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Bigdata-based university reputation measurement. Towards conceptualizing AI-based university reputation score (URS)

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ABSTRACT The competition inside higher education institutions, namely universities, is tightening, putting emphasize on competitive intelligence (CI) function. At the same time, communication has shifted to digital channels, this trend was largely influenced by Corona virus pandemic. This presents a challenge for university reputation measurement and ranking, while the electronic word to mouth (E-wom) is more challenging to measure, control or influence than the issues measured in traditional university rankings. While traditional metrics are based on measuring academic reputation via surveys and gathering data from research organisations, this paper presents a way to include AI, namely chatGPT and big-data based media-analytics with social media sentiment to aid analysing the reputation of a University. Results based on Finnish universities indicate, that differences between media visibility and sentiment exist, and can be to some extent utilized in rating universities in local level and also generalize to global level, finally targeting to URS (University reputation score) -index. Due to complexity of measuring the reputation of the university strictly via AI and automated opinion mining, several limitations exist. The context of Finnish universities were chosen in order to limit the scope of the analysis.

KEYWORDS: automated university reputation measurement, opinion mining, generative AI

1. INTRODUCTION

This paper aims to explore the possibilities of integrating media monitoring, with digital algorithm based tools to university reputation measurement, belonging to a field of competitive intelligence, helping in rating universities, and also marketing and branding function with analytic tool development. This research analyzes a large number of both editorial material and also web discussions on the Social Media (SoMe) from that point of view.

The need for measuring University reputation has further increased due to coronavirus pandemic, transferring millions of people to online work and education, while increasing electronic word-to-mouth communication eWom (Rani & Shivaprasad, 2021). So this paper is aimed to fill an existing research gap related to integrating media monitoring to detect and measure University reputation in real-time with a comparison to other universities (Garcia-Alsina et al, 2016), helping in positioning universities against their competitors. Managerial research-gap in this case is mainly related to benefitting from measurement and to plan actions.

At the same time, to fill this research gap, advanced measurement can be utilized, based on BigData. Societies are expecting a lot of recent trends in technology developments, such as generative AI, an increase in digital data, supported by more advanced analytics often known as artificial intelligence or AI, towards predictive and then prescriptive analytics, where analytical models specify optimal future behaviors and actions (Cearley *et al*, 2016).

The theoretical foundation for this paper provides an overview of the key literature-based perspectives applicable to the research focus, including Social Media Monitoring(SMM) with opinion mining(M-Brain, 2015), combined with generative AI. Theoretical concepts are defined in the literature chapter.

The main scope of this paper is to develop and utilize the latest technologies in continuous University reputation measurement namely, media monitoring with opinion mining enhanced with machine learning, combined with generative AI or alternatively human-based research phase to discover the implications to managerial level in universities.

Main RQ is formulated as. ***How to integrate SMM and generative AI to 24/7 reputation measurement? What are the managerial and theoretical implications? (See Figure 1)***

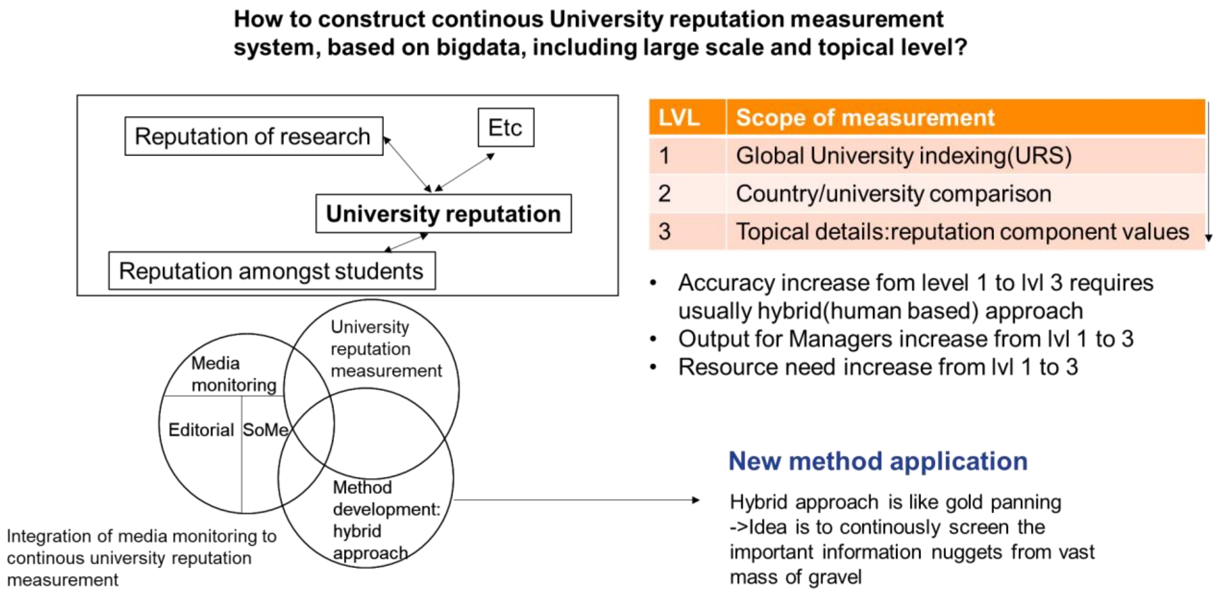

Figure 1. Research basis

Figure 1 presents the main research problem in this paper, which is formulated as: how can you measure reputation of a university, including eWOM and stakeholder's view of a university's reputation while comparing the results to other universities, and get also the reputation details automatically in real time?

In a hybrid approach, suggested by Nuortimo 2021, the final stage after large quantity data analysis is manually made classification. However, generative AI may prove beneficial in this context, by providing indicative university reputation components mined from its large training data set. In this paper, the generative AI was tested as the last stage in the hybrid approach to get an indication, of whether it can retrieve university reputation components, and in general, how reliable are the results.

