionality empowers users to tailor their queries precisely, enhancing the precision and relevance of the search results. Additionally, the query formulation panel is ingeniously integrated as the first section (a) of figure 4.2. Furthermore, the interactive nature of the panel fosters an iterative search process, allowing users to adapt their queries based on the emerging results and insights gained from previous search iterations. This iterative approach is particularly valuable in complex and information-rich datasets, where the users' understanding of the content evolves as they interact with the system. The query formulation panel plays a pivotal role in our research mechanism by empowering users to initiate their searches effortlessly, guiding them through the exploratory process with intelligent keyword suggestions which are semantically related to the typed words, and providing them with dynamic visualizations to enhance their query refinement. As a result, users can efficiently navigate through vast amounts of data, discover new information, and accomplish their information-seeking goals with greater ease and effectiveness.

Figure 4.2: Query Dispatching Panel

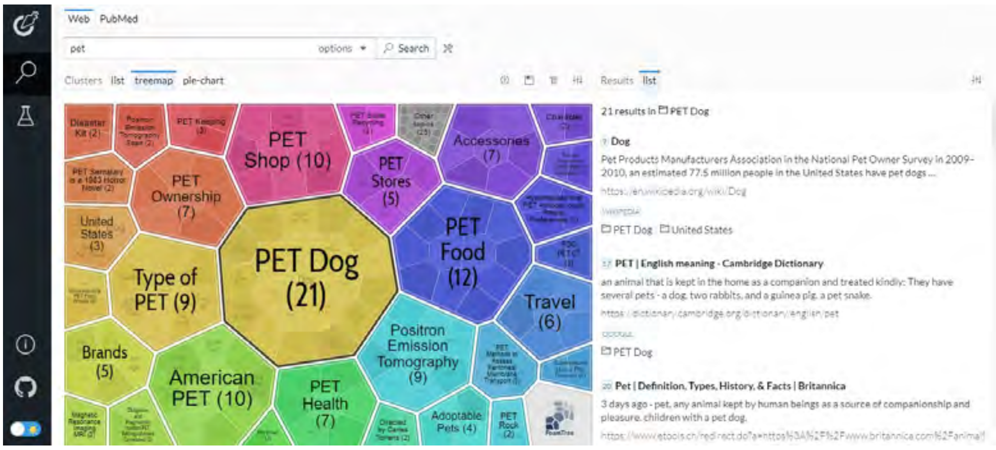
4.2.2 Tree-map Panel

The implementation of tree-maps in our research mechanism brings a host of advantages that significantly enhance data exploration and analysis. One of the most notable benefits is the ability to identify extreme values and major patterns within vast databases with remarkable ease and efficiency. By presenting complex datasets in a visually intuitive manner, tree-maps empower users to navigate through the information landscape effortlessly, gaining valuable insights that might have otherwise been obscured in traditional data representations. This interactive and engaging approach ensures that users can extract and utilize valuable information effectively, leading to more informed decision-making and a deeper understanding of the underlying data [Jadeja and Shah (2015)].

The system's implementation of the tree-map visualization offers users a user-friendly interface with rapid, reversible, and incremental query control. Users can interact with the tree-map to explore different aspects of the data, zooming in on specific regions or clusters to examine details further. The size of the tree-map cells is determined by the number of multimedia snippets contained within each cell which can be shown in section (b) of figure 4.3a , providing an instant visual impression of the distribution and density of information across the dataset. Each tree-map cell's colour shows the clusters of that particular size along with color as mentions in section (c)of figure 4.3a. Notably, this tree-map representation extends beyond textual data, incorporating multimedia documents, as depicted in figure (a) 4.3. This feature sets our system apart from other search engines, such as Carrot2 (b)4.3, which primarily focus on textual medical articles within a specific domain. Our system's tree-map visualization is more versatile and generic, accommodating various types of multimedia content, making it a valuable tool for a wide range of research and exploration tasks. One of the unique strengths of the tree-map interface lies in its intuitive and efficient selection process.

Rather than relying on traditional typing, users can seamlessly make selections by simply pointing and interacting directly with the tree-map cells as shown in the section of figure 4.3a . This feature sets our system apart from other search. This natural interaction allows users to quickly explore the content of specific cells, fostering a more intuitive and fluid search experience. By enabling direct access to multimedia documents through the interactive tree-map, users can efficiently navigate through the dataset, gaining rapid insights and making connections between different pieces of information. This level of interactivity not only accelerates the research process but also encourages users to delve deeper into the data, leading to more thorough and comprehensive analyses. section (d) of figure 4.3a allow user to switch between other non-linear representation of multimedia documents.

(a)



(b)

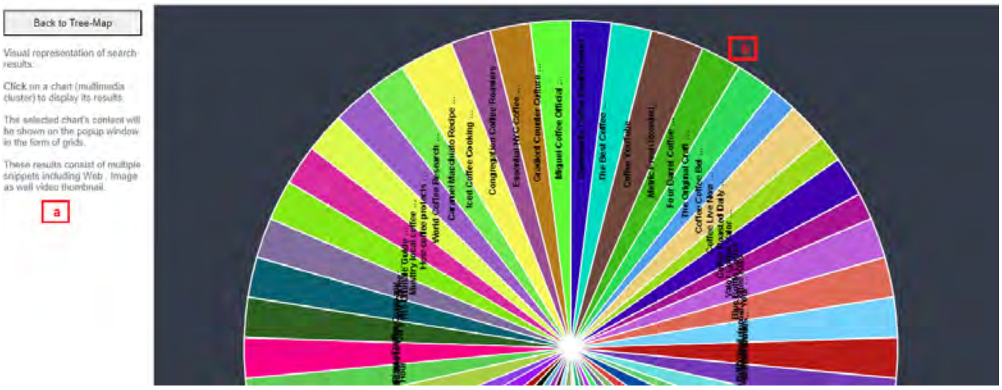
Figure 4.3: (a)Research SUI Tree-map with Summarized Results (b)Traditional Carrot2 Search Engine Tree-map with Article's Titles

4.2.3 Pie-chart Panel

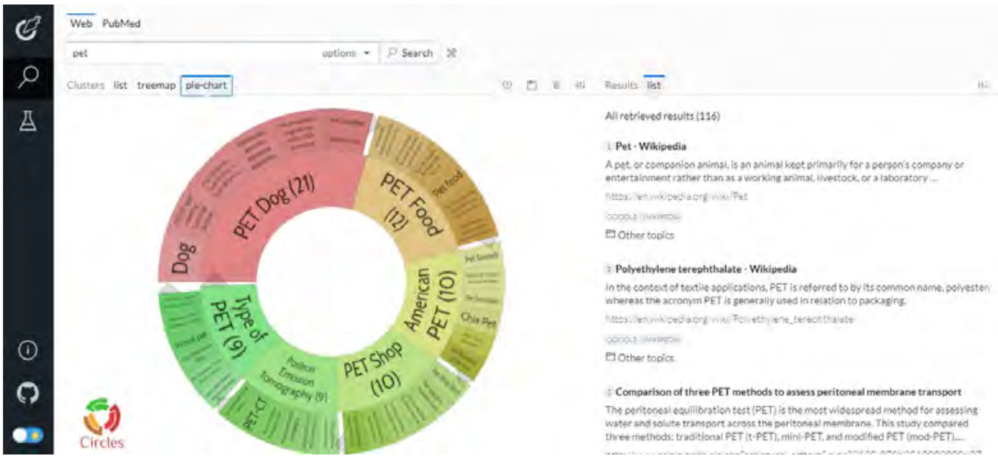
The pie-chart representation offered by this panel presents a visually appealing and informative summary of the multimedia search results derived from the user's query. This intuitive approach serves as a powerful tool for users to efficiently explore and grasp the distribution of information categories within the dataset. Each segment of the pie-chart corresponds to a specific category, making it easy for users to identify the relative proportions of different multimedia content types in their search results. By providing a clear and concise overview of the data, users can quickly discern which categories contain the most relevant information, thereby streamlining their exploration process and guiding them towards their required information.

Within this user-friendly interface, selections can be made effortlessly by simply pointing at the desired segment of the pie-chart, as demonstrated in section (b) of figure 4.4a. This seamless interaction enables users to delve deeper into specific categories of interest, triggering pop-up windows that display the relevant multimedia snippets within a grid view. This dynamic display allows users to explore the content associated with each category in a detailed and organized manner, empowering them to quickly access the relevant multimedia documents they seek. Moreover, to ensure that users make the most of this pie-chart interface, comprehensive user support is readily available shown in section (a) of figure 4.4a. Clear guidance and tool tips accompany the pie-chart, informing users of the various features and interactions available to them. This user-centric approach fosters a positive and efficient exploration experience, enabling users to make informed decisions and derive valuable insights from their multimedia search results.

Furthermore, the pie-chart representation serves as an effective cognitive engagement tool, as it promotes a deeper understanding of the dataset's content distribution. Users can readily observe the relative sizes of the segments, which helps them grasp the varying proportions of different multimedia types at a glance. This cognitive visualization aids users in identifying patterns and trends, making it easier to discern significant content clusters or potential gaps in the data. The interactive nature of the pie-chart interface empowers users to dynamically refine their queries and explore different facets of the dataset, guiding them towards more comprehensive and insightful research outcomes. The traditional carrot2 search engine for textual articles in depicted in (b) figure 4.4 while the research framework for multimedia documents in presented in (a) of figure 4.4.



