IZMIR UNIVERSITY OF ECONOMICS

FACULTY OF ENGINEERING

FENG 497 FINAL PROJECT REPORT

Career Guidance Assistant

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1. Abstract

This study presents an AI-based personalized career guidance system developed for the students of Izmir University of Economics. However, since collecting data for such a comprehensive project would take a considerable amount of time, we chose the Department of Electrical and Electronics Engineering at Izmir University of Economics as a sample group. The developed assistant is designed as an accessible chatbot via Telegram using API integration of the OpenAI large language model and n8n automation infrastructure. The system brings together multi-dimensional data sources, including students' academic transcripts, specially prepared career test results, course history, interests, and sector analysis, to determine the most suitable EEE sub-disciplines and generates recommendations for appropriate elective courses, faculty members and sector skills. In addition, the assistant analyzes real-time job postings, identifies prominent competencies in the sector, and offers personalized skill development recommendations by comparing them with the student's current profile. The system's integration with Telegram strengthens accessibility by allowing students to interact directly without needing an additional tool. The results of the project show that a data-driven guidance mechanism specific to the department increases students' career awareness, allows for the systematic analysis of strengths and weaknesses, and provides meaningful outputs that can be used for curriculum improvements at the university. The designed system has a flexible architecture that can be easily adapted to different departments and universities if the dataset is expanded.

2. Introduction

The career planning processes of university students, especially in departments with a very broad field of study such as Electrical and Electronics Engineering, are often shaped by uncertainties and information gaps. In today's world, where both technology and industry expectations are rapidly changing, it has become more important than ever for students to identify their areas of interest, make the right course choices, and see which competencies they need to develop. Despite this, many students struggle to understand the sub-disciplines that suit them, find up-to-date information about the industry, and plan their career path systematically. This need has made a new generation approach that can offer personalized recommendations and guide students by analyzing their own data **[3], [5].**

The widespread use of AI-based large language models has made it possible to develop personalized guidance systems in education. Such systems can generate more relevant and consistent recommendations by integrating students' academic backgrounds and interests with industry-oriented skill expectations **[3], [5], [6].** Especially when combined with frequently used platforms in daily life, such as Telegram, students can access quickly and easily accessible counseling support without needing to use an additional application. The fundamental starting point of this project is the need for more accurate, realistic, and accessible guidance for students in their career journeys.

2.1 Problem Statement

Artificial Intelligence (AI) technologies have developed rapidly in recent years, and now they are being used in countless fields, from education to healthcare. One of the most used areas of these developments has been personalized guidance and orientation systems. Especially during university career planning processes, general recommendations are often unqualified because each student has different interests, abilities, and goals. This can make it difficult for university students. Because many university departments cover a wide variety of subjects, it can be difficult for students to decide which areas they should focus on to develop their skills. Furthermore, because the job market and technology are constantly evolving, what is considered important also changes over time **[6]**. Therefore, a system that analyzes a student's academic performance, interests, and strengths and provides personalized recommendations can be quite beneficial.

2.2 Motivation

This is precisely where this project comes in. This system, developed for students, but in the first place, we developed this project for the Electrical and Electronics Engineering department at Izmir University of Economics, is designed as an AI-based career guidance assistant. The system uses a large language model from Open AI API, and the n8n automation platform. This assistant, which operates via Telegram, offers personalized recommendations on a platform easily accessible to students.

The system analyzes students' transcripts and a specially designed career test to determine which subfields are most suitable for them. Based on these results, it then provides students with recommendations for elective courses, faculty members and industry-relevant skills. The system also analyzes current job postings to identify which skills are most prominent in the industry and guides students on how to develop them.

This project will allow students to better understand their own interests and talents, allowing them to clearly see which areas they need to pursue. The university will also be able to analyze students' areas of weakness and tailor its curriculum to the industry.

Ultimately, this study aims to provide students with more personalized, accessible, and effective career guidance using artificial intelligence. It is anticipated that this system could be easily implemented in other departments and universities in the future, given sufficient data availability.

2.3 Alignment with Sustainable Development Goals

This Career Guidance Assistant project was aligned with the Sustainable Development Goals, specifically targeting Goals 4, 8, and 9. Regarding Goal 4 (Quality Education), the system supports inclusive and equitable education by providing personalized, data-driven guidance to every student regardless of counseling availability. By helping students select elective courses that match their abilities, it directly contributes to development of qualified students that are ready for the future, equipped with relevant technical skills. The project also addresses Goal 8 (Decent Work and Economic Growth) by bridging the gap between academic theory and industry reality. Through the analysis of real-world job postings, the system helps students identify high-demand skills that they personally can work on. Finally, the project was aligned with Goal 9 (Industry, Innovation, and Infrastructure), the study uses a large language model that was applied in a messaging app to modernize educational guidance for students.

3. Literature Review

The development of AI-driven chatbots for educational and career-guidance systems has recently gained significant academic and practical attention. These systems aim the provide students with personalized, accessible, and data-driven support for academic and professional decision-making. The reviewed literature indicates that such chatbots have the potential not only to increase the accessibility of guidance resources but also to improve the quality of recommendations by making use of structured data, performance indicators, and user preferences. As educational institutions face growing student populations and limited counseling resources, AI-powered guidance systems offer a scalable solution that can deliver consistent, evidence-based advice while freeing human advisors to focus on complex cases requiring nuanced judgment and emotional support. Moreover, these systems can operate continuously without fatigue, ensuring that students receive timely support even during peak advising periods such as course registration or career fair seasons when human counselors are often overwhelmed with appointment requests.

Accessibility plays a vital role in the effectiveness of digital guidance systems. Phuttawong & Chatwattana (2025) stress that allowing students the ability to access AI-driven counseling "anytime and anywhere" widens educational opportunities and increases inclusion. Likewise, Suresh et al. (2021) show how chatbots stored on familiar platforms like Facebook Messenger make career counseling more accessible, particularly in environments with scarce human advisors. Building on these insights, our project puts a premium on accessibility by embedding an LLM-powered chatbot in Telegram using n8n automation. Because students are already using Telegram every day, they could interact with the system right away with no learning curve, and no registration barrier. This is a very conscious design choice: making it accessible does more than increase usage; it turns accessibility from a technical feature to a pedagogical one. By meeting students where they already are, the system acknowledges that effective guidance must consider not only what information is provided but also how easily students can access it within their daily routines and technological habits.

Nguyen et al. (2022) presented ITCareerBot, a personalized career counseling system for the IT field. The findings revealed that being domain-specific allows the chatbot to make context-aware, accurate, and relevant suggestions by linking student skills with labor-market expectations. Domain specificity enables the system to develop a specialized knowledge base that includes field-specific terminology, career pathways, required competencies, and industry trends that generic guidance systems cannot adequately address. Our project adopts this concept in the context of EEE. The chatbot analyzes each student's transcript, academic performance, and interests to recommend suitable subfields in EEE, such as power systems or embedded systems. In addition, using LinkedIn to pull real-time insights, it informs students about trending skills, useful electives, and relevant university clubs. Thus, our chatbot increases the value of a domain-specific system by combining personalized academic guidance with real data on the labor market in a local setting. The integration of live labor market data represents a crucial advancement over static career guidance approaches, as it ensures recommendations reflect current industry demands rather than outdated occupational information that may no longer align with employer needs or emerging technological developments. By continuously updating its knowledge base with current market signals, the system can alert students to emerging specializations and declining career paths, enabling more forward-looking decision-making that anticipates rather than merely reacts to industry changes.

According to A Study on the Effectiveness of Chatbot-Based Career Guidance System, CRD Journal, 2023, data from open-ended chat conversations are often scattered and inconsistent. The authors remark that structured data collection, like that obtained through guided forms, helps in keeping information organized and largely improves the accuracy of personalized recommendations. This finding aligns with research in human-computer interaction showing that structured inputs reduce cognitive load on both users and AI systems, leading to more efficient processing and higher-quality outputs. In our project, this approach is used directly: before interacting with the chatbot, students fill in a form with crucial information like personality traits, academic results, interests, and transcripts. The system then provides more consistent and logical suggestions when determining the most suitable EEE subfield, since the input is structured. It also ensures that further modules, like LinkedIn skill analysis and CV feedback, work with organized and comparable data, making the whole guidance process more logical and efficient. Furthermore, structured data collection enables longitudinal tracking of student development, allowing the system to identify growth patterns, evolving interests, and changing competency levels over time, which can inform more adaptive and developmentally appropriate guidance as students' progress through their academic journey.

