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Digital technologies in linguistic education: Experience of development and implementation

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ABSTRACT The aim of this study was to share our experience of developing a digital Natural Language Processing Tool and its implementation in the process of training future linguists. In this article, we demonstrate the process of creating the web application SENTIALIZER, which is a multilingual Sentiment Analysis Tool developed with the help of the Python programming language and its libraries NLTK, BS4, TextBlob, Googletrans. The integration of Sentiment Analysis Tools into the educational framework is relied on the Unified Theory of Acceptance and Use of Technology (UTAUT) as its foundation. The results show that students see the prospects of using Sentiment Analysis Tools in their educational and professional activities, are ready to use them in the future, but are not ready to participate personally in projects to develop and improve such technologies. The reasons for this attitude are discussed. The presented study has a clear focus on student learning outcomes, which is an important criterion for the successful integration of technology into the educational process.

Keywords: *Digital technologies, Higher education, Learning outcomes, Linguistic education, UTAUT*

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INTRODUCTION

Digital transformation initiatives in educational institutions are currently in the focus of researchers' attention, and the activities of influential European and global organizations such as the European Commission, UNESCO and UNICEF are focused on them. Higher education institutions are undergoing a transition towards a novel university model known as the digital university (Fernández et al., 2023). The process of developing the university of the future is influenced by the changing world of work, the emergence of new non-traditional competitors in the field of educational services, the development of students' digital behavior and their expectations from learning, global mobility and the transition to lifelong learning (Halloran & Friday, 2018). According to Fernández et al. (2023), digital transformation is characterized by the development of a fresh strategic business framework within an organization, employing cutting-edge digital technologies to deliver substantial value to all stakeholders involved.

In the information age universities have steered numerous initiatives to explore unique digital technologies to enhance students' experience in learning (Mohamed Hashim et al., 2022). Numerous studies show that the introduction of digital technologies in the educational process has a positive impact on the quality of education, changes its nature and form, promotes active participation of students in classroom and extracurricular activities, and prepares them to enter the labor market (Ben Youssef et al., 2015; Bond et al., 2018; Mancillas & Brusoe, 2016; Pinto & Leite, 2020).

There are extensive studies, in particular using the UTAUT model, on the adoption of digital education and technologies by university students, which show that most students adapt to the requirements of digital learning, attach great importance to favorable conditions of the digital learning environment (Aliaño et al., 2019; Bouznif, 2018; Lehmann et al., 2023; Romero-Rodríguez et al., 2020; Salloum & Shaalan, 2019).

When examining the digital technologies utilized by students, a trend emerged revealing three predominantly employed types out of the nine identified (Pinto & Leite, 2020). To facilitate their learning, students most often use Learning Management Systems (LMS), Publish and Share tools and Information and Communication Technologies (ICT). Technologies that are grouped under the category of ICT are software or web-based applications. Many studies describe positive experiences with both types of ICT. For example, the successful trial of mobile learning, using handheld devices and online material, in an undergraduate biology class for a wildlife survey (Chapple et al., 2017), students' use of Google Drive Spreadsheet and Arquimedes software for budgeting and measurement goals in the Building Engineering context (García-Vera & Chiner Sanz, 2017), development and implementation of an intelligent mobile game application Quiz Time! (Quiz Time! is an intelligent mobile game-based learning application designed to assess and enhance students' proficiency in the programming language (Troussas et al., 2020), to determine the impact of nano-learning technology such as cloud and Mat Lab app on the academic performance and cognitive load of further mathematics students (Feng, 2023).

Digital technologies play an important role in language education. The study (Kanoksilapatham, 2022) assesses the impacts of incorporating digital technology into English education with regard to Thai university students' linguistic gain by using sets of strategically selected grammar online lessons. By aggregating a large-scale corpus into a linguistic learning network, the study (Zhang, 2021) observes and evaluates how data extracting, model exploring, verifying and falsifying are interacted in students' linguistic learning process. Wang (2023) explores a wide range of innovative e-learning tools/resources, such as EdPuzzle interactive video lectures, VR applications, Flipgrid video sharing, and the Wikibook project, which have been fairly well integrated into the teaching of an undergraduate level linguistics course at The Education University of Hong Kong. Darmoroz (2017) investigates the professional training aspects of computer linguistics specialists using the University of Stuttgart as a case study. It delineates the components of curricula that encompass both theoretical and practical facets of computer linguistics, aiming to equip contemporary specialists with the ability to grasp the intricacies of the field and to adapt to the challenges of a globalized world. The possibilities of integrating ChatGPT into language courses and programs in higher education are also being explored (Baskara & Mukarto, 2023).

Rapid progress in the field of Natural Language Processing (NLP) makes it possible to develop and implement new digital technologies in linguistic education. The availability of modern tools and free access to huge text corpora makes it possible to teach students basic NLP operations: to automatically tokenize text into sentences and sentences into words; search for synonyms, synonymic sets (groups of synonymous words), and hypernyms; apply spelling correction; tag words with parts of speech; classify texts; create a frequency dictionary for a particular text corpus. To perform these tasks, students can develop their own code using a programming language and special libraries or use both specialized software and corresponding web applications.

An important area of NLP is Sentiment Analysis, a technique used to determine whether a data is emotionally positive, negative, or neutral. Mäntylä et al. (2018) highlights Sentiment Analysis as a rapidly expanding domain within computer science. This growth is attributed to the proliferation of subjective content on the internet and the substantial publication of articles on computer-driven Sentiment Analysis techniques. Sentiment Analysis and opinion mining have become increasingly pivotal in both commercial endeavors and research pursuits, owing to their potential utility across diverse fields of application, including business, social networks and education (Bisio et al., 2017; Kastrati et al., 2021). In business, Sentiment Analysis can progress focused insight, enhance client benefit, accomplish better brand picture, and upgrade competitiveness (Tiwari et al., 2019). For example, Sentiment Analysis is used to improve the quality of Mobility Network services (Kokkinogenis et al., 2015), study the opinions of airline customers (Tiwari et al., 2019), adverse drug reaction detection from text posted by patients in Twitter and Daily Strength (Sarker & Gonzalez, 2015), decision-making approach, in e-marketing situations (Bueno et al., 2022), predicting stock market movements (Pagolu et al., 2016), etc.

Today, millions of people express their opinions and feelings on social media. A number of studies have been devoted to the Sentiment Analysis of social media posts (Birjali et al., 2021; Piryani et al., 2017; Pozzi et al., 2017; Yadav & Vishwakarma, 2020). Users' posts on Twitter, Facebook, Instagram, YouTube, etc. have become the basis to predict election results (Chauhan et al., 2021), determine the weather impacts human emotion (Sinnott et al., 2016), for depression detection (Babu & Kanaga, 2022), disaster monitoring (Sufi & Khalil, 2022), etc. Recently, a new deep learning-based Sentiment Analysis method enhanced with emojis in microblog social networks has been proposed (Li et al., 2023).

In the field of education, Sentiment Analysis is used to determine students' feedback in learning platform environments (Kastrati et al., 2021) and the level of student satisfaction with the course, massive open online course (Hew et al., 2020), and to students' academic achievement predictions (Pooja & Bhalla, 2022), etc. As illustrated in his research paper, Faizi (2023) introduced a lexical-based approach capable of discerning the sentiments expressed in individual student reviews, thereby allowing educators to evaluate the level of satisfaction with online learning resources and instructional methods. To bolster the effectiveness of this method, a new educational sentiment lexicon was developed. This lexical approach to Sentiment Analysis has demonstrated its ability to identify the sentiment polarities in the vast majority of student feedback accurately.

