

OTDK-dolgozat

2025

SZÉCHENYI ISTVÁN EGYETEM
KAUTZ GYULA GAZDASÁGTUDOMÁNYI KAR



HALLGATÓI ELÉGEDETTSÉG ELEMZÉSE A SZÉCHENYI ISTVÁN
EGYETEM KÖZÖSSÉGI MÉDIA PLATFORMJAI VONATKOZÁSÁBAN:
FELTÁRÓ KÉRDŐÍVES KUTATÁS

ANALYSING STUDENT SATISFACTION OF SOCIAL MEDIA
PLATFORMS AT SZÉCHENYI ISTVÁN UNIVERSITY: AN
EXPLORATORY SURVEY RESEARCH

Szerző / Author: Hamuth Mónika

Konzulens / Supervisor: Dr. Buics László

Kézirat lezárásának dátuma: 2024. 04. 02.

Table of Contents

1.Introduction.....	1
2.Systematic Literature Review.....	4
2.1. Methodology.....	4
2.2. Results of Mapping Study.....	7
2.3. Discussions.....	13
2.3.1. Website.....	13
2.3.2. Facebook.....	14
2.3.3. Instagram.....	14
2.3.4. Twitter.....	15
2.3.5. LinkedIn.....	16
2.3.6. TikTok.....	16
2.4. Summary.....	17
3.Széchenyi István University.....	19
3.1. History.....	19
4.Previous Research Findings: Platform Analytics.....	21
4.1. Website.....	21
4.2. Széchenyi István University Social Media Sites.....	23
4.3. Summary.....	28
4.3.1. Website.....	28
4.3.2. Facebook.....	29
4.3.3. Instagram.....	29
4.3.4. Twitter.....	30
4.3.5. LinkedIn.....	30
4.3.6. TikTok.....	30
5.Survey Research.....	32
5.1. Descriptive Statistics.....	32
5.2. Factor Analysis.....	37
5.2.1. Factor 1: University Website Satisfaction.....	38
5.2.2. Factor 2: Instagram and TikTok Usage.....	39
5.2.3. Factor 3: Demographic Characteristics and Professional Networking.....	39
5.2.4. Factor 4: Awareness of the University Social Media Platforms.....	40
5.2.5. Factor 5: Awareness of Faculties and Courses on University Online Platforms.....	40

5.2.6. Factor 6: Twitter Usage and Satisfaction with the University Account.....	41
5.3. T-test Analysis.....	41
5.3.1. Non-significant Values.....	42
5.3.2. Significant Values	43
5.4. Cluster Analysis.....	45
5.4.1. Age and LinkedIn Usage	46
5.4.2. Faculty and Facebook Page Satisfaction	48
5.4.3. Age and University Website Satisfaction [Transparency]	51
5.4.4. Sharing Content on Facebook and Facebook Page Satisfaction	52
5.4.5. TikTok and Instagram Account Satisfaction	55
5.4.6. TikTok and LinkedIn Account Satisfaction.....	57
5.5. Text Mining.....	59
5.2.1. Manual Examination.....	60
5.2.2. Examination with Python	61
6. Conclusion	63
6.1. Website	63
6.2. Facebook	64
6.3. Instagram.....	66
6.4. Twitter	68
6.5. LinkedIn	69
6.6. TikTok	70
7.Appendix	73
7.1. Hungarian Survey	73
7.2.English Survey.....	80
7.3.Python Code - Factor Analysis.....	87
7.4.Python Code – T-Test and Cluster Analysis (snippet).....	94
7.5.Python Code – Text Mining	100
8.References.....	103

1.Introduction

The term 'Web 2.0' was first introduced in 2004 by O'Reilly Media, which led to the development of social media (SM) (*Kaplan and Haenlein, 2010*). SM platforms use a Web 2.0 format that provides users a dynamic environment for personal interaction where they can interact with like-minded people, as opposed to a Web 1.0 format where the user is a passive recipient (*Chandran, 2016; Schroeder, 2014*). The Web 3.0 format represents the next phase in the evolution of the Web/Internet and could potentially be as powerful a paradigm shifts as Web 2.0. Web 3.0 is based on the core concepts of decentralization, openness, and increased user value through artificial intelligence, which can also have a major impact on social networking sites (*Sridhara and Dr. Raghunandana 2019*).

Social media can be considered a style of electronic or online communication where the shared content is manipulated or created by the users themselves. User-Generated Content (UGC) can cause higher engagement (*Hamm et al., 2013*). Examples of common social media channels/platforms include blogs, social networking sites such as Facebook, Instagram, and LinkedIn; microblogs such as Twitter, wikis; and collaborative information projects such as Wikipedia; and content communities such as YouTube and TikTok (*Risiling et al., 2017*).

The aim of this study is to fill the research gap by reviewing the recent academic literature on social media marketing, especially for HEI marketing. It also aims to investigate the potential of the Széchenyi István University's academic social network sites (SNS) with the goal of increasing student engagement and ultimately student satisfaction. The University has been using 5 social media platforms (SMP) which includes Facebook, Instagram, Twitter, LinkedIn and TikTok.

The research questions the study seeks to answer are:

RQ1: How do universities use websites and social media platforms to reach current students?

RQ2: How satisfied and informed do students feel about Széchenyi István University's website and social media presence?

RQ3: What differentiates the satisfaction levels and informational awareness regarding Széchenyi István University's website and social media presence between Hungarian and international students?

Methods: For the RQ1, the author has conducted a Systematic Literature Review (SLR) to gain a broad and up-to-date overview of the recent researches in the academic social media's field. For the observation Scopus and ScienceDirect databases have been used. The chosen researches have been analysed by Excel. The PRISMA methodology was also used to increase transparency and comprehensibility through a visual flowchart of the SLR process.

For RQ2 and RQ3, a Hungarian and an English survey were used to collect information about the opinions of Hungarian and international students on the website and SM platforms of Széchenyi István University. 1116 responses were collected, which help to explore the students' thoughts with the methods of descriptive statistics, correlation, factor analysis, cluster analysis and text mining. The exploratory survey research was utilized with Python programming language by importing the responses into a CSV file. For RQ2, the 2 surveys were merged and for RQ3 the surveys were analyzed separately.

Organizations have recognized the importance of SM in communicating and engaging audiences. As the number of active users on these platforms continues to grow, universities have also come to realize the need to establish their presence. This enables them to connect and effectively engage with prospective students, current students, and alumni. Regarding academic SM marketing articles, there is currently relatively little research about the Higher Education Institution (HEI) SM marketing effectiveness (*Brauer and Bernrioder 2015; Fong et al., 2020*).

SM platforms are immensely important for higher education institutions since they can effectively convey the university's mission and core values to students and staff members. Universities use a variety of social media strategies, using images, blogs, and polls as gamification tools to effectively engage students (*Al-Daihani and Abrahams 2018*). Visual storytelling and multimedia content create an immersive experience that fosters community and active participation. Blogs facilitate in-depth communication and encourage insightful discussions, while polls and quizzes add interactivity while fun, and UGC provides subconscious satisfaction for the user (*Hanus et al. 2015., Sanmugan et al., Kuo et al., 2016; Damico and Krutka D. G. 2018*).

Discussing content in the comments section can also generate ideas and responses, leading to the formation of social capital and social networks (*Fong et al., 2020*). By integrating these elements, the university increases student engagement, effectively communicates its mission, and increases a strong sense of identity and connection within the student body. Based on *Hall and Witek's (2016)*

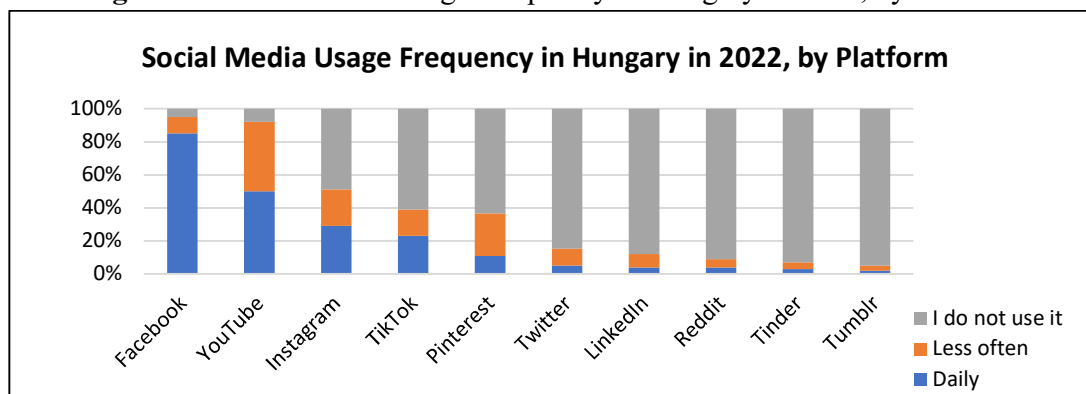
research, the future of higher education marketing involves outreach to students through social media networks such as Facebook, YouTube, or Twitter. The authors argue that social media is a cost-effective and efficient way to reach the target market, which in this case the college students. Therefore, universities can use social media as an important marketing tool to establish and build relationships with students.

The data which can be seen on *table 1* was collected from a survey of 4,000 respondents aged 16 years and older, who were internet users in Hungary. The survey was conducted in November 2022, using computer-assisted web interviews (CAWI). The respondents were asked to indicate how often they used various social media platforms, such as Facebook, YouTube, Instagram, TikTok, Pinterest, Twitter, LinkedIn, Reddit, Tinder, and Tumblr. The response options were: daily, less often, or I do not use it. The data was weighted to reflect the demographics of the internet population in Hungary.

The results show that Facebook was the most widely used social media platform in Hungary in 2022, with 85 percent of the respondents accessing it on a daily basis. This was followed by YouTube, with 50 percent of daily users, while Instagram ranked third as 29 percent of survey participants used it every day. TikTok, Pinterest, Twitter, LinkedIn, Reddit, Tinder, and Tumblr had lower daily usage rates, ranging from 23 percent to 2 percent. The results also indicate that a significant proportion of respondents did not use some of the social media platforms at all, especially Reddit, Tinder, and Tumblr, which had more than 90 percent of non-users.

The 5 examined platforms used by Széchenyi István University have been listed in the 10 most used SM platforms which indicates the university up-to-datedness.

Figure 1. Social Media Usage Frequency in Hungary in 2022, by Platform



Data source: <https://www.statista.com/statistics/1401610/hungary-social-media-usage-frequency-byplatform>

2. Systematic Literature Review

A systematic literature review (SLR) is a method of conducting research that aims to answer a specific question by collecting, evaluating, and synthesizing all the relevant studies on that topic. An SLR follows a clear and rigorous process that reduces the risk of bias and produces more trustworthy results and conclusions for decision making. An SLR includes all the empirical evidence that meets the criteria defined beforehand (*Tranfield et al., 2003; Briner and Denyer, 2012; Denyer and Tranfield, 2009*). The systematic literature review of the author's previous research titled *Students' Media Consumption Habits on the Social Platforms of Széchenyi István University* proved highly relevant to this research (Hamuth, 2023). Therefore, it was incorporated along with the Quartile Ranking of Journals and the Average H-Index by Publication Topics to enrich the study's analytical depth and academic rigor.

The PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) methodology was also employed to ensure clarity and understanding through the process of developing a visual flowchart illustrating the steps of the SLR process.

2.1. Methodology

The systematic review is a type of SLR that uses faster and simpler methods to produce a literature review in a shorter time. A systematic review may use a narrower search strategy, search fewer databases, limit the time period for finding articles, skip checking the references and journals related to the topic, or involve fewer reviewers in the process of selecting, extracting, and assessing the data (*Reyen et al., 2017; Hamel et al., 2020*).

During keyword identification, the research study also took into account the most common synonyms and alternatives for HEI Social Media Marketing. Based on this approach the following keywords were identified and used in the research:

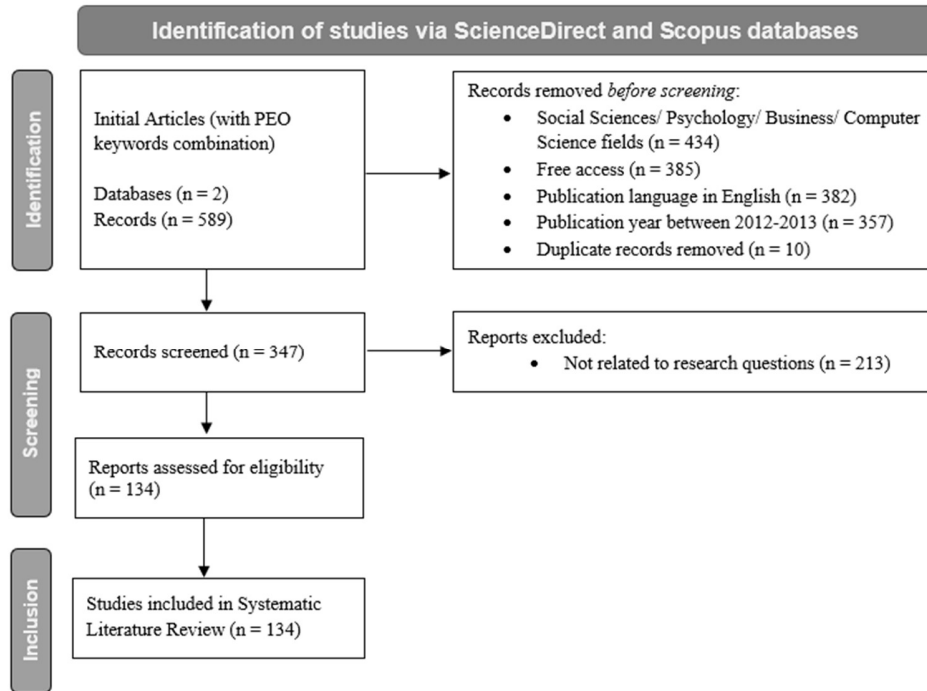
Student, University Student, University, Higher Education, Social Media, Marketing, Communication, Website, Facebook, Instagram, Twitter, LinkedIn, TikTok, Engagement, Retention, Interaction, Satisfaction, Effectiveness

The PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) methodology is a critical component of the systematic review process, providing a representation of the selection and inclusion of studies. Developed as part of the PRISMA guidelines, the flowchart provides

researchers and readers with a clear and transparent visual overview of the study selection process, from the initial identification of records to the final inclusion of studies in the review. This graphical tool plays a central role in ensuring methodological accuracy and transparency in systematic reviews and meta-analyses, facilitating reproducibility and critical evaluation of research findings (Page MJ *et al.*, 2021).

The findings of the Systematic Literature Review have been presented through a PRISMA Flow Chart, depicted in *Figure 2*, in order to enhance the transparency and comprehensibility of the research. Identification, screening and inclusion are critical stages in the systematic literature review process, each with its own importance. Identification involves the comprehensive search for relevant studies using predefined search strategies to ensure the depth of the review. Screening, on the other hand, involves the careful assessment of search results against predefined inclusion and exclusion criteria with the aim of selecting studies that meet the research objectives. This phase is crucial for filtering out irrelevant or poor-quality studies, thereby ensuring the integrity and reliability of the review findings. Finally, inclusion involves the incorporation of selected studies into the review, where their relevance and contribution to the research question are carefully considered. Taken together, these stages serve to methodically gather, analyse and summarise the available literature, thereby underpinning the validity of the systematic review process.

Figure 2. PRISMA Flowchart



Source: Created by the author

The PEO (Population, Exposure, Outcome) framework is used to categorize the keywords into three main groups (see *Table 1*) to help structure the database search and obtain more relevant research results. (Saltikov, 2012).

Three major questions help us to separate the keywords are:

- Population (P): Who are you studying?
- Exposure (E): What is your population exposed to?
- Outcome (O): What is the result of the exposure on your population?

Table 1. Keywords Categorized based on PEO (Population, Exposure, Outcomes)

Population	Exposure		Outcomes
Student	Social Media	Website	Engagement
University Student	Marketing	Facebook	Retention
University	Communication	Instagram	Interaction
Higher Education		Twitter	Satisfaction
		LinkedIn	Effectiveness
		TikTok	

Source: Created by the author

Population is the category in which the research question is focused, which is in this case the higher education institution and the university students. The Exposure category refers to anything that influences the Population category. Outcome is the category that specifies the effects of exposure on the population (*Buics et al., 2021*). To improve the search for relevant literature, complex keyword combinations were created using Boolean operators to combine three or four keywords. However, ScienceDirect has a limit of eight Boolean connectors, so only the keyword combination of two were used for this database. For Scopus, combinations of three or four keywords were operated.

During the preparation of the systematic literature review, the following inclusion and exclusion criteria were formulated:

1. The articles have to be related to Social Sciences/Psychology/Business/Computer Science fields.
2. The articles have to be freely accessible.
3. The articles have to be written in English.
4. The articles have to be published between 2012 and 2023.
5. The articles which are present in both databases have to be eliminated to avoid duplication.
6. The articles have to be related to the research question (RQ1.).

2.2. Results of Mapping Study

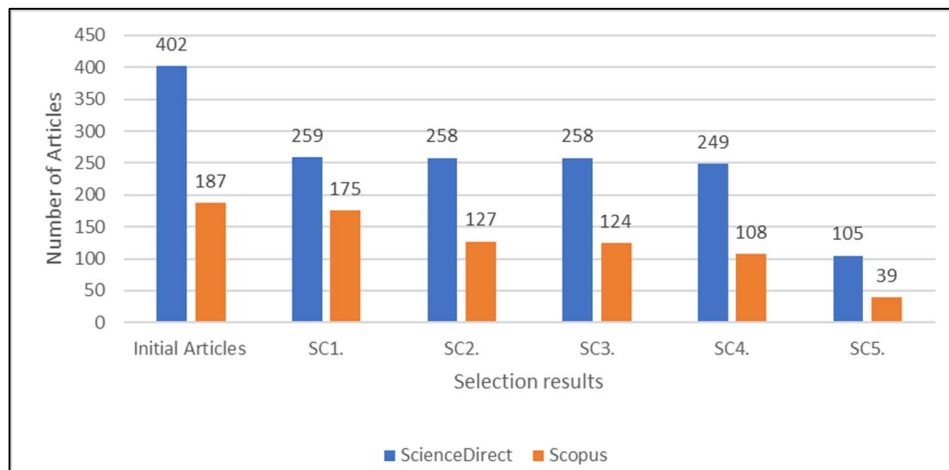
The number of articles collected and selected is shown in *Table 2*, where, after the initial search with the different combinations of keywords, each row shows the results of applying the inclusion and exclusion criteria one by one. For a more visual presentation, *Figure 3* shows the selection results step by step in a column chart.

401 papers from the ScienceDirect database and 187 studies from the Scopus database were initially gathered with the usage of the above-mentioned keyword combinations. This finding may also indicate the research gap in this field, as the total number of articles available on Scopus is 44,737 and on ScienceDirect 39,516 on 13/10/2023. After the articles were chosen based on the four criteria, there were 357 papers left. 249 papers, or 42.35% of all the papers chosen from the ScienceDirect database, and 108 papers, or 18.34% of all the papers chosen from the Scopus Database. In addition, a thorough analysis of the titles and abstracts of the papers was conducted in accordance with the study questions, resulting a total of 144 articles from both databases. A total of 134 papers were left after 10 duplicated studies were eliminated.

Table 2. Details of the Number Selection

Criteria	Keyword Queries in ScienceDirect	Keyword Queries in Scopus
Initial Articles (with keywords combination)	402	187
SC1.: Social Sciences/ Psychology/ Business/ Computer Science fields	259	175
SC 2.: Free Access	258	127
SC 3.: Publication Language is English	258	124
SC 4.: Publication Year between 2012-2023	249	108
Articles after SC 4.	357	
SC 5.: Related to Research Questions	105	39
Removal of Article Duplication	10	
Final Paper Number to Review	134	

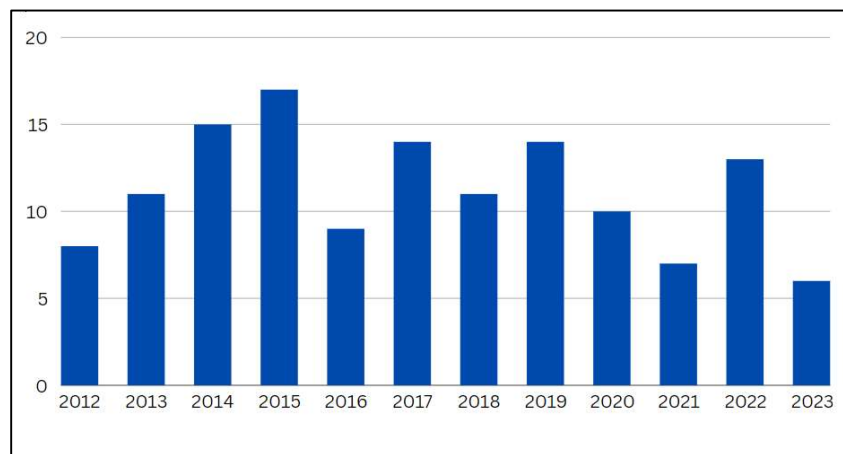
Source: Created by the author

Figure 3. Selection Results

Source: Created by the author

The 134 selected articles have been analysed by the publication year and publication topics. *Figure 4* demonstrates the published articles between 2012 and 2023. In general, the number of publications in HEI Social Media Marketing is low in the examined period of time. The publication figures indicate a huge research gap that would be beneficial to fill, as in the context of higher education, SMPs play an important role in mobilizing information through interactive communication, such as engaging students, raising awareness of faculty research, and gaining media coverage for university recruitment, thereby creating a competitive advantage (*L. Duque. 2016*).

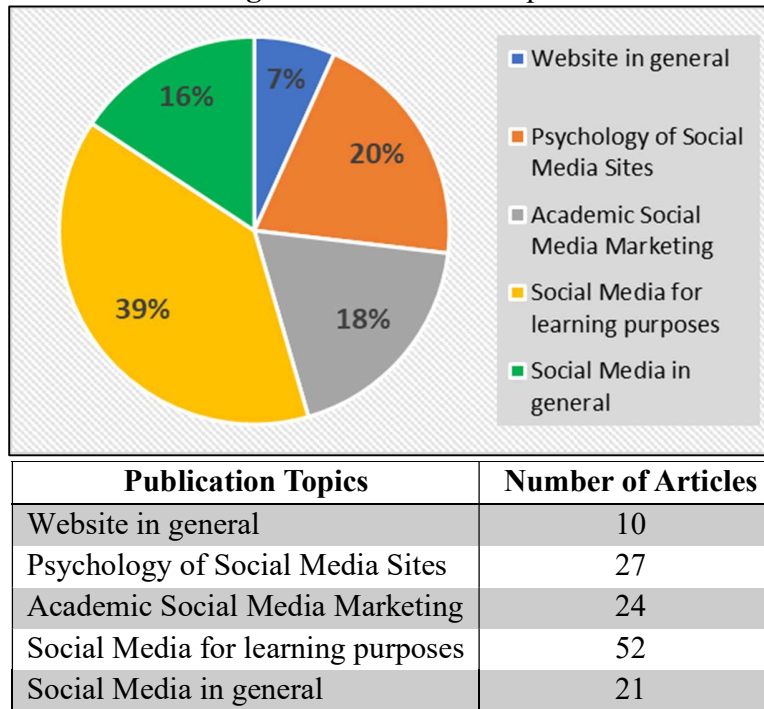
Figure 4. Number of Articles per Year



Source: Created by the author

Figure 5 informs the publication topics of reviewed articles. The research papers were divided into five groups, determined by the author based on the content of the paper. The five groups are *Website in general*, *Social Media in general*, *Psychology of Social Media Sites*, *Academic Social Media Marketing*, and *Social Media for learning purposes*.

Figure 5. Publication Topics



Source: Created by the author

Website in general: This group of studies examined the key aspects of website design that influence user experience and satisfaction. The studies covered topics such as web interface design, navigation and visibility, brand management, and promotion of triple helix. These topics were relevant to this research paper and were addressed by 10 articles (7%) in the literature review.

Psychology of Social Media Sites: The articles in this group examined the psychological effects of SMPs, with researchers highlighting the importance of their potential impact on academic pursuits and the different types of disorders these platforms can cause. The topic was investigated by 27 articles (20%) that were useful for this research paper.

Academic Social Media Marketing: This group of articles is the most closely related to the research questions of this paper. They explore the role of social media marketing in enhancing the reputation and attractiveness of HEIs. They also suggest ways to improve the effectiveness of SM marketing by increasing brand value and measuring student engagement and social media consumption. Out of the reviewed articles, 24 research papers (18%) addressed the topic of social media marketing in the academic context. Among them, 11 articles focused on how higher education institutions'

libraries can use social media to promote their services, while 13 articles discussed the promotional strategies and outcomes of social media marketing for HEIs.

Social Media for learning purposes: In this group, articles explored the possible impact of learning by using SMPs in higher education. The researchers examined how different SMPs were used for learning purposes, such as Facebook (14 studies), Twitter (13 studies), Instagram (3 studies), LinkedIn (3 studies) and TikTok (1 study). Some researchers also explored how different features of social media, such as gamification, videos, and Facebook groups, influenced the learning effectiveness and engagement of the college students. 52 articles (39%) were relevant to this topic, making it the largest group of articles that matched the keywords and databases used.

Social Media in general: In this group, the articles focused on specific social media platforms such as Facebook, Instagram, and Twitter. In addition, some studies discussed the algorithm of SMPs, the website and the design and visualisation of SMPs. Out of the 134 articles reviewed, 21 (16%) related research papers have remained after the application of keyword combinations.

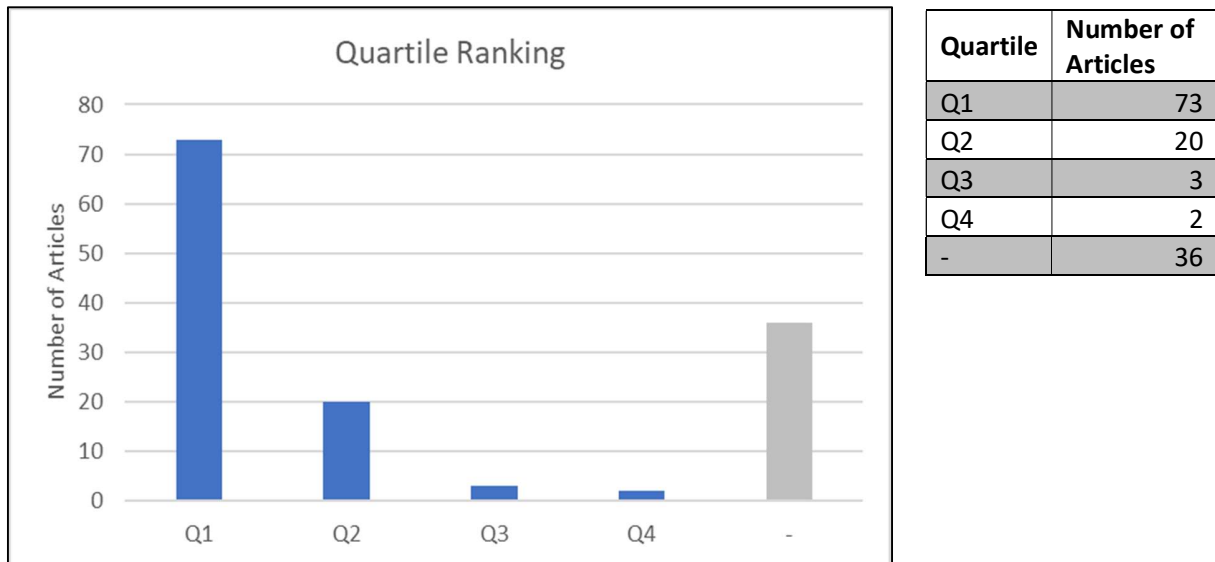
The author has also examined the quality of the used journals with SCImago Journal & Country Rank which is a publicly available portal that provides information on scientific indicators from the Scopus® database (Elsevier B.V.). These indicators can be used to assess and evaluate scientific domains. The citation data is available for over 34,100 titles from more than 5,000 international publishers and country performance metrics from 239 countries worldwide (*SCImago, 2024*).

The 2 main indicators that the author took into account were the quartile ranking and the H index. Each journal subject category is divided into four quartiles referred to as Q1, Q2, Q3, and Q4. Q1 represents the top 25% of journals, Q2 includes journals in the 25-50% range, Q3 includes journals in the 50-75% range, and Q4 includes journals in the 75-100% range. H index is the journal's number of articles (h) that have received at least h citations over the whole period of time (*SCImago, 2024*).

Figure 6 illustrates the quality assessment of the articles incorporated into this study. Of the total articles considered, 98 are retrievable from the SCImago database, while 36 are not available within this database. Among these, 73 studies are positioned within the top quartile, denoting the highest quality, while 20 studies fall within the 50-25% range, indicating a moderate quality level.

Furthermore, 3 studies are classified within the 75-50% range, and 2 studies are positioned in the 100-75% range, suggesting varying degrees of quality within the dataset. However, in terms of publications found in the database, 74.49% of them were selected from the top 25% of journals.

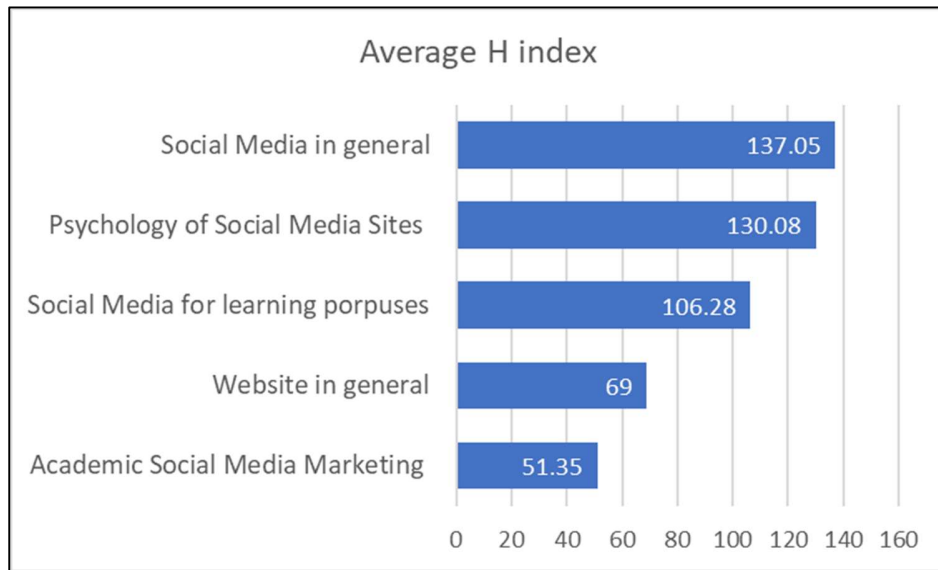
Figure 6. Quartile Ranking of Journals



Source: Created by the author

The mean H-index was computed for each publication topic. *Figure 7* presents the distribution of citations, highlighting notable trends for the examined five allocated topic areas. It demonstrates that the majority of citations were garnered by journals pertaining to the "Social Media in General" topic, with an average of 137.05 citations per journal. Conversely, the least cited publication topic was "Academic Social Media Marketing," averaging 51.35 citations per journal. This observation also suggests a potential research gap in HEI social media marketing, as discussed earlier in the study.