Using structured transcript data in chatbot-based guidance systems allows recommendations to be grounded in students’ recorded academic performance rather than self-assessment alone. By incorporating GPA, course history, and letter grades, virtual advisers can distinguish between areas of strength and difficulty and can adapt their suggestions accordingly. For instance, warning a student about repeatedly failing or risk-intensive courses while highlighting fields where their grades are consistently high. According to a study by Öncü (2025), who introduced The Virtual Academic Adviser, generative AI-based chatbots that explicitly consider letter grades and academic risk patterns provide more precise and context-aware course and pathway recommendations than generic systems that ignore this data, thereby improving both decision quality and student satisfaction with the advising process. The use of transcript data also addresses the well-documented problem of student overconfidence or underconfidence in self-assessment, providing an objective benchmark that grounds career exploration in demonstrated capabilities rather than perception alone. This evidence-based approach is particularly valuable in helping students recognize patterns they might not perceive themselves, such as consistent success in analytical courses despite struggling with theoretical ones, which can reveal aptitudes and suggest career directions that align with their actual performance rather than their assumptions about their abilities.

Beyond internal performance data, several studies emphasize the importance of systematically linking students' competencies to explicit job market and curriculum requirements. According to Westman et al. (2021), AI-enabled career guidance systems that aggregate job advertisements, qualification frameworks, and programme outcomes can compare a student's current skills with target role requirements, perform a competency gap analysis, and then propose concrete developmental steps such as suitable courses, micro-credentials, or work-based learning opportunities. This competency and requirement matching transforms chatbots from simple information providers into tools that support data-driven career roadmapping: students not only receive suggestions about what to study but also see why certain routes are recommended and which missing skills must be addressed. As a result, guidance becomes more realistic, actionable, and better aligned with evolving labour-market needs. The transparency of this matching process builds students' confidence in the recommendations, as they can understand the logical connection between their current competencies and suggested pathways, making career planning feel less abstract and more grounded in concrete, achievable steps.

Building on person–environment fit perspectives, the literature contends that career guidance is most effective when it starts from students' interests and values and seeks environments that match them, rather than treating career choice as primarily skills. In a large-scale study of undergraduates, Quinlan and Renninger (2022) show that students' interest in their academic subject predicts career decidedness, and that this relationship is mediated by their desire to pursue that interest in their future work, highlighting the importance of connecting guidance to what students find meaningful and engaging. This perspective is consistent with Holland's RIASEC theory, which proposes that matching individuals with their vocational interest types (Realistic, Investigative, Artistic, Social, Enterprising, Conventional) with congruent work environments leads to higher satisfaction, persistence, and performance (Holland, 1997). Holland's framework has been validated across diverse cultural contexts and remains one of the most empirically supported models in vocational psychology, suggesting that interest-based matching should be a foundational component of any comprehensive guidance system. In the context of AI-based tools, drawing on such interest-based frameworks means designing chatbots that treat students' interests and values as core inputs, then integrate transcript and labour-market information to generate recommendations that are both feasible and personally meaningful. By synthesizing interest assessments with performance data and labor market intelligence, AI guidance systems can help students navigate the often-difficult balance between passion and pragmatism, identifying career pathways that offer both personal fulfillment and viable employment prospects. This holistic approach acknowledges that sustainable career success requires not only competence and market fit but also intrinsic motivation and alignment with personal values, factors that significantly influence long-term job satisfaction and professional persistence.

4. Methodology

4.1 System Architecture & Workflow

The system's workflow operates on the n8n platform, using Telegram for interacting with user, using Open AI API for the large language model and Google sheets for obtaining the student's test results. The main workflow architecture is divided into 2 distinct but interconnected pipelines. The first pipeline handles the first interaction with the student via Telegram, while the second pipeline is responsible for analyzing students test results to deliver 5 separate personalized career recommendation messages via telegram.

The first pipeline starts whenever a student interacts with the system through Telegram. An AI Agent, powered by the Open AI API, processes the incoming input before passing it through a logic router node designed to check if the user is interacting with the chatbot for the first time. If the system identifies a new user, it triggers an automatic welcome message providing general information about the Electrical and Electronics Engineering field. This message concludes with a specific link directing the user to a character test in Google Sheets to examine their academic interests. If the user has already interacted with the chatbot before, the system bypasses the introduction and sends the interaction to a LLM for general messaging via Telegram. The n8n workflow of the first pipeline can be found at Figure1.

The second pipeline is responsible for generating personalized career guidance messages and is triggered automatically when the student has completed the career test in Google Sheets. The workflow operates on a linear sequence of five distinct analysis stages, each optimized by prompt engineering to structure the LLM's output. In the first stage, the system ingests specific field data alongside the user's career test results. In this stage the system processes this information to generate a structured suggestion regarding which two EEE sub-fields, such as signal processing or embedded systems, align best with the student's profile. After this information is obtained the LLM sends a response message about suggesting suitable EEE fields via Telegram structured by prompt engineering.

Following the field suggestion, the workflow advances to transcript analysis. Since the user uploads their transcript as a PDF in the final question of the career test, the system employs an HTTP Request node to retrieve the file and a file extraction node to parse the PDF content into text readable by the LLM. This parsed data is fed into the second stage which was about Transcript Analysis, evaluating the student's academic history against their test results to generate a specific response. The system then proceeds to the third stage regarding elective courses. By retrieving a dataset of available courses and cross-referencing it with the user's identified interests, the LLM constructs a recommendation message suggesting the most suitable elective courses for that specific student.

The workflow concludes with two final stages regarding instructor suggestion and job suggestion. In the fourth stage, the system inputs a dataset containing instructor profiles of the IEU, which LLM analyzes and recommends instructors considering the student's interest areas. In addition to this, by using the student’s interest areas graduation project topics were also suggested along with instructor suggestions in the same message. Finally, the process ends with a fifth stage focused on job suggestions. Here, the job posting data obtained from LinkedIn were used along with the student’s interest areas to generate a Field-Job Suggestion message. The goal of the last stage was to provide real world perspectives to students to help create a realistic point of view about their career planning, suggesting possible jobs that might be considered by the student for the future. The n8n workflow of the second pipeline can be found at Figure 2 and Figure 3. The sequence diagram of the project can be found in Figure 4.