(a)



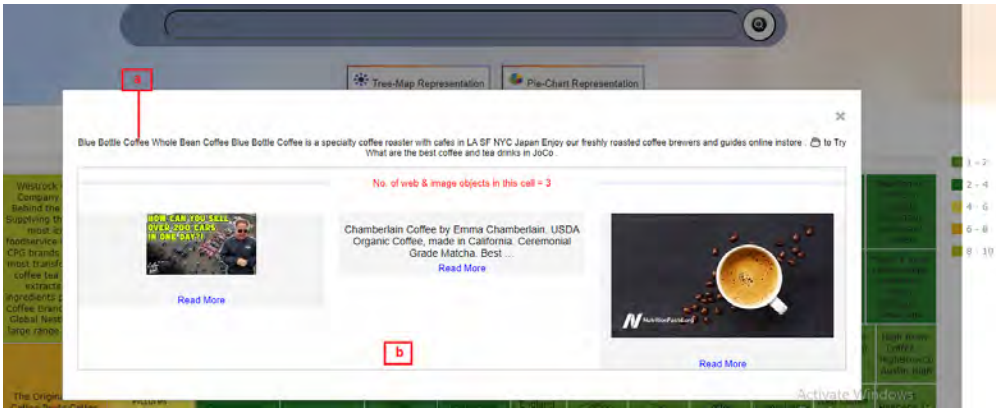
(b)

Figure 4.4: (a)Research SUI Pie-chart with Summarized Results (b)Traditional Carrot2 Search Engine Tree-map with Article's Titles

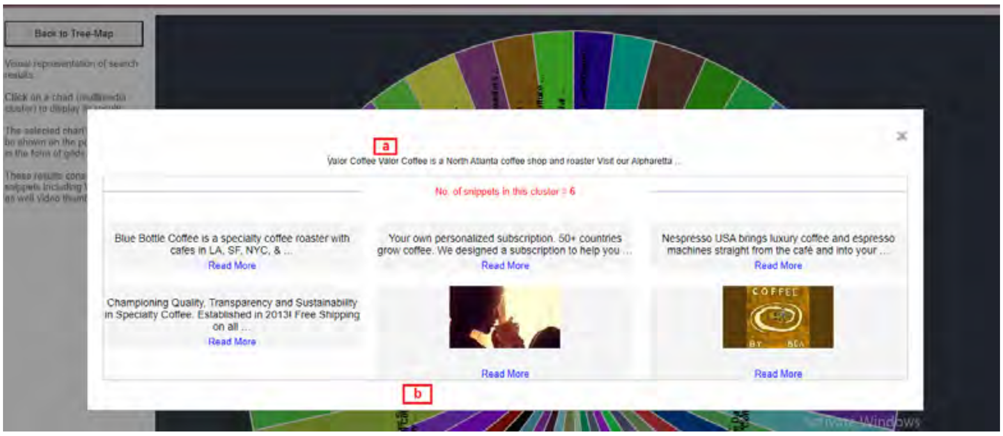
4.2.4 Grid View of Multimedia Snippets

The fourth panel of our system introduces a versatile and user-friendly grid view of multimedia objects, designed to optimize the user's navigation experience and provide easy access to the desired information. With this interactive grid view, users can seamlessly browse through a wide array of multimedia content, effortlessly locating and accessing specific documents or resources they seek. The grid view's visually organized layout presents multimedia objects in a structured and coherent manner, streamlining the exploration process and enhancing the user's ability to quickly identify relevant items. This intuitive interface not only expedites the information-seeking journey but also fosters contextual understanding and cognitive engagement, enabling users to extract valuable insights and make well-informed decisions based on the available multimedia data. The grid view's presentation style complements the visual richness of the tree-map and pie-chart representations, as users can seamlessly transition from these views to the detailed grid view whenever they click on a summarized multimedia document cell or patch, as shown in sections in figure 4.5.

This dynamic integration of different visualization techniques ensures a comprehensive range of exploration options, allowing users to interact effectively with the multimedia content. Whether users prefer a high-level overview through the tree-map or a more detailed examination using the pie-chart, they can effortlessly zoom in on specific multimedia objects by utilizing the grid view. This versatility accommodates different user preferences and information-seeking strategies, enhancing the overall usability and accessibility of our system. The grid view's efficient and user-centric design further contributes to the overall research experience, encouraging users to delve deeper into the multimedia dataset and uncover valuable connections and patterns. With its well-organized layout, users can make intuitive selections and explore content in a structured manner, reducing the time and effort required to find relevant information. Additionally, the seamless integration with the other panels encourages users to engage more extensively with the data, facilitating a more thorough and rewarding exploration process. By providing a holistic and interactive approach to multimedia data visualization, our system empowers users to make the most of their research endeavors, unlocking hidden insights, and facilitating knowledge discovery with ease.



(a)



(b)

Figure 4.5: (a) Tree-map Grid View of Searched Results (b) Pie-chart Grid View of Searched Results

4.3 Case Study

Forming an understanding of the search results that have been returned and leading to fresh insights and concepts is the essence of information exploration. This can be promoted by using various information encoding, offering search results understanding, improving information foraging and sense-making, the user's non-linear travel pattern and berry-picking. Figure 4.6 describe a scenario where a search activity is initiated by the user after entering the query "Coffee" into search bar which take the query as a full-text. The user query is dispatched to the Google by system and the search results in response to the user query are presented to the user, where the user browses through the search results, shown in Figure. Users click on a multimedia document they find interesting along the way. The clicked multimedia document, which contains all the multimedia objects therein, is quickly summarized in the multimedia document grid panel, as illustrated in 4.6(b). The user finds the cluster of the clicked multimedia intriguing (see Figure 4.6(c). The system displays all of the available multimedia materials inside the chosen cluster, and the non-linear information organisation makes it easier for the user to explore the cluster exploration. Since information researching tasks are quite diverse and include information lookup activities and information exploration, the user may also switch between different non-linear representations of the multimedia documents Figure 4.6(d). Our developed interfaces for exploration and grid view for lookup activities, respectively. In doing so, the user continues to explore and learn new, interesting details.

Figure 4.6: User Interface Interaction (a)Query Dispatching Panel (b)Searched Results Browsing (c)Interesting Multimedia Document Overview (d)Switch to other Multimedia Documents Representation

4.4 Comparison & Discussion

Lack of information causes the need for the information to arise during a task that the user is performing. An anomalous state of knowledge is defined as a recognized information demand [Belkin et al. (1982)]. The user refers to the information retrieval system to begin the information searching journey during the recognized anomalous condition of knowledge [Marchionini (1995)]. During this voyage, the user gathers vital information in the same way that an animal gathers berries strewn throughout the forest; they must be chosen one at a time [Bates (1989)]. In a manner similar to this analogy, the user must forage for information and select objects from information patches that have the greatest information relevancy [Pirolli and Card (1999)]. Information smells are clues that aid the user in making sense of the information presented. It can be improved by engaging in sense making activities. It entails making sense of data during data analysis, looking for representation, and encoding data to satisfy specific task demands [Russell et al. (1993)].

A non-linear data model is seen to be the most advantageous when the task is exploratory in nature [Rashid and Bhatti (2017)]. In this instance, the user's information needs are always changing and are frequently not met by the perfect document set. The proposed multimedia research interface offered multimedia snippets, multimedia documents, and pie-chart and tree-map representations of the search results to help users make sense of the information. The search results are grouped semantically to make it easier to find information, while summary, and universally established coloring guidelines are used to enhance information scent. The summarized parameters are presented in table 4.1. A non-linear search results can be included throughout the entire information-seeking process. Researchers must use their knowledge and experience to create search systems that actively engage searchers by utilizing semantics, and meaningful categorization. To do this non-linear search of the information successfully, researchers must leverage their skills and experience [White and Roth (2009)]. The proposed interface offered a non-linear graph-based mechanism for detailed multimedia document exploration to support the user's challenging information-seeking trip. The interactive non-linear visualization that was used throughout the entire process was also helpful. In most cases, the user is unable to precisely state what is required to fix the information anomaly [Belkin et al. (1982)].

In situations when the user cannot accurately conceive and communicate an information demand, it frequently leads to the deficiencies of the current retrieval systems, resulting in low accuracy of the retrieval systems [Belkin et al. (1982)]. In these situations, the users' information demands are not completely met by a single final set of information retrieved, but rather by a series of selections of individual pieces of information at each stage of the constantly evolving search methods [Bates (1989)]. These tasks call for improved filtering abilities and a preference for recall over precision [Tablan et al. (2015)]. When determining information relevance, we must take into account the user's perspective and how well the topic of the information retrieved corresponds to the user's area of interest [Harter (1992)]. We also need to think about how to convey information that causes the user's cognitive state to change. The suggested discovery interface uses endless scrolling, strong visual cues, and exploration of the data at several granularity levels, where each level raises the quantity of information items that are available, to maximize recall.

The comparative analysis of the proposed System User Interface (SUI) with state-of-the-art approaches is presented in Table 4.1. Functionalities provided are marked with a tick sign ("+"), while absent features are represented by with blank space. The analysis encompasses several critical parameters for evaluating SUI effectiveness. In terms of information representation, the proposed system introduces versatile options including linear, grid, tree-map, and pie-chart representations. Notably, it excels in employing graph-based and non-linear approaches, while also offering unique visualization options like tree-map and pie-chart, setting it apart from other methods. The research mechanism reveals that the proposed system combines linear, hierarchical, and non-linear structures, providing users with varying perspectives for data exploration. The inclusion of non-linear structures adds an innovative aspect that is not uniformly present in the state-of-the-art approaches.

Furthermore, the information trail in the proposed system is substantiated through thumbnails and summarization techniques, catering to users' pref-

Table 4.1: SUI Comparative Analysis

Analysis Parameter	Analysis Parameter Value	Publication & Year										
		[Rashid and Bhatti (2015)]	[Rashid and Bhatti (2017)]	[Khan et al. (2021)]	[Paul et al. (2019)]	[Rashid et al. (2016a)]	[Khan and Rashid (2021)]	[Rashid et al. (2021)]	[Khan et al. (2023)]	[Kanjanakuha et al. (2019)]	[Zhang et al. (2018b)]	Proposes System
Information Representation	Graph			+	+		+		+	+	+	
	Linear	+	+	+		+	+	+				
	Grid	+	+	+		+	+	+				+
	Tree-map	+	+	+		+	+	+				+
	Pie-chart	+	+	+		+	+	+				+
Interpretation technique	Clustering	+	+					+				+
	Non-clustering			+			+		+			
Research mechanism	Linear		+	+	+		+		+	+		
	Hierarchical	+	+			+	+					+
	Non-linear			+				+				+
Information trail	Thumbnail											+
	Summarization	+	+	+	+	+	+	+	+	+	+	+
Information Seeking	Sentimental				+					+	+	+
	Containment	+	+	+		+	+	+	+			
Visualization affirmation	Details on Demand		+	+			+	+	+	+		+
	Results Overview			+		+	+		+		+	+

erences for both detailed examination and quick insights. It covers the breadth of information seeking by accommodating sentimental and containment-based exploration, thus addressing varying user needs. Visualization affirmation options include "Details on Demand" and "Results Overview," underscoring the system's dedication to providing in-depth exploration and quick overviews. This comparison showcases the proposed system's comprehensive and adaptable nature, making it a versatile tool for a wide range of users and contexts.