Figure 7. Average H index by Publication Topics



Source: Created by the author

2.3. Discussions

The author summarised the main results and key findings for universities' website and for each of the five SMPs that were relevant to the research questions. These SMPs were Facebook, Instagram, Twitter, LinkedIn, and TikTok (Hamuth, 2023).

2.3.1. Website

The visibility and accessibility of higher education websites is essential to effectively attract and convert prospective students into current students. Students can also find out about the latest news from the university and important information about their studies. The standards for evaluating university websites are often unclear and unfamiliar to many developers, resulting in a poor user experience for students navigating these sites (*M. Manzoor et al., 2019*).

The website of a university serves a diverse range of users, who can be classified into internal and external categories. Internal users are those who belong to the institution, such as prospective and current students, faculty members, and administrative staff. External users are those who access the website for information purposes, such as parents, industry partners, and the general public. The usability requirements of different users vary according to their goals and interests. For instance, students may seek information on admissions, scholarships, syllabus, contacts, and other relevant topics. Faculty members may look for information on current events, class schedules,

seminars, workshops, and so on. External users may search for potential academic collaborators to address an industry problem or to learn more about the institution's achievements and offerings (Çerri 2014; Roy et al. 2014).

The paper from Li Y et al. (2018) studies how small firms' growth is affected by their networks with businesses, governments, and universities (Triple Helix). It uses a new method of analysing company websites to measure these networks. It finds that Triple Helix networks are good for firm growth and that firm size, website size, and low-carbon applications also matter.

2.3.2. Facebook

Facebook is the biggest platform among all SMPs; therefore, it is a beneficial opportunity for marketing experts to promote businesses and their products/services on Facebook. Meanwhile, advertisers are taking advantage of the opportunity to generate more business profits due to the huge number of page views on Facebook. It is therefore worth analysing the reasons for using Facebook for digital advertising (Wang, 2019).

The study from Ertugan (2017) focused on university students, who are among the most active users of Facebook, and who are exposed to a wide range of advertisements on this platform, where promotions may not align with their lifestyles, desires, and values. Facebook advertising is a pervasive phenomenon that influences this segment of users. Most advertisements are designed to reach large diverse audiences, rather than targeting specific demographics.

Soares, J. C. et al. (2020) has examined the impact of interactivity and vividness on user engagement with Facebook posts in the context of higher education institutions. The results indicate that there is a negative correlation between the level of interactivity of the posts and the amount of likes they receive from the users. Moreover, the posts that exhibit high vividness attract more likes, but fewer comments and shares from the users.

2.3.3. Instagram

Instagram is an image-based SMP that enables users to share their life experiences through photographs in real time. The initial intention of Instagram was to provide a platform for users to narrate their life stories through visual media. Previous studies have indicated that social interaction is one of the main motivations for using Instagram. (Geurin-Eagleman, and Burch 2016.; Pittman and Reich., 2016).

Besides social interaction, another significant motivation for using Instagram is self-expression. Instagram offers users the opportunity to express themselves and manage their impressions through high-quality photographs, which are more effective than plain text in conveying visual information (Marwick, 2015).

The researchers, *Rosa-Castillo et al., (2022)*, experimented on the gamification on Instagram by creating an Instagram-based game. The game was implemented for the subject “Dietetics and Nutrition” where bachelor nursing students had to give diet and nutrition advice to help fictional astronauts choose the most appropriate diet given their individual needs. The majority of the respondents (71.7 %) expressed positive views on the gamification experience and its impact on their learning outcomes. They indicated that the gamification activities enhanced their understanding of the course content and reinforced their learning process. Furthermore, they suggested that gamification could be beneficial for other courses as well.

2.3.4. Twitter

Twitter is a micro-blogging SNS which allows users to create posts with a limited number of characters. Twitter is considered as a useful tool for direct communication among peers. Recent studies demonstrated that it also improves active learning and enhances learning incentives. Students gain confidence, fluency in expressing ideas and they also enhance their social skills. Collaborative learning process can be courageous by using Twitter (*Chen and Chen, 2012; Gao, Luo and Zhang, 2012*).

Prestridge (2013) researched the usage of Twitter in order to support first-year students and identified the types of interaction that emerged, such as connectivity, academic culture, and resourcefulness. The professor established a connection with the students by using a traditional approach to responding to their tweets. However, the interaction between the students was limited. Students also cultivated academic culture by summarising the content of lectures, sharing images and links, and retweeting relevant posts. However, students faced some challenges in using this technology, such as managing multiple tasks, adopting academic protocols, and getting used to the 140-character limitation (the maximum tweet length increased to 280 in 2023).

The study from *Pérez-Bonaventura and Rodríguez-Llorente (2023)* examined 83 Spanish universities’ Facebook, Instagram, Twitter, and YouTube platforms. The article found that the student population was a significant predictor of their social media performance, as it was

positively correlated with the number of followers on all platforms and the engagement rate on Facebook, Twitter, and YouTube. Universities' ranking also influenced their follower count on all examined platforms except YouTube. In addition, the university's number of followers on each platform was positively associated with its ranking position and engagement rate on Facebook and Twitter.

2.3.5. LinkedIn

LinkedIn has emerged as the most convenient and effective website for employers and job seekers, according to several studies. A study researched by *S. del Cerro (2017)* revealed that LinkedIn (94%) was the most preferred platform among SNSs for recruiting candidates for vacant job roles, followed by Facebook (65%) and Twitter (55%).

López-Carril et al. (2020) explored the potential of LinkedIn in creating a learning environment for blended and online learning, where students can develop both content and their professional profile. They emphasized the convenience of integrating LinkedIn with other social media platforms such as YouTube and other educational resources such as TED Talks.

The study by *López-Carril, S. (2022)* investigated the effectiveness of blended learning in sports management using LinkedIn. Students were able to master the use of LinkedIn through video tutorials. They had to work together in private LinkedIn groups on specific content of the course. The conclusion of the study is that most students did not have a LinkedIn account prior to the course or were inactive users. This finding suggests a lack of familiarity with the use of SM from a professional perspective, as LinkedIn was mostly unused by the students.

2.3.6. TikTok

TikTok is a leading destination for short-form videos on mobile. In 2016 TikTok launched in China and reached the international market in 2017. It was the most downloaded mobile application in both the United States and worldwide in 2020 (*Nakafuji, 2021*).

TikTok is a SMP that enables users to create and share short videos, varying from a few seconds to up to 10 minutes since February 2022. It offers a diverse range of content, including practical advice, motivational messages, dance challenges, queries and responses, and humorous or unusual videos (*Alley and Hanshew. 2022*).

In the study by *Alley and Hanshew (2022)*, the authors investigated how academic libraries in the United States use TikTok by conducting a content analysis. They had originally planned to select a sample of peer libraries with active TikTok accounts, but there were not enough libraries available; therefore, they had to change their approach. Instead, they searched for TikTok user accounts using terms such as 'academic library', 'college library', and 'university library' (or 'libraries'). They then analysed the fifteen libraries with the highest number of TikTok followers. The content analysis showed that the most common type of content in these libraries was categorized as 'humanization/fun', making up 61.4% of the videos. This suggests that the main purpose of using TikTok among these users is to consume engaging and entertaining content.

2.4. Summary

The research findings highlight the need for a comprehensive and in-depth examination of the marketing strategies employed by higher education institutions (HEIs). This systematic literature review has revealed not only the available articles but also a noticeable research gap in the area of HEI marketing strategies.

The majority of the articles reviewed focused on the use of websites and specific social media platforms such as Facebook, Instagram, Twitter, LinkedIn, and TikTok in the context of teaching and learning. However, only 24 articles on HEIs' social media strategies met the five selection criteria for this review, indicating a lack of research on this topic.

This gap is significant because the digital world is constantly evolving, with a variety of platforms that offer different features, target different audiences, and require different engagement strategies. It is not enough to acknowledge the presence of HEIs on social media platforms; it is essential to understand how they can leverage the power of online interaction to build meaningful relationships with potential students, alumni, and other stakeholders.

Moreover, the effectiveness of marketing strategies on social media platforms in the context of higher education remains a topic of considerable research interest. There are many unanswered questions about how different types of content, posting frequencies, interactive elements, and multimedia formats affect user engagement, brand perception, and ultimately, enrolment rates. Therefore, this review calls for more empirical studies that can provide insights and guidance for HEIs to develop and implement effective social media marketing strategies.

In summary, addressing the research gap in higher education institutions' social media strategies is essential for adapting to the evolving digital sphere. By conducting more empirical studies, we can unlock valuable insights, enabling institutions to craft effective and impactful online marketing strategies for fostering meaningful connections with their audience.

3.Széchenyi István University

This research paper examines the digital presence of Széchenyi István University on various social media platforms. The second research question (RQ2) investigates the website and social media usage patterns of university students. By SLR the literature on the examined platforms were analysed and utilized practically in the section of website and SM platform analytics.

3.1. History

The predecessor of today's Széchenyi István University, the College of Transport and Telecommunications, was founded in 1968. Its focus was on the training of engineers specialising in transport and telecommunications infrastructure, but the range of courses on offer has expanded continuously over the past decades, especially since the regime change. The institution has been named after István Széchenyi since 1986, first as the István Széchenyi College of Transport and Telecommunications Engineering, and then as the István Széchenyi College since 1990, when the range of courses was expanded. Economic, health and social education were introduced in the first half of the 1990s, followed by legal education a few years later - initially as an affiliated programme of a university in the capital, and from 2002 as an autonomous programme. Music education was also integrated into the institution. These developments increased the number of students, enhanced the academic qualifications of the teaching staff and diversified the range of training programmes offered by the institution. Consequently, the institution obtained university status on January 1, 2002.

The institution offers all levels of higher education from assistant to undergraduate, specialist training, and master's degrees to doctoral studies. Currently, there are 9 faculties, 5 doctoral schools belonging to the university in Győr, and it is also the maintainer of a primary and secondary school institution. The undergraduate programs (BA, BSc) are usually 7 semesters long, after which students can continue their studies in master's programs for one and a half or two years. More than twelve thousand students' study at some program in full-time, correspondence or distance learning mode in Hungarian or in some cases in English.

Regional competitiveness is at the core of the university development program, and the key to this is primarily the development of innovation capacity and R&D&I (Research and Development and Innovation) potential. The planned investments will ensure an efficient two-way flow of knowledge between business and education, promoting the continuous renewal of human resources, the market

orientation of the institution's training offer, and the increased international integration of its research activities (*Széchenyi István University, 2023*).

Faculties of Széchenyi István University

- Apáczai Csere János Faculty of Humanities, Education and Social Sciences
- Audi Hungaria Faculty of Automotive Engineering
- Faculty of Agriculture and Food Sciences
- Faculty of Architecture, Civil Engineering and Transport Sciences
- Faculty of Health and Sport Sciences
- Faculty of Mechanical Engineering, Informatics and Electrical Engineering
- Faculty of Law
- Faculty of Performing Arts
- Kautz Gyula Faculty of Business and Economics

Doctoral Schools

- Doctoral Program in Business Administration Sciences
- Doctoral School of Law and Political Sciences
- Doctoral School of Multidisciplinary Engineering Sciences
- Doctoral School of Regional- and Economic Sciences
- Wittmann Antal Multidisciplinary Doctoral School of. Plant, Animal and Food Sciences

4.Previous Research Findings: Platform Analytics

In the authors' previous research called *Students' media consumption habits on the social platforms of Széchenyi István University* performed a platform and a content analysis by examining the website of Széchenyi István University and its social media sites, which include Facebook, Instagram, Twitter, LinkedIn and TikTok. Using Facepager version 4.5.3, the content of the SM posts, their number of comments and reactions (e.g.: likes, shares) were imported into a CSV file and analysed using Excel and the Python programming language. The results show the patterns of online engagement and interaction between the students and the university, as well as the strengths and weaknesses of each platform.

This chapter is a summary that outlines how the researcher analyzed the data and shares key findings. These findings are essential to the survey analysis in the current study and help to understand how students engage with university SM platforms. This understanding is critical for designing surveys that accurately capture the dynamics of online interaction within the university.

4.1. Website

The authors' previous research explores the Search Engine Optimization aspects related to the domain of Széchenyi István University's website, *sze.hu*. It analyzes the traffic data from 2006 onwards, detailing the geographical locations of visitors at the time of access, as well as the search terms utilized by users to navigate to specific sections within the *sze.hu* domain.

Table 3 presents a subset of the three most commonly employed keywords, as monitored by Semrush throughout 2023. Among the most visited pages within the *sze.hu* domain was the Neptun system, the official website, and *szelearning*. The "Traffic (%)" column denotes the proportion of total traffic attributed to each keyword. Meanwhile, the "Volume" column represents the average monthly frequency of user searches for a particular keyword. Semrush derived this value by averaging the monthly searches over the preceding 12 months.

Table 3. Estimated Keyword Overview for *sze.hu*

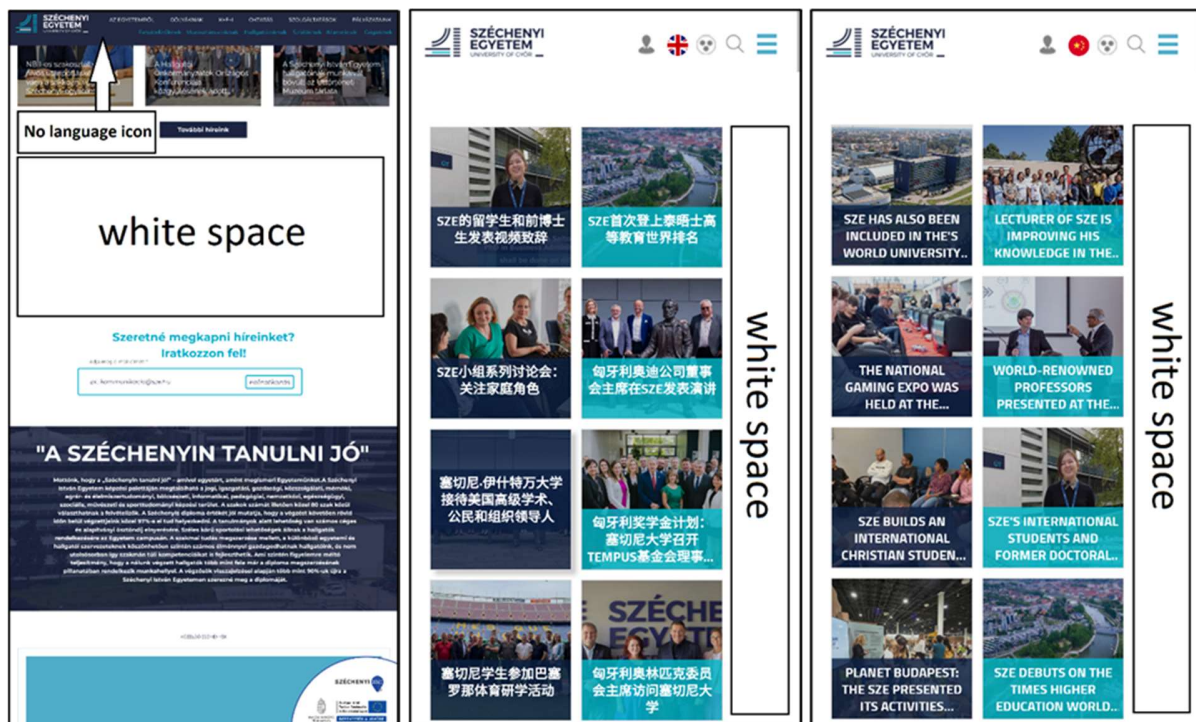
Keyword	Traffic	Traffic (%)	Volume	URL
neptun sze	26.500	15.39	31.000	netw6.nnet.sze.hu/
széchenyi istván egyetem	14.500	8.41	18.100	uni.sze.hu/
szelearning	9.700	5.62	12.100	szelearning.sze.hu/

Source: <https://www.semrush.com/analytics/traffic/overview/?q=sze.hu>

The authors' earlier study also overviewed the official website of the university, uni.sze.hu, and its subpages, available in Hungarian, English, and Chinese. The sites were examined from desktop and mobile view as it can be seen on *figure 8*. Navigation inconsistencies exist among languages, particularly evident on faculty subpages. While the Hungarian site is at uni.sze.hu, English and Chinese versions are at admission.sze.hu. Users can switch languages using a flag icon. Despite consistent design, unnecessary white space between content on Hungarian and English sites may affect user-friendliness (*Manzoor et al., 2019*).

Moreover, the absence of a flag icon on the Hungarian site from mobile view may present a challenge for foreign users seeking access to the English or Chinese versions. Additionally, the university's English and Chinese sites are not displayed among search results for the frequently used keywords related to the site's content. Therefore, it would be advantageous to include a language button on the Hungarian site to address these issues effectively.

Figure 8. Hungarian, Chinese, English Website on the sze.hu Domain



Source: <https://www.uni.sze.hu/>; <https://admissions.sze.hu/chinese-home>; <https://admissions.sze.hu/welcome>

4.2. Széchenyi István University Social Media Sites

The prior research scraped the university's social media sites' user- and content data. Facebook data (*Széchenyi István Egyetem* main page) was collected by using Facepager version 4.5.3, a tool that can fetch publicly available data from YouTube, Facebook, and other websites based on APIs (Application Programming Interface) and web scraping (Jünger, and Keyling, 2019). Instagram data (@*szechenyi.istvan.egyetem* main account) was collected with a python library called Instaloader. TikTok data (@*university_gyor* main account) was collected manually because of the lack of TikTok scraping tool. The data collection period was from September 1, 2022, to September 31, 2023. The data were loaded to an CSV file and the analysis was performed using the Python programming language.

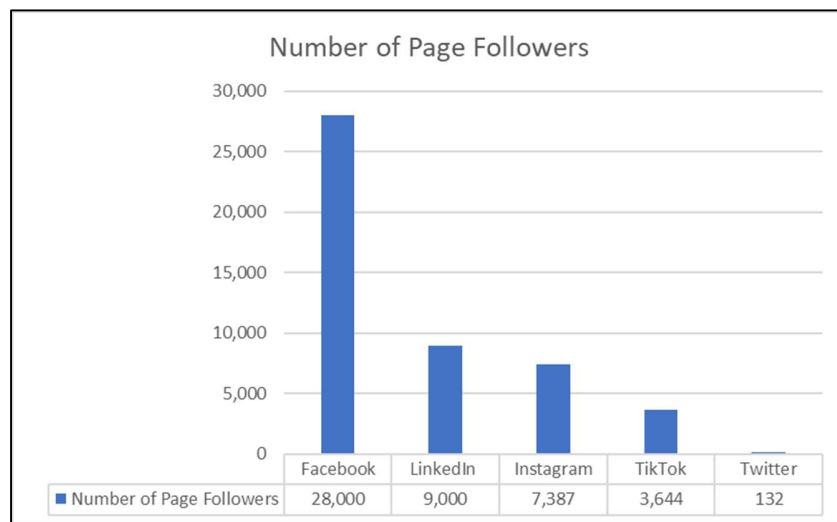
Concerning the data from Facebook, Instagram, and TikTok, the author conducted Descriptive Statistics, Post Text Statistics, Monthly and Daily Engagement analysis, as well as Correlation and Regression analyses. Several key findings derived from these analyses are outlined below for discussion.

The university's LinkedIn data (*Széchenyi István Egyetem* main profile) could not be gathered because their terms and conditions prohibited the scrapping of posts into a CSV file (*LinkedIn* 2023). It is not possible for Twitter profiles (*Széchenyi István Egyetem - University of Győr* main profile) either, because following Elon Musk's acquisition of the company and his transformation into X, the free scraping service for academic research is no longer available (*Twitter* 2023). Consequently, an overview was crafted without utilizing API commands.

Figure 9 displays the follower counts on various platforms as of November 2023, indicating significant engagement across the university's social media channels. The university's main Facebook page attracted a considerable audience, boasting 28,000 followers, while its LinkedIn presence garnered 9,000 followers, indicating a strong professional network. On Instagram, the university's main account maintained an impressive following of 7,387 users, demonstrating its popularity among visually-driven audiences. Additionally, the university captured attention on TikTok with 3,644 followers, showcasing its ability to engage with younger demographics through short-form video content. Despite a smaller following, the university maintained a presence on Twitter with 132 followers. Collectively, these findings underscored the university's active

engagement across diverse social media platforms, each serving as valuable channels for communication and outreach to its varied audience segments.

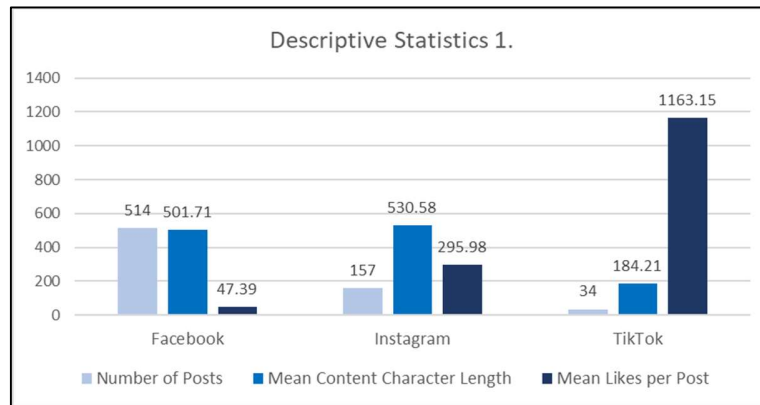
Figure 9. Number of Followers on Széchenyi István University’s SM Platforms
(November 2023)



Source: Created by the author

An analysis of social media data from three major platforms—Facebook, Instagram, and TikTok—reveals distinct patterns in user engagement and content characteristics on *figure 10*. The data, comprising 514 posts on Facebook, 157 on Instagram, and 34 on TikTok, demonstrates variations in both the quantity and quality of content across platforms. Interestingly, while Facebook hosts the highest number of posts, TikTok exhibits a substantially lower count. However, TikTok posts feature significantly shorter content character lengths (mean of 184.21) compared to Facebook (mean of 501.71) and Instagram (mean of 530.58). This suggests a preference for concise, visually-driven communication on TikTok. Additionally, the mean likes per post reveal an intriguing trend, with TikTok boasting the highest engagement rate (mean of 1163.15 likes per post), followed by Instagram (mean of 295.98), and then Facebook (mean of 47.39). Further investigation revealed that there are some outliers regarding post likes on the TikTok profile such as interviews with well-known singers. These findings underscore the importance of platform-specific content strategies for effective social media engagement.

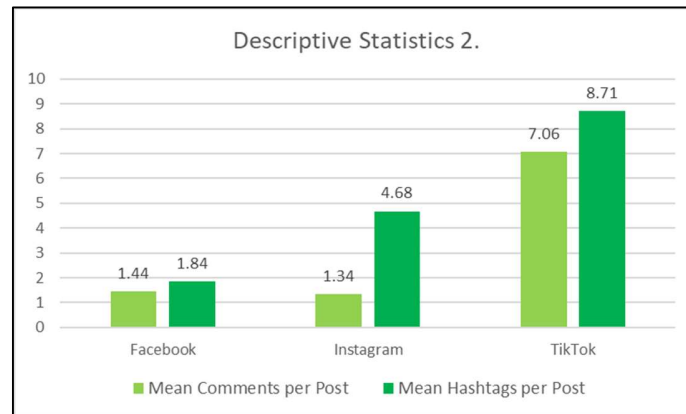
Figure 10. Széchenyi István University's SM Descriptive Statistics 1.



Source: Created by the author

Figure 11 reveals distinct trends in user engagement through comments and the use of hashtags. TikTok emerges as the platform with the highest average number of comments per post, with an average of 7.06 comments, followed closely by Instagram with an average of 4.68 comments per post, while Facebook follows with a more modest average of 1.44 comments per post. This disparity highlights a pronounced preference for interactive discourse among TikTok users, driven by the platform's immersive content format. Similarly, the data reveals a consistent pattern in terms of average hashtags per post, TikTok is leading with 8.71 hashtags, followed by Instagram with 4.68 and Facebook with 1.84. This underscores the need for customized engagement strategies that recognize platform-specific nuances in user behavior, particularly evident in TikTok's extensive hashtag usage, likely aimed at improving content discoverability and increasing reach within its dynamic environment.

Figure 11. Széchenyi István University's SM Descriptive Statistics 2.



Source: Created by the author

The analysis of the relationship between engagement metrics on various social media platforms revealed distinct patterns of correlation by Python programming language (*table 4*).

Specifically, in examining positive correlations, it is evident that there is a consistent relationship between engagement rate and certain variables across platforms. For Facebook, the engagement rate was calculated by adding the number of likes, reactions, comments, and shares together and dividing by the current number of page followers. For Instagram, the number of likes and comments combined was added, and the result was divided by the total number of page followers to determine the engagement rate.

On Facebook, a moderate positive correlation is observed between engagement rate and both shares ($r = 0.67$) and comments ($r = 0.40$). Similarly, Instagram demonstrates a strong positive correlation between engagement rate and likes ($r = 0.998$). Regarding TikTok, there is a strong correlation between likes and both comments ($r = 0.97$) and reposts ($r = 0.97$), indicating that engaging posts increase user activity. Moreover, there is a moderate positive correlation between the number of hashtags used in a video and the number of views it receives ($r = 0.31$). This indicates that videos with a higher number of hashtags tend to garner more views, albeit with a moderate strength of correlation. Additionally, a weak positive correlation is observed between video length and views ($r = 0.12$), implying that longer videos may slightly correlate with increased views, though the relationship is not as strong as that between views and hashtags. These insights highlight factors that may influence the visibility and popularity of videos on TikTok by the algorithm, offering

valuable considerations for the university's content creators aiming to optimize their reach and engagement on the platform.

The negative correlations observed between post length and other variables across Facebook, Instagram, and TikTok shed light on how content length impacts user engagement on these platforms. In particular, a weak negative correlation is identified between post length and the number of likes on both Facebook ($r = -0.11$) and Instagram ($r = -0.15$), indicating that shorter posts tend to receive more likes. Similarly, a weak negative correlation is observed between post length and engagement rate on both Facebook ($r = -0.11$) and Instagram ($r = -0.15$), suggesting that shorter posts lead to higher engagement rates. On TikTok, a slightly stronger negative correlation is found between post length and views ($r = -0.28$), indicating that shorter videos are more likely to receive higher view counts. Additionally, a weak negative correlation is observed between post length and engagement rate on TikTok ($r = -0.20$), suggesting that shorter videos may also lead to higher engagement rates.

These findings underscore the importance of concise and impactful content across social media platforms, as shorter posts and videos tend to fare better in terms of user interaction and overall engagement.

Table 4. Correlation Analysis

Positive Correlation				
Platform	Variable X	Variable Y	r	Strength
Facebook	Engagement rate	Shares	0.67	Moderate
Facebook	Engagement rate	Comments	0.40	Moderate
Instagram	Engagement rate	Likes	0.998	Strong
Instagram	Engagement rate	Number of Hashtags	0.21	Weak
TikTok	Likes	Comments	0.97	Strong
TikTok	Likes	Reposts	0.97	Strong
TikTok	Views	Number of hashtags	0.31	Moderate
TikTok	Views	Video Length	0.12	Weak
Negative Correlation				
Platform	Variable X	Variable Y	r	Strength
Facebook	Post Length	Number of likes	-0.11	Weak
Facebook	Post Length	Engagement rate	-0.11	Weak
Instagram	Post Length	Number of likes	-0.15	Weak
Instagram	Post Length	Engagement rate	-0.15	Weak
TikTok	Post length	Views	-0.28	Weak
TikTok	Post length	Engagement rate	-0.20	Weak

Source: Created by the author

4.3. Summary

In this part, the findings have been summarized and some recommendations and conclusions have been added for the website and each of the platforms.

4.3.1. Website

In conclusion, the investigation of Széchenyi István University's domain (sze.hu) was carried out using specialized tools, notably the Semrush, a comprehensive digital marketing analytics

platform. These tools provided valuable insights into website usage patterns, enabling the analysis of metrics such as pages per visit and average visit duration. The findings indicated that the website has successfully attracted a significant number of users, with keyword analytics identifying key terms driving traffic to the site. Furthermore, the analysis suggested areas for improvement, specifically enhancing mobile responsiveness and adding a language button to the main Hungarian site on mobile devices. Overall, these methodologies were crucial in conducting a thorough examination of the domain, offering valuable recommendations for its further development and optimization.

4.3.2. Facebook

For a clear and consistent image of Széchenyi István University, each department and faculty would use a Facebook page and each course would have a Facebook group. As the university is internationalizing, all the posts should be translated into English, as the information could be useful for foreign students as well. It is very important to emphasize the quality of the posts rather than the quantity. December showed high engagement despite fewer posts, indicating that well-curated, relevant content captures the audience's attention. Tuesdays, Wednesdays, and Thursdays consistently had higher post counts. It is recommended to focus on important announcements, events, and engaging content on these days when audience activity is at its peak. Despite lower post counts, engagement rates were higher on Sundays. Posting important updates or engaging content on Sundays would be beneficial as it would capture the attention of a more engaged audience. Writing concise posts, using more strategic hashtags, and encouraging likes, shares, and comments to increase social media engagement are also recommended.