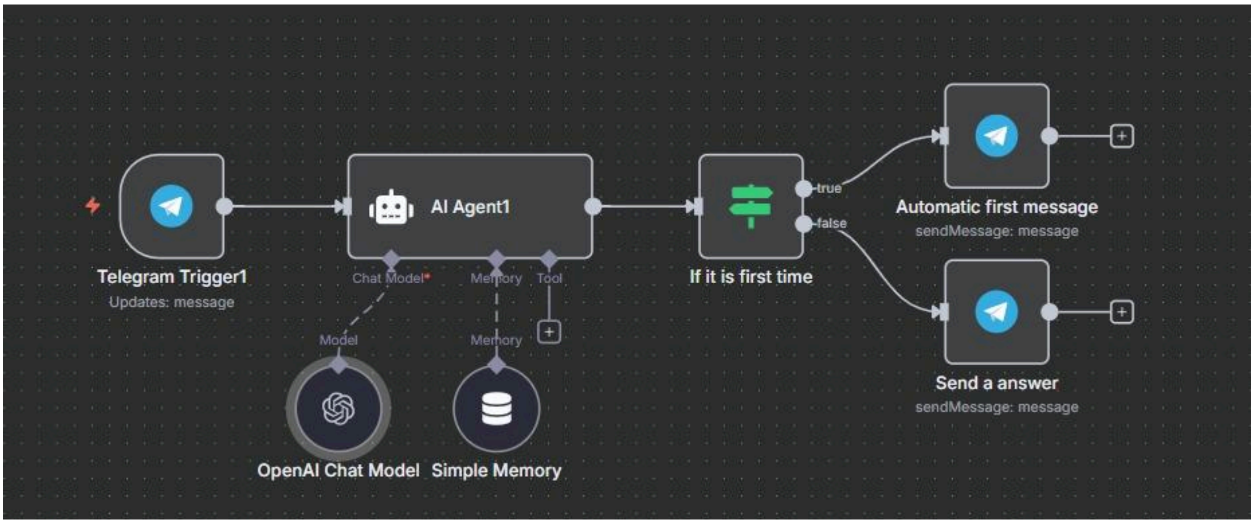

Figure 1: Demonstrating the pipeline 1 n8n workflow

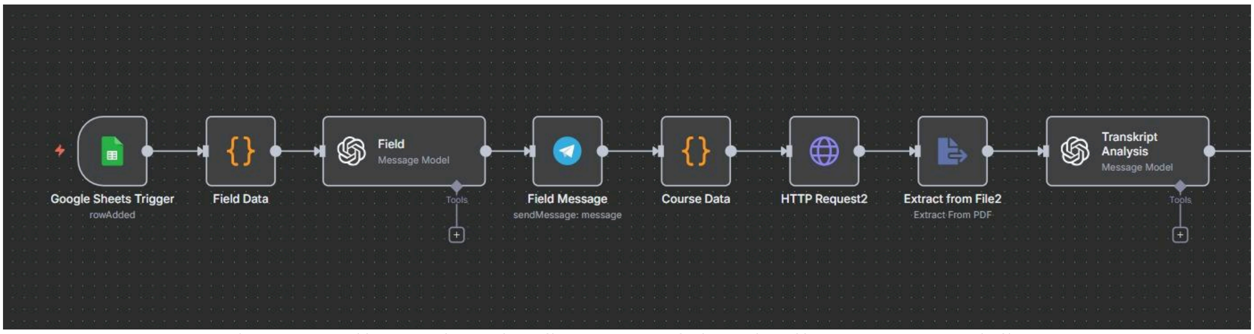

Figure 2: Illustrating the first part of the pipeline 2 n8n workflow

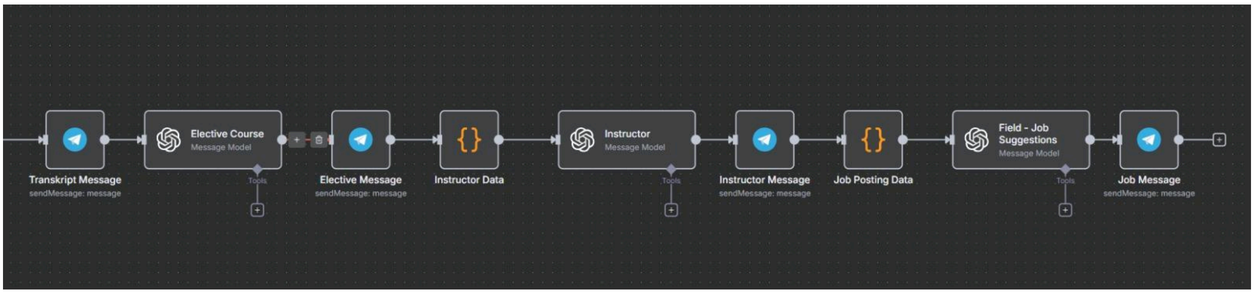

Figure 3: Illustrating the second part of the pipeline 2 n8n workflow

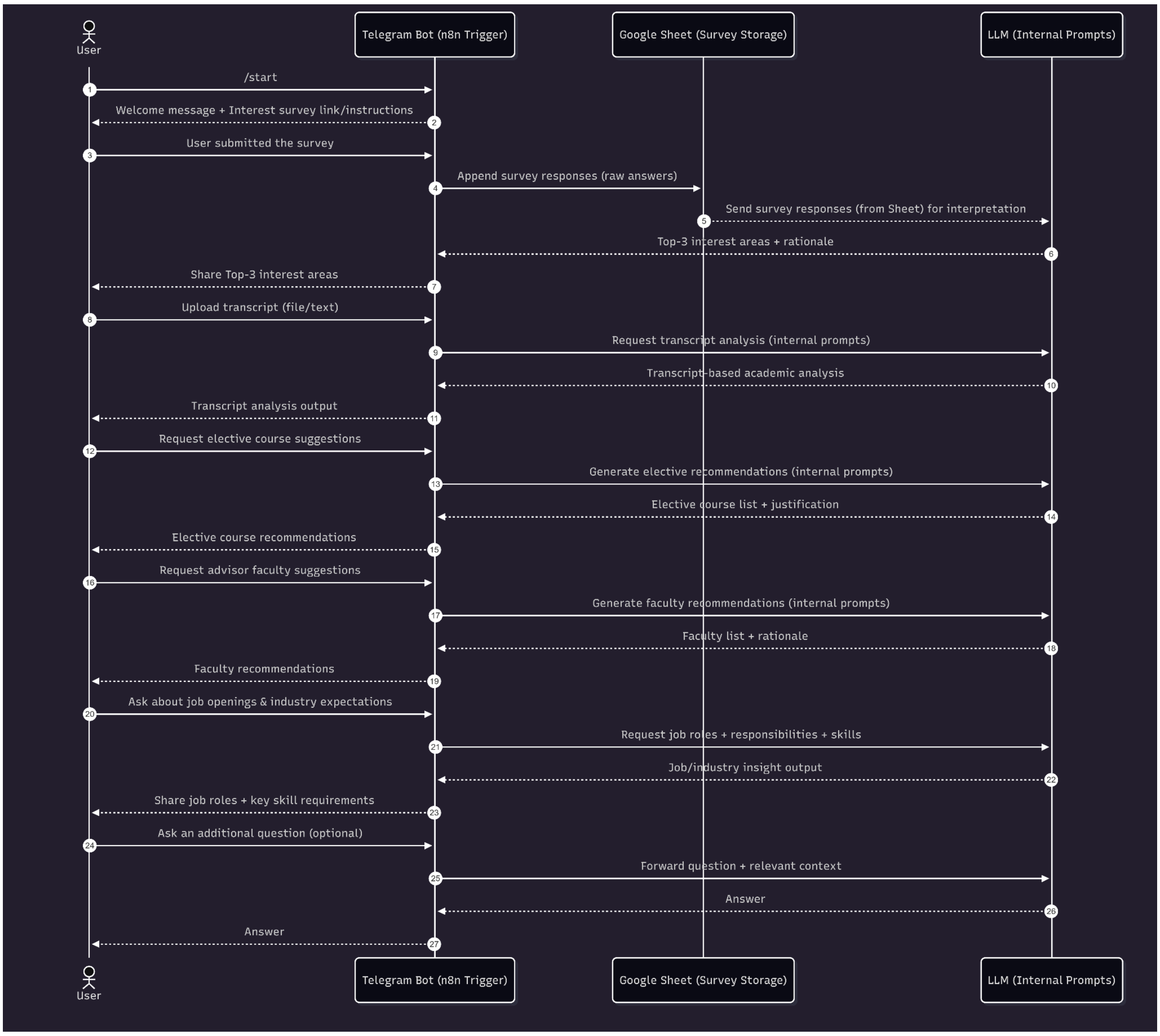

Figure 4: Illustrating the sequence diagram of the n8n workflow operations

4.2 Data Collection & Knowledge Base

The system workflow uses various datasets to utilize the student's personal career test results alongside official university records and real job examples. The goal of that is to make sure that every recommendation provided by the system is directly linked to the actual EEE curriculum and current job market. The system uses career test results, field dataset, parsed transcript information, course dataset, instructor dataset and job dataset. The field dataset was created manually by senior EEE students. The course and instructor datasets were obtained from the IEU website, and the job dataset were obtained from LinkedIn. Example data about the field, elective, instructor and job datasets can be found at **Appendix B**.

