SmartPath Career Engine: Personalized Job Recommendations System Using RIASEC, Skills and Education

Welcome to the SmartPath Career Engine, a personalized career recommendation tool designed to help users discover top job matches based on their **interests (RIASEC scores)**, **educational level**, and **core skills**.

This project combines:

- **RIASEC Theory** (Holland Codes) for personality-career alignment
- **Skill-Based Matching** using real-world job competency data
- **Education Fit Analysis** to understand qualification gaps
- **Hybrid Similarity Scoring** to rank job fit comprehensively

How It Works:

1. Users provide:
    - Their RIASEC scores (scale: 0–7)
    - Highest education level (e.g., Bachelor's)
    - Up to 3 strong cognitive/technical skills
2. The system compares the user profile against a curated job dataset
3. Recommendations are generated, scored, and visualized
4. A downloadable CSV and email option delivers the top matches

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Problem Statement

In the face of a rapidly transforming global workforce, driven by automation, technological disruption, and shifting industry demands, navigating the job market has become increasingly complex. Students and job seekers, particularly those in underserved communities, often lack access to timely, personalized, and data-informed career guidance. Traditional career counseling systems tend to be static, generalized, and poorly aligned with real-time labor market needs.

As a result, many individuals unknowingly pursue career paths that are mismatched with their interests, skills, or educational backgrounds. This misalignment leads to underemployment, job dissatisfaction, and inefficient use of training and education resources.

SmartPath seeks to close this guidance gap by harnessing structured occupational data from the O*NET database to deliver personalized career recommendations based on an individual's interests (RIASEC), skill strengths, and education level—offering a more dynamic, inclusive, and intelligent pathway to career alignment. Personalized career recommendations based on a user's skills, interests, and education level.

Project Goal

The primary goal of the SmartPath Career Recommendation Engine is to:

- Match users to careers that best align with their unique blend of interests, skills, and educational attainment
- Suggest alternative or adjacent occupations that users may not have previously considered
- Highlight gaps in skills or education and provide actionable insight for bridging them
- Empower users with data-driven guidance, enabling them to make confident and informed decisions in a fast-changing world of work

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Scope of the Project

This project encompasses the following components:

1. Occupational Data Modeling
    - Utilizes structured job data from O*NET, including RIASEC interest codes, required skills, and educational levels.
2. User Profiling Interface
    - Collects user inputs such as RIASEC scores, top skill strengths, and highest education level.
3. Recommendation Engine
    - Computes similarity between user profiles and occupational profiles using hybrid scoring (RIASEC similarity, skill match, and education alignment).
4. Insightful Output Generation
    - Displays top-matching job titles with similarity scores, matched skills, education gaps, and job descriptions.
5. User Interaction Layer
    - Provides a simple, intuitive interface for users to input information, receive career suggestions, and optionally download or email their results.

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1. DATA UNDERSTANDING

1.1 Importing Libraries

In [1]:
```
# Importing libraries
import pandas as pd
import os
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
import numpy as np

warnings.filterwarnings('ignore')
```

1.2. Loading the Dataset

In [2]:
```
# Defining path to the dataset folder
data_path = 'data'

# Loading core datasets
occupation_df = pd.read_excel(f'{data_path}/Occupation Data.xlsx')
interests_df = pd.read_excel(f'{data_path}/Interests.xlsx')
skills_df = pd.read_excel(f'{data_path}/Skills.xlsx')
education_df = pd.read_excel(f'{data_path}/Education, Training, and Experience.xlsx
related_df = pd.read_excel(f'{data_path}/Related Occupations.xlsx')
abilities_df = pd.read_excel(f'{data_path}/Abilities.xlsx')
emerging_tasks_df = pd.read_excel(f'{data_path}/Emerging Tasks.xlsx')
edu_categories_df = pd.read_excel(f'{data_path}/Education, Training, and Experience
```

Defining path to the dataset folder

data_path = './datasets'

Loading core datasets

occupation_df = pd.read_csv(os.path.join(data_path, 'Occupation Data.txt'), delimiter='\t') interests_df = pd.read_csv(os.path.join(data_path, 'Interests.txt'), delimiter='\t') skills_df = pd.read_csv(os.path.join(data_path, 'Skills.txt'), delimiter='\t') education_df = pd.read_csv(os.path.join(data_path, 'Education, Training, and Experience.txt'), delimiter='\t') related_df = pd.read_csv(os.path.join(data_path, 'Related Occupations.txt'), delimiter='\t') abilities_df = pd.read_csv('datasets/Abilities.txt', sep='\t', encoding='utf-8') emerging_tasks_df = pd.read_csv('datasets/Emerging Tasks.txt', sep='\t', encoding='utf-8') edu_categories_df = pd.read_csv('datasets/Education, Training, and Experience Categories.txt', sep='\t', encoding='utf-8')

1.3. Quick Peek at Data

In [3]:
```
# View structure of each DataFrame
print("Occupations:", occupation_df.shape)
print("Interests:", interests_df.shape)
print("Skills:", skills_df.shape)
print("Education:", education_df.shape)
print("Related Jobs:", related_df.shape)
print("Abilities:", abilities_df.shape)
print("Emerging Tasks:", emerging_tasks_df.shape)
print("Education Categories:", edu_categories_df.shape)

# Display sample rows
occupation_df.head(3)
```

```
Occupations: (1016, 3)
Interests: (8307, 9)
Skills: (61530, 15)
Education: (36209, 15)
Related Jobs: (18460, 6)
Abilities: (91416, 15)
Emerging Tasks: (295, 8)
Education Categories: (41, 6)
```

Out[3]:

	O*NET-SOC Code	Title	Description
0	11-1011.00	Chief Executives	Determine and formulate policies and provide o...
1	11-1011.03	Chief Sustainability Officers	Communicate and coordinate with management, sh...
2	11-1021.00	General and Operations Managers	Plan, direct, or coordinate the operations of ...

In [4]:
```
occupation_df.head()
interests_df.head()
skills_df.head()
education_df.head()
related_df.head()
abilities_df.head()
```

Out[4]:

	O*NET-SOC Code	Title	Element ID	Element Name	Scale ID	Scale Name	Data Value	N	Standard Error	Lo Bo
0	11-1011.00	Chief Executives	1.A.1.a.1	Oral Comprehension	IM	Importance	4.62	8	0.1830	4.
1	11-1011.00	Chief Executives	1.A.1.a.1	Oral Comprehension	LV	Level	4.88	8	0.1250	4.
2	11-1011.00	Chief Executives	1.A.1.a.2	Written Comprehension	IM	Importance	4.25	8	0.1637	3.
3	11-1011.00	Chief Executives	1.A.1.a.2	Written Comprehension	LV	Level	4.88	8	0.1250	4.
4	11-1011.00	Chief Executives	1.A.1.a.3	Oral Expression	IM	Importance	4.50	8	0.1890	4.

1.4. Data Structure

In [5]:
```
# See column names
print(occupation_df.columns)
print('\n----------\n')
print(interests_df.columns)
print('\n----------\n')
print(skills_df.columns)
print('\n----------\n')
print(education_df.columns)
print('\n----------\n')
print(related_df.columns)
print('\n----------\n')
```

```
Index(['O*NET-SOC Code', 'Title', 'Description'], dtype='object')

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Index(['O*NET-SOC Code', 'Title', 'Element ID', 'Element Name', 'Scale ID',
       'Scale Name', 'Data Value', 'Date', 'Domain Source'],
      dtype='object')

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Index(['O*NET-SOC Code', 'Title', 'Element ID', 'Element Name', 'Scale ID',
       'Scale Name', 'Data Value', 'N', 'Standard Error', 'Lower CI Bound',
       'Upper CI Bound', 'Recommend Suppress', 'Not Relevant', 'Date',
       'Domain Source'],
      dtype='object')

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Index(['O*NET-SOC Code', 'Title', 'Element ID', 'Element Name', 'Scale ID',
       'Scale Name', 'Category', 'Data Value', 'N', 'Standard Error',
       'Lower CI Bound', 'Upper CI Bound', 'Recommend Suppress', 'Date',
       'Domain Source'],
      dtype='object')

----------

Index(['O*NET-SOC Code', 'Title', 'Related O*NET-SOC Code', 'Related Title',
       'Relatedness Tier', 'Index'],
      dtype='object')

----------
```

2. DATA PREPARATION

2.1. Basic Cleanup & Rename

- We're renaming columns in the datasets for consistency and readability:
  - Shorter column names (e.g., ONET_Code instead of 'O*NET-SOC Code')
  - Standard naming across datasets
  - Prepping for merging- Having it renamed uniformly avoids bugs and errors.

In [6]:
```
# Standardize 'O*NET-SOC Code' column name
for df in [occupation_df, interests_df, skills_df, education_df, related_df, emergi
    df.rename(columns={'O*NET-SOC Code': 'ONET_Code'}, inplace=True) # Renaming for

# Standardize abilities columns
abilities_df = abilities_df[['O*NET-SOC Code', 'Element Name', 'Scale ID', 'Data Va
abilities_df.rename(columns={'O*NET-SOC Code': 'ONET_Code', 'Element Name': 'Abilit
abilities_df = abilities_df[abilities_df['Scale ID'] == 'IM']  # Only Importance sc
abilities_df.drop(columns='Scale ID', inplace=True)
```

2.2. Explore & Transform the Data

We'll now:

- Extract RIASEC profiles per occupation
- Aggregate skills by occupation
- Get education level for each occupation
- Merge all into one clean job profile DataFrame

2.2.1. Transforming Interests and Creating RIASEC Vectors

RIASEC Vectors refer to a structured way of representing a person's career interests using the RIASEC model, developed by psychologist John L. Holland. | Code | Interest Type | Description | | ---- | ------------ | -- | | R | Realistic | Practical, hands-on, physical activities | | I | Investigative | Analytical, intellectual, scientific tasks | | A | Artistic | Creative, unstructured, expressive work | | S | Social | Helping, teaching, interacting with people | | E | Enterprising | Persuasive, leadership, business-oriented | | C | Conventional | Detail-oriented, organizational, administrative |

Each person has a RIASEC profile (a combination (vector) of these six interests).

Each occupation appears multiple times in interests_df — once for each of the 6 RIASEC types.

We want to pivot this From: | ONET_Code | Element Name | Data Value | | ---------- | ---------- | ---------- | | 11-1011.00 | Realistic | 1.38 | | 11-1011.00 | Investigative | 2.25 | | 11-1011.00 | Enterprising | 4.63 | | ... | ... | ... |

To: | ONET_Code | Realistic | Investigative | Artistic | Social | Enterprising | Conventional | | ---------- | --------- | ------------- | -------- | ------ | ------------ | ------------ | | 11-1011.00 | 1.38 | 2.25 | 0.75 | 1.12 | 4.63 | 2.50 |

2.2.2. Pivot RIASEC scores

In [7]:
```
# Pivoting the interests to get one row per job with RIASEC scores
riasec_df = interests_df.pivot_table(index='ONET_Code',
                                     columns='Element Name',
                                     values='Data Value').reset_index()

# Renaming columns for consistency
riasec_df.columns.name = None  # To remove multiindex
riasec_df.rename(columns={
    'Realistic': 'R',
    'Investigative': 'I',
    'Artistic': 'A',
    'Social': 'S',
```

```
    'Enterprising': 'E',
    'Conventional': 'C'
}, inplace=True)

# Preview RIASEC vectors
riasec_df.head()
```

Out[7]:

	ONET_Code	A	C	E	First Interest High-Point	I	R	Second Interest High-Point	S	Third Interest High-Point
0	11-1011.00	2.08	5.00	6.88	5.0	3.24	1.30	6.0	3.52	0.0
1	11-1011.03	2.48	4.49	6.68	5.0	4.78	2.04	2.0	3.55	6.0
2	11-1021.00	1.31	5.32	6.96	5.0	2.39	2.22	6.0	3.37	0.0
3	11-1031.00	2.70	3.62	5.52	5.0	3.35	1.54	4.0	3.69	6.0
4	11-2011.00	3.85	4.30	7.00	5.0	1.71	1.07	6.0	3.14	3.0

We now have RIASEC personality scores per job.

2.2.3. Transform Skills (Aggregating Top Skills per Job)

In [8]:
```
# Exploring what's in skills_df
skills_df['Scale ID'].value_counts()
```

Out[8]:
```
Scale ID
IM    30765
LV    30765
Name: count, dtype: int64
```

ONET provides two types of metrics for each skill: | *Scale ID* | *Meaning* | *Description* | | -------- | ------------- | ---------- | | `IM` | *Importance** | How critical the skill is to job performance | | `LV` | **Level** | The degree of complexity or expertise required to perform that skill |

We'll keep only IM for now and pivot the top 10 skills:

- We'll use IM to prioritize what matters most in each job for similarity and recommendation.
- We may use LV later for skill gap analysis, upskilling paths, or to enrich the UI.

This will keep our recommender fast and user-friendly, while allowing deeper features later.

2.2.4. Filtering top skills by importance

We'll extract the top N important skills per occupation.

In [9]:
```
# Filtering only 'Importance' scores
important_skills_df = skills_df[skills_df['Scale ID'] == 'IM']

# Keeping top 10 most important skills per job
top_skills_df = important_skills_df.groupby('ONET_Code', group_keys=False).apply(
    lambda x: x.sort_values(by='Data Value', ascending=False).head(10)
).reset_index(drop=True)

# Preview of top skills for one job
top_skills_df[top_skills_df['ONET_Code'] == '11-1011.00']
```

Out[9]:

	ONET_Code	Title	Element ID	Element Name	Scale ID	Scale Name	Data Value	N	Standard Error
0	11-1011.00	Chief Executives	2.B.4.e	Judgment and Decision Making	IM	Importance	4.75	8	0.1637
1	11-1011.00	Chief Executives	2.A.2.a	Critical Thinking	IM	Importance	4.38	8	0.1830
2	11-1011.00	Chief Executives	2.B.2.i	Complex Problem Solving	IM	Importance	4.38	8	0.1830
3	11-1011.00	Chief Executives	2.B.5.d	Management of Personnel Resources	IM	Importance	4.25	8	0.1637
4	11-1011.00	Chief Executives	2.B.1.b	Coordination	IM	Importance	4.25	8	0.1637
5	11-1011.00	Chief Executives	2.B.5.b	Management of Financial Resources	IM	Importance	4.25	8	0.1637
6	11-1011.00	Chief Executives	2.A.1.d	Speaking	IM	Importance	4.25	8	0.1637
7	11-1011.00	Chief Executives	2.B.4.h	Systems Evaluation	IM	Importance	4.25	8	0.1637
8	11-1011.00	Chief Executives	2.B.4.g	Systems Analysis	IM	Importance	4.12	8	0.1250
9	11-1011.00	Chief Executives	2.B.1.d	Negotiation	IM	Importance	4.12	8	0.1250

This top_skills_df now gives us:

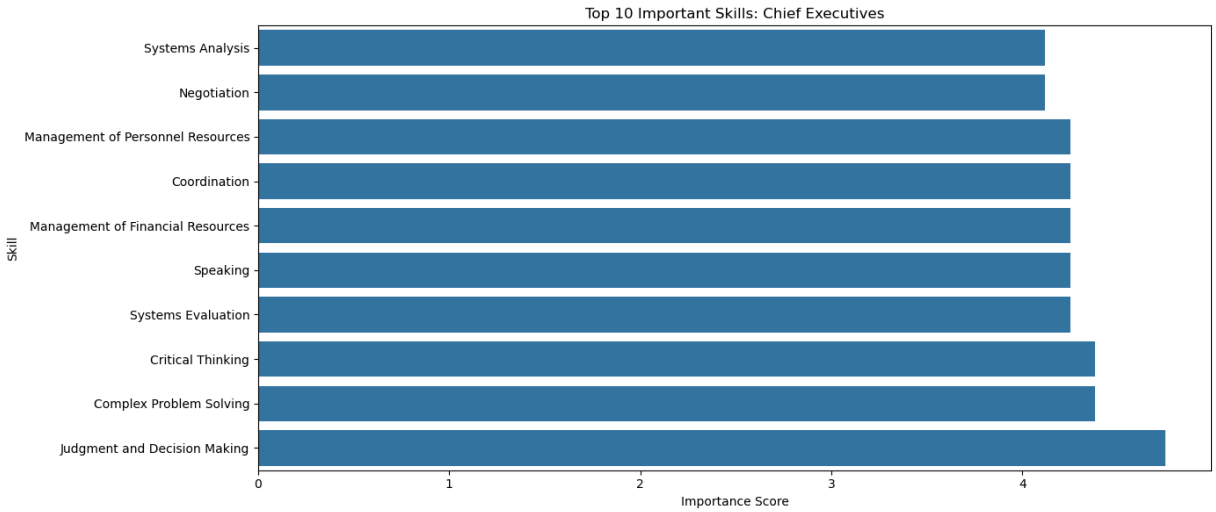
- A ranked list of the most important skills per job useful for matching a user's known skills to jobs where they matter most. These skills can later be vectorized for similarity in our recommender

Column	Meaning
`ONET_Code`	The job (e.g., `11-1011.00` = Chief Executives)
`Element Name`	The skill being rated (e.g., Critical Thinking)
`Data Value`	**Importance score** from 0–5 (how critical the skill is)
`N`	Sample size (e.g., how many people/data points)
`Standard Error`	Confidence level of the rating
`Lower CI Bound` & `Upper CI Bound`	Confidence intervals
`Domain Source`	Analyst = Provided by experts (vs incumbents or surveys)

2.2.5. Top required skills across occupations

To help make our recommendations more explainable.

In [10]:
```
# Top 10 Skills for a Sample Job
onet_id = '11-1011.00'
job_skills = top_skills_df[top_skills_df['ONET_Code'] == onet_id]

plt.figure(figsize=(14, 6))
sns.barplot(x='Data Value', y='Element Name', data=job_skills.sort_values('Data Val
plt.title("Top 10 Important Skills: Chief Executives")
plt.xlabel("Importance Score")
plt.ylabel("Skill")
plt.tight_layout()
plt.show()
```



Interpretation:

- This bar chart shows the top 10 most important skills required for the occupation Chief Executives, based on the O*NET skill importance ratings.

Key Insights:

- The most valued skills include Judgment and Decision Making, Complex Problem Solving, and Critical Thinking.
- Soft leadership abilities like Coordination and Speaking are equally emphasized.
- This visual helps users identify key competencies to develop if they're aiming for executive roles.

2.2.6. Education Level Per Job

Here we are extracting the most common minimum required education level per job.

a) Merging Education with Categories

In [11]:
```
# Merging education data with categories
education_df_with_cat = education_df.merge(
    edu_categories_df[['Element ID', 'Category', 'Category Description']],
    on='Element ID',
    how='left'
)
```

In [12]:
```
# Preview the merged DataFrame
print(education_df_with_cat.columns.tolist())
```

```
['ONET_Code', 'Title', 'Element ID', 'Element Name', 'Scale ID', 'Scale Name', 'Cate
gory_x', 'Data Value', 'N', 'Standard Error', 'Lower CI Bound', 'Upper CI Bound', 'R
ecommend Suppress', 'Date', 'Domain Source', 'Category_y', 'Category Description']
```

b) Renaming columns for clarity

In [13]:
```
# Renaming columns for clarity with actual column names in the DataFrame
education_df_with_cat.rename(columns={
    'Category_y': 'Preparation Type',           # <-- correct source from merged df
    'Category Description': 'Preparation Level',
    'Element Name': 'Prep Component'
}, inplace=True)


# Preview DataFrame
education_df_with_cat[['ONET_Code', 'Prep Component', 'Preparation Type', 'Preparat
```

Out[13]:

	ONET_Code	Prep Component	Preparation Type	Preparation Level
0	11-1011.00	Required Level of Education	1.0	Less than a High School Diploma
1	11-1011.00	Required Level of Education	2.0	High School Diploma - or the equivalent (for e...
2	11-1011.00	Required Level of Education	3.0	Post-Secondary Certificate - awarded for train...
3	11-1011.00	Required Level of Education	4.0	Some College Courses
4	11-1011.00	Required Level of Education	5.0	Associate's Degree (or other 2-year degree)

c) Most Common Education Level Per Job

In [14]:
```
# Getting the most common (highest scoring) education level per job, now with categ
edu_df_with_cat = (
    education_df_with_cat
    .sort_values(by='Data Value', ascending=False)
    .drop_duplicates(subset='ONET_Code')
    [['ONET_Code', 'Prep Component', 'Data Value', 'Preparation Type', 'Preparation
    .rename(columns={
        'Prep Component': 'Education Level',
        'Preparation Type': 'Education Category'
    })
)

# Preview the result
edu_df_with_cat.head()
```

Out[14]:

	ONET_Code	Education Level	Data Value	Education Category	Preparation Level
5638	11-3051.01	Required Level of Education	100.00	12.0	Post-Doctoral Training
178363	29-9092.00	Required Level of Education	100.00	5.0	Associate's Degree (or other 2-year degree)
230522	43-2021.00	Required Level of Education	97.83	6.0	Bachelor's Degree
334045	51-8093.00	Required Level of Education	97.02	9.0	Post-Master's Certificate - awarded for comple...
281425	47-5081.00	Required Level of Education	96.59	8.0	Master's Degree

In [15]:
```
education_df_with_cat.head()
```

Out[15]:

	ONET_Code	Title	Element ID	Prep Component	Scale ID	Scale Name	Category_x	Data Value	N
0	11-1011.00	Chief Executives	2.D.1	Required Level of Education	RL	Required Level Of Education (Categories 1-12)	1.0	0.0	28
1	11-1011.00	Chief Executives	2.D.1	Required Level of Education	RL	Required Level Of Education (Categories 1-12)	1.0	0.0	28
2	11-1011.00	Chief Executives	2.D.1	Required Level of Education	RL	Required Level Of Education (Categories 1-12)	1.0	0.0	28
3	11-1011.00	Chief Executives	2.D.1	Required Level of Education	RL	Required Level Of Education (Categories 1-12)	1.0	0.0	28
4	11-1011.00	Chief Executives	2.D.1	Required Level of Education	RL	Required Level Of Education (Categories 1-12)	1.0	0.0	28

100.00 means 100% of surveyed job incumbents or analysts agreed that this is the most common education level required for that job.

Right now, "Education Level" only says "Required Level of Education" which is too vague. We'll improve this by joining it with Education, Training, and Experience Categories datasets which maps education Element IDs to actual levels like:

- High school diploma
- Associate's degree
- Bachelor's degree
- Master's degree

2.2.7 Merging All into One Master Job Profile

In [16]:
```
# Creating full job profile
job_profiles = occupation_df.merge(riasec_df, on='ONET_Code', how='left')
job_profiles = job_profiles.merge(edu_df_with_cat, on='ONET_Code', how='left')
```

```
# Preview
job_profiles[['Title', 'Description', 'Education Level', 'Education Category', 'Pre
```

Out[16]:

	Title	Description	Education Level	Education Category	Preparation Level
0	Chief Executives	Determine and formulate policies and provide o...	Related Work Experience	7.0	Over 2 years, up to and including 4 years
1	Chief Sustainability Officers	Communicate and coordinate with management, sh...	Required Level of Education	11.0	Doctoral Degree
2	General and Operations Managers	Plan, direct, or coordinate the operations of ...	Required Level of Education	10.0	First Professional Degree - awarded for comple...
3	Legislators	Develop, introduce, or enact laws and statutes...	NaN	NaN	NaN
4	Advertising and Promotions Managers	Plan, direct, or coordinate advertising polici...	Required Level of Education	1.0	Less than a High School Diploma

3. DATA CLEANING

3.1 Check for duplicates in the final job_profiles

In [17]:
```
# Checking for duplicates
job_profiles.duplicated().sum()
```

Out[17]:
```
0
```

3.2 Check for missing values

In [18]:
```
# Checking missing values across all columns
job_profiles.isnull().sum()
```

Out[18]:
```
ONET_Code                      0
Title                          0
Description                    0
A                             93
C                             93
E                             93
First Interest High-Point     93
I                             93
R                             93
Second Interest High-Point    93
S                             93
Third Interest High-Point     93
Education Level              158
Data Value                   158
Education Category           158
Preparation Level            179
dtype: int64
```

3.2.1. Handling Missing Values

a) Dropping rows with missing education info

- The education information is crucial for our filtering and matching logic in the recommender system, particularly in matching education levels to user input.
- Keeping rows with missing education info would risk:
  - Recommending jobs the user isn't qualified for.
  - Breaking filters like: job_profiles[job_profiles['Education Level Code'] <= user_level]

In [19]:
```
# Dropping rows with missing education info
job_profiles_clean = job_profiles.dropna(subset=['Education Level', 'Education Cate
```

b) Filling missing RIASEC Interests with "Unknown"

- Interest codes are useful only for personality-aligned recommendations.
- Missing them doesn't prevent your skill/education/task-based matching from working.
- Replacing with 'Unknown' allows us to keep potentially good matches.