4.3.3. Instagram

The Instagram account of Széchenyi István University (@szechenyi.istvan.egyetem) is an effective way of promoting the university's brand, values, and achievements to a wide and diverse audience. The account posts high-quality photos and videos that showcase the university's modern facilities, academic programs, research projects, student life, and social events. The account also engages with its followers by asking questions, sharing stories, and using hashtags. The account has almost 8000 followers and receives hundreds of likes and comments on each post. The account's marketing strategy reflects the university's motto: "Széchenyin tanulni jó!" (It is good to study at Széchenyi!)

The research highlights the dynamic nature of audience interaction on Instagram, exemplified by the interplay between posting frequency, seasonal patterns and engagement rates. This insight enables the university to effectively tailor its content strategies, increase audience engagement, and foster a vibrant online community. In particular, the study suggests that universities could optimise their social media posting schedules by focusing on mid-week content on Instagram, particularly on Wednesdays and Thursdays, to maximise engagement rates. The findings highlight the key role of consistent posting schedules, efficient use of hashtags, concise messaging and active audience engagement through likes during the specified years. Adapting to these patterns appears to have positively influenced the University's social media marketing strategies, fostering increased engagement and interaction within its online community.

4.3.4. Twitter

The Széchenyi István University's Twitter page effectively uses a mix of content to engage with its audience. However, with only 135 followers, there is potential for growth in the university's Twitter presence. By increasing audience engagement, promoting the Twitter page, and using hashtags, the university could significantly enhance its online presence and reach a larger audience.

4.3.5. LinkedIn

In November 2023, the university successfully leveraged its LinkedIn platform to engage a global audience of approximately 9,000 followers and a growing alumni network of 9,232 past students. By consistently sharing achievement highlights, informational updates, and alumni spotlights in English, the university effectively communicated its message to a diverse audience. Through strategic content creation and active engagement, the university will further enhance its online presence, fostering meaningful relationships with its audience and alumni community.

4.3.6. TikTok

In conclusion, the analysis of TikTok engagement and posting data provided valuable insights into user behaviour and content distribution at the university. The study revealed clear patterns in user activity throughout the week, with distinct levels of engagement observed from Monday to Saturday. Furthermore, the research identified intriguing correlations and regressions, including a cyclical trend in university TikTok activities over months and years, and the strong interconnections between views, likes, comments, and reposts, indicating the interconnected nature of user interactions. The use of hashtags was found to be associated with specific topics, and shorter

messages and lower engagement rates were linked to certain video characteristics. These findings provide a comprehensive understanding of the university's TikTok dynamics, offering valuable information for future content strategies and user engagement efforts.

5. Survey Research

The author conducted a survey among students to gather their opinions regarding the aforementioned analyzed platforms. The survey was created with Google Forms. The research aimed to assess student satisfaction levels with both the university website and social media platforms, identify prevailing issues, and explore potential remedies. A total of 1116 responses were collected from both Hungarian (915) and international (201) students. Data analysis was conducted collectively and separately for each group to account for potential divergences in their respective concerns and challenges.

The survey consists of a total of 52 questions, of which 50 are closed-ended and 2 are open-ended. The survey included a comprehensive set of questions covering various demographic and behavioural factors, as well as perceptions of specific platforms and university-related entities. These questions were organized into distinct groups to facilitate systematic analysis and interpretation. Categories included demographic variables such as gender and age, active student status and faculty affiliation. In addition, questions explored social media usage patterns, including account ownership and profile usage on platforms such as Facebook, Twitter, Instagram, LinkedIn, and TikTok. Respondents were also asked about their engagement on these platforms, including frequency of use and content sharing practices. The survey also measured awareness and satisfaction with the university's social media presence, as well as the SZE's official website ratings on dimensions such as content, appearance, transparency, timeliness, and ease of use. Students were asked about their familiarity with faculty and course websites within the university domain, as well as their engagement with course-specific social media presences and the perceived usefulness of course social media platforms (SMPs). This comprehensive approach allowed for a nuanced understanding of student perceptions and behaviours in the digital and academic realms.

5.1. Descriptive Statistics

Descriptive statistics conducted using the Python programming language reveal several key findings about the demographic, academic characteristics, SMP usage and satisfaction of the sample population. The responses have been decoded (*table 5* and *table 6*) and analysed.

The gender distribution shows a slight skew towards males, with an average gender code of 1.45. The age distribution shows that the majority of respondents are between the ages of 19 and 21, with an average age code of 2.77. Active student status is prevalent among participants, with an average

code of 1.06 indicating that most respondents are currently students. In terms of faculty affiliation, the data suggests a diversity of faculties, but the Kautz Gyula Faculty of Business and Economics is dominant. In addition, the majority of respondents are pursuing BA/Bsc level courses, with an average course level code of 2.26. These findings provide valuable insights into the composition of the sample population and can inform further analysis and decision making.

Table 5. Survey Codes

Age	Code	Gender	Code	Course level	Code	Yes/No	Code
14-18	1	Male	1	FOSZK	1	Yes	1
19-21	2	Female	2	BA/Bsc	2	No	2
22-25	3			MA/MSc	3		
26-30	4			Undivided	4		
31-40	5			PhD	5		
41-	6						

Source: Created by the author

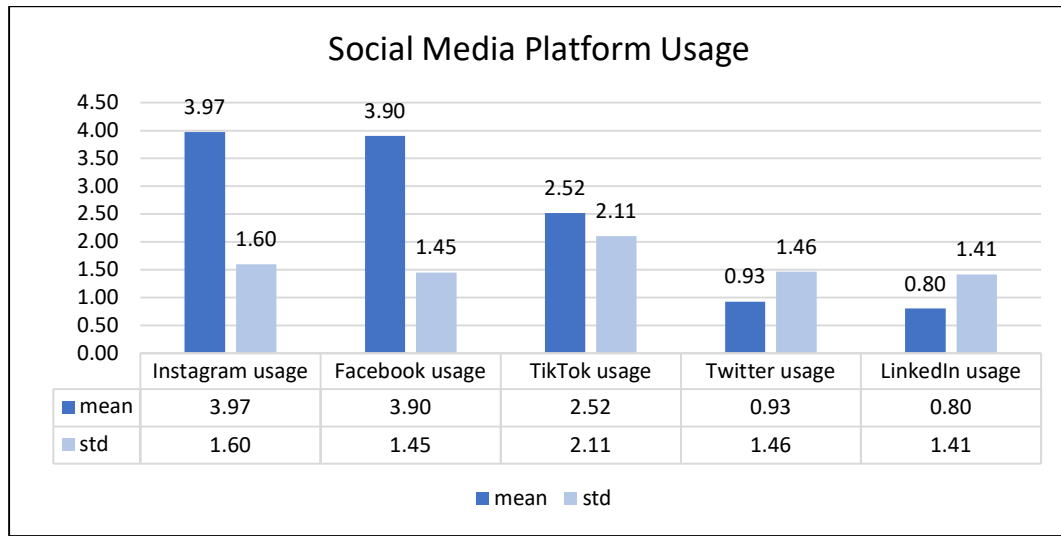
Table 6. Respondents' Faculties

Faculty	Quantity	Code
Kautz Gyula Faculty of Business and Economics	782	3
Faculty of Mechanical Engineering, Informatics and Electrical Engineering	130	5
Audi Hungaria Faculty of Automotive Engineering	62	1
Faculty of Architecture, Civil Engineering and Transport Sciences	53	2
PhD program	35	10
Apáczai Csere János Faculty of Humanities, Education and Social Sciences	26	8
Faculty of Law	13	7
Faculty of Performing Arts	7	6
Faculty of Health and Sport Sciences	4	9
Faculty of Agriculture and Food Sciences	4	4

Source: Created by the author

The mean scores for social media usage (*figure 12*) indicate a strong preference for Facebook and Instagram, with means of 3.90 and 3.97 respectively out of 5. TikTok exhibits a lower mean score of 2.52, while Twitter and LinkedIn have even lower mean scores of 0.93 and 0.80 respectively. Standard deviations reveal varying levels of dispersion around these means, with Facebook and Instagram showing relatively higher variability compared to TikTok, Twitter, LinkedIn, and Facebook. These findings suggest a consistent trend of higher engagement on Facebook and Instagram among university members, with potential for targeted efforts to increase activity on other platforms.

Figure 12. Social Media Platform Usage



Source: Created by the author

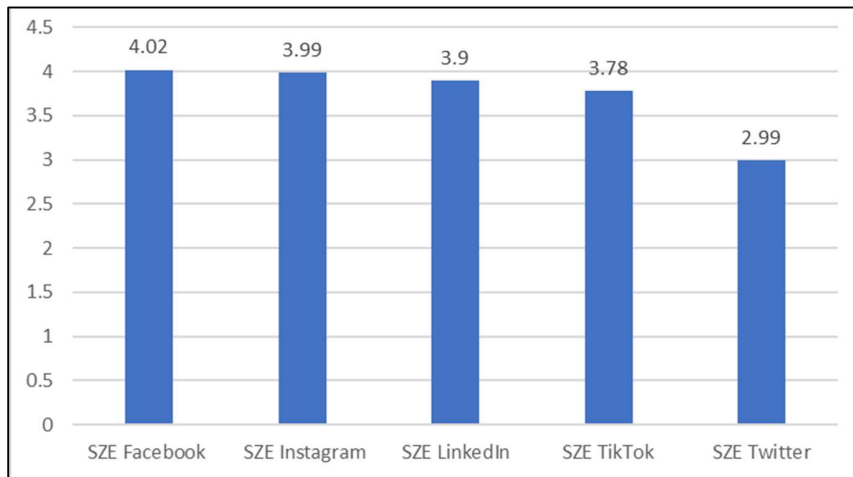
The survey also examined the propensity of SZE students to share content across various social media platforms. Results indicate that Instagram leads in content sharing, with a mean score of 1.87 out of 5, followed closely by Facebook with a mean score of 1.28. Twitter and TikTok show lower levels of content sharing, with mean scores of 0.72 and 0.69, while LinkedIn exhibits the lowest mean score of 0.33. However, there is considerable variability in content sharing behaviour, as indicated by the standard deviations. These findings suggest that while Instagram and Facebook are the preferred platforms for content sharing, there may be untapped potential for increased engagement on Twitter, LinkedIn, and TikTok through targeted content strategies and community-building initiatives.

The survey revealed that 994 students are aware of at least one of the university's SM accounts, while 124 students indicated they were not familiar with any. The most followed university accounts regarding the SMP are, in order, Facebook (775), Instagram (601), TikTok (220), Twitter (128) and LinkedIn (113).

The 1-5 Likert scale question about averages for SZE's presence on various social media platforms (*figure 13*) suggest several key assumptions. Firstly, higher scores indicate greater satisfaction, with Facebook and Instagram being the most preferred platforms, boasting average scores of 4.02 and 3.99 respectively. LinkedIn and TikTok follow closely behind with moderate satisfaction levels,

averaging 3.90 and 3.78. However, Twitter lags behind with an average score of 2.99, indicating comparatively lower satisfaction levels.

Figure 13. Respondents' Satisfaction with the University's SMP Accounts



Source: Created by the author

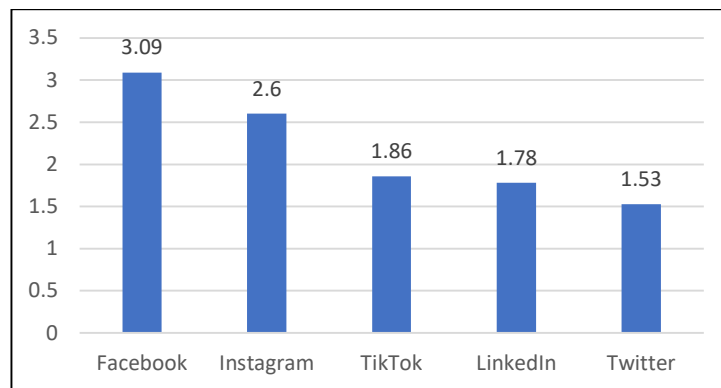
Table 7. Number of Respondent Registration on SMP's

	Facebook	Instagram	TikTok	Twitter	LinkedIn
Registered	1020	859	595	468	367
Not registered	96	257	521	648	749

Source: Created by the author

The mean awareness levels of students following their own courses across various university social media platforms reveal intriguing patterns as it showcased *on figure 14*. Facebook emerges as the most widely recognized platform for students' courses, with a mean awareness score of 3.09, indicating a significant presence and engagement among users. Instagram follows with a slightly lower mean score of 2.60, suggesting a solid but somewhat lesser degree of awareness compared to Facebook. TikTok trails behind with a mean awareness score of 1.86, indicating a comparatively lower level of engagement or visibility for students' courses on this platform. Similarly, LinkedIn and Twitter exhibit even lower mean awareness scores of 1.78 and 1.53 respectively, suggesting relatively limited awareness or visibility of students' courses on these platforms. These findings highlight the need for tailored promotional efforts across different social media channels to enhance awareness and engagement with students' courses, particularly on platforms where awareness is relatively low.

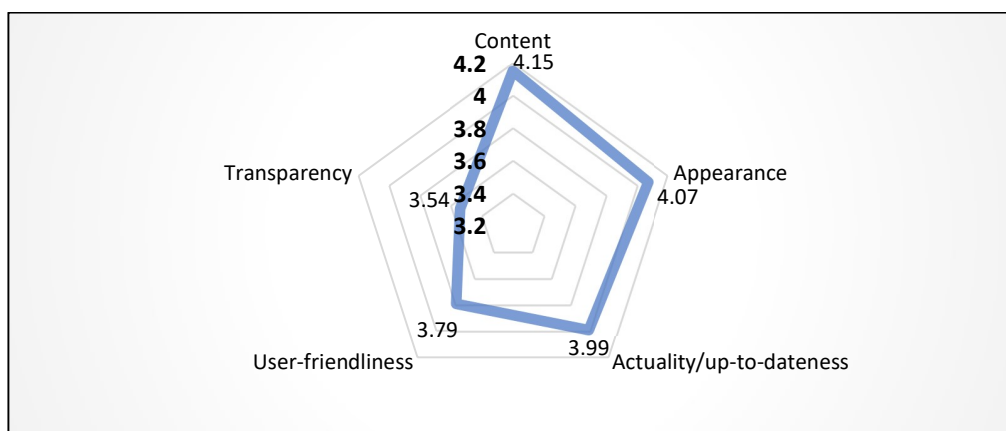
Figure 14. Average of Following Own Course on SMPs'



Source: Created by the author

The average satisfaction levels with various aspects of the university's website provide valuable insights into user perceptions as *figure 15* shows. Notably, content receives the highest average satisfaction score of 4.15, indicating that users find the information provided on the website to be comprehensive and valuable. Appearance closely follows with an average score of 4.07, suggesting that users generally find the website visually appealing. The aspect of actuality or up-to-dateness receives a slightly lower but still respectable average score of 3.99, indicating that users perceive the website's content to be reasonably current. However, user-friendliness and transparency receive comparatively lower average scores of 3.79 and 3.54 respectively, suggesting areas where improvements could enhance the overall user experience. These findings emphasize the importance of continuously evaluating and refining the website to meet user needs and expectations, particularly in terms of ease of use and transparency.

Figure 15. Average University Website Satisfaction



Source: Created by the author

5.2. Factor Analysis

Given the extensive set of 52 questions, it is imperative to undertake a systematic grouping process to elucidate latent relationships among variables and to reduce data. In response to this necessity, the study employs Exploratory Factor Analysis (EFA), a widely recognized statistical method. Through the application of EFA, the study aims to uncover underlying structures and interrelations within the dataset. This analytical approach enhances the depth of understanding regarding the phenomena under examination, thus contributing to the scholarly discourse in the field.

The Kaiser-Meyer-Olkin (KMO) measure assesses the adequacy of the data for conducting factor analysis. With a KMO measure of 0.8045 calculated with the help of FactorAnalyzer Python library, the data can be considered moderately suitable for factor analysis. This value falls within the acceptable range of 0 to 1, where higher values indicate better suitability for factor analysis. A KMO measure above 0.6 is generally acceptable for factor analysis, suggesting that the variables in the dataset share enough common variance to warrant the extraction of underlying factors (*Williams et al. 2010*). Therefore, based on the KMO measure of 0.8045, The author could conduct factor analysis on the dataset and expect meaningful results in identifying underlying latent factors.

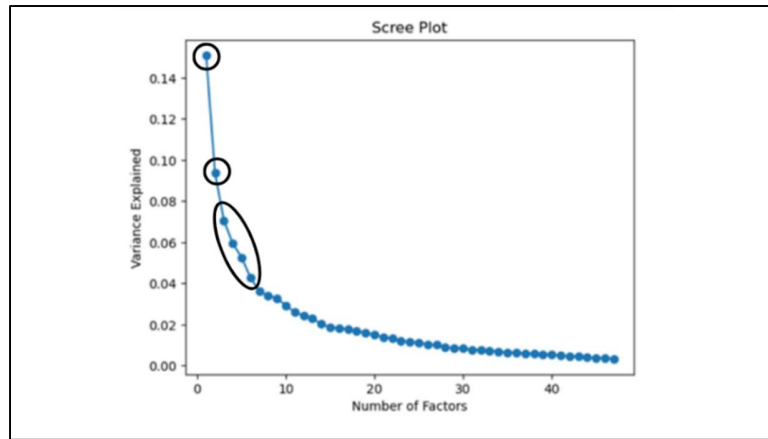
To ascertain the optimal number of factors, the author has utilized various established techniques in Python programming language such as scree plots, original eigenvalues based on the Kaiser criterion. These methodologies are widely recognized in the field for their effectiveness in determining the appropriate number of factors within a model (*Persson and Khojasteh 2021*).

The eigenvalue indicates the proportion of variance explained by each factor. Each factor extracted will possess an eigenvalue, which is a multiple of the original vector. The initial factor extracted aims to capture the maximum variance, resulting in subsequent eigenvalues being smaller than the first. The Scree Plot criterion identifies the "elbow" point in the curve and chooses all components just before the curve starts to flatten out (*Persson and Khojasteh 2021*).

The findings from the factor analysis reveal a nuanced understanding of the underlying structure within the dataset. With the highest variance explained at 0.14, the analysis identified six factors that surpassed the "elbow point" signifying their significance in capturing substantial variance within the data (*figure 16*). This observation suggests that while the factors delineate distinct patterns, the variance explained by each factor remains relatively modest. Despite this, the

identification of six factors provides valuable insight into the multidimensional nature of the dataset, shedding light on the interplay between various latent constructs.

Figure 16. Scree Plot



Source: Created by the author

The factor analysis conducted on the dataset reveals compelling insights into the underlying structures and relationships within the data. The factor loadings represent the correlations between observed variables and latent factors.

5.2.1. Factor 1: University Website Satisfaction

Factor 1 unveils a significant association with satisfaction regarding various aspects of the university's website. Variables such as satisfaction with its appearance, transparency, and user-friendliness exhibit strong loadings on this factor. This suggests that individuals who express high levels of satisfaction with the website tend to perceive it positively in terms of its visual appeal, transparency of information, and ease of use. These findings underscore the importance of user experience in shaping overall satisfaction with online platforms.

Table 8. Factor 1

<i>Observed Variables</i>	<i>Factor Loadings</i>
<i>SZE website satisfaction [Content]</i>	0.80
<i>SZE website satisfaction [Appearance]</i>	0.76
<i>SZE website satisfaction [Transparency]</i>	0.81
<i>SZE website satisfaction [Actuality/up-to-datedness]</i>	0.78
<i>SZE website satisfaction [User-friendliness]</i>	0.84

Source: Created by the author

5.2.2. Factor 2: Instagram and TikTok Usage

Factor 2 sheds light on social media usage patterns, particularly on platforms like Instagram and TikTok. Variables such as Instagram and TikTok usage, along with satisfaction with their appearance, demonstrate notable loadings on this factor. This suggests a strong association between active engagement with these platforms and individuals' perceptions of their visual appeal. The findings imply that individuals who use Instagram and TikTok frequently are likely to prioritize aesthetics and visual content when evaluating these platforms.

Table 9. Factor 2

<i>Observed Variables</i>	<i>Factor Loadings</i>
<i>Instagram usage</i>	0.45
<i>TikTok usage</i>	0.66
<i>Satisfaction - SZE Instagram appearance</i>	0.52
<i>Satisfaction - SZE TikTok appearance</i>	0.71
<i>Following own course [Instagram]</i>	0.42
<i>Following own course [TikTok]</i>	0.51

Source: Created by the author

5.2.3. Factor 3: Demographic Characteristics and Professional Networking

Factor 3 reveals intriguing connections between demographic characteristics and engagement with LinkedIn, a professional networking platform. Variables such as age, course level, and LinkedIn usage exhibit substantial loadings on this factor. This indicates that factors such as age and educational background may influence individuals' propensity to engage with LinkedIn for professional networking purposes. Moreover, satisfaction with the appearance of one's LinkedIn profile also contributes to this factor, highlighting the importance of visual presentation in the professional context.

Table 10. Factor 3

<i>Observed Variables</i>	<i>Factor Loadings</i>
<i>Age</i>	0.47
<i>Course level</i>	0.54
<i>LinkedIn usage</i>	0.81
<i>Sharing content on LinkedIn</i>	0.44
<i>Satisfaction - SZE LinkedIn appearance</i>	0.68
<i>Following own course [LinkedIn]</i>	0.47

Source: Created by the author

5.2.4. Factor 4: Awareness of the University Social Media Platforms

Factor 4 uncovers factors associated with awareness of the university on social media platforms. Variables such as awareness of the university on platforms like Facebook and Instagram demonstrate significant loadings on this factor. This suggests that individuals who are more aware of the university's presence on social media platforms are likely to engage with its content and updates, potentially indicating a stronger affiliation or interest in the institution's activities and offerings.

Table 11. Factor 4

<i>Observed Variables</i>	<i>Factor Loadings</i>
<i>SZE SMP awareness</i>	0.46
<i>Following SZE on Facebook</i>	0.59
<i>Following SZE on Instagram</i>	0.42

Source: Created by the author

5.2.5. Factor 5: Awareness of Faculties and Courses on University Online Platforms

Factor 5 provides insights into individuals' awareness of specific academic content related to the university. Variables such as awareness of faculties' and courses' webpages exhibit substantial loadings on this factor. This suggests that individuals who are more aware of these academic resources are likely to be actively engaged with the university's educational offerings, indicating a strong interest or involvement in academic pursuits within the institution.

Table 12. Factor 5

<i>Observed Variables</i>	<i>Factor Loadings</i>
<i>Awareness of SZE faculties' webpages</i>	0.47
<i>Awareness of SZE courses' webpages</i>	0.62
<i>Own course SZE webpage awareness</i>	0.64
<i>Own course SZE on SM awareness</i>	0.62

Source: Created by the author

5.2.6. Factor 6: Twitter Usage and Satisfaction with the University Account

Finally, Factor 6 delves into Twitter usage patterns and perceptions of its appearance. Variables such as Twitter usage frequency and satisfaction with its appearance demonstrate noteworthy loadings on this factor. This suggests that individuals who use Twitter frequently are likely to have specific preferences or expectations regarding its visual presentation. The findings underscore the importance of aesthetics and user experience in shaping individuals' perceptions of social media platforms.

Table 13. Factor 6

<i>Observed Variables</i>	<i>Factor Loadings</i>
<i>Twitter usage</i>	0.78
<i>Sharing content on Twitter</i>	0.43
<i>Satisfaction - SZE Twitter appearance</i>	0.38
<i>Following own course [Twitter]</i>	0.51

Source: Created by the author

Overall, the factor analysis provides a comprehensive understanding of the underlying dimensions within the dataset, highlighting key patterns and associations that offer valuable insights into user behaviour, preferences, and perceptions across the above-mentioned online platforms and demographic groups.

5.3. T-test Analysis

T-test is a statistical method employed to compare the means of two distinct groups. The significance level, referred to as alpha, represents the likelihood of rejecting the null hypothesis

when it is true. Null hypothesis states that there is no significant difference between the means of the two groups. If the p-value is less than or equal to the significance level, the null hypothesis is rejected in favour of the alternative hypothesis. The alternative hypothesis is that there are significant differences between the two datasets. Conversely, if the p-value is greater than the significance level, the null hypothesis is not rejected (*Yim et al. 2010*).

The two surveys were also examined separately. The aim is to find the similarities and differences between the Hungarian and international students' opinion and their satisfaction about the Széchenyi István University's website and SM platforms, therefore the author performed a Two-Sample T-Test due to the presence of two datasets. T-test analysis was done by Python programming language.

5.3.1. Non-significant Values

The analysis revealed 10 non-significant findings out of the 47 columns, indicated by p-values greater than or equal to 0.05 as it can be seen on *table 14*. Notably, variables such as gender, own profiles on Twitter and Instagram, Twitter usage, sharing content on Facebook, following the institution on Instagram, satisfaction with the appearance of institution's Instagram and TikTok profiles, as well as satisfaction with the transparency of the institution's website, did not exhibit statistically significant differences between the two groups. Similarly, following one's own course on Twitter also failed to show significant differentiation. These results suggest that these aspects may not significantly influence the observed differences between the groups in the surveyed population and null hypothesis has been accepted.

The result implies that there is a similar level of satisfaction with the university's TikTok appearance (0.88), and the two samples share content with the same periodicity on Facebook (0.85). The registration frequency of Hungarian and international students is similar on Instagram (0.84) and Twitter (0.77). The distribution of their satisfaction with the university's Instagram appearance (0.66) and website satisfaction in terms of transparency (0.38) is similar. As were the averages of following intuition on Instagram (0.31) and their own course on Twitter (0.18). The gender distribution was also similar between Hungarian and international students (0.14).

Table 14. Non-significant Values

Column	P-value
Satisfaction - SZE TikTok appearance	0.88
Sharing content on Facebook	0.85
Own profile [Instagram]	0.84
Own profile [Twitter]	0.77
Satisfaction - SZE Instagram appearance	0.66
SZE website satisfaction [Transparency]	0.38
Following SZE on Instagram	0.31
Following own course [Twitter]	0.18
Gender	0.14

Source: Created by the author

5.3.2. Significant Values

The key findings from the analysis highlight significant differences between Hungarian and international students across 37 factors examined within the dataset (*table 15*). Notably, the course level exhibited an extremely low p-value of 3E-53, indicating a strong association with other variables examined, suggesting that the distribution of course levels between Hungarian and international students differs significantly. This discrepancy underscores the diverse academic backgrounds and interests represented amongst survey respondents.

Furthermore, demographic characteristics such as age also demonstrated a considerable impact, with a p-value of 9E-16, suggesting that the age composition between Hungarian and international students varies significantly within the survey datasets. This finding reflects the diverse age demographics within each student population and may indicate differing educational pathways or life stages among Hungarian and international students.

Additionally, factors related to social media presence and engagement, such as satisfaction with the university's Facebook appearance, engagement with official SZE websites, and following the university on social media platforms, emerged as statistically significant factors. These findings suggest that Hungarian and international students may exhibit distinct preferences and behaviours regarding their digital interactions with the university and its online platforms.

Conversely, while some factors, such as satisfaction with SZE Twitter appearance and engagement with Twitter, showed statistical significance, they displayed comparatively higher p-values, indicating a less pronounced impact compared to other variables. This suggests that while there may be differences in Twitter usage between Hungarian and international students, these differences may not be as significant as those observed in other areas.

Overall, these findings provide valuable insights into the unique characteristics and preferences of Hungarian and international students at SZE. Understanding these differences is crucial for tailoring educational services, communication strategies, and support initiatives to meet the diverse needs of both student populations effectively. Further research and analysis may explore additional factors contributing to the differences observed and inform targeted interventions to enhance the academic experience and support the success of all students at SZE, irrespective of their nationality or background.

Table 15. Significant Values

Column	P-value	Column	P-value
Course level	3E-53	Course SMP usefulness	7E-08
Satisfaction - SZE LinkedIn appearance	4E-37	TikTok usage	4E-07
Sharing content on LinkedIn	4E-34	SZE website satisfaction [Appearance]	9E-07
LinkedIn usage	3E-33	Own profile [Facebook]	3E-06
Own profile [LinkedIn]	5E-29	Following SZE on TikTok	3E-06
Following own course [Facebook]	3E-19	SZE website satisfaction [Content]	9E-06
SZE SMP awareness	6E-17	Own profile [TikTok]	1E-04
Own course SZE on SM aweranness	5E-16	Following own course [Instagram]	1E-04
Age	9E-16	Satisfaction - SZE Facebook appearance	1E-04
Satisfaction - SZE Twitter appearance	2E-13	Following own course [TikTok]	5E-04
Following SZE on LinkedIn	7E-13	Sharing content on Instagram	1E-03
Faculty	7E-13	SZE website satisfaction [Actuality/up-to-dateness]	2E-03
Awareness of SZE faculties' webpages	2E-11	SZE website satisfaction [User-friendliness]	2E-03
Official SZE website awareness	3E-11	Instagram usage	1E-02
Following SZE on Facebook	4E-11	Sharing content on Twitter	3E-02
Awareness of SZE courses' webpages	3E-10	Sharing content on TikTok	3E-02
Facebook usage	5E-10	Active student status	3E-02
Following own course [LinkedIn]	3E-08	Following SZE on Twitter	4E-02
Own course SZE webpage awareness	4E-02		

Source: Created by the author

5.4. Cluster Analysis

For answering the RQ2, the author has examined different segments with the help of cluster analysis. The used variables were considered regards to the previous research results such as the platform analysis, correlation, factor analysis and T-test.

Cluster analysis is a widely used data mining process aimed at revealing latent patterns and groupings within a dataset (*Härdle and Simar 2019*). This technique has evolved over nearly a century of computerization and machine learning development. It serves as an example of unsupervised machine learning, where data patterns are identified without user input, as highlighted by *Kettenring (2006)*, thus eliminating the need for users to provide classification criteria for the algorithm.

For this study, the k-means method of the Python programming language was applied. This algorithm first creates k clusters and then assigns each data point to the cluster with the closest mean. Initially, the clusters may be somewhat imperfect because the algorithm defines "means" in a somewhat arbitrary manner. Once all points have been assigned to clusters, new averages are computed within each cluster. The data points are then reassigned to the cluster with the closest mean. This iterative process continues until the means between the previous and current iterations of clusters are nearly identical. As dataset size increases, manual clustering becomes exponentially more complex.