Let's look at some Sentiment Analysis Tools available to a wide range of users.

Linguistic Inquiry and Word Count (LIWC) aims to analyze texts to identify emotional, social, and cognitive words (Boukes et al., 2019). The program contains more than 80 linguistic, psychological, and thematic categories to which the words of the text under analysis are assigned. The core of the program is a dictionary containing words belonging to these categories. Dictionaries for many languages are available. Boyd and Schwartz (2021) believe that LIWC has made the prospect of objective, automated, and transparent psychological text analysis a reality.

Lexalytics Semantria API is a cloud-based text analytics and sentiment analysis service based on advanced machine learning and NLP. It performs the multilevel analysis of sentences incorporating parts of speech, assignment of a sentiment score from dictionaries, application of intensifiers, and determination of the final sentiment score based on machine learning techniques. This tool provides an API for Excel, contributes feasibility in terms of usage and configuration (Ikram et al., 2018).

MonkeyLearn offers a suite of powerful no-code machine learning and AI tools to analyze text from internal CRM systems, social media, emails, documents, online reviews, and more (Wolff, 2020). The pre-trained Sentiment Analysis model developed by the MonkeyLearn platform has shown high accuracy in processing text data related to the emergency response (Contreras et al., 2022) and identifying critical sentiments such as extremism (Basmmi et al., 2020).

Text2Data is an Excel or Google Sheets add-in with a Sentiment Analysis API. It classifies text into five categories: very negative, negative, neutral, positive, and very positive. The API is based on a NLP engine and this system contains specially prepared classification models for Twitter and other social media content, trained on billions of manually verified entries. Text2Data has been used in studies that have examined the supports and advice that women with intimate partner violence experience received in online health communities (Hui et al., 2023).

However, it should be noted that Sentiment Analysis methods and tools have a number of limitations and drawbacks. The works (Birjali et al., 2021; Nandwani & Verma, 2021; Wankhade et al, 2022) highlight the following methodological problems of Sentiment Analysis: the difficulty of detecting sarcasm and irony in the text; difficulties in processing messages containing emoticons, little-known abbreviations and acronyms, slang, idiomatic expressions, grammatical errors; the lack of neutral opinions when collecting data for analysis, as people tend to express positive or negative opinions on the internet; the presence of several emotions in one sentence; and the computational costs of using machine learning in the process of creating Sentiment Analysis Tools. Boukes et al. (2019) presented a study that evaluates the performance of five off-the-shelf Sentiment Analysis Tools and two tailor-made dictionary-based approaches. The researchers conclude that the results of off-the-shelf sentiment analysis tools differ greatly both from each other and from the results of the dictionary-based approach, requiring manual validation for the specific language, domain, and genre of the research project at hand.

Despite these problems, automated Sentiment Analysis of various types of texts is widely used in various fields of human activity, as it is cost-effective, especially for large numbers of texts (Boukes et al., 2019). Therefore, it can be argued that Sentiment Analysis Tools is one of the digital technologies that should be implemented in linguistic education, its use increases students' motivation to learn and chances for further employment, gives the educational process practical relevance, and contributes to the development of digital competencies. One approach to teaching students Sentiment Analysis is to use ready-made programs and tools available online. The problem with this approach is that such tools usually do not support languages other than English (Pérez et al., 2023). But multilingual analysis is necessary (Konate & Du, 2018), so the question arises of creating tools that analyze languages other than English. This problem has been successfully solved in a number of studies for some regional languages (Kapočiūtė-Dzikienė et al., 2019; Kemaloğlu et al., 2021; Konate & Du, 2018; Pérez at al., 2023; Zahidi et al. 2021).

The development of a digital Sentiment Analysis Tool that processes some regional language or performs multilingual analysis can be the topic of a student project. This study presents the experience of creating a web-based multilingual Sentiment Analysis application, which took place as a part of a qualification (bachelor's) project. The article highlights the technical approach to creating the application, justifies the choice of tools for implementation, and demonstrates the results of testing this software product. It goes on to discuss how students majoring in Applied Linguistics and Translation perceived the opportunity to learn Sentiment Analysis Tools and evaluated the work of the developed application. To find out the students' opinions, a survey was conducted before and after the course. The questionnaire was developed using the UTAUT model.

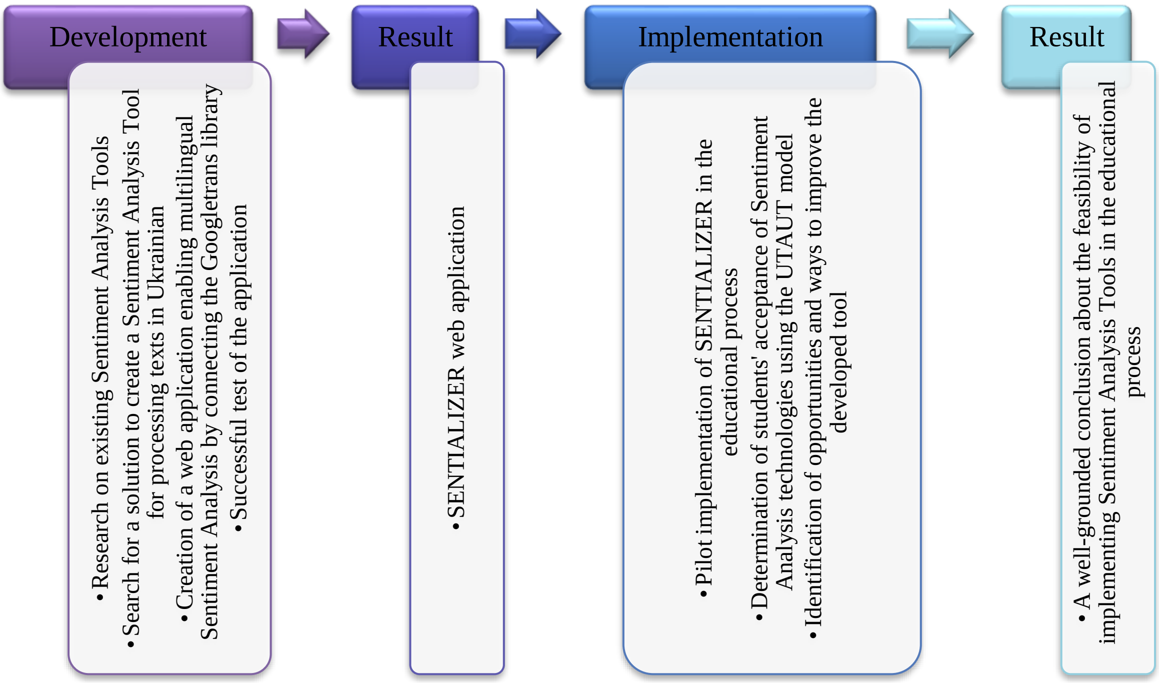
DESIGN CONTEXT

This study was conducted in two stages. At the first stage, the multilingual Sentiment Analysis Tool SENTIALIZER was developed, successfully tested and deployed. The second stage was the implementation of the developed tool in the educational process. The results of the surveys made it possible to decide on the feasibility of teaching students to use Sentiment Analysis Tools and gave impetus to finding ways to improve the developed application. The generalized scheme of the study is shown in Figure 1.

The development of the Sentiment Analysis Tool and its implementation in the educational process was carried out at the Chair of Translation, General and Applied Linguistics of Volodymyr Vynnychenko Central Ukrainian State University as part of the qualification work of the 2021-2022 academic year and in the spring semester of the 2022-2023 academic year.