The selected analysis group includes Finnish QS-indexed universities. The final aim is to create an index for University reputation measurement, URS. In this paper, the basis for the index, University Visibility score(UBV) and reputation components via generative AI, are explored. Results are left indicative.

This paper is organized as follows: First, literature and traditional university indexes are reviewed, namely QS-index, to find out what the traditional metrics are measuring and how they are formed. Then the large media dataset is explored to gain insights into media-visibility of Finnish universities. Next, an early proposal of UBV-score(University Brand Visibility) is formulated, while presenting the further findings, opportunities and problematics that occurred via the data analytics. Finally, the paper is concluded.

Literature: University reputation and its measurement in the digital age

To highlight the differences between companies, in the modern business landscape, corporate reputation plays a critical role in shaping stakeholder perceptions and influencing business outcomes. The formation, management, and measurement of corporate reputation involves a complex interplay between online and offline factors (Mandelli & Cantoni, 2010). Companies must actively shape their corporate identity, manage stakeholder experiences, and effectively communicate their strategic choices and values (Jones et al, 2009). In the digital age, online environments introduce new challenges, as stakeholders rely on various information sources and engage in online discussions that significantly impact corporate reputation. To thrive in this dynamic landscape, businesses need to embrace proactive reputation management strategies, monitor online channels, and adapt swiftly to changing stakeholder perceptions.

By understanding the multifaceted nature of reputation formation and leveraging both offline and online channels, companies can build and maintain a strong and resilient corporate reputation. Corporate reputation has been studied to be one essential intangible assets of a company, being increasingly influenced by information available in the online environment (Floreddu *et al*, 2014). Furthermore, the reputation measurement side gathers information about online corporate reputation, meaning the representation of multiple stakeholder's perceptions of a company derived from online data. Social and online media monitoring tools (M-brain, 2015) are developed to gather company, in this case, university-related information from online data, and hence, can be viewed as an opportunity to monitor online university reputation in real-time.

Generally, it is agreed, that reputation is a perceptual phenomenon –emerging from observers 'collective judgments about an organization based on the assessment of the organization's performance over time in essential areas (Barnett *et al.*, 2006). Research has shown that reputation is also contingency-based, an organization's reputation may vary across stakeholder groups depending on the degree to which each group recognizes that the organization fulfills its expectations (Bromley, 2002). The most famous reputation measurement framework is the RepTrak framework, which has been used to study reputation in companies worldwide and has been adopted by Forbes Magazine in review of the World's Most Respected Companies (Vidaver-Cohen, 2007). Traditional reputation measurement involves surveys, rankings, research metrics, and assessments of graduate outcomes and community perceptions, usually divided to measurable components such as Governance, Financial performance, Innovation, responsibility, leadership, dialogue, workplace and products and services (T-Media, Vidaver-Cohen, 2007).

When moving from companies towards universities, the competitive landscape in the higher education setting has influenced universities into adopt strategies that create competitive advantage, such as building a positive brand image (Panda et al., 2019). University reputation management falls under PR management and is shaped by a multitude of factors, including academic quality, research output, student success, alumni achievements, and institutional culture (Giroux, 2002).

To gain a competitive advantage via better reputation measurement, this paper suggests the measurement of University reputation via utilizing opinion mining, with a combination of large dataset analytics and generative AI. From automated reputation tracking, suggestions such as Brand Index (Nuortimo, 2019) and Reputation Tracker (Rust, 2021), can be used as a methodological basis of this paper The focus area, the University reputation, has different features than corporate reputation tracking, due to nature of academic institutions. In this setting, the academic contribution of the university is not solely defining the popularity of university, thus different aspects emphasize in popularity amongst different stakeholders and student's.

University reputation is formed through a combination of factors that contribute to stakeholders' perceptions of the institution, such as students accrediting agencies, alumni, donors; parents, other institutions or providers, vendors and suppliers, employers, taxpayers, non-government organizations and government (Marshall & Marshall, 2018)

The pivotal role of students' value co-creation behavior in creating and sustaining university reputation is emphasized (Foroudi *et al.*, 2019). University brand (UniBrand) is the most recent concept, however, its theoretical modeling is still partly inadequate, while student satisfaction and trust were demonstrated to impact the relationship between perceived service quality, brand performance, brand image and behavioral intention of education (Sultan & Wong, 2019).

The recent COVID-19 pandemic has shifted universities fast to online learning, which has increased the student e-WOM(electronic word-to-mouth communication) which quality will influence universities' image (Shehzadi *et al.*, 2020).On the other hand, the image and reputation management of a university is a complex issue, the way stakeholders perceive universities is not always in line with the image the latter wish to project (Lafuente-Ruiz-de-Sabando *et al*, 2018).

In this setting, A media analysis-based reputation index could provide a practical and dynamic approach to understanding and managing university's reputation. It considers real-time media coverage, sentiment analysis, and visibility metrics, offering valuable insights for reputation management strategies. While it differs from traditional university rankings, it provides a targeted and data-driven assessment of reputation that can complement and enhance existing ranking systems.

As moving to the data-analysis stage, in Finland, the goals set for the performance of a university are guided by Finnish law from universities (Yliopistolaki, 2021), while the mission of the university is set to promote research and scientific education at its highest level, while implementing high level of ethics and good scientific practices. The law itself does not give any performance metrics for universities, however, the university would need a measurement system to improve its performance and competitiveness.