To determine the necessary clusters, the elbow method was implemented, a widely used technique in data analysis to determine the optimal number of clusters in a data set. In Python, the application process was the following. First, essential libraries such as NumPy, Pandas, and Matplotlib are imported for data manipulation and visualization. Next, the data set is loaded into the Python environment using Pandas. Then, any necessary data preprocessing steps, such as handling missing values or scaling functions, are performed. The K-means algorithm from the scikit-learn library is then applied to cluster the data into different groups. Then, the elbow method is applied, iterating over different numbers of clusters and plotting the sum of the squared distances of the samples to their closest cluster centre against the number of clusters. From this plot, the "elbow point" is identified, which indicates the optimal number of clusters at which inertia begins to decrease at a slower rate. Finally, the clustering process is completed by reapplying K-means with the determined optimal number of clusters, and the results are visualized using scatter plots or other

relevant visualization techniques to aid in interpretation. Through these steps, the elbow method is effectively applied in Python to determine the appropriate number of clusters for the dataset and perform K-means clustering accordingly.

5.4.1. Age and LinkedIn Usage

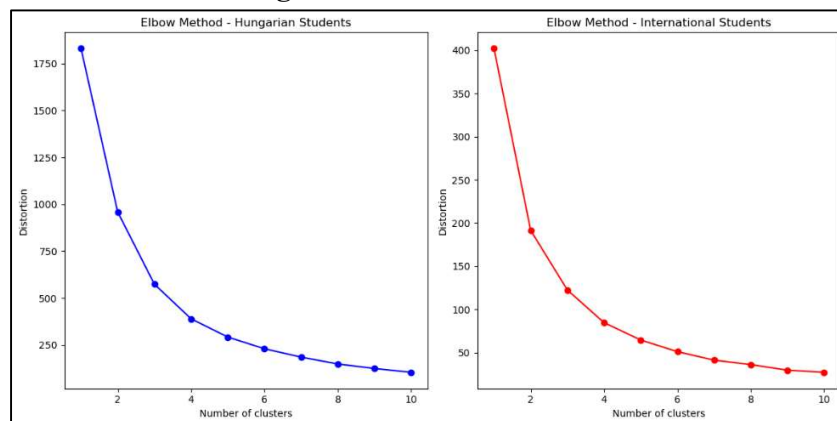
The factor analysis showed strong correlations between age and LinkedIn usage, and the T-test revealed a significant difference between these variables regarding Hungarian and international students. For these reasons, cluster analysis was applied for these variables in order to define the possible segmentations for both Hungarian and international student respondents at Széchenyi István University.

Survey question regards to LinkedIn usage was measured in Likert Scale:

*“How often do you use the following platforms? Facebook, Instagram, TikTok, Twitter, **LinkedIn** (0- not registered, 1- hardly ever, 5-on a daily basis)”*

The elbow method has identified 5 clusters based on age and LinkedIn usage, as illustrated in the *figure 17* below:

Figure 17. Elbow Method 1.



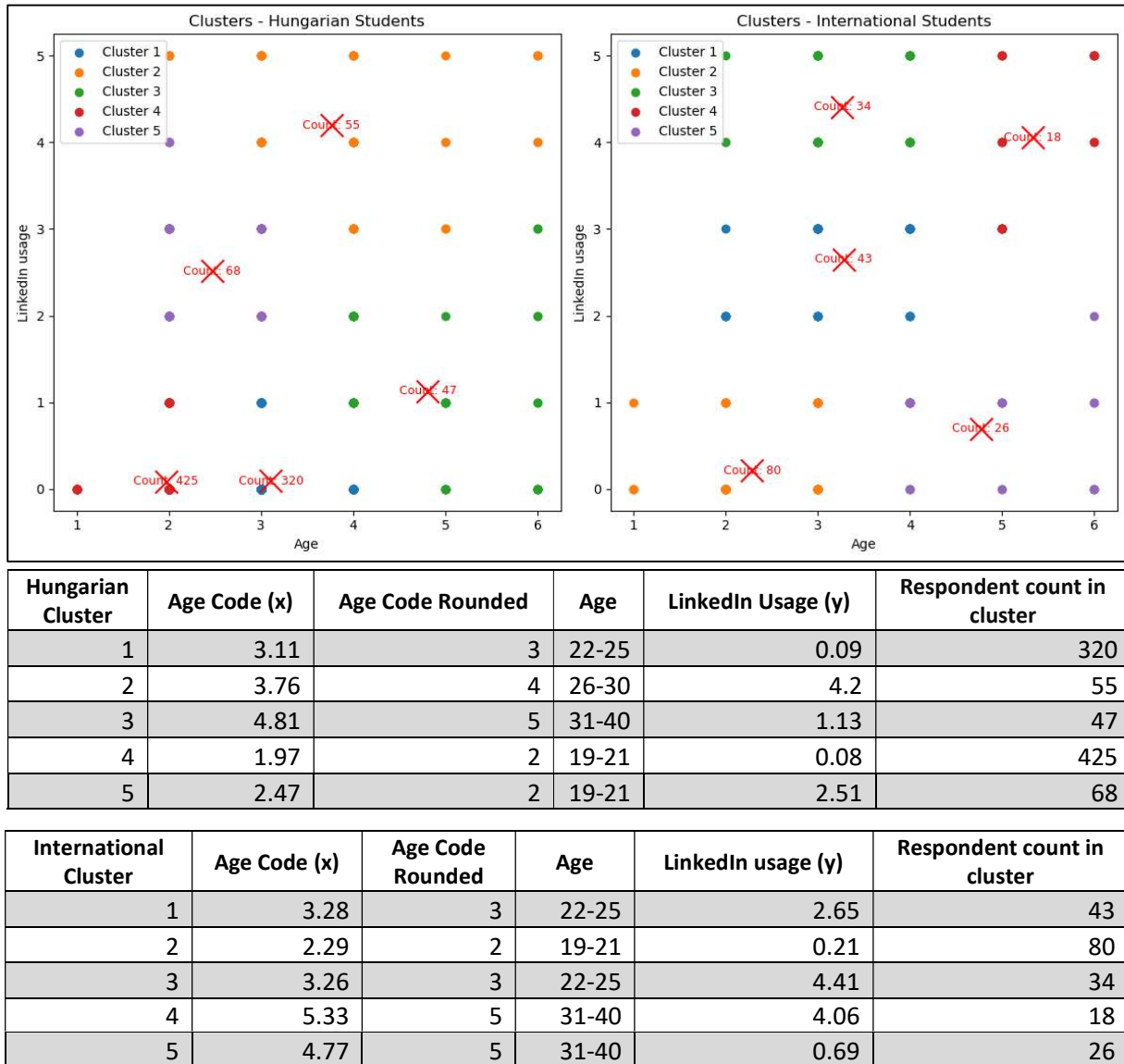
Source: Created by the author

The analysis of Hungarian clusters has revealed distinct trends in age distribution and LinkedIn usage across various age groups. Cluster 1, representing individuals aged 22-25, exhibits a relatively low level of LinkedIn usage, with 320 respondents not registered on the platform (0.09). In contrast, Cluster 2, comprising individuals aged 26-30, demonstrates the highest LinkedIn usage among the clusters, with 55 respondents reporting frequent usage on the Likert scale (4.2). Cluster

3, consisting of individuals aged 31-40, displays a moderate level of LinkedIn usage, with 47 respondents reporting sporadic usage (1.13). Interestingly, Clusters 4 and 5, representing individuals aged 19-21, present divergent LinkedIn usage patterns, with Cluster 4 indicating minimal usage (0.08) with 425 respondents and Cluster 5 showing moderate usage (2.51) with 68 respondents. These findings underscore the influence of age on LinkedIn engagement, suggesting a need for targeted strategies tailored to different age demographics to effectively optimize outreach efforts and engagement on the platform.

The analysis of international clusters also defined distinct patterns in age distribution and LinkedIn usage among respondents (*figure 18*). Cluster 1, representing individuals aged 22-25, shows moderate LinkedIn usage, with 43 respondents. In contrast, Cluster 2, comprising individuals aged 19-21, exhibits minimal LinkedIn usage, with a significantly higher respondent count of 80. Cluster 3, also representing individuals aged 22-25, demonstrates the highest LinkedIn usage among the clusters, with 34 respondents. Cluster 4, consisting of individuals aged 31-40, displays high LinkedIn usage, with 18 respondents. Conversely, Cluster 5, also representing individuals aged 31-40, indicates lower LinkedIn usage, with 26 respondents.

Figure 18. Cluster Analysis 1.



Source: Created by the author

5.4.2. Faculty and Facebook Page Satisfaction

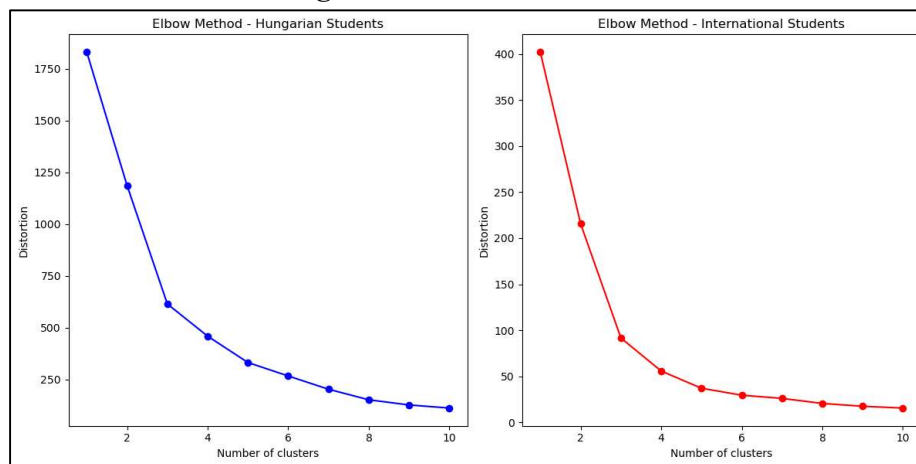
The examination sought to understand the satisfaction levels of students regarding the Official Facebook page of Széchenyi István University, employing a nuanced approach that considered the clustering of students based on their faculties. By dissecting satisfaction levels within clusters, each representing distinct groups of students from various faculties, the study aimed to uncover intricate patterns or discrepancies in satisfaction across different academic disciplines.

Survey question regards to Facebook page appearance satisfaction was measured in Likert Scale:

*“How satisfied are you with the official platforms of the University? **Facebook**, Instagram, TikTok, Twitter, LinkedIn (0-not registered, 1-not at all, 5-absolutely)”*

The elbow method has successfully identified 5 distinct clusters based on both faculty and University’s Official Facebook page appearance Satisfaction patterns, as visually depicted in the accompanying *figure 19*.

Figure 19. Elbow Method 2.

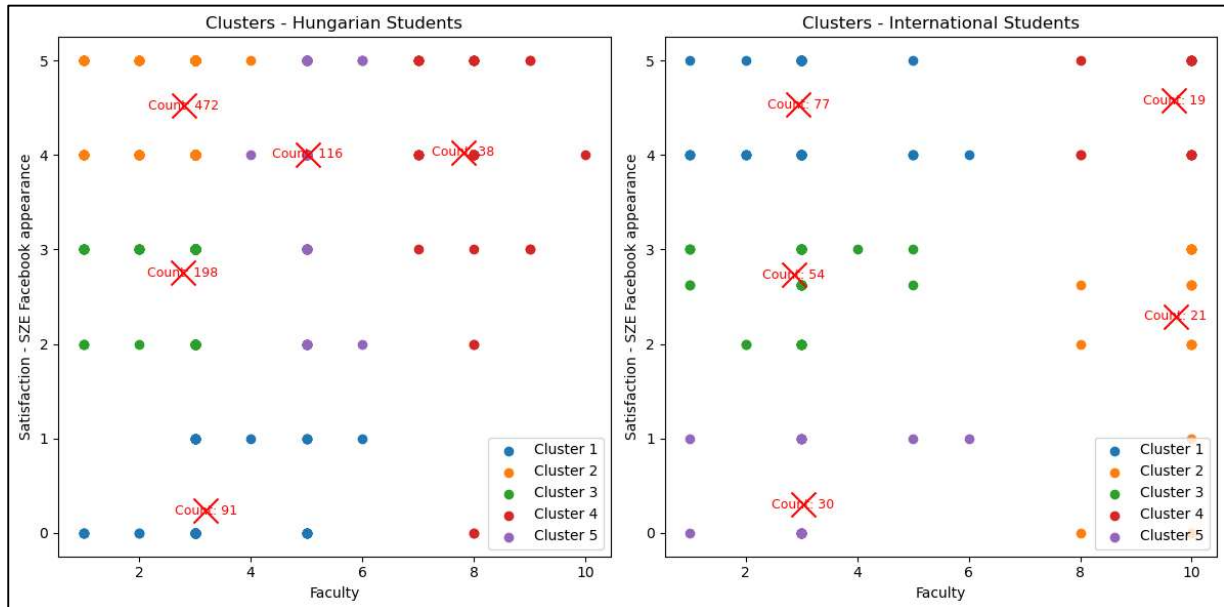


Source: Created by the author

The analysis of satisfaction levels among students regarding Széchenyi István University's Official Facebook page uncovers specific insights within each faculty cluster. In the Hungarian dataset, students from the Kautz Gyula Faculty of Business and Economics exhibit a range of satisfaction levels, with one cluster reporting low registration on Facebook (Cluster 1), while another demonstrates significantly high satisfaction (Cluster 2). The Apáczai Csere János Faculty of Humanities, Education, and Social Sciences (Cluster 4) and the Faculty of Mechanical Engineering, Informatics and Electrical Engineering (Cluster 5) display high satisfaction level.

In the International dataset, the Kautz Gyula Faculty of Business and Economics also shows high satisfaction levels, underscoring the importance of engagement strategies. Notably, the PhD program cluster presents mixed satisfaction levels, indicating the need for targeted approaches to address the unique needs of this academic group. These findings emphasize the significance of faculty-specific analyses in understanding and enhancing student satisfaction with university communication channels.

Figure 20. Cluster Analysis 2.



Hungarian Cluster	Faculty Code (x)	Faculty Code Rounded	Faculty	Satisfaction - SZE Facebook appearance (y)	Respondent count in cluster
1	3.2	3	Kautz Gyula Faculty of Business and Economics	0.23	91
2	2.81	3	Kautz Gyula Faculty of Business and Economics	4.53	472
3	2.78	3	Kautz Gyula Faculty of Business and Economics	2.75	198
4	7.82	8	Apáczai Csere János Faculty of Humanities, Education and Social Sciences	4.03	38
5	5.03	5	Faculty of Mechanical Engineering, Informatics and Electrical Engineering	4.01	116

International Cluster	Faculty Code (x)	Faculty Code Rounded	Faculty	Satisfaction - SZE Facebook appearance (y)	Respondent count in cluster
1	2.95	3	Kautz Gyula Faculty of Business and Economics	4.53	77
2	9.71	10	PhD program	2.29	21
3	2.87	3	Kautz Gyula Faculty of Business and Economics	2.73	54
4	9.68	10	PhD program	4.58	19
5	3.03	3	Kautz Gyula Faculty of Business and Economics	0.3	30

Source: Created by the author

5.4.3. Age and University Website Satisfaction [Transparency]

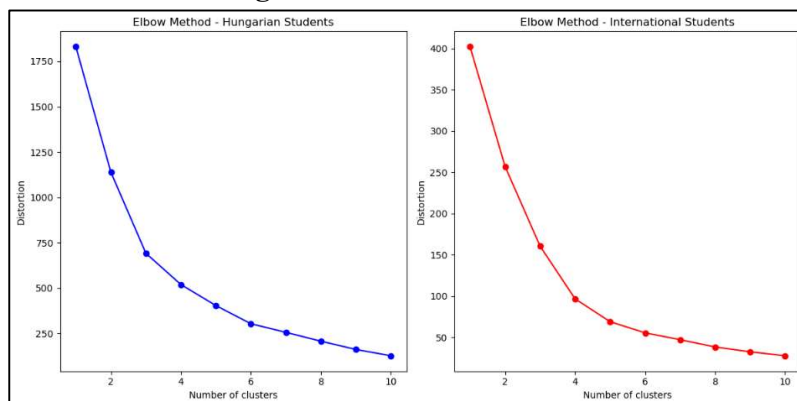
The official website transparency of Széchenyi István University received the lowest average satisfaction rating, scoring 3.54 out of 5. To explore this further, the author examined whether specific age clusters encountered difficulties with the transparency of the website, or if it remained problematic irrespective of the duration spent at the university.

Survey question regards to the official website transparency of Széchenyi István University was measured in Likert Scale:

*“How satisfied are you with the Széchenyi István University website according to the following aspects: Content; Appearance; **Transparency**; Actuality/up-to-dateness; User-friendliness (1-not at all, 5- completely)”*

The elbow method has also revealed 5 clusters determined by age and Széchenyi István University’s Official Website Satisfaction [Transparency], depicted in the accompanying figure:

Figure 21. Elbow Method 3.



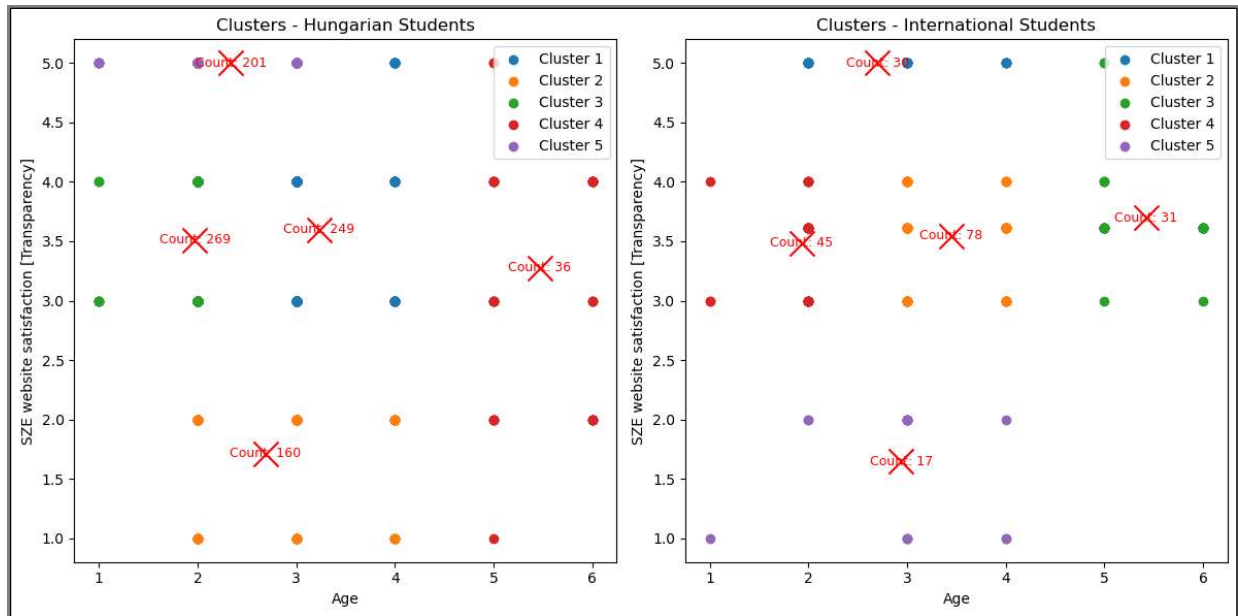
Source: Created by the author

Despite receiving the lowest average satisfaction rating, the transparency of the university's website demonstrates varying levels of satisfaction across different age clusters. In the Hungarian cluster, individuals aged 22-25 (Cluster 1 and 2) and 19-21 (Cluster 3) exhibit diverse levels of satisfaction, indicating potential disparities in their website expectations or experiences.

Similarly, in the international cluster, respondents aged 22-25 (Cluster 1, 2, and 5) and 19-21 (Cluster 4) also display varying satisfaction levels. These findings suggest that website transparency issues may not be uniformly experienced across age groups but rather influenced by individual expectations or preferences. To address these disparities, targeted interventions tailored

to the specific needs and preferences of different age clusters may be necessary to enhance website satisfaction effectively.

Figure 22. Cluster Analysis 3.



Hungarian Cluster	Age Code (x)	Age Code Rounded	Age	SZE website satisfaction [Transparency] (y)	Respondent count in cluster
1	3.23	3	22-25	3.6	249
2	2.69	3	22-25	1.71	160
3	1.97	2	19-21	3.51	269
4	5.47	5	31-40	3.28	36
5	2.34	2	19-21	5	201

International Cluster	Age Code (x)	Age Code Rounded	Age	SZE website satisfaction [Transparency] (y)	Respondent count in cluster
1	2.7	3	22-25	5	30
2	3.45	3	22-25	3.55	78
3	5.42	5	31-40	3.7	31
4	1.93	2	19-21	3.49	45
5	2.94	3	22-25	1.65	17

Source: Created by the author

5.4.4. Sharing Content on Facebook and Facebook Page Satisfaction

Analysing clusters based on student sharing content frequency on Facebook and Széchenyi István University's official Facebook page appearance satisfaction is crucial for understanding the dynamics of student engagement on social media platforms. By examining how students'

satisfaction levels with the university's Facebook page appearance correlate with their frequency of sharing content, valuable insights can be gained into the effectiveness of the university's social media communication strategy. These clusters can help identify distinct groups with varying levels of engagement and satisfaction, enabling the university to tailor its content and design to better resonate with specific audience segments. Understanding these clusters can inform targeted interventions aimed at enhancing engagement and satisfaction levels among students, ultimately contributing to a more meaningful and impactful online presence for the university.

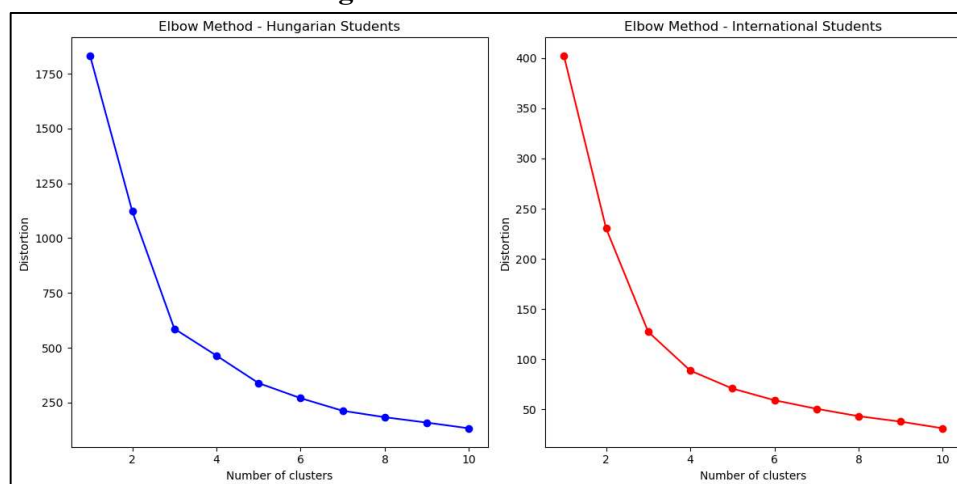
Survey questions regards to Facebook page appearance satisfaction and content sharing were measured in Likert Scale:

*“How satisfied are you with the official platforms of the University? **Facebook**, Instagram, TikTok, Twitter, LinkedIn (0-not registered, 1-not at all, 5-absolutely)”*

*How often do you share any content on following platforms? **Facebook**, Instagram, TikTok, Twitter, LinkedIn (0- not registered, 1- hardly ever, 5-on a daily basis)”*

The elbow method revealed 4 clusters to work with, as shown in *figure 23*:

Figure 23. Elbow Method 4.



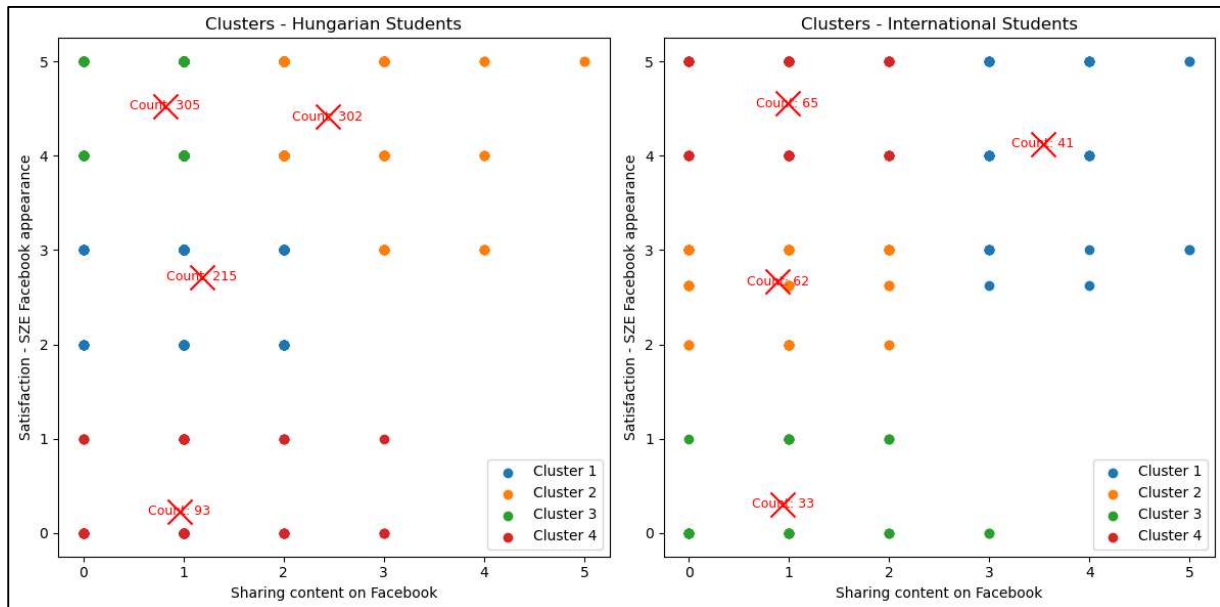
Source: Created by the author

Analysing the clusters based on satisfaction with Széchenyi István University's official Facebook page and the frequency of content sharing on the platform reveals distinct behavioural patterns and satisfaction levels among students (*figure 24*). In the Hungarian dataset, Cluster 1 portrays students with moderate satisfaction levels and limited engagement in content sharing, suggesting a segment

that may benefit from increased interaction with university content on social media. Cluster 2 represents students with higher satisfaction levels but moderate engagement, indicating a group that values the platform's content but not actively participate in sharing content. Conversely, Cluster 3 shows high satisfaction with minimal content sharing, while Cluster 4 displays low satisfaction and minimal content sharing.

In the International dataset, Cluster 1 demonstrates high satisfaction levels and frequent content sharing, signifying proactive and engaged students. Cluster 2 depicts disengaged students with moderate satisfaction and minimal content sharing frequency, while Clusters 3 represents students with low satisfaction and minimal engagement, and Cluster 4 represents high satisfaction with rare content sharing, respectively.

Figure 24. Cluster Analysis 4.



Hungarian Cluster	Sharing content on Facebook (x)	Satisfaction - SZE Facebook appearance (y)	Respondent count in cluster
1	1.19	2.72	215
2	2.44	4.42	302
3	0.82	4.53	305
4	0.96	0.23	93

International Cluster	Sharing content on Facebook (x)	Satisfaction - SZE Facebook appearance (y)	Respondent count in cluster
1	3.54	4.13	41
2	0.89	2.67	62
3	0.94	0.3	33
4	0.98	4.55	65

Source: Created by the author

5.4.5. TikTok and Instagram Account Satisfaction

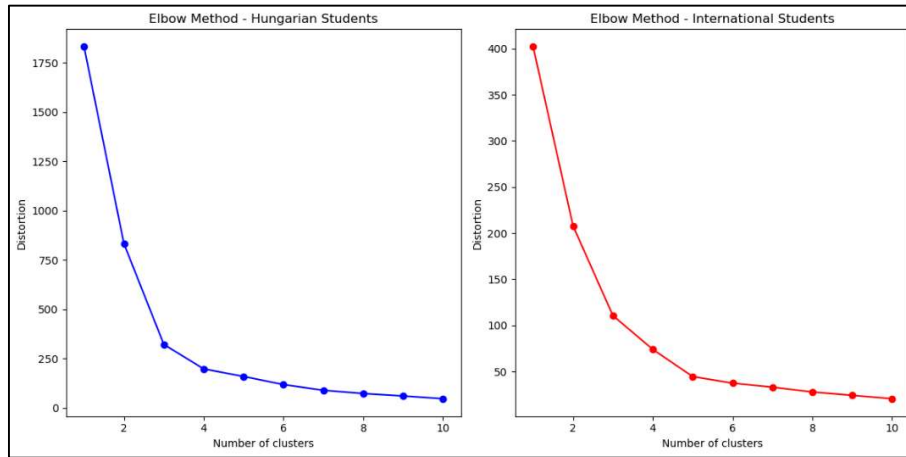
Examining clusters based on satisfaction with Széchenyi István University's Official TikTok and Instagram account appearance offers valuable insights into student perceptions and engagement on these popular social media platforms. Understanding the distinct clusters based on satisfaction levels can provide the university with targeted information regarding students' preferences, interests, and expectations regarding the university's presence on TikTok and Instagram. By analysing these clusters, the university can identify trends, patterns, and discrepancies in satisfaction levels among different student groups, allowing for customized communication strategies and content creation approaches.

Survey questions based on TikTok and Instagram page appearance satisfaction was measured in Likert Scale:

*“How satisfied are you with the official platforms of the University? Facebook, **Instagram**, **TikTok**, Twitter, LinkedIn (0-not registered, 1-not at all, 5-absolutely)”*

4 clusters have been defined with the help of the elbow method depicted on *figure 25*.

Figure 25. Elbow Method 5.