4.5 Summary

This chapter deals the research question How can a Search User Interface (SUI) be designed to provide the research and exploration of aggregated vertical web search results in a useful way?. This chapter begins with an overview of the search user interface, followed by an in-depth exposition of the proposed framework. This comprehensive analysis takes into account a thorough comparison with other search engines, such as the Carrot2 search engine, highlighting the distinctive features and advantages of the proposed solution. Lastly, the evaluation concludes with a comprehensive juxtaposition of the proposed framework against the mechanisms employed by state-of-the-art System User Interfaces (SUIs). This systematic approach provides a holistic understanding of the proposed framework's strengths and differentiating factors, enhancing its position in the field of information retrieval and user interface design.

Chapter 5

Evaluation

5.1 Empirical Evaluation

The effectiveness of the aggregated search technique is still not subject to standardized empirical evaluation measures [Li et al. (2017)]. The majority of evaluations of these methods are based on the precision and recall that were attained [Rashid and Bhatti (2017)] and judgement reports from human experts [Ruotsalo et al. (2018)]. It is not easy to determine precision and recall for every task, the data's nature is primarily the cause. So, instead of using previously labelled data from human experts, we take into consideration the real dataset. The majority of the indicators we use for our empirical evaluation don't even need to have initial data labels. To assess the internal cluster model stability and accuracy of clustering based on the opinions of the human experts, we employed internal clustering stability metrics. By sending pre-defined queries to real dataset of Google, we were able to receive stability and accuracy scores.

We gathered queries from the 10 million distinct record ORCAS dataset, which was just published [Craswell et al. (2020)]. It was impractical to choose every query in the dataset for examination. So, using the ORCAS dataset, we conducted tri and bi-gram query analysis. Following that, we chose 25 inquiries from the top 100 tri and bi-gram combinations that were repeated the most. 2.5 words was chosen as the standard question length for this examination. The length was chosen because a recent study by [Degbelo and Teka (2019)] found that users' average query length ranged from 2.44 to 2.67 words, confirming that their information demands are evolving to be more exploratory. Because user needs in exploratory search are vague and getting an overview of the information is the main goal. In contrast to the well-articulated longer questions used in lookup search contexts, users tend to type shorter inquiries [Athukorala et al. (2016)]. We chose questions that covered a variety of topics. Consequently, based on the words that were average of 2.44 and 2.67, a query length contain 2.5 words was taken into consideration.

5.1.1 Stability & Accuracy for Internal Clustering

To create multimedia documents the agglomerative clustering is used. To generate the appropriate number of clusters, we established cut-off threshold for the cluster creation procedure. By calculating the ideal average mean value for stability of internal cluster metrics, the θ we chose empirically. To determine the stability of internal cluster, we utilized the well-known Silhouette Coefficient [Rousseeuw (1987)], DaviesBouldin [Davies and Bouldin (1979)] and Calinski-Harabasz [Caliński and Harabasz (1974)] indices. By conducting five experiments and using the mean value of those experiments for the multimedia documents creation, we were able to determine θ_1 the average mean value, as shown in table 5.1. Finally, clustering model was parameterized for multimedia documents using empirically acquired values, as shown in table 5.1.

Table 5.1: Empirical Evaluation Experiments

Experiment	Iteration	Optimal θ_1	# of Clusters	Silhouette Coefficient	Calinski-Harabasz index	Davies-Bouldin Index
1	1	15	210	0.11	3.40	1.15
	2	9	245	0.15	5.88	0.88
	3	12	200	0.12	3.82	0.83
	4	14	220	0.11	3.59	0.98
	5	10	205	0.15	5.60	0.75
Mean		12	216	0.13	4.46	0.92
2	1	14	225	0.10	3.39	0.97
	2	15	230	0.09	3.56	1.27
	3	15	240	0.11	3.36	1.28
	4	16	195	0.08	3.62	1.50
	5	13	250	0.15	4.08	0.74
Mean		14.6	228	0.11	3.60	1.15
3	1	13	220	0.08	3.49	1.08
	2	15	245	0.10	3.36	1.11
	3	13	210	0.10	4.01	1.01
	4	16	255	0.09	4.51	1.59
	5	15	200	0.12	3.48	1.12
Mean		14.4	226	0.10	3.77	1.18
4	1	14	240	0.12	3.94	1.01
	2	14	250	0.10	3.80	1.20
	3	14	210	0.09	3.06	1.06
	4	13	225	0.12	3.22	0.81
	5	13	255	0.17	4.47	0.88
Mean		13.6	236	0.12	3.70	0.99
5	1	14	230	0.10	4.04	1.16
	2	13	190	0.09	3.85	1.00
	3	12	260	0.10	3.58	1.09
	4	14	200	0.10	4.06	0.96
	5	12	240	0.14	5.46	0.92
Mean		12.8	224	0.11	4.20	1.03
6	1	15	245	0.12	4.01	1.10
	2	14	200	0.11	3.89	1.07
	3	14	210	0.10	3.75	1.14
	4	16	220	0.12	4.08	0.98
	5	17	230	0.14	4.56	0.93
Mean		15.2	221	0.11	4.06	1.04
7	1	16	195	0.10	3.77	1.12
	2	15	215	0.11	3.62	1.05
	3	14	250	0.12	4.10	0.97
	4	14	205	0.09	3.96	1.20
	5	15	235	0.13	4.50	0.88
Mean		14.8	220	0.11	3.99	1.04
Mean Average		14.48	224.57	0.11	3.95	1.05

5.1.2 Precision of Clusters

According to [Rashid and Bhatti (2017)], precision is defined as the proportion of relevant outcomes that were found out of all relevant results. Precision in clustering is the proportion of relevant results to all other outcomes inside a cluster. Cross-matching acquired cluster results with appropriately labelled data is a common method of calculating precision. In real dataset labelling of the data is not available in a real dataset.To get over this problem, throughout the empirical model parameterization of internal clustering phase, we logged the results obtained from the pre-defined queries. Four human experts were then given these logged search results to categorize the irrelevant and relevant search results within each cluster and label these results. The two human experts were graduates who had no prior experience with technical elements of computers. The other two were human experts who were computer science graduates who possesses extensive technical computer-related knowledge including the clustering concepts as well. Their varied backgrounds aided in obtaining objective confirmation of our clustering methodology. The conclusions reached by the human experts are displayed in Table 5.2. We conducted seven iterations of experiments, with seven sub-experiments per iteration. From each iteration we took into consideration the mean scores and averaged them over the course of seven iterations.The acquired experimental results reveal no appreciable variation in the relevance judgement scores for multimedia documents from the expert judge (99.58%) and novice judge (99.48%). The agreement between the expert and novice judges for multimedia document is (k = 0.2) which is fair agreement between them.

5.2 Usability Evaluation

5.2.1 Users

A total of 24 participants displayed presented by pie-chart shown in 5.1 from diverse background are selected for this evaluation These participants are from international and national regions. Seventy percent of the participants had no prior research experience while thirty person participants had prior knowledge of research. The participants were split into two groups. In each group, we categorized the users into three categories. The first category

Table 5.2: Empirical Evaluation Experimental Results

Experiment	Iteration	Novice Judges		Expert Judges	
		% (P)	% (P)	% (P)	% (P)
1	1	100.00	100.00	100.00	100.00
	2	100.00	100.00	100.00	100.00
	3	100.00	96.70	96.70	96.70
	4	96.60	88.00	88.00	88.00
	5	100.00	100.00	100.00	100.00
2	1	100.00	100.00	100.00	100.00
	2	100.00	100.00	100.00	100.00
	3	100.00	100.00	100.00	100.00
	4	100.00	100.00	100.00	100.00
	5	100.00	100.00	100.00	100.00
3	1	100.00	100.00	100.00	100.00
	2	100.00	100.00	100.00	100.00
	3	100.00	100.00	100.00	100.00
	4	100.00	100.00	100.00	100.00
	5	96.60	100.00	100.00	100.00
4	1	98.10	100.00	100.00	100.00
	2	100.00	100.00	100.00	100.00
	3	96.90	96.90	96.90	96.90
	4	100.00	100.00	100.00	100.00
	5	100.00	100.00	100.00	100.00
5	1	100.00	100.00	100.00	100.00
	2	100.00	100.00	100.00	100.00
	3	100.00	96.60	100.00	100.00
	4	100.00	100.00	100.00	100.00
	5	100.00	100.00	100.00	100.00
6	1	99.50	98.70	98.70	98.70
	2	97.80	96.50	96.50	96.50
	3	100.00	99.32	99.32	99.32
	4	99.38	100.00	100.00	100.00
	5	99.38	100.00	100.00	100.00
7	1	99.58	99.48	99.38	99.38
	2	100.00	100.00	100.00	100.00
	3	100.00	100.00	100.00	100.00
	4	100.00	100.00	100.00	100.00
	5	100.00	100.00	100.00	100.00
Mean Average		99.58		99.48	
Mean		99.38			
Cohen's Kappa		0.20			

comprised students from various academic fields, such as computer science, history, mathematics, information technology, physics, botany, and Artificial Intelligence. The second group consisted of professionals, including pump operator, lieutenant commander, lecturers, research assistant, lawyer, engineers, and freelancers. There were diverse qualifications of all the participants, ranging from metric to graduation degree. Overall, 16 females and 32 males were taken from which the 37.5% participants were students while the remaining 62.5% were professionals The minimum participant's age was 17 years and maximum age was 45 years respectively, so the average age is 31 years and standard deviation is 14 years. All participants agreed on this evaluation. Figure 5.2 shows the field of the users either they are from IT background or non-IT background.