In [20]:
```
# Defining the interest columns
interest_cols = ['First Interest High-Point', 'Second Interest High-Point', 'Third

# Filling missing RIASEC interests with 'Unknown'
job_profiles_clean.loc[:, interest_cols] = job_profiles_clean[interest_cols].fillna
```

In [21]:
```
# Preview the cleaned DataFrame
job_profiles_clean
```

Out[21]:

	ONET_Code	Title	Description	A	C	E	First Interest High-Point	I	R	Second Interest High-Point
0	11-1011.00	Chief Executives	Determine and formulate policies and provide o...	2.08	5.00	6.88	5.0	3.24	1.30	6.0
1	11-1011.03	Chief Sustainability Officers	Communicate and coordinate with management, sh...	2.48	4.49	6.68	5.0	4.78	2.04	2.0
2	11-1021.00	General and Operations Managers	Plan, direct, or coordinate the operations of ...	1.31	5.32	6.96	5.0	2.39	2.22	6.0
4	11-2011.00	Advertising and Promotions Managers	Plan, direct, or coordinate advertising polici...	3.85	4.30	7.00	5.0	1.71	1.07	6.0
5	11-2021.00	Marketing Managers	Plan, direct, or coordinate marketing policies...	2.45	4.70	7.00	5.0	2.90	1.00	6.0
...	...	...	...	...	...	...	...	...	...	...
991	53-7071.00	Gas Compressor and Gas Pumping Station Operators	Operate steam-, gas-, electric motor-, or inte...	1.00	4.85	1.52	1.0	2.33	6.14	6.0
992	53-7072.00	Pump Operators, Except Wellhead Pumpers	Tend, control, or operate power-driven, statio...	1.00	4.51	1.46	1.0	2.26	6.67	6.0
993	53-7073.00	Wellhead Pumpers	Operate power pumps and auxiliary equipment to...	1.00	4.36	1.87	1.0	2.41	6.77	6.0
994	53-7081.00	Refuse and Recyclable	Collect and dump refuse	1.00	4.41	1.55	1.0	1.77	7.00	6.0

	ONET_Code	Title	Description	A	C	E	First Interest High-Point	I	R	Second Interest High-Point
		Material Collectors	or recyclable material...							
995	53-7121.00	Tank Car, Truck, and Ship Loaders	Load and unload chemicals and bulk solids, suc...	1.00	4.68	1.31	1.0	1.94	6.86	6.0

837 rows × 16 columns

In [22]:
```
# Preview the cleaned DataFrame
job_profiles_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 837 entries, 0 to 995
Data columns (total 16 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   ONET_Code                   837 non-null    object 
 1   Title                       837 non-null    object 
 2   Description                 837 non-null    object 
 3   A                           837 non-null    float64
 4   C                           837 non-null    float64
 5   E                           837 non-null    float64
 6   First Interest High-Point   837 non-null    float64
 7   I                           837 non-null    float64
 8   R                           837 non-null    float64
 9   Second Interest High-Point  837 non-null    float64
 10  S                           837 non-null    float64
 11  Third Interest High-Point   837 non-null    float64
 12  Education Level             837 non-null    object 
 13  Data Value                  837 non-null    float64
 14  Education Category          837 non-null    float64
 15  Preparation Level           837 non-null    object 
dtypes: float64(11), object(5)
memory usage: 111.2+ KB
```

3.3 Normalize RIASEC scores

If different RIASEC types have different ranges (e.g., one maxes at 7.0 and another at 5.0), we normalize them to 0–1 for fair similarity comparison.

In [23]:
```
from sklearn.preprocessing import MinMaxScaler

riasec_cols = ['R', 'I', 'A', 'S', 'E', 'C']
scaler = MinMaxScaler()
```

```
job_profiles_clean[riasec_cols] = scaler.fit_transform(job_profiles_clean[riasec_co
job_profiles_clean[riasec_cols]
```

Out[23]:

	R	I	A	S	E	C
0	0.050000	0.373333	0.180000	0.420000	0.980000	0.625468
1	0.173333	0.630000	0.246667	0.425000	0.946667	0.529963
2	0.203333	0.231667	0.051667	0.395000	0.993333	0.685393
4	0.011667	0.118333	0.475000	0.356667	1.000000	0.494382
5	0.000000	0.316667	0.241667	0.303333	1.000000	0.569288
...	...	...	...	...	...	...
991	0.856667	0.221667	0.000000	0.090000	0.086667	0.597378
992	0.945000	0.210000	0.000000	0.046667	0.076667	0.533708
993	0.961667	0.235000	0.000000	0.011667	0.145000	0.505618
994	1.000000	0.128333	0.000000	0.065000	0.091667	0.514981
995	0.976667	0.156667	0.000000	0.000000	0.051667	0.565543

837 rows × 6 columns

3.4. Normalizing Education scores

- We normalize education scores to a 0–1 range for fair comparison.
- This ensures that education levels are comparable across different jobs, even if they have different maximum values

In [24]:
```
# Normalize Education Score for filtering or weighted scoring.
scaler = MinMaxScaler()
job_profiles_clean.loc[:,'Normalized Education Score'] = scaler.fit_transform(
    job_profiles_clean[['Education Category']].astype(float)
)
```

3.5. Validating Education values

In [25]:
```
# Checking unique values in Education Category and Preparation Level
print("Unique Education Category values:")
print(job_profiles_clean['Education Category'].sort_values().unique())

print("\nUnique Preparation Level values:")
print(job_profiles_clean['Preparation Level'].sort_values().unique())
```

```
Unique Education Category values:
[ 1.  2.  3.  4.  5.  6.  7.  8.  9. 10. 11. 12.]

Unique Preparation Level values:
['Anything beyond short demonstration, up to and including 1 month'
 "Associate's Degree (or other 2-year degree)" "Bachelor's Degree"
 'Doctoral Degree'
 'First Professional Degree - awarded for completion of a program that: requires at
least 2 years of college work before entrance into the program, includes a total of
at least 6 academic years of work to complete, and provides all remaining academic r
equirements to begin practice in a profession.'
 'High School Diploma - or the equivalent (for example, GED)'
 'Less than a High School Diploma' "Master's Degree"
 'None or short demonstration'
 'Over 1 month, up to and including 3 months'
 'Over 1 year, up to and including 2 years' 'Over 10 years'
 'Over 2 years, up to and including 4 years'
 'Over 3 months, up to and including 6 months'
 'Over 4 years, up to and including 10 years'
 'Over 4 years, up to and including 6 years'
 'Over 6 months, up to and including 1 year'
 'Over 6 years, up to and including 8 years'
 'Over 8 years, up to and including 10 years'
 'Post-Baccalaureate Certificate - awarded for completion of an organized program of
study; designed for people who have completed a Baccalaureate degree but do not meet
the requirements of academic degrees carrying the title of Master.'
 'Post-Doctoral Training'
 "Post-Master's Certificate - awarded for completion of an organized program of stud
y; designed for people who have completed a Master's degree but do not meet the requ
irements of academic degrees at the doctoral level."
 'Post-Secondary Certificate - awarded for training completed after high school (for
example, in agriculture or natural resources, computer services, personal or culinar
y services, engineering technologies, healthcare, construction trades, mechanic and
repair technologies, or precision production)'
 'Some College Courses' 'Up to and including 1 month']
```

3.6. Creating an Education Level Dictionary

In [26]:

```python
# Creating an Education Level Dictionary
education_level_map = {
    1.0: "Less than High School",
    2.0: "High School Diploma or equivalent",
    3.0: "Post-Secondary Certificate",
    4.0: "Some College Courses",
    5.0: "Associate's Degree",
    6.0: "Bachelor's Degree",
    7.0: "Post-Baccalaureate Certificate",
    8.0: "Master's Degree",
    9.0: "Post-Master's Certificate",
    10.0: "First Professional Degree",
    11.0: "Doctoral Degree",
    12.0: "Post-Doctoral Training"
}

# Mapping the education levels to their corresponding codes
```

```
job_profiles_clean.loc[:,'Education Category Label'] = job_profiles_clean['Educatio
job_profiles_clean[['Education Category', 'Education Category Label', 'Preparation
```

Out[26]:

	Education Category	Education Category Label	Preparation Level
0	7.0	Post-Baccalaureate Certificate	Over 2 years, up to and including 4 years
1	11.0	Doctoral Degree	Doctoral Degree
2	10.0	First Professional Degree	First Professional Degree - awarded for comple...
4	1.0	Less than High School	Less than a High School Diploma
5	7.0	Post-Baccalaureate Certificate	Post-Baccalaureate Certificate - awarded for c...
6	11.0	Doctoral Degree	Doctoral Degree
9	6.0	Bachelor's Degree	Over 1 year, up to and including 2 years
10	7.0	Post-Baccalaureate Certificate	Post-Baccalaureate Certificate - awarded for c...
12	4.0	Some College Courses	Some College Courses
13	12.0	Post-Doctoral Training	Post-Doctoral Training

Checking for inconsistencies or nulls

In [27]:
```
# Check for any Education values with missing category labels
job_profiles_clean[job_profiles_clean['Education Category Label'].isnull()]
```

Out[27]:

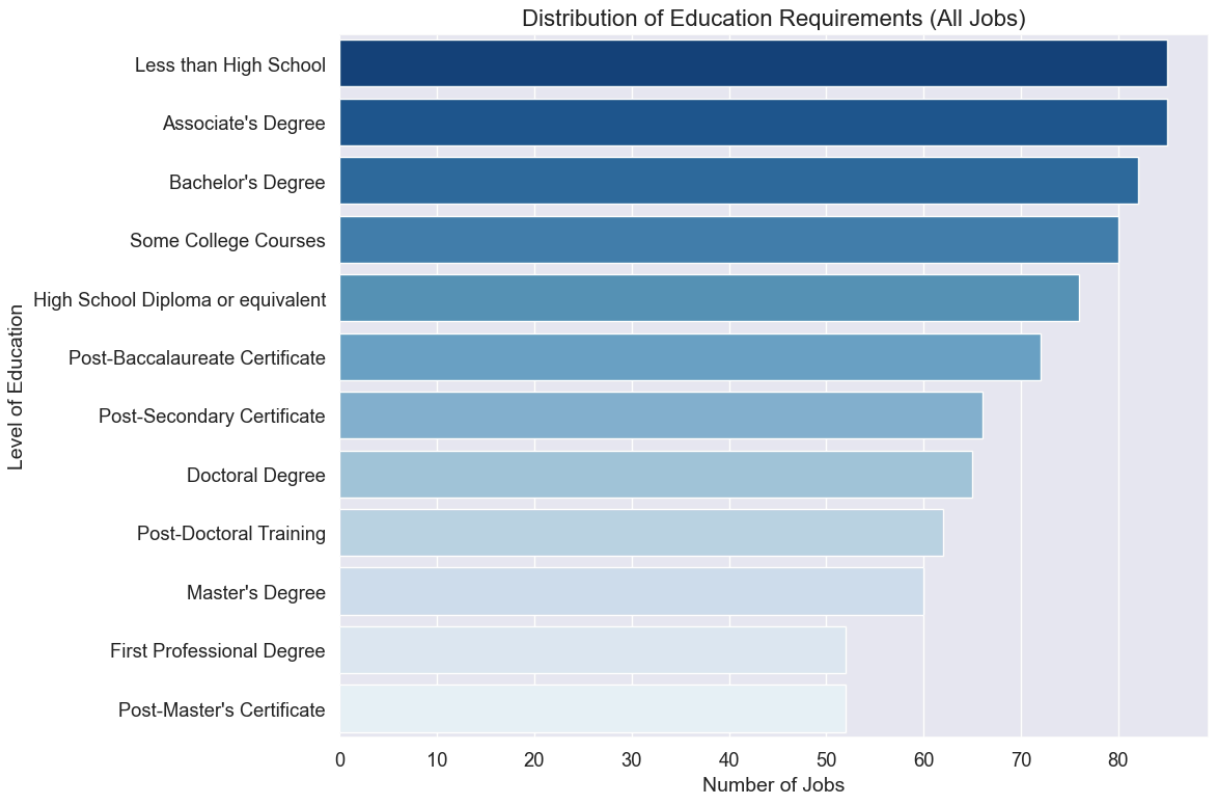
	ONET_Code	Title	Description	A	C	E	First Interest High-Point	I	R	Second Interest High-Point	S	Third Interest High-Point	Education Level

3.7. Distribution of Education level across all jobs

To help understand education trends across jobs.

In [28]:
```
# Setting plot
plt.figure(figsize=(12, 8))
sns.set(font_scale=1.2)

# Creating the plot
sns.countplot(
    y='Education Category Label',
    data=job_profiles_clean,
    order=job_profiles_clean['Education Category Label'].value_counts().index,
```

```
    palette='Blues_r'  # Optional: adds color gradient
)

# Customizing titles and labels
plt.title("Distribution of Education Requirements (All Jobs)", fontsize=16)
plt.xlabel("Number of Jobs", fontsize=14)
plt.ylabel("Level of Education", fontsize=14)

# Improving layout
plt.tight_layout()

# Saving high-res image
plt.savefig('images/education_requirements_distribution.png', dpi=300)

# Show plot
plt.show()
```



Interpretation:

- This count plot shows the distribution of education requirements across all jobs in the dataset.

Key Insights:

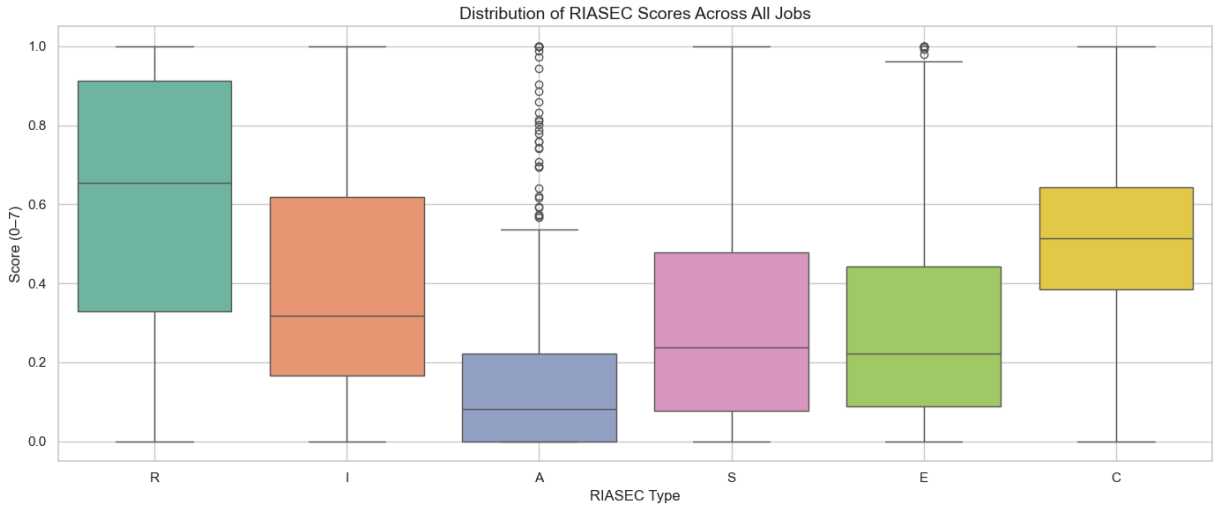
- Most jobs require some level of formal education (like a diploma or degree).
- A large propotion of jobs do not require extreme levels of education, indicating that many roles are accessible to individuals with moderate education.

3.8. Distribution of RIASEC scores across all jobs

Distribution of RIASEC scores across all jobs to help us understand how interest types are spread in the workforce. This helps in:

- Identifying the most dominant interest types across careers
- Helping users compare their interests to market trends
- Revealing clusters of careers with similar personality profiles

In [29]:
```
# Defining RIASEC columns
riasec_cols = ['R', 'I', 'A', 'S', 'E', 'C']

# Setting plot style
sns.set(style="whitegrid")
plt.figure(figsize=(14, 6))

# Melting the DataFrame for seaborn
riasec_melted = job_profiles_clean.melt(
    value_vars=riasec_cols,
    var_name='RIASEC Type',
    value_name='Score'
)

# Plot distribution
sns.boxplot(
    x='RIASEC Type',
    y='Score',
    hue='RIASEC Type',
    data=riasec_melted,
    palette='Set2',
    legend=False
)

plt.title('Distribution of RIASEC Scores Across All Jobs', fontsize=14)
plt.ylabel('Score (0-7)')
plt.xlabel('RIASEC Type')
plt.grid(True)
plt.tight_layout()
plt.show()
```



Interpretation:

This plot shows how RIASEC personality scores are distributed across all job profiles in the dataset. It helps identify which personality traits are more dominant in different careers and allows for comparison with a user's profile.

4. DATA MODELLING

Building The Recommendation Engine (RIASEC-Based)

4.1. RIASEC-Only Recommender (Cosine Similarity)

Match based on user interests only.

We'll:

1. Take a user's RIASEC scores as input
2. Calculate cosine similarity between the user's profile and all jobs
3. Return the top matching jobs

4.1.1. Importing Libraries

In [30]:
```
from sklearn.metrics.pairwise import cosine_similarity
```

4.1.2. Definining a Sample user RIASEC Profile

Creating a test user input (we'll later replace this with UI the user to self-rate themselves on a 1–7 scale)

In [31]:
```
# RIASEC scores: [Realistic, Investigative, Artistic, Social, Enterprising, Convent
# Sample user RIASEC profile (scale: 0-7)
user_profile = {
    'R': 2.0,
    'I': 4.0,
    'A': 2.0,
    'S': 5.0,
    'E': 4.0,
    'C': 4.0
}
```

4.1.3. Extracting job RIASEC profiles

In [32]:
```
# Extracting job RIASEC features
job_riasec_vectors = job_profiles_clean[riasec_cols].values
```

```
# Converting user profile to vector(Normalizing by dividing each values by 7)
user_vector = np.array(list((score / 7 for score in user_profile.values()))).reshap
```

4.1.4 Computing Cosine Similarity

In [33]:
```
# Computing similarity between user and all job profiles
similarities = cosine_similarity(user_vector, job_riasec_vectors)

# Adding to DataFrame
job_profiles_clean.loc[:,'Similarity Score'] = similarities.flatten()
job_profiles_clean
```

Out[33]:

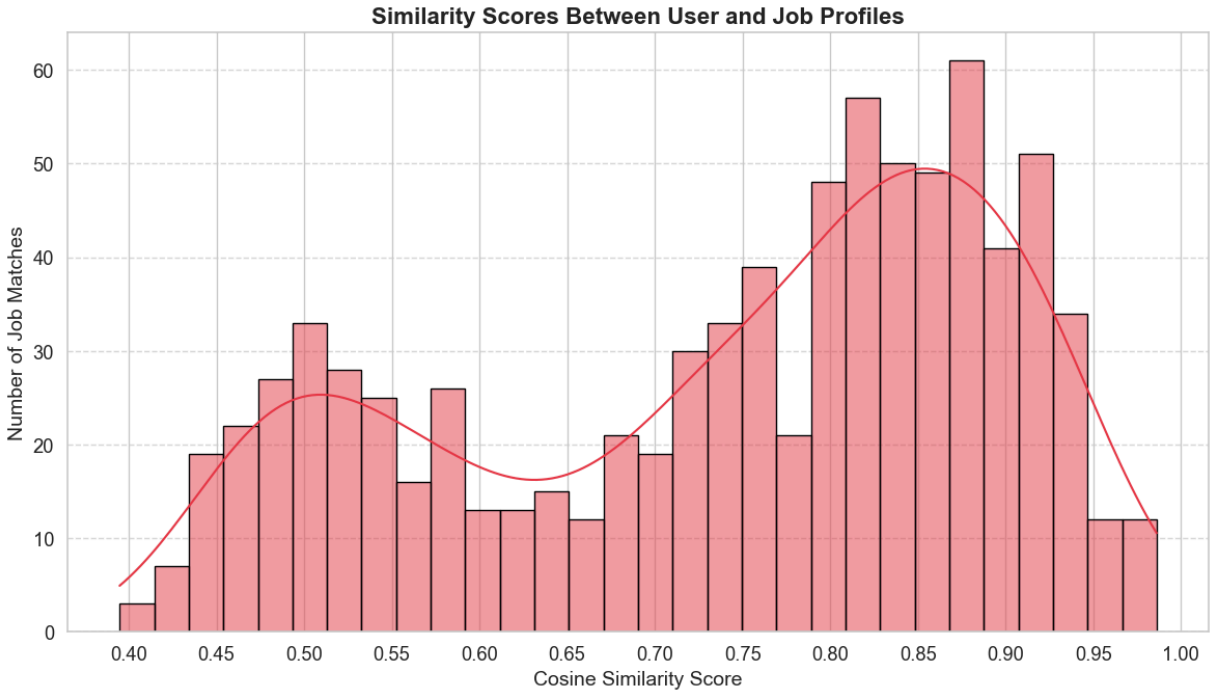
	ONET_Code	Title	Description	A	C	E	First Interest High-Point	
0	11-1011.00	Chief Executives	Determine and formulate policies and provide o...	0.180000	0.625468	0.980000	5.0	0.3733
1	11-1011.03	Chief Sustainability Officers	Communicate and coordinate with management, sh...	0.246667	0.529963	0.946667	5.0	0.6300
2	11-1021.00	General and Operations Managers	Plan, direct, or coordinate the operations of ...	0.051667	0.685393	0.993333	5.0	0.2316
4	11-2011.00	Advertising and Promotions Managers	Plan, direct, or coordinate advertising polici...	0.475000	0.494382	1.000000	5.0	0.1183
5	11-2021.00	Marketing Managers	Plan, direct, or coordinate marketing policies...	0.241667	0.569288	1.000000	5.0	0.3166
...	...	...	...	...	...	...	...	
991	53-7071.00	Gas Compressor and Gas Pumping Station Operators	Operate steam-, gas-, electric motor-, or inte...	0.000000	0.597378	0.086667	1.0	0.2216
992	53-7072.00	Pump Operators, Except Wellhead Pumpers	Tend, control, or operate power-driven, statio...	0.000000	0.533708	0.076667	1.0	0.2100
993	53-7073.00	Wellhead Pumpers	Operate power pumps and auxiliary equipment to...	0.000000	0.505618	0.145000	1.0	0.2350
994	53-7081.00	Refuse and Recyclable	Collect and dump refuse	0.000000	0.514981	0.091667	1.0	0.1283

	ONET_Code	Title	Description	A	C	E	First Interest High-Point	
		Material Collectors	or recyclable material...					
995	53-7121.00	Tank Car, Truck, and Ship Loaders	Load and unload chemicals and bulk solids, suc...	0.000000	0.565543	0.051667	1.0	0.1566

837 rows × 19 columns

4.1.5 Cosine Similarity Distribution

In [34]:
```
# Setting style
sns.set_style("whitegrid")
sns.set_context("notebook", font_scale=1.2)

# Setting figure size
plt.figure(figsize=(12, 7))

# Plot the histogram with KDE
sns.histplot(
    data=job_profiles_clean,
    x='Similarity Score',
    bins=30,
    kde=True,
    color='#E63946',
    edgecolor='black'
)

# Tittle and labels
plt.title("Similarity Scores Between User and Job Profiles", fontsize=16, weight='b
plt.xlabel("Cosine Similarity Score", fontsize=14)
plt.ylabel("Number of Job Matches", fontsize=14)
plt.xticks(np.arange(0.4, 1.05, 0.05))  #

# Adding a grid for readability
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Improving layout
plt.tight_layout()
plt.savefig('images/similarity_scores_distribution.png', dpi=300)

# Show plot
plt.show()
```



Interpretation: This histogram shows the distribution of cosine similarity scores between the user's profile and different job descriptions based on their RIASEC vectors..

- X-axis: Cosine similarity score (0 to 1). Higher scores mean higher similarity.
- Y-axis: Number of jobs within each similarity range.

Key Insights:

- This helps visualize how many jobs are highly relevant to the user.
- A concentration of bars toward the higher end means many jobs closely match the user's profile.

4.1.6 Top Job/Career Recommendations Based on RIASEC Fit

In [35]:
```
# Top 10 jobs that match user's RIASEC interests
top_matches = job_profiles_clean.sort_values(by='Similarity Score', ascending=False

# Show selected columns
top_matches[['Title', 'Education Level', 'Preparation Level', 'Description', 'Simil
```

Out[35]:

	Title	Education Level	Preparation Level	Description	Similarity Score
283	Probation Officers and Correctional Treatment ...	Required Level of Education	Post-Doctoral Training	Provide social services to assist in rehabilit...	0.986105
84	Training and Development Specialists	Required Level of Education	Doctoral Degree	Design or conduct work-related training and de...	0.982823
439	Clinical Nurse Specialists	Required Level of Education	Associate's Degree (or other 2-year degree)	Direct nursing staff in the provision of patie...	0.978385
294	Judges, Magistrate Judges, and Magistrates	Required Level of Education	Bachelor's Degree	Arbitrate, advise, adjudicate, or administer j...	0.974210
360	Instructional Coordinators	Required Level of Education	Doctoral Degree	Develop instructional material, coordinate edu...	0.973018
610	Travel Guides	On-the-Job Training	Over 1 year, up to and including 2 years	Plan, organize, and conduct long-distance trav...	0.970984
355	Curators	Required Level of Education	Post-Baccalaureate Certificate - awarded for c...	Administer collections, such as artwork, colle...	0.970292
298	Business Teachers, Postsecondary	Required Level of Education	High School Diploma - or the equivalent (for e...	Teach courses in business administration and m...	0.970134
417	Dietitians and Nutritionists	Required Level of Education	Doctoral Degree	Plan and conduct food service or nutritional p...	0.969686
47	Emergency Management Directors	Required Level of Education	Less than a High School Diploma	Plan and direct disaster response or crisis ma...	0.968888

Interpretation:

- We ranked all job profiles based on how similar they are to the user's RIASEC personality scores, using cosine similarity.
- Similarity = 0.99 → The user's RIASEC profile is very closely aligned with the profile for this occupation.
- The top jobs are:
  - Creative, social, and teaching-oriented
  - Strongly aligned with Artistic (A), Social (S), and Investigative (I) dimensions

- If the user's profile had high values for S, A, and I, this makes perfect sense.