Currently, universities are rated based mostly on manually created ratings/rankings, such as the QS-index (QS, 2021). Universities actively manage their reputation through social media, via marketing communications, but also engage its stakeholders via strategic communication. (Farinloye, *et al*, 2020) and crisis management (Olsson, 2014). University rankings, based on reputation indicators and other criteria, provide a comparative assessment of institutions and play a significant role in shaping institutional reputations within the higher education landscape (QS index, 2021). Different variables associated with an academic reputation, such as research experience and teaching quality and their effect on academic reputation, have been studied by Escandon-Barbosa *et al*, 2023.

University Reputation Management

Universities actively manage their reputation through various strategies and initiatives, such as strategic communication (Holtzhausen & Zerfass, 2014). Universities communicate their mission, values, achievements, and academic offerings through targeted marketing and public relations efforts (Bamberger, *et al*, 2020). This includes highlighting faculty expertise, research breakthroughs, student success stories, and community engagement. Universities engage with students, faculty, staff, alumni, industry partners, and the broader community to build strong relationships. Meaningful engagement involves effective communication, collaboration, and fostering a positive campus culture(Fitzgerald *et al*, 2020). Universities proactively address and manage potential crises or negative incidents that could impact their reputation, while transparent and timely communication, proactive measures, and effective resolution of issues are essential in maintaining trust and credibility (Toklucu *et al*, 2022). Universities also focus on continuous improvement of academic programs, faculty development, and research excellence. Accreditation processes and external quality assessments help ensure high standards and build reputation (Pham, 2018).

University Reputation Measurement

Measuring university reputation involves both qualitative and quantitative methods. Reputation surveys, conducted among academics, employers, and industry professionals, can gather perceptions of universities' reputations(T-media. 2021). These surveys often assess aspects such as academic quality, research output, and alumni achievements. Prominent university rankings, such as the QS World University Rankings (QS, 2021), Times Higher Education World University Rankings, and Academic Ranking of World Universities (ARWU) (Mussard & James, 2018) incorporate reputation indicators. Research Bibliometric indicators (Durieux & Gevenois 2010) such as citation counts and research impact measures, assess the scholarly output and influence of a university's research. These metrics contribute to reputation measurements, particularly in the field of research-intensive institutions. Tracking the success of graduates (Scott & Wilson, 2002) in terms of employment rates, career advancement, and contributions to society provides insights into the reputation of universities. Alumni surveys and career outcome data (Volkwein, 2010) help gauge the impact of a university's education on students' professional lives.

Monitoring public sentiment, media coverage, and social media discussions surrounding a university can offer insights into its reputation (He *et al*, 2013). Online sentiment analysis and media monitoring tools assist in understanding public perception and identifying potential reputation risks.

Theoretical basis

The development and application of a university reputation index draw upon several theories and concepts related to reputation and stakeholder perception. Some relevant theories related to university reputation include stakeholder theory (Freeman *et al*, 2010), which implies that universities, have stakeholders with diverse interests and expectations, such as students, faculty, staff, alumni, employers, and the broader community.

Social identity theory emphasizes the role of identity and group affiliation in shaping individual behavior and perceptions (Ashforth., & Mael, 1989). Stakeholders may form perceptions of a university based on their social identity and the values and characteristics associated with the institution (Phillips, 2011)

The URS index would take into account how media coverage and sentiment analysis contribute to the construction of a university's social identity and reputation.

University rankings and reputation

University rankings serve as a widely recognized measure of institutional reputation. These rankings assess various aspects, including academic reputation, faculty qualifications, research output, student-to-faculty ratio, international diversity, and employer reputation. Prominent university rankings utilize a combination of quantitative indicators, surveys, and reputation assessments to determine an institution's overall standing(QS, 20201).

It is important to note that university rankings are not without limitations (Mussard & James, 2018). They often rely on subjective assessments, the inclusion of specific indicators may favor certain types of institutions, and their methodologies may evolve over time. Nonetheless, university rankings seem to continue to be influential in shaping public perception and informing stakeholders' choices.

There exist several international university rankings aiming to classify universities based on different metrics, such as the QS-index (Qs-index, 2020), consisting of six metrics. Universities included in these lists can utilize the information in their marketing and branding. The QS index is based on the following metrics, which are Academic Reputation (-40% influence) based on a survey, Employer Reputation-10% (survey), Faculty/Student Ratio-20% numerical measurement/comparison, Citations per faculty, International Faculty Ratio and International Student Ratio (Qs-methodology, 2021).

This paper aims to introduce a new component to ranking via measurement opinion mined university sentiment and visibility both in editorial media and in SoMe, which indicates also the eVOM component of the University's brand reputation. Table 1 presents the QS-rankings of selected universities

Table 1. The status of different universities in QS-rankings (QS-rankings, 2020)

University Name	Country	Rating in QS rankings/ Overall Score 2020
Massachusetts Institute of Technology (MIT)	USA	1
Stanford University	USA	2
Harvard University	USA	3
University of Oxford	USA	4
California Institute of Technology (Caltech)	USA	5
ETH Zurich (Swiss Federal Institute of Technology)	Switzerland	6
University of Cambridge	UK	7
UCL (University College London)	UK	8
Imperial College London	UK	9
University of Chicago	UK	10
Helsingin yliopisto (University of Helsinki)	Finland	107
Aalto yliopisto (Aalto University)	Finland	134
(Turun yliopisto) University of Turku	Finland	287
Oulun yliopisto (University of Oulu)	Finland	374
Tampereen yliopisto	Finland	395

QS-index development in Finnish universities in general has seen a decline from 2015.

To further investigate the possibility of forming a University Reputation Score, the research approach presented in this paper consists of starting the research via media monitoring black box software-based analysis from a large dataset, including opinion mining analysis via Five Finnish Universities, presented as table 2, complementing it with generative Ai in the later stage.