For the field data suggestion, the main information used for determining a student's career profiling interests was stored within Google Sheets. This dataset consists of 50 multiple-choice questions, manually crafted by senior Electrical and Electronics Engineering students at Izmir University of Economics to ensure alignment with the local academic curriculum. Each question consists of five distinct options, with every answer strictly mapped to one of eight specific EEE sub-fields such as Power Systems, Control and Automation, or Renewable Energy. These sub-fields were identified by the senior EEE students considering university’s course lists and personal academic experiences. This data helped identify the students' preferred EEE subfields. Example questionnaire can be found at **Appendix A**.

For the transcript analysis two separate data were used. First data that was used by the system was a field dataset. The dataset contains the eight distinct sub-discipline of Electrical and Electronics Engineering created by senior IEU students. The data set provides a concise definition, associated industrial sectors, typical job roles, and the specific technical skills required for that path for each subfield. The dataset was created in JSON format for n8n compatibility, preventing potential errors. The second data that was used was transcript information obtained from the student. Inside the Google Sheets Career test, in addition to the 50 multiple-choice questions, a 51st question exists, asking the student to upload their transcript in PDF format. Then, the system parses the transcript into plain text. Next, both the parsed text of the transcript and field dataset was given to the LLM, allowing the system to analyze the student's academic history in full context, categorizing both mandatory and elective courses by their prerequisites and relevance to the eight EEE sub-fields.

For the elective course message both the career test results and course dataset were used. The course dataset was obtained from the IEU website and was in JSON format. The dataset divides courses into mandatory and elective course groups. Each course data contains course code, name, semester, 2 related EEE subfields of the course and most related EEE subfield information. The related EEE subfield information was created manually by the senior EEE students while the remaining information was obtained from the IEU website. In addition to this, the dataset contains a chains section, demonstrating the prerequisite of each course. Lastly, the dataset categorizes each elective course into separate EEE subfield branches to prevent the LLM suggesting a course unrelated with the student's preferred subfield. Overall, this dataset ensures the LLM receives both mandatory and elective course information along with their related subfield information to give suitable elective course suggestions and to prevent giving mandatory course suggestions.

For the Instructor message, along with career test results, instructor dataset were used. The dataset was obtained from the IEU website and was in JSON format. This dataset contains information regarding the IEU instructors with columns such as name, focus area, EEE subfield alignment and notes. The alignment and notes columns were created manually by the senior EEE students, while the remaining columns were obtained from the IEU website. The alignment column links the EEE subfields with the lecturer and the notes section gives a brief description of what areas the lecturer specializes in.

The last message was the job suggestion message. For this message both career test results and job dataset were used. The job dataset consists of 10 different job posts from LinkedIn obtained on December 5. The dataset was in JSON format. The dataset contains company name, position, field, job responsibilities and required skill qualifications of the job. All the job posts in the dataset were aligned with the EEE subfields covering nearly all subfields with different job posts. This dataset was especially crucial for the project, making sure suggestions from the LLM are based on real world expectations.

4.3. Prompt Engineering

The prompt engineering process was required to ensure that LLM message responses were accurate and well-structured. The creation of the prompt engineering process conducted by several iterations, to eliminate encountered problems and create desired structure of the messages. The general prompt structure of the messages can be divided into 5 sections: System Role, Input Data, Selection Rules, Output Rules and Output Structure. Example prompt used for the project can be found in **Appendix C**.

The system role section was added to make the LLM respond in a suitable tone required for the message. For the field analysis and transcript analysis messages the LLM was assigned as EEE Career Guidance Specialist. For the elective course message, the LLM was assigned as Academic Advisor for EEE. For the instructor message the LLM was assigned as Academic Mentor & Graduation Project Advisor. Lastly, for the job message the LLM was assigned as Industry Insight Advisor for EEE students.

The input data section was added for implementing the specific datasets that were used by the LLM for each message. This part ensures the LLM knows exactly what dataset to use. An example for this is the field dataset put into the input data section: {{ $('Field').item.json.content.text }}.

The Selection Rules section was added to ensure LLM does exactly what was expected from it when doing operations. In this section it was explained to them LLM how to proceed with the given tasks. For the transcript message it was stated to never give assumptions or never referring to how the data was proceeded. This ensured to prevent problematic responses that occurred in the previous iterations. It was also stated in this part that in case of students not uploading the transcript or missing information on the transcript, the LLM should keep statements general and cautious. Another example is the elective course message prompt. Here the LLM was instructed to recommend exactly 3 elective courses and each recommended course must appear in the official elective course catalog. This ensures that LLM will only suggest the elective courses and not mandatory courses. In addition to this the LLM was instructed to not mention any frequencies or statistical information as they can be accessed by LLM via Google Sheets result section.

The output rules section serves mainly as the general filter for the responses. The second pipeline of the n8n structure consists of a singular line of nodes that are connected one by another. This created a problem that every time a new dataset was implemented to the system it is kept in memory of the LLM. This means a potential problem where the LLM could use a dataset that was not intended for the task. To prevent this issue the output rules section was added in the prompt. In this section the LLM is instructed as what not to mention. An example is the instructor suggestion prompt. In there it was stated that the LLM should not mention quizzes, scores or calculation as well as any backend process in the workflow. Moreover, the tone was also stated in this section, telling the AI to have a practical and project-oriented tone. For the job posting output rules part it was stated to not mention any quizzes, scores calculations, assumptions, automation or how the job was selected. It was also asked to not encourage applying or recruiting language and the tone must be practical and informative.

The last section is output structure. This part is responsible for creating the Telegram message structure. The prompt in this part focuses on strict locations and sentence types the LLM should respond to. An example is that elective course prompt. There, the LLM was tasked to follow the exact given structure. This practice was applied for every prompted message in this project. The structure for the elective course prompt consists of career focus, recommended electives and academic outlook parts. Another example is the job prompt. In the prompt it was asked to LLM to first give industry insight. Then an aligned target role is stated, then the responsibilities and industry expectations should be stated in bullet points and lastly a focus point that highlights the most important capability the student should strengthen should be written.

4.4 User Experience Flow

In this section complete user experience is explained when using career guidance chatbot. Firstly, the user enters the Telegram and receives a welcome message(Figure 6). The student clicks the link and completes the career test in Google Sheets. After that the user receives 5 different messages one after another. The user receives field suggestion (Figure 7), transcript analysis(Figure 8), elective course (Figure 9), instructor (Figure 10) and job suggestion (Figure 11) messages respectively. The full experience of the user was demonstrated in Figure 5 as flowchart.

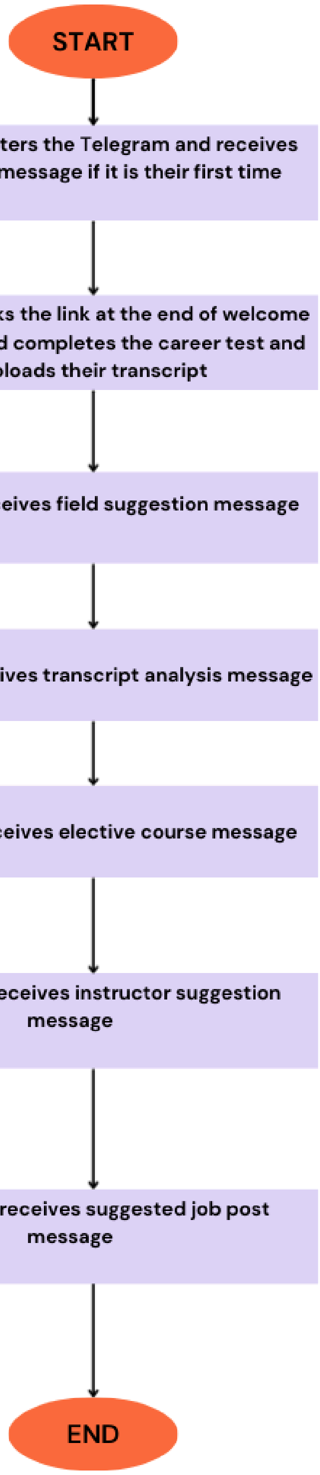

Figure 5: demonstrating the user experience flowchart of the career guidance chatbot