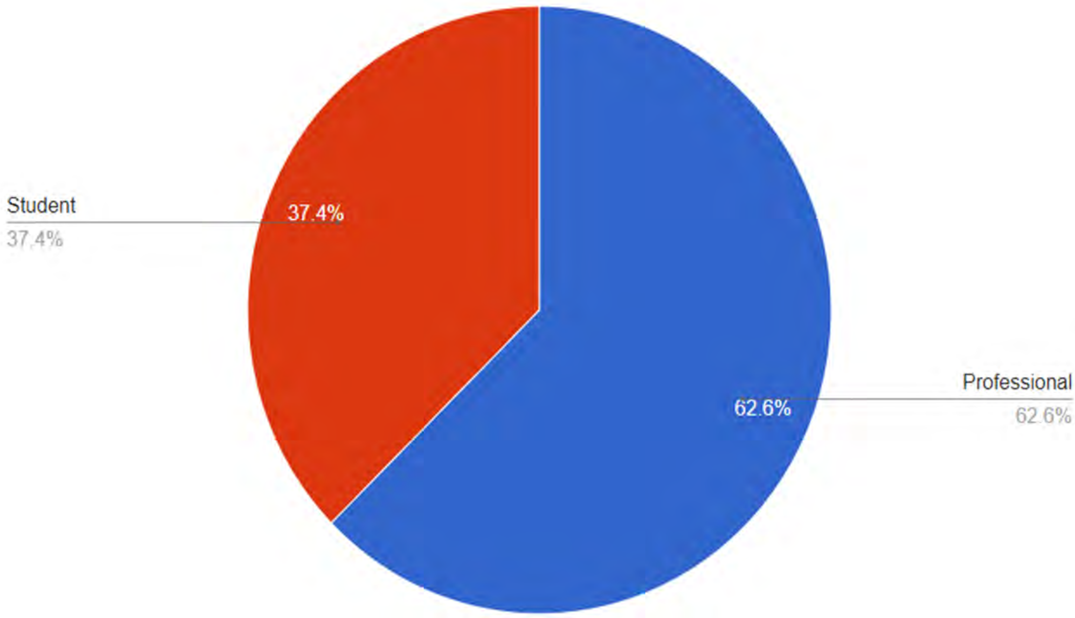


Figure 5.1: Users Categories

5.2.2 Tasks

We designed multiple search tasks for the evaluation of proposed as well as base system. These tasks include both lookup and exploratory information seeking. We divide these tasks into two groups. The first group contained

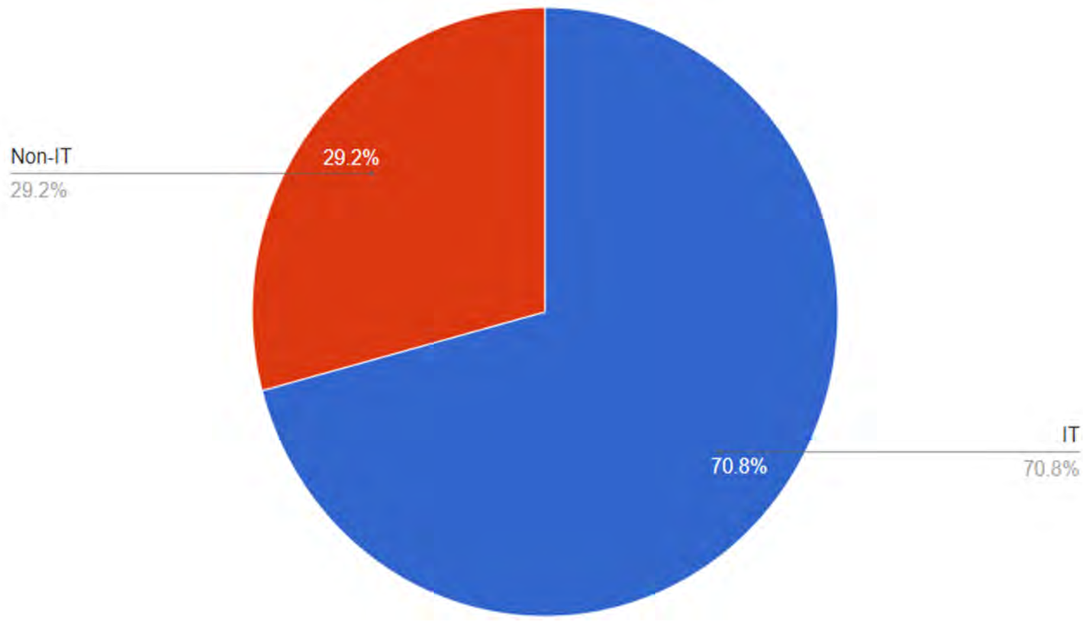


Figure 5.2: Users Educational Background

multiple guided tasks while the other group contained multiple unstructured tasks. These guided tasks composed of detailed instructions. The most familiar task had to be chosen by users. This well-known structured challenge had the dual objectives of increasing tool familiarity and maximizing panel usage. The unguided tasks, in contrast to the guided task, solely involved an exploration search situation without any specific guidelines. The user was required to choose an unguided task based on their level of prior task knowledge. As a result, dynamic exploratory behavior could flourish without user biases due to prior information interfering with the evaluation process.

Guided Tasks

Task-1: Please begin the search by typing the query “Coffee” into the search query panel. After initiating the query you got searched results at one place in the form of tree-map chart. These searched results are actually the summarized multimedia documents. Explore multimedia document without much scrolling by examining the summary with mouse hover over the tree-map cell. To check the number of snippets in that particular multimedia document hover over the cell of tree-map chart. To examine the multimedia snippet (image, web etc.) click on the tree-map cell the snippet will appear in grid-view on pop-up window, explore the multimedia snippet by clicking on the "Read More" button. Open the "Pie-Chart Representation" window to get the more attractive visual representation of multimedia documents. To examine the multimedia snippet (image, web etc.) click on the pie-chart patch the snippet will appear in grid-view on pop-up window, explore the multimedia snippet by clicking on the "Read More" button that appear below that snippet.

Task-2: Please begin the search by typing the query "Animals" into the search query panel. After initiating the query you got searched results at one place in the form of tree-map chart. These searched results are actually the summarized multimedia documents. Explore multimedia document without much scrolling by examining the summary with mouse hover over the tree-map cell. To check the number of snippets in that particular multimedia document hover over the cell of tree-map chart. To examine the multimedia snippet (image, web etc.) click on the tree-map cell the snippet will appear in grid-view on pop-up window, explore the multimedia snippet by clicking on the "Read More" button. Open the "Pie-Chart Representation" window to get the more attractive visual representation of multimedia documents. To examine the multimedia snippet (image, web etc.) click on the pie-chart patch the snippet will appear in grid-view on pop-up window, explore the multimedia snippet by clicking on the "Read More" button that appear below that snippet.

Unguided Tasks

Task-1: There are many counties in the world. Please explore the information about "Countries", what are the most recent developments in countries.

Task-2: There are numerous technological advancements around the globe. Please delve into information about "Technological Innovations" and discover the latest developments in this field by typing the query Technology.

5.2.3 Instruments

The effectiveness of proposed system majorly depends on usability user engagement as well as interface satisfaction. The User Engagement Scale-Short Form (UES-SF) is improved in order to quantify user engagement [O'Brien et al. (2018)]. The System Usability Scale (SUS) [Brooke, 1996] is used to assess usability, and the Questionnaire for User Interface Satisfaction (QUIS) [Chin et al. (1988)] to assess user interface satisfaction. From study [Mao et al. (2018)] we utilized a five-point Likert scale for knowledge acquisition, task complexity measurement, and user interest by search experience satisfaction. The demographic of the users is taken according to the study [Son et al. (2017)] which is based on the literacy scale.

5.2.4 Procedure

Users were given a quick overview of the proposed system's working during the evaluation. The presentation highlighted key features and functionalities to ensure a foundational understanding. In order for the user to become familiar with the nonlinear exploration choices made available by interaction, a comprehensive 5-minute video session was meticulously crafted, showcasing various scenarios and usage patterns of the proposed tool.

Before beginning their interactive session, participants were encouraged to engage in an open dialogue, addressing any queries or clarifications they had concerning the system. This facilitated a comfortable environment, fostering active participation and enhancing user engagement. Following this preliminary interaction, participants proceeded to delve into the tool's capabilities.

Upon the completion of these initial procedures, participants were handed a demographic questionnaire. This questionnaire aimed to gather comprehensive personal information such as computer literacy level, prior experience, and user preferences. The insights gleaned from this questionnaire allowed for a more nuanced analysis of user interactions and experiences.

Throughout the session, meticulous records were maintained to capture each user's unique search behavior. These records would later contribute to a deeper understanding of user interaction patterns and preferences. As users engaged with the tool, they were encouraged to provide feedback on its usability through the QUIS-Questionnaires. This feedback mechanism served as a valuable channel for users to share their perspectives, to refine and optimize the tool's design based on user insights.

5.3 Usability Evaluation: Results and Discussions

The user behavior, user satisfaction and system usability, are used to gauge usability. Utilizing standardized questionnaires, user satisfaction and system usability are evaluated. The use of the search interface is demonstrated by measuring user behavior in relation to time utilized by user.

5.3.1 System Usability

In the pursuit of a thorough evaluation of the proposed system's usability, a meticulous approach has been adopted, incorporating three widely recognized and standardized questionnaires. The utilization of the Computer Usability Satisfaction Questionnaire (CUSQ) and the System Usability Scale (SUS) serves as a robust methodology to comprehensively assess the overall usability and user-friendliness of the system. The CUSQ delves into various facets of user satisfaction, exploring user experiences across different dimensions of system interaction. Meanwhile, the SUS offers a concise yet insightful measure of perceived usability, capturing users' perceptions of the system's efficiency, effectiveness, and learnability. The inclusion of these meticulously crafted questionnaires underscores the commitment to obtaining a comprehensive understanding of user experiences. For convenient access and reference, these pivotal questionnaires have been thoughtfully compiled and presented in the Appendix section. This strategic placement not only ensures transparency but also provides interested readers and stakeholders with a valuable resource for further analysis and in-depth exploration of the usability assessment process.