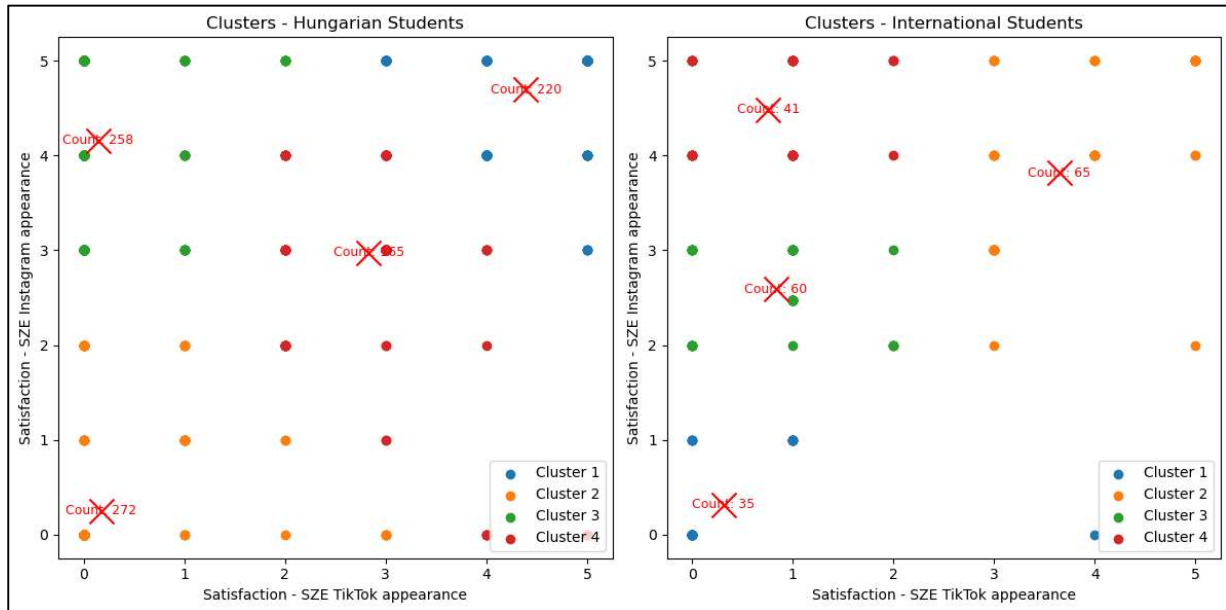


Source: Created by the author

In the Hungarian dataset, Cluster 1 emerges as a segment with high satisfaction levels with both TikTok and Instagram appearances, indicating a positive reception among students. Conversely, Cluster 2 displays significantly lower satisfaction levels with both platforms, indicating non-registrations. Cluster 3 stands out with high satisfaction levels on Instagram but considerably lower levels on TikTok, highlighting students having Instagram account but not TikTok account. Cluster 4 exhibits moderate satisfaction levels on both TikTok and Instagram, indicating similar interest among respondents in this cluster (*figure 26*).

In the International dataset, Cluster 1 represents a cohort with notably low satisfaction levels on both TikTok and Instagram, indicating non-registered students in the cluster. Conversely, Cluster 2 showcases high satisfaction levels with both platforms, suggesting effective engagement strategies and content alignment with international student preferences. Cluster 3 and Cluster 4 demonstrates relatively high satisfaction on Instagram but lower levels on TikTok close to 0, indicating that more students registered and use Instagram than TikTok.

Figure 26. Cluster Analysis 5.



Hungarian Cluster	Satisfaction - SZE TikTok appearance (x)	Satisfaction - SZE Instagram appearance (y)	Respondent count in cluster
1	4.39	4.7	220
2	0.18	0.25	272
3	0.14	4.16	258
4	2.83	2.98	165

International Cluster	Satisfaction - SZE TikTok appearance (x)	Satisfaction - SZE Instagram appearance (y)	Respondent count in cluster
1	0.31	0.31	35
2	3.65	3.82	65
3	0.83	2.59	60
4	0.76	4.49	41

Source: Created by the author

5.4.6. TikTok and LinkedIn Account Satisfaction

Examining clusters based on Széchenyi István University's official TikTok and LinkedIn account appearance satisfaction provides insights into student engagement and preferences across diverse digital platforms. These clusters provide a bit of understanding of how students interact with and perceive the university's presence on TikTok and LinkedIn, enabling sufficient marketing strategies to enhance their digital experience. Furthermore, the results of correlation and factor analysis revealed an intriguing trend: students who actively engage with TikTok are less inclined to use

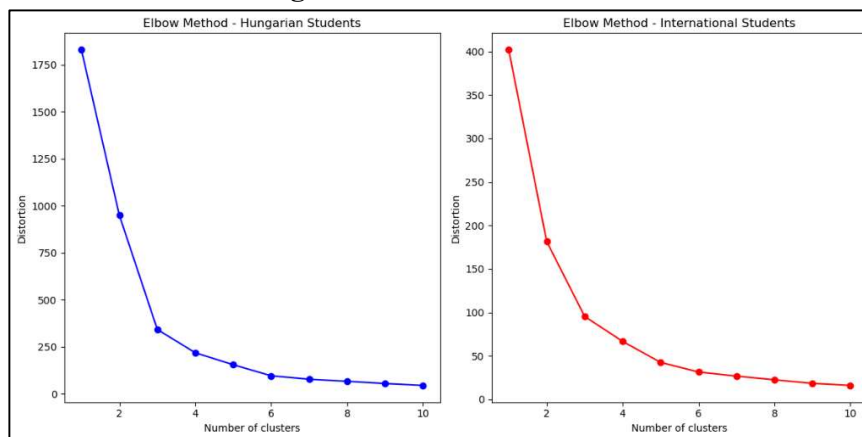
LinkedIn, and vice versa. This insight underscores the importance of segmenting student populations based on their platform preferences and behaviours.

Survey questions based on TikTok and Instagram page appearance satisfaction was measured in Likert Scale:

*“How satisfied are you with the official platforms of the University? Facebook, Instagram, **TikTok**, Twitter, **LinkedIn** (0-not registered, 1-not at all, 5-absolutely)”*

5 clusters have been defined with the help of the elbow method as it can be seen on *figure 27*.

Figure 27. Elbow Method 6.

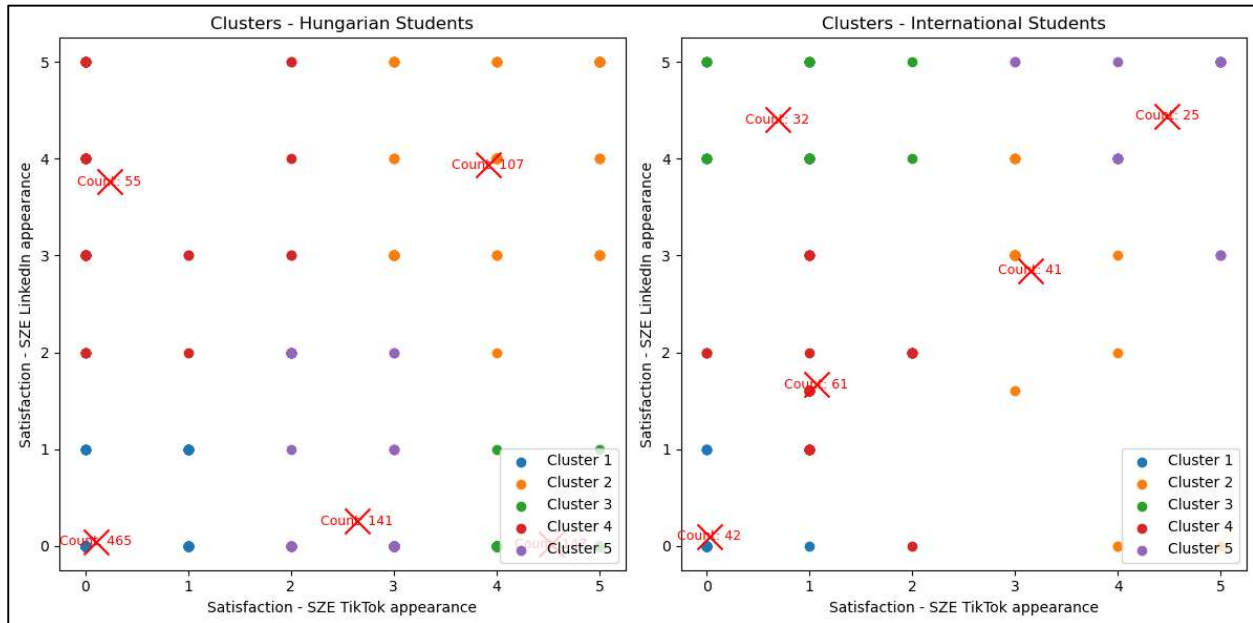


Source: Created by the author

In the Hungarian dataset, Cluster 1 stands out with low registration number on both TikTok and LinkedIn. Cluster 2 exhibits high satisfaction levels with both TikTok and LinkedIn, indicating a group that perceives the university positively across digital channels. Conversely, Cluster 3 displays high satisfaction with TikTok and low registration number on LinkedIn, highlighting a potential disparity in platform preferences among Hungarian students. Cluster 4 contains respondents who are satisfied with the university’s LinkedIn account but do not use TikTok. Cluster 5 demonstrate moderate satisfaction level on TikTok and non-registered students on LinkedIn, indicating varied perceptions and engagement behaviours within the clusters (*figure 28*).

In the International dataset, similar trends emerge, with Cluster 1 showing minimal registration on both platforms, Cluster 2 exhibiting moderate satisfaction levels, and Cluster 3 showcasing high satisfaction with LinkedIn but low satisfaction with TikTok. In cluster 4, international students dissatisfied with both LinkedIn and TikTok that might be because the lack of English content. Cluster 5 display high satisfaction levels on TikTok and LinkedIn

Figure 28. Cluster Analysis 6.



Hungarian Cluster	Satisfaction - SZE TikTok appearance (x)	Satisfaction - SZE LinkedIn appearance (y)	Respondent count in cluster
1	0.1	0.04	465
2	3.92	3.93	107
3	4.53	0.01	147
4	0.24	3.76	55
5	2.65	0.26	141

International Cluster	Satisfaction - SZE TikTok appearance (x)	Satisfaction - SZE LinkedIn appearance (y)	Respondent count in cluster
1	0.02	0.1	42
2	3.15	2.84	41
3	0.69	4.41	32
4	1.07	1.67	61
5	4.48	4.44	25

Source: Created by the author

5.5. Text Mining

Two open-ended questions were included in both surveys to allow respondents the opportunity to provide additional insights regarding the university's and the respondents' program presence on various social media platforms. It is important to note that respondents were not obligated to respond to these questions. Following data collection, responses were analyzed manually and also by using the Python programming language.

5.2.1. Manual Examination

This section entails the analysis of responses to two open-ended questions, focusing on students' perceptions regarding the presence of the university and their programs on various social media platforms (SMPs), as well as any emerging issues. The questions in consideration are as follows:

1. *Please share your opinion about the University's presence on different social media platforms (Do you find it useful, why/why not?)*

391 Hungarian students responded to the question out of the total of 915, while 104 international students provided answers out of the total of 201. The majority of both Hungarian and international respondents also perceive the university's social media platforms (SMPs) as valuable due to their effectiveness in reaching Generation Z through online channels, which facilitates the dissemination of current information. However, three main issues were identified by the students:

1. Lack of Website Transparency:

Students encounter difficulty in navigating to desired information on the website. The inconsistency across faculty webpages compounds this issue, leading to students missing essential information.

2. Timeliness of Social Media Platforms:

Students have pointed out that information shared on SMPs is often outdated, causing them to miss opportunities such as sports programs and social support initiatives.

3. Language Barrier:

Certain international students have raised concerns regarding the predominance of Hungarian language in posts on the university's official social media platforms. As a result, they miss out on important events or information. This problem was highlighted the authors' previous research during platform analysis.

2. *Please share you opinion about your program being present on the different social media platforms. (Do you find it useful? Why/why not?)*

Out of the total of 915 respondents, 267 Hungarian students answered the question, and out of 201 respondents, 74 international students provided responses. The majority of students find the interaction useful on SMP's regarding to the student program. Most of the student highlighted the value of the Facebook groups for each programme where students can interact with each other and

the Student Union share the latest course related information. These course groups are great ways to form communities and help with course related things. However, all the above-mentioned issues emerged in both of the survey responds especially the lack of transparency within websites and Facebook groups and the language barrier. There was another issue regarding the answers:

1.Lack of knowledge of program being present on social media platforms:

Certain Hungarian and international students have expressed a lack of awareness regarding the presence of their programs on various social media platforms, such as Facebook groups. There is a recognized need for more effective communication to ensure students are informed about relevant SMPs. Implementing strategies such as sending multiple email reminders to students, specifically highlighting the SMPs that align with their interests, could enhance awareness and engagement with these platforms.

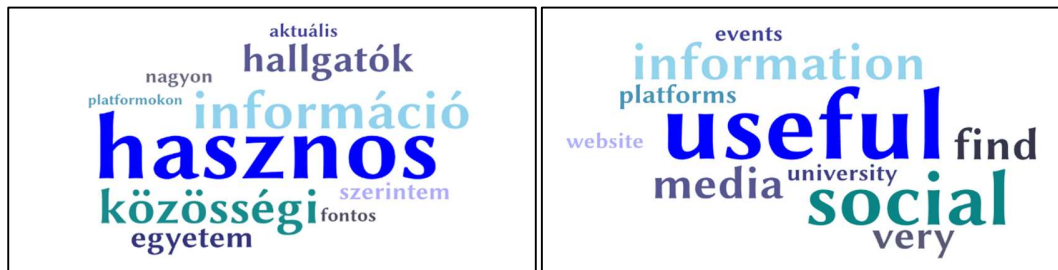
5.2.2. Examination with Python

The answers have been analyzed also by the Python programming language. The analysis of responses to the open-ended questions regarding the usefulness of Széchenyi István University's SM presence yielded valuable insights and assumptions. The top 10 relevant keywords from the Hungarian survey indicate a strong emphasis on the utility of the university's SM presence, with "hasznos" (useful) being the most frequently occurring term. This suggests that a significant portion of respondents find the university's SMP's beneficial in providing information. Furthermore, keywords such as "információ" (information), "közösségi" (social), and "hallgatók" (students) underscore the importance of these platforms in facilitating communication and engagement within the university community. The recurrence of terms like "szerintem" (I think) and "fontos" (important) suggests that respondents perceive the university's SM presence as personally relevant and significant. Additionally, the inclusion of terms like "aktuális" (actuality) and "platformokon" (on platforms) highlights the expectation for up-to-date and accessible information on these platforms.

The English survey keywords also emphasize the utility of the university's social media presence, with terms such as "useful," "information," and "social" recurring frequently. The prominence of keywords like "find," "events," and "website" suggests a desire among respondents for easily accessible and relevant information regarding university events and online resources.

Overall, these findings suggest a positive perception of Széchenyi István University's social media presence among respondents, with an emphasis on its utility, relevance, and accessibility in facilitating communication and engagement within the university community. The 10 most used relevant keywords have been showcased on 2 tag clouds with the help of WordArt.

Figure 29. Top 10 Hungarian and English Keywords from Surveys



Top 10 Relevant Keywords from Hungarian Survey	Occurrence	English Translation
hasznos	341	useful
információ	114	information
közösségi	93	social
hallgatók	59	students
egyetem	58	university
szerintem	44	I think
nagyon	29	very
fontos	27	important
aktuális	26	actuality
platformokon	22	on platforms

Top 10 Relevant Keywords from English Survey	Occurrence
useful	49
social	29
information	29
media	27
find	26
very	22
university	14
platforms	14
events	13
website	12

Source: Created by the author

6. Conclusion

This section presents the summarized conclusions drawn from the analysis of online platforms. The findings from online platforms have been compared with used literature, and Research Questions 2 and 3 have been addressed. Furthermore, recommendations specific to each examined online platform have been provided based on the findings.

6.1. Website

The literature underscores the significance of university websites in attracting prospective students and meeting the needs of current students. However, the complexity of these websites poses challenges for developers in creating effective pages where information is easily accessible (*Manzoor et al., 2019; Fong et al., 2020*). This research reveals that students encounter difficulties navigating university websites, particularly due to issues with transparency and outdatedness, such as inconsistencies across faculties and deadlines from previous semesters. Moreover, design elements present challenges, as the language button is inaccessible in the mobile view, making it harder for international students to access essential information.

For answering RQ2, descriptive statistics and factor analysis were applied for the merged survey data that contains 1116 responds. In terms of satisfaction, respondents were asked to rate their levels of satisfaction on a scale of 1 to 5 (1-"not satisfied" and 5-"totally satisfied") regarding various aspects of the university's website, including its content, appearance, up-to-datedness, user-friendliness, and transparency. The findings revealed that content garnered the highest satisfaction score of 4.15, indicating a strong level of satisfaction among respondents in this regard. However, transparency received the lowest score of 3.54, suggesting a need for improvement in providing clear and easily accessible information across the website. Factor analysis has also underscored the importance of various website components to users, as evidenced by their grouping into Factor 1. This confluence of factors, including the above-mentioned aspects, highlights their collective importance in shaping users' perceptions and experiences. It suggests that a holistic approach to website design and management that comprehensively addresses these key aspects is essential to improving user satisfaction and engagement.

For RQ3, the study needed to examine the Hungarian and international survey separately and apply cluster analysis and text mining for both of the dataset. In the cluster analysis, the author examined how age links with satisfaction regarding the transparency of the university's website. Despite

transparency receiving the lowest average satisfaction rating, the analysis revealed differing levels of satisfaction across various age clusters. In the Hungarian cluster, individuals aged 22-25 and 19-21 showed diverse levels of satisfaction, suggesting potential differences in their website expectations or experiences. Similarly, in the international cluster, respondents aged 22-25 (and 19-21 displayed varying satisfaction levels. These findings indicate that transparency issues on the website may not be uniformly experienced across age groups but could be influenced by individual expectations or preferences. Addressing these disparities may require targeted interventions tailored to the specific needs and preferences of distinct age clusters to effectively enhance website satisfaction. In summary, understanding the nuanced relationship between age and satisfaction with website transparency highlights the importance of customized interventions in optimizing user experiences across diverse demographic segments.

To enhance the usability and effectiveness of university websites, several recommendations emerge from the findings of this research. Firstly, addressing issues with transparency and up-to-datedness is crucial, particularly inconsistencies across faculties and outdated information. Implementing standardized formats for every faculty and ensuring regular updates can mitigate these issues. Secondly, improving navigation through clear menus, search functions, and streamlined content can enhance user experience. Additionally, implementing a chatbot feature can provide users with an easy and intuitive way to navigate the website, find information, and get assistance in real-time. Thirdly, optimizing mobile accessibility, including making language options accessible in the mobile view, is essential for accommodating users accessing the website on mobile devices, particularly international students. Moreover, implementing user-friendly design elements, providing multilingual support, and establishing a regular feedback mechanism can further enhance website usability and effectiveness. By implementing these recommendations, Széchenyi István University can create a more user-centric website experience that meets the diverse needs of students, faculty, and other stakeholders.

6.2. Facebook

Facebook emerges as the most popular social media platform in Hungary and globally, underlining its significance for universities in attracting students (*Statista, 2022; Wang, 2019; Soares et al., 2020*). Respondents from Széchenyi István University indicated high usage of Facebook, with almost all participants reporting usage (average of 3.97 out of 5). Additionally, Instagram slightly

surpasses Facebook in usage among Generation Z respondents. Hence, it is imperative for the university to establish a robust presence on Facebook, providing valuable information and conveying a compelling image to effectively engage with current and prospective students.

Regarding RQ2, the descriptive statistics shows that Széchenyi István University students are the most satisfied with the official Facebook page with the average of 4.02 out of the 5 in comparison with the other examined SMPS's. Most of the students are also following their own course Facebook pages and groups with 3.09 frequency out of the 5. That highlight the importance of the student community on Facebook and one of the most effective ways to convey information to students.

Regarding RQ3, the T-test results indicate significant differences in the average data between Hungarian and international students concerning owning a Facebook profile, usage frequency of Facebook, following the university, and following their own courses on Facebook. This suggests that international students may not find the official Facebook page as appealing as Hungarian students, or they may prefer using other platforms over Facebook for university-related engagement. Analysing clusters based on satisfaction with Széchenyi István University's official Facebook page and content sharing frequency reveals distinct behavioural patterns and satisfaction levels among students. In the Hungarian dataset, clusters range from moderate satisfaction with limited engagement to high satisfaction with minimal content sharing. Conversely, the international dataset shows clusters ranging from proactive engagement with high satisfaction to disengagement with low satisfaction. These findings highlight the importance of tailored communication strategies to address diverse engagement behaviours and satisfaction levels across different clusters, ultimately enhancing the university's social media presence and fostering meaningful interactions with its student community. Additionally, faculty-specific analyses underscore the importance of understanding and improving student satisfaction with university communication channels within specific academic contexts. Text mining analysis has unveiled that both Hungarian and international students perceive social media platforms as useful. However, Hungarian students expressed concerns regarding the transient nature of important information on Facebook, while international students emphasized the scarcity of English-translated posts and events, potentially leading to missed opportunities. This scarcity of English posts was also highlighted in the authors' previous research in the platform analysis section.

To address the issues identified through text mining analysis regarding the usefulness of SMPS' among Hungarian and international students, several recommendations can be proposed. Firstly, to mitigate concerns about important information on Facebook being easily overlooked by Hungarian students, implementing a "feed pin" feature could be beneficial. This feature allows universities to highlight crucial posts by pinning them to the top of their Facebook feed, ensuring they remain visible to users for an extended period. Additionally, to alleviate the scarcity of English-translated content highlighted by international students, universities should prioritize translating important posts and events into English to ensure inclusivity and accessibility for all students. Moreover, regular communication with international students via email or other channels could be employed to alert them to important updates and events. By implementing these recommendations, the university can enhance the effectiveness of their social media presence and better meet the diverse needs of their student community.

6.3. Instagram

The literature has indicated that social interaction is one of the main motivations for using Instagram. (*Geurin-Eagleman and Burch 2016.; Pittman and Reich., 2016*). Considering this finding is essential when universities need to convey information via Instagram. Trends and aesthetic post images help effectiveness. *Rosa-Castillo et al. (2022)* experimented a gamification feature on Instagram that enhanced students' understanding on the specific topics. The survey respondents have been using Instagram the most frequently (3.97 out of 5) that indicates the importance of engage students via this platform with visualisation and gamification.

Concerning RQ2, descriptive statistics indicate that students of Széchenyi István University express the highest satisfaction levels with the official Instagram page, following Facebook, with an average rating of 3.99 out of 5. Additionally, some students are actively following their own courses on Instagram with a frequency rating of 2.6 out of 5. These findings underscore the significance of the student presence on Instagram and suggest it as one of the most effective channels for conveying information to students. Factor analysis offers valuable insights into social media usage patterns, particularly on platforms like Instagram and TikTok since the variables link to these SMPS' were grouped into a factor. Key variables such as the frequency of using Instagram and TikTok, along with satisfaction regarding their appearance, show substantial loadings on this factor. This underscores a strong correlation between active involvement on these platforms and

individuals' perception of their visual appeal. These findings imply that users who engage frequently with Instagram and TikTok tend to prioritize aesthetics and visual content when evaluating these platforms.

Regarding RQ3, the T-test reveals similar registration numbers for Hungarian and International students on Instagram, yet disparities exist in usage frequency and following courses on the platform between the two groups. In the cluster analysis the satisfactions of the university's Instagram and TikTok accounts' appearance were clustered due to the similar interests of these platforms' target audiences. The Hungarian dataset unveils Cluster 1 as highly satisfied with both TikTok and Instagram appearances, while Cluster 2 shows significantly lower satisfaction levels, indicating non-registrations. Cluster 3 exhibits high Instagram satisfaction but lower TikTok satisfaction, suggesting users with Instagram but not TikTok accounts, whereas Cluster 4 displays moderate satisfaction levels on both platforms, indicating similar interest among respondents. In the International dataset, Cluster 1 comprises non-registered students with notably low satisfaction levels on both platforms, contrasting Cluster 2's high satisfaction levels, indicative of effective engagement strategies. Clusters 3 and 4 demonstrate high Instagram satisfaction but low TikTok satisfaction, suggesting greater Instagram usage. These insights emphasize the importance of tailored content and engagement strategies to meet the diverse preferences of students across clusters, ultimately enhancing the university's digital presence and engagement on TikTok and Instagram platforms.

To specifically increase engagement on Instagram, the Széchenyi István University can implement targeted strategies based on the preferences of both Hungarian and international students. First, running giveaway campaigns on Instagram can be highly effective in increasing interaction and fostering a sense of community among students. By offering prizes such as university merchandises and incorporating gamification elements, such as interactive quizzes or challenges, universities can encourage active participation and increase user engagement on the platform. Additionally, leveraging Instagram features such as Stories, Reels, and Live Sessions can provide opportunities for real-time interaction and content sharing, further increasing student engagement and building a stronger digital community. By consistently delivering valuable and visually appealing content that resonates with students, universities can effectively leverage Instagram as a powerful tool for communication, engagement, and community building.

6.4. Twitter

Twitter, a micro-blogging social networking site (SNS), facilitates communication with limited characters and is valued for direct peer-to-peer interaction. Studies by *Chen and Chen (2012)* and *Gao, Luo, and Zhang (2012)* highlight its role in promoting active learning and enhancing educational motivation. *Prestridge (2013)* explored Twitter's use in supporting first-year students, noting interactions such as connectivity, academic discussions, and resource sharing. Although professors engaged with students through traditional responses, student-to-student interaction was limited. Despite challenges like multitasking and adapting to academic norms, students fostered an academic culture by summarizing lectures and sharing relevant content. However, they grappled with the 140-character limit, later expanded to 280 characters in 2023.

Regarding RQ 2, findings indicate that out of 1116 respondents, 648 are not registered on Twitter. Among those registered, usage is minimal. The satisfaction score regards to the university's Twitter account amongst students having Twitter profile is only 2.99 out of the 5. This is the lowest satisfaction score regarding the other scores of the university's SMP satisfactions. That might indicate that the university's Twitter account is neglected due to the few numbers of followers (132). Factor analysis defined a factor that contains Twitter engagement variables such as the frequency of Twitter usage, content sharing on Twitter and satisfaction with the university's appearance show significant loadings on this factor.

Regarding RQ3, T-test analysis reveals that the number of students owning a profile on Twitter and following programs on Twitter is similar between the Hungarian and international student datasets. This indicates a lack of popularity of the platform among the respondents. However, satisfaction with the university's Twitter account varied between the two datasets. International students reported higher satisfaction with the profile compared to Hungarian students. This suggests that international students may perceive the university's Twitter account more positively than their Hungarian counterparts.

Several strategies can be considered to improve the university's Twitter profile and address the satisfaction gap between Hungarian and international students. First, implementing an integrated marketing strategy to promote the Twitter profile could help increase its visibility and attract more followers. By utilizing other communication channels such as email newsletters, university websites, and other social media platforms, the Twitter profile can be effectively promoted to a

wider audience. In addition, actively engaging with followers by providing regular updates, responding to questions, and sharing relevant content can help increase satisfaction and build a stronger sense of community. Furthermore, conducting surveys or feedback sessions to gather insights from both Hungarian and international students can provide valuable feedback to refine the content and strategy of the Twitter profile to better meet their needs and expectations. Ultimately, by prioritizing engagement, promotion, and responsiveness, the university can improve its Twitter profile and better connect with its diverse student body.

6.5. LinkedIn

According to various studies, LinkedIn has emerged as the preferred and most effective website for both employers and job seekers. Research conducted by *S. del Cerro (2017)* found that LinkedIn (94%) was the top choice among social networking sites for recruiting candidates for vacant job roles, followed by Facebook and Twitter. This study can confirm that student respondents are using LinkedIn mainly for career options; although, only 367 survey respondents out of the 1116 are registered on the platform.

In relation to the RQ2, descriptive statistics indicate that LinkedIn is the least used social media platform (SMP) among the respondents, with an average usage rating of 0.8 (where 0 denotes not being registered). However, the average satisfaction level with the university's LinkedIn account is 3.9, which can be deemed as a positive score. Furthermore, factor analysis unveiled a factor encompassing professional variables such as age, course level, frequency of LinkedIn usage, frequency of content sharing on LinkedIn, and satisfaction with the university's LinkedIn account. This suggests the presence of a student community that recognizes the value of LinkedIn for professional networking and engagement with the university's offerings.

Regarding Research Question 3, the T-test analysis suggests notable differences in variables related to LinkedIn among Hungarian and international students. This includes owning a LinkedIn profile, satisfaction with the university's LinkedIn account, and the frequency of content sharing on LinkedIn. Delving into the cluster analysis for Hungarian students reveals distinct trends in age distribution and LinkedIn usage across various age groups. Cluster 1, representing individuals aged 22-25, demonstrates relatively low LinkedIn usage, with a considerable number of respondents not registered on the platform. In contrast, Cluster 2, comprising individuals aged 26-30, shows the highest LinkedIn usage among the clusters. Cluster 3, consisting of individuals aged 31-40,

displays a moderate level of LinkedIn usage. Interestingly, Clusters 4 and 5, representing individuals aged 19-21, exhibit divergent LinkedIn usage patterns, with one indicating minimal usage and the other showing moderate usage. These findings underscore the impact of age on LinkedIn engagement, highlighting the necessity for tailored strategies to effectively optimize outreach and engagement on the platform across different age demographics. Similarly, the analysis of international clusters unveils distinct patterns in age distribution and LinkedIn usage. Moderate usage is observed among certain age groups, while others exhibit minimal or high usage, indicating the need for nuanced approaches to cater to the varied preferences and behaviours of international students on LinkedIn.

Based on the researches, several recommendations can be proposed to increase LinkedIn engagement among both Hungarian and international students. First, targeted outreach campaigns should be developed to encourage registration and active participation on LinkedIn, especially among age groups with lower usage rates. This could include highlighting the professional benefits of LinkedIn, such as networking opportunities and access to career resources. In addition, customized content strategies should be implemented to address the different preferences and behaviours observed across age demographics. For example, targeted messaging and content themes could be developed to resonate with younger students, while more career-focused content could be created for older age groups. In addition, regular monitoring and analysis of LinkedIn engagement metrics should be conducted to track progress and refine strategies over time. By implementing these recommendations, universities can effectively leverage LinkedIn as a valuable platform for professional networking and engagement, ultimately improving the overall student experience and career prospects.