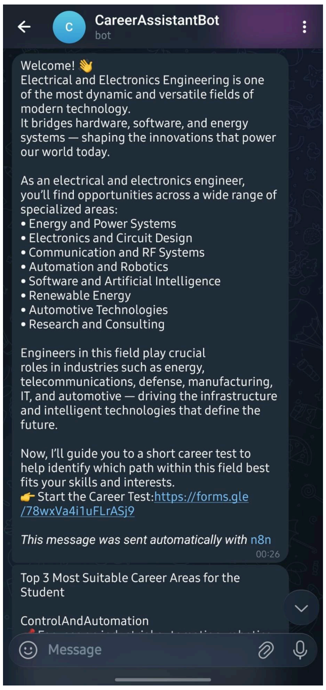

Figure 6: Showing welcome message

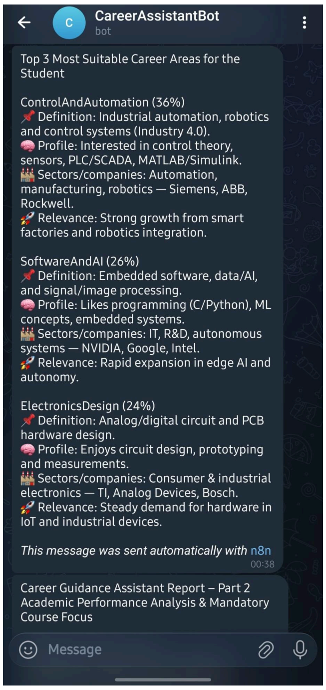

Figure 7: Illustrating field suggestion message

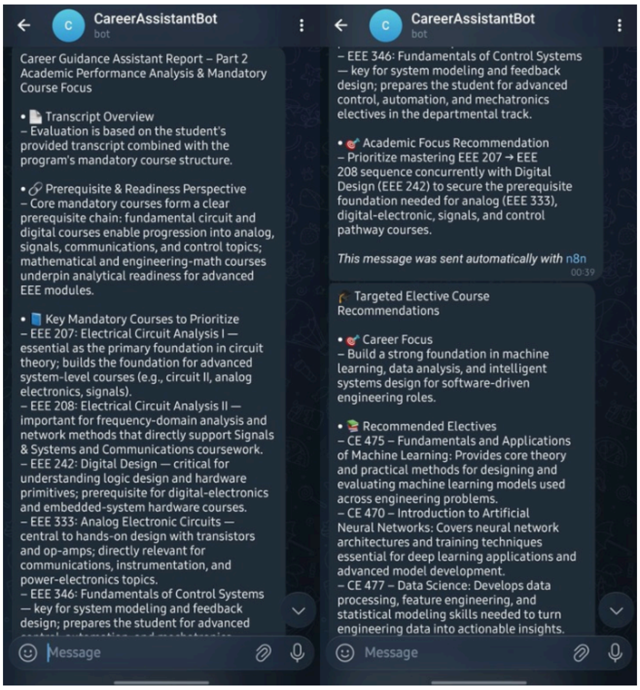

Figure 8: Demonstrating the transcript message

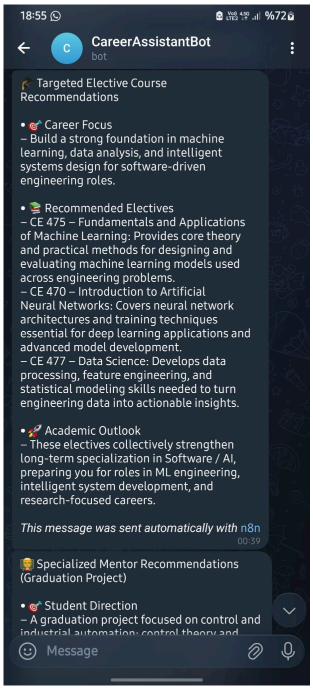

Figure 9: Showing elective course message

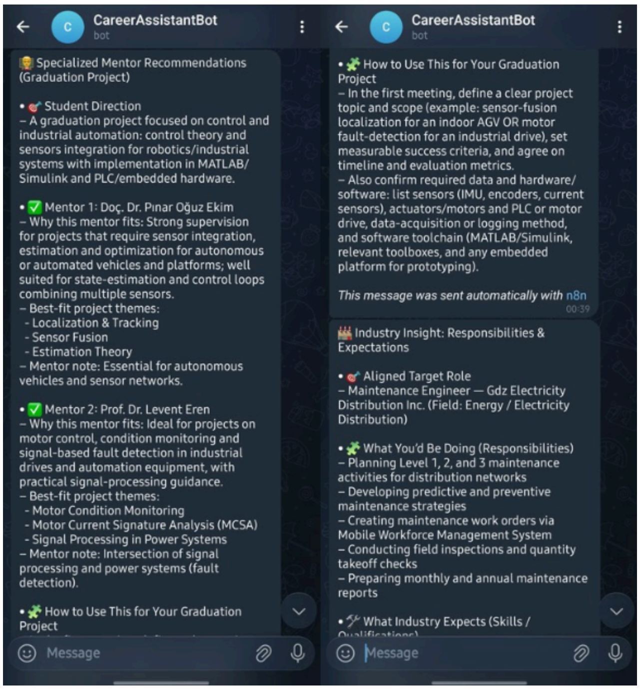

Figure 10: Displaying instructor message

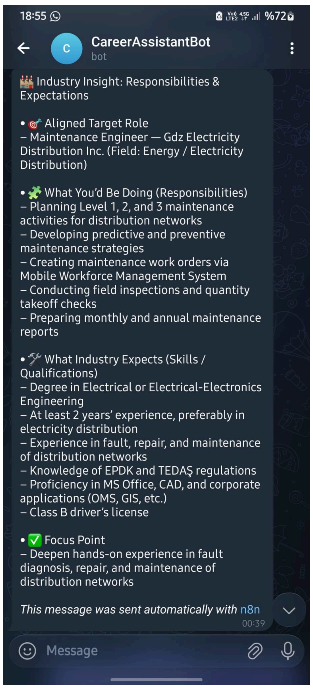

Figure 11: Demonstrating job message

4.5 Cost Analysis

This section presents a scenario-based cost analysis for scaling the proposed Telegram-based career guidance chatbot. Operational costs are primarily influenced by user volume, interaction length, and document processing, such as PDF uploads. The current proof-of-concept (PoC) usage serves as the baseline for estimating future costs under various deployment scenarios. This methodology supports a financially grounded discussion while avoiding unsupported assumptions regarding fixed pricing in future model or API versions.

4.5.1 Baseline Cost (Reference Point)

During the proof-of-concept (PoC) stage, the system operated with a restricted number of users, brief conversations, and limited document processing. Within this scope, the observed monthly API-related cost was: Baseline (PoC): ~26 USD

This value serves as the reference point for scenario-based cost comparisons.

4.5.2 Cost Drivers

As the system scales, costs are expected to increase primarily due to the following factors:

1. Higher user volume (more concurrent and total interactions)
2. Longer conversations and history needs (more context to process per session)
3. Document uploads and summarization (e.g., transcript/PDF processing increasing token usage)
4. Potential need for a higher-capability API/model (larger context and improved stability at scale)

A practical implication is that storing user profiles and summaries in an external database, rather than repeatedly transmitting all context to the model, can reduce token usage and enhance cost efficiency.

4.5.3 Scenario-Based Cost Estimation

Future monthly costs are estimated by applying a relative usage multiplier to the baseline cost of 26 USD. These multipliers reflect anticipated growth in requests and context size, and should be interpreted as approximate planning values rather than precise budget figures.

Table 1: Displaying scenario based cost estimation

Deployment Scenario	Relative Usage Level (Multiplier)	Estimated Monthly Cost (USD)
Proof of Concept (Current)	1x	~26
Department-level deployment (EEE-only)	3-5x	~78–130
Faculty-wide deployment (multiple engineering departments)	8-12x	~208–312
University-wide deployment	15-20x	~390–520

4.5.4 Interpretation and Practical Implications

These estimates indicate that, although the current API configuration is financially feasible for PoC-level usage, broader deployment may necessitate cost-aware architectural decisions, such as:

- Storing user profiles, transcript summaries, and prior outputs in a database and passing only relevant context to the model,
- Using summarization or staged prompting to reduce repeated long-context calls,
- Evaluating alternative API/model options if a larger context and reliability become necessary.