CSUQ

A common method employed by researchers and practitioners to comprehensively gauge the usability of a diverse array of interactive systems is the Computer System Usability Questionnaire CSUQ [Lewis (1995)]. This structured assessment tool comprises 19 distinct items, each rated on a Likert scale ranging from 1 to 7, where 1 signifies "strongly disagree" and 7 conveys "strongly agree." The CSUQ offers a multifaceted evaluation encompassing the overall usability of interactive systems, dissected into three key dimensions: system usefulness (items 1–8), information quality (items 9–15), and interface quality (items 16–19). Table 5.3 provides a comprehensive overview of the empirical findings obtained through CSUQ-driven experiments, encapsulating the discernible trends in usability assessments.

This empirical evidence encompasses the CSUQ scores assigned by individual participants during the evaluation process, culminating in an aggregated overall usability score, all of which are meticulously documented within the same table. Notably, our proposed framework garners an impressive usability rating of 85% on a scale of 100, indicating a noteworthy level of excellence in user experience. Delving deeper into the nuanced components, the assessment highlights the system's notable attributes: a commendable 84% rating for system usefulness, reflective of its practical value; an equally commendable 86% rating for interface quality, signifying the users' positive perception of the system's interface; and a remarkable 84% rating for information quality, underscoring the system's capability to deliver accurate and relevant information. These compelling outcomes collectively underscore the uniform enthusiasm exhibited by diverse user groups towards the holistic usability of the interactive system, with equal emphasis on both overall usability and its distinctive usability dimensions. The graphical representation of CUSQ is shown in figure 5.3 in the form of pie-chart.

Table 5.3: Usability Assessment Scores (CUSQ)

Users	Overall	Usefulness	Info. Quality	Interface Quality
P1	5.71	3.38	6.06	5.71
P2	6.34	5.88	7	6.34
S1	5.28	5.99	5.76	5.28
S2	6.05	5.89	6.05	6.05
P3	6.33	6.13	6.33	6.33
P5	6.9	6.88	7	6.9
S3	6.18	6.03	6.03	6.18
P4	6.95	6.32	7	6.95
P6	6.11	6.11	6.11	6.11
S4	6.72	6.27	6	6.72
P7	5.5	7	6	5.5
S5	3.68	2.13	2.44	3.68
P8	6.77	6.88	6	6.77
S6	6.11	4.5	5.27	6.11
P9	7	6.38	7	7
P10	6.78	6.75	6.78	6.78
P11	6.85	6.38	7	6.85
S7	6.93	6.88	7	6.93
S8	6.15	6.25	6	6.15
S9	5.96	5.13	5.57	5.96
P13	6.15	6.63	6	6.15
P14	6.24	5.25	6	6.24
P15	5.82	5.13	5.82	5.82
Avg	5.99	5.9	6.05	5.89
Score	0.85	0.84	0.86	0.84

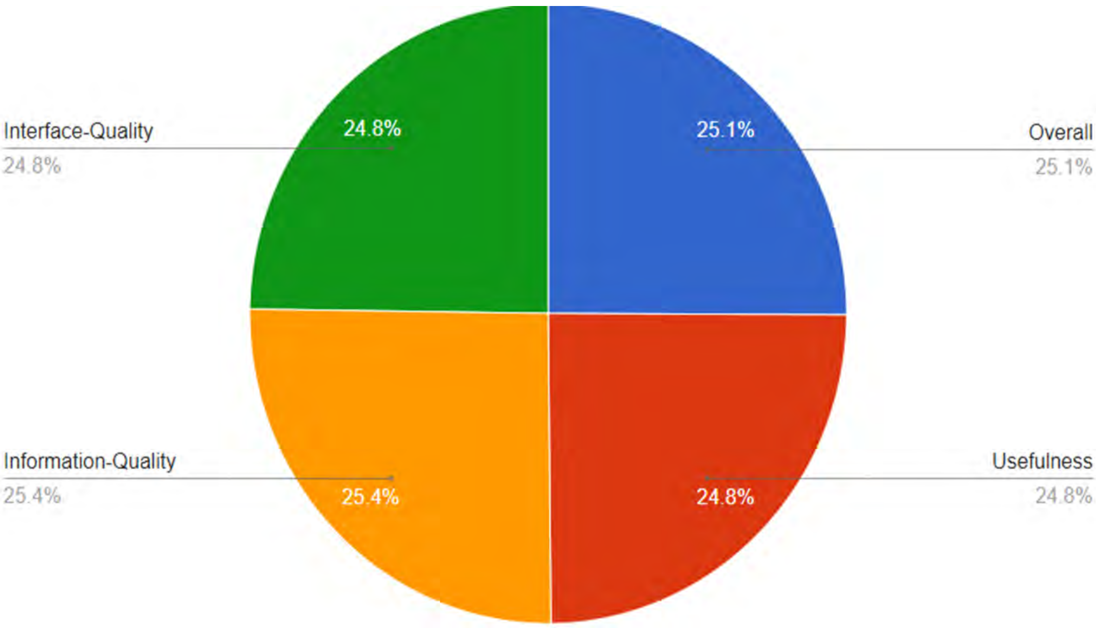


Figure 5.3: CUSQ

System Usability Scale (SUS)

The System Usability Scale (SUS) serves as a vital tool for evaluating the usability of a given system. Comprising ten distinct questions, each rated on a Likert scale spanning from 1 to 5 points, the SUS facilitates a comprehensive assessment of user experience. The total SUS score operates within a spectrum ranging from 0, indicative of the least favorable usability, to 100, signifying the pinnacle of usability achievement. Within the SUS questionnaire, the distribution of odd-numbered questions encompasses an evaluation of positive aspects, while even-numbered questions pivot toward the scrutiny of negative facets. Each individual item's score spans from 0 to 4, with the score for negative attributes being deduced from 5. Furthermore, a deduction of 1 point is applied to questions concerning positive elements, in alignment with their respective significance.

Subsequently the cumulative scores from all questions are aggregated and subsequently multiplied by a factor of 2.5. This multiplication yields a comprehensive value that extends across the 0 to 100 range, encapsulating the overarching usability assessment. The amalgamation of these intricate processes within the SUS framework renders it a versatile and robust tool for gauging the usability of diverse systems, contributing significantly to the field of user-centered design and evaluation. The evaluation of the proposed system's performance yielded notable results. In particular, the System Usability Scale (SUS) was employed to quantify its usability, producing an average score of 80.41 for the first task and 75.83 for the second task, encompassing both task-1 and task-2, as detailed in table 5.4. Considering the overall spectrum of tasks, the composite average SUS score emerged at 78.12, characterized by a standard deviation of 2.29.

In accordance with the established rating scale presented in the seminal work of [Lewis and Sauro (2018)], the proposed system garnered an impressive "B+" grade. This categorization situates the system within the esteemed 80 to 84 percentile range, a testament to its commendable performance. These acquired scores collectively underscore a discernible level of usability and user satisfaction, effectively affirming the system's prowess in meeting user needs and engendering positive experiences.

Table 5.4: SUS (System Usability Scale)

Task	User ID	Q:1	Q:2	Q:3	Q:4	Q:5	Q:6	Q:7	Q:8	Q:9	Q:10	SUS Score
T-1	P1	3	5	3	5	3	5	3	2	3	2	85
	P2	2	5	3	5	3	5	3	3	2	3	85
	S1	2	4	3	1	3	4	3	4	2	2	70
	S2	2	4	1	2	2	4	2	4	2	3	65
	P3	2	5	2	4	2	5	3	4	2	4	82.5
	P5	2	5	2	2	1	3	2	3	2	3	62.5
	S3	2	5	3	4	3	5	3	5	2	4	90
	P4	2	5	2	4	2	4	2	4	2	4	77.5
	P6	3	5	3	5	3	5	3	5	3	2	92.5
	S4	2	4	3	3	3	4	3	3	3	1	72.5
	P7	2	4	2	4	1	5	3	5	1	4	77.5
	S5	3	5	3	4	3	5	2	4	2	4	87.5
Average Score												80.41
T-2	P8	2	4	3	1	3	4	3	4	2	2	70
	S6	2	4	3	4	2	4	2	4	2	3	75
	P9	2	5	2	4	2	5	2	5	2	4	82.5
	P10	2	5	2	4	2	4	2	5	2	4	80
	P11	2	5	3	3	3	5	3	5	2	4	87.5
	P12	2	4	3	3	3	4	3	3	3	1	72.5
	S7	2	5	2	4	2	4	2	4	2	4	77.5
	S8	1	2	3	4	2	3	1	3	0	3	55
	S9	2	4	2	4	3	5	2	4	2	5	82.5
	P13	2	5	3	5	3	5	3	3	2	3	85
	P14	2	4	3	1	3	4	3	4	2	2	70
	P15	2	5	3	3	3	5	3	5	2	4	87.5
Average Score												75.83

5.3.2 User Satisfaction

The assessment of user satisfaction plays a pivotal role in evaluating the effectiveness of the proposed tool's mechanism as well as the overall user experience with the task. To comprehensively gauge these aspects, a combination of well-established metrics has been employed: the Questionnaire for User Interface Satisfaction (QUIS), which offers insights into users' contentment with the tool's interface; the assessment of Experience with Tasks, which delves into users' familiarity and comfort with the assigned tasks; and lastly, the Task Difficulty Ratings, which provide valuable data regarding the perceived complexity of the tasks. These selected evaluation instruments have been chosen for their proven reliability and validity in the realm of user experience assessment. Detailed information and results obtained through these metrics can be found in the Appendix section of this documentation. By utilizing this multifaceted approach, a comprehensive understanding of user satisfaction, task execution, and perceived difficulty is obtained, contributing to a well-rounded evaluation of the tool's functionality and its alignment with user needs and expectations.

QUIS

The QUIS (Questionnaire for User Interface Satisfaction) serves as a valuable instrument for gauging users' satisfaction with a specific interface. It effectively breaks down its assessment into four distinct categories, each offering insights into how users perceive and interact with the interface. These categories encompass a comprehensive evaluation, ranging from the general reception of the tool to the clarity of terminologies, the layout of the interface screen, the learning process, and the availability of system information and capabilities. With a total of 27 questions, each question is accompanied by a Likert scale, a tried-and-true metric that ranges from 1 to 9. This scale intuitively captures the spectrum of user sentiment, with a rating of 1 indicating strong disagreement and a rating of 9 denoting strong agreement.