Given the growing relevance of Sentiment Analysis, in 2021 it was decided to include this topic in the list of qualifying works performed by bachelors majoring in Applied Linguistics.

Figure 1.
The Generalized Scheme of the Study



Tools

The first task was to identify tools for creating our own Sentiment Analysis program and sources of text data for processing. To support Sentiment Analysis, various approaches are used: toolkits such as the Natural Language Toolkit (NLTK), open CV, Pattern, and SK Learn packages NLTK support preprocessing of tweet text contents (Sinnott et al., 2016). Python programming language together with NLTK libraries provides an opportunity to create Sentiment Analysis Tools (Gujjar & Kumar, 2021; Gupta et al., 2017; Kumar et al., 2020; Rathee et al., 2018; Saura et al., 2019). It was decided to create Sentiment Analysis Tools using Python, its libraries NLTK, Beautiful Soup 4, TextBlob and use text data from web pages, social media posts, csv files as resources for processing.

NLTK (https://www.nltk.org/) has been described as "an excellent resource for teaching and working in computational linguistics with Python," and as "an incredible library for exploring natural language."

(Mertz, 2004). Among other things, this library contains the tokenize package, which is important for Sentiment Analysis, whose methods allow you to split text into separate words or sentences. When creating a Sentiment Analysis program, the method of splitting text into sentences is used, because a certain message, i.e. a sentence or a set of sentences, is a subject of analysis.

The Beautiful Soup 4 (BS4, https://pypi.org/project/beautifulsoup4/) library is used for web scraping, i.e. extracting text data from HTML and XML files. This library does not provide for the use of complex regular expressions and text parsing (Hajba, 2018).

As per its official documentation, TextBlob is a Python library designed for handling textual data. It offers a straightforward API to address typical NLP tasks like extracting noun phrases, tagging parts of speech, translating, classifying, conducting sentiment analysis, and more. (Source: https://textblob.readthedocs.io/en/dev/). The TextBlob contains the sentiment method, which has two parameters: polarity and subjectivity. The polarity of the text is represented by a numerical value in the range from -1 to 1, which indicates the range of the text's polarity from negative to positive. The subjectivity value ranges from 0 to 1. The higher the value is, the more subjective the text message is. For example, analyzing the simple sentence "I really enjoy watching them grow in their prospects" using the blob sentiment statement gives the following results:

```
Sentiment(polarity=0.4, subjectivity=0.5).
```

Here, the polarity of the text can be interpreted as positive, with an average level of subjectivity.

It was also decided to develop the Sentiment Analysis program as an interactive web application with the ability to send data to the server for processing and receiving results. The tools for this task were identified as the Flask framework (https://flask.palletsprojects.com/en/3.0.x/) and the Requests library (https://pypi.org/project/requests/), which provides the ability to retrieve data from a web page on request.

At the first exploratory stage of the qualification study, we researched and analyzed existing Sentiment Analysis Tools, identified their functionality, advantages, and disadvantages. Constructed using Python and Flask, the web application Sentalizer (https://thecodinginterface.com/blog/text-analytics-app-with-flask-and-textblob/) was developed specifically to conduct text analytics on online content sources like blog pages (McQuistan, 2019). For text analytics tasks, a developer employs Requests to retrieve web pages, Beautiful Soup 4 to parse HTML and extract visible text, and applies the TextBlob package to analyze sentiment.

The algorithm for creating a Sentalizer web application is the following:
1. Install Flask Environment and TextBlob, Beautiful Soup 4, Requests on your computer.
2. Develop the Python code for Building the Flask Sentalizer Text Analytics App.
3. Create Jinja HTML templates, which are used to directly display information in a browser window.
4. Create a CSS file to style the HTML pages.
5. Establish a relationship between a Python program and HTML templates.
6. Create an input element with the type="text" attribute to enter the URL to the HTML template.
7. Execute the text analysis function by utilizing the BeautifulSoup class from the bs4 package and the TextBlob class from the textblob package.
8. Develop a tailored Python class named PageSentiment responsible for storing details about a page's URL, heading, overall sentiment, and sentences exhibiting the most extreme sentiment outcomes.
9. Display the sentiment data of the submitted url in the results.html template.

Testing of the Sentalizer web application has shown that it works correctly.

Development

Sentalizer, like many other tools, supports analysis of English-language texts only. When looking for different ways to create Sentiment Analysis Tools for Ukrainian-language texts, we eventually chose a method involving machine translation using the Googletrans library, which uses the Google Translate API. Although this method is not as accurate as using pre-compiled polarity dictionaries for each language separately, it allows us to cover 108 languages at once, use fragments of the Sentalizer code without changing existing tools.

Experience has been gained in generating subjectivity analysis resources in a regional language by leveraging the tools and resources available in English. A prerequisite for this method is the presence of a connection between English and the chosen target language, such as a bilingual dictionary or a parallel corpus. Bilingual dictionaries have served as the foundation for constructing a tonal dictionary for German (Kim & Hovy, 2006) and a lexicon of subjectivity for Romanian (Mihalcea et al., 2007). This approach offers the advantage of simplicity and efficiency (a dictionary with over 5000 entries can be created within seconds), although its drawback lies in the lower accuracy of analysis compared to the use of pre-annotated corpora or tonal dictionaries in the target language. Additionally, it is noteworthy that automatic translation presents a viable alternative for developing resources and tools for subjectivity analysis in a new target language (Banea et al., 2008).

Thus, the result of the qualification study was the development of the SENTIALIZER web application designed to perform multilingual Sentiment Analysis. In the course of the program's operation, the text received from the user is firstly translated into English, and then Sentiment Analysis is performed. The Googletrans module was used for machine translation. Googletrans is a free Python library that supports the Google Translate API. The library contains methods for translation and automatic source language detection (https://py-googletrans.readthedocs.io/en/latest/)

Here is a code snippet to determine the language of the text entered by the user:

```
input_data = request.form["user_text"]
identified_lang = translator.detect(input_data)
identified_lang = identified_lang.lang
if identified_lang == "en":
    pass
else:
    input_list = tokenize.sent_tokenize(input_data)
    input_list_translated = []
    for message in input_list:
        message = translator.translate(message, dest="en")
        message_translated = message.text
        input_list_translated.append(message_translated)
```

Occurs:

1. Determination of the source language.
2. If the language is not English, two lists are created: one with sentences in the source language and one in the target language (English).
3. Sentiment Analysis in English.
4. Create a list of Sentiment Analysis results.

Next, it is advisable to create a Python dictionary in which sentences in English are compared with the corresponding sentences in the original language:

```
lang_dictionary = dict(zip(input_list_translated, input_list))
```

To display the results on the screen, the obtained values are passed to the corresponding variables:

```
if identified_lang != "en" or '':
    self.most_polar_message = \
            lang_dictionary[self.most_polar_message]
    self.least_polar_message = \
            lang_dictionary[self.least_polar_message]
    self.most_objective_message = \
            lang_dictionary[self.most_objective_message]
    self.most_subjective_message = \
            lang_dictionary[self.most_subjective_message]
```

Also, the SENTIALIZER web application has implemented the ability to visualize the results of Sentiment Analysis by building pie charts. For this purpose, the Python libraries Pandas and Matplotlib were used.