6.6. TikTok

Several studies have underscored the growing benefits of TikTok, which allows users to produce videos ranging from a few seconds to 10 minutes since February 2022. The platform offers a wide array of content, encompassing practical tips, inspirational messages, dance challenges, Q&A sessions, and entertaining or unconventional videos (*Alley and Hanshew 2022*). Despite this, there is a lack of literature investigating TikTok within higher education institutions. This study seeks to address this research gap.

In relation to RQ2, the findings reveal that respondents express moderate satisfaction with the university's TikTok account, with an average satisfaction score of 3.78 out of 5. This indicates a generally positive perception of the content and engagement offered by the university on the TikTok platform. Additionally, the average usage rate among students stands at 2.52, underscoring the significance of TikTok as a channel for information dissemination and engagement. These findings suggest that the university's presence on TikTok is valued by students and serves as an effective medium for sharing relevant updates and fostering interaction within the student community.

In relation to RQ3, the T-test reveals that while the average satisfaction with the university's TikTok appearance is comparable between Hungarian and international students, there are notable differences in other aspects. Specifically, the averages for TikTok usage, registration on TikTok, and content sharing on TikTok exhibit distinct patterns between Hungarian and international students. Additionally, a cluster analysis was conducted to examine student satisfaction with the university's official Instagram and LinkedIn profiles. Interestingly, the analysis revealed a negative correlation between users of these platforms. Cluster analysis in both the Hungarian and international datasets reveals nuanced patterns of platform registration and satisfaction among students. Within the Hungarian dataset, Cluster 1 emerges with low registration numbers on TikTok and LinkedIn, suggesting minimal engagement with digital channels. Conversely, Cluster 2 shows high satisfaction levels with both TikTok and LinkedIn, indicating a positive perception of the university's digital presence. Cluster 3, on the other hand, shows high satisfaction with TikTok but low registration on LinkedIn, indicating potential differences in platform preferences among Hungarian students. Cluster 4 includes respondents who are satisfied with the university's LinkedIn account but do not actively use TikTok, while Cluster 5 shows moderate satisfaction with TikTok among students who are not registered on LinkedIn, reflecting different perceptions and engagement behaviours. Similar trends are observed in the international dataset, with different clusters showing different levels of registration and satisfaction across platforms. Notably, dissatisfaction with platforms such as TikTok among international students can be attributed to a lack of English content. These findings underscore the importance of customizing strategies to optimize engagement on both TikTok and LinkedIn platforms, taking into account the different preferences of students in different clusters.

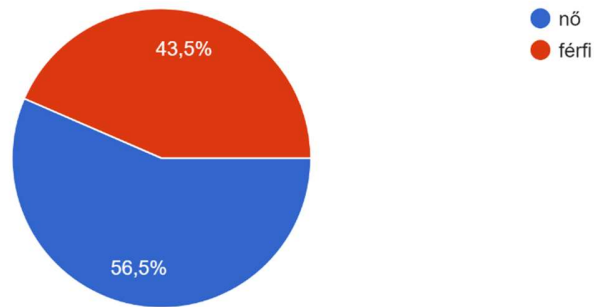
Based on the findings, several recommendations can be made to improve the university's TikTok account. First, since satisfaction with the appearance of the TikTok account is relatively consistent among both Hungarian and international students, the university should focus on maintaining the visual appeal of its content. Second, given the differences in TikTok usage, profile owners, and content sharing patterns between Hungarian and international students, the university should target its TikTok content to better connect with each group. This could include creating content in multiple languages to engage international students, while also addressing the preferences and interests of Hungarian students. In addition, the university should actively engage with its audience on TikTok by responding to comments, participating in trends, and encouraging user-generated content to encourage a community feel and interaction. Finally, given the negative correlation between Instagram and LinkedIn users, the university should explore opportunities to integrate content with these platforms to maximize reach and engagement across channels. By implementing these recommendations, the university can effectively utilize TikTok as a valuable tool for student engagement and communication.

7.Appendix

7.1. Hungarian Survey

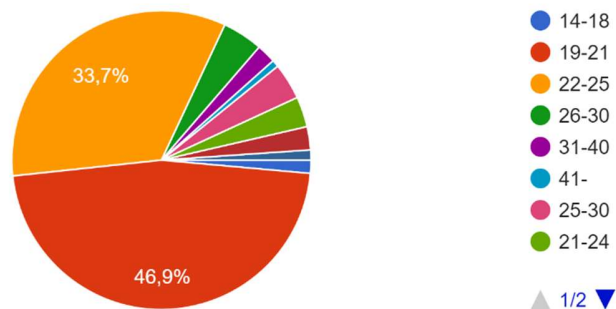
Az Ön neme

915 válasz



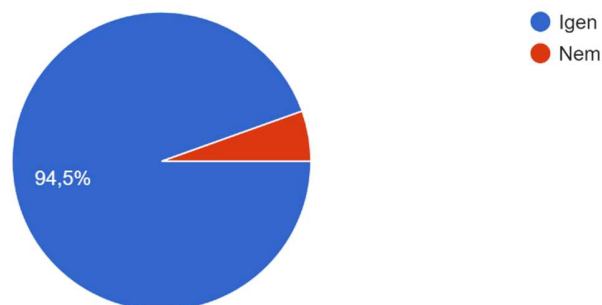
Az Ön életkora

915 válasz



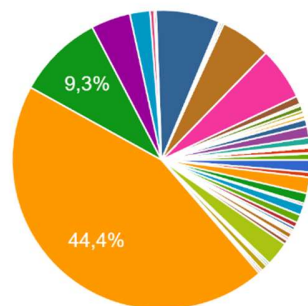
Rendelkezik jelenleg aktív hallgatói jogviszonnyal a Széchenyi István Egyetemen?

915 válasz



Kérem válassza ki a listából melyik szakot végzi jelenleg, vagy melyik szakot végezte el korábban! (a választás során kérem figyeljen az sz...intjének jelölésére- FOSZK, Ba, Bsc, Ma, Msc, PhD)

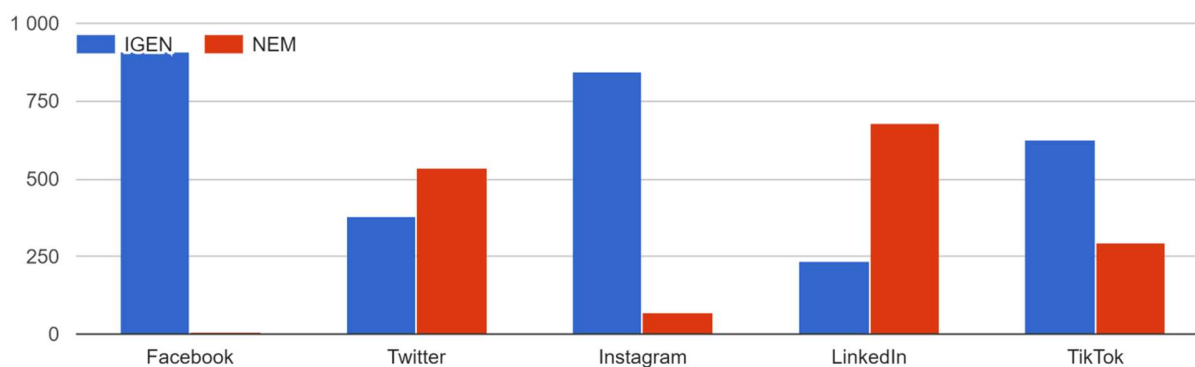
915 válasz



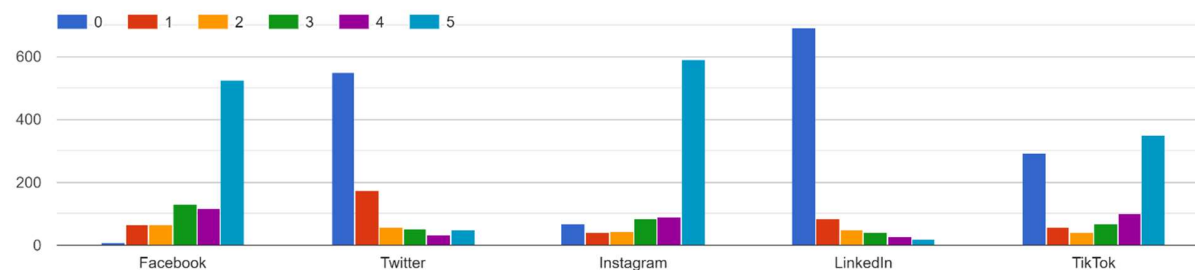
- Járműmérnöki Bsc
- Környezetmérnöki Bsc
- Logisztikai mérnök Bsc
- Műszaki menedzser Bsc
- Járműmérnöki Msc
- Logisztikai mérnök Msc
- Műszaki menedzser Msc
- Gyógypedagógiai BA

▲ 1/13 ▼

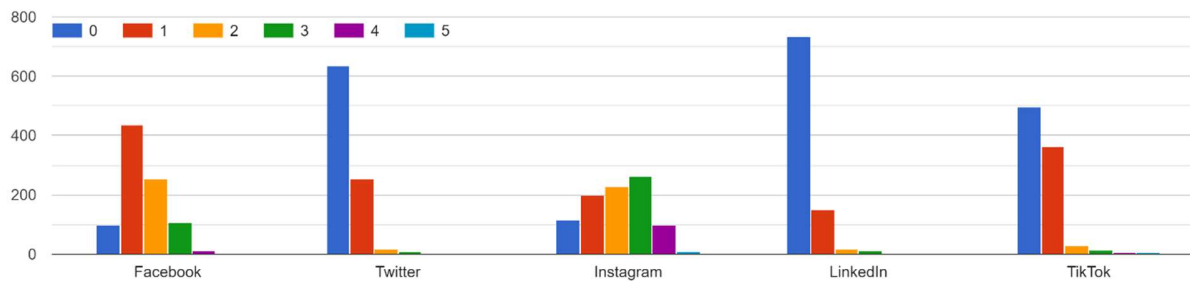
Ön rendelkezik saját profillal az alábbi platformokon?



Milyen gyakran használja az alábbi platformokat? (0-nem regisztrált, 1-nagyon ritkán, 5-napi szinten)

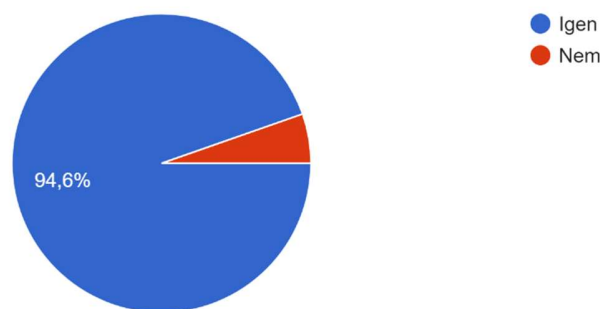


Ön milyen gyakorisággal tesz közzé tartalmat az alábbi platformokra? (0- nem regisztrált, 1-szinte soha; 5- napi szinten)

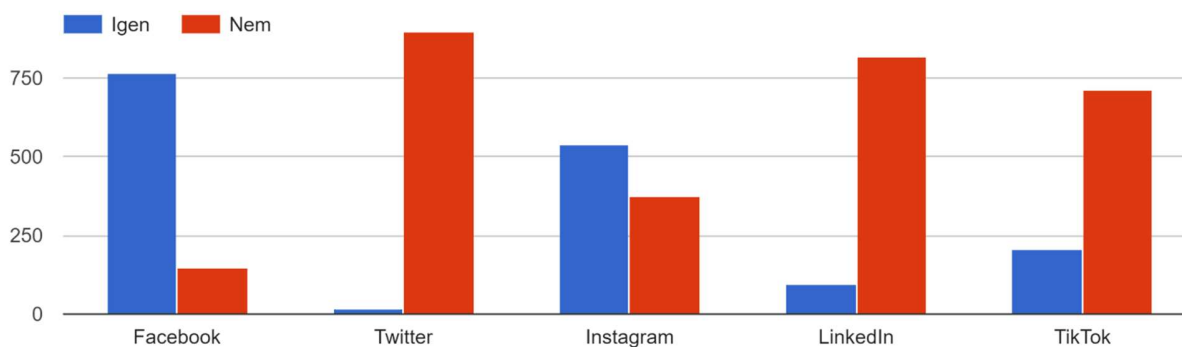


Van tudomása arról, hogy a Széchenyi István Egyetem rendelkezik saját hivatalos közösségi média felületekkel? (Hivatalos= egyetemi kollégák vagy szervezet által moderált közösségi oldal)

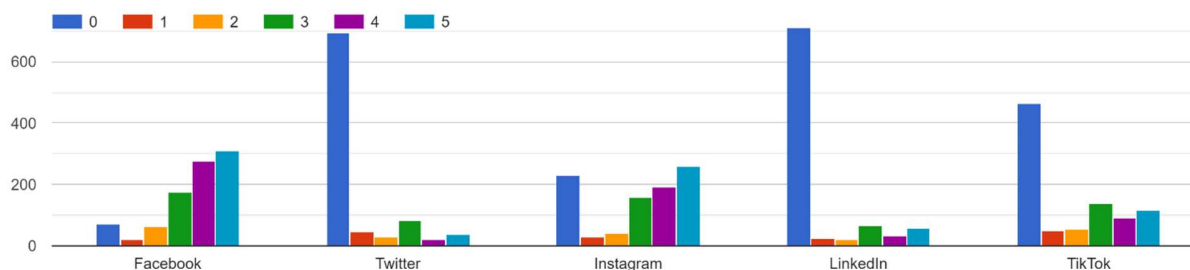
915 válasz



Követi a Széchenyi István Egyetemet az alábbi közösségi média felületeken?

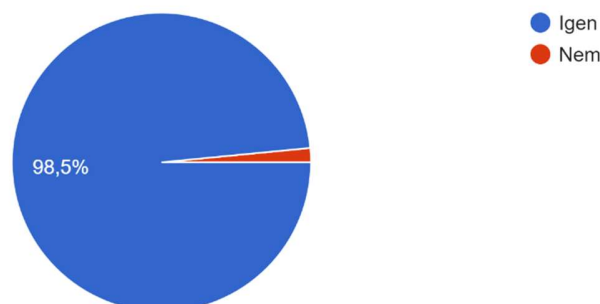


Ön mennyire elégedett az egyetem megjelenésével az alábbi felületeken? (0- nem regisztrált, 1-egyáltalán nem, 5- teljes mértékben)

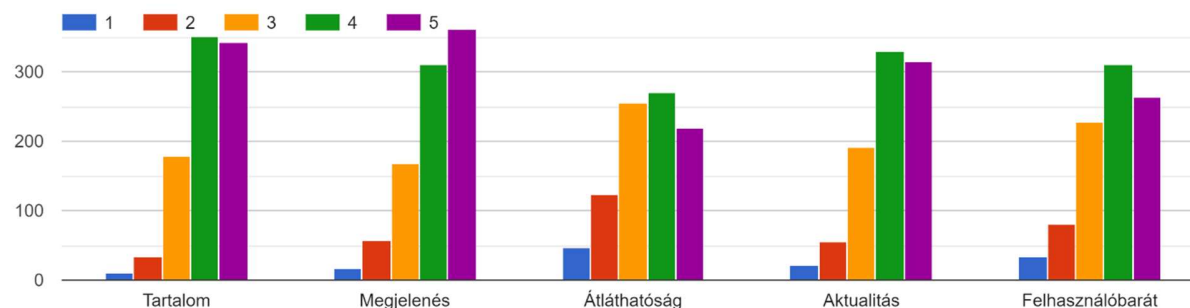


Van tudomása arról, hogy az egyetem rendelkezik saját hivatalos honlappal? (Hivatalos= egyetemi kollégák vagy szervezet által moderált felület)

915 válasz

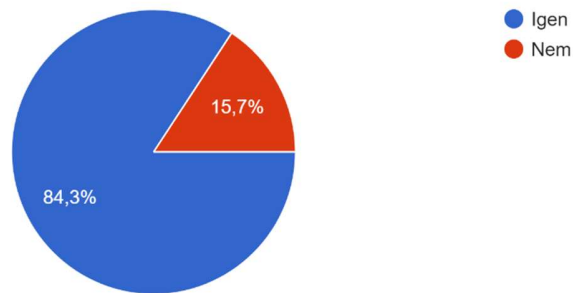


Mennyire elégedett a Széchenyi István Egyetem honlapjával az alábbi szempontok szerint: (1-egyáltalán nem, 5- teljes mértékben)



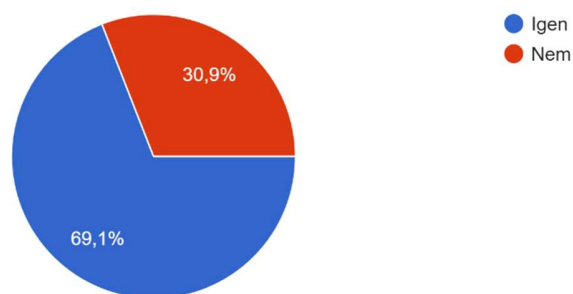
Van arról tudomása, hogy a Széchenyi István Egyetem karjai rendelkeznek saját hivatalos honlappal? (Hivatalos= egyetemi kollégák vagy szervezet által moderált felület)

915 válasz



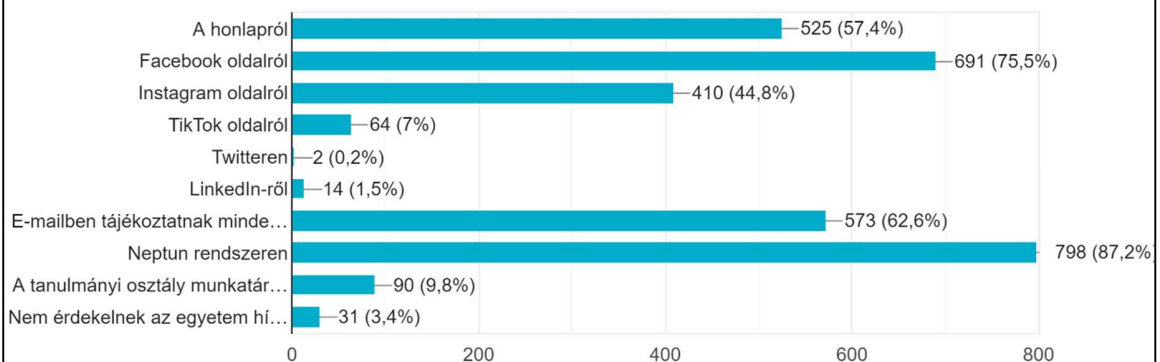
Van arról tudomása, hogy a Széchenyi István Egyetem szakjai rendelkeznek saját hivatalos honlappal? (Hivatalos= egyetemi kollégák vagy szervezet által moderált felület)

915 válasz



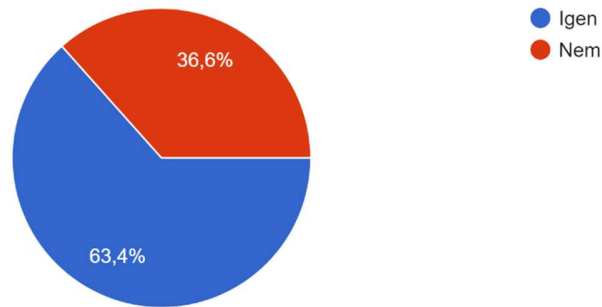
Ön honnan tájékozódik az egyetem híreiről, aktuális eseményeiről? (Több válasz is lehetséges)

915 válasz



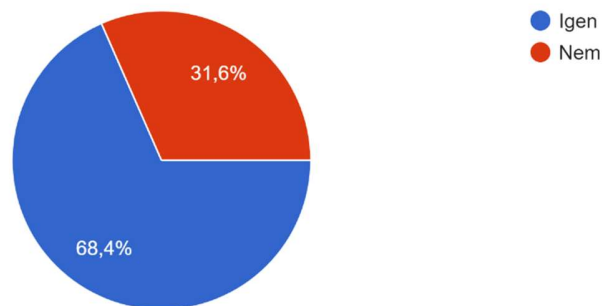
Van tudomása arról, hogy az Ön szakja rendelkezik hivatalos honlappal? (Hivatalos= egyetemi kollégák vagy szervezet által moderált felület)

915 válasz

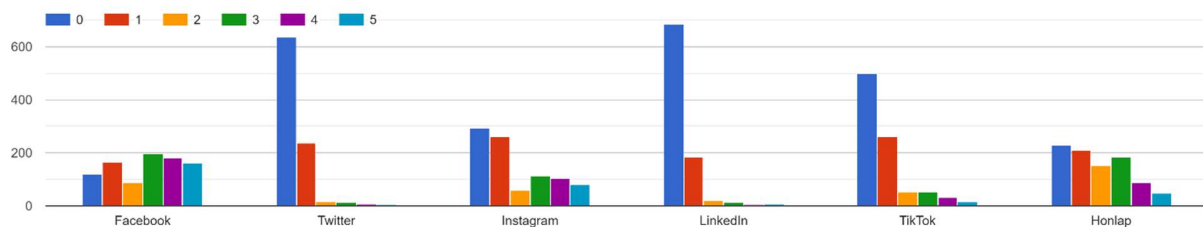


Van tudomása arról, hogy az Ön szakja rendelkezik hivatalos social media felületekkel? (Hivatalos= egyetemi kollégák vagy szervezet által moderált felület)

915 válasz

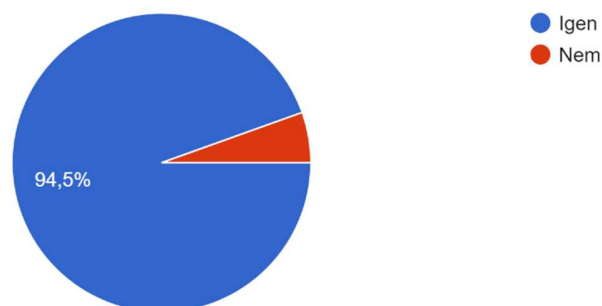


Ön aktívan követi szakját a social media platformokon vagy a honlapon? (0- nem rendelkezik ilyen felülettel, 1-nem követi, 2-nagyon ritkán, 3-néha, 4-rendszerezsen, 5- napi szinten)



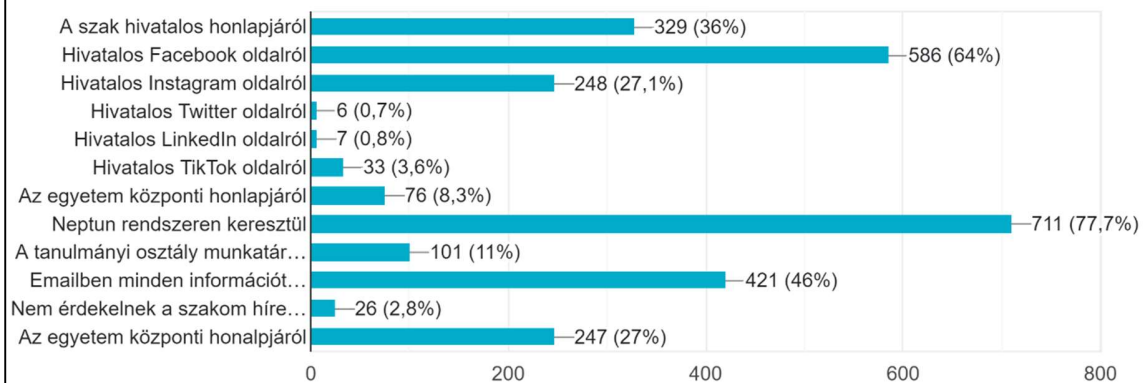
Hasznosnak tartja, ha egy szaknak van saját online megjelenése?

915 válasz



Ön honnan tájékozódik szakjának híreiről, aktuális eseményeiről? (Több válasz is lehetséges)

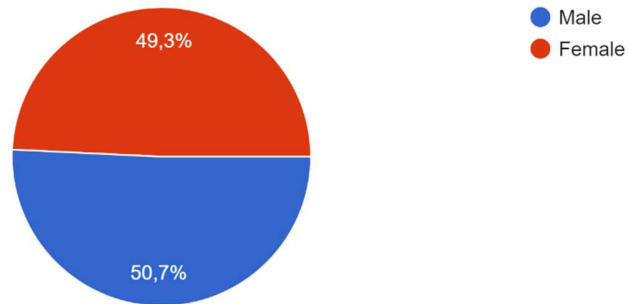
915 válasz



7.2.English Survey

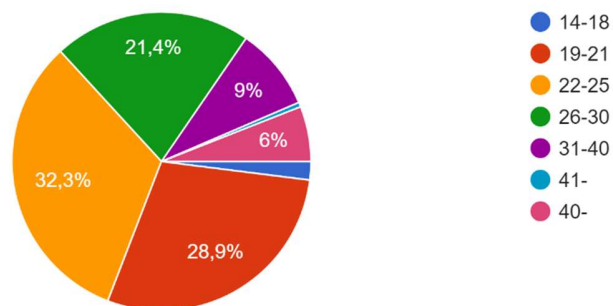
Gender

201 válasz



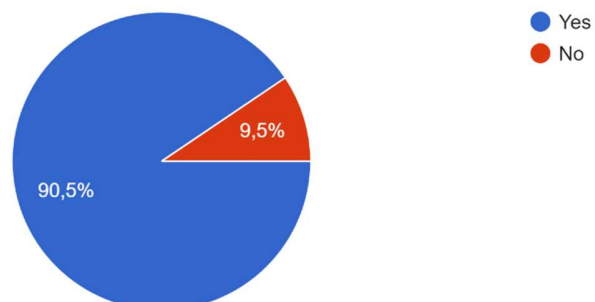
Age

201 válasz

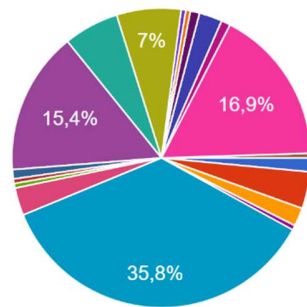


Do you currently have an active student status at Széchenyi István Universtiy?

201 válasz

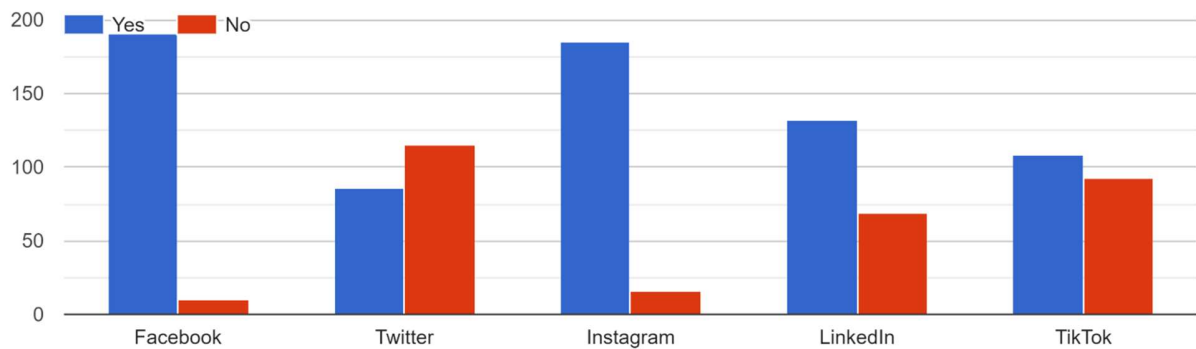


Please select from the list which major you are currently studying or which major you have previously completed! (when choosing, please pay a...degree level of the major - Ba, Bsc, Ma, Msc, PhD)
201 válasz

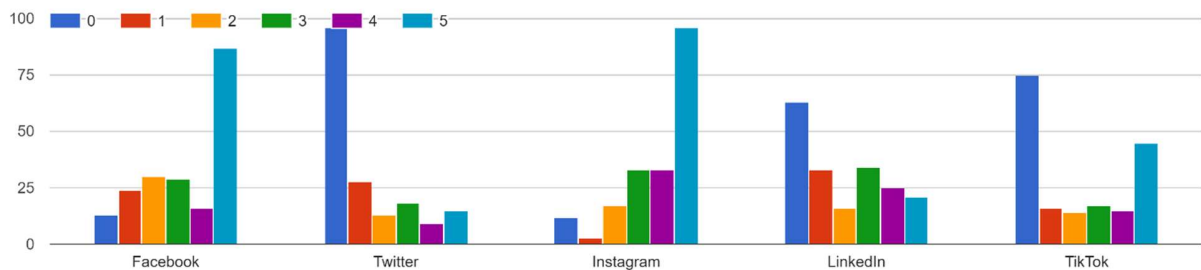


- Bsc in Vehicle Engineering
 - Bsc in Logistic Engineering
 - Bsc in Civil Engineering
 - Bsc in Agricultural Engineering
 - Bsc in Food Engineering
 - Bsc in Business Administration and M...
 - BA in International Relations
 - Msc in Vehicle Engineering
- ▲ 1/4 ▼

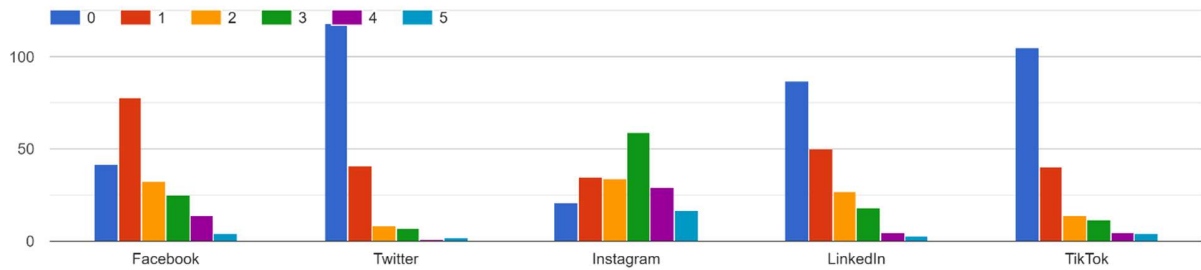
Do you have your own profile on the following platforms?