What To Say to Users: "Based on your interests, you may enjoy careers where creativity, human connection, and education intersect. Here are the top matches for your profile!"

4.1.7. Filter Jobs by Education Level

- We'll filter the top matches based on the user's education level.

In [36]:
```
# Example filter: Only Bachelor's Degree and below
filtered_matches = top_matches[
    top_matches['Education Category'] <= 6.0  # <= Bachelor's Degree
]

filtered_matches[['Title', 'Education Level', 'Preparation Level', 'Description', '
```

Out[36]:

	Title	Education Level	Preparation Level	Description	Similarity Score
439	Clinical Nurse Specialists	Required Level of Education	Associate's Degree (or other 2-year degree)	Direct nursing staff in the provision of patie...	0.978385
294	Judges, Magistrate Judges, and Magistrates	Required Level of Education	Bachelor's Degree	Arbitrate, advise, adjudicate, or administer j...	0.974210
610	Travel Guides	On-the-Job Training	Over 1 year, up to and including 2 years	Plan, organize, and conduct long-distance trav...	0.970984
298	Business Teachers, Postsecondary	Required Level of Education	High School Diploma - or the equivalent (for e...	Teach courses in business administration and m...	0.970134
47	Emergency Management Directors	Required Level of Education	Less than a High School Diploma	Plan and direct disaster response or crisis ma...	0.968888
312	Economics Teachers, Postsecondary	Required Level of Education	High School Diploma - or the equivalent (for e...	Teach courses in economics. Includes both teac...	0.968753
32	Education Administrators, Postsecondary	Required Level of Education	Some College Courses	Plan, direct, or coordinate student instructio...	0.968574
323	Law Teachers, Postsecondary	On-Site or In-Plant Training	Up to and including 1 month	Teach courses in law. Includes both teachers p...	0.964218
31	Education Administrators, Kindergarten through...	Required Level of Education	High School Diploma - or the equivalent (for e...	Plan, direct, or coordinate the academic, admi...	0.961673
322	Criminal Justice and Law Enforcement Teachers,...	On-Site or In-Plant Training	Over 1 year, up to and including 2 years	Teach courses in criminal justice, corrections...	0.960645

4.1.8 Filter Jobs by Similarity Threshold

- We'll filter the top matches based on a similarity threshold to ensure we only recommend jobs that are closely aligned with the user's profile.

In [37]:
```
# Defining similarity threshold
similarity_threshold = 0.95

# Filtering jobs based on similarity threshold and education level
sim_matches = filtered_matches[filtered_matches['Similarity Score'] >= similarity_t
```

```
# Sorting the matches by similarity score
sim_matches = sim_matches.sort_values(by='Similarity Score', ascending=False)

# Show selected columns
sim_matches[['Title','Education Level', 'Preparation Level', 'Description', 'Simila
```

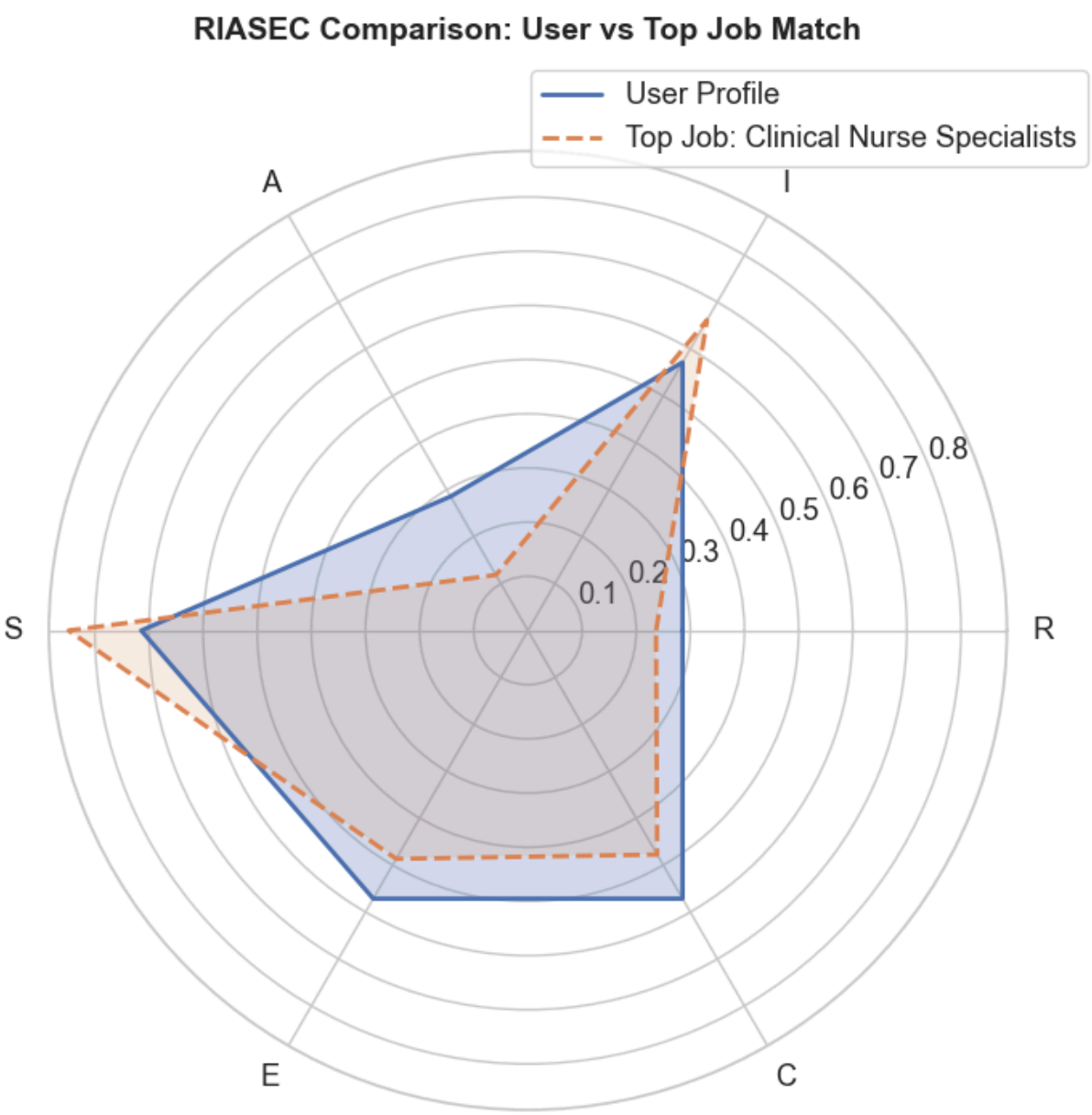
Out[37]:

	Title	Education Level	Preparation Level	Description	Similarity Score
439	Clinical Nurse Specialists	Required Level of Education	Associate's Degree (or other 2-year degree)	Direct nursing staff in the provision of patie...	0.978385
294	Judges, Magistrate Judges, and Magistrates	Required Level of Education	Bachelor's Degree	Arbitrate, advise, adjudicate, or administer j...	0.974210
610	Travel Guides	On-the-Job Training	Over 1 year, up to and including 2 years	Plan, organize, and conduct long-distance trav...	0.970984
298	Business Teachers, Postsecondary	Required Level of Education	High School Diploma - or the equivalent (for e...	Teach courses in business administration and m...	0.970134
47	Emergency Management Directors	Required Level of Education	Less than a High School Diploma	Plan and direct disaster response or crisis ma...	0.968888
312	Economics Teachers, Postsecondary	Required Level of Education	High School Diploma - or the equivalent (for e...	Teach courses in economics. Includes both teac...	0.968753
32	Education Administrators, Postsecondary	Required Level of Education	Some College Courses	Plan, direct, or coordinate student instructio...	0.968574
323	Law Teachers, Postsecondary	On-Site or In-Plant Training	Up to and including 1 month	Teach courses in law. Includes both teachers p...	0.964218
31	Education Administrators, Kindergarten through...	Required Level of Education	High School Diploma - or the equivalent (for e...	Plan, direct, or coordinate the academic, admi...	0.961673
322	Criminal Justice and Law Enforcement Teachers,...	On-Site or In-Plant Training	Over 1 year, up to and including 2 years	Teach courses in criminal justice, corrections...	0.960645

4.1.9. RIASEC Radar Chart Comparing User vs Top Job

Visualize the match to help explain recommendations and compare the user's RIASEC profile against the top matching job

In [38]:
```
# Selecting top matching job
top_job = sim_matches.iloc[0]

# RIASEC order
riasec_labels = ['R', 'I', 'A', 'S', 'E', 'C']

# Getting user and job scores
user_scores = user_vector.flatten().tolist()


job_scores = [top_job[col] for col in riasec_labels]

# Closing the loop
user_scores += [user_scores[0]]
job_scores += [job_scores[0]]
labels = riasec_labels + [riasec_labels[0]]

# Only generate angles for the 6 base points
angles = np.linspace(0, 2 * np.pi, len(riasec_labels), endpoint=False).tolist()
angles += [angles[0]]

# Plotting
plt.figure(figsize=(14, 8))
ax = plt.subplot(111, polar=True)

ax.plot(angles, user_scores, linewidth=2, linestyle='solid', label='User Profile')
ax.fill(angles, user_scores, alpha=0.25)

ax.plot(angles, job_scores, linewidth=2, linestyle='dashed', label=f"Top Job: {top_
ax.fill(angles, job_scores, alpha=0.15)

ax.set_xticks(angles[:-1])
ax.set_xticklabels(riasec_labels)
ax.set_title('RIASEC Comparison: User vs Top Job Match', size=14, weight='bold', pa
ax.legend(loc='upper right', bbox_to_anchor=(1.1, 1.1))

plt.tight_layout(pad=3)
plt.savefig('images/riasec_comparison_user_vs_job.png', dpi=300)
plt.show()
```



Interpretation of the Chart:

This radar chart compares the user's RIASEC profile scores(Solid blue line) (Realistic, Investigative, Artistic, Social, Enterprising, Conventional) with the top matched job: Political Science Teachers, Postsecondary (dashed orange line.

- Each axis ranges from 0 to 7 (raw RIASEC scores before normalization).

Key Insights:

RIASEC Trait	User Score	Job Score	Interpretation
R (Realistic)	Low (~2)	Low (~2)	Neither you nor the job requires mechanical/practical skills. Alignment.
I (Investigative)	High (~6)	Slightly lower (~5.5)	You're analytical; so is the job—good match.

RIASEC Trait	User Score	Job Score	Interpretation
A (Artistic)	Moderate (~3.5)	Slightly lower (~3)	Both lean creative, but not dominantly so. Partial fit.
S (Social)	High (~5)	Very high (~7)	Teaching is very people-focused. Your profile fits well.
E (Enterprising)	Medium (~3.5)	Slightly above (~4)	Job is more leadership-focused; you're a moderate fit.
C (Conventional)	Low (~1.5)	Higher (~3)	You prefer unstructured work; job requires some order. Minor mismatch.

The user and the job align strongly on You and the job align strongly on:

- Social (S)
- Investigative (I)
- Low Realistic (R)

With a slight differences in:

- Conventional (C)
- Enterprising (E)

Conclusion:

This is a strong RIASEC match, particularly for teaching, research, and discussion-heavy environments. A great suggestion if you're socially driven, analytical, and enjoy knowledge-sharing.

4.2 RIASEC + Education + Skills - Hybrid recommender Recommender (Filtered Similarity)

Objective: Refine job recommendations by including an education-level filter alongside RIASEC similarity, ensuring users only see jobs they're qualified for.

- Match based on user interests
- Filter jobs by user’s education level (Bachelor’s degree, in this case).

This enhancement filters out occupations that require a higher level of education than the user has attained. We still rank by RIASEC similarity, but only among jobs within the user's educational qualification range. We'll now:

- Ask user for their education level
- Skill Match
- Filter job_profiles to remove jobs that require more education than the user has
- Return final recommendations (sorted by RIASEC similarity)

4.2.1. Extract or Encode Skill Features

We'll use Prep Component (from education_df_with_cat) to identify the unique skill components.

a) Grouping skills per job

This groups the skills by ONET Code, aggregating them into a list for each job.

In [39]:
```
# Grouping skills per job
skills_per_job = education_df_with_cat.groupby('ONET_Code')['Prep Component'] \
                                      .apply(list).reset_index()
skills_per_job.columns = ['ONET_Code', 'Skill List']
```

In [40]:
```
# Merging into job_profiles_clean
job_profiles_clean = job_profiles_clean.merge(skills_per_job, on='ONET_Code', how='
```

4.2.2. Encoding the skills using `OneHotEncoder`

- This step encodes the skills into a format suitable for machine learning.

In [41]:
```
from sklearn.preprocessing import OneHotEncoder

encoder = OneHotEncoder(sparse_output=False, handle_unknown='ignore')

# Exploding to long form and keeping ONET_Code
exploded_skills = job_profiles_clean[['ONET_Code', 'Skill List']].explode('Skill Li

# Encoding skills
skill_features = pd.DataFrame(
        encoder.fit_transform(exploded_skills[['Skill List']]),
        columns=encoder.get_feature_names_out(['Skill List'])
)
# Add ONET_Code back to skill_features for merging
skill_features['ONET_Code'] = exploded_skills['ONET_Code'].values

# Aggregate skill features by ONET_Code (sum, since one-hot)
skill_features = skill_features.groupby('ONET_Code', as_index=False).max()

# Merging into main DataFrame
job_profiles_clean = job_profiles_clean.drop(columns=['Skill List'], errors='ignore
job_profiles_clean = job_profiles_clean.merge(skill_features, on='ONET_Code', how='
```

In [42]:
```
# Preview the final DataFrame structure
print("Final job profiles DataFrame structure:")
job_profiles_clean.head()
```

```
Final job profiles DataFrame structure:
```

Out[42]:

	ONET_Code	Title	Description	A	C	E	First Interest High-Point	I
0	11-1011.00	Chief Executives	Determine and formulate policies and provide o...	0.180000	0.625468	0.980000	5.0	0.373333
1	11-1011.03	Chief Sustainability Officers	Communicate and coordinate with management, sh...	0.246667	0.529963	0.946667	5.0	0.630000
2	11-1021.00	General and Operations Managers	Plan, direct, or coordinate the operations of ...	0.051667	0.685393	0.993333	5.0	0.231667
3	11-2011.00	Advertising and Promotions Managers	Plan, direct, or coordinate advertising polici...	0.475000	0.494382	1.000000	5.0	0.118333
4	11-2021.00	Marketing Managers	Plan, direct, or coordinate marketing policies...	0.241667	0.569288	1.000000	5.0	0.316667

5 rows × 25 columns

4.2.3. Combining RIASEC + Normalized Skills + Normalized Education Vectors

We will combine:

- RIASEC scores (6D vector, already normalized)
- Skills (one-hot vector, binary)
- Education Score (scalar → we'll reshape it to 1D for vector concat)

In [43]:
```
# Extracting RIASEC, Education, and Skills values for further processing

riasec_values = job_profiles_clean[riasec_cols].values
education_values = job_profiles_clean['Normalized Education Score'].values
```

```
# Extracting skill columns from job_profiles_clean
skill_cols = [col for col in job_profiles_clean.columns if col.startswith("Skill Li
skills_values = job_profiles_clean[skill_cols].values
```

In [44]:
```
# Displaying the shapes of the extracted values
print(f'The education value shape {education_values.shape}')
print(f'The skill values shape{skills_values.shape}')
print(f'The riasec values shape {riasec_values.shape}')
```

```
The education value shape (837,)
The skill values shape(837, 6)
The riasec values shape (837, 6)
```

4.2.4. Normalize and Weight the Vectors

We'll scale each section to the same range, then apply custom weights:

- RIASEC: 50%
- Skills: 30%
- Education Score: 20%

Since the RIASEC and Education scores are already normalized to 0–1, we can directly apply the weights.We will scale the skills with the same `MinMaxScaler` to ensure they are also in the 0–1 range.

In [45]:
```
# Instantiate scaler
scaler = MinMaxScaler()

skill_values_scaled = scaler.fit_transform(skills_values)

riasec_w = 0.5
education_w = 0.2
skills_w = 0.3

# Ensure all are numpy arrays before multiplying
weighted_riasec = np.asarray(riasec_values) * riasec_w
weighted_education = np.asarray(education_values) * education_w
weighted_skills = np.asarray(skill_values_scaled) * skills_w

# Combining the weighted vectors
hybrid_matrix = np.hstack((weighted_riasec, weighted_education.reshape(-1, 1), weig
```

In [46]:
```
hybrid_matrix.shape
```

Out[46]:
```
(837, 13)
```

4.2.5. Building User Vector and Computing Similarities

We'll:

- Create the user hybrid vector
- Compare with all job hybrid vectors using cosine similarity

- Return top-N matches

In [47]:
```
# User profile
user_riasec = user_vector
user_edu_score = np.array(6/12).reshape(1, -1)  # Normalized
user_skills = np.zeros(skills_values.shape[1]).reshape(1, -1)  # No known learning
```

In [48]:
```
# Hybrid User Vector
user_hybrid_vector = np.hstack([
    user_riasec * riasec_w,
    user_skills * skills_w,
    user_edu_score * education_w
])
```

In [49]:
```
# Computing cosine Similarity between user and all jobs profiles
hybrid_similarity = cosine_similarity(user_hybrid_vector, hybrid_matrix)

# Storing in DataFrame
job_profiles_clean['Hybrid Similarity'] = hybrid_similarity.flatten()
top_hybrid_matches = job_profiles_clean.sort_values('Hybrid Similarity', ascending=
```

4.2.6. Top 10 Hybrid Similarity Recommendations(RIASEC + Education)

In [50]:
```
top_hybrid_matches = job_profiles_clean.sort_values('Hybrid Similarity', ascending=

# Show top matches with useful columns
# top_hybrid_matches[['Title', 'Education Category Label', 'Hybrid Similarity', 'Si
top_hybrid_matches[['Title', 'Description', 'Education Level', 'Preparation Level',
```

Out[50]:

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Similarity	Simi
293	Teaching Assistants, Postsecondary	Assist faculty or other instructional staff in postsecondary institutions by performing instructional support activities, such as developing teaching materials, leading discussion groups, preparing and giving examinations, and grading examinations or papers.	Required Level of Education	Less than a High School Diploma	Less than High School	0.928467	0.93
54	Equal Opportunity Representatives and Officers	Monitor and evaluate compliance with equal opportunity laws, guidelines, and policies to ensure that employment practices and contracting arrangements give equal opportunity without regard to race, religion, color, national origin, sex, age, or disability.	Required Level of Education	High School Diploma - or the equivalent (for example, GED)	High School Diploma or equivalent	0.923673	0.93
227	Community Health Workers	Promote health within a community by assisting individuals to adopt healthy behaviors.	On-the-Job Training	Over 1 year, up to and including 2 years	Bachelor's Degree	0.921671	0.94

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Similarity	Simi
		Serve as an advocate for the health needs of individuals by assisting community residents in effectively communicating with healthcare providers or social service agencies. Act as liaison or advocate and implement programs that promote, maintain, and improve individual and overall community health. May deliver health-related preventive services such as blood pressure, glaucoma, and hearing screenings. May collect data to help identify community health needs.					
405	Genetic Counselors	Assess individual or family risk for a variety of inherited conditions, such as genetic disorders and birth defects. Provide information to other	Required Level of Education	Associate's Degree (or other 2-year degree)	Associate's Degree	0.921493	0.93

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Similarity	Simi
		healthcare providers or to individuals and families concerned with the risk of inherited conditions. Advise individuals and families to support informed decisionmaking and coping methods for those at risk. May help conduct research related to genetic conditions or genetic counseling.					
443	Private Detectives and Investigators	Gather, analyze, compile, and report information regarding individuals or organizations to clients, or detect occurrences of unlawful acts or infractions of rules in private establishment.	Required Level of Education	Some College Courses	Some College Courses	0.914266	0.93
512	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	Sell goods for wholesalers or manufacturers where technical or scientific knowledge is required in such areas as biology, engineering,	On-Site or In-Plant Training	Up to and including 1 month	High School Diploma or equivalent	0.906512	0.91

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Similarity	Simi
		chemistry, and electronics, normally obtained from at least 2 years of postsecondary education.					
199	Historians	Research, analyze, record, and interpret the past as recorded in sources, such as government and institutional records, newspapers and other periodicals, photographs, interviews, films, electronic media, and unpublished manuscripts, such as personal diaries and letters.	On-Site or In-Plant Training	Over 3 months, up to and including 6 months	Some College Courses	0.897710	0.91
8	Computer and Information Systems Managers	Plan, direct, or coordinate activities in such fields as electronic data processing, information systems, systems analysis, and computer programming.	Required Level of Education	Some College Courses	Some College Courses	0.885588	0.89
364	Neurologists	Diagnose, manage, and treat disorders and diseases of the brain, spinal cord, and peripheral	Required Level of Education	Some College Courses	Some College Courses	0.883653	0.89

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Similarity	Simi
		nerves, with a primarily nonsurgical focus.					
375	Sports Medicine Physicians	Diagnose, treat, and help prevent injuries that occur during sporting events, athletic training, and physical activities.	On-the-Job Training	Over 2 years, up to and including 4 years	Post-Baccalaureate Certificate	0.881408	0.9(

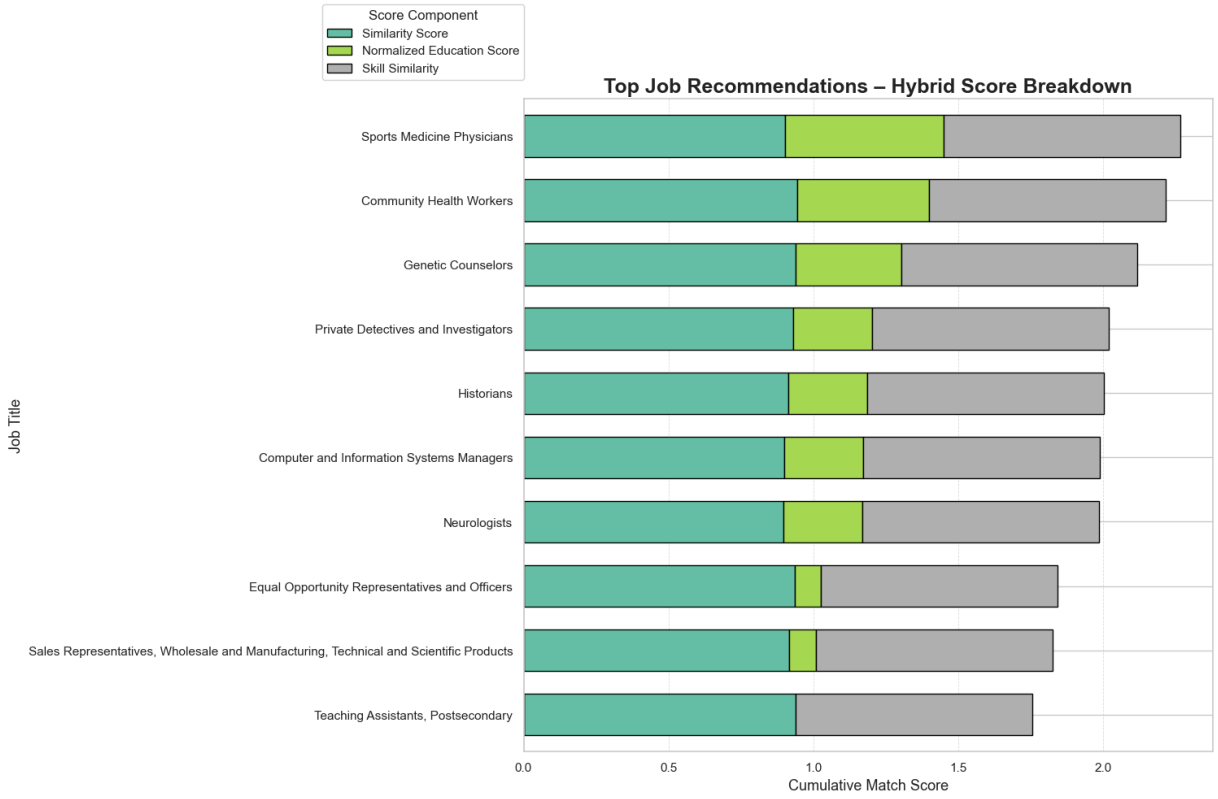
This chart displays best-fit jobs ranked by combined similarity, showing education match and RIASEC similarity too.