Testing

The web application was tested on materials in Ukrainian and German. The posts of Ukrainian-speaking users on Twitter were analyzed at the request of Eurovision. It should be noted that the original text of the posts was preserved for the purposes of the study. For convenience, the tweets were placed in an Excel spreadsheet with the pseudonyms of the authors (see Figure 2):

Figure 2.
Structure of a File with Messages in Ukrainian

no.	source	username	message
1	Twitter	hellcat_stories	Крім перемоги Калуш зробили ще одну дуже важливу річ. І вона, мабуть, важливіша за перемогу. Цього року Євробачення дивилося близько 200 мільйонів глядачів. 200 мільйонів почули про Азовсталь.
2	Twitter	logvynenko	Євробачення без русні — це репетиція майбутнього Європи. По-моєму, дуже вдало проведена.
3	Twitter	karohsi	тільки українці могли подумати, що їх дискваліфікують з євробачення, а потім перемогти у цьому євробаченні.
4	Twitter	kohairii	ти стефанія > народжуєш сина > він пише про тебе пісню > ???? > ця пісня виграє євробачення 2022.
5	Twitter	blessedvirgin_m	Слова про Маріуполь та Азовсталь на сцені євробачення це наче дійсність прориває якийсь симулякр дійсності для привілейованих.
6	Twitter	darkprincess5_5	Знаєте така різниця в менталітеті. Британці радіють за нас і за своє срібло. А знаєте що пишуть іспанці? Що вони не виграли євробачення, а ми не виграємо війну. Іспанці, йдіть *****! А Каталонії передаю привіт!
7	Twitter	BChanAbs	Українці: треба виграти Євробачення, головне, щоб Україну не дискваліфікували. Калуш: врятуйте Маріуполь та захисників Азовсталі! Українці: ***** на Євробачення, навіть якщо дискваліфікують, Калуш однаково найкращий.
8	Twitter	dashkaboichenko	Я живу в країні, де люди збирають 30 млн грн на БПЛА за 24 години. де Євробачення можна подивитись в апці з електронним паспортом. де люди випадково грузять 2 тонни гуманітарки в Німеччині і везуть в Україну. де за тиждень вичистили вулицю від згорівших руснявих танків...

Лист1

The file analysis function in the SENTIALIZER web application is designed so that the unit of analysis is the content of a message cell, not each sentence separately. The result of the analysis is the following:

```
Polarity: positive
Most Polar Sentence: 0.49
```

Ukrainians: we need to win Eurovision, the main thing is that Ukraine is not disqualified. Kalush: save

Mariupol and the defenders of Azovstal! Even if disqualified, Kalush is still the best.

```
Least Polar Sentence: -0.3
```

You know such a difference in mentality. The British are happy for us and their silver. Do you know what the Spaniards write? That they didn't win Eurovision, and we won't win the war. And I say hello to Catalonia!

```
Most Objective Sentence: 0%
```

This year, Eurovision was watched by about 200 million viewers.

```
Most Subjective Sentence: 0%
```

I think it was very well done.

Figure 3 shows a web page with the results of tweet analysis with a Ukrainian-language interface.

Figure 3.
Results of the Analysis of Posts in Ukrainian

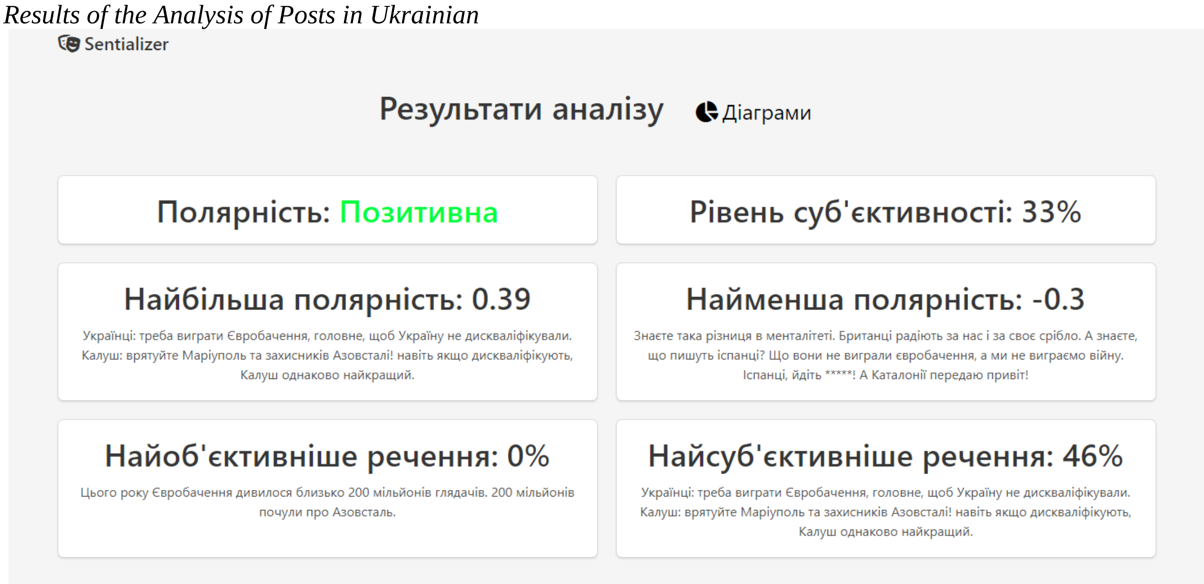
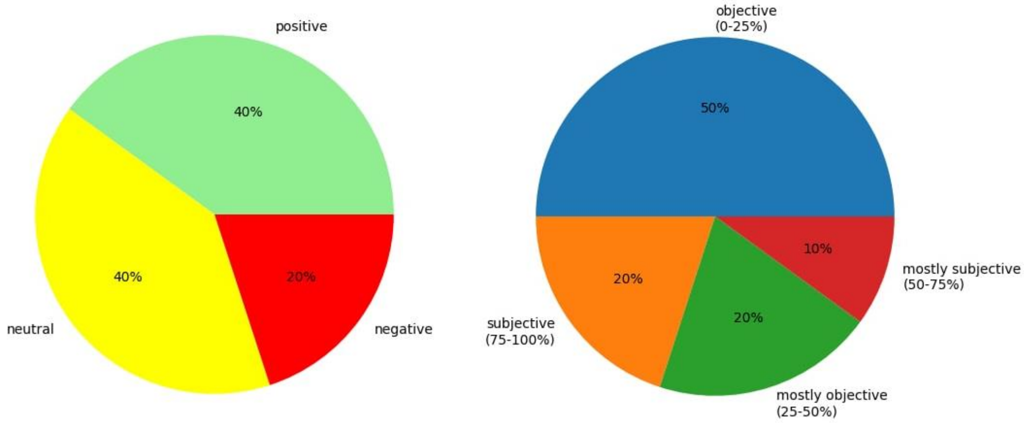


Figure 4 shows the diagrams created based on the results of the analysis.

Figure 4.
Diagrams Based on the Results of the Analysis of Posts in Ukrainian



To analyze the texts in German, we selected news from the Deutsche Welle website. The links to the articles from Deutsche Welle and the results of the analysis of polarity and subjectivity for each of them are shown in Table 1.

The results are predictable, because news text is characterized by an objective presentation of information with a small amount of expressiveness.

However, not all of the test results were unambiguously correct. For example, a piece of text that neutrally reported on the German banking system was rated by SENTIALIZER as positive, even with a low level of subjectivity. The news about the earthquake was interpreted by the app as neutral, while in the opinion of the developers, it had a negative polarity. In other words, SENTIALIZER, like other Sentiment Analysis Tools, does not always demonstrate correctness of work, some results require manual validation (Boukes et al., 2019). However, in most cases SENTIALIZER has demonstrated reliable performance, and it has been placed on the Pythonanywhere hosting at https://sentializer.pythonanywhere.com/.