Examining the findings presented in table 5.5, it becomes evident that the QUIS experiment yielded a wealth of valuable insights. Notably, the analysis takes into consideration the diverse user groups participating in the study. Among users falling within the student demographic, a noteworthy level of satisfaction emerges. Similarly, professionals engaging with the interface display a commendable range of satisfaction levels Overall the obtained QUIS score is 87%

Drawing closer to the core of the results, a remarkable consistency in user appreciation surfaces. On average, a substantial 86% of users respond positively to the framework, indicative of the interface's broad appeal and effectiveness. This user endorsement extends to various facets of the interface, including its utility, vocabulary, and system capabilities, all of which receive impressive scores of 87%. Furthermore, the learning outcomes linked to the use of the proposed tool achieve commendable scores of 85% and 83%, respectively. Across all user categories, the in-depth analysis consistently underscores the interface's exceptional design, unearthing a profound sense of satisfaction and acceptance linked to the System User Interface (SUI) of the proposed system. This resounding confirmation of user contentment not only underscores the interface's triumph but also affirms its potential to resonate effectively across diverse user segments. The graphical representation of QUIS is shown in figure 5.4 in the form of pie-chart.

Table 5.5: (QUIS) Users' Satisfaction Scores

Users	Overall	Screen	Term.	Learn.	Capab.
P1	8.22	7.9	7.7	8.5	7.75
P2	7.8	8.5	8.25	7.75	8.01
S1	8.5	7.7	8.44	7.93	7.89
S2	7.95	7.71	7.75	8.22	7.75
P3	8.44	7.75	7.85	7.7	8.32
P5	7.75	8.23	7.93	7.7	8.21
S3	8.5	8.03	7.71	7.85	7.7
P4	7.8	7.75	8.05	8.44	7.75
P6	7.93	8.21	7.7	8.32	7.75
S4	8.21	7.75	7.85	7.7	8.44
P7	7.75	7.7	8.21	8.01	7.89
S5	8.44	7.89	7.75	8.5	7.7
P8	8.25	8.5	7.75	7.7	7.95
S6	7.7	7.75	8.01	7.85	8.21
P9	8.21	8.44	7.7	7.75	7.93
P10	7.75	7.85	8.32	8.21	7.7
P11	8.44	7.75	7.93	7.7	8.25
S7	8.5	7.7	7.75	8.44	7.75
S8	7.75	7.93	8.21	8.03	7.7
S9	7.85	8.32	7.7	7.75	8.21
P13	8.01	8.21	7.75	7.89	7.7
P14	7.75	7.7	8.44	8.25	7.93
P15	7.93	7.89	8.21	7.75	8.01
Avg	7.9	7.75	7.89	7.7	7.5
Score	0.87	0.86	0.87	0.85	0.83

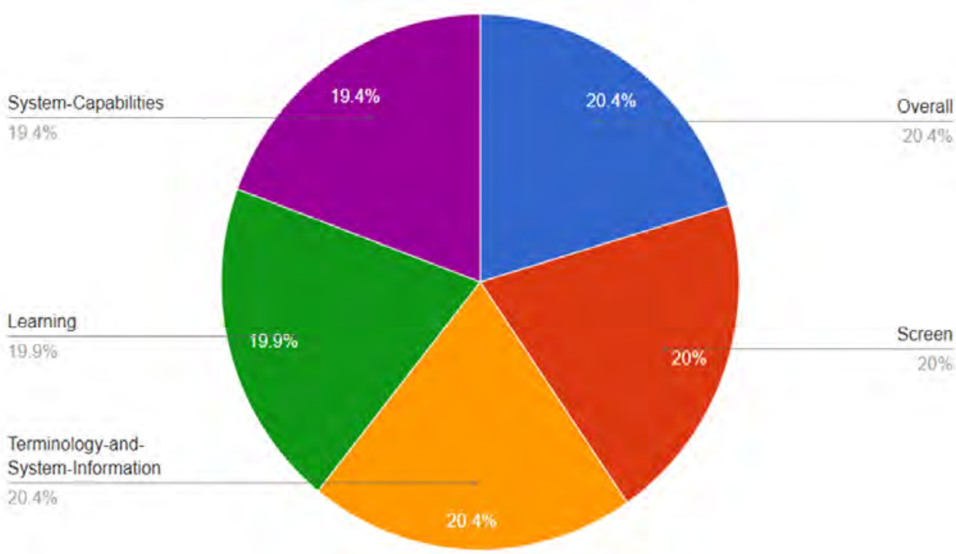


Figure 5.4: QUIS

Task Difficulty Ratings

A pivotal tool utilized to gauge the intricacy of user tasks is the task difficulty rating, as introduced by [Fitzgerald et al. (1997)]. This approach provides a structured methodology for assessing the perceived difficulty of various tasks undertaken by users. A fundamental component of this technique involves presenting participants with a specific inquiry, urging them to quantify the level of complexity they experienced while engaging in a task. To facilitate this assessment, a 6-point Likert scale is employed, where respondents are requested to assign a rating that encapsulates the task's level of difficulty. The scale ranges from 0, denoting "Very Easy," to 5, representing the pinnacle of challenge, labeled as "Most Difficult." Remarkably, the resulting ratings exhibit an inverse correlation, with lower scores signaling greater task difficulty, while higher scores indicate tasks that were comparatively easier to accomplish.

As we delve into the data presented in table, illuminating insights arise regarding users' perceptions of task difficulty. Professionals, in particular, found it relatively straightforward to navigate and complete tasks, underscoring their adeptness and familiarity with the tasks at hand. In contrast, novices and students expressed that the tasks were most effortlessly executed. This variation in perspectives reveals a fascinating interplay between experience levels and the perceived intricacy of tasks.An intriguing trend emerges from the findings, found the tasks comparatively more challenging, with an average rating of 48%.

Despite these differences, a unifying observation can be drawn from the data: the tasks, on the whole, seem to be comprehensible and manageable, as suggested by the average results. With the range of possible ratings spanning from a maximum of 4, indicating a high level of challenge, to a

Table 5.6: User's Difficulty Rating with Task

Users	Difficulty Rating
P1	2.01
P2	2.51
S1	2.55
S2	2.47
P3	2.6
P5	2.47
S3	2.36
P4	2.47
P6	2.51
S4	2.26
P7	2.68
S5	2.01
P8	2.32
S6	2.01
P9	2.58
P10	2.72
P11	2.51
S7	2.46
S8	2.68
S9	2.56
P13	2.33
P14	2.33
P15	2.5
Avg	2.4
Score	0.48

minimum of 0, indicating extreme ease, it is apparent that users' responses manifest a tendency towards the simpler end of the spectrum. This collective sentiment reinforces the idea that the interface and tasks were designed with a focus on user-friendliness and accessibility, providing users with tasks that are approachable yet engaging.

Experience with Task

The evaluation of user experience serves as a pivotal metric aimed at comprehending the efficacy of users' interactions with various tools as they engage in task performance. This methodology, as introduced by [Kules et al.

(2009)], illuminates the multi-faceted nature of user engagement, encapsulating the intricacies of their interactions, perceptions, and feelings. The user experience assessment is constructed around a set of five distinct dimensions, each of which offers a unique vantage point into the user's engagement with the task. These dimensions are scrutinized by users who provide their feedback through a five-point Likert scale, enabling a nuanced evaluation of how the task aligns with their feelings of familiarity, confidence, accomplishment, completeness, and adaptability. The responses provided by users are instrumental in unraveling the nuanced tapestry of user engagement, offering insights into how tasks resonate with their individual perspectives.

The significance of the Likert scale employed in this assessment cannot be overstated. Positioned as a quintessential tool, it enables users to rate their experiences along a spectrum that spans from the most favorable to the least. In this construct, the highest position on the Likert scale signifies a positive and fulfilling user experience, while the opposite end represents a less favorable encounter. Referencing the findings in table 5.7, a rich tapestry of insights emerges with regard to how various user segments perceive their engagement with the assigned tasks. Notably, novices emerge as the group that most profoundly rates their experiences as highly positive. Their evaluations shed light on the assignments' resonance with their experience levels, indicating a sense of familiarity, confidence, accomplishment, completeness, and adaptability.

Conversely, the collective sentiments of students and professionals converge toward a consensus of favorable experiences. While the exact nature of these perceptions may vary, their shared inclination toward a positive appraisal suggests that the tasks resonate favorably across different user categories. This congruence of positive sentiments from these distinct user seg-

Table 5.7: User's Experience with Task

Users	**Experience Score**
P1	3.52
P2	4.21
S1	4.31
S2	4.22
P3	4.65
P5	4.28
S3	3.82
P4	4.19
P6	4.46
S4	3.96
P7	4.79
S5	3.52
P8	3.91
S6	3.53
P9	4.58
P10	4.76
P11	4.37
S7	4.29
S8	4.86
S9	4.58
P13	3.98
P14	4.05
P15	4.61
Avg	4.1
Score	0.82

ments underscores the versatile and user-centric nature of the tasks, capturing the essence of a fulfilling user experience. In this light, the assessment of user experience stands as a vital tool in discerning how well-designed and effective these tasks are in facilitating user engagement, regardless of their familiarity or expertise.

5.3.3 User behavior

Time Analysis

The user behavior for the proposed framework is measured through the utilization of the user's time while they performing the tasks. For both tasks (i.e guided as well as unguided), the amount of time the users spent while interacting with the verticals aggregation research framework's panels is recorded. The user interactions that were logged provide information regarding time usage. The duration of each task is calculated to display user interaction. The effectiveness is contrasted in relation to two variables: users and time. All the Students as well as the professional users of each type complete the tasks. The time factor is taken into account for each panel of the search interface.