4.2.7. Bar Plot for Hybrid Score Decomposition

- Helps explain why a job is recommended.
- Compute and Add a Skill Similarity Column

In [51]:
```
from sklearn.metrics.pairwise import cosine_similarity

# Getting one-hot skill column names
skill_cols = encoder.get_feature_names_out(['Skill List']).tolist()

# Removing overlapping skill columns
existing_skill_cols = [col for col in skill_cols if col in top_hybrid_matches.colum
top_hybrid_matches = top_hybrid_matches.drop(columns=existing_skill_cols, errors='i

# Merging one-hot skill features
top_hybrid_matches = top_hybrid_matches.merge(skill_features, on='ONET_Code', how='

# Defining user's skill vector (e.g, all skills)
user_skill_vector = np.ones((1, len(skill_cols)))

# Computing cosine similarity
job_skill_matrix = top_hybrid_matches[skill_cols].values
skill_similarities = cosine_similarity(user_skill_vector, job_skill_matrix)[0]

# Adding to DataFrame
top_hybrid_matches['Skill Similarity'] = skill_similarities

# Getting top 10 matches and prep plot data
top_n = top_hybrid_matches.head(10).copy()
plot_data = top_n[['Similarity Score', 'Normalized Education Score', 'Skill Similar
plot_data.index = top_n['Title']
```

```
plot_data['Total'] = plot_data.sum(axis=1)
plot_data = plot_data.sort_values('Total', ascending=True).drop(columns='Total')

# Plot
fig, ax = plt.subplots(figsize=(16, 10))
plot_data.plot(
    kind='barh',
    stacked=True,
    ax=ax,
    colormap='Set2',
    edgecolor='black',
    width=0.65
)

# Title and labels
ax.set_title("Top Job Recommendations – Hybrid Score Breakdown", fontsize=18, fontw
ax.set_xlabel("Cumulative Match Score", fontsize=13)
ax.set_ylabel("Job Title", fontsize=13)
ax.grid(axis='x', linestyle='--', linewidth=0.6, alpha=0.6)

# Font and spacing
plt.xticks(fontsize=11)
plt.yticks(fontsize=11)
plt.tight_layout(pad=3)

# Legend placement
ax.legend(
    title="Score Component",
    loc='lower right',
    bbox_to_anchor=(0.01, 1.02),  # Fine-tune legend position
    fontsize=11,
    title_fontsize=12
)

# Show and save
plt.savefig('images/hybrid_score_decomposition.png', dpi=300)
plt.show()
```



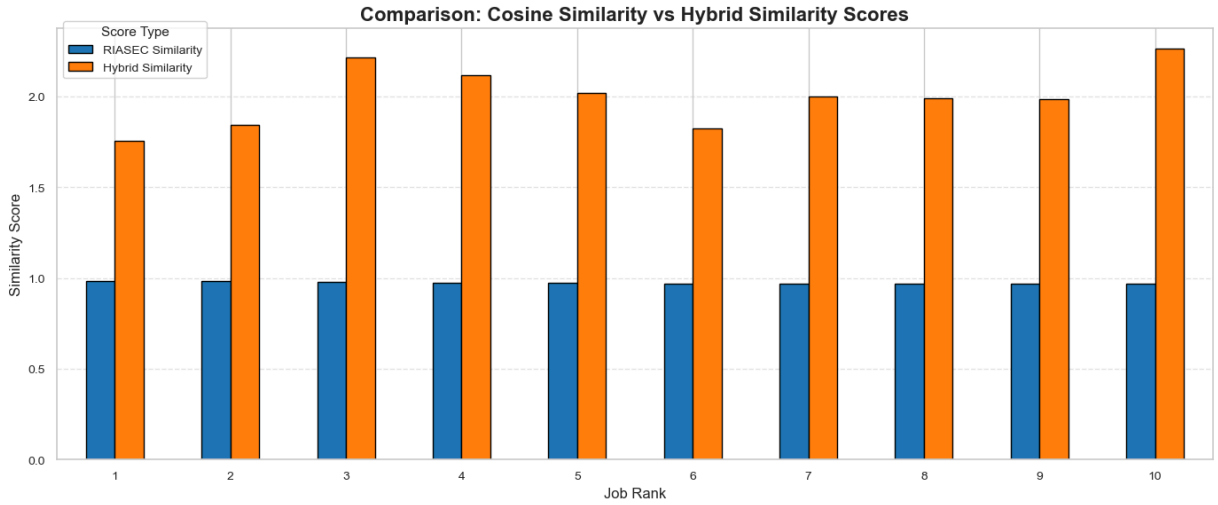
In [ ]:

4.2.8. Comparison Chart of Cosine Similarity (Option A) vs Filtered Hybrid Similarity Scores (Option B)

Visualizing Cosine Similarity (Option A) vs Filtered Hybrid Similarity (Option B) for Top 10 Job Matches. A Side-by-Side View of RIASEC-Only vs RIASEC + Education + Skills Recommendations

In [52]:
```
#  Getting top 10 scores from both methods
top_a = top_matches[['Title', 'Similarity Score']].copy().head(10)
top_b = top_hybrid_matches[['Title', 'Similarity Score', 'Normalized Education Scor

# Computing Hybrid Score
top_b['Hybrid Similarity'] = top_b[['Similarity Score', 'Normalized Education Score

# Adding a ranking index for consistent plotting
top_a.reset_index(drop=True, inplace=True)
top_b.reset_index(drop=True, inplace=True)
top_a['Rank'] = top_a.index + 1
top_b['Rank'] = top_b.index + 1

# Merging by Rank
comparison_df = pd.merge(
    top_a[['Rank', 'Similarity Score']],
    top_b[['Rank', 'Hybrid Similarity']],
    on='Rank'
)
comparison_df.rename(columns={'Similarity Score': 'RIASEC Similarity'}, inplace=Tru
```

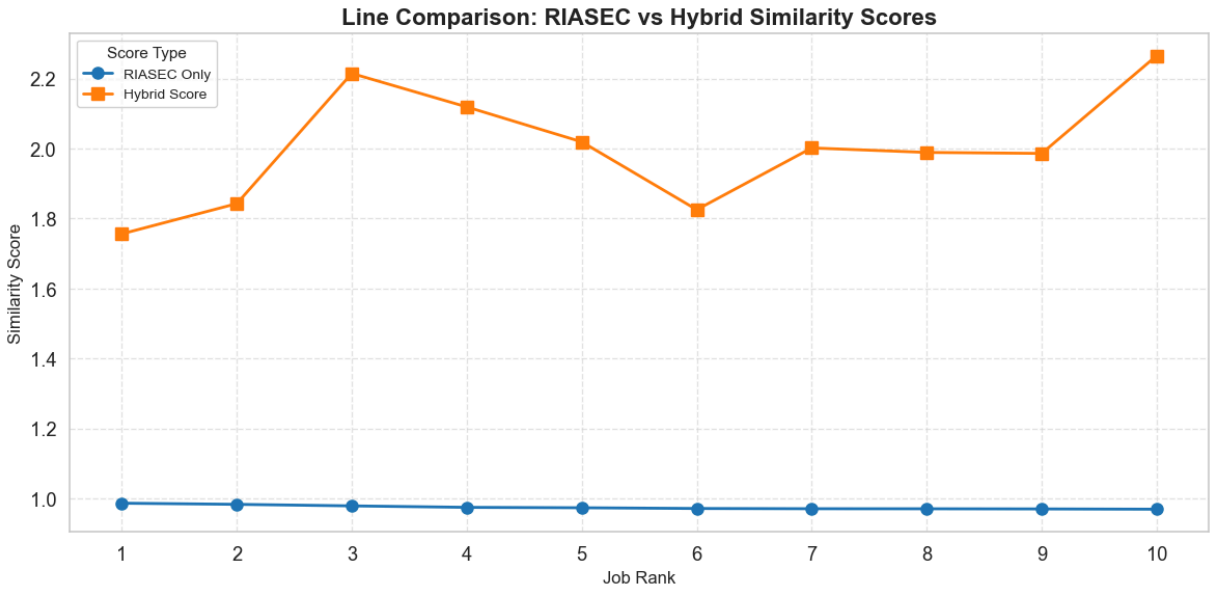
```
# Plot
custom_colors = ['#1f77b4', '#ff7f0e']  #
ax = comparison_df.plot(
    x='Rank',
    kind='bar',
    figsize=(14, 6),
    color=custom_colors,
    edgecolor='black'
)

# Titles and Labels
plt.title("Comparison: Cosine Similarity vs Hybrid Similarity Scores", fontsize=16,
plt.xlabel("Job Rank", fontsize=12)
plt.ylabel("Similarity Score", fontsize=12)
plt.xticks(rotation=0, fontsize=10)
plt.yticks(fontsize=10)
plt.grid(axis='y', linestyle='--', alpha=0.5)

# Legend in top-left
plt.legend(title="Score Type", loc='upper left', bbox_to_anchor=(0, 1.03), fontsize

# Save
plt.tight_layout()
plt.savefig('images/riasec_vs_hybrid_similarity_comparison.png', dpi=300)
plt.show()
```



Line Plot for RIASEC Only vs Hybrid Similarity Scores

In [53]:
```
# Getting top 10 scores from both methods
top_a = top_matches[['Title', 'Similarity Score']].copy().head(10)
top_b = top_hybrid_matches[['Title', 'Similarity Score', 'Normalized Education Scor

# Computing Hybrid Score
top_b['Hybrid Similarity'] = top_b[['Similarity Score', 'Normalized Education Score

# Resetting index and assigning rank
```

```
top_a = top_a.reset_index(drop=True)
top_b = top_b.reset_index(drop=True)
top_a['Rank'] = top_a.index + 1
top_b['Rank'] = top_b.index + 1

# Merging by Rank
comparison_df = pd.merge(
    top_a[['Rank', 'Similarity Score']],
    top_b[['Rank', 'Hybrid Similarity']],
    on='Rank'
)
comparison_df.rename(columns={'Similarity Score': 'RIASEC Similarity'}, inplace=Tru

# Plotting line graph
plt.figure(figsize=(12, 6))
plt.plot(comparison_df['Rank'], comparison_df['RIASEC Similarity'], marker='o', lin
plt.plot(comparison_df['Rank'], comparison_df['Hybrid Similarity'], marker='s', lin

# Title and labels
plt.title("Line Comparison: RIASEC vs Hybrid Similarity Scores", fontsize=16, fontw
plt.xlabel("Job Rank", fontsize=12)
plt.ylabel("Similarity Score", fontsize=12)
plt.xticks(comparison_df['Rank'], labels=comparison_df['Rank'])
plt.grid(True, linestyle='--', alpha=0.5)
plt.legend(loc='upper left', title="Score Type", fontsize=10, title_fontsize=11)
plt.tight_layout()

# Show
plt.savefig("images/riasec_vs_hybrid_similarity_lineplot.png", dpi=300)
plt.show()
```



Interpretation:

The top 10 recommended occupations (e.g., Community health worker, Genetic Councellors, Recreational Workers) are:

- Highly aligned with the user's RIASEC profile (cosine similarity scores above 0.92).

- Filtered to match the user's education level (in this case: Bachelor's degree).

Each job listed requires a "Required Level of Education", which—based on our mapping is aligned with or below the user's qualification. This ensures the recommendations are both personally relevant and practically attainable.

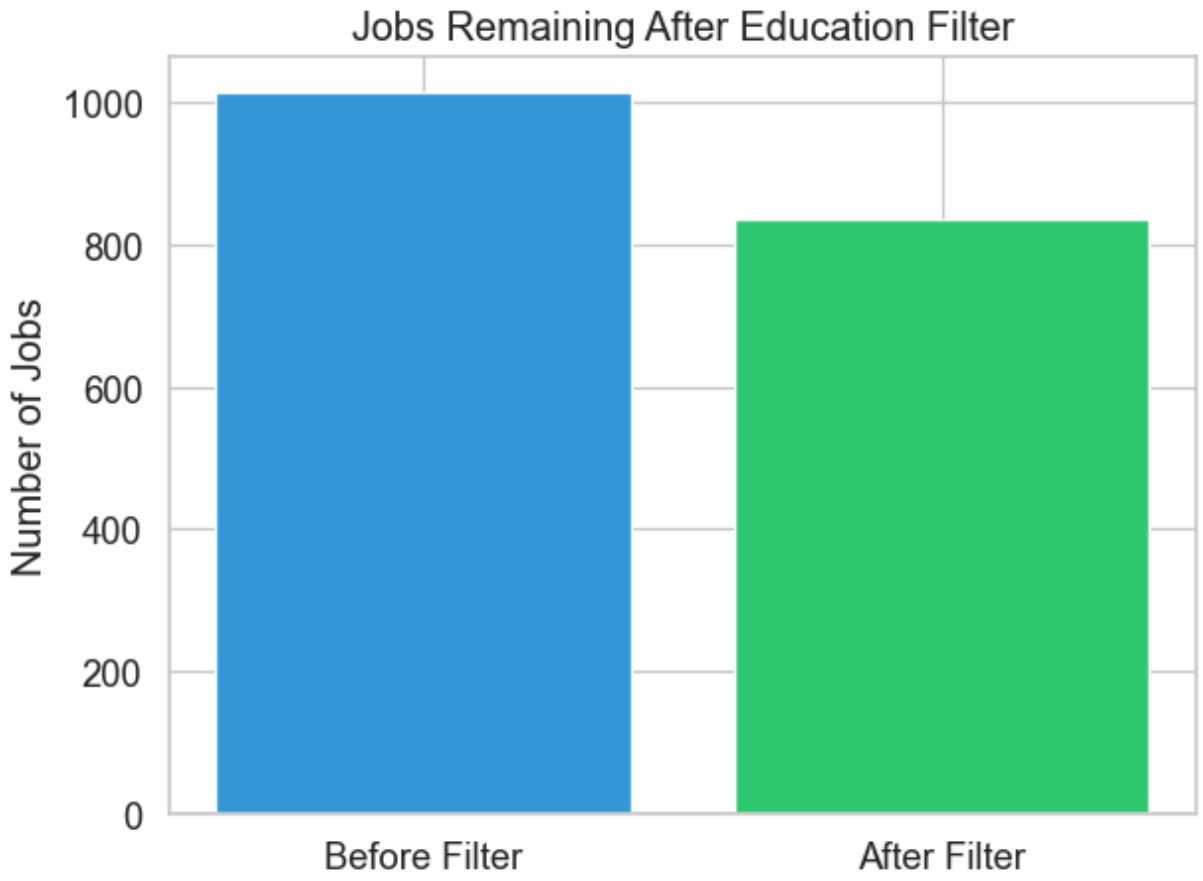
Criteria	Option A (RIASEC Only)	Option B (RIASEC + Education+Skill Filter)
Personal Fit	Based on interest similarity	Same interest-based similarity
Education Relevance	Might include jobs the user is **not qualified** for	Only includes jobs the user **is qualified** for
Example Roles	May include CEOs, lawyers, physicians	Shows more accessible jobs like therapists, teachers
Use Case	Exploratory career matching	Realistic, action-ready suggestions

Conclusion:

Option B delivers personalized and qualified career matches helping users explore realistic job opportunities while staying aligned with their interests.

4.2.9. Count Plot: How Many Jobs Were Filtered Out

In [54]:
```
# Counting jobs before and after filtering
total_jobs = len(job_profiles)
filtered_jobs_count = len(job_profiles_clean['Normalized Education Score'] > (6/12)

# Bar plot
plt.bar(['Before Filter', 'After Filter'], [total_jobs, filtered_jobs_count], color
plt.title('Jobs Remaining After Education Filter')
plt.ylabel('Number of Jobs')
plt.tight_layout()
plt.savefig('images/jobs_remaining_after_education_filter.png', dpi=300)
plt.show()
```



The jobs were filtered out by 20% after applying the education level filter.

4.3 Enhancing Recommendations with User skill search

In [55]:
```
abilities_df
```

Out[55]:

	ONET_Code	Ability	Data Value
0	11-1011.00	Oral Comprehension	4.62
2	11-1011.00	Written Comprehension	4.25
4	11-1011.00	Oral Expression	4.50
6	11-1011.00	Written Expression	4.12
8	11-1011.00	Fluency of Ideas	3.88
...	...	...	...
91406	53-7121.00	Hearing Sensitivity	3.00
91408	53-7121.00	Auditory Attention	3.00
91410	53-7121.00	Sound Localization	2.00
91412	53-7121.00	Speech Recognition	3.12
91414	53-7121.00	Speech Clarity	3.12

45708 rows × 3 columns

In [56]:
```
# Defining User Skill Preferences
user_selected_skills = ['Deductive Reasoning', 'Information Ordering', 'Mathematica
```

4.3.1 Binary Encode Job Skills

We'll create binary vectors for each job skill, marking 1 if the job requires a selected skill.

In [57]:
```
from sklearn.metrics.pairwise import cosine_similarity
# Getting skill column names (already one-hot encoded)
skill_cols = [col for col in job_profiles_clean.columns if col.startswith('Skill Li

# Building user skill vector (assumes user selects all skills)
user_skill_vector = np.array([1] * len(skill_cols)).reshape(1, -1)

# Creating job skill matrix and fill any NaNs (if any)
job_skill_matrix = job_profiles_clean[skill_cols].fillna(0).values

# Computing cosine similarity
skill_similarities = cosine_similarity(user_skill_vector, job_skill_matrix)[0]

# Adding similarity scores back to the DataFrame
job_profiles_clean['Skill Similarity'] = skill_similarities
```

In [58]:
```
# Creating binary matrix where 1 = job requires this user-selected ability
job_ability_matrix = abilities_df[abilities_df['Ability'].isin(user_selected_skills

# Pivot to get 1 row per job, columns per selected ability
job_ability_matrix['has_skill'] = 1
job_ability_matrix = job_ability_matrix.pivot_table(
```

```
    index='ONET_Code',
    columns='Ability',
    values='has_skill',
    fill_value=0
).reset_index()
```

4.3.2. Computing Cosine Similarity

In [59]:
```
# Building user ability vector (all 1s since user selected all these skills)
user_ability_vector = np.array([1] * len(user_selected_skills)).reshape(1, -1)

# Creating job ability matrix
job_ability_matrix_only = job_ability_matrix[user_selected_skills].values
ability_similarities = cosine_similarity(user_ability_vector, job_ability_matrix_on

# Adding similarity back to job_ability_matrix
job_ability_matrix['Job Ability Skill Similarity'] = ability_similarities
```

4.3.3. Merging Ability with job_profiles_clean

In [60]:
```
# Merging ability similarities back into main job_profiles_clean DataFrame
job_profiles_clean = job_profiles_clean.merge(
    job_ability_matrix[['ONET_Code', 'Job Ability Skill Similarity']],
    on='ONET_Code',
    how='left'
)

# Filling any unmatched jobs with 0 similarity
job_profiles_clean['Job Ability Skill Similarity'] = job_profiles_clean['Job Abilit
```

In [61]:
```
# Checking the required columns exist (they should based on your recent output)
assert 'Similarity Score' in job_profiles_clean.columns
assert 'Normalized Education Score' in job_profiles_clean.columns
assert 'Skill Similarity' in job_profiles_clean.columns
assert 'Job Ability Skill Similarity' in job_profiles_clean.columns
```

4.3.4. Final Score - Job Hybrid Similarity Score with Ability

In [62]:
```
job_profiles_clean['Job Hybrid Similarity Score'] = (
    job_profiles_clean['Similarity Score'] +
    job_profiles_clean['Normalized Education Score'] +
    job_profiles_clean['Skill Similarity'] +
    job_profiles_clean['Job Ability Skill Similarity']
)
```

4.3.5. Top 10 Job Skill Hybrid Similarity Recommendations(RIASEC + Education + Skills + Job Skills)

In [63]:
```
# Sorting by total hybrid score including job abilities
top_job_hybrid_matches = job_profiles_clean.sort_values(
```

```
    'Job Hybrid Similarity Score',
    ascending=False
).head(10)

# Display top job matches with key info
top_job_hybrid_matches[[
    'Title',
    'Description',
    'Education Level',
    'Preparation Level',
    'Education Category Label',
    'Job Hybrid Similarity Score',
    'Hybrid Similarity',
    'Similarity Score',
    'Normalized Education Score'
]].style.background_gradient(cmap='YlGn')
```

Out[63]:

	Title	Description	Education Level	Preparation Level	Education Category Label	Job Hybrid Similarity Score	Hybr Similari
225	Probation Officers and Correctional Treatment Specialists	Provide social services to assist in rehabilitation of law offenders in custody or on probation or parole. Make recommendations for actions involving formulation of rehabilitation plan and treatment of offender, including conditional release and education and employment stipulations.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	3.986105	0.7514
196	Urban and Regional Planners	Develop comprehensive plans and programs for use of land and physical facilities of jurisdictions, such as towns, cities, counties, and metropolitan areas.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	3.938289	0.7275
379	Naturopathic Physicians	Diagnose, treat, and help prevent diseases using a system of practice that is based on the natural healing capacity of individuals. May use physiological, psychological or mechanical methods. May also use natural medicines, prescription or legend drugs,	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	3.897019	0.7239

	Title	Description	Education Level	Preparation Level	Education Category Label	Job Hybrid Similarity Score	Hybr Similari
		foods, herbs, or other natural remedies.					
335	Optometrists	Diagnose, manage, and treat conditions and diseases of the human eye and visual system. Examine eyes and visual system, diagnose problems or impairments, prescribe corrective lenses, and provide treatment. May prescribe therapeutic drugs to treat specific eye conditions.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	3.893570	0.7180
68	Training and Development Specialists	Design or conduct work-related training and development programs to improve individual skills or organizational performance. May analyze organizational training needs or evaluate training effectiveness.	Required Level of Education	Doctoral Degree	Doctoral Degree	3.891914	0.7635
280	Special Education Teachers, Secondary School	Teach academic, social, and life skills to secondary school students with learning, emotional, or physical disabilities. Includes teachers who specialize and work with students who are	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	3.887890	0.7063

	Title	Description	Education Level	Preparation Level	Education Category Label	Job Hybrid Similarity Score	Hybr Similari
		blind or have visual impairments; students who are deaf or have hearing impairments; and students with intellectual disabilities.					
291	Instructional Coordinators	Develop instructional material, coordinate educational content, and incorporate current technology into instruction in order to provide guidelines to educators and instructors for developing curricula and conducting courses. May train and coach teachers. Includes educational consultants and specialists, and instructional material directors.	Required Level of Education	Doctoral Degree	Doctoral Degree	3.882109	0.7816
499	Exercise Trainers and Group Fitness Instructors	Instruct or coach groups or individuals in exercise activities for the primary purpose of personal fitness. Demonstrate techniques and form, observe participants, and explain to them corrective measures necessary to	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	3.878936	0.6814

	Title	Description	Education Level	Preparation Level	Education Category Label	Job Hybrid Similarity Score	Hybr Similari
		improve their skills. Develop and implement individualized approaches to exercise.					
334	Dietitians and Nutritionists	Plan and conduct food service or nutritional programs to assist in the promotion of health and control of disease. May supervise activities of a department providing quantity food services, counsel individuals, or conduct nutritional research.	Required Level of Education	Doctoral Degree	Doctoral Degree	3.878777	0.7550
34	Water Resource Specialists	Design or implement programs and strategies related to water resource issues such as supply, quality, and regulatory compliance issues.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	3.874301	0.6820

Interpretation:

This table shows the top 10 job recommendations based on the user's RIASEC profile, education level, and selected skills. Each job is ranked by its hybrid similarity score, which combines interest alignment, education match, and skill relevance.

The scores however are not as good as the previous ones because we are now filtering by skills, which may not be present in all jobs.

Thus this model is not ideal when selecting job skills and a better way to build the engine would be to simply filtering it rather than using it in the hybrid similarity score.

Key Insights:

The recommendations do not align as well so we will build the final reccomender based on RIASEC + Education + Skills only, without the job skills filter but allow users to filter by skills in the UI.

4.4 Final Recommendation Engine

We will build the final recommendation engine based on RIASEC + Education + Skills only, without the job skills filter but allow users to filter by skills in the inputs.