How often do you use the following platforms? (0- not registered, 1- hardly ever, 5-on a daily basis)

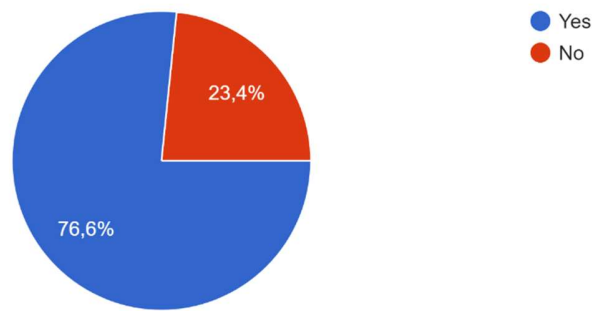


How often do you share any content on following platforms? (0- not registered, 1- hardly ever, 5-on a daily basis)

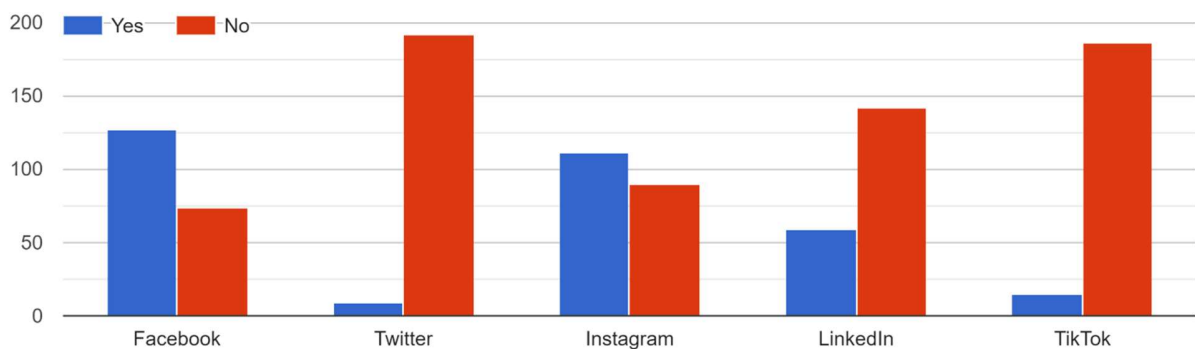


Are you aware of any official social media platforms that Széchenyi István University might have? (Official = moderated by university colleagues or organizations)

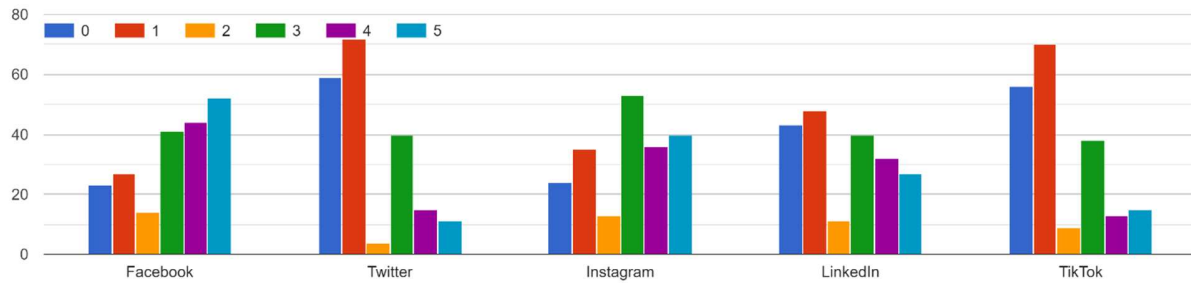
201 válasz



Do you follow the University on any of the following platforms?

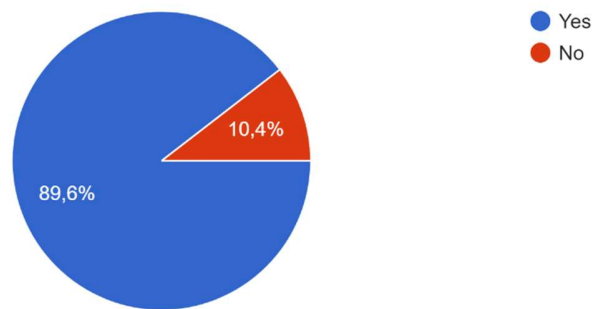


How satisfied are you with the appearance of the University on the following platforms? (0-not registered, 1-not at all, 5- absolutely)

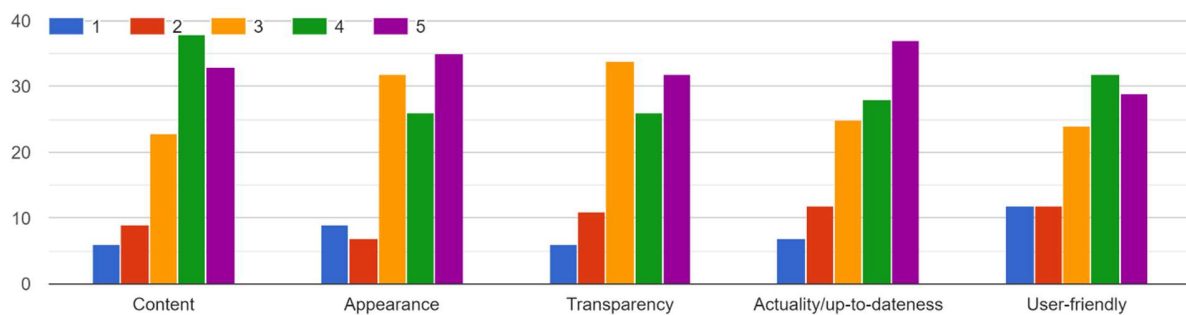


Are you aware of the official website that Széchenyi István University has? (Official = moderated by university colleagues or organizations)

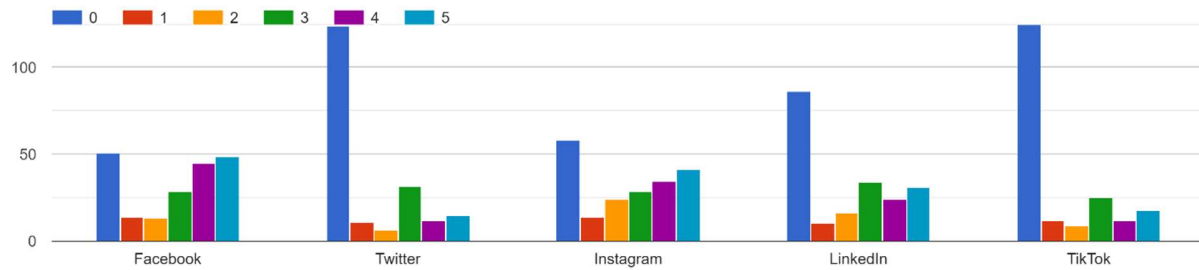
201 válasz



How satisfied are you with the Széchenyi István University website according to the following aspects: (1- not at all, 5- completely)

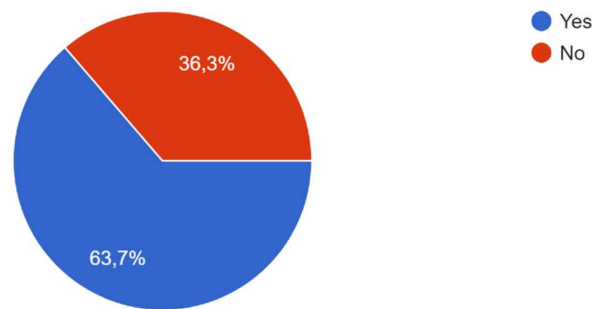


How satisfied are you with the official platforms of the University? (0- not registered, 1-not at all, 5- absolutely)



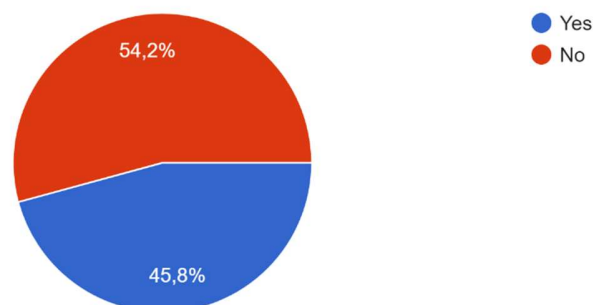
Are you aware that the faculties of Széchenyi István University have their own official website? (Official = moderated by university colleagues or organizations)

201 válasz



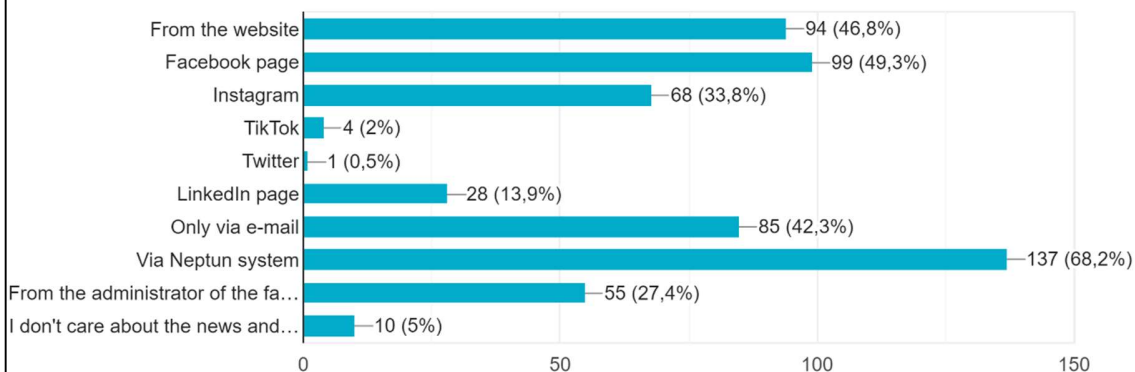
Are you aware that the different bachelor, master and PhD programs of Széchenyi István University have their own official website? (Official = moderated by university colleagues or organizations)

201 válasz



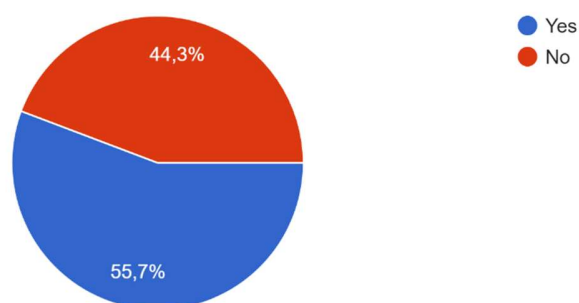
Where do you usually get information about the the news and events of the Universtiy? (Multiple sources can be chosen)

201 válasz



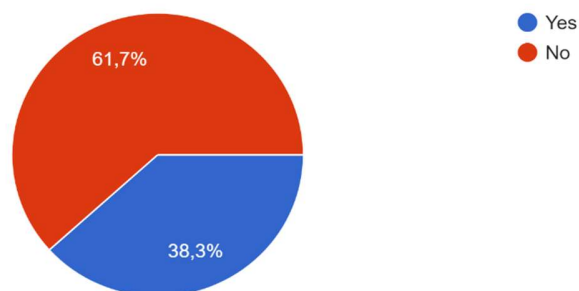
Are you aware that your pogram has an official website? (Official = moderated by university colleagues or organizations)

201 válasz

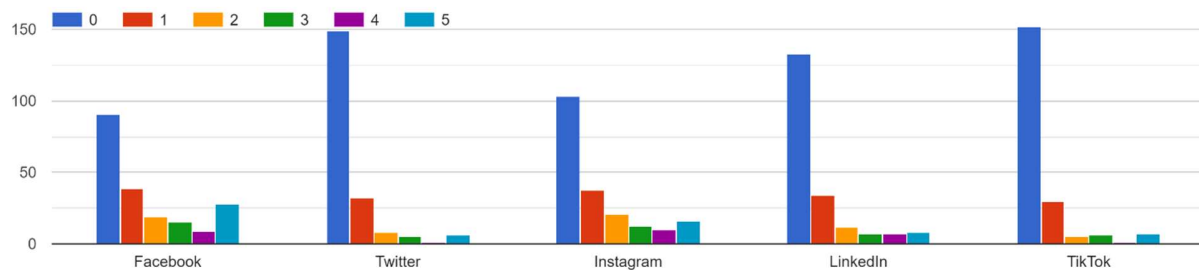


Are you aware that your program has any presence on social media platforms?

201 válasz

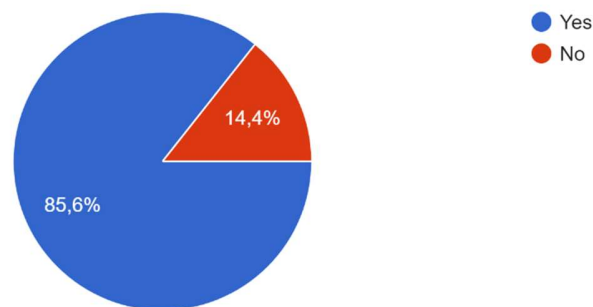


Do you actively follow your program on the following platforms? (0- not registered, 1- not at all, 2- rarely, 3- sometimes, 4- often, 5- on a daily basis)



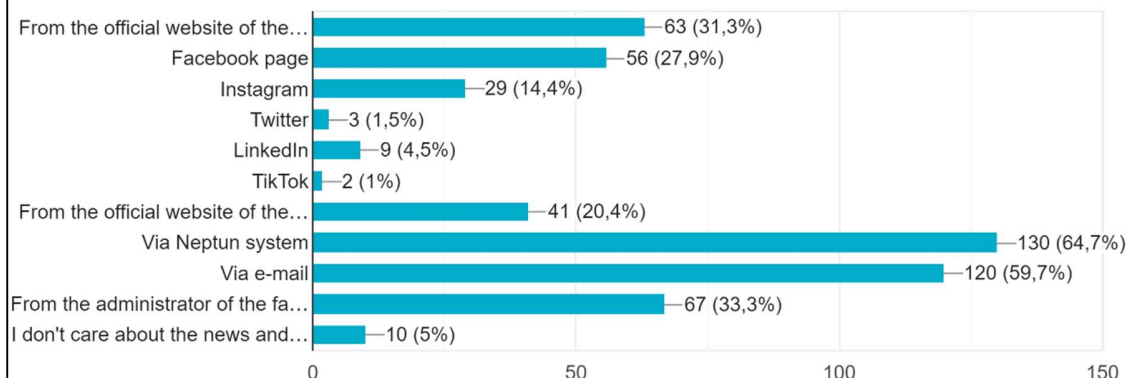
Do you find it useful, if a program has its own social media platforms?

195 válasz



Where do you usually get information about the the news and events regarding your program?

201 válasz



7.3. Python Code- Factor Analysis

```
In [1]: 1 pip install factor-analyzer
```

```
Requirement already satisfied: factor-analyzer in c:\users\moni\anaconda3\lib\site-packages (0.5.1)
Requirement already satisfied: scikit-learn in c:\users\moni\anaconda3\lib\site-packages (from factor-analyzer) (1.2.1)
Requirement already satisfied: scipy in c:\users\moni\anaconda3\lib\site-packages (from factor-analyzer) (1.10.0)
Requirement already satisfied: numpy in c:\users\moni\anaconda3\lib\site-packages (from factor-analyzer) (1.23.5)
Requirement already satisfied: pandas in c:\users\moni\anaconda3\lib\site-packages (from factor-analyzer) (1.5.3)
Requirement already satisfied: pytz>=2020.1 in c:\users\moni\anaconda3\lib\site-packages (from pandas->factor-analyzer) (2022.7)
Requirement already satisfied: python-dateutil>=2.8.1 in c:\users\moni\anaconda3\lib\site-packages (from pandas->factor-analyzer) (2.8.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\moni\anaconda3\lib\site-packages (from scikit-learn->factor-analyzer) (2.2.0)
Requirement already satisfied: joblib>=1.1.1 in c:\users\moni\anaconda3\lib\site-packages (from scikit-learn->factor-analyzer) (1.1.1)
Requirement already satisfied: six>=1.5 in c:\users\moni\anaconda3\lib\site-packages (from python-dateutil>=2.8.1->pandas->factor-analyzer) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

```
In [2]: 1 import pandas as pd
2 from factor_analyzer import FactorAnalyzer
3
4 data = pd.read_csv('merged_survey.csv', header=0)
```

```
In [4]: 1 num_columns = data.shape[1]
2 print("Number of columns:", num_columns)
```

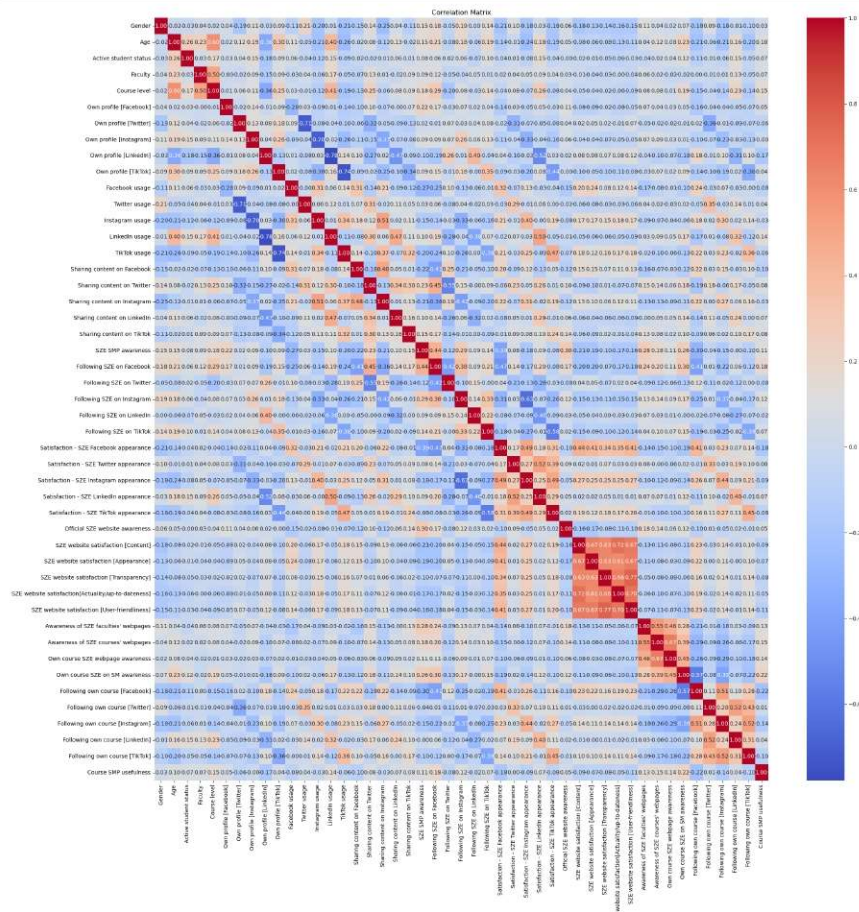
Number of columns: 47

```
In [19]: 1 pd.set_option('display.max_columns', None)
2 pd.set_option('display.max_rows', None)
3 data.describe() #descriptive statistics
```

Out[19]:

	Gender	Age	Active student status	Faculty	Course level	Own profile [Facebook]	Own pr [Twi
count	1116.000000	1116.000000	1116.000000	1116.000000	1116.000000	1116.000000	1116.000
mean	1.445341	2.766129	1.061828	3.500896	2.256272	1.014337	1.58
std	0.497226	0.972242	0.240951	1.726865	0.659328	0.118929	0.49
min	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.00
25%	1.000000	2.000000	1.000000	3.000000	2.000000	1.000000	1.00
50%	1.000000	3.000000	1.000000	3.000000	2.000000	1.000000	2.00
75%	2.000000	3.000000	1.000000	3.000000	2.000000	1.000000	2.00
max	2.000000	6.000000	2.000000	10.000000	5.000000	2.000000	2.00

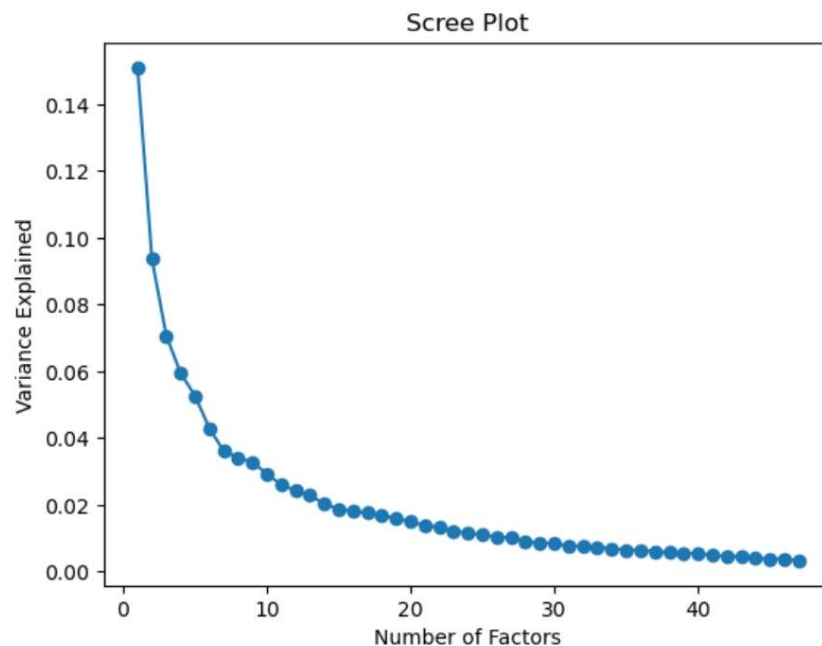
```
In [6]: 1 import matplotlib.pyplot as plt
2 import seaborn as sns
3
4 # Calculate correlation matrix
5 correlation_matrix = data.corr()
6
7 # Determine font size for annotations
8 fontsize = 10 # Smaller font for better readability
9
10 # Create heatmap with adjustments for 50 columns
11 plt.figure(figsize=(25, 25)) # Size adjusted for 50 columns
12 sns.heatmap(
13     correlation_matrix,
14     annot=True,
15     cmap='coolwarm',
16     fmt=".2f",
17     annot_kws={"fontsize": fontsize}
18 )
19 plt.title('Correlation Matrix')
20 plt.show()
21
```



```

In [7]: 1 # Perform EFA
2 # Specify the number of factors
3 n_factors = 6
4 efa = FactorAnalyzer(n_factors, rotation=None)
5 efa.fit(data)
6
7 # Get the eigenvalues and variance explained
8 eigenvalues = efa.get_eigenvalues()
9 variance_explained = eigenvalues[0] / eigenvalues[0].sum() # Access the first row
10
11 # Exclude number 0 values
12 variance_explained = variance_explained[variance_explained != 0]
13
14 # Plot eigenvalues to determine the number of factors
15 plt.plot(range(1, len(variance_explained) + 1), variance_explained, marker='o')
16 plt.title('Scree Plot')
17 plt.xlabel('Number of Factors')
18 plt.ylabel('Variance Explained')
19 plt.show()
20
21 # Based on the scree plot, decide on the number of factors to retain
22
23 # Refit the model with the chosen number of factors and rotate for interpretability
24 efa = FactorAnalyzer(n_factors, rotation='varimax')
25 efa.fit(data)
26
27 # Get factor Loadings
28 factor_loadings = efa.loadings_
29
30 # Interpret factor Loadings
31 # Analyze factor Loadings to interpret underlying factors

```



```

In [8]: 1 # Create a DataFrame for factor Loadings
2 factor_loadings_df = pd.DataFrame(factor_loadings, index=data.columns,
3
4 factor_loadings_df

```

Out[8]:

	Factor_1	Factor_2	Factor_3	Factor_4	Factor_5	Factor_6
Gender	-0.128698	-0.231959	-0.026188	0.199046	0.045659	0.269248
Age	-0.052315	-0.335221	0.474948	0.052562	0.130698	-0.152877
Active student status	-0.021078	-0.122248	0.229416	0.019141	0.020248	-0.084779
Faculty	0.004059	-0.028639	0.254154	0.083778	-0.014719	-0.029402
Course level	0.006833	-0.181945	0.538911	0.134536	0.095794	-0.080418
Own profile [Facebook]	-0.047445	-0.033183	0.007255	0.241599	0.063859	0.011353
Own profile [Twitter]	0.035469	-0.087627	0.036720	0.086886	-0.068488	-0.785315
Own profile [Instagram]	0.019203	-0.403166	-0.023539	0.331535	-0.084997	-0.145423
Own profile [LinkedIn]	0.079560	0.044411	-0.778740	0.062959	-0.151332	-0.066718
Own profile [TikTok]	-0.006889	-0.658402	0.213184	0.064947	-0.048917	-0.115480
Facebook usage	0.147711	-0.043387	0.045631	-0.479580	-0.059244	-0.072927
Twitter usage	-0.042697	-0.048488	0.013453	-0.068952	0.044886	0.778271
Instagram usage	0.094884	0.451555	-0.001362	-0.453178	0.097514	0.100637
LinkedIn usage	-0.056957	-0.058747	0.813122	-0.112097	0.154291	0.062287
TikTok usage	0.078441	0.656080	-0.190281	-0.200445	-0.001299	-0.014799
Sharing content on Facebook	0.049377	0.075801	-0.092756	-0.509451	-0.071797	0.015703
Sharing content on Twitter	0.000220	0.096789	0.339076	0.261201	0.238822	0.434120
Sharing content on Instagram	-0.011129	0.388134	0.024788	-0.571832	-0.021282	-0.047338
Sharing content on LinkedIn	-0.081329	0.068416	0.440660	-0.008118	0.129534	0.175162
Sharing content on TikTok	-0.052333	0.396514	0.112283	0.154002	0.177511	0.090415
SZE SMP awareness	-0.134393	-0.055498	0.106959	0.460311	0.260568	0.019712
Following SZE on Facebook	-0.086468	-0.092639	0.244951	0.593832	0.294215	0.107051
Following SZE on Twitter	-0.052027	-0.103186	-0.352519	-0.281475	-0.128785	-0.197353
Following SZE on Instagram	-0.081122	-0.402380	-0.063755	0.415767	0.166214	0.085386
Following SZE on LinkedIn	-0.005199	-0.108555	-0.433106	0.151030	0.068881	-0.036254
Following SZE on TikTok	-0.073538	-0.528566	0.033104	0.061303	0.156110	0.055369
Satisfaction - SZE Facebook appearance	0.440599	0.217873	0.069971	-0.341544	-0.235295	-0.008416
Satisfaction - SZE Twitter appearance	0.116166	0.184516	0.229530	0.230474	-0.091291	0.382437
Satisfaction - SZE Instagram appearance	0.272729	0.518366	0.151465	-0.224593	-0.155368	0.041060
Satisfaction - SZE LinkedIn appearance	0.095734	0.150176	0.681396	0.127158	0.002326	0.122052
Satisfaction - SZE TikTok appearance	0.181597	0.708102	0.072550	0.111455	-0.168336	0.010350
Official SZE website awareness	-0.104748	0.067883	0.022429	0.289909	0.111249	-0.014455
SZE website satisfaction [Content]	0.796950	0.074375	-0.020207	-0.181661	-0.077520	-0.038353

	Factor_1	Factor_2	Factor_3	Factor_4	Factor_5	Factor_6
SZE website satisfaction [Appearance]	0.762886	0.012988	-0.023880	-0.194367	-0.055630	-0.036744
SZE website satisfaction [Transparency]	0.811339	0.112795	-0.019528	0.003899	-0.033116	0.014972
SZE website satisfaction [Actuality/up-to-dateness]	0.783314	0.093188	-0.049377	-0.122330	-0.035819	-0.001527
SZE website satisfaction [User-friendliness]	0.842147	0.095973	-0.067678	-0.095254	-0.072633	-0.043710
Awareness of SZE faculties' webpages	-0.027712	0.078079	-0.008099	0.263247	0.474358	0.042441
Awareness of SZE courses' webpages	-0.030528	-0.017212	0.031334	0.123896	0.623623	-0.006994
Own course SZE webpage awareness	-0.016935	-0.010443	-0.022782	0.012723	0.638465	-0.035274
Own course SZE on SM awareness	-0.042627	-0.079690	0.153194	0.140032	0.622800	-0.002447
Following own course [Facebook]	0.165502	0.191420	-0.122389	-0.285432	-0.524884	-0.024138
Following own course [Twitter]	-0.021970	0.141215	0.096825	0.090919	-0.278206	0.510595
Following own course [Instagram]	0.067020	0.418187	0.008810	-0.137974	-0.492289	0.043898
Following own course [LinkedIn]	-0.014225	0.120506	0.468591	0.062339	-0.253167	0.225827
Following own course [TikTok]	0.059608	0.509116	-0.039888	0.070743	-0.375195	0.108516
Course SMP usefulness	-0.073345	-0.040828	0.135665	0.083133	0.243653	0.036995

```
In [9]: 1 from factor_analyzer.factor_analyzer import calculate_kmo
2
3 # Calculate the KMO measure
4 kmo_all, kmo_model = calculate_kmo(data)
5
6 # Print the KMO measure
7 print("KMO measure for the data:", kmo_model)
8
```

KMO measure for the data: 0.8044961146386247

C:\Users\Moni\anaconda3\lib\site-packages\factor_analyzer\utils.py:244: UserWarning: The inverse of the variance-covariance matrix was calculated using the Moore-Penrose generalized matrix inversion, due to its determinant being at or very close to zero.
warnings.warn(

```
In [10]: 1 factor1 = factor_loadings_df[factor_loadings_df['Factor_1'] > 0.5]['Factor_1']
2
3 factor1_rounded = factor1.map('{:.2f}'.format)
4
5 factor1_df = pd.DataFrame(factor1_rounded, columns=['Factor_1'])
6
7 factor1_df
```

```
Out[10]:
```

	Factor_1
SZE website satisfaction [Content]	0.80
SZE website satisfaction [Appearance]	0.76
SZE website satisfaction [Transparency]	0.81
SZE website satisfaction [Actuality/up-to-dateness]	0.78
SZE website satisfaction [User-friendliness]	0.84

```
In [11]: 1 factor2 = factor_loadings_df[factor_loadings_df['Factor_2'] > 0.4]['Factor_2']
2
3 factor2_rounded = factor2.map('{:.2f}'.format)
4
5 factor2_df = pd.DataFrame(factor2_rounded, columns=['Factor_2'])
6
7 factor2_df
```