Overall, the cost profile demonstrates that scalability presents both technical and operational budgeting challenges, which should be addressed in future system planning.

4.5.5 Additional Consideration: Requirement for More Capable LLMs at Scale

Table 1 uses the same LLM setup as the proof-of-concept stage. For larger deployments, a more advanced model might be needed to handle longer conversations and retain more context. This is especially important if students submit longer transcripts or if the assistant needs to manage more complex interactions. In these cases, the cost per interaction may be higher than shown in Table 1. Table 1 should be seen as a baseline estimate for the current model, and future deployments may require a larger budget for a more capable and possibly more expensive LLM.

4.5.6 Practical Implications and Cost Control (Future Planning)

To make sure the system stays affordable as it grows, future versions can use cost-saving strategies like these:

- using structured summaries to avoid repeating long prompts,
- saving outputs that are used often,
- pulling out only the needed parts of transcripts instead of sending entire documents,
- and, if necessary, managing context outside the system, such as storing user summaries, to avoid sending the same information with every request.

In summary, the cost analysis shows that the current solution works for a proof of concept, but expanding it will need careful planning for both technology and budget, especially if usage grows or the system needs more advanced LLM features.

4.6 Project Execution Timeline

The Career Guidance Assistant was developed over a structured 10-week timeline, as illustrated in Figure 12. The project progressed from problem definition and data planning (Weeks 1-3) to technical design (Weeks 4-6), concluding with workflow implementation, testing, and reporting (Weeks 7-10).

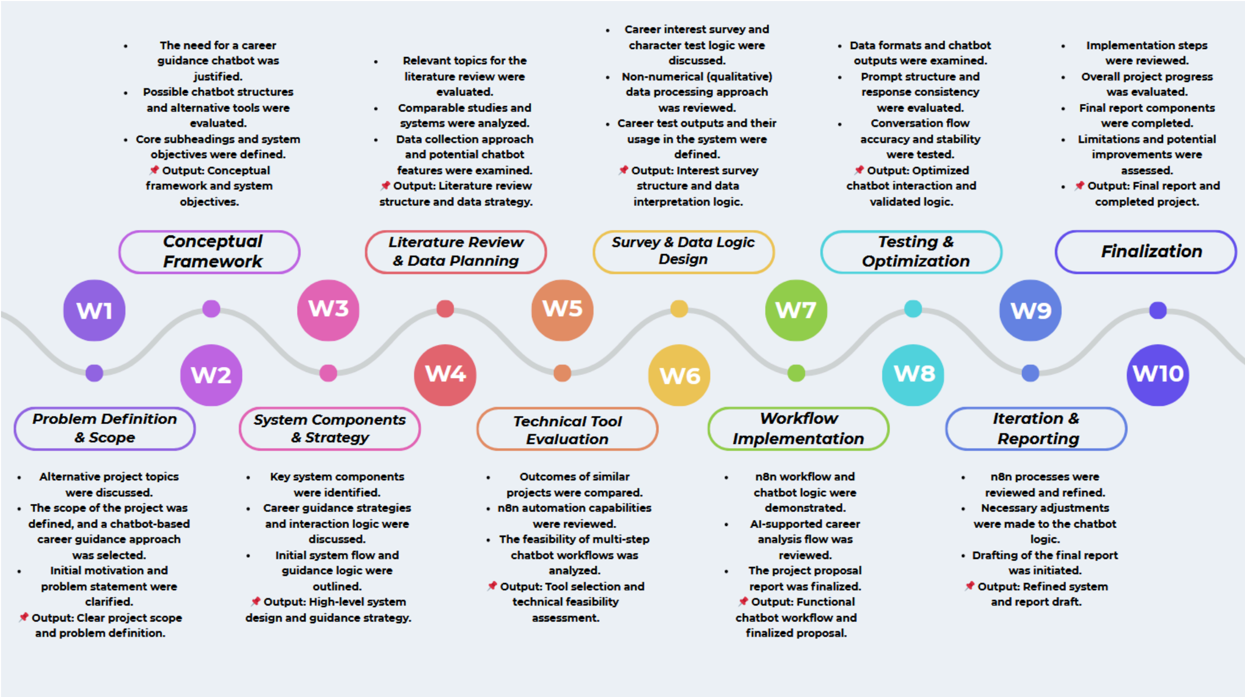

Figure 12: demonstrating an infographic for the project execution timeline

5. Results and Discussions

This section presents the prototype results and explains their implications for the project goals and research on AI-based career guidance systems. The analysis looks at how the system works, such as matching based on interests, providing structured academic and career advice, and allowing users to interact through conversation. By reviewing the system's outputs and how users interact with it, this section assesses how well the approach turns student input into useful guidance within the project's scope.

5.1 Main Findings

The main result of this project is a working prototype of a career guidance assistant. This assistant is a Telegram chatbot that provides personalized advice to Electrical and Electronics Engineering (EEE) students using automated steps. Telegram enables direct communication with the language model, while n8n manages the workflow in the background. When a student messages the bot, it introduces itself and requests the completion of a short interest survey. The survey responses are stored in Google Sheets, which simply tracks the data and does not participate in decision-making. The language model then reviews the survey answers and generates a ranked list of the top three interest areas for the student, including brief explanations and alignment indicators. This approach ensures that the advice is tailored to the student's interests rather than being generic.

After the system identifies a student's interests, it transitions to a chat-based guidance mode. Students can seek assistance at any time, and the system responds with step-by-step guidance tailored to their questions. Advice is available regarding elective course selection, recommendations for instructors or mentors, and information about jobs and industries that align with student interests. When using the elective module, the assistant suggests courses that suit the student's interests and provides justifications for each recommendation. The instructor module recommends suitable instructors or mentors and explains their relevance to the student's academic journey. For career exploration, the job or industry module outlines possible roles, typical responsibilities, and essential skills in the chosen area. All responses are delivered through the same chat interface, making the system intuitive and consistent with standard messaging platforms.

The results demonstrate that the prototype is capable of transforming student interest data into practical recommendations, delivered in a format that suits Telegram and supports early career planning. System screenshots and sequence diagrams illustrate that the assistant can (i) establish a personalized starting point by identifying the top three interests from survey responses and (ii) provide follow-up advice through individual, user-activated modules for electives, instructors, and job market information.

Table 2: Illustrative pilot output from a single example session (for demonstration)

Step	Example user request	Example system output (summary)
Interest survey result	The user completes the survey.	The top 3 interest areas returned with alignment scores
Elective recommendations	“Could you suggest electives in these areas?”	A curated list of electives aligned with identified interest areas, with short explanations of relevance
Instructor recommendations	“Could you recommend instructors based on their fields?”	Mentor/instructor list aligned with interest areas and project directions
Job insights	“What job openings exist, and what tasks/skills are needed?”	Example role + responsibilities + qualifications + suggested focus points

Table 2 shows an example from one pilot-style interaction to illustrate what the outputs look like in practice. Since it is based on just one example, it serves as a demonstration or case illustration, not as a statistically generalizable evaluation.

5.2. Scientific and Practical Meaning of the Results

5.2.1 Scientific meaning (in relation to literature)

A central theme in the career guidance literature is that effective guidance tools should incorporate (i) user interest/aptitude signals and (ii) actionable pathways such as skill requirements, courses, and role expectations. Classic vocational guidance theory (e.g., Holland’s person–environment fit) emphasizes that aligning personal interests with environments and roles is a foundational principle for career decision-making [8]. In addition, modern AI-based career guidance discussions highlight the need for systems that are accessible, responsive, and capable of supporting iterative exploration rather than giving a one-shot recommendation [6].

The prototype aligns with these principles in three ways:

1. **Interest-driven personalization:**
   The system's first major output—a list of the top three interest areas—implements a structured "starting point" for personalization. This is consistent with career counseling chatbot approaches that aim to adapt responses to user preferences and goals [2], [3], [4].
2. **Iterative guidance through conversation:**
   Rather than producing a single static recommendation, the bot supports follow-up questions and additional guidance requests (electives, instructors, job expectations). This conversational iteration is consistent with the direction of AI-driven advising systems that emphasize ongoing interaction and incremental refinement [6].
3. **Bridging education and employability:**
   The system connects interest outputs with practical academic decisions (electives and instructor consultation) and career-market understanding (roles and skill expectations). This reflects the broader point that interest development and employability planning are linked processes rather than separate tasks [7]. It is also consistent with work emphasizing AI-supported academic advising and course selection support [5].