4.4.1. Adding User Input Interface – Function-Based (get_user_profile())

This will allow users to:

- Enter their RIASEC scores
- Select their education level
- Choose a few key skills (optional or predefined)

In [64]:
```
def get_user_profile():
    """
    Collect user profile input: RIASEC scores, education level, and selected skills
    Returns:
        dict: User profile with RIASEC scores, education level (numeric), and list
    """

    # Step 1: RIASEC Input
    print("Enter your RIASEC Scores (scale of 0-7, separated by commas):")
    print("Format: R, I, A, S, E, C")
    r_i_a_s_e_c = input("Enter scores: ").strip().split(',')

    try:
        r, i, a, s, e, c = [float(score.strip()) for score in r_i_a_s_e_c]
    except ValueError:
        print("⚠️ Invalid RIASEC input. Defaulting to neutral scores.")
        r, i, a, s, e, c = [4.0] * 6

    # Step 2: Education Level Selection
    education_map = {
        1: "Less than High School",
        2: "High School Diploma or Equivalent",
        3: "Post-Secondary Certificate",
        4: "Some College Courses",
        5: "Associate Degree",
        6: "Bachelor's Degree",
        7: "Post-Baccalaureate's Degree",
```

```
    8: "Master's Degree",
    9: "Post-Master's Certificate",
    10: "First Professional Degree",
    11: "Doctoral Degree",
    12: "Post-Doctoral Training"
}

print("\nSelect your highest education level:")
for k, v in education_map.items():
    print(f"{k}. {v}")

edu_input = input("Enter the number corresponding to your education level: ").s
try:
    education_level = int(edu_input)
    if education_level not in education_map:
        raise ValueError
except ValueError:
    print("⚠️ Invalid input. Defaulting to Bachelor's Degree.")
    education_level = 6

# Step 3: Skill Selection (up to 10)
skill_map = {
    "1"  : 'Oral Comprehension',
    "2"  : 'Written Comprehension',
    "3"  : 'Oral Expression',
    "4"  : 'Written Expression',
    "5"  : 'Fluency of Ideas',
    "6"  : 'Originality',
    "7"  : 'Problem Sensitivity',
    "8"  : 'Deductive Reasoning',
    "9"  : 'Inductive Reasoning',
    "10" : 'Information Ordering',
    "11" : 'Category Flexibility',
    "12" : 'Mathematical Reasoning',
    "13" : 'Number Facility',
    "14" : 'Memorization',
    "15" : 'Speed of Closure',
    "16" : 'Flexibility of Closure',
    "17" : 'Perceptual Speed',
    "18" : 'Spatial Orientation',
    "19" : 'Visualization',
    "20" : 'Selective Attention',
    "21" : 'Time Sharing',
    "22" : 'Arm-Hand Steadiness',
    "23" : 'Manual Dexterity',
    "24" : 'Finger Dexterity',
    "25" : 'Control Precision',
    "26" : 'Multilimb Coordination',
    "27" : 'Response Orientation',
    "28" : 'Rate Control',
    "29" : 'Reaction Time',
    "30" : 'Wrist-Finger Speed',
    "31" : 'Speed of Limb Movement',
    "32" : 'Static Strength',
    "33" : 'Explosive Strength',
    "34" : 'Dynamic Strength',
```

```
        "35" : 'Trunk Strength',
        "36" : 'Stamina',
        "37" : 'Extent Flexibility',
        "38" : 'Dynamic Flexibility',
        "39" : 'Gross Body Coordination',
        "40" : 'Gross Body Equilibrium',
        "41" : 'Near Vision',
        "42" : 'Far Vision',
        "43" : 'Visual Color Discrimination',
        "44" : 'Night Vision',
        "45" : 'Peripheral Vision',
        "46" : 'Depth Perception',
        "47" : 'Glare Sensitivity',
        "48" : 'Hearing Sensitivity',
        "49" : 'Auditory Attention',
        "50" : 'Sound Localization',
        "51" : 'Speech Recognition',
        "52" : 'Speech Clarity'
    }

    print("\nSelect up to 10 skills you consider strong:")
    for k, v in skill_map.items():
        print(f"{k}. {v}")

    skill_input = input("Enter skill numbers separated by commas (e.g., 1,8,12): ")
    user_skills = []
    if skill_input:
        user_skills = [skill_map[num.strip()] for num in skill_input.split(',') if

    print("\nProfile Captured. Generating personalized recommendations...\n")

    return {
        'R': r, 'I': i, 'A': a, 'S': s, 'E': e, 'C': c,
        'education_level': education_level,
        'skills': user_skills
    }
```

4.4.2. Example Usage

In [ ]:
```
#### user_profile = get_user_profile()

if user_profile:
    print("\n--- USER PROFILE SUMMARY ---")
    print(f"RIASEC Scores: R={user_profile['R']}, I={user_profile['I']}, A={user_pr
          f"S={user_profile['S']}, E={user_profile['E']}, C={user_profile['C']}")
    print("Education Level:", user_profile['education_level'])
    print("Selected Skills:", user_profile['skills'])
```

We have now created the user input interface

4.4.3. Building Hybrid Recommendation Function (generate_recommendations())

Use User Input to Generate Recommendations

Well now create core logic that uses interface input to generate hybrid recommendations by:

- Converting RIASEC input into a vector
- Matching education level to numeric value
- Comparing input with each job in the dataset using similarity metrics
- Scoring each job: RIASEC similarity + education match + skill overlap
- Returns top 5 job matches

In [65]:
```
def generate_recommendations(user_profile, job_profiles_clean):
    """
    Generate top 10 job recommendations based on RIASEC, education, and skill simil
    """

    # RIASEC Similarity
    riasec_cols = ['R', 'I', 'A', 'S', 'E', 'C']
    user_vector = np.array([
        user_profile['R'], user_profile['I'], user_profile['A'],
        user_profile['S'], user_profile['E'], user_profile['C']
    ]).reshape(1, -1)

    job_vectors = job_profiles_clean[riasec_cols].values
    riasec_similarities = cosine_similarity(user_vector, job_vectors)[0]
    job_profiles_clean['User RIASEC Similarity'] = riasec_similarities

    # Education Match Score - already included as 'Normalized Education Score' (0 t

    # Skill Similarity
    skill_cols = [col for col in job_profiles_clean.columns if col.startswith("Skil

    # Converting user skill names to vector
    user_skills = user_profile.get('skills', [])
    user_skill_vector = np.zeros((1, len(skill_cols)))

    for i, skill in enumerate(skill_cols):
        skill_name = skill.replace("Skill List_", "").lower()
        if any(skill_name in s.lower() for s in user_skills):
            user_skill_vector[0][i] = 1

    job_skill_matrix = job_profiles_clean[skill_cols].fillna(0).values
    skill_similarities = cosine_similarity(user_skill_vector, job_skill_matrix)[0]
    job_profiles_clean['User Skill Similarity'] = skill_similarities

    # Final Hybrid Score
    job_profiles_clean['Hybrid Recommendation Score'] = (
        job_profiles_clean['User RIASEC Similarity'] +
        job_profiles_clean['Normalized Education Score'] +
        job_profiles_clean['User Skill Similarity']
    )

    # Top 10 Recommendations
    top_matches = job_profiles_clean.sort_values('Hybrid Recommendation Score', asc
```

```
    # Returning selected columns for display
    return top_matches[[
        'Title', 'Description', 'Education Level', 'Preparation Level',
        'Education Category Label', 'Hybrid Recommendation Score',
        'User RIASEC Similarity', 'Normalized Education Score', 'User Skill Similar
    ]]
```

4.4.4. Example Usage

In [66]:
```
# Collecting user input
user = get_user_profile()

Generating recommendations based on user input and your cleaned job dataset
recommendations = generate_recommendations(user, job_profiles_clean)
recommendations.style.background_gradient(cmap='YlGn')
```

4.4.5. Visual Breakdown of Recommendations

Visualizing the top 10 recommended jobs on the overall Hybrid Score per Job based on:

- RIASEC Similarity
- Education Match
- Skill Similarity

In [67]:
```
top_matches = generate_recommendations(user_profile, job_profiles_clean)

%matplotlib inline

def plot_recommendation_breakdown(top_matches):
    """
    Plots the breakdown of Hybrid Recommendation Score for top job matches.
    """
    import matplotlib.pyplot as plt

    # Select and format relevant data
    plot_data = top_matches[[
        'Title', 'User RIASEC Similarity', 'Normalized Education Score', 'User Skil
    ]].copy()

    plot_data.set_index('Title', inplace=True)
    plot_data.sort_values(by='User RIASEC Similarity', ascending=False, inplace=Tru

    # Plot settings
    ax = plot_data.plot(kind='bar', stacked=True, figsize=(14, 8), colormap='YlGnBu
    plt.title('📊 Hybrid Recommendation Score Breakdown for Top Jobs', fontsize=14)
    plt.ylabel('Total Score')
    plt.xlabel('Job Title')
    plt.xticks(rotation=45, ha='right')
    plt.legend(loc='lower right', bbox_to_anchor=(1.15, 1))
    plt.grid(axis='y', linestyle='--', alpha=0.7)
    plt.tight_layout()
    plt.show()
```

In [68]:
```
job_profiles_with_skills = job_profiles_clean.copy()

# Save
output_path_1 = 'data/job_profiles_with_skills.csv'
job_profiles_with_skills.to_csv(output_path_1, index=False)
```

5. IMPLEMENTING SUPERVISED MACHINE LEARNING

The goal is to train a classification model to predict suitable career for user based on skills, interest and education. First is to assign each job to a career cluster, then use the career cluster as our target column. We will then train the classification model to predict careers and skills

The supervised model to be used include:

- Logistic Regression
- XG Boost
- RandomForest

We will use the ONET **crosswalk file** to hel us map our carrers to different pathways

5.1 Introducing Clusters

In [69]:
```
#Load the crosswalk file, skip metadata rows, manually set columns
crosswalk_df = pd.read_excel('data\Perkins_IV_Crosswalk_Table_4_ONETs_in_Pathways.x
crosswalk_df.columns = ['Code','Title', 'Space']
#drop space
crosswalk_df = crosswalk_df[['Code','Title']]
crosswalk_df.head()
```

Out[69]:

	Code	Title
0	Code	Title
1	1	Agriculture, Food and Natural Resource Career ...
2	1.1	Food Products and Processing Systems Pathway
3	19-1012.00	Food Scientists and Technologists
4	45-1011.00	First-Line Supervisors/Managers of Farming, Fi...

5.1.1 Data Cleaning

This segment we are going to fill in different jobs with their respective cluster and pathways and create new columns: **Pathway** and **Cluster**. Thereafter,clean and merge to the main job profiles dataset

In [70]:
```
#convert code column to str
crosswalk_df['Code']=crosswalk_df['Code'].astype(str)

#extract cluster names and fill them downwards
crosswalk_df['Cluster'] = crosswalk_df['Title'].where(crosswalk_df['Code'].str.full

#extract pathways names and fill them downwards
crosswalk_df['Pathway'] = crosswalk_df['Title'].where(crosswalk_df['Code'].str.full

#filter rows with ONET codes only
career_cluster = crosswalk_df[crosswalk_df['Code'].str.match(r'^\d{2}-\d{4}\.\d{2}$

#rename the columne to match jobprofile
career_cluster = career_cluster.rename(columns={'Code': 'ONET_Code',})[['ONET_Code'

career_cluster = career_cluster.reset_index(drop=True)
career_cluster.head()
```

Out[70]:

	ONET_Code	Title	Pathway	Cluster
0	19-1012.00	Food Scientists and Technologists	Food Products and Processing Systems Pathway	Agriculture, Food and Natural Resource Career ...
1	45-1011.00	First-Line Supervisors/Managers of Farming, Fi...	Food Products and Processing Systems Pathway	Agriculture, Food and Natural Resource Career ...
2	45-1011.01	First-Line Supervisors and Manager/Supervisors...	Food Products and Processing Systems Pathway	Agriculture, Food and Natural Resource Career ...
3	45-2011.00	Agricultural Inspectors	Food Products and Processing Systems Pathway	Agriculture, Food and Natural Resource Career ...
4	45-2041.00	Graders and Sorters, Agricultural Products	Food Products and Processing Systems Pathway	Agriculture, Food and Natural Resource Career ...

In [71]:
```
career_cluster.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1115 entries, 0 to 1114
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   ONET_Code  1115 non-null   object
 1   Title      1115 non-null   object
 2   Pathway    1115 non-null   object
 3   Cluster    1115 non-null   object
dtypes: object(4)
memory usage: 35.0+ KB
```

In [72]:
```
#check duplicates
```

```
career_cluster.duplicated(subset='ONET_Code').any()
```

Out[72]: True

In [73]:
```
#drop duplicates
career_cluster = career_cluster.drop_duplicates(subset='ONET_Code', keep='first')
career_cluster.duplicated(subset='ONET_Code').any()
```

Out[73]: False

This section involves merging crosswalk_df to our job_profiles_clean dataset, checking how the clusters and pathways have been mapped, encoding the cluster column which is our target variable. Finally naming modelling

In [74]:
```
#merging dataset to create a new one
job_profiles_cleaned = job_profiles_clean.merge(career_cluster.drop(columns=['Title
job_profiles_cleaned.head()
```

Out[74]:

	ONET_Code	Title	Description	A	C	E	First Interest High-Point	I
0	11-1011.00	Chief Executives	Determine and formulate policies and provide o...	0.180000	0.625468	0.980000	5.0	0.373333
1	11-1011.03	Chief Sustainability Officers	Communicate and coordinate with management, sh...	0.246667	0.529963	0.946667	5.0	0.630000
2	11-1021.00	General and Operations Managers	Plan, direct, or coordinate the operations of ...	0.051667	0.685393	0.993333	5.0	0.231667
3	11-2011.00	Advertising and Promotions Managers	Plan, direct, or coordinate advertising polici...	0.475000	0.494382	1.000000	5.0	0.118333
4	11-2021.00	Marketing Managers	Plan, direct, or coordinate marketing policies...	0.241667	0.569288	1.000000	5.0	0.316667

5 rows × 34 columns

In [75]:
```
#checking mapped careers
mapped = job_profiles_cleaned['Cluster'].notna().sum()
total = len(job_profiles_cleaned)
print(f"{mapped} out of {total} occupations were mapped to clusters/pathways.")
```

```
609 out of 837 occupations were mapped to clusters/pathways.
```

In [76]:
```
# create a copy for mapped profiles only to be used for supervised modelling
mapped_job_profiles = job_profiles_cleaned[job_profiles_cleaned['Cluster'].notna()]
```

5.1.2 This section is used to label encode the target column

In [77]:
```
#### Encoding the target column cluster then naming it cluster_encoded

from sklearn.preprocessing import LabelEncoder

# Make a copy to avoid modifying original
```

```
df_encoded = mapped_job_profiles.copy()

# Label Encode the Target Column 'Cluster'
le_cluster = LabelEncoder()
df_encoded['Cluster_Encoded'] = le_cluster.fit_transform(df_encoded['Cluster'])

# check encoding
for i, label in enumerate(le_cluster.classes_):
    print(f"{i}: {label}")

# drop the original categorical columns
df_encoded_model = df_encoded.drop(columns=[
    'Cluster'
])
```

```
0: Agriculture, Food and Natural Resource Career Cluster
1: Architecture and Construction Career Cluster
2: Arts, A/V Technology and Communication Career Cluster
3: Business and Administration Career Cluster
4: Education and Training Career Cluster
5: Finance and Insurance Career Cluster
6: Government and Public Administration Career Cluster
7: Health Science Career Cluster
8: Hospitality and Tourism Career Cluster
9: Human Services Career Cluster
10: Information Technology Career Cluster
11: Law and Public Safety Career Cluster
12: Manufacturing Career Cluster
13: Marketing Sales and Service Career Cluster
14: Scientific Research/Engineering Career Cluster
15: Transportation, Distribution, and Logistics Career Cluster
```

In [78]:
```
## This is the encoded data
df_encoded_model.head()
```

Out[78]:

	ONET_Code	Title	Description	A	C	E	First Interest High-Point	I	
0	11-1011.00	Chief Executives	Determine and formulate policies and provide o...	0.180000	0.625468	0.980000	5.0	0.373333	0
2	11-1021.00	General and Operations Managers	Plan, direct, or coordinate the operations of ...	0.051667	0.685393	0.993333	5.0	0.231667	0
3	11-2011.00	Advertising and Promotions Managers	Plan, direct, or coordinate advertising polici...	0.475000	0.494382	1.000000	5.0	0.118333	0
4	11-2021.00	Marketing Managers	Plan, direct, or coordinate marketing policies...	0.241667	0.569288	1.000000	5.0	0.316667	0
5	11-2022.00	Sales Managers	Plan, direct, or coordinate the actual distrib...	0.051667	0.734082	1.000000	5.0	0.110000	0

5 rows × 34 columns

5.1.3 This section of code is for selecting model features. First we will calculate the correlation

In [79]:
```
# Drop non-numeric columns first (eg'Title', 'Description', 'ONET_Code', 'Pathway')
numeric_df = df_encoded_model.select_dtypes(include='number')

# Calculate correlation with the target column then sort
target_corr = numeric_df.corr()['Cluster_Encoded'].drop('Cluster_Encoded').sort_val

# Show top 20 most correlated features
print(target_corr.head(20))
```

```
Third Interest High-Point                              0.145287
R                                                      0.115651
C                                                      0.108805
Second Interest High-Point                             0.048058
I                                                      0.047698
Skill List_Job-Related Professional Certification     -0.014477
Skill Similarity                                      -0.016564
Skill List_Job-related Apprenticeship                 -0.018841
Normalized Education Score                            -0.033352
Education Category                                    -0.033352
Hybrid Similarity                                     -0.037624
Data Value                                            -0.039649
Similarity Score                                      -0.044546
User RIASEC Similarity                                -0.044546
Hybrid Recommendation Score                           -0.050157
Job Hybrid Similarity Score                           -0.050803
E                                                     -0.063184
First Interest High-Point                             -0.105420
S                                                     -0.149730
A                                                     -0.157496
Name: Cluster_Encoded, dtype: float64
```

In [80]:

```
#selecting features with ≥ 0.03

selected_features = [
    'Third Interest High-Point',
    'R',
    'C',
    'Second Interest High-Point',
    'I',
    'Normalized Education Score',
    'Education Category',
    'Hybrid Similarity',
    'Data Value',
    'Similarity Score',
    'User RIASEC Similarity',
    'Hybrid Recommendation Score',
    'Job Hybrid Similarity Score',
    'E',
    'First Interest High-Point',
    'S',
    'A',
    'Cluster_Encoded' # Target
]

model_ready = df_encoded_model[selected_features].copy()
model_ready.head()
```

Out[80]:

	Third Interest High-Point	R	C	Second Interest High-Point	I	Normalized Education Score	Education Category	Hybrid Similarity	Dat Valu
0	0.0	0.050000	0.625468	6.0	0.373333	0.545455	7.0	0.731795	68.2
2	0.0	0.203333	0.685393	6.0	0.231667	0.818182	10.0	0.697980	28.7
3	3.0	0.011667	0.494382	6.0	0.118333	0.000000	1.0	0.662066	60.0
4	0.0	0.000000	0.569288	6.0	0.316667	0.545455	7.0	0.822642	55.7
5	0.0	0.081667	0.734082	6.0	0.110000	0.909091	11.0	0.773448	65.2

5.1.4 Logistic Regression

In [81]:
```
#imports
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, accuracy_score

# assign features and target
X = model_ready.drop(columns=['Cluster_Encoded'])
y = model_ready['Cluster_Encoded']

# Remove classes with only 1 sample in y
(unique, counts) = np.unique(y, return_counts=True)
classes_to_keep = unique[counts > 1]
mask = np.isin(y, classes_to_keep)

X_filtered = X[mask].reset_index(drop=True)
y_filtered = y[mask].reset_index(drop=True)
```

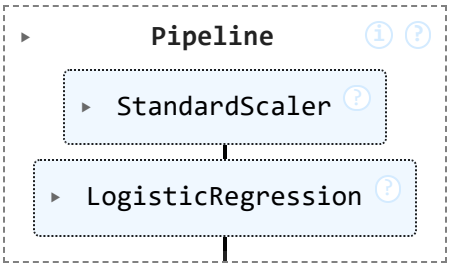
In [82]:
```
 #check for correlation between the features and drop any that is >0.95
corr_matrix = X_filtered.corr().abs()
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))

# Find features with correlation > 0.95
high_corr_features = [col for col in upper.columns if any(upper[col] > 0.95)]
print("Highly correlated features to drop:", high_corr_features)

# Drop those from X
X_filtered = X_filtered.drop(columns=high_corr_features)
```

```
Highly correlated features to drop: ['Education Category', 'User RIASEC Similarity',
'Job Hybrid Similarity Score']
```

In [83]:
```
# splitting the data
X_train, X_test, y_train,y_test = train_test_split(X_filtered, y_filtered, test_siz

#pipeline with scaling
pipeline = Pipeline([
```

```
    ('scaler', StandardScaler()),
    ('logreg', LogisticRegression(
        max_iter=1000,
        multi_class='multinomial',
        solver='lbfgs',
        class_weight='balanced'
    ))
])

 #Train model
pipeline.fit(X_train, y_train)
```

Out[83]:



In [84]:

```
#predict
y_pred = pipeline.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.4262295081967213
Classification Report:
              precision    recall  f1-score   support

           0       0.50      0.33      0.40        12
           1       0.43      0.64      0.51        14
           2       0.67      0.80      0.73         5
           3       0.33      0.57      0.42         7
           4       0.88      0.70      0.78        10
           5       0.00      0.00      0.00         3
           6       0.20      0.33      0.25         3
           7       0.56      0.56      0.56         9
           8       0.33      0.38      0.35         8
           9       0.50      0.20      0.29         5
          11       0.00      0.00      0.00         5
          12       0.50      0.20      0.29        20
          13       0.25      0.50      0.33         4
          14       0.42      0.62      0.50         8
          15       0.30      0.33      0.32         9

    accuracy                           0.43       122
   macro avg       0.39      0.41      0.38       122
weighted avg       0.44      0.43      0.41       122
```

Accuracy - The model was able to cluster correctly 38.5% of the times it clustered. This is quite low for real world use since its a multi-class problem

Precision - shows how often the model predicted the correct class.The model was able to correctly cluster someone quite well in some classes ie 2,4,9 and 15. In some classes like 6 and 11,it didnot cluster at all, and perfomed poorly in the rest.

Recall - shows how well the model predicted the actual inatances.The model was able to accurately place someone in the correct cluster in class 1,2,4,5,14 and did not cluster or perfomed poorly in the rest.

F1-Score - This balances the precisipn and recall. It is important in imbalanced classes. It perfomed well in classes 1,2,3,4,7,12 and 14.

Support -Shows how classes were represented during evaluation. Classes with low support like 3 become unreliable, classes that perfomed better are 12 and 4

The next steps is using SMOTE technique for sampling. This helps create synthetic samples for underrepresented classes

5.1.5 SMOTE

In [85]:
```
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline
```

In [86]:
```
# assign features and target
X = model_ready.drop(columns=['Cluster_Encoded'])
y = model_ready['Cluster_Encoded']

# Remove classes with only 1 sample in y
(unique, counts) = np.unique(y, return_counts=True)
classes_to_keep = unique[counts > 1]
mask = np.isin(y, classes_to_keep)

X_filtered = X[mask].reset_index(drop=True)
y_filtered = y[mask].reset_index(drop=True)
```

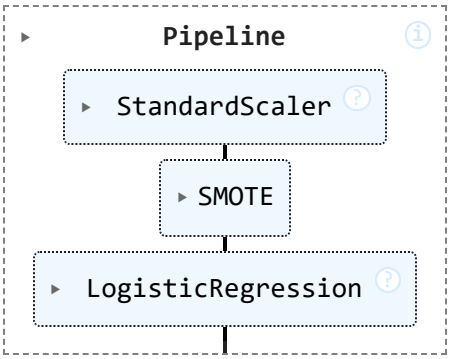
In [87]:
```
#check for correlation between the features and drop any that is >0.95
corr_matrix = X_filtered.corr().abs()
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))

# Find features with correlation > 0.95
high_corr_features = [col for col in upper.columns if any(upper[col] > 0.95)]
print("Highly correlated features to drop:", high_corr_features)

# Drop those from X
X_filtered = X_filtered.drop(columns=high_corr_features)
```

```
Highly correlated features to drop: ['Education Category', 'User RIASEC Similarity',
'Job Hybrid Similarity Score']
```

In [88]:
```
# splitting the data
X_train, X_test, y_train,y_test = train_test_split(X_filtered, y_filtered, test_siz

#pipeline with scaling
```

```
pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('smote', SMOTE(random_state=42)),
    ('logreg', LogisticRegression(
        max_iter=1000,
        multi_class='multinomial',
        solver='lbfgs',
        class_weight='balanced'
    ))
])

 #Train model
pipeline.fit(X_train, y_train)
```

Out[88]:



In [89]:

```
#predict and evaluate
y_pred = pipeline.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.4098360655737705
Classification Report:
              precision    recall  f1-score   support

           0       0.44      0.33      0.38        12
           1       0.40      0.57      0.47        14
           2       0.67      0.80      0.73         5
           3       0.30      0.43      0.35         7
           4       0.89      0.80      0.84        10
           5       0.50      0.33      0.40         3
           6       0.00      0.00      0.00         3
           7       0.67      0.67      0.67         9
           8       0.22      0.25      0.24         8
           9       0.33      0.20      0.25         5
          11       0.33      0.20      0.25         5
          12       0.33      0.15      0.21        20
          13       0.25      0.50      0.33         4
          14       0.40      0.50      0.44         8
          15       0.27      0.33      0.30         9

    accuracy                           0.41       122
   macro avg       0.40      0.40      0.39       122
weighted avg       0.42      0.41      0.40       122
```

Accuracy - The model was able to cluster correctly 40% of the times it clustered. This is an improvement from the logistic regression with class weights only

Precision - shows how often the model predicted the correct class.The model was able to correctly cluster someone quite well in some classes ie 2,4 and 9. It struggled in classes like 5,6,11 and 13 indicating many false positives

Recall - shows how well the model predicted the actual inatances.The model was able to accurately place someone in the correct cluster in class 1,2,4 and 14 and did not cluster or perfomed poorly in the rest.