As mentioned earlier in chapter 4 there are six SUI panels starting from query formulation panel (QFP), tree-map panel(TMP), tree-map grid view panel (TMGVP), pie-chart panel (PChP), pie-chart grid view panel (PchGVP) and last one is user guidance panel (UGP). The heat maps show how much time users spent on the panel performing exploring tasks. The heat maps display time-on-panel as decimal numbers in seconds along with various color variations (from light to dark) of the primary (red and green) hue colors. The darkest hues of green and red represent the users' maximum and least time usage of the panels, respectively. The yellow color depicts how frequently panels are used on average. The various hue variations span from red to green with varying ranges (smallest to largest) and from darkest red shifting gradients to darkest green. These changes are interpreted by users as variations in time spent on the panel. The heat maps of Tasks 1 and 2 are shown in figure 5.5 and 5.6 respectively.

- **Structured Task:** The Query Formulation Panel (QFP) is where users are most likely to start when entering their search queries. It seems that users' typical time spent on this site fluctuates. Others require less time (1-2 seconds), while some take longer (7 seconds). There is a wide range in how long people spend on the Tree-Map Panel. Students generally seem to spend less time (1-2 seconds), whereas professionals can be more engaged for longer periods of time (1-7 seconds). The time spent on the Tree-Map Grid View Panel varies once more. The engagement times of professionals and students differ widely (1–7 seconds). Diverse interaction times are also displayed in the Pie-Chart Panel. Students often interact for a shorter period of time (1–5 seconds), whereas professionals exhibit a wider variety of interaction periods (1–7 seconds). There is variation in interaction timings, just like there is in the other panels.

  Students and experts both put in varying amounts of time (between 1 and 7 seconds). There are regular usage patterns for the User Guidance Panel. While professionals show a wider range of interaction times (1-6 seconds), students often spend more time (2–7 seconds). Students have a tendency to spend less time on most panels compared to professionals. They spend more time on the Tree-Map Panel and the User Guidance Panel, indicating an interest in exploring these aspects. Their usage of the Tree-Map Grid View Panel is consistent with their other panel interactions, generally ranging from 1-2 seconds. On the other hand Professionals tend to exhibit a wider range of interaction times on all panels.

  They spend more time on the User Guidance Panel, suggesting they are interested in the guidance and help features. The Tree-Map Panel and the Tree-Map Grid View Panel show a similar range of interaction times for professionals. There is noticeable variation in time spent on the

Pie-Chart Panel and the Pie-Chart Grid View Panel. Overall panels like the User Guidance Panel and the Tree-Map Grid View Panel take more time because they likely provide important instructions and intricate visualizations that require careful examination. Panels like the Pie-Chart Panel, Pie-Chart Grid View Panel, and Query Formulation Panel take less time because the nature of their content allows for quicker understanding and interaction. Figure 5.5 display the heat-map for the structured task and figure 5.7 shows the overall time taken by each user for the open-ended task.

User ID	QFP	TMP	TMGVP	PChP	PchGVP	UGP
P1	2.5	2	7	3	1	1
P2	3	7	3	4	4	1
S1	1	6	2	4	2	3
S2	4	6	6	7	2	1
S3	5	5	5	3	6.5	2
P3	5	7	6.5	5	5	3
P4	1	3	4	7	7	0.5
P5	5	6	3	7	2	0.5
S4	2	4	6.5	1	6.5	2
S5	5.5	6	2	4	3	3
S6	1	7	3	3	3	0.2
S7	6	6	4	4	5	1
S8	2	7	1.5	2	3.5	2
S9	6	5	2	6	6	3
P6	4.5	6	3	7	3	3
P7	4	5	7	5	2	0.2
P8	5	3	6	4.5	7	1
P9	3.5	4	4	5	5	0
P10	3	4	4	5	5	1
P11	2	5	1	4	6	1
P12	6	7	5	7	3	0.5
P13	4	6	3	6	2	0.5
P14	1	7	3	4	2	2
P15	4	6.5	2	5.5	6	1

Figure 5.5: Heat-map for the Structured Task

- **Open-Ended Task:** The scenario-based open-ended task 2 gives users the freedom to engage in any activities they choose within the simulation. In this task both students professional users seem to be spending more time on the Query Formulation Panel but overall less then the structured tasks. Here, professionals exhibit more dependable usage patterns and longer contact periods (2–5 seconds). Additionally, students' involvement times increase, suggesting that instruction may have encouraged them to become more involved in the question creation process. The Tree-Map Panel receives less attention from students overall, suggesting that even with instruction, they may not find it particularly interesting. Professionals communicate with the panel less frequently than they did in the guided task, which suggests that guidance may have a big impact on their interaction.

Both students and professionals without guidance appear to have similar or somewhat shorter interaction times on the Tree-Map Grid View Panel. This shows that while the guidance may have brought clarity, it may not have significantly altered the panel's involvement pattern. Both students and professionals interact with the Pie-Chart Panel at different rates, although they all tend to be shorter than they were for the unguided work. Pie charts may still be perceived by consumers as quick and simple to comprehend even with instruction, resulting in shorter engagement times. For both students and professionals with supervision, interaction times on the Pie-Chart Grid View Panel reduce, just like they do on the Pie-Chart Panel. Pie chart visualizations may continue to be easy for users to understand, resulting in comparatively quicker engagement times.

It's interesting to see that as students and professionals receive guidance, their involvement times on the User Guidance Panel increase like they are more interesting to explore more. This would suggest that when users are already familiar with the panels, they are more effective in comprehending and using the supplied instructions. Certain panels, such as the Query Formulation Panel, display longer periods of participation from both students and professionals, proving that they are more curious for exploration. Shorter interaction duration's for panels like the Pie-Chart Panel and the Pie-Chart Grid View Panel indicate that users find these visualizations easy to understand even without assistance. Figure 5.6 display the heat-map for the open-ended task and figure 5.8 shows the overall time taken by each user for the open-ended task.

User ID	QFP	TMP	TMGVP	PChP	PchGVP	UGP
P1	2.5	2	5	3	1	1
P2	3	5	3	4	4	0.1
S1	1	3	2	4	2	3
S2	4	3	3	5	2	1
S3	5	5	0.5	3	5	0.2
P3	5	2.5	3.5	0.5	5	1
P4	1	3	4	5	5	0.5
P5	5	3	3	0.5	2	0.5
S4	2	4	0	1	3.5	2
S5	5.5	0.3	2	4	3	3
S6	1	5	3	3	3	0.2
S7	3	3	4	0.4	5	1
S8	2	5	1.5	2	3.5	2
S9	3	0	2	3	3	1.5
P6	3	3	3	2	3	3
P7	4	5	4.5	5	2	0.2
P8	5	0.3	3	3	0.5	1
P9	3.5	4	4	5	5	0
P10	3	4	4	0	5	1
P11	2	5	1	4	3	1
P12	3	5	5	5	3	1.5
P13	4	3	3	3	0.2	1
P14	1	5	0.3	4	2	2
P15	4	3.5	2	5.5	3	0

Figure 5.6: Heat-Map for the Open-Ended Task

Figure 5.8 shows the average time spent by the both user types stu-

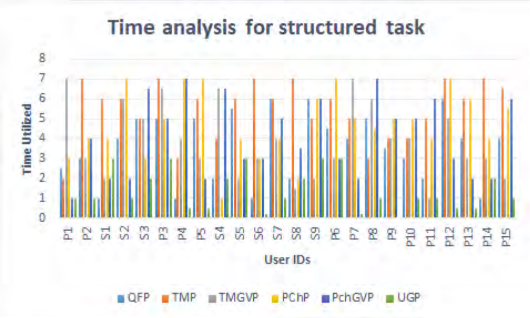


Figure 5.7: Overall Time taken for the Structured Task

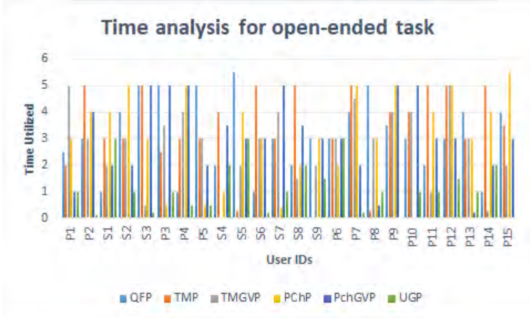


Figure 5.8: Overall Time taken for the Open-Ended Task

dents and professionals next to each panel.

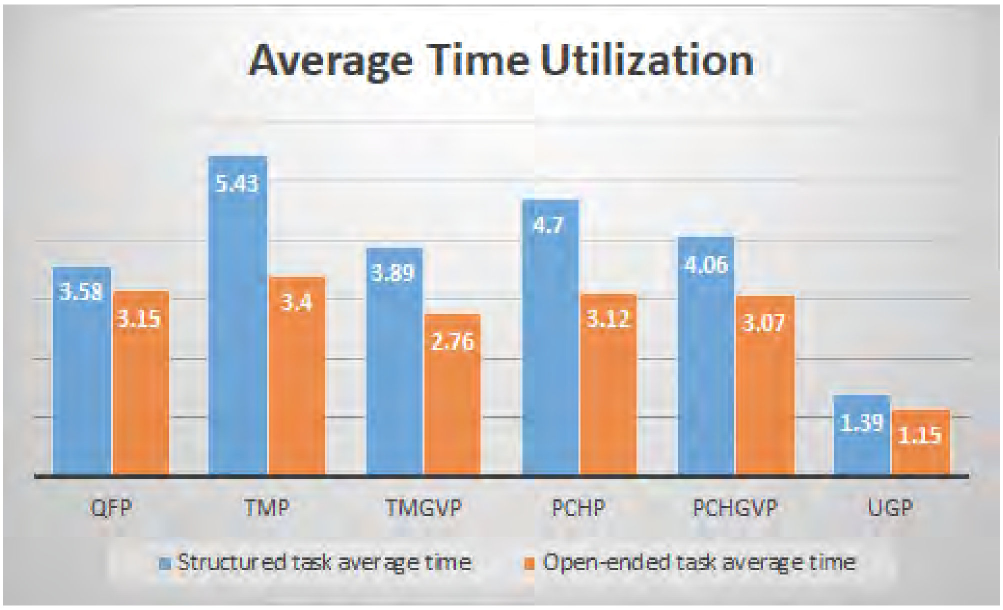


Figure 5.9: Average Time taken for the both Tasks

CTR Analysis

The Tree-Map Grid View Panel (TMGVP) stands out with the highest average CTR of 5, indicating that users are particularly drawn to its combined tree map visualization and grid layout, which likely present information comprehensively and in an accessible manner. The Tree-Map Panel (TMP) also demonstrates a noteworthy average CTR of 3.4, suggesting users find value in the visual representation it offers. Similarly, the Pie-Chart Grid View

Panel (PchGVP) garners a relatively high average CTR of 4.5, showcasing users' interest in the combined view of pie charts with a grid layout. On the other hand, the User Guidance Panel (UGP) records the lowest average CTR of 1.15, indicating that the user engagement with the guidance content is lower. Panels like the Query Formulation Panel (QFP) and Pie-Chart Panel (PChP) share moderate average CTRs of 3, reflecting users' moderate engagement and appreciation for their respective functionalities. The average click through rate against each panel is represented in figure 5.10.