Table 1.

Results of the Analysis of Web Pages from Deutsche Welle

Web page	Polarity	Subjectivity
Meinung: Russland für den Wiederaufbau der Ukraine zur Verantwortung ziehen https://www.dw.com/de/meinung-russland-f%C3%BCr-den-wiederaufbau-der-ukraine-zur-verantwortung-ziehen/a-61841071	Neutral	32%
EU will Energieimporte aus Russland beenden https://www.dw.com/de/eu-will-energieimporte-aus-russland-beenden/a-61840988	Neutral	31%
Was ist ein Gefangenenaustausch? https://www.dw.com/de/was-ist-ein-gefangenenaustausch/a-61830136	Neutral	30%
TikTok im Schutzkeller: Die Geschichte von Valeria Shashenok aus Tschernihiw https://www.dw.com/de/valeria-shashenok-tschernihiw-tiktok-lesereise/a-61767290	Neutral	34%
Mit regionaler Landwirtschaft gegen die Klimakrise https://www.dw.com/de/mit-regionaler-landwirtschaft-gegen-die-klimakrise/a-61815088	Neutral	39%

Educational outcomes

Working on a project to create a digital tool for processing natural language texts makes it possible to solve a number of educational problems:
- development of professional knowledge and skills necessary for solving certain tasks in the field of computational linguistics;
- the development of professional knowledge and skills necessary for the effective use and creation of digital technologies for NLP;
- the formation of a student's digital competence at the highest eighth level in accordance with Digcomp 2.2 (Vuorikari et al., 2022);
- the development of self-regulation, which is one of the components of success in university studies, as well as in later continuing education (Schneider & Preckel, 2017); self-regulation involves abilities that empower students to establish and strive for goals, make decisions, act independently, and reflect both individually and collaboratively with others, realize environmental constraints and affordance (Sailer et al., 2021), in this case of the development environment;
- development of Computer Thinking through programming (Romero et al., 2017; Tikva & Tambouris, 2021);
- modeling of linguistic and technological processes that enables the development of complex cognitive skills (Chernikova et al., 2020);
- creating an authentic learning context (Barab et al., 2000), solving a practical task related to a professional field;
- implementation of constructive learning and research activities using digital technologies;
- leveraging the power of technology to offer a quality experience;

- fostering a positive attitude towards the creation and use of digital technologies.

This knowledge, skills, and attitudes are some of the main learning outcomes of the Applied Linguistics program, and they are the basis for further learning and professional development in the digital environment.

METHOD

After successful testing by the developers of the SENTIALIZER web application, the question arose of the feasibility of its implementation in the educational process. For this purpose, a pilot training on Sentiment Analysis was conducted using SENTIALIZER and two other web applications. In order to arrive at a well-informed decision, it was imperative to assess students' perspectives regarding learning Sentiment Analysis and its associated tools. Sailer et al. (2021) underscore attitudes toward digital technology as a primary motivator for participation in learning endeavors related to digital tools. It was also important to find out the students' readiness to work on improving SENTIALIZER. We conducted a survey both before and after delving into the topic of Sentiment Analysis. The questionnaire was developed using the technology UTAUT model.

The hypotheses of this study were developed on the basis of the UTAUT model.
Hypothesis 1: Performance expectancy positively affects students' intentions to use Sentiment Analysis Tools.
Hypothesis 2: Effect expectancy positively affects students' intentions to use Sentiment Analysis Tools.
Hypothesis 3: Social influence positively affects students' intentions to use Sentiment Analysis Tools.
Hypothesis 4: Facilitating conditions positively affect students' use behaviors of actually using Sentiment Analysis Tools.
Hypothesis 5: Students' personal initiatives and characteristics are directed toward the use and improvement of Sentiment Analysis Tools.
Hypothesis 6: Students' behavioral intentions are directed to their readiness to use Sentiment Analysis Tools in the future.

Participants

The pilot implementation involved 36 students of the 3rd and 4th years of bachelor's degree in Applied Linguistics (15 students) and Translation (21 students). The age range of the participants was 18-22 years old. Ukrainian is the native language for all participants without exception. All participants are also fluent in English and German (B2 Level). Some of them are learning Polish and Spanish at their own request. At this point, the students completed the course "Programming for Linguists," had knowledge of the computer model in the context of programming and the principles of encoding characters in various formats, and acquired skills in processing text data using Python, such as creating frequency dictionaries, basic encryption, using files in programming, and using regular expressions to search and replace data in text arrays. The students also gained user experience with such linguistic computer programs as Trados RWS, Memoque. Through a preliminary survey, it was determined that only two of the 36 students had previous experience with Sentiment Analysis.

Students were briefed on the voluntary nature of their involvement in the survey and the assurance of anonymity regarding the responses gathered via questionnaires.

Pilot Implementation of Sentiment Analysis Tools in the Educational Process

Classes on Sentiment Analysis were integrated into the discipline "Programming for Linguists" for students majoring in Applied Linguistics and into the discipline "Practice of Translation" for students majoring in Translation. Meetings with the teacher were held online on the Google Classroom platform.

The pilot implementation program included the following items:
1. discussion of the theoretical foundations of Sentiment Analysis;
2. familiarization with Sentiment Analysis Tools;
3. testing three Sentiment Analysis web applications and analyzing the results;
4. analysis of the SENTIALIZER project code; familiarization with the Beautiful Soup 4, TextBlob, Googletrans libraries and the features of their use; development of software projects that involve importing these libraries.

The students were offered to test and analyze the results:

MonkeyLearn (https://monkeylearn.com/sentiment-analysis-online/) offers a comprehensible and user-friendly graphical interface, enabling users to generate custom text classification and extraction analysis effortlessly.

text2data (https://text2data.com/text-analytics-platform) is a text analytics solution that helps to analyze content across various social media channels including Twitter and Facebook using NLP and machine learning algorithms.

SENTIALIZER (https://sentializer.pythonanywhere.com/) – the multilingual text analysis tool considered above.

The tasks for students to test web applications are given below.

Task 1. Task 1 is about testing texts in English. Students were asked to select fragments of texts of different genres (scientific, fiction, colloquial, journalistic), determine their polarity and subjectivity using the tools listed above. The data obtained were tabulated (Table 2), the results were compared, and conclusions were drawn.

Table 2.
Template for Entering the Results of Task 1

Genre	A fragment of the text	Monkey Learn		text2data		SENTIALIZER	
		Polarity	Subjectivity	Polarity	Subjectivity	Polarity	Subjectivity

Task 2. Task 2 was devoted to testing texts in Ukrainian. Students were asked to select fragments of texts of the same genres, determine their polarity and subjectivity using SENTIALIZER. To make their own assessment of the polarity and subjectivity of the text and compare it with the results of the SENTIALIZER program. Enter the data in the table (Table 3), compare the results, and draw conclusions.

Task 3. Task 3 is about testing texts in any language. Students were asked to select fragments of texts of different genres, determine their polarity and subjectivity using SENTIALIZER. Make their own assessment of the polarity and subjectivity, compare it with the results of the SENTIALIZER program. Enter the data in the table (Table 3), compare the results, and draw conclusions.

The test of Task 3 showed that students most often chose German and Polish for testing. One student researched texts in Spanish and Italian.