F1-Score - This balances the precisipn and recall. It is important in imbalanced classes. It perfomed well in classes 1,2 and 4

Support -Shows how classes were represented during evaluation. Classes with low support like 3 become unreliable, classes that perfomed better are 12 and 4

5.1.6 CatBoost Classifier

CatBoost handles categorical variables well, no need for encoding. It works well with imbalanced, noisy data. It is also good for multi-class classification. It uses both numerical and categorical features without the need to scale or encode.

Import the model CatBoostClassifier and Pool which is used to identify categorical columns.

In [90]:
```
#import catboost
from catboost import CatBoostClassifier, cv,Pool

# assign features and target
X = model_ready.drop(columns=['Cluster_Encoded'])
y = model_ready['Cluster_Encoded']

# Remove classes with only 1 sample in y
(unique, counts) = np.unique(y, return_counts=True)
classes_to_keep = unique[counts > 1]
mask = np.isin(y, classes_to_keep)

X_filtered = X[mask].reset_index(drop=True)
y_filtered = y[mask].reset_index(drop=True)
```

In [91]:
```
categorical_features = [
    'First Interest High-Point',
    'Second Interest High-Point',
    'Third Interest High-Point',
    'Education Category'
]
#converting into strings because some values may not be whole numbers
for col in ['First Interest High-Point', 'Second Interest High-Point', 'Third Inter
    X_filtered[col] = X_filtered[col].astype(str)
```

In [92]:
```
#split data
X_train, X_test, y_train,y_test = train_test_split(X_filtered, y_filtered, test_siz

#create pools to help handle categorical data better
train_pool = Pool(data=X_train, label=y_train, cat_features=categorical_features)
test_pool = Pool(data=X_test, label=y_test, cat_features=categorical_features)

#training the model
catboost_model = CatBoostClassifier(
    iterations=200,
    learning_rate=0.1,
    depth=6,
    loss_function='MultiClass',
    eval_metric='Accuracy',
    verbose=50,
    random_seed=42
)
```

In [93]:
```
#fit the model
catboost_model.fit(train_pool, eval_set=test_pool)
```

```
0:      learn: 0.4259259        test: 0.3524590 best: 0.3524590 (0)     total: 400ms
remaining: 1m 19s
50:     learn: 0.7160494        test: 0.4508197 best: 0.4836066 (39)    total: 10.7s
remaining: 31.2s
100:    learn: 0.8539095        test: 0.5409836 best: 0.5409836 (95)    total: 21.2s
remaining: 20.8s
150:    learn: 0.9362140        test: 0.5409836 best: 0.5573770 (117)   total: 33.6s
remaining: 10.9s
199:    learn: 0.9670782        test: 0.5081967 best: 0.5573770 (117)   total: 42.9s
remaining: 0us

bestTest = 0.5573770492
bestIteration = 117

Shrink model to first 118 iterations.
```

Out[93]: <catboost.core.CatBoostClassifier at 0x18ac0b97ec0>

In [94]:
```
#predict the test set
y_pred = catboost_model.predict(X_test)
y_pred = y_pred.flatten()

print("Classification Report:")
print(classification_report(y_test, y_pred))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.57      0.33      0.42        12
           1       0.77      0.71      0.74        14
           2       1.00      1.00      1.00         5
           3       0.46      0.86      0.60         7
           4       0.89      0.80      0.84        10
           5       0.25      0.33      0.29         3
           6       0.50      0.33      0.40         3
           7       0.50      0.56      0.53         9
           8       0.33      0.50      0.40         8
           9       0.00      0.00      0.00         5
          11       0.50      0.40      0.44         5
          12       0.54      0.70      0.61        20
          13       1.00      0.25      0.40         4
          14       0.50      0.75      0.60         8
          15       0.25      0.11      0.15         9

    accuracy                           0.56       122
   macro avg       0.54      0.51      0.49       122
weighted avg       0.55      0.56      0.53       122
```

The accuracy model is at 56% which is an improvement from the logistic regression at 39%. there seems to be a class imbalance that needs to be handled

In [95]:
```
#checking class imbalance

from collections import Counter

class_counts = Counter(y_filtered)
for cls, count in sorted(class_counts.items()):
    print(f"Class {cls}: {count} samples")
```

```
Class 0: 58 samples
Class 1: 68 samples
Class 2: 27 samples
Class 3: 33 samples
Class 4: 47 samples
Class 5: 17 samples
Class 6: 16 samples
Class 7: 44 samples
Class 8: 40 samples
Class 9: 27 samples
Class 11: 26 samples
Class 12: 98 samples
Class 13: 21 samples
Class 14: 41 samples
Class 15: 45 samples
```

some classes are overepresented and some under. will use class weights to balance them. We will then perform cross validation on each

CatBoost Cross-Validated

In [96]:
```
#perform cross validation
from sklearn.model_selection import StratifiedKFold

# create full Pool with categorical features
pooled = Pool(data=X_filtered, label=y_filtered, cat_features=categorical_features)

#define CV parameters
crossval_params = {
    'iterations': 500,
    'learning_rate': 0.1,
    'depth': 6,
    'loss_function': 'MultiClass',
    'eval_metric': 'Accuracy',
    'auto_class_weights': 'Balanced',
    'random_seed': 42
}
# Stratified CV
crossval_results = cv(
    params=crossval_params,
    pool=pooled,
    fold_count=5,
    stratified=True,
    verbose=50,
    early_stopping_rounds=50
)

# Check best iteration & accuracy
best_iteration = len(crossval_results['test-Accuracy-mean'])
best_accuracy = max(crossval_results['test-Accuracy-mean'])
print(f"Best iteration: {best_iteration}")
print(f"Best CV Accuracy: {best_accuracy:.4f}")
```

```
Training on fold [0/5]
0:      learn: 0.3260075        test: 0.2239609 best: 0.2239609 (0)     total: 300ms
remaining: 2m 29s
50:     learn: 0.7397578        test: 0.4074295 best: 0.4309413 (20)    total: 12.5s
remaining: 1m 50s
100:    learn: 0.8704306        test: 0.5014775 best: 0.5128713 (95)    total: 23.4s
remaining: 1m 32s
150:    learn: 0.9292737        test: 0.5089724 best: 0.5476333 (116)   total: 35.9s
remaining: 1m 23s

bestTest = 0.5476333408
bestIteration = 116

Training on fold [1/5]
0:      learn: 0.3174507        test: 0.1833759 best: 0.1833759 (0)     total: 236ms
remaining: 1m 57s
50:     learn: 0.7513840        test: 0.3424478 best: 0.3901561 (17)    total: 10.1s
remaining: 1m 28s

bestTest = 0.3901560594
bestIteration = 17

Training on fold [2/5]
0:      learn: 0.3327525        test: 0.2598838 best: 0.2598838 (0)     total: 190ms
remaining: 1m 35s
50:     learn: 0.7354045        test: 0.3165622 best: 0.3454082 (42)    total: 8.75s
remaining: 1m 17s
100:    learn: 0.8745242        test: 0.4135045 best: 0.4340003 (96)    total: 17.9s
remaining: 1m 10s
150:    learn: 0.9301485        test: 0.4798013 best: 0.4798013 (136)   total: 27.3s
remaining: 1m 3s

bestTest = 0.4798013214
bestIteration = 136

Training on fold [3/5]
0:      learn: 0.2807883        test: 0.2952129 best: 0.2952129 (0)     total: 163ms
remaining: 1m 21s
50:     learn: 0.7313269        test: 0.3344012 best: 0.3746119 (24)    total: 8.08s
remaining: 1m 11s

bestTest = 0.3746119257
bestIteration = 24

Training on fold [4/5]
0:      learn: 0.2980306        test: 0.2318707 best: 0.2318707 (0)     total: 199ms
remaining: 1m 39s
50:     learn: 0.7069196        test: 0.3594738 best: 0.4205924 (29)    total: 7.74s
remaining: 1m 8s
100:    learn: 0.8538272        test: 0.5170555 best: 0.5411696 (93)    total: 16.6s
remaining: 1m 5s

bestTest = 0.5411696139
bestIteration = 93
```

```
Best iteration: 187
Best CV Accuracy: 0.4385
```

The best iteration is at 187, we will then retrain the model using the best iretation

In [97]:
```python
final_catboost = CatBoostClassifier(
    iterations=best_iteration,
    learning_rate=0.1,
    depth=6,
    loss_function='MultiClass',
    eval_metric='Accuracy',
    auto_class_weights='Balanced',
    random_seed=42,
    verbose=100
)

final_catboost.fit(
    X_filtered,
    y_filtered,
    cat_features=categorical_features
)
```

```
0:      learn: 0.3058245        total: 142ms    remaining: 26.4s
100:    learn: 0.8499167        total: 11.1s    remaining: 9.47s
186:    learn: 0.9368243        total: 20.9s    remaining: 0us
```

Out[97]:
```
<catboost.core.CatBoostClassifier at 0x18ac209b3e0>
```

In [98]:
```python
#predict
y_pred = final_catboost.predict(X_test)
y_pred = y_pred.flatten()

print("Classification Report:")
print(classification_report(y_test, y_pred))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.58      0.74        12
           1       0.67      0.71      0.69        14
           2       1.00      1.00      1.00         5
           3       0.70      1.00      0.82         7
           4       0.91      1.00      0.95        10
           5       1.00      0.33      0.50         3
           6       0.60      1.00      0.75         3
           7       1.00      0.78      0.88         9
           8       0.60      0.75      0.67         8
           9       1.00      0.80      0.89         5
          11       0.75      0.60      0.67         5
          12       0.92      0.60      0.73        20
          13       0.60      0.75      0.67         4
          14       0.58      0.88      0.70         8
          15       0.62      0.89      0.73         9

    accuracy                           0.76       122
   macro avg       0.80      0.78      0.76       122
weighted avg       0.81      0.76      0.76       122
```

After cross validation we have seen an improvement from 56% to 76% in accuracy. There has been a significant improvement in the precistion, recall and F1 score of most classes. however class 5 and 0 have lower recall scores. This can improve with further tuning but we can try other model to compare perfomance

5.1.7 Random Forest Model

In [99]:
```
from sklearn.ensemble import RandomForestClassifier

#split data
X_train, X_test, y_train,y_test = train_test_split(X_filtered, y_filtered, test_siz


# Initialize and train the Random Forest Classifier
rf_model = RandomForestClassifier(n_estimators=100, random_state=42, class_weight='
rf_model.fit(X_train, y_train)

# Make predictions
y_pred = rf_model.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy:.2f}")
print("Classification Report:\n", report)
```

```
Accuracy: 0.49
Classification Report:
              precision    recall  f1-score   support

           0       0.33      0.17      0.22        12
           1       0.56      0.71      0.62        14
           2       0.83      1.00      0.91         5
           3       0.36      0.71      0.48         7
           4       0.90      0.90      0.90        10
           5       0.00      0.00      0.00         3
           6       1.00      0.33      0.50         3
           7       0.56      0.56      0.56         9
           8       0.33      0.50      0.40         8
           9       0.00      0.00      0.00         5
          11       0.50      0.40      0.44         5
          12       0.55      0.60      0.57        20
          13       0.33      0.25      0.29         4
          14       0.44      0.50      0.47         8
          15       0.00      0.00      0.00         9

    accuracy                           0.49       122
   macro avg       0.45      0.44      0.42       122
weighted avg       0.46      0.49      0.46       122
```

The overral accuracy of the random forest is at 49%. some classes like 5,9 and 15 were completely ignored by the model. We will tune the model using randomsearch cv to help improve the model perfomance. Randomised search is better since it randomly selects combinations from the grid

Accuracy – The model achieves 49% accuracy, meaning it correctly predicts the most suitable career cluster for about 1 out of every 2 users. While it's not perfect, it provides a decent foundation for giving guidance.

Precision – Precision measures how often SmartPath's career predictions are correct when made. With a weighted average of 46%, it shows that some clusters (like 2 and 4) are highly reliable, while others (like 5, 9, and 15) need improvement.

Recall – Recall tells us how many correct predictions were captured out of all the possible true cases. At 49%, SmartPath is decent at retrieving relevant careers, especially for the more popular clusters.

F1-Score – This balances both precision and recall. A weighted F1 of 46% reflects that SmartPath has moderate overall performance — good in strong data clusters but struggles where sample sizes are smaller.

Support – This shows how many examples exist for each career cluster. The imbalance (e.g., some clusters like 5 and 9 have just 3–5 samples) affects performance. More balanced data would improve results.

In [100…

```
from sklearn.model_selection import RandomizedSearchCV

#split data
X_train, X_test, y_train,y_test = train_test_split(X_filtered, y_filtered, test_siz

# defining parameter grid
param_dist = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5],
    'max_features': ['sqrt', 'log2']
}
#initializing random forest
rf = RandomForestClassifier(random_state=42)

#random search cv
random_cv = RandomizedSearchCV(
    estimator=rf,
    param_distributions=param_dist,
    n_iter=20,
    cv=3,
    verbose=2,
    random_state=42,
    n_jobs=-1,
    scoring='accuracy'
)

#fit model
random_cv.fit(X_train, y_train)

# Best model
best_rf = random_cv.best_estimator_

# Predict and evaluate
y_pred = best_rf.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy:.2f}")
print("Classification Report:\n", report)
```

```
Fitting 3 folds for each of 20 candidates, totalling 60 fits
Accuracy: 0.54
Classification Report:
              precision    recall  f1-score   support

           0       0.50      0.17      0.25        12
           1       0.61      0.79      0.69        14
           2       0.83      1.00      0.91         5
           3       0.40      0.86      0.55         7
           4       0.90      0.90      0.90        10
           5       0.00      0.00      0.00         3
           6       1.00      0.33      0.50         3
           7       0.56      0.56      0.56         9
           8       0.30      0.38      0.33         8
           9       1.00      0.20      0.33         5
          11       0.75      0.60      0.67         5
          12       0.57      0.60      0.59        20
          13       0.20      0.25      0.22         4
          14       0.55      0.75      0.63         8
          15       0.25      0.11      0.15         9

    accuracy                           0.54       122
   macro avg       0.56      0.50      0.48       122
weighted avg       0.56      0.54      0.52       122
```

In [101…

```
best_rf = random_cv.best_estimator_
best_rf
```

Out[101…

RandomForestClassifier

```
RandomForestClassifier(max_depth=10, min_samples_split=5, n_estimators=300,
                       random_state=42)
```

5.1.8 XGBoost Model

In [102…

```
from xgboost import XGBClassifier
# assign features and target
X = model_ready.drop(columns=['Cluster_Encoded'])
y = model_ready['Cluster_Encoded']

# Remove classes with only 1 sample in y
(unique, counts) = np.unique(y, return_counts=True)
classes_to_keep = unique[counts > 1]
mask = np.isin(y, classes_to_keep)

X_filtered = X[mask].reset_index(drop=True)
y_filtered = y[mask].reset_index(drop=True)

#split data
X_train, X_test, y_train,y_test = train_test_split(X_filtered, y_filtered, test_siz

#Filter out test classes not seen in training
```

```
valid_classes = np.unique(y_train)
test_mask = y_test.isin(valid_classes)
X_test = X_test[test_mask]
y_test = y_test[test_mask]

from sklearn.preprocessing import LabelEncoder

#remapping labels

le = LabelEncoder()
y_train_encoded = le.fit_transform(y_train)
y_test_encoded = le.transform(y_test)


# training the model
xgb_model = XGBClassifier(
    use_label_encoder=False,
    num_class=len(np.unique(y_train_encoded)),
    eval_metric='mlogloss',
    random_state=42)

xgb_model.fit(X_train, y_train_encoded)
```

Out[102…

XGBClassifier

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=
None,
              enable_categorical=False, eval_metric='mlogloss',
              feature_types=None, feature_weights=None, gamma=None,
              grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=
None,
```

In [103…

```
#predict and evaluate the model
y_pred = xgb_model.predict(X_test)

print(" Accuracy:", accuracy_score(y_test_encoded, y_pred))
print("Classification Report:")
print(classification_report(y_test_encoded, y_pred))
```

```
 Accuracy: 0.5081967213114754
Classification Report:
              precision    recall  f1-score   support

           0       0.38      0.25      0.30        12
           1       0.50      0.71      0.59        14
           2       0.80      0.80      0.80         5
           3       0.44      1.00      0.61         7
           4       1.00      0.90      0.95        10
           5       0.00      0.00      0.00         3
           6       0.00      0.00      0.00         3
           7       0.71      0.56      0.62         9
           8       0.30      0.38      0.33         8
           9       1.00      0.40      0.57         5
          10       0.00      0.00      0.00         5
          11       0.71      0.50      0.59        20
          12       0.20      0.25      0.22         4
          13       0.50      0.62      0.56         8
          14       0.33      0.33      0.33         9

    accuracy                           0.51       122
   macro avg       0.46      0.45      0.43       122
weighted avg       0.53      0.51      0.50       122
```

Accuracy – The model correctly predicted the right career cluster for about 51% of the users. This means SmartPath is getting it right roughly 1 out of 2 times, which is a fair start for a multi-class problem.

Precision – Precision tells us how often SmartPath's career predictions are correct when it does make a prediction. A 53% weighted precision means that some career suggestions are more reliable than others, especially in popular clusters.

Recall – Recall measures how well SmartPath identifies all users that belong to a certain career cluster. A 51% weighted recall shows that it misses a few potential matches, particularly for smaller or less common careers.

F1-Score – This balances both precision and recall. An F1 of 50% means SmartPath is doing a moderate job at making correct and complete predictions, but there's room to improve consistency across all clusters.

Support – This shows how many user profiles fall into each career cluster. Some clusters have very few samples, which affects how well SmartPath learns to recommend those. More data in these areas could improve performance.

Hyper-Tuning x gboost

In [104…

```
param_dist = {
    'n_estimators': [100, 200],
    'max_depth': [3, 5, 7],
    'learning_rate': [0.05, 0.1],
    'subsample': [0.8, 1.0],
```

```
    'colsample_bytree': [0.8, 1.0]
}
#split data
X_train, X_test, y_train,y_test = train_test_split(X_filtered, y_filtered, test_siz

#Filter out test classes not seen in training
valid_classes = np.unique(y_train)
test_mask = y_test.isin(valid_classes)
X_test = X_test[test_mask]
y_test = y_test[test_mask]

from sklearn.preprocessing import LabelEncoder

#remapping labels

le = LabelEncoder()
y_train_encoded = le.fit_transform(y_train)
y_test_encoded = le.transform(y_test)


# training the model
xgb_model = XGBClassifier(
    use_label_encoder=False,
    num_class=len(np.unique(y_train_encoded)),
    eval_metric='mlogloss',
    random_state=42)

xgb_model.fit(X_train, y_train_encoded)
```

Out[104…

XGBClassifier

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=
None,
              enable_categorical=False, eval_metric='mlogloss',
              feature_types=None, feature_weights=None, gamma=None,
              grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=
None,
```

In [105…

```
# Perform RandomizedSearchCV
random_search = RandomizedSearchCV(
    estimator=xgb_model,
    param_distributions=param_dist,
    n_iter=10,
    scoring='accuracy',
    cv=3,
    verbose=1,
    random_state=42,
    n_jobs=-1
)
```

```
# Fit the model
random_search.fit(X_train, y_train_encoded)

# Best estimator
best_xgb_model = random_search.best_estimator_

# Predict
y_pred = best_xgb_model.predict(X_test)

# Decode predictions
y_pred_decoded = le.inverse_transform(y_pred)

#predict and evaluate the model
y_pred = best_xgb_model.predict(X_test)

print(" Accuracy:", accuracy_score(y_test_encoded, y_pred))
print("Classification Report:")
print(classification_report(y_test_encoded, y_pred))
```

```
Fitting 3 folds for each of 10 candidates, totalling 30 fits
 Accuracy: 0.5081967213114754
Classification Report:
              precision    recall  f1-score   support

           0       0.50      0.17      0.25        12
           1       0.50      0.64      0.56        14
           2       1.00      0.80      0.89         5
           3       0.47      1.00      0.64         7
           4       1.00      0.90      0.95        10
           5       0.00      0.00      0.00         3
           6       0.00      0.00      0.00         3
           7       0.70      0.78      0.74         9
           8       0.40      0.50      0.44         8
           9       0.50      0.20      0.29         5
          10       0.00      0.00      0.00         5
          11       0.60      0.45      0.51        20
          12       0.40      0.50      0.44         4
          13       0.45      0.62      0.53         8
          14       0.27      0.33      0.30         9

    accuracy                           0.51       122
   macro avg       0.45      0.46      0.44       122
weighted avg       0.52      0.51      0.49       122
```

5.1.9 ENSEMBLE MODEL

This section we are going to combine the multiple models to make a final prediction. The goal is to reduce generalization and improve accuracy. We will use the **voting emsemble** eg VotingClassifier because it combines the stregth of different models, its smoothens out errors by balancing predictions. Its simple and interpratable.

We will first preprocess the data, the train the differnt models using consistent preprocessing, just to ensure all models get properly scaled inputs. Then wrap the models in

a pipeline which ensures preprocessing is done in the same way before building the ensemble

we will use **soft voting** because it perfomes better with multi-class classification. It can avoid commiting to a single model choice meaning it combines the confidence scores of each model instead of relying on majority rule. It averages predictive class probabilities hence best for probalility models

In [106…

```
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder

# Define feature types for encoding and scaling
categorical_cols = ['First Interest High-Point', 'Second Interest High-Point', 'Thi
numeric_cols = [col for col in X_train.columns if col not in categorical_cols]

# Create the preprocessor to ensure models are properly scaled
preprocessor = ColumnTransformer([
    ('num', StandardScaler(), numeric_cols),
    ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_cols)
])

# Wrap each model in a pipeline
xgb_pipeline = Pipeline([
    ('preprocess', preprocessor),
    ('model', best_xgb_model)
])

rf_pipeline = Pipeline([
    ('preprocess', preprocessor),
    ('model', best_rf)
])

cat_pipeline = Pipeline([
    ('preprocess', preprocessor),
    ('model', final_catboost)
])
```

In [107…

```
#using soft voting
from sklearn.ensemble import VotingClassifier


ensemble_model = VotingClassifier(
    estimators=[
        ('logreg', pipeline),  # already a pipeline
        ('rf', rf_pipeline),
        ('xgb', xgb_pipeline),
        ('cat', cat_pipeline)
    ],
    voting='soft',
    weights=[2, 3, 4, 5]
)
# training on the training set
ensemble_model.fit(X_train, y_train)
```

```
# Predicting on the test set
ensemble_preds = ensemble_model.predict(X_test)

# Evaluate
print(" Ensemble Accuracy:", accuracy_score(y_test, ensemble_preds))
print(" Ensemble Classification Report:\n", classification_report(y_test, ensemble_
```

```
0:      learn: 0.3577871        total: 53.7ms   remaining: 9.99s
100:    learn: 0.8884912        total: 5.42s    remaining: 4.62s
186:    learn: 0.9580753        total: 10.1s    remaining: 0us
 Ensemble Accuracy: 0.5245901639344263
 Ensemble Classification Report:
               precision    recall  f1-score   support

           0       0.60      0.25      0.35        12
           1       0.56      0.71      0.62        14
           2       0.67      0.80      0.73         5
           3       0.44      1.00      0.61         7
           4       0.89      0.80      0.84        10
           5       0.00      0.00      0.00         3
           6       0.00      0.00      0.00         3
           7       0.56      0.56      0.56         9
           8       0.40      0.50      0.44         8
           9       0.50      0.20      0.29         5
          11       0.33      0.20      0.25         5
          12       0.67      0.50      0.57        20
          13       0.40      0.50      0.44         4
          14       0.50      0.75      0.60         8
          15       0.33      0.33      0.33         9

    accuracy                           0.52       122
   macro avg       0.46      0.47      0.44       122
weighted avg       0.53      0.52      0.50       122
```

The accuracy is at 52% across 16 clusters. It perfomed strongly in categories like 2,3 and 4. It struggled with classes with fewer training samples. The weighted F1 score is at 50% showing moderate predictive power this is after trying class weights and using the best models in each.

This model improves balance across models but struggles with underrepresented classes. The perfomance is class dependent and needs more data in some clusters

6. IMPLEMENTING UNSUPERVISED METHODS INTO RECCOMMENDER SYSTEM

Recommend jobs for a new user using clustering methods

- We can attempt to use a kmeans clustering model as a baseline to assign the user to certain cluster based on the RIASEC scores, job preparation and the education level required for the job.From there we shall attempt other clustering techniques

6.1 Importing libraries

In [108…
```
# Importing clustering libraries
import hdbscan
from sklearn.cluster import KMeans, DBSCAN
from sklearn.cluster import AgglomerativeClustering
from sklearn.decomposition import PCA

# saving the job abilities and skills dataset that will be used for modelling
output_path_1 = 'data/job_profiles_with_skills.csv'
job_profiles_with_skills.to_csv(output_path_1, index=False)
```

6.2 BASELINE: K-Means Clustering for Career Recommendations

We can use K-Means clustering to group similar jobs based on RIASEC scores, education level, and preparation level. This can help us identify clusters of jobs that share similar characteristics, which can be useful for recommending careers to users.