5.2.2 Practical meaning (for students and universities)

From a practical standpoint, the results demonstrate that a lightweight, widely used platform (Telegram) can deliver a meaningful advising experience without requiring a separate application. In real use, this matters because students often abandon guidance tools that demand additional onboarding or complicated interfaces.

Concretely, the prototype can reduce friction in early-stage career planning by:

- Giving students a quick, interpretable "direction signal" (Top-3 interest areas),
- Translating that direction into actionable next steps (electives, instructors, focus points),
- Supporting career-market awareness (responsibilities, skills, qualifications),

- Enabling students to ask follow-up questions in natural language.

5.3 Factors Influencing the Observed Results

Various factors are at play in determining the quality and specificity of the guidance that the system is able to offer. How the interest survey questions are asked is especially important for matching the user with their career. Since the top-3 interest clusters are derived from the survey questions, these questions should be designed in a way that distinguishes between various sub-fields, and not just between fields, in order for the suggestions to be very specific.

Another key factor is that the system uses a large language model to make decisions. Allowing the model to interpret information and suggest options, rather than following fixed rules, makes the system more flexible and better able to justify its choices. However, the results depend on how well the prompts guide the model to connect interest data with academic and career information. So, the quality of recommendations depends more on how prompts are written and what limits are set, not just on the data itself.

The availability and organization of domain-specific datasets also affect the system's performance. Suggestions for courses, instructors, and jobs depend on well-structured information about curriculum, expertise, and industry needs. When datasets include enough detail, such as focus areas or skill links, the system can give more specific and useful advice. Limited or overly general datasets broaden the recommendations. The system is also important. Rather than following a set path, the system provides guidance tailored to different user requests. This approach is similar to real advising, but it also means that the quality and focus of the advice depend on the questions users ask and what they want to explore. So, both the system's design and users' engagement with it shape the results.

These factors explain why the system aims to provide general guidance and encourage exploration rather than strict career advice. The results reflect a mix of user interests, the language model's reasoning, the details in the datasets, and how users interact with the system within the project's limits.

5.4 Discussion in Relation to Prior Work

The results of this study are similar to earlier research on AI-based career guidance and academic advising, which emphasize the need for personalization, accessibility, and ongoing exploration. Like earlier chatbot counseling methods, the system uses a conversational approach that allows users to explore career questions step by step rather than receiving a single fixed answer. This approach is similar to real advising and helps students gradually build their understanding of academic and career options.

This system stands out from other studies by helping students turn their interests into real academic and career steps. It links students' interests to suggested elective courses, recommended instructors, and job expectations. This demonstrates that interest-based guidance can provide practical decision support **[7], [8].**

The system is designed to keep data storage and reasoning separate, following new trends in AI guidance tools that use straightforward data collection and flexible, model-based analysis. Overall, the findings suggest that conversational AI can help link student self-assessment, academic choices, and understanding of industry needs. These systems are meant to support, not replace, traditional advising.

5.5. Summary of the Results and Discussion

In summary, the prototype shows a complete conversational process for interest-based career guidance. It includes a survey, uses an LLM to identify the top three interests, offers on-demand information about electives, instructors, or jobs, and **provides follow-up Q&A**. These results are practical because they link career interests to specific academic and professional steps. They also support research on the benefits of personalized, accessible, and ongoing AI-based career guidance [2], [3], [4], [5], [6], [7], [8]. However, these findings should be viewed as a demonstration of the prototype**.** Any single-example output table, such as Table 2, should be clearly labeled or placed in the appendix to ensure accurate reporting.

5.6 Future Work

The career guidance assistant developed in this study is, in its current form, a sample system working with limited data; however, it is possible to expand and improve it in various aspects in the future. One of the priority development areas is the integration of a CV review and feedback module into the system. In this situation, the aim is to analyze students' resumes according to the positions they are targeting and industry expectations. Identify weaknesses and offer content-focused revision suggestions.

Another important area of development is the personalized job posting and recommendation system. In future versions, the system can be improved to analyze job postings on career platforms. For example, LinkedIn and Kariyer.net. After that suggest positions suitable for the student's academic background and interests. This situation will allow students not only to be guided to job postings but also to understand why these positions are suitable for them.

Furthermore, it is planned to expand the system to offer effective interview preparation support in later stages. Students will be able to practice technical and behavioral interview questions specific to the fields they are considering applying for, contributing to a more informed and prepared approach to interview processes.In addition, creating information and guidance modules for internship application processes, especially for students at the beginning of their careers, will enable the delivery of structured guidance on application dates, required documents, and evaluation criteria.

From an interface perspective, while the current Telegram-based structure offers an advantage in terms of accessibility, a transition to a mobile application or web-based platform is planned for the future. This will allow for more advanced visualizations, long-term career tracking, and user progress analysis.

Finally, expanding the scope of the system is an important area of future work. Although the current application is only developed for the Electrical and Electronics Engineering department, a scalable career assistant can be created for all departments and different universities if the necessary academic and institutional data are provided by the universities. The same approach can be extended to departments outside of engineering by adapting field-specific surveys and evaluation criteria. With access to larger and more diverse datasets, the accuracy and usefulness of the system can be significantly increased.

6. Conclusions

This study resulted in the creation and implementation of an AI-powered career guide distribution system for Electrical and Electronics Engineering departments at Izmir University of Economics. The developed system considers interests, academic backgrounds, and current industry information together, supporting students in learning about their academic and early career planning in advance.

The system does not attempt to predict a student's skills or determine a single "right" career path. Instead, it is designed as a decision-supporting tool that helps students better understand themselves, clearly identifying their strengths and areas for improvement. Interest surveys determine the student's inclination towards specific subfields, while transcript analysis assesses the extent to which these interests correlate with academic performance. The combined consideration of these two dimensions provides opportunities for both process-oriented and student-centered recommendations.

Designed as a Telegram-based chatbot, the system simplifies usage and offers the possibility of receiving guidance through a platform already present in the fragmented daily world. The planned n8n automation structure and controlled request design used in the background ensure the presentation, repeatability, and explainability of the recommendations. Thus, instead of recording random or focused guidance, the system offers a guidance process where each step is based on the previous stage.

The current version of this product is a proof-of-concept presented with boundary data. The limited number of survey sales and the lack of direct access to large, enterprise-wide data sources limit the scope and accuracy level of the system's offerings. However, these limitations do not indicate misguidance; on the contrary, they strengthen the infrastructure, which, supported by more data, can produce much stronger and more comprehensive results.

In conclusion, this project offers an accessible, transparent, and student-centered approach to the career planning processes of university students. Positioning artificial intelligence as a tool, not an "authority," in its deployment is one of its most important contributions. The developed system, as a solution with complementary academic funding components, provides a sustainable foundation open to future development with broader data packages and scopes.

7. References

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8. Appendices

8.1 Appendix A

This appendix consists of the first five questions from the career test.

1. Which task excites you the most in a project team?

A) Planning power distribution and circuit connections

B) Improving solar panel or battery efficiency

C) Designing the motor driver circuit

D) Processing sensor data and writing decision algorithms

E) Performing object recognition from camera images

2. When a device breaks down, what is your first reaction?

A) Using measurement tools to find where current is not flowing

B) Opening the PCB and inspecting the components

C) Checking the microcontroller software

D) Measuring the input line and fuses

E) Testing temperature, gas, or motion sensors

3. Which project attracts you more?

A) Building a solar-powered vehicle

B) AI system that detects defects from images

C) Autonomous mini robotic arm

D) Electric vehicle motor driver

E) Smart-sensor drone

4. What motivates you most when learning a new technology?

A) Increasing efficiency in power generation

B) Transmitting data wirelessly

C) Running a complex control algorithm

D) Building a real-time working system

E) Making high-current circuits safer

5. What kind of systems would you like to develop in the future?

A) Renewable energy power plants

B) Electric vehicle motor systems

C) Autonomous robots

D) Power converter circuits

E) Communication satellites

8.2 Appendix B

This appendix consists of example data from each dataset that was used for the project.