Table 3.
Template for Entering the Results of Tasks 2 and 3

Genre	A fragment of the text	SENTIALIZER		Subjective assessment	
		Polarity	Subjectivity	Polarity	Subjectivity

Data Collection and Data Analysis

To assess students' perspectives regarding the integration of Sentiment Analysis into the educational process, both pre- and post-use surveys were conducted, following the UTAUT model (Venkatesh et al., 2003). Of the 36 students who participated in the pilot implementation, all agreed to take the survey and answered both the pre- and post-use questionnaires.

UTAUT is a valid and robust model, vastly used to analyze technology acceptance in several domains, including education (Raffaghelli et al., 2022). It consists of four constructs (i.e., effort expectancy, performance expectancy, social factors, and facilitating conditions) and four moderating variables (i.e., age, gender, education, and voluntariness of use). In the current study, the survey is focused on the practical relevance of Sentiment Analysis and students' willingness to improve existing tools. Therefore, it was decided to use the four constructs mentioned above, and to choose personal initiative and intention as moderating variables (Gao et al., 2011; Hsu, 2012). All questionnaire items were measured using a 5-point Likert-type scale including 1 – Strongly disagree, 2 – Disagree, 3 – Neither agree nor disagree, 4 – Agree, 5 – Strongly agree (Joshi et al., 2015).

In total, the Pre-usage Survey contained 17 questions: 11 questions are based on the UTAUT model, three questions are about personal initiatives and characteristics to determine student acceptance of new technology, and one question is about behavioral intentions. The questionnaire was supplemented with questions about the student's specialty and previous experience with Sentiment Analysis Tools. T The Post-usage Survey included identical questions, except for the one pertaining to previous experience. Table 4 displays the pre-post usage UTAUT questions utilized in the survey.

Table 4.
Constructs and Items

Constructs	Items
Performance Expectancy (PE)	1. Using the Sentiment Analysis Tools is useful for my learning 2. Using the Sentiment Analysis Tools increases my employment opportunities 3. Using coding techniques increases my employment opportunities.
Effort Expectancy (EE)	1. My interaction with the Sentiment Analysis Tools would be clear and understandable. 2. I would find the Sentiment Analysis Tools easy to use.
Social Influence (SI)	1. People who influence my behavior would think that I should use the Sentiment Analysis Tools to be more competitive 2. People who are important to me would think that I should use the Sentiment Analysis Tools to be more competitive 3. The people that are in my social circle would think that I should use the Sentiment Analysis Tools to be more competitive.
Facilitating Conditions (FC)	1. I have the resources necessary to use the Sentiment Analysis Tools. 2. I have the knowledge necessary to use the Sentiment Analysis Tools. 3. If I have problems using Sentiment Analysis Tools, I could solve them very quickly.
Personal Initiatives and Characteristics (PIC)	1. Using the Sentiment Analysis Tools give me an advantage over those who don't. 2. I would like the Sentiment Analysis Tools to develop and improve. 3. I could take part in a project to develop and improve the Sentiment Analysis Tools.
Behavioral Intention (BI)	1. I am willing to use the Sentiment Analysis Tools in the future.

The questionnaire was posted on the university's LimeSurvey platform.

RESULTS

The reliability was analyzed through the Cronbach Alpha. The overall coefficient for the test is .897, and the values for each construct are shown in Table 5.

Table 5.
Reliability of Research Constructs

	Cronbach Alpha
Performance Expectancy	.803
Effort Expectancy	.649
Social Influence	.897
Facilitating Conditions	.830
Personal Initiatives and Characteristics. Behavioral intention	.811

The validity of the test was assessed by Pearson correlation analysis. Table 6 shows the correlation for the variables included in the measurement model. The names of the constructs with the x index indicate their values before using Sentiment Analyzes Tools, and with the y index - after using them.

Table 6.
Correlation of Research Constructs

		PEx	*EEx*	*SIx*	*FCx*	*PICx*	*BIx*	*PEy*	*EEy*	*SIy*	*FCy*	*PICy*	*BIy*
Pre-Usage	PEx	1											
	EEx	.684	1										
	SIx	.687	.579	1									
	FCx	.620	.758	.563	1								
	PICx	.813	.600	.770	.374	1							
	BIx	.933	.794	.618	.511	.830	1						
Post-Usage	PEy	.566	.314	.298	.321	.255	.297	1					
	EEy	.487	.590	.577	.529	.398	.481	.536	1				
	SIy	.343	.515	.597	.345	.229	.217	.631	.563	1			
	FCy	.401	.280	.323	.558	-.323	.288	.400	.856	.220	1		
	PICy	.597	.458	.324	.321	.541	.248	.611	.340	.377	.293	1	
	BIy	.890	.758	.654	.411	.944	.931	.311	.607	.381	.321	.530	1

The correlation coefficients for all pairs of constructs for the pre- and post-survey are positive. Negative correlation is observed between two constructs from the pre-survey and post-survey: PICx is negatively correlated with FCy.

Taking into account the need to compare the results of the pre- and post-survey, Student's t-test was used for a significance level of .05 and a critical T = 2.03. For all scales, there are differences before and after using Sentiment Analyzes tools, with the confirmation effect observed for the PE, EEx, SIx, FCx, BI constructs and the disconfirmation effect for the PIC construct, as shown in Table 7.

Table 7.
The Results of the Statistical Analysis

Constructs	Performance Expectancy	Effort Expectancy	Social Influence	Facilitating Conditions	Personal Initiatives and Characteristics	Behavioral intention
t-test	-0.78	-2.83	-1.26	-3.15	1.29	-4.84
p-value	.439	.008	.218	.003	.206	<.001

As can be seen from the data, students generally agreed with the usefulness of Sentiment Analysis Tools, saw prospects for their use in the future, but were not ready for further improvement. To confirm this assumption, an additional analysis of each survey item was conducted for the constructs Facilitating Conditions, Personal Initiatives and Characteristics (with the highest t-test value), Behavioral intention (with a negative t-test value).

The number of students who gave 4 and 5 points for Facilitating Conditions increased for the post-survey (Table 8). For FC2, the increase was 36.1%.

Table 8.
Facilitating Conditions (FC)

	Questionnaire Item	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
		1	2	3	4	5
Pre-Usage	FC1: I have the resources necessary to use the Sentiment Analysis Tools	0 0.0%	7 19.4%	11 30.6%	**18** **50.0%**	**0** **0.0%**
	FC2: I have the knowledge necessary to use the Sentiment Analysis Tools	2 5.6%	8 22.2%	16 44.4%	**9** **25.0%**	**1** **2.8%**
	FC3: If I have problems using Sentiment Analysis Tools. I could solve them very quickly	0 0.0%	5 13.9%	17 47.2%	**12** **33.3%**	**2** **5.6%**
Post-Usage	FC1: I have the resources necessary to use the Sentiment Analysis Tools	1 2.8%	0 0.0%	8 22.2%	**22** **61.1%**	**5** **13.9%**
	FC2: I have the knowledge necessary to use the Sentiment Analysis Tools	0 0.0%	1 2.8%	7 19.4%	**22** **61.1%**	**6** **16.7%**
	FC3: If I have problems using Sentiment Analysis Tools. I could solve them very quickly	1 2.8%	3 8.3%	13 36.1%	**14** **38.9%**	**5** **13.9%**

Students made sure that they had the necessary knowledge and resources to use Sentiment Analysis Tools (see Figure 5).