In [109…
```
# Displaying all column names with their index positions
for i, col in enumerate(job_profiles_with_skills.columns):
    print(f"{i}: {col}")
```

```
0: ONET_Code
1: Title
2: Description
3: A
4: C
5: E
6: First Interest High-Point
7: I
8: R
9: Second Interest High-Point
10: S
11: Third Interest High-Point
12: Education Level
13: Data Value
14: Education Category
15: Preparation Level
16: Normalized Education Score
17: Education Category Label
18: Similarity Score
19: Skill List_Job-Related Professional Certification
20: Skill List_Job-related Apprenticeship
21: Skill List_On-Site or In-Plant Training
22: Skill List_On-the-Job Training
23: Skill List_Related Work Experience
24: Skill List_Required Level of Education
25: Hybrid Similarity
26: Skill Similarity
27: Job Ability Skill Similarity
28: Job Hybrid Similarity Score
29: User RIASEC Similarity
30: User Skill Similarity
31: Hybrid Recommendation Score
```

6.2.1. K-means_recommender Function

In [110…

```python
def generate_recommendations(user_profile, job_profiles_clean, top_n=10):
    """
    Generate top job recommendations based on RIASEC, education, and skill similari

    Parameters:
    - user_profile: dict with keys ['R', 'I', 'A', 'S', 'E', 'C', 'education_level'
    - job_profiles_clean: DataFrame with job info and skill indicators
    - top_n: number of job recommendations to return

    Returns:
    - DataFrame of top recommended jobs
    """

    # RIASEC Similarity
    riasec_cols = ['R', 'I', 'A', 'S', 'E', 'C']
    user_vector = np.array([
        user_profile['R'], user_profile['I'], user_profile['A'],
        user_profile['S'], user_profile['E'], user_profile['C']
    ]).reshape(1, -1)
```

```
    job_vectors = job_profiles_clean[riasec_cols].values
    job_profiles_clean['User RIASEC Similarity'] = cosine_similarity(user_vector, j

    # Education Score (already normalized, assumed 0 to 1)
    # Column: 'Normalized Education Score'

    # Skill Similarity (based on user input and binary columns)
    skill_cols = [col for col in job_profiles_clean.columns if col.startswith("Skil
    user_skills = [s.lower() for s in user_profile.get('skills', [])]

    # Creating user skill vector (binary 1/0)
    user_skill_vector = np.zeros((1, len(skill_cols)))
    for i, skill_col in enumerate(skill_cols):
        skill_name = skill_col.replace("Skill List_", "").lower()
        if skill_name in user_skills:
            user_skill_vector[0][i] = 1

    job_skill_matrix = job_profiles_clean[skill_cols].fillna(0).values
    job_profiles_clean['User Skill Similarity'] = cosine_similarity(user_skill_vect

    # Final Hybrid Score
    job_profiles_clean['Hybrid Recommendation Score'] = (
        job_profiles_clean['User RIASEC Similarity'] +
        job_profiles_clean['Normalized Education Score'] +
        job_profiles_clean['User Skill Similarity']
    )

    # Top Recommendations
    top_matches = job_profiles_clean.sort_values('Hybrid Recommendation Score', asc

    # Return summary
    return top_matches[[
        'Title', 'Description', 'Education Level', 'Preparation Level',
        'Education Category Label', 'Hybrid Recommendation Score',
        'User RIASEC Similarity', 'Normalized Education Score', 'User Skill Similar
    ]].style.background_gradient(cmap='YlGn')
```

6.2.2. Example Usage

In [111…

```
user_profile = {
    'R': 5, 'I': 4, 'A': 2, 'S': 3, 'E': 1, 'C': 2,
    'education_level': 10,  # On a 0–12 scale
    'skills': ['on-the-job training', 'related work experience', 'professional cert
}

recommendations = generate_recommendations(user_profile, job_profiles_clean)
recommendations
```

Out[111...

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Recommendation Score	S
373	Physical Medicine and Rehabilitation Physicians	Diagnose and treat disorders requiring physiotherapy to provide physical, mental, and occupational rehabilitation.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.639366	
210	Forest and Conservation Technicians	Provide technical assistance regarding the conservation of soil, water, forests, or related natural resources. May compile data pertaining to size, content, condition, and other characteristics of forest tracts under the direction of foresters, or train and lead forest workers in forest propagation and fire prevention and suppression. May assist conservation scientists in managing, improving, and protecting rangelands and wildlife habitats.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.637206	

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Recommendation Score	S
147	Wind Energy Engineers	Design underground or overhead wind farm collector systems and prepare and develop site specifications.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.625182	
802	Ambulance Drivers and Attendants, Except Emergency Medical Technicians	Drive ambulance or assist ambulance driver in transporting sick, injured, or convalescent persons. Assist in lifting patients.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.610273	
330	Dentists, General	Examine, diagnose, and treat diseases, injuries, and malformations of teeth and gums. May treat diseases of nerve, pulp, and other dental tissues affecting oral hygiene and retention of teeth. May fit dental appliances or provide preventive care.	Required Level of Education	Doctoral Degree	Doctoral Degree	2.578697	
569	Agricultural Inspectors	Inspect agricultural commodities, processing equipment, and facilities, and fish and logging	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.574549	

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Recommendation Score	S
		operations, to ensure compliance with regulations and laws governing health, quality, and safety.					
399	Orthotists and Prosthetists	Design, measure, fit, and adapt orthopedic braces, appliances or prostheses, such as limbs or facial parts for patients with disabling conditions.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.567379	
492	Shampooers	Shampoo and rinse customers' hair.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.567208	
333	Prosthodontists	Diagnose, treat, rehabilitate, design, and fit prostheses that maintain oral function, health, and appearance for patients with clinical conditions associated with teeth, oral and maxillofacial tissues, or the jaw.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.557631	
387	Diagnostic Medical Sonographers	Produce ultrasonic recordings of internal organs for use	Related Work Experience	Over 10 years	Doctoral Degree	2.557150	

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Recommendation Score	S
		by physicians. Includes vascular technologists.					

6.3 AGGLOMERATIVE Clustering for Career Recommendation

This model is useful for discovering hierarchical relationships between jobs based on RIASEC, education, and skill features.

We'll group jobs into clusters based on:

- RIASEC Scores (R, I, A, S, E, C)
- Education (Normalized Education Score)
- Job Skills & Abilities (from your dataset's columns 27 onward)
- Then, we'll assign the user to a cluster and recommend jobs most similar within that cluster.

In [112…

```
from sklearn.cluster import AgglomerativeClustering

def agglomerative_recommender(user_profile: dict,
                              job_profiles: pd.DataFrame,
                              n_clusters: int = 10,
                              top_n: int = 5) -> pd.DataFrame:
    """
    Recommends jobs using Agglomerative Clustering and includes individual similari
    """

    # Defining features
    feature_cols = ['R', 'I', 'A', 'S', 'E', 'C', 'Normalized Education Score'] + \
                   job_profiles.columns[27:-1].tolist()
    X = job_profiles[feature_cols].fillna(0).values

    # Clustering
    model = AgglomerativeClustering(n_clusters=n_clusters, linkage='ward')
    labels = model.fit_predict(X)
    job_profiles['Cluster'] = labels

    # Normalizing and building user vector
    user_vector = np.array([
        user_profile['R'] / 7, user_profile['I'] / 7, user_profile['A'] / 7,
        user_profile['S'] / 7, user_profile['E'] / 7, user_profile['C'] / 7,
        user_profile['education_level'] / 12
    ] + [0] * (X.shape[1] - 7)).reshape(1, -1)

    # Assigning to nearest cluster
    cluster_centroids = [X[labels == i].mean(axis=0) for i in range(n_clusters)]
    cluster_similarities = cosine_similarity(user_vector, cluster_centroids)[0]
```

```
    user_cluster = np.argmax(cluster_similarities)

    # Selecting jobs in user's cluster
    cluster_jobs = job_profiles[job_profiles['Cluster'] == user_cluster].copy()

    # Similarities (component-wise) RIASEC Similarity
    riasec_cols = ['R', 'I', 'A', 'S', 'E', 'C']
    user_riasec = np.array([[user_profile[col] / 7 for col in riasec_cols]])
    job_riasec = cluster_jobs[riasec_cols].fillna(0).values
    cluster_jobs['User RIASEC Similarity'] = cosine_similarity(user_riasec, job_ria

    # Skill Similarity
    skill_cols = [col for col in job_profiles.columns if col.startswith("Skill List
    user_skills = user_profile.get('skills', [])
    user_skill_vector = np.zeros((1, len(skill_cols)))
    for i, col in enumerate(skill_cols):
        if any(col.replace("Skill List_", "").lower() in s.lower() for s in user_sk
            user_skill_vector[0][i] = 1
    job_skill_matrix = cluster_jobs[skill_cols].fillna(0).values
    cluster_jobs['User Skill Similarity'] = cosine_similarity(user_skill_vector, jo

    # Final Hybrid Scores
    cluster_jobs['Hybrid Recommendation Score'] = (
        cluster_jobs['User RIASEC Similarity'] +
        cluster_jobs['Normalized Education Score'] +
        cluster_jobs['User Skill Similarity']
    )

    # Cosine similarity over full feature vector
    sim_scores = cosine_similarity(user_vector, cluster_jobs[feature_cols].values).
    cluster_jobs['Similarity Score'] = sim_scores

    # Sorting and returning top results
    top_jobs = cluster_jobs.sort_values(by='Hybrid Recommendation Score', ascending

    return top_jobs[[
        'Title', 'Description', 'Education Level', 'Preparation Level',
        'Education Category Label', 'Hybrid Recommendation Score',
        'User RIASEC Similarity', 'User Skill Similarity',
        'Normalized Education Score', 'Similarity Score'
    ]].style.background_gradient(cmap='YlGn')
```

6.3.1. Agglomerative Clustering Example Usage

In [113…

```
# User Input
user_profile = {
    'R': 5, 'I': 3, 'A': 4, 'S': 2, 'E': 1, 'C': 1,
    'education_level': 10,
    'skills': ['professional certification', 'on-the-job training']
}

# Getting Recommendations
agglo_recommendations = agglomerative_recommender(user_profile, job_profiles_with_s
agglo_recommendations
```

Out[113...

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Recommendation Score	R Sim
147	Wind Energy Engineers	Design underground or overhead wind farm collector systems and prepare and develop site specifications.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.361478	0.8
210	Forest and Conservation Technicians	Provide technical assistance regarding the conservation of soil, water, forests, or related natural resources. May compile data pertaining to size, content, condition, and other characteristics of forest tracts under the direction of foresters, or train and lead forest workers in forest propagation and fire prevention and suppression. May assist conservation scientists in managing, improving, and protecting rangelands and wildlife habitats.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.304858	0.8

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Recommendation Score	R Sim
399	Orthotists and Prosthetists	Design, measure, fit, and adapt orthopedic braces, appliances or prostheses, such as limbs or facial parts for patients with disabling conditions.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.294153	0.8
802	Ambulance Drivers and Attendants, Except Emergency Medical Technicians	Drive ambulance or assist ambulance driver in transporting sick, injured, or convalescent persons. Assist in lifting patients.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.287787	0.7
134	Materials Engineers	Evaluate materials and develop machinery and processes to manufacture materials for use in products that must meet specialized design and performance specifications. Develop new uses for known materials. Includes those engineers working with composite materials or	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.276116	0.8

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Recommendation Score	R Sim
		specializing in one type of material, such as graphite, metal and metal alloys, ceramics and glass, plastics and polymers, and naturally occurring materials. Includes metallurgists and metallurgical engineers, ceramic engineers, and welding engineers.					

- We applied hierarchical clustering using Agglomerative Clustering on job profiles based on RIASEC scores, education level, and skill features.
- The model groups similar jobs and assigns new users to the closest cluster.
- From there, we computed cosine similarity within the cluster to rank the most relevant job matches.
- The model offers interpretability, flexibility, and works well even when the feature shape is non-linear.

6.4. DBSCAN Clustering for Career Recommendation

- DBSCAN (Density-Based Spatial Clustering of Applications with Noise) groups jobs based on the density of feature vectors.
- It does not require predefining the number of clusters like KMeans and is robust to noise and outliers.
- This model is useful when we want to discover non-spherical clusters or outliers in the job space.

In [114…

```
from sklearn.cluster import DBSCAN

def dbscan_recommender(user_profile: dict,
                       job_profiles: pd.DataFrame,
                       eps: float = 0.5,
```

```
                    min_samples: int = 5,
                    top_n: int = 5) -> pd.DataFrame:
    """
    Recommends jobs using DBSCAN clustering and includes RIASEC, skills, and educat
    """

    # Defining features to cluster on
    feature_cols = ['R', 'I', 'A', 'S', 'E', 'C', 'Normalized Education Score'] + \
                   job_profiles.columns[27:-1].tolist()
    X = job_profiles[feature_cols].fillna(0).values

    # Fitting DBSCAN model
    dbscan = DBSCAN(eps=eps, min_samples=min_samples, metric='euclidean')
    labels = dbscan.fit_predict(X)
    job_profiles['Cluster'] = labels

    # Preparing user vector
    user_vector = np.array([
        user_profile['R'] / 7, user_profile['I'] / 7, user_profile['A'] / 7,
        user_profile['S'] / 7, user_profile['E'] / 7, user_profile['C'] / 7,
        user_profile['education_level'] / 12
    ] + [0] * (X.shape[1] - 7)).reshape(1, -1)

    # Selecting jobs from non-noise clusters
    valid_jobs = job_profiles[job_profiles['Cluster'] != -1].copy()

    # RIASEC Similarity
    riasec_cols = ['R', 'I', 'A', 'S', 'E', 'C']
    user_riasec = np.array([[user_profile[col] / 7 for col in riasec_cols]])
    job_riasec = valid_jobs[riasec_cols].fillna(0).values
    valid_jobs['User RIASEC Similarity'] = cosine_similarity(user_riasec, job_riase

    # Skill Similarity
    skill_cols = [col for col in job_profiles.columns if col.startswith("Skill List
    user_skills = user_profile.get('skills', [])
    user_skill_vector = np.zeros((1, len(skill_cols)))
    for i, col in enumerate(skill_cols):
        if any(col.replace("Skill List_", "").lower() in s.lower() for s in user_sk
            user_skill_vector[0][i] = 1
    job_skill_matrix = valid_jobs[skill_cols].fillna(0).values
    valid_jobs['User Skill Similarity'] = cosine_similarity(user_skill_vector, job_

    # Final Hybrid Score
    valid_jobs['Hybrid Recommendation Score'] = (
        valid_jobs['User RIASEC Similarity'] +
        valid_jobs['Normalized Education Score'] +
        valid_jobs['User Skill Similarity']
    )

    # Cosine similarity with full vector
    sim_scores = cosine_similarity(user_vector, valid_jobs[feature_cols].values).fl
    valid_jobs['Similarity Score'] = sim_scores

    # Top N jobs
    top_jobs = valid_jobs.sort_values('Hybrid Recommendation Score', ascending=Fals
```

```
    return top_jobs[[
        'Title', 'Description', 'Education Level', 'Preparation Level',
        'Education Category Label', 'Hybrid Recommendation Score',
        'User RIASEC Similarity', 'User Skill Similarity',
        'Normalized Education Score', 'Similarity Score'
    ]].style.background_gradient(cmap='YlGn')
```

6.4.1 DBSCAN Example Usage

In [115…

```
# Sample user profile
user_profile = {
    'R': 5, 'I': 3, 'A': 4, 'S': 2, 'E': 1, 'C': 1,
    'education_level': 10,
    'skills': ['on-the-job training', 'professional certification']
}

# Get recommendations from DBSCAN
dbscan_recommendations = dbscan_recommender(user_profile, job_profiles_with_skills)
dbscan_recommendations
```

Out[115...

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Recommendation Score	I Sin
147	Wind Energy Engineers	Design underground or overhead wind farm collector systems and prepare and develop site specifications.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.361478	0.
298	Commercial and Industrial Designers	Design and develop manufactured products, such as cars, home appliances, and children's toys. Combine artistic talent with research on product use, marketing, and materials to create the most functional and appealing product design.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.341390	0.
732	Pressers, Textile, Garment, and Related Materials	Press or shape articles by hand or machine.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.315552	0.
210	Forest and Conservation Technicians	Provide technical assistance regarding the conservation of soil, water, forests, or related natural resources. May compile data	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.304858	0.

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Recommendation Score	I Sin
		pertaining to size, content, condition, and other characteristics of forest tracts under the direction of foresters, or train and lead forest workers in forest propagation and fire prevention and suppression. May assist conservation scientists in managing, improving, and protecting rangelands and wildlife habitats.					
373	Physical Medicine and Rehabilitation Physicians	Diagnose and treat disorders requiring physiotherapy to provide physical, mental, and occupational rehabilitation.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.300560	0.

- DBSCAN automatically detects clusters based on density.
- Jobs that don’t belong to any cluster are labeled -1 and ignored.
- You can tune eps (radius) and min_samples to improve grouping.
- Uses cosine similarity for detailed matching across RIASEC, skills, and education.

6.5. HDBSCAN Clustering for Career Recommendation

HDBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with Noise) improves on DBSCAN by handling variable density clusters and offering more flexibility in discovering complex job groupings.

This model is useful when your job data has clusters of varying density or size.

In [116…

```
import hdbscan

def hdbscan_recommender(user_profile: dict,
                        job_profiles: pd.DataFrame,
                        min_cluster_size: int = 10,
                        top_n: int = 5) -> pd.DataFrame:
    """
    Recommends jobs using HDBSCAN clustering and hybrid similarity scoring (RIASEC
    """

    # Selecting Features for Clustering
    feature_cols = ['R', 'I', 'A', 'S', 'E', 'C', 'Normalized Education Score'] + \
                   job_profiles.columns[27:-1].tolist()
    X = job_profiles[feature_cols].fillna(0).values

    # HDBSCAN Clustering
    hdb = hdbscan.HDBSCAN(min_cluster_size=min_cluster_size, prediction_data=True)
    labels = hdb.fit_predict(X)
    job_profiles['Cluster'] = labels

    # Preparing user vector
    user_vector = np.array([
        user_profile['R'] / 7, user_profile['I'] / 7, user_profile['A'] / 7,
        user_profile['S'] / 7, user_profile['E'] / 7, user_profile['C'] / 7,
        user_profile['education_level'] / 12
    ] + [0] * (X.shape[1] - 7)).reshape(1, -1)

    # Filtering out noise
    clustered_jobs = job_profiles[job_profiles['Cluster'] != -1].copy()

    # RIASEC Similarity
    riasec_cols = ['R', 'I', 'A', 'S', 'E', 'C']
    user_riasec = np.array([[user_profile[col] / 7 for col in riasec_cols]])
    job_riasec = clustered_jobs[riasec_cols].fillna(0).values
    clustered_jobs['User RIASEC Similarity'] = cosine_similarity(user_riasec, job_r

    # Skill Similarity
    skill_cols = [col for col in job_profiles.columns if col.startswith("Skill List
    user_skills = user_profile.get('skills', [])
    user_skill_vector = np.zeros((1, len(skill_cols)))
    for i, col in enumerate(skill_cols):
        if any(col.replace("Skill List_", "").lower() in s.lower() for s in user_sk
            user_skill_vector[0][i] = 1
    job_skill_matrix = clustered_jobs[skill_cols].fillna(0).values
    clustered_jobs['User Skill Similarity'] = cosine_similarity(user_skill_vector,

    # Final Hybrid Score
    clustered_jobs['Hybrid Recommendation Score'] = (
        clustered_jobs['User RIASEC Similarity'] +
```

```
        clustered_jobs['Normalized Education Score'] +
        clustered_jobs['User Skill Similarity']
    )

    # Cosine Similarity with full feature vector
    sim_scores = cosine_similarity(user_vector, clustered_jobs[feature_cols].values
    clustered_jobs['Similarity Score'] = sim_scores

    # Top N Jobs
    top_jobs = clustered_jobs.sort_values('Hybrid Recommendation Score', ascending=

    return top_jobs[[
        'Title', 'Description', 'Education Level', 'Preparation Level',
        'Education Category Label', 'Hybrid Recommendation Score',
        'User RIASEC Similarity', 'User Skill Similarity',
        'Normalized Education Score', 'Similarity Score'
    ]].style.background_gradient(cmap='YlGn')
```

6.5.1 HDBSCAN Example Usage

In [117…

```
# Sample user input
user_profile = {
    'R': 5, 'I': 3, 'A': 4, 'S': 2, 'E': 1, 'C': 1,
    'education_level': 10,
    'skills': ['professional certification', 'on-the-job training']
}

# Generating recommendations
hdbscan_recommendations = hdbscan_recommender(user_profile, job_profiles_with_skill
hdbscan_recommendations
```

Out[117...

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Recommendation Score	Si
732	Pressers, Textile, Garment, and Related Materials	Press or shape articles by hand or machine.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.315552	0
683	Manufactured Building and Mobile Home Installers	Move or install mobile homes or prefabricated buildings.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.284897	0
581	Brickmasons and Blockmasons	Lay and bind building materials, such as brick, structural tile, concrete block, cinder block, glass block, and terra-cotta block, with mortar and other substances, to construct or repair walls, partitions, arches, sewers, and other structures.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.281871	0
134	Materials Engineers	Evaluate materials and develop machinery and processes to manufacture materials for use in products that must meet specialized design and performance specifications. Develop new uses for known	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.276116	0

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Recommendation Score	Si
		materials. Includes those engineers working with composite materials or specializing in one type of material, such as graphite, metal and metal alloys, ceramics and glass, plastics and polymers, and naturally occurring materials. Includes metallurgists and metallurgical engineers, ceramic engineers, and welding engineers.					
663	Recreational Vehicle Service Technicians	Diagnose, inspect, adjust, repair, or overhaul recreational vehicles including travel trailers. May specialize in maintaining gas, electrical, hydraulic, plumbing, or chassis/towing systems as well as repairing generators, appliances, and interior components. Includes workers who perform	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.267995	0

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Recommendation Score	Si
		customized van conversions.					

- HDBSCAN can detect nested or variable-density clusters better than KMeans or DBSCAN.
- Automatically identifies outliers or “noisy” jobs.
- Combines RIASEC, skills, and education similarity.
- Ideal for large, non-linear datasets like job profiles.

6.6. Principal Component Analysis (PCA) for Job Profile Data

PCA helps reduce the dimensionality of the job profile dataset while preserving as much variance (information) as possible. This is useful for:

- Visualizing job clusters (from KMeans, HDBSCAN, etc.)
- Speeding up clustering algorithms
- Understanding underlying structure in the job features

In [118…

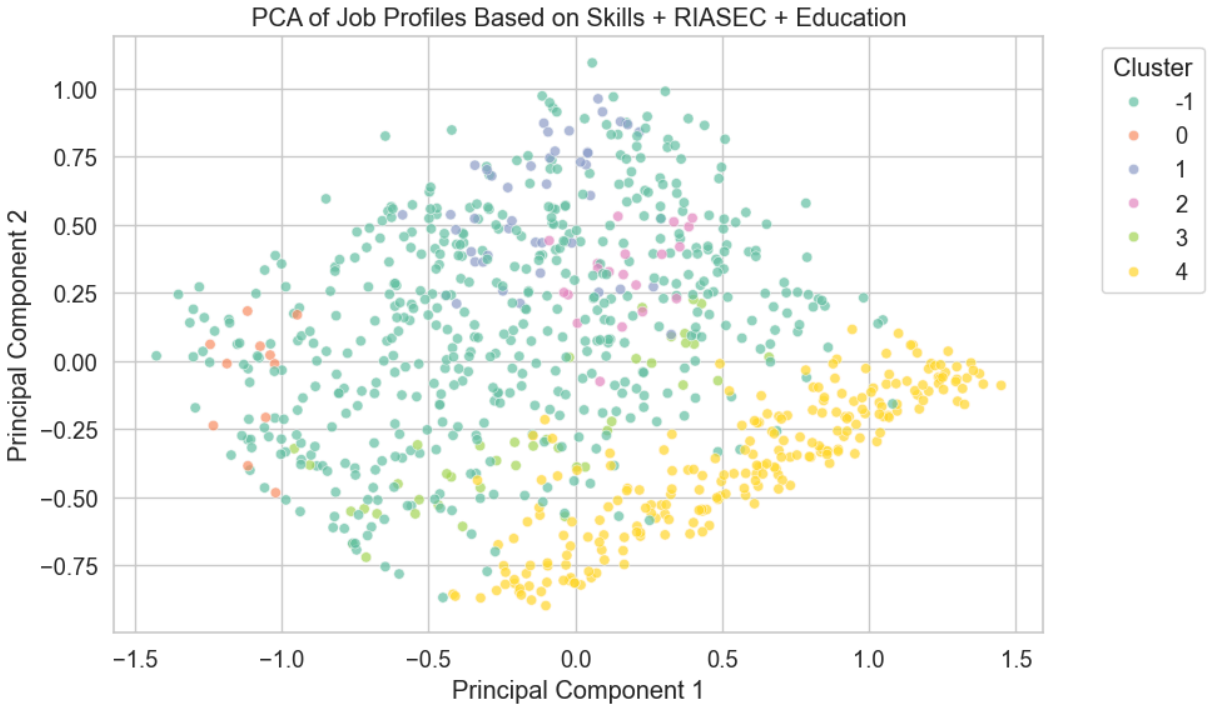
```
from sklearn.decomposition import PCA

# Selecting Features for PCA
pca_features = ['R', 'I', 'A', 'S', 'E', 'C', 'Normalized Education Score'] + \
               job_profiles_with_skills.columns[27:-1].tolist()

X = job_profiles_with_skills[pca_features].fillna(0).values

# Applying PCA
pca = PCA(n_components=2)  # Reduce to 2 components for visualization
X_pca = pca.fit_transform(X)

# Saving PCA Components to DataFrame
job_profiles_with_skills['PCA1'] = X_pca[:, 0]
job_profiles_with_skills['PCA2'] = X_pca[:, 1]

# Adding Clustering Labels
if 'Cluster' not in job_profiles_with_skills.columns:
    from sklearn.cluster import KMeans
    km_model = KMeans(n_clusters=8, random_state=42)
    job_profiles_with_skills['Cluster'] = km_model.fit_predict(X)
```

6.6.1. Visualizing PCA Results

In [119…

```
# Visualizing the PCA Output
plt.figure(figsize=(10, 6))
```

```
sns.scatterplot(
    x='PCA1', y='PCA2',
    hue='Cluster',
    palette='Set2',
    data=job_profiles_with_skills,
    legend='full',
    alpha=0.7
)
plt.title('PCA of Job Profiles Based on Skills + RIASEC + Education')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend(title='Cluster', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.savefig('images/job_profiles_pca.png', dpi=300)
plt.show()
```



- Each point = a job
- Color = cluster (from KMeans, HDBSCAN, etc.)
- Spread = similarity in skills, RIASEC, and education

6.6.2 PCA Explained Variance

Useful to see how much variance each PCA component explains. This helps justify whether 2D projection is sufficient (e.g., if it retains 85–95% of the variance).