Table 2. Selected Universities

University/search words	Time /months	Total hits
Turku university	12	37847
Aalto University	12	7433
Helsinki University	12	51532
Tampere University	12	36247
Oulu University	12	24724

From the selected Universities, large-scale analysis highlights the differences in University's media attention in order to discover University's reputation-related details and guide managerial actions. It is noted, that this dataset will contain multiple errors both from search words and also from sentiment classification. In general, Aalto University seemingly had the largest amount of error hits.

Methods: opinion mining via media analytics and generative AI

This paper utilizes opinion mining from large dataset as the first step, with commercial black box media monitoring software M-Adaptive (Nuortimo, 2021). (Figure 2).

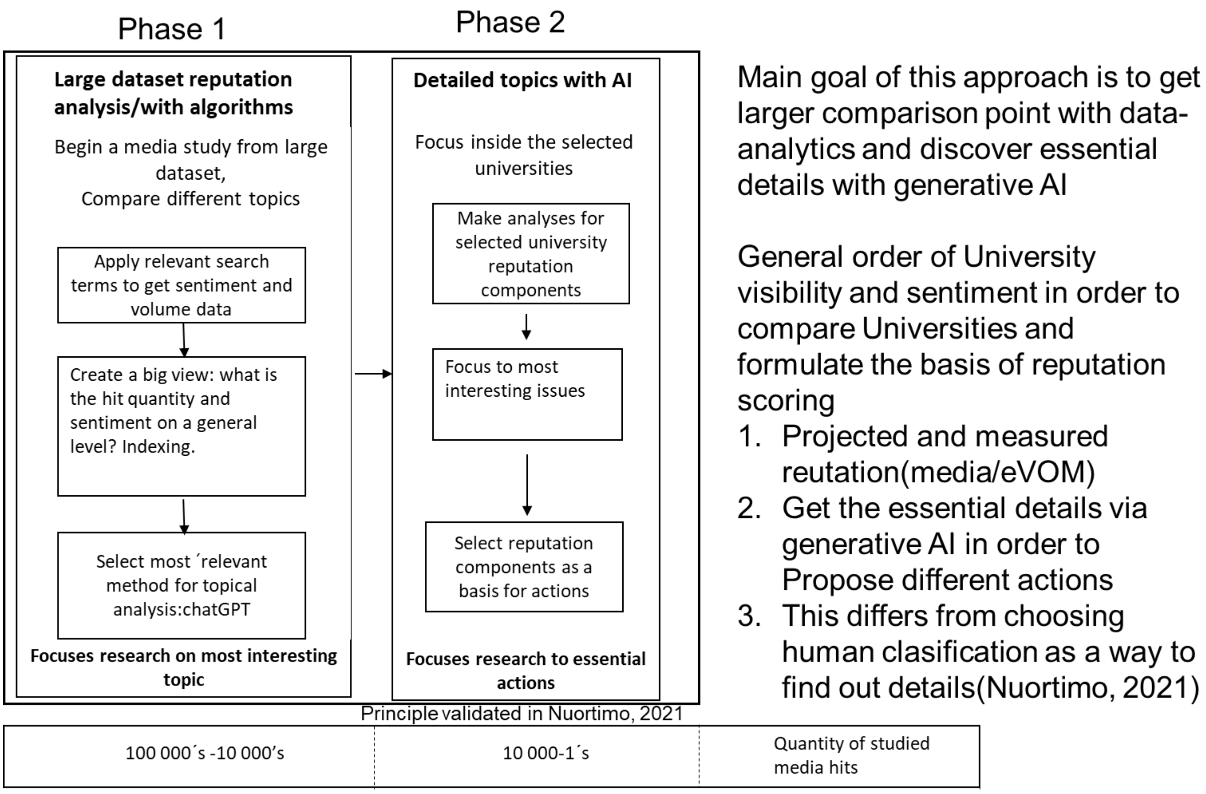

Figure 2. Used methodological approach in the paper

The used software (M-Brain, 2015) has a capability to utilize a large dataset (236 regions, 71 languages in 3 million social media platforms and 100,000 news outlets) both from SoMe sources and editorial media. The software includes different lexicons for several languages, from which the algorithm defines first local sentiments of a document and then compares those to the search terms, while the result is presented for the whole document (Neutral, negative, positive, mixed or unknown). The accuracy of sentiment classification is closer to 80%, while topical match would require detailed content analysis. After the opinion mining, the university sentiments are grouped and compared with implications for further research stages.

Opinion mining

The use of sentiment analysis, also referred as opinion mining, is growing since the number of views being shared on SoMe sites is increasing, via the categorization of emotions into three, positive, negative and neutral (Liu, 2022) Sentiment analysis has been used for example in evaluating qualitative students' responses (Dake & Gyimah, 2023). The essential component of this paper Opinion mining are natural language processing (NLP) and machine learning (ML) on social media via AI application (Astarkie *et al*, 2023).

chatGPT

The current artificial intelligence tools, such as ChatGPT (OpenAI, 2023) can be used as an indicative tools for a) providing evidence of the logic behind the proposed theoretical logic, b) providing an indication of increased communication and its relation to action, and c) setting a starting point for the deeper analysis. An artificial intelligence chatbot developed by OpenAI, namely ChatGPT (OpenAI, 2023) has emerged as a new AI based tool and is applied in this paper to assess its applicability for analysing the University reputation components, thus supplementing the opinion mining data-analysis as a last stage of hybrid approach (Nuortimo 2021). ChatGPTs has a potential in data analysis (Biswass, 2023), while it has not been found to be capable of statistical analyses, and it advises about its limitations only if expressively requested (Cascella *et al.*, 2023). , it has seen to have language processing capability (Qin *et al.*, 2023; Kocoń *et al.*, 2023) which makes it a potential candidate to be tested for the purpose of analysing university reputation. In this paper, ChatGPT is used to aid in analyzing a large quantity of University data while formulating a conclusion. AI can also be used to generate entire pieces of academic paper (Thorp, 2023), however, this paper points out that it can be used as data-analysis research method as well. The goal is to gain experimental results and find possibilities to take advantage of the opportunities (van Dis et al., 2023). The ability to produce meaningful insights and sentiment from large volumes of text (Bouschery et al., 2023) seems to exist. ChatGPT may still have its inadequacies in reasoning (Borji, 2023). Haleem et al. (2023) have discovered use of ChatGPT for sentiment analysis, while only one case of this has been found (Haque *et al.*, 2022). Finnish university reputation analysis