```
Out[11]:
```

	Factor_2
Instagram usage	0.45
TikTok usage	0.66
Satisfaction - SZE Instagram appearance	0.52
Satisfaction - SZE TikTok appearance	0.71
Following own course [Instagram]	0.42
Following own course [TikTok]	0.51

```
In [12]: 1 factor3 = factor_loadings_df[factor_loadings_df['Factor_3'] > 0.4]['Factor_3']
2
3 factor3_rounded = factor3.map('{:.2f}'.format)
4
5 factor3_df = pd.DataFrame(factor3_rounded, columns=['Factor_3'])
6
7 factor3_df
```

```
Out[12]:
```

	Factor_3
Age	0.47
Course level	0.54
LinkedIn usage	0.81
Sharing content on LinkedIn	0.44
Satisfaction - SZE LinkedIn appearance	0.68
Following own course [LinkedIn]	0.47

```
In [13]: 1 factor4 = factor_loadings_df[factor_loadings_df['Factor_4'] > 0.4]['Factor_4']
2
3 factor4_rounded = factor4.map('{:.2f}'.format)
4
5 factor4_df = pd.DataFrame(factor4_rounded, columns=['Factor_4'])
6
7 factor4_df
```

```
Out[13]:
```

	Factor_4
SZE SMP awareness	0.46
Following SZE on Facebook	0.59
Following SZE on Instagram	0.42

```
In [14]: 1 factor5 = factor_loadings_df[factor_loadings_df['Factor_5'] > 0.4]['Factor_5']
2
3 factor5_rounded = factor5.map('{:.2f}'.format)
4
5 factor5_df = pd.DataFrame(factor5_rounded, columns=['Factor_5'])
6
7 factor5_df
```

```
Out[14]:
```

	Factor_5
Awareness of SZE faculties' webpages	0.47
Awareness of SZE courses' webpages	0.62
Own course SZE webpage awareness	0.64
Own course SZE on SM awareness	0.62

```
In [15]: 1 factor6 = factor_loadings_df[factor_loadings_df['Factor_6'] > 0.3]['Factor_6']
2
3 factor6_rounded = factor6.map('{:.2f}'.format)
4
5 factor6_df = pd.DataFrame(factor6_rounded, columns=['Factor_6'])
6
7 factor6_df
```

```
Out[15]:
```

	Factor_6
Twitter usage	0.78
Sharing content on Twitter	0.43
Satisfaction - SZE Twitter appearance	0.38
Following own course [Twitter]	0.51

7.4. Python Code – T-Test and Cluster Analysis (snippet)

```
In [19]: from scipy.stats import ttest_ind
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import numpy as np

df1 = pd.read_csv('t_test_hun_survey.csv')
df2 = pd.read_csv('t_test_en_survey.csv')

# Check if column names match
if not df1.columns.equals(df2.columns):
    print("Column names do not match in the two CSV files.")
else:
    # Get the column names
    columns = df1.columns

    # Perform t-test for each pair of columns
    for column in columns:
        data1 = df1[column]
        data2 = df2[column]
        t_stat, p_value = ttest_ind(data1, data2)
        print("Column:", column)
        print("T-statistic:", t_stat)
        print("P-value:", p_value)
        print()
```

Column: Gender
T-statistic: -1.4870104015300614
P-value: 0.13729503354953349

Column: Age
T-statistic: -8.162801704305828
P-value: 8.784608549280765e-16

Column: Active student status
T-statistic: -2.1282240469827816
P-value: 0.033537526475455146

Column: Faculty
T-statistic: -7.259226010323386
P-value: 7.288715398643329e-13

Column: Course level
T-statistic: -16.21277623206345
P-value: 3.096199932637258e-53

Column: Own profile [Facebook]
T-statistic: -4.706437194351979
P-value: 2.83755284702169e-06

Column: Own profile [Twitter]
T-statistic: 0.2981584613960822
P-value: 0.765637823471339

Column: Own profile [Instagram]
T-statistic: -0.20270180276733016
P-value: 0.8394051281545132

Column: Own profile [LinkedIn]
T-statistic: 11.508477618770762
P-value: 4.865386855980279e-29

Column: Own profile [TikTok]
T-statistic: -3.899803363797611
P-value: 0.00010202721042531963

Column: Facebook usage
T-statistic: 6.2872714465200925
P-value: 4.6302691244999264e-10

Column: Twitter usage
T-statistic: -1.7566270899256538
P-value: 0.07925611684869194

Column: Instagram usage
T-statistic: 2.4553338345935334
P-value: 0.014227338436418227

Column: LinkedIn usage
T-statistic: -12.426848465644513
P-value: 2.6864066883548675e-33

Column: TikTok usage
T-statistic: 5.085008001134916
P-value: 4.309918234038911e-07

Column: Sharing content on Facebook
T-statistic: -0.18544293500276565
P-value: 0.8529153927154309

Column: Sharing content on Twitter
T-statistic: -2.1565282860052752
P-value: 0.031255905776380315

Column: Sharing content on Instagram
T-statistic: -3.2808144481354753
P-value: 0.0010671525834385373

Column: Sharing content on LinkedIn
T-statistic: -12.60035619556018
P-value: 3.955831776972829e-34

Column: Sharing content on TikTok
T-statistic: -2.129902521957641
P-value: 0.03339835057528693

Column: SZE SMP awareness
T-statistic: -8.51015736581656
P-value: 5.53926803626342e-17

Column: Following SZE on Facebook
T-statistic: -6.668892885373894
P-value: 4.049439246452877e-11

Column: Following SZE on Twitter
T-statistic: 2.0996927423923117
P-value: 0.03598036610429679

Column: Following SZE on Instagram
T-statistic: -1.0158620278731019
P-value: 0.3099156697001036

Column: Following SZE on LinkedIn
T-statistic: 7.267300374564259
P-value: 6.884757734941743e-13

Column: Following SZE on TikTok
T-statistic: -4.694508146531721
P-value: 3.0048338945319976e-06

Column: Satisfaction - SZE Facebook appearance
T-statistic: 3.8206601033083434
P-value: 0.00014044774346241325

Column: Satisfaction - SZE Twitter appearance
T-statistic: -7.443786616880722
P-value: 1.9527196652525502e-13

Column: Satisfaction - SZE Instagram appearance
T-statistic: -0.4356576904379967
P-value: 0.6631695072633456

Column: Satisfaction - SZE LinkedIn appearance
T-statistic: -13.208899792522592
P-value: 4.1004934236225106e-37

Column: Satisfaction - SZE TikTok appearance
T-statistic: 0.15346061415004578
P-value: 0.8780628408414851

Column: Official SZE website awareness
T-statistic: -6.6929615111383045
P-value: 3.4578746245711285e-11

```

data1 = df1[column]
data2 = df2[column]
t_stat, p_value = ttest_ind(data1, data2)
p_values[column] = p_value

significant_columns = {column: p_value for column, p_value in p_values.items() if p_value < 0.05}
non_significant_columns = {column: p_value for column, p_value in p_values.items() if p_value >= 0.05}

# Print significant columns
print("Significant columns (p-value < 0.05):")
for column, p_value in significant_columns.items():
    print(f"Column: {column}")
    print(f"T-statistic: {t_stat}")
    print(f"P-value: {p_value}")
    print()

```

```

In [21]: # Print non-significant columns
print("Non-significant columns (p-value >= 0.05):")
for column, p_value in non_significant_columns.items():
    print(f"Column: {column}")
    print(f"T-statistic: {t_stat}")
    print(f"P-value: {p_value}")
    print()

```

Age and SZE website satisfaction [Transparency]

```
In [22]: # Extract relevant columns
X1 = df1[["Age", "SZE website satisfaction [Transparency]"]]
X2 = df2[["Age", "SZE website satisfaction [Transparency]"]]

# Standardize the data
scaler1 = StandardScaler().fit(X1)
X1_scaled = scaler1.transform(X1)

scaler2 = StandardScaler().fit(X2)
X2_scaled = scaler2.transform(X2)

# Function to calculate the distortion at various cluster numbers
def calculate_distortion(X):
    return [KMeans(n_clusters=k, random_state=42).fit(X).inertia_ for k in range(1, 11)]

# Calculate distortions for both datasets
```

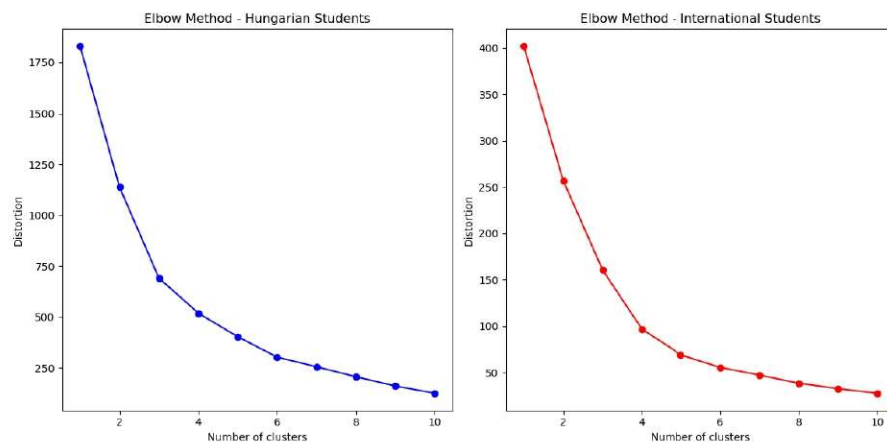
```
distortions1 = calculate_distortion(X1_scaled)
distortions2 = calculate_distortion(X2_scaled)

# Plot elbow method for both datasets
plt.figure(figsize=(12, 6))

plt.subplot(1, 2, 1)
plt.plot(range(1, 11), distortions1, marker='o', linestyle='--', color='b')
plt.xlabel('Number of clusters')
plt.ylabel('Distortion')
plt.title('Elbow Method - Hungarian Students')

plt.subplot(1, 2, 2)
plt.plot(range(1, 11), distortions2, marker='o', linestyle='--', color='r')
plt.xlabel('Number of clusters')
plt.ylabel('Distortion')
plt.title('Elbow Method - International Students')

plt.tight_layout()
plt.show()
```



```
In [23]: # Extract relevant columns
X1 = df1[["Age", "SZE website satisfaction [Transparency]"]]
X2 = df2[["Age", "SZE website satisfaction [Transparency]"]]

# Determine the optimal number of clusters
optimal_clusters = 5

# Plot dataset 1 with 5 clusters
plt.figure(figsize=(12, 6))

plt.subplot(1, 2, 1)
kmeans1 = KMeans(n_clusters=optimal_clusters, random_state=42)
clusters1 = kmeans1.fit_predict(X1)
cluster_counts1 = np.bincount(clusters1) # Count occurrences of each cluster

for i in range(optimal_clusters):
    plt.scatter(X1[clusters1 == i]["Age"], X1[clusters1 == i]["SZE website satisfaction [Transparency]"],
               marker='o', color=i, s=50)
    plt.scatter(kmeans1.cluster_centers_[i, 0], kmeans1.cluster_centers_[i, 1], marker='x', color='black', s=100)
    plt.text(kmeans1.cluster_centers_[i, 0], kmeans1.cluster_centers_[i, 1], f'Cluster {i}', color='black',
             align='center', fontweight='bold', size=12)

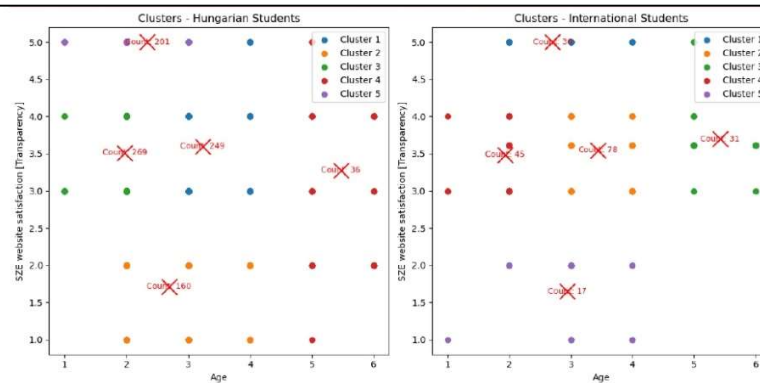
plt.xlabel('Age')
plt.ylabel('SZE website satisfaction [Transparency]')
plt.title('Clusters - Hungarian Students')
plt.legend()

# Plot dataset 2 with 5 clusters
plt.subplot(1, 2, 2)
kmeans2 = KMeans(n_clusters=optimal_clusters, random_state=42)
clusters2 = kmeans2.fit_predict(X2)
cluster_counts2 = np.bincount(clusters2) # Count occurrences of each cluster

for i in range(optimal_clusters):
    plt.scatter(X2[clusters2 == i]["Age"], X2[clusters2 == i]["SZE website satisfaction [Transparency]"],
               marker='o', color=i, s=50)
    plt.scatter(kmeans2.cluster_centers_[i, 0], kmeans2.cluster_centers_[i, 1], marker='x', color='black', s=100)
    plt.text(kmeans2.cluster_centers_[i, 0], kmeans2.cluster_centers_[i, 1], f'Cluster {i}', color='black',
             align='center', fontweight='bold', size=12)

plt.xlabel('Age')
plt.ylabel('SZE website satisfaction [Transparency]')
plt.title('Clusters - International Students')
plt.legend()

plt.tight_layout()
plt.show()
```



```
In [24]: # Create DataFrame for cluster coordinates and occurrences for dataset 1
df_cluster1 = pd.DataFrame({
    'Cluster': range(1, optimal_clusters + 1),
    'Age': kmeans1.cluster_centers[:, 0],
    'SZE website satisfaction [Transparency]': kmeans1.cluster_centers[:, 1],
    'Occurrences': cluster_counts1
})

# Round the cluster coordinates to two decimal places
df_cluster1[['Age', 'SZE website satisfaction [Transparency]']] = df_cluster1[['Age', 'SZE website satisfaction [Transparency]']].round(2)

# Create DataFrame for cluster coordinates and occurrences for dataset 2
df_cluster2 = pd.DataFrame({
    'Cluster': range(1, optimal_clusters + 1),
    'Age': kmeans2.cluster_centers[:, 0],
    'SZE website satisfaction [Transparency]': kmeans2.cluster_centers[:, 1],
    'Occurrences': cluster_counts2
})

# Round the cluster coordinates to two decimal places
df_cluster2[['Age', 'SZE website satisfaction [Transparency]']] = df_cluster2[['Age', 'SZE website satisfaction [Transparency]']].round(2)

# Display the DataFrames
print("Cluster coordinates and occurrences for dataset 1:")
df_cluster1
```

```
Out[24]:
```

	Cluster	Age	SZE website satisfaction [Transparency]	Occurrences
0	1	3.23	3.60	249
1	2	2.69	1.71	160
2	3	1.97	3.51	269
3	4	5.47	3.28	36
4	5	2.34	5.00	201

```
In [25]: print("\nCluster coordinates and occurrences for dataset 2:")
df_cluster2
```

```
Out[25]:
```

	Cluster	Age	SZE website satisfaction [Transparency]	Occurrences
0	1	2.70	5.00	30
1	2	3.45	3.55	78
2	3	5.42	3.70	31
3	4	1.93	3.49	45
4	5	2.94	1.65	17

7.5.Python Code – Text Mining

```
In [35]: 1 import pandas as pd
          2
          3 # Read CSV files
          4 en_df = pd.read_csv('en_text.csv')
          5 hun_df = pd.read_csv('hun_text.csv')
```

```
In [36]: 1 en_df
```

```
Out[36]:
```

	Opinion about SZE on SM (useful?)	Opinion about course on SMP (useful?)
0	Noanswer	Noanswer
1	Noanswer	Noanswer
2	Yes, it is useful, sometimes it shows informat...	Noanswer
3	yes it is helpful in many different ways	yes I find it useful
4	Noanswer	Noanswer
...	...	...
195	Noanswer	Noanswer
196	I find the facebook page very useful because t...	It is very helpful.
197	Yes but i don't get informed a lot of times.	Yes, but i don't get informed all the times.
198	I think they are modern and trying to stay in ...	I find it usefull aswell becuase getting to pe...
199	Yes it's useful because you will get all the n...	Yes I think it's useful because sometimes you ...

200 rows × 2 columns

```
In [23]: 1 en_counts = en_df.eq("Noanswer").sum()
          2
          3 print("Column-wise counts of 'noanswer':")
          4 print(en_counts)
```

```
Column-wise counts of 'noanswer':
Opinion about SZE on SM (useful?)    99
Opinion about course on SMP (useful?) 132
dtype: int64
```

```

In [47]: 1 text_series = hun_df.stack().astype(str)
          2
          3 # Use built-in pandas functions to count word frequencies
          4 word_counts = text_series.str.split().explode().value_counts()
          5
          6 # Select the top 10 most frequent words
          7 top_50_words = word_counts.head(50)
          8
          9 # Showcase the result in a DataFrame
         10 result_df = pd.DataFrame(top_50_words.reset_index())
         11 result_df.columns = ['Word', 'Frequency']
         12
         13 result_df

```

Out[47]:

	Word	Frequency
0	Noanswer	1174
1	a	619
2	az	324
3	mert	157
4	Hasznos,	132
5	és	131
6	nem	104
7	hogy	99
8	közösségi	93
9	is	80
10	így	79
11	hasznos,	75
12	hasznos	68
13	Hasznos	66
14	mivel	60
15	hallgatók	59
16	egyetem	58
17	A	53
18	hiszen	47
19	lehet	47

20	információt	45
21	Szerintem	44
22	Nem	44
23	egy	43
24	több	42
25	sok	40
26	mint	37
27	minden	36
28	ha	36
29	információk	36
30	van	34
31	információ	33
32	csak	32
33	de	31
34	Igen,	31
35	nagyon	29
36	meg	28
37	el	27
38	fontos	27

	Word	Frequency
39	aktuális	26
40	Igen	26
41	Hasznosnak	26
42	könnyebben	24
43	szerint	23
44	tudok	22
45	platformokon	22
46	Az	22
47	ezen	21
48	tudnak	20
49	jelen	19

```

In [48]: 1 text_series = en_df.stack().astype(str)
          2
          3 # Use built-in pandas functions to count word frequencies
          4 word_counts = text_series.str.split().explode().value_counts()
          5
          6 # Select the top 10 most frequent words
          7 top_50_words = word_counts.head(50)
          8
          9 # Showcase the result in a DataFrame
         10 result_df = pd.DataFrame(top_50_words.reset_index())
         11 result_df.columns = ['Word', 'Frequency']
         12
         13 result_df

```

Out[48]:

	Word	Frequency
0	Noanswer	231
1	the	112
2	I	82
3	to	75
4	and	58
5	it	52
6	is	49
7	useful	49
8	of	44
9	in	35
10	because	34
11	on	33
12	social	29
13	information	29
14	media	27
15	find	26
16	be	24
17	not	23
18	very	22
19	have	21

20	about	20
21	are	20
22	more	19
23	that	19
24	a	18
25	can	17
26	It	17
27	for	16
28	but	15
29	or	14
30	university	14
31	platforms	14
32	Yes	14
33	events	13
34	think	13
35	get	13
36	program	13
37	most	12
38	website	12

	Word	Frequency
39	with	11
40	useful,	11
41	don't	11
42	they	11
43	there	11
44	it's	11
45	all	10
46	news	10
47	any	10
48	good	10
49	if	10

8. References

- A Al Mammun, A Prayogo, L Buics (2021) The Effects of the Application of Artificial Intelligence in Material Handling—A Systematic Literature Review, *LIMEN*, 139-150
- A.E. Marwick (2015). Instafame: Luxury selfies in the attention economy, *Public Culture*, 27 (1 75) (2015), pp. 137-160
- A.N. Geurin-Eagleman, L.M. Burch. (2016). Communicating via photographs: A gendered analysis of Olympic athletes' visual self-presentation on Instagram, *Sports Management Review*, 19 (2), pp. 133-145
- Adam Alley, Jody Hanshew. (2022). A long article about short videos: A content analysis of U.S. academic libraries' use of TikTok. *The Journal of Academic Librarianship*, 6, p. 102611.
- A. Rosa-Castillo, O. García-Pañella, E. Maestre-Gonzalez, A. Pulpón-Segura, A. Roselló-Novella, M. Solà-Pola (2022). Gamification on Instagram: Nursing students' degree of satisfaction with and perception of learning in an educational game, *Nurse Educ. Today*, 118 (2022), Article 105533
- Bettany-Saltikov, J. (2012). *How to do a Systematic Literature Review in Nursing A step-by-step guide* (New ed. Edition). Open University Press.
- Brauer C. & Edward W.N. Bernrioder (2015). *Social Media Analytics with Facebook – The Case of Higher Education Institutions*. Lecture Notes in Computer Science book series. (LNISA, volume 9191)
- Briner, R. B., & Denyer, D. (2012). Systematic Review and Evidence Synthesis as a Practice and Scholarship Tool. In D. M. Rousseau (Ed.), *The Oxford Handbook of Evidence-Based Management* (pp.112–129). Oxford University Press.
- Chandran, D. (2016). Social media and HIV/AIDS: Implications for social work education. *Social Work Education*, 35 (3), Pages 333–343
- Chen, L., & Chen, T.-L. (2012). Use of Twitter for formative evaluation: Reflections on trainer and trainees' experiences. *British Journal of Educational Technology*, 43(2), 49–52.
- Cohen, L., Domizi, D.P. (2013). Microblogging to foster connections and community in a weekly graduate seminar course. *TechTrends*, 57(1), 43–51.
- Denyer, D., & Tranfield, D. (2009). Producing a Systematic Review. In D. Buchanan & A. Bryman (Eds.), *The SAGE Handbook of Organizational Research Methods* (pp. 671–689). SAGE Publications Ltd.
- Domizi, D.P. (2013). Microblogging to foster connections and community in a weekly graduate seminar course. *TechTrends*, 57(1), 43–51.
- Erdmann, A., & Ponzoa, J.M. (2021). Digital inbound marketing: Measuring the economic performance of grocery e-commerce in Europe and the USA. *Technological Forecasting and Social Change*, Volume 162

- Ertugan, A. (2017). Using statistical reasoning techniques to describe the relationship between Facebook advertising effectiveness and benefits gained. *Procedia computer science*, 120, 132-139.
- Hall, H., & Witek, L. (2016). Conditions, contemporary importance and prospects of higher education marketing on the example of Polish universities. *Procedia Economics and Finance*, 39, 206–211.
- Hamm, M., Chisholm, A., Shulhan, J., Milne, A., Scott, S., Given, L., & Hartling, L. (2013). Social media use by patients and careers: A scoping review. *BMJ Open*, 3(5), Pages 1-9.
- Hamel, C., Michaud, A., Thuku, M., Skidmore, B., Stevens, A., Nussbaumer-Streit, B., & Garritty, C. (2021). Defining rapid reviews: a systematic scoping review and thematic analysis of definitions and defining characteristics of rapid reviews. *Journal of Clinical Epidemiology*, 129, 74–85.
- Hanus, M. D., & Fox, J. (2015). Assessing the effects of gamification in the classroom: A longitudinal study on intrinsic motivation, social comparison, satisfaction, effort, and academic performance. *Computers & education*, (2), 80, Pages 152-161
- Härdle, W.K. and Simar, L. (2019). “Cluster analysis”, *Applied Multivariate Statistical Analysis*, Springer, New York, NY, pp. 363-393.
- Isaiah Persson & Jam Khojasteh (2021). Python Packages for Exploratory Factor Analysis, Structural Equation Modeling: A Multidisciplinary Journal, 28:6, 983-988, DOI: 10.1080/10705511.2021.1910037
- Jünger, J. and Keyling, T. (2019). Facepager. An application for automated data retrieval on the web. Source code and releases available at <https://github.com/strohne/Facepager/>
- Kaplan A., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of social media. *Business Horizons*, 53 (1), Pages 59–68.
- K.C.H. Fong, C.H. Au, E.T.H. Lam, D.K.W. Chiu (2020). Social network services for academic libraries: A study based on social capital and social proof, *The Journal of Academic Librarianship*, 46 (1) (2020), Article 102091
- Kettenring, J.R. (2006). “The practice of cluster analysis”, *Journal of Classification*, Vol. 23 No. 1, pp. 3-30, doi: 10.1007/s00357-006-0002-6.
- L. Duque. (2016). How academics and researchers can get more out of social media, *Harvard Business Review*
- Li Y, Arora S, Youtie J, Shapira P. (2018). Using web mining to explore Triple Helix influences on growth in small and mid-size firms. *Technovation*. 76:3–14 pp. doi: 10.1016/j.technovation.2016.01.002.
- López-Carril, S., Alguacil, M., & Anagnostopoulos, C. (2022). LinkedIn in sport management education: Developing the students’ professional profile boosting the teaching-learning process. *The International Journal of Management Education*, 20(1),

López-Carril, S., V. Añó, M.H. González-Serrano (2020). Introducing TED Talks as a pedagogical resource in sport management education through YouTube and LinkedIn, *Sustainability*, 12 (23) (2020), pp. 1-17.

M. Pittman, B. Reich. (2016). Social media and loneliness: Why an Instagram picture may be worth more than a thousand Twitter words, *Computers in Human Behavior*, 62 (2016), pp. 155-167

M. Hamuth (2023) Students' media consumption habits on the social Platforms of Széchenyi István University. Scientific Students' Associations Conference. Széchenyi István University

M. Manzoor, W. Hussain, O. Sohaib, F. K. Hussain, and S. Alkhalaf (2019). Methodological investigation for enhancing the usability of university websites. *Journal of Ambient Intelligence and Humanized Computing*, 10, 531-549.

Nicole Damico & Daniel G. Krutka (2018). Social media diaries and fasts: Educating for digital mindfulness with pre-service teachers, *Teaching and Teacher Education*, Volume 73, July 2018, Pages 109-119

Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD (2020). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ* 2021;372:n71. doi: 10.1136/bmj.n71

Pérez-Bonaventura, Marc; Rodríguez-Llorente, Carolina (2023). "Activity of universities in social networks. Correlations of rankings, students, followers and interactions". *Profesional de la información*, v. 32, n. 1, e320109. <https://doi.org/10.3145/epi.2023.ene.09>

Prestridge, S. (2013). Using Twitter in higher education. In H. Carter. M. Gosper and J. Hedberg (eds.). *Electric Dreams: Proceedings of the 30th Ascilite Conference* (pp.694-705). Sydney: Ascilite.

R N, Sridhara and M, Dr. Raghunandana (2019). Awareness of Web 3.0 Technology among the Researchers and Faculty member of Medical, Rajiv Gandhi University of health science: A Study Library Philosophy and Practice (e-journal). 2231.

Reynen, E., Robson, R., Ivory, J., Hwee, J., Straus, S. E., Pham, B., & Tricco, A. C. (2018). A retrospective comparison of systematic reviews with same-topic rapid reviews. *Journal of Clinical Epidemiology*, 96, 23–34.

Risling, T., Risling, D., & Holtslander, L. (2017). Creating a social media assessment tool for family nursing. *Journal of Family Nursing*, 23, (1), Pages 13-33.

Roy S, Pattnaik PK, Mall R (2016). Quality assurance of academic websites using usability testing: an experimental study with AHP. *International Journal of System Assurance Engineering and Management*:1-11

R. Nakafuji (2021). TikTok overtakes Facebook as world's most downloaded app, *Nikkei Asia*

Schroeder, H. (2014). Social media in business strategy: The learning and development implications. *Development and Learning in Organizations: An International Journal*, 28 (6), Pages 12–15.

S. del Cerro, C. Rodríguez, S. Vidal, M. Escabrós, U. Oberst. (2017). Interpersonal perception of LinkedIn profiles and employability, *Aloma: Revista de Psicología*

Soares, J. C. Sarquis, A. B. Cohen, E. D. & Soares, T. C. (2019). Social media marketing communication: effect of interactivity and vividness on user engagement. *Brazilian Journal of Marketing*, 18(4), 244-258

Sultan M. Al-Daihani & Abrahams A. (2018). Analysis of Academic Libraries' Facebook Posts: Text and Data Analytics Volume 44, Issue 2, March 2018, Pages 216-225

Tranfield, D., Denyer, D., & Smart, P. (2003). Study on and instrument to assess knowledge supply chain systems using advanced kaizen activity in SMEs. *British Journal of Management*, 14, 207–222.

Yim KH, Nahm FS, Han KA, Park SY. (2010). Analysis of statistical methods and errors in the articles published in the Korean journal of pain. *Korean J Pain*. 23:35–41.

Wang, C., and Hung, J. C. (2019). Comparative analysis of advertising attention to Facebook social network: evidence from eye-movement data. *Computers in Human Behavior*. 100, 192–208

Williams, D., (2006) – On and off the 'net: scales for social capital in an online era. *J. Comput.-Mediat. Commun.*, Pages 593–628

Williams, B., Onsmann, A., & Brown, T. (2010). Exploratory Factor Analysis A Five-Step Guide for Novices. *Australasian Journal of Paramedicine*, 8, 1-13.

Links:

<https://www.uni.sze.hu/about-us> (Accessed 01/10/2023)

<https://admissions.sze.hu/welcome> (Accessed 01/10/2023)

<https://admissions.sze.hu/chinese-home> (Accessed 01/10/2023)

<https://munkatars.sze.hu/tanevi-idobeosztas> (Accessed 12/10/2023)

<https://www.semrush.com/blog/bounce-rate/> (Accessed 04/10/2023)

<https://support.google.com/urchin/answer/28325?hl=en> (Accessed 14/10/2023)

<https://www.semrush.com/kb/257-keyword-overview> (Accessed 14/10/2023)

<https://admissions.sze.hu/chinese-home> (Accessed 01/10/2023)

<https://admissions.sze.hu/welcome> (Accessed 01/10/2023)

<https://www.facebook.com/Uni.SZE.Gyor> (Accessed 15/10/2023)

<https://www.instagram.com/szechenyi.istvan.egyetem> (Accessed 23/10/2023)

<https://www.linkedin.com/school/unisze/?originalSubdomain=hu>

(Accessed 29/10/2023)

<https://www.semrush.com/> (Accessed 14/11/2023)

https://www.tiktok.com/@university_gyor (Accessed 04/11/2023)

https://twitter.com/university_gyor (Accessed 25/10/2023)

<https://www.uni.sze.hu> (Accessed 21/09/2023)