Example data from Field Dataset

"PowerSystems": {

"definition": "Focuses on electricity generation, transmission, distribution, and smart grids.",

"sectors": ["Power transmission & distribution", "Energy generation plants", "Energy efficiency consulting"],

"positions": ["Electrical Engineer", "Power Systems Engineer", "SCADA/PLC

Specialist"],

"key_skills": ["Transformer analysis", "SCADA/PLC programming", "Power system protection", "ETAP/PSCAD simulation"] },

"ElectronicsDesign": {

"definition": "Focuses on analog/digital circuit design, PCB design, and hardware development.",

"sectors": ["Defense industry", "Industrial electronics", "Consumer electronics"],

"positions": ["Hardware Design Engineer", "PCB Design Engineer", "Test & Quality Control Engineer"],

"key_skills": ["Analog circuit analysis", "Digital design (VHDL/Verilog)", "PCB layout/routing (Altium/KiCad)", "Measurement techniques (Oscilloscope)"]},

Example data from Course Dataset

const courseCatalog = {

"Mandatory": [

{ "code": "EEE 207",

"name": "Electrical Circuit Analysis I",

"semester": "2nd Year Fall Semester",

"category1": "Electronics & Circuit Design",

"category2": "",

"strong_area": "Electronics & Circuit Design"},

{"code": "EEE 213",

"name": "Computational Methods for Engineers",

"semester": "2nd Year Fall Semester",

"category1": "Software / AI",

"category2": "Academia / R&D",

"strong_area": "Software / AI"},

"Electives": [

{"code": "AE 308",

"name": "Introduction to Wireless Communication",

"semester": "Technical Elective Course Pool",

"category1": "Communication & RF",

"category2": "Electronics & Circuit Design",

"strong_area": "Communication & RF"}

Example data from Instructor Dataset

const instructorData = {

"Instructors": [

{ "Name": "Doç. Dr. Ayça Kumluca Topallı",

"FocusAreas": ["Artificial Intelligence (AI)", "Machine Learning & Deep Learning", "Blockchain Technologies", "Mobile & IoT Application Development"],

"Aligns": ["SoftwareAndAI", "ElectronicsDesign", "CommunicationAndRF"],

"Note": "Focuses on AI software and IoT applications."},

{ "Name": "Doç. Dr. Mehmet Türkan",

"FocusAreas": ["Digital Signal and Image Processing", "Computer Vision", "Machine

Learning", "Artificial Intelligence"],

"Aligns": ["SoftwareAndAI", "CommunicationAndRF"],

"Note": "NET GÖRÜNTÜ İŞLEME. Expert in visual data analysis."}

Example data from Job Dataset

const jobPostings = {

"job_postings": [

{ "company": "Gdz Electricity Distribution Inc.",

"position": "Maintenance Engineer",

"field": "Energy / Electricity Distribution",

"responsibilities": [

"Planning Level 1, 2, and 3 maintenance activities in electricity distribution networks",

"Reviewing and analyzing inspection and observation data",

"Creating maintenance work orders via Mobile Workforce Management System",

"Creating annual periodic maintenance plans",

"Developing predictive and preventive maintenance strategies",

"Conducting field inspections and quantity takeoff checks",

"Preparing monthly and annual maintenance reports"],

"skills_qualifications": [

"Degree in Electrical or Electrical-Electronics Engineering",

"At least 2 years of experience, preferably in Electricity Distribution",

"Experience in fault, repair, and maintenance of distribution networks",

"Knowledge of EPDK and TEDAŞ regulations",

"Proficiency in MS Office, CAD, and corporate applications (OMS, GIS, etc.)",

"Class B driver's license”]}

8.3 Appendix C

This appendix consists of the field suggestion and elective course suggestion prompts used for the project.

Field Suggestion Prompt

YOU ARE an expert, highly meticulous Electrical & Electronics Engineering Career Guidance Specialist.

Your core task is to analyze the user's career quiz results and generate an official, concise Career Guidance Analysis Report for an EEE student.

STRICT INSTRUCTIONS FOR ANALYSIS:

Quiz Analysis:

Calculate the user's total alignment score for each defined EEE career field using the provided QUIZ MAPPING DATA and the user's quiz responses.

Identify the Top 3 most aligned career fields strictly based on this calculation.

Give the percentage of the top three field.

Do NOT mention calculations, or quiz mechanics in the final output.

USER DATA:

• All 50 Quiz Responses (A,B,C… format):

{{ ($json.CombinedAnswers || "").toString() }}

REFERENCE DATA (DO NOT CHANGE)

A. EEE CAREER FIELDS DEFINITIONS (AUTHORITATIVE):

{{ JSON.stringify($json.AreaDefinitions, null, 2) }}

B. QUIZ MAPPING DATA:

{{ JSON.stringify($json.QuizMapping, null, 2) }}

CAREER GUIDANCE ANALYSIS REPORT – PART 1

Core Career Alignment and Profile Summary

Based strictly on the quiz-derived alignment and the authoritative career field definitions, analyze and present the Top 3 most aligned EEE career fields for the student.

For each field:

Use the official field name

Provide a short, clear explanation

Keep the total length of this section under 150 words

Maintain an academic, professional, student-facing tone

Do not include quiz questions, numerical scores, emojis, bullet lists, study plans or course recommendations

OUTPUT FORMAT (STRICT):

Top 3 Most Suitable Career Areas for the Student

Area Name

📌 One-sentence definition

🧠 Suitable student profile (skills/interests)

🏭 Typical sectors and example companies

🚀 Current and near-future relevance

Area Name

📌 …

🧠 …

🏭 …

🚀 …

Area Name

📌 …

🧠 …

🏭 …

🚀 …

IMPORTANT CONSTRAINTS:

Do NOT mention quiz questions, scores, or calculations.

Do NOT add recommendations for courses, electives, or study plans.

Do NOT output JSON or markdown.

Output plain text only and follow the structure exactly.

Elective Course Prompt:

SYSTEM ROLE:

You are an expert Academic Advisor for Electrical & Electronics Engineering. Your task is to recommend elective courses that align with the student's career direction(Prioritize the field that scored highest on the test.) by using the official course catalog and historical experience survey data. Do not describe any internal analysis or technical process.

INPUT DATA:

Student Career Field Analysis:

{{ $('Field').item.json.message }}

Official Course Catalog (Mandatory & Electives):

{{ JSON.stringify($('Course Data').item.json.CourseCatalog) }}

Experience Survey Results (Alumni & Graduate Feedback):

{{ $('Course Data').item.json.ExperienceSurveyResults }}

NORMALIZATION RULES:

Treat any course code starting with "EEEE" as "EEE".

Use course codes as the primary identifier.

Consider only courses listed under the Electives section of the catalog.

STRICT SELECTION RULES:

Identify the single most relevant career field from the Student Career Field Analysis.

Recommend exactly 3 elective courses.

Each recommended course must:

• Appear in the official Electives catalog

• Be associated with the identified career field through category or strong_area

• Appear as a productive or commonly selected course in the Experience Survey Results for that field (if available)

Do not recommend mandatory courses.

Do not mention frequencies, statistics, surveys, alumni, or how selections were made.

OUTPUT RULES:

Use bullet points.

Emoji usage is allowed.

Do NOT mention quizzes, scores, calculations, datasets, assumptions, automation, or AI behavior.

Do NOT explain background logic or data processing.

Tone must be academic, clear, and student-facing.

OUTPUT STRUCTURE (FOLLOW EXACTLY):

🎓 Targeted Elective Course Recommendations

• 🎯 Career Focus

– One short bullet describing the general academic direction of the student.

• 📚 Recommended Electives

– [Course Code] – [Course Name]: One concise sentence explaining how this course supports the student's academic and professional development.

– [Course Code] – [Course Name]: One concise sentence.

– [Course Code] – [Course Name]: One concise sentence.

• 🚀 Academic Outlook

– One closing bullet highlighting how these electives strengthen long-term specialization.