For the possibility to discover how well universities are present in both editorial and social media during one year, analysis based on 150 000 media hits was committed with 2020 years data, in order to be comparable to chatgpt data, ending in Autumn 2021. The analysis included main Finnish QS-ranked universities from Oulu, Turku, Helsinki, Aalto University and Tampere.

One year 2020 unfiltered/cleaned media visibility for selected universities is presented at the Figure 3.

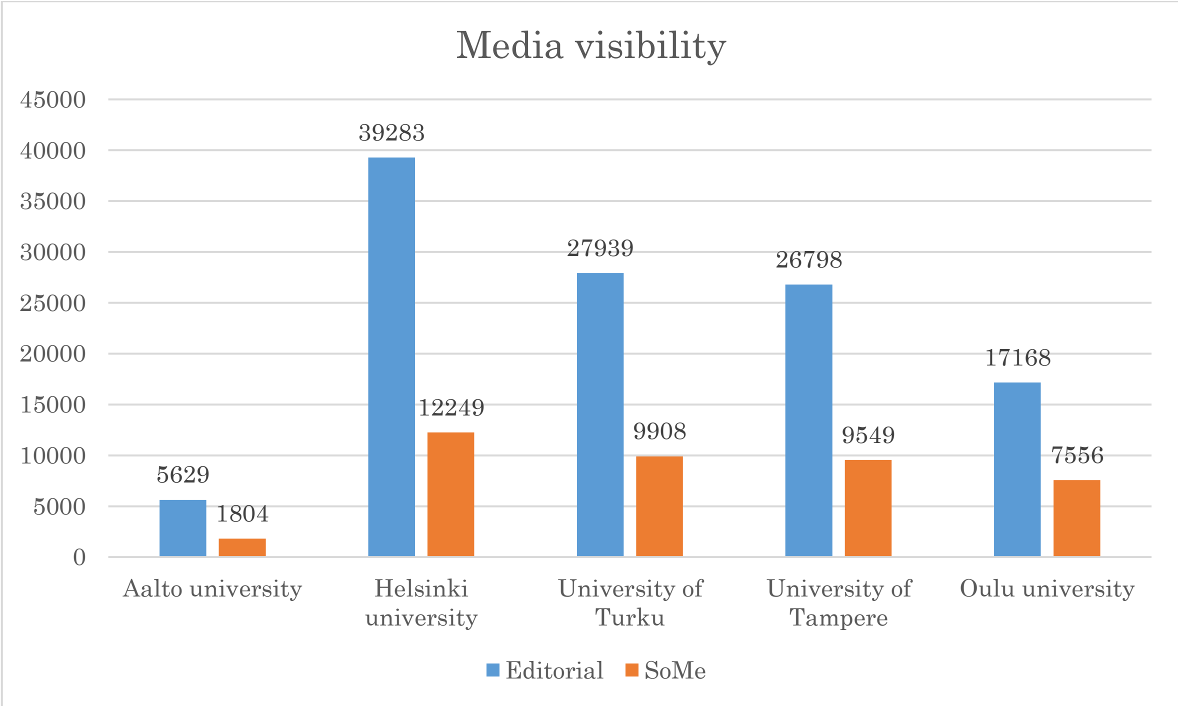

Figure 3. One year university media sentiment

From the large dataset analysis, it is visible that generally editorial media received larger amount of hits compared to social media, which is an indication of non-popularity. This would be in-line with general assumption concerning university's reputation. The quantity of hits is generally in line with size and position of QS ranking of an university, exept for Aalto university, from which the main conclusion is, that dataseries can contain more error than the others.