Figure 5.
Facilitating Conditions Scaling Results

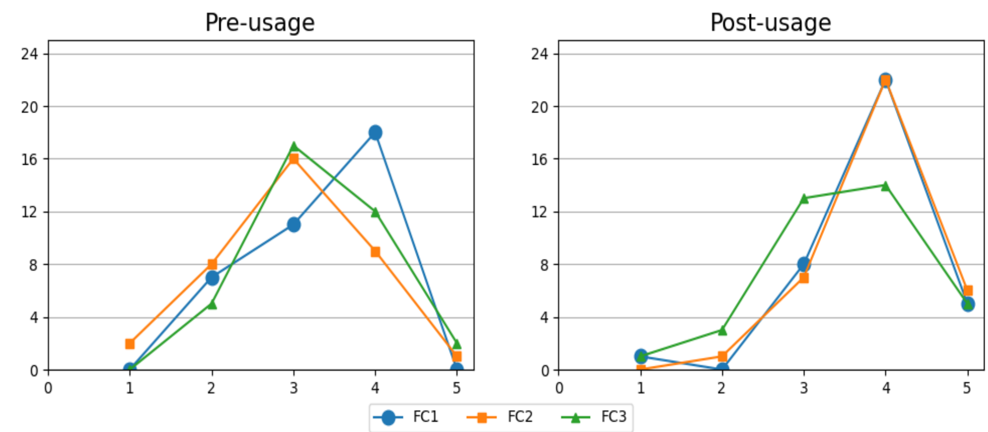


Table 9 provides a clear picture of the change in students' personal initiatives and characteristics before and after using Sentiment Analysis Tools. For the post-survey, the number of students who gave 4 and 5 points for PIC1 and PIC2 increased by 19.4% and 5.6% respectively, but decreased by 13.9% for PIC3. We have seen an 11.1% increase in the number of students who scored 1 and 2 for PIC3.

Table 9.
Personal Initiatives and Characteristics (PIC)

	Questionnaire Item	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
		1	2	3	4	5
Pre-Usage	PIC1: Using the Sentiment Analysis Tools give me an advantage over those who don't	2 5.6%	5 13.9%	14 38.9%	**12** **33.3%**	**3** **8.3%**
	PIC2: I would like the Sentiment Analysis Tools to develop and improve	0 0.0%	1 2.8%	16 44.4%	**16** **44.4%**	**3** **8.3%**
	PIC3: I could take part in a project to develop and improve the Sentiment Analysis Tools	**1** **2.8%**	**9** **25.0%**	17 47.2%	9 25.0%	0 0.0%
Post-Usage	PIC1: Using the Sentiment Analysis Tools give me an advantage over those who don't	0 0.0%	5 13.9%	9 25.0%	**20** **55.6%**	**2** **5.6%**
	PIC2: I would like the Sentiment Analysis Tools to develop and improve	0 0.0%	3 8.3%	12 33.3%	**19** **52.8%**	**2** **5.6%**
	PIC3: I could take part in a project to develop and improve the Sentiment Analysis Tools	**1** **2.8%**	**13** **36.1%**	18 50.0%	4 11.1%	0 0.0%

Students see the need and prospects for using Sentiment Analysis Tools, want them to improve, but do not want to be personally involved in projects to develop and improve them (see Figure 6).

Figure 6.
Personal Initiatives and Characteristics Scaling Results

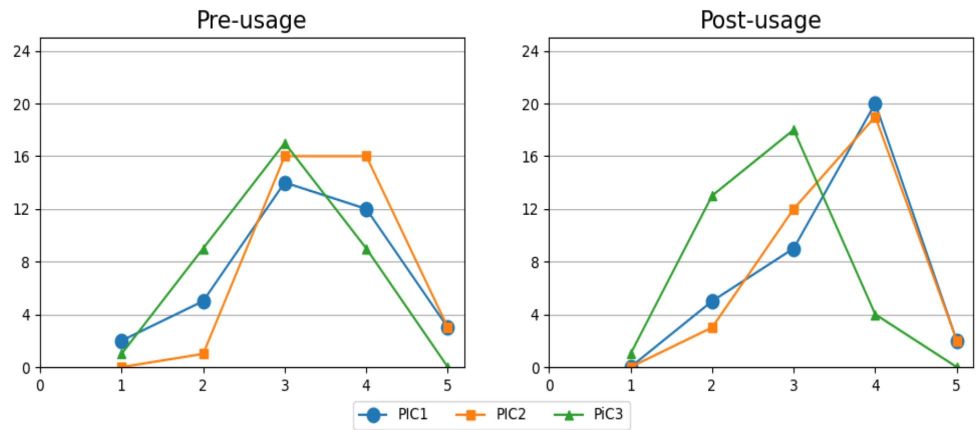


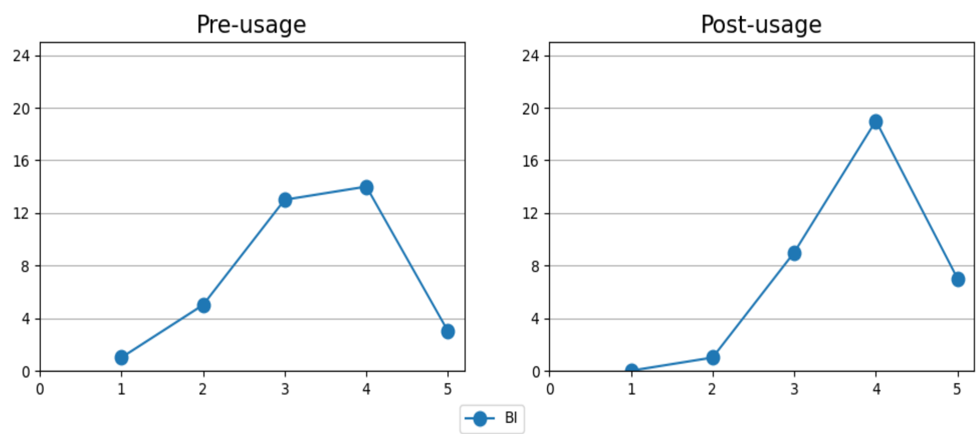
Table 10 shows the students' opinion about their readiness to use Sentiment Analysis Tools in the future. For the post-survey, the number of students who gave 4 and 5 points for BI1 increased by 25.0% in total.

Table 10.
Behavioral Intention (BI)

	Questionnaire Item	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
		1	2	3	4	5
Pre-Usage	BI1: I am willing to use the Sentiment Analysis Tools in the future	1	5	13	**14**	**3**
		2.8%	13.9%	36.1%	**38.9%**	**8.3%**
Post-Usage	BI1: I am willing to use the Sentiment Analysis Tools in the future	0	1	9	**19**	**7**
		0.0%	2.8%	25.0%	**52.8%**	**19.4%**

The vast majority of students (72.2%) believe that they are ready to use Sentiment Analysis Tools, giving 4 and 5 points (see Figure 7).

Figure 7.
Behavioral Intention Scaling Results



The findings indicate that Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions positively influence students' intentions to utilize Sentiment Analysis Tools. Students' behavioral intentions are directed to the readiness to use Sentiment Analysis Tools in the future. Personal initiatives and student characteristics are predictive of the use of these tools, but not of their improvement (Table 11).