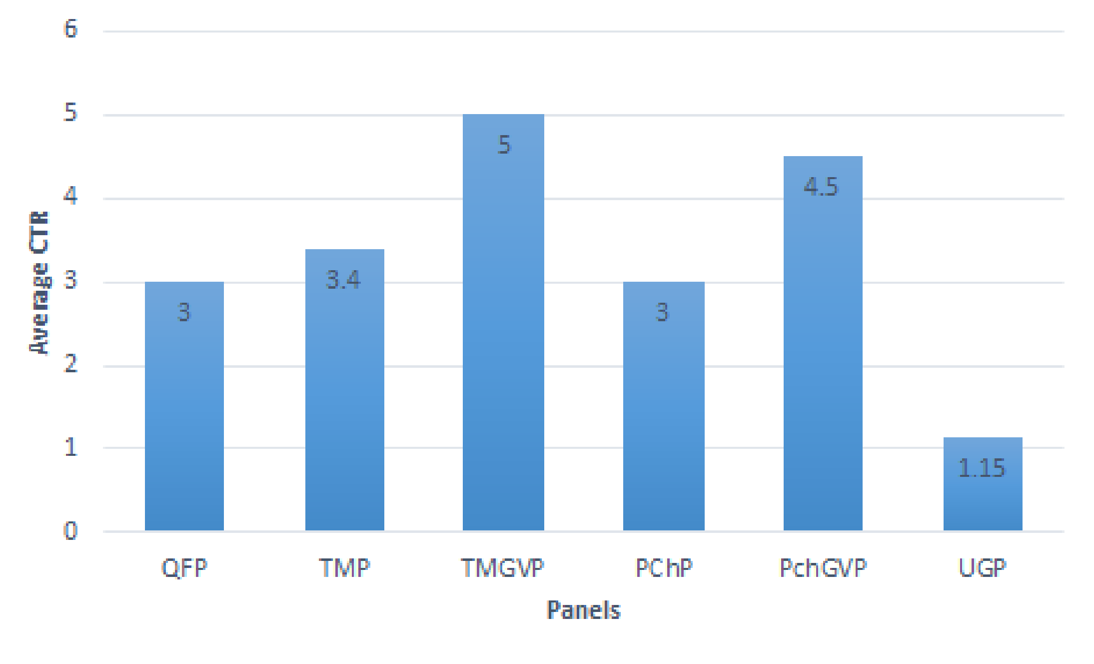


Figure 5.10: CTR Analysis

5.4 Summary

The research question Do the SUI design, connected exploration mechanism, and aggregated vertical web search results research tool enable a usable exploration of vertical web search results? is answered in this chapter. This chapter initiates its evaluation by delving into the state-of-the-art evaluation measures. The evaluation process commences with a comprehensive analysis of clusters, incorporating three distinct techniques. Building upon this analysis, an empirical evaluation is conducted, guided by expert judgments. Furthermore, to assess the system's usability, its interaction, and the overall user behavior during interactions, standardized questionnaires are employed. These questionnaires serve as a robust tool to gauge the various facets of usability measures. This multi-faceted approach ensures a comprehensive evaluation of the system's effectiveness and user-friendliness. As we explore the evaluation process in-depth, we unravel the intricate interplay between empirical methodologies, expert insights, and user-centric perspectives. This intricate web of evaluation strategies contributes to a well-rounded understanding of the system's performance and its impact on user experience.

Chapter 6

Conclusion

6.1 Research Contributions

Our research contributions are as follows:

1. In the realm of Augmented Search Engine Research, our focus revolves around enhancing exploratory capabilities through Unified SUIs (Search User Interfaces). These interfaces seamlessly support overview, exploration, and in-depth research.

2. We employ a Generic Exploration Mechanism grounded in semantics, empowering users with a more intuitive and context-aware search experience.

3. We provide a fully non-linear representations of search results that through tree-map and pie-chart that reduce the excesive scrolling.

4. Our approach integrates a Real Data Model, ensuring the practical applicability of our research findings.

5. The commitment to rigorous evaluation practices ensures that our empirical results boast statistical significance, reinforcing the credibility and impact of our contributions in advancing search engine capabilities.

6.2 Future Directions

Here are the future directions that can be addressed:

1. The research framework can be used to specific datasets to provide the facilities for specific domain.
2. To increase cluster efficiency, a variety of clustering approaches can be applied. Machine learning techniques can be used to enhance the threshold criterion for the cluster.
3. The inquiry experience will be improved by utilizing the recommendations. The dynamic alternative queries can introduced for providing the user better recommendations.

6.3 Conclusion

In this research, we have successfully proposed a comprehensive framework and an engaging Search User Interface (SUI) to address the limitations of conventional search engines and vertical-based search activities. By aggregating search results from various verticals and employing clustering and summarization techniques, our system facilitates seamless exploration of multimedia documents. The non-linear represen- tations of tree-map and pie-chart visualizations provide users with an intuitive and efficient way to navigate through vast datasets, enhancing the overall data exploration experience. Our framework enables users to explore and gather information without the need to switch between different verticals, thereby preserving exploration context.

The interactive and user-friendly SUI fosters cognitive engagement and supports comprehensive research mechanisms. The evaluation of our proposed system showcased promising results as attained an empirical evaluation shows the Stability & Accuracy for Internal Clustering as 99.38% while the system usability provide the effective results as 85% for CUSQ and ”B+” grade for SUS, placing it within the 80 to 84 percentile range, validating the effectiveness and efficiency of the proposed approach. On the other hand the user satisfaction for the proposed framework is 87% value of QUIS which an excellent value for measuring the SUI satisfaction. By promoting a more visual and interactive exploration of multimedia content, our system paves the way for more informed decision-making and knowledge discovery in the evolving landscape of web search.

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Appendix A

Questionnaires

Very Easy	0	1	2	3	4	5	Most Difficult

Figure A.1: Task Difficulty Ratings

Questions		1	2	3	4	5	
How familiar were you with this subject when you began this task?	Not Familiar						Very familiar
How difficult was it to accomplish this task?	Very Difficult						Very Easy
I am confident that I fulfilled the task asked of me	Strongly disagree						Strongly Agree
To what extent did completing this task involve finding a single item versus finding multiple items?	Single Item						Multiple Items
To what extent did you change what you were looking for based on the results you found?	Not at all						A lot

Figure A.2: User's Tasks Experience

OVERALL REACTION TO THE SOFTWARE		**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**		**NA**
1.	terrible											wonderful	
2.	difficult											easy	
3.	frustrating											satisfying	
4.	inadequate power											adequate power	
5.	dull											stimulating	
6.	rigid											flexible	
SCREEN		**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**		**NA**
7. Reading characters on the screen	hard											easy	
8. Highlighting simplifies task	not at all											very much	
9. Organization of information	confusing											very clear	
10. Sequence of screens	confusing											very clear	
TERMINOLOGY AND SYSTEM INFORMATION		**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**		**NA**
11. Use of terms throughout system	inconsistent											consistent	
12. Terminology related to task	never											always	
13. Position of messages on screen	inconsistent											consistent	
14. Prompts for input	confusing											clear	
15. Computer informs about its progress	never											always	
16. Error messages	unhelpful											helpful	

Figure A.3: Questionnaire for User Interface Satisfaction

		1	2	3	4	5	6	7		NA
1. Overall, I am satisfied with how easy it is to use this system	strongly disagree								strongly agree	
2. It was simple to use this system	strongly disagree								strongly agree	
3. I can effectively complete my work using this system	strongly disagree								strongly agree	
4. I am able to complete my work quickly using this system	strongly disagree								strongly agree	
5. I am able to efficiently complete my work using this system	strongly disagree								strongly agree	
6. I feel comfortable using this system	strongly disagree								strongly agree	
7. It was easy to learn to use this system	strongly disagree								strongly agree	
8. I believe I became productive quickly using this system	strongly disagree								strongly agree	
9. The system gives error messages that clearly tell me how to fix problems	strongly disagree								strongly agree	
10. Whenever I make a mistake using the system, I recover easily and quickly	strongly disagree								strongly agree	
11. The information (such as online help, on-screen messages, and other documentation) provided with this system is clear	strongly disagree								strongly agree	
12. It is easy to find the information I needed	strongly disagree								strongly agree	
13. The information provided for the system is easy to understand	strongly disagree								strongly agree	
14. The information is effective in helping me complete the tasks and scenarios	strongly disagree								strongly agree	
15. The organization of information on the system screens is clear	strongly disagree								strongly agree	
16. The interface of this system is pleasant	strongly disagree								strongly agree	

Figure A.4: Computer System Usability Questionnaire

	Strongly Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Strongly Agree
1. I think I would like to use this tool frequently.					
2. I found the tool unnecessarily complex.					
3. I thought the tool was easy to use.					
4. I think that I would need the support of a technical person to be able to use this system.					
5. I found the various functions in this tool were well integrated.					
6. I thought there was too much inconsistency in this tool.					
7. I would imagine that most people would learn to use this tool very quickly.					
8. I found the tool very cumbersome to use.					
9. I felt very confident using the tool.					
10. I needed to learn a lot of things before I could get going with this					

How likely are you to recommend this website to others? (please circle your answer)

Not at all likely	0	1	2	3	4	5	6	7	8	9	10	**Extremely likely**

Figure A.5: System Usability System