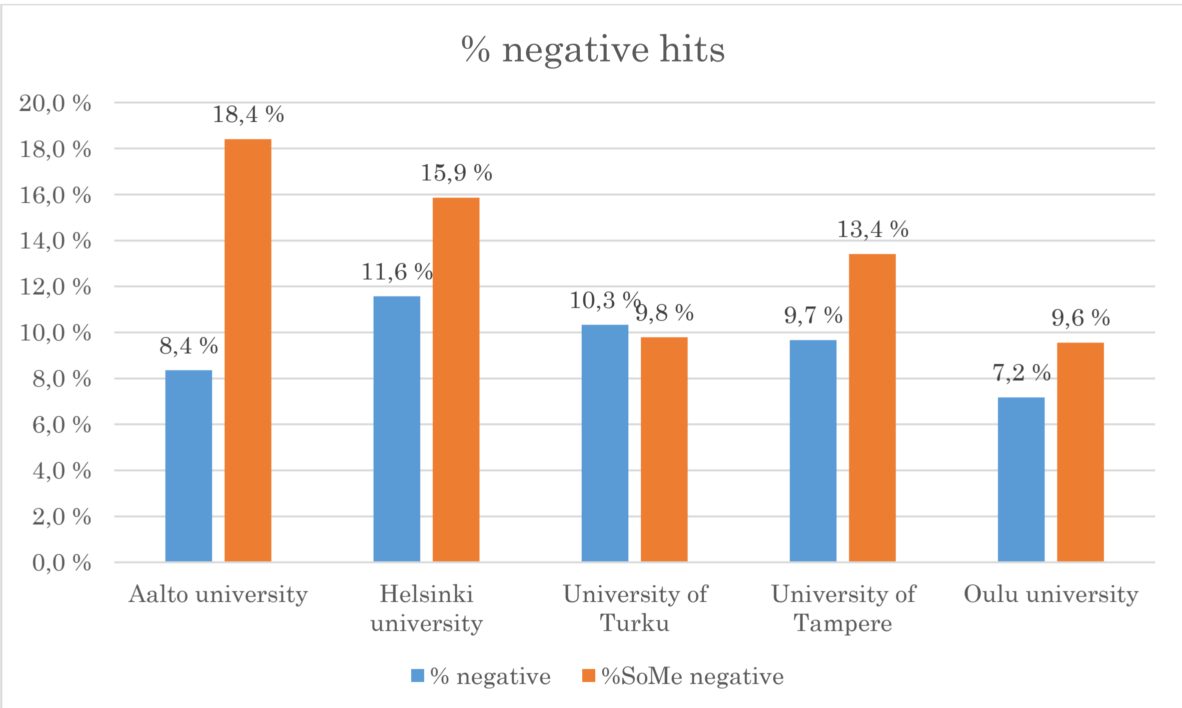

Figure 4. Negative sentiment classification

From the figure 4 it is visible, that the editorial negative hits were concentrated mainly to larger universities with higher QS-scores, while negative SoMe sentiment had more diversity. Oulu and Turku universities had lowest negative scores, Oulu had also lowest editorial negative sentiment (%).
The main insight from preliminary data-analysis was, that media visibility and sentiment based analysis could bring added value both to ranking a university, and also providing insight to different functions, such and marketing and planning.

Chatgpt analysis
In order to get automated view on reputation components, chatGPT was utilized. The other alternative would be to manually classify media hits, which would have provided more details. The results are presented as Table 3.

Table 3. University reputation components from chatGPT

University	Reputation components
University of Oulu	Academic Excellence, Research Focus, Technology and Engineering, Entrepreneurship and Innovation: International Environment Facilities and Resources:
University of Turku	Academic Excellence, Research Output and Impact, Interdisciplinary Approach, Internationalization and Global Outlook, Student Experience and Success, Community Engagement and Impact:
University of Helsinki	Academic Excellence, Research Output, Interdisciplinary Approach, Global Recognition, Strong Faculty, Student Success, Community Engagement, Cultural Heritage, Commitment to Sustainability
Aalto University	Strong Focus on Innovation, Academic Excellence, Research Impact, Interdisciplinary Collaboration, Collaboration with Industry, Design and Art Focus, International Outlook, Student Experience, Sustainability Commitment, Community Engagement
Tampere university	Academic Excellence, Research Impact, Interdisciplinary research, social science focus, communication and engagement, Internationalization, Student support and Experience, Language and communication studies, Collaboration with industry, Commitment to sustainability

The reputation components chatGPT provided from universities are quite general, academic excellence was present in all of the universities. Some focus areas were spotted, such as communication studies for Tampere, design focus for Aalto, and Technology and engineering for Oulu. University of Helsinki was the only one associated with global recognition.

Generally it can be observed, that chatGPT answers are in-line with literature, and can be used as a complimentary feature for opinion mining. However, to differentiate between universities and form competitive advantage, more details would be required. This would implicate either detailed content analysis from media feed, or traditional reputation measurement via questionnaires and interviews. While chatGPT produced results in-line with common understanding, there were usually on few different components/university, not so much suitable for building branding or competitive intelligence strategy. The information from reputation components can be used in principle to quide actions in marketing, communications, competitive intelligence and strategic planning, if there would be more differentiation between the universities.

Towards URS, University reputation score

To follow the reasoning by Nuortimo & Härkönen, 2019 from brand indexing, the brand visibility index for finnish universities could be generated with similar logic. This could a starting point for the more general URS index, in order to score universities automatically in real time.

Preliminary UBV scores from Finnish universities are presented as Figure 5:

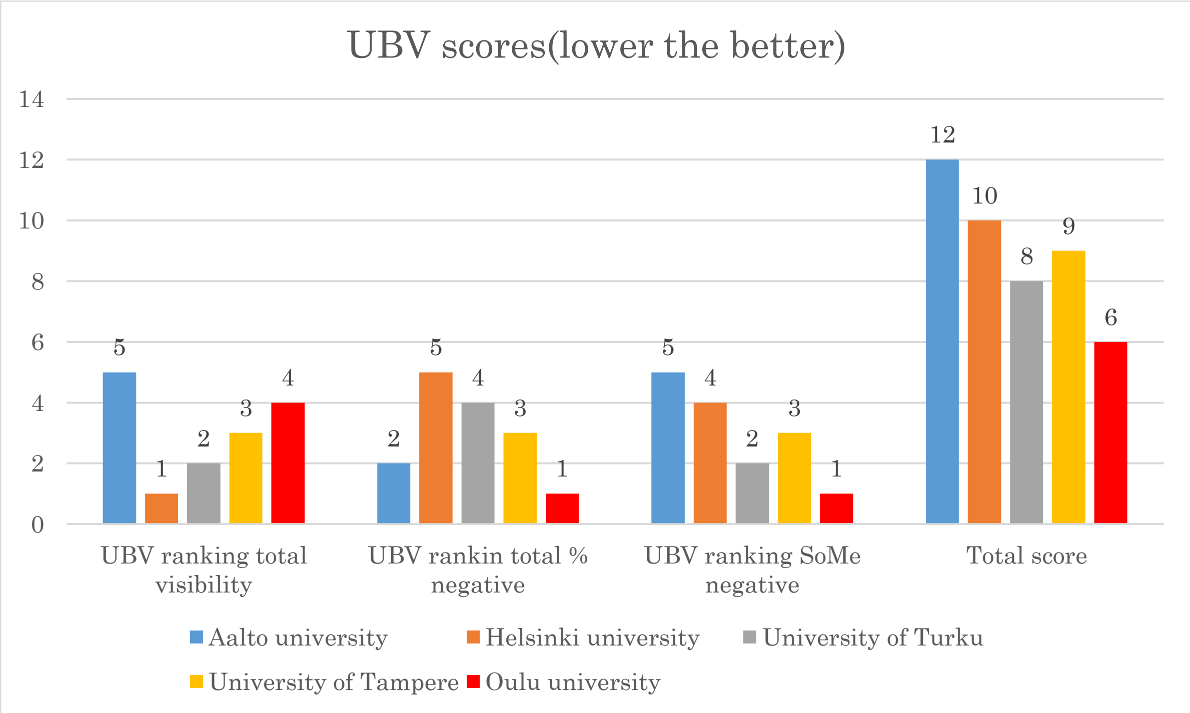

Figure 5. Preliminary UBV-scores

Preliminary UBV(University brand visibility, Based on a Brand index), which could be used as basis for final URS-index, are interesting. Total media visibility would not play such an essential part of the index, while other components, such as total negative sentiment and SoMe negative sentiment play a more role. The total score, measured with lower the better scale, is almost opposite to QS-ranking, while Oulu, Turku and Tampere would take the key positions due to generally more positive sentiment.
So the challenge after data-analysis and preliminary UBV indexing remains, in addition to general indexing challenge, can we establish further analysis from content automatically via generative AI? This should be a crucial step for more accurate measurement needed as a basis for the final URS. Can we establish measurable component for a university reputation? Which component in media attention measures reputation? Can we establish a measurable component for e-wom-related to university? Can we establish a component for research visibility? In this paper, chatGPT is used as a complimentary method for gaining insights from university's reputation, however, clearly with limitations.

The discussion chapter tackles these questions, while presenting solutions based on preliminary analytics.

Discussion

As basis from literature and data-analysis, the main RQ on this paper can be answered as:The formulation of a university reputation score (URS) based on media analysis and opinion mining can provide insights into the perception and visibility of a university in the public sphere. This type of index combines quantitative metrics, such as the total visibility of the university and the percentage of negative media hits, to assess the overall reputation of the institution. However, reputation components related to each university, relevant for the final URS formulation, are explored to be indicatively obtained via generative AI. It is clear, that in this point, results are not explicit enough to formulate URS.

Comparison to University Rankings

While both media analysis-based reputation indexes and university rankings provide insights into university reputation, they differ in several aspects. Media analysis-based indexes primarily rely on media coverage, online discussions, and sentiment analysis to assess reputation, whereas university rankings often incorporate a broader set of indicators, including academic reputation surveys, faculty qualifications, research output, and student-to-faculty ratios. University rankings typically employ complex methodologies that combine multiple indicators and assign weights to different criteria. Media analysis-based indexes, on the other hand, focus more specifically on media coverage and sentiment analysis, providing a more targeted assessment of reputation based on these factors. University rankings often involve subjective assessments through surveys, which can be influenced by respondent biases and regional preferences. Media analysis-based indexes leverage automated analysis and opinion mining techniques, providing a more objective and data-driven perspective of reputation. Media analysis-based indexes offer real-time insights into reputation, allowing universities to monitor and respond to emerging issues promptly. University rankings, on the other hand, are typically released on an annual or periodic basis and may not capture recent developments or changes in reputation.

So it is clear, that when finally created, automated University Reputation score (URS) would not completely replace University rankings, however, could be used as a complementary tool in University reputation management.

Main findings

This research has an approach for analyzing the reputation of selected Finnish QS-indexed universities from large dataset via commercial software, complemented with generative AI based topical analysis. This approach is based on Nuortimo, 2021, and a multidisciplinary view from digital humanities studies, however, without detailed human made content analysis. The human was replaced by generative AI, namely cahtGPT, in this case. While this type of approach was interesting, it did not bring a 100% applicaple solution.

Suggested approach aims to reveal the university reputation continuously with related details. In first stage, media-analysis including multiple sources, is aimed to find the university media visibility and sentiment, while comparing it to other universities. It is to be noted that during this analysis it was clear, that details such as: why was the university had large visibility or some particular sentiment? How can these issues be turned to supporting marketing messaging? Is the positive/negative media hit measuring university reputation or something else? In what way we would target our marketing efforts? Is the competitive rating provided, reliable?

The details were brought in second stage via chatGPT. After this step, the detailed topical level analysis is possible to be made, namely to devide the university reputation to components, and can then be used to compare the AI based analysis results.. If university wants to be projected a place which produces high quality research papers, then this topic can be scanned from communication eVOM, random discussions in the SoMe.

The main findings include:

1) The large dataset based analysis can reveal differences related to Universities, namely media visibility and sentiment. However, any details are not visible; why the sentiment was negative for some universities. most interesting question would be in this point:why is the sentiment so negative, and what can be done to reveal details. Also what details are interesting, should be systematically defined.
2) In second stage, preliminary UBV rating based on a brand index (Nuortimo *et al.*, 2019) was formulated, with implications that the index is measuring universities differently than the traditional QS-rankings. This could be a value-bringing element.
3) As a suggested final stage, generative AI can provide insight into University reputation details. This stage has the

potential in bringing details needed for managerial actions.
4) The added value from this type of reputation scoring would come from continuous follow up with fast reactions and also from focusing marketing efforts and target marketing messages in order to build and manage University reputation. Comparison to other universities would bring input for MI-function.