Table 11.
The Confirmation of Hypotheses

Hypotheses	Confirmed
H1: Performance expectancy positively affects students' intentions to use Sentiment Analysis Tools	Yes
H2: Effect expectancy positively affects students' intentions to use Sentiment Analysis Tools	Yes
H3: Social influence positively affects students' intentions to use Sentiment Analysis Tools	Yes
H4: Facilitating conditions of web-tools positively affects students' use behaviors of actually using Sentiment Analysis Tools	Yes
H5: Personal initiative and students' characteristics in Sentiment Analysis Tools usage and improvements	Partially
H6: Students' behavior and intentions in future Sentiment Analysis Tools usage	Yes

DISCUSSIONS AND CONCLUSIONS

This study presents the peculiarities of creating and using Sentiment Analysis Tools that contribute to the modernization of linguistic education. According to the literature, the use of digital technologies by university students in academic activities has a positive impact on the learning process, develops digital skills, provides a positive change in prospective critical and creative thinking, activates learning and cognitive activities, and meets learning expectations (Ben Youssef et al, 2015; Bond et al., 2018; Halloran & Friday, 2018; Mancillas & Brusoe, 2016; Pinto & Leite, 2020; Yılmaz, 2021), enables the transition to a digital university model (Fernández et al, 2023), promotes foreign language learning (Gedik Bal, 2024; Kanoksilapatham, 2022), promotes students' acquisition in linguistics (Zhang, 2021), and provides an opportunity to understand the methods and tools of computer linguistics (Darmoroz, 2017).

The results of the study show that the creation of NLP tools is a promising topic for student research projects, and the Python programming language and its libraries NLTK, BS4, TextBlob, Googletrans are effective tools for their implementation (Gujjar & Kumar, 2021; Gupta et al., 2017; Hajba, 2018; Kumar et al., 2020; Mertz, 2004; Rathee et al., 2018; Saura et al., 2019; Sinnott et al, 2016).

The SENTIALIZER web application presented in this article is a multilingual Sentiment Analysis Tool with the ability to visualize results in the form of pie charts. Working on such a project makes it possible to give the student's educational and research activities a constructive character and achieve significant educational outcomes, the most significant of which are: the development of professional knowledge and skills, the formation of a student's digital competence at the highest level (Vuorikari et al., 2022), the development of computational thinking (Romero et al., 2017; Tikva & Tambouris, 2021), modeling linguistic and technological processes, solving a practical problem related to a professional field.

Tikva and Tambouris (2021) describe programming as an ideal medium for the development of computer thinking and 21st century skills in general. The creation of SENTIALIZER involved not only writing code, but also analyzing the situation, identifying its key components, modeling data and processes, which leads to the development of computational thinking (Romero et al., 2017).

The UTAUT model proved to be relevant for determining students' acceptance of digital technology. Overall, students found Sentiment Analysis Tools useful for learning and developing their professional skills. The survey shows that they agree that Sentiment Analysis Tools will help them to increase their own productivity and provide more job opportunities. This finding is consistent with previous studies that argue that engaging students in ICT use increases their digital competencies (Ben Youssef et al, 2015; Bond et al., 2018; Halloran & Friday, 2018; Pinto & Leite, 2020; Salloum & Shaalan, 2019), has a positive impact on academic performance (Mancillas & Brusoe, 2016; Pinto & Leite, 2020), and prepares them to enter the labor market (Ben Youssef et al., 2015; Bond et al., 2018).

Students admitted that their interactions with Sentiment Analysis Tools were clear and understandable, which positively influenced their adoption of the technology. Aliaño et al. (2019) and Bouznif (2018) argue that performance expectancy, as well as effort expectancy, had a direct and important impact on their inclination to use digital technologies. However, Aliaño et al. (2019) note that the digital environment is a natural space for the youth, and they associate task difficulty not with the use of digital technology, but with the type of task that must be developed during the learning process. Therefore, researchers believe that in the near future the inclusion of this variable in the research model will no longer be valid.

Social influence is a key construct of the UTAUT model (Venkatesh et al., 2003). In our study, as well as in the study by Salloum and Shaalan (2019), social influence was defined as a factor of behavioral intention to use digital technology. However, in Bouznif (2018) and Romero-Rodríguez et al. (2020), this construct is defined as having only a negligible effect on behavioral intention. Lehmann et al. (2023) argue that in the case of social influence, the findings of the previous research are fairly inconsistent.

As for the facilitating conditions, it was observed that the students consider themselves equipped with the necessary knowledge and resources to use Sentiment Analysis Tools. To a certain extent, they rely on quick help from the teacher or technical support. Such results echo the findings of studies conducted by Aliaño et al. (2019), Lehmann et al. (2023), Salloum and Shaalan (2019), which emphasize the strong direct effect of facilitating conditions on students' satisfaction with.

The students expressed their readiness to use Sentiment Analysis Tools in the future. The analysis of students' feedback showed that working with SENTIALIZER and other Sentiment Analysis Tools increases their motivation, makes the learning process more interesting as they are faced with acquiring new knowledge and using new technologies. These results come close to those obtained in studies conducted by Aliaño et al. (2019), Lehmann et al. (2023).

The negative change in personal initiatives was unexpected. Students recognized the benefits of knowing how to use Sentiment Analysis Tools and expressed a desire for these tools to be developed and improved. However, they were not ready to put in the effort and personally participate in projects to develop and improve Sentiment Analysis Tools, and they demonstrated this unwillingness in the post-survey. The literature describes cases where students are disappointed in the use of digital technology in whole or in part. For example, Raffaghelli et al. (2022) highlights the disconfirmation effect between the overall acceptance of early warning system in Higher Education in the pre- and post-use stages. The researchers explain this result by the phenomenon of unconfirmed high expectations and warn against the unreasonable introduction of artificial intelligence systems into the educational process.

In our case, the negative attitude of students to the work on the development and improvement of Sentiment Analysis Tools can be explained by the difficulties they encountered at the stage of familiarization with the Python language tools for creating applications, parsing and writing program code. Students' problems in learning programming have been the subject of research for a long time (Kiesler & Pfülb, 2023; Özmen & Altun, 2014; Sobral, 2021). We believe that the problems that caused students to react negatively were: 1) the transition from structural to object-oriented programming; 2) the need to install a certain number of additional libraries; 3) the unusual format of working with the Flask framework; 4) the need to develop code for the Frontend and Backend simultaneously. These problems are consistent with those highlighted in Sobral (2021).

Despite some negative results, the authors believe that it is worthwhile for future linguists to study Sentiment Analysis. They are encouraged by the positive feedback from students on the use of SENTIALIZER, such as "In general, our views on the text coincided, there were no contradictions, which I think is a good result," "SENTIALIZER did a good job with the Ukrainian language, it is interesting that in the scientific style column there is my own translation of a scientific and journalistic article and that SENTIALIZER evaluated the English and Ukrainian text almost identically," "The site was able to recognize a humorous message."

Concerning the limitations of this study, it should be noted that there was only one attempt to implement Sentiment Analysis Tools in the educational process, and the sample size was small. Also, the results are not easily generalizable to the implementation of other digital technologies in linguistic education. Therefore, it would be desirable to repeat the implementation of Sentiment Analysis Tools in different courses with a larger sample size, so that we can study students' acceptance of this digital technology and their intentions for its use in a more in-depth way. Prospects for further research are seen in improving SENTIALIZER using Lexicon Based Approach or / and Machine Learning Approach (Nandwani & Verma, 2021; Wankhade et al, 2022). The lexical approach can be implemented using the SentiStrength program, which is available as a Python package and has a lexicon of 1125 words and 1364-word stems, each with a score for positive or negative sentiment. The development and implementation of other digital NLP tools in the educational process is also of interest.

It is fair to say that, despite its limitations, this study adds to the body of work on the results of the introduction of digital technologies in higher education. It has a clear focus on student learning outcomes, which is an important criterion for the successful integration of technology into the educational process. This paper also validates the UTAUT model, which has proven to be reliable for applied research on student adoption of new digital technologies.

Ethical Statement

Certificate of ethics committee approval was received from the Ethics Committee from the university where the study was carried out.

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