Practical/Managerial Implications

The managerial implications of the paper are related to discovering new approaches to university reputation measurement. If the university's management would take the benefit of utilizing automated reputation measurement, this could possibly enhance related marketing management and Competitive Intelligence(CI) potential. Media analysis and opinion mining provide a way to monitor the university's reputation in real-time. By analyzing media coverage and online discussions, universities can identify emerging reputation risks, potential issues, and negative sentiments, allowing them to respond promptly and proactively manage their reputation. The index can guide universities in developing targeted reputation management strategies. For instance, by assessing the percentage of negative media hits, universities can identify areas of concern and prioritize actions to mitigate negative perceptions. It helps in identifying reputation gaps and areas that require improvement. The index also enables universities to benchmark their reputation against competitors or peer institutions, acting a bit similar way in this regard as the university rankings. By comparing the reputation scores with those of other universities, institutions can gain insights into their relative strengths and weaknesses, informing strategic decisions and resource allocation, and CI-function.

Theoretical Implications

Theoretical research method implications concern mainly the utilization of different data-analysis methods in researching the formula for university reputation score(URS). When general specifications for university reputation score are concerned, those would need to be holistic while including details, and include both academic contribution and stakeholder view. This paper is not yet capable of formulating the final URS index. The media analysis-based reputation index recognizes that reputation is multidimensional and shaped by various factors, while reputation is not solely based on objective measures but also influenced by subjective interpretations and media portrayals. This aligns with the theoretical understanding that reputation is socially constructed and encompasses different stakeholder perspectives. The index reflects the dynamic nature of reputation by considering real-time media coverage and sentiment analysis. It acknowledges that reputation is not static and can evolve over time based on new information, media narratives, and stakeholder perceptions. This aligns with the understanding that reputation is a dynamic and evolving concept that requires continuous monitoring and management.

Limitations

The Limitations of this paper are related data validity, 100% research data validity is not neither targeted, or achieved (Figure 6).

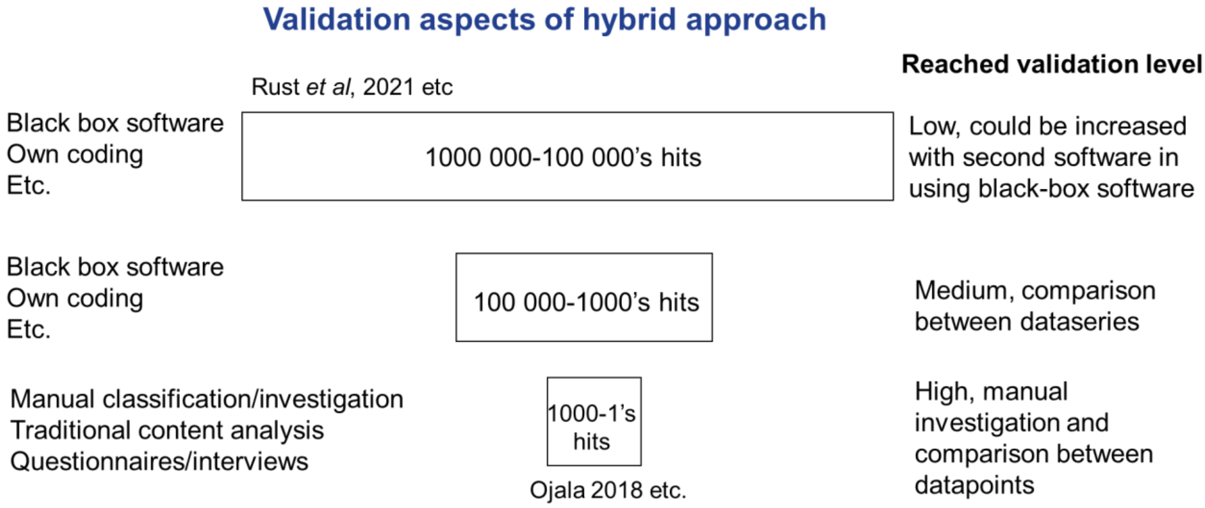

Figure 6. Validation aspect of this paper

From Figure 6, it is visible that larger datasets present challenges for data validity, while the human research is time intensive. Study of Mercedes brand in the internet discussion forum took app. 8 years (Ojala, 2018), while media-analytics can be done in seconds. Second software would have been benefial to be used for better data validity, however, for budgetary reasons it was not available for this study.

University name brings one component of inaccuracy in UBV dataset. Aalto was the most inaccurate one, due to the general meaning of the word in Finnis language (wave).

Datasets both in opinion mining and generative AI are limited to the year 2021, however, presenting a way for URS building.

General chatGPT limitation are considered as (chatGPT, 2023):lack of common sense, it's not able to access the internet, is not able to multitask, has limited knowledge, lacks creativity, cannot provide in-depth information, has difficulty with specialised topic, can provide biased answers, is not able to understand the contex, is not able to express emotion, has issues with complex mathematical problems, needs fine-tuning, has a lot of grammatical errors and typos.

So the limitation of this study leave the research results indicative with increased probability towards possibility of University Reputation Score(URS).

Conclusion

This paper is suggesting that a URS index for rating universities and revealing their competitive position against others is possible to be created, acting as a basis for automated university reputation measurement and competitive university rating. However, this idea is still on a pathway in discovering both methodologies and principles, how this type of index could be created in practice.

University ratings based on UBV, a precursor component for URS, could follow the reasoning from corporate brand visibility index (Nuortimo, 2019), but it is clearly visible, that to discover the differences between targeted image to projected and measured reputation, while with large data set analysis, perceived result are too general to plan further managerial actions.

This analysis was complemented via chatGPT analysis of University's reputation components, giving a summary about the bigdata based reputation. From this stage, managerial implications of detailed actions can be obtained, but on with also on very generic level.

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