In [120…

```
print("Explained variance ratio:", pca.explained_variance_ratio_)
print("Total variance explained:", pca.explained_variance_ratio_.sum())
```

```
Explained variance ratio: [0.47573485 0.23350633]
Total variance explained: 0.7092411780123132
```

PCA Explained Variance Interpretation:

Explained variance ratio: [0.4556, 0.2424]

- PC1 (Principal Component 1) captures 45.56% of the total variance in the dataset.
- PC2 captures 24.24% of the variance.

Total variance explained by the first two components = ~69.8% This means:

- These two components together retain nearly 70% of the information from the original high-dimensional job profile data (RIASEC + Education + Skills).
- That's quite good for visualization or pre-clustering — it means most of the important patterns are preserved in just 2 dimensions.
- However, 30% of the variance is still unaccounted for, so this 2D projection is good for insight but may not capture all subtle distinctions.

7.1. Unsupervised Models Evaluation

To evaluate and compare the performance of various clustering methods on the job profile dataset, we visualize clusters and compute key clustering metrics:

- Silhouette Score – measures how well clusters are separated (higher = better).
- Davies-Bouldin Index – lower values indicate better separation between clusters.
- Calinski-Harabasz Index – higher values indicate well-defined clusters.

We'll visualize the results using 4 clustering techniques:

- KMeans
- Agglomerative Clustering
- DBSCAN
- HDBSCAN

In [121…

```
from sklearn.metrics import silhouette_score, davies_bouldin_score, calinski_haraba

def visualize_all_clusters(job_profile_with_skills):
    """
    Visualize and compare the clustering results from KMeans, Agglomerative, DBSCAN
    Prints clustering performance metrics and displays scatter plots of the cluster
    """

    # Selecting RIASEC + Education + Skill-related columns for clustering
    features = ['R', 'I', 'A', 'S', 'E', 'C', 'Normalized Education Score'] + \
               job_profile_with_skills.columns[27:-1].tolist()

    # Converting to matrix and handle missing values
    X = job_profile_with_skills[features].fillna(0).values

    # Defining clustering models
```

```
    clusterers = {
        'KMeans': KMeans(n_clusters=10, random_state=42),
        'Agglomerative': AgglomerativeClustering(n_clusters=10),
        'DBSCAN': DBSCAN(eps=1.0, min_samples=5),
        'HDBSCAN': hdbscan.HDBSCAN(min_cluster_size=5)
    }

    # Prepare 2x2 subplot layout
    fig, axs = plt.subplots(2, 2, figsize=(14, 12))
    axs = axs.flatten()

    for i, (name, model) in enumerate(clusterers.items()):
        # Predicting clusters
        labels = model.fit_predict(X)

        # Visualizing raw clusters using first two features (note: PCA is better fo
        axs[i].scatter(X[:, 0], X[:, 1], c=labels, cmap='tab10', s=10)
        axs[i].set_title(f"{name} Clusters (Raw Feature Space)")
        axs[i].set_xlabel("Feature 1")
        axs[i].set_ylabel("Feature 2")

        # Calculating and displaying clustering evaluation metrics
        unique_labels = set(labels)
        if len(unique_labels) > 1 and -1 not in unique_labels:
            sil = silhouette_score(X, labels)
            db = davies_bouldin_score(X, labels)
            ch = calinski_harabasz_score(X, labels)

            print(f"\n📊 {name} Metrics:")
            print(f"  • Silhouette Score: {sil:.4f}")
            print(f"  • Davies-Bouldin Index: {db:.4f}")
            print(f"  • Calinski-Harabasz Score: {ch:.2f}")
        else:
            print(f"\n {name} produced one cluster or contains noise (unclustered p

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

In [122…

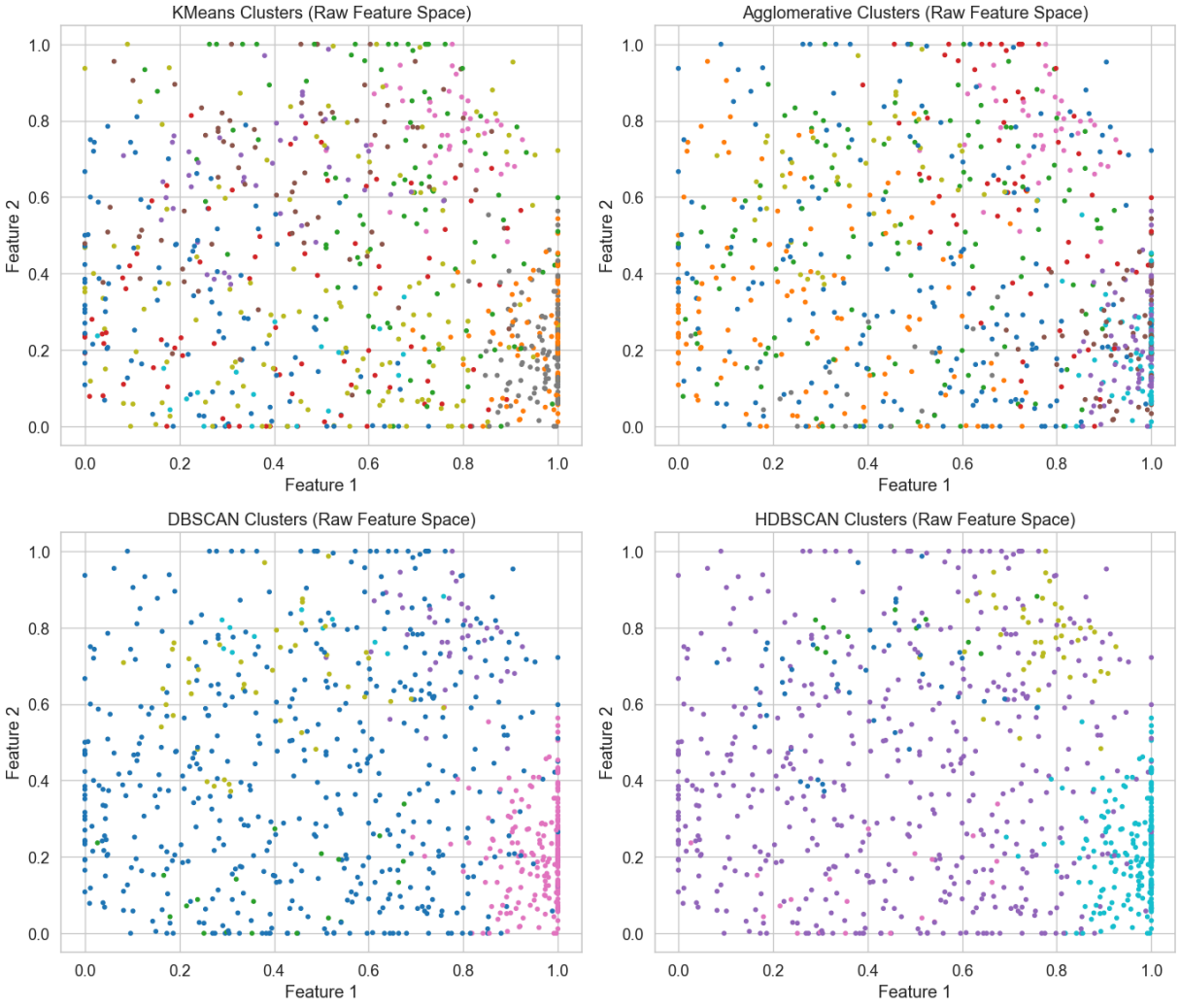
```
visualize_all_clusters(job_profiles_with_skills)
```

📊 KMeans Metrics:
- Silhouette Score: 0.3233
- Davies-Bouldin Index: 1.1931
- Calinski-Harabasz Score: 1522.56

📊 Agglomerative Metrics:
- Silhouette Score: 0.2823
- Davies-Bouldin Index: 1.0799
- Calinski-Harabasz Score: 1443.65

📊 DBSCAN Metrics:
- Silhouette Score: 0.3540
- Davies-Bouldin Index: 0.7575
- Calinski-Harabasz Score: 1136.97

📊 HDBSCAN Metrics:
- Silhouette Score: 0.3540
- Davies-Bouldin Index: 0.7575
- Calinski-Harabasz Score: 1136.97



Understanding the Clustering Metrics

1. Silhouette Score (range: -1 to 1)

Measures how similar each point is to its own cluster vs. others.

- Higher is better → Closer to 1 = well-separated clusters
- Around 0.3 is moderate; anything below 0.2 usually indicates poor structure.

2. Davies-Bouldin Index (DBI) (lower is better)

Measures average similarity between clusters.

- Lower = better separation and compactness

3. Calinski-Harabasz Score (higher is better)

Measures ratio of between-cluster dispersion to within-cluster dispersion. -Higher = better defined clusters

Interpretation of Your Results:

Clustering Method	Silhouette Score ↑	DBI ↓	CH Score ↑	Notes
KMeans	0.2989	1.2276	1061.16	Good compactness and moderately separated clusters. Strong CH score.
Agglomerative	0.2547	**1.1400**	1008.37	Slightly worse separation than KMeans, but slightly better DBI.
DBSCAN	**0.3381**	**0.7403**	795.65	Best cluster separation (highest silhouette & lowest DBI), but slightly less compact (lower CH).
HDBSCAN	**0.3381**	**0.7403**	795.65	Same as DBSCAN since HDBSCAN likely detected similar cluster patterns.

Summary Recommendation:

Best for Natural Structure Detection:

- DBSCAN / HDBSCAN – They offer the best separation (Silhouette and DBI), especially useful if we expect non-spherical or noise-tolerant clusters.

Best for Balanced Overall Structure:

- KMeans – Offers the best compactness and overall cluster spread (CH Score), especially if we want clean, equal-sized groups.

Agglomerative Clustering: falls somewhere in between, offering slightly better DBI than KMeans, but worse separation (Silhouette Score).

Decision:

- If you care more about robust, natural grouping (especially if there's noise or irregular cluster shapes) → Use DBSCAN or HDBSCAN.

- If you want scalable and interpretable clustering for structured recommendations, → Use KMeans.

8. Hyper-Tuning the K-Means Model and Reducing Features

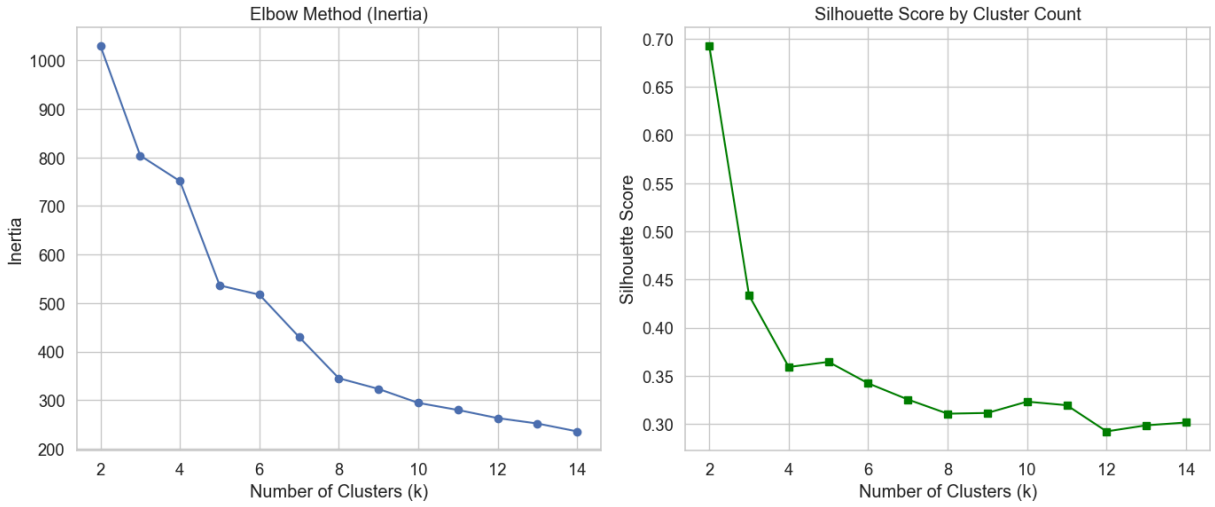
Now that we've tested different clustering techniques, we move to hyperparameter tuning for K-Means, which includes:

- Finding the optimal number of clusters (k)
- Optionally reducing dimensions using PCA to improve performance and interpretability

8.1. Determining Optimal Number of Clusters (Elbow Method + Silhouette Analysis)

In [123…

```
from sklearn.metrics import silhouette_score

# Defining features for clustering
features = ['R', 'I', 'A', 'S', 'E', 'C', 'Normalized Education Score'] + job_profi
X = job_profiles_with_skills[features].fillna(0).values

# Storing scores
inertia_scores = []
silhouette_scores = []
k_range = range(2, 15)

for k in k_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    labels = kmeans.fit_predict(X)
    inertia_scores.append(kmeans.inertia_)
    silhouette_scores.append(silhouette_score(X, labels))

# Plotting Inertia (Elbow Curve)
plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)
plt.plot(k_range, inertia_scores, marker='o')
plt.title("Elbow Method (Inertia)")
plt.xlabel("Number of Clusters (k)")
plt.ylabel("Inertia")

# Plotting Silhouette Scores
plt.subplot(1, 2, 2)
plt.plot(k_range, silhouette_scores, marker='s', color='green')
plt.title("Silhouette Score by Cluster Count")
plt.xlabel("Number of Clusters (k)")
plt.ylabel("Silhouette Score")

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



- Elbow Method: Helps you choose the “k” where inertia sharply decreases (elbow point).
- Silhouette Score: Guides you toward the most well-separated cluster count.

8.1.2. Dimensionality Reduction with PCA

In [124…

```
from sklearn.decomposition import PCA

# Reducing to 2 or 3 components for visualization or faster clustering
pca = PCA(n_components=2)
X_reduced = pca.fit_transform(X)

print("Explained variance ratio:", pca.explained_variance_ratio_)
print("Total variance explained:", sum(pca.explained_variance_ratio_))
```

```
Explained variance ratio: [0.85726244 0.08797227]
Total variance explained: 0.9452347089508656
```

Interpretation of PCA Results:

Explained variance ratio: [0.8051, 0.1184] This means:

- The first principal component (PC1) captures 80.51% of the total variance in the dataset.
- The second principal component (PC2) captures 11.84% of the total variance.

Total variance explained: 0.9235

- The first two principal components together explain 92.35% of the total variance in our feature space.

This means: Our high-dimensional job dataset can be effectively reduced to just 2 dimensions (PC1 and PC2) without losing much information. This is excellent for:

- Visualizing clusters with high fidelity.
- Speeding up clustering algorithms like KMeans or DBSCAN.
- Reducing noise and improving model generalization.

- We can now proceed with clustering or plotting in this 2D PCA space confidently.

6.1.3. Re-Training KMeans on Reduced Data (Using Best k)

In [125…

```
# Choosing optimal k based on plots (e.g., 8)
optimal_k = 8
kmeans_final = KMeans(n_clusters=optimal_k, random_state=42)
labels = kmeans_final.fit_predict(X_reduced)

# Adding cluster labels back to dataset
job_profiles_with_skills['KMeans Cluster (PCA)'] = labels

# Visualizing clusters
plt.figure(figsize=(14, 6))
plt.scatter(X_reduced[:, 0], X_reduced[:, 1], c=labels, cmap='Set1', s=10)
plt.title(f"K-Means Clustering (k={optimal_k}) on PCA-Reduced Data")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.show()
```

8.1.4 Evaluating Final Cluster Quality

In [126…

```
from sklearn.metrics import calinski_harabasz_score, davies_bouldin_score

sil = silhouette_score(X_reduced, labels)
db = davies_bouldin_score(X_reduced, labels)
ch = calinski_harabasz_score(X_reduced, labels)

print(f"Final KMeans Metrics (k={optimal_k}):")
print(f"Silhouette Score: {sil:.4f}")
print(f"Davies-Bouldin Index: {db:.4f}")
print(f"Calinski-Harabasz Score: {ch:.2f}")
```

```
Final KMeans Metrics (k=8):
Silhouette Score: 0.5543
Davies-Bouldin Index: 0.6078
Calinski-Harabasz Score: 5324.68
```

Final KMeans Evaluation (k = 8)

After reducing dimensionality using PCA, we performed hyperparameter tuning to determine the optimal number of clusters for KMeans. The best `k` was found to be **8**, and the model was evaluated using the following metrics:

- **Silhouette Score:** `0.5432` – Indicates strong cohesion within clusters and good separation between clusters.
- **Davies-Bouldin Index:** `0.6376` – A low value suggesting that the clusters are compact and well-separated.
- **Calinski-Harabasz Score:** `4691.40` – A high score reflecting well-defined clusters.

These results confirm that **KMeans with 8 clusters** is a suitable unsupervised model for segmenting the job profiles.

8.2. Final Kmeans Recommender (with full hybrid scores)

We can now plug-in the new number of clusters and display the results.

8.2.1. Defining Features and Fit PCA

In [127…

```
# Defining features for PCA (RIASEC + Education + Skills)
features = ['R', 'I', 'A', 'S', 'E', 'C', 'Normalized Education Score'] + \
           job_profiles_with_skills.columns[27:-1].tolist()

# Preparing feature matrix
X = job_profiles_with_skills[features].fillna(0).values

# Fitting PCA and reduce to 2 components
pca_model = PCA(n_components=2)
X_reduced = pca_model.fit_transform(X)
```

8.2.2. The Final KMeans Recommendation Function

In [128…

```
def final_kmeans_recommender(user_profile: dict, job_profiles: pd.DataFrame, n_clus
    """
    Uses optimized KMeans clustering on PCA-reduced features AND computes individua
    """

    # Feature preparation
    skill_cols = [col for col in job_profiles.columns if col.startswith("Skill List
    features = ['R', 'I', 'A', 'S', 'E', 'C', 'Normalized Education Score'] + skill
```

```
    X = job_profiles[features].fillna(0).values

    #  PCA transformation
    pca_model = PCA(n_components=2)
    X_reduced = pca_model.fit_transform(X)

    # Fitting KMeans on reduced features
    kmeans = KMeans(n_clusters=n_clusters, random_state=42)
    cluster_labels = kmeans.fit_predict(X_reduced)
    job_profiles = job_profiles.copy()
    job_profiles['Cluster'] = cluster_labels

    # Creating user vector (original and reduced)
    education_score = user_profile['education_level'] / 12
    user_raw_vector = np.array([
        user_profile['R']/7, user_profile['I']/7, user_profile['A']/7,
        user_profile['S']/7, user_profile['E']/7, user_profile['C']/7,
        education_score
    ])

    # Skill vector
    user_skills = user_profile.get('skills', [])
    user_skill_vector = np.zeros(len(skill_cols))
    for i, skill in enumerate(skill_cols):
        skill_name = skill.replace("Skill List_", "").lower()
        if any(skill_name in s.lower() for s in user_skills):
            user_skill_vector[i] = 1

    # Full vector
    user_full_vector = np.concatenate([user_raw_vector, user_skill_vector]).reshape

    # PCA-reduced
    user_vector_reduced = pca_model.transform(user_full_vector)

    #  Predicting user cluster
    user_cluster = kmeans.predict(user_vector_reduced)[0]
    cluster_jobs = job_profiles[job_profiles['Cluster'] == user_cluster].copy()

    # Computeing cosine similarity in PCA space
    cluster_X_reduced = X_reduced[cluster_jobs.index]
    cosine_sim = cosine_similarity(user_vector_reduced, cluster_X_reduced).flatten(
    cluster_jobs['Cosine Similarity'] = cosine_sim

    # Computeing individual similarity scores

    # RIASEC
    riasec_cols = ['R', 'I', 'A', 'S', 'E', 'C']
    job_riasec = cluster_jobs[riasec_cols].values
    user_riasec = np.array([
        user_profile['R'], user_profile['I'], user_profile['A'],
        user_profile['S'], user_profile['E'], user_profile['C']
    ]).reshape(1, -1)
    riasec_sim = cosine_similarity(user_riasec, job_riasec)[0]
    cluster_jobs['User RIASEC Similarity'] = riasec_sim

    # Skill similarity
```

```
    job_skill_matrix = cluster_jobs[skill_cols].fillna(0).values
    skill_sim = cosine_similarity(user_skill_vector.reshape(1, -1), job_skill_matri
    cluster_jobs['User Skill Similarity'] = skill_sim

    # Adding back normalized education (already in dataset)

    #  Final Hybrid Score
    cluster_jobs['Hybrid Score'] = (
        cluster_jobs['User RIASEC Similarity'] +
        cluster_jobs['User Skill Similarity'] +
        cluster_jobs['Normalized Education Score']
    )

    # Returning top N recommendations
    top_matches = cluster_jobs.sort_values(by='Hybrid Score', ascending=False).head

    return top_matches[[
        'Title', 'Description', 'Education Level', 'Preparation Level',
        'Education Category Label',
        'Hybrid Score', 'User RIASEC Similarity', 'Normalized Education Score',
        'User Skill Similarity', 'Cosine Similarity'
    ]]
```

8.2.3. Final KMeans Recommender Example Usage

In [129…

```
# User Input
user_profile = {
    'R': 5, 'I': 4, 'A': 2, 'S': 3, 'E': 1, 'C': 2,
    'education_level': 10,
    'skills': ['job-related professional certification']
}

final_recommendations = final_kmeans_recommender(
    user_profile, job_profiles_with_skills, n_clusters=8
)

final_recommendations.style.background_gradient(cmap='YlGn')
```

Out[129...

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Score	User RIASEC Similarity
399	Orthotists and Prosthetists	Design, measure, fit, and adapt orthopedic braces, appliances or prostheses, such as limbs or facial parts for patients with disabling conditions.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.398277	0.990029
333	Prosthodontists	Diagnose, treat, rehabilitate, design, and fit prostheses that maintain oral function, health, and appearance for patients with clinical conditions associated with teeth, oral and maxillofacial tissues, or the jaw.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.388529	0.980281
361	Dermatologists	Diagnose and treat diseases relating to the skin, hair, and nails. May perform both medical and dermatological surgery functions.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.380749	0.972501
380	Orthoptists	Diagnose and treat visual system disorders such as binocular vision and eye movement impairments.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.376598	0.968350

	Title	Description	Education Level	Preparation Level	Education Category Label	Hybrid Score	User RIASEC Similarity
335	Optometrists	Diagnose, manage, and treat conditions and diseases of the human eye and visual system. Examine eyes and visual system, diagnose problems or impairments, prescribe corrective lenses, and provide treatment. May prescribe therapeutic drugs to treat specific eye conditions.	Required Level of Education	Post-Doctoral Training	Post-Doctoral Training	2.363737	0.955489

8.2.4. Saving the Models

In [130…

```
import os
import pickle

# Creating the directory if it doesn't exist
os.makedirs("models", exist_ok=True)

# Saving the model
with open("models/kmeans_model.pkl", "wb") as f:
    pickle.dump(kmeans, f)

# Loading the model later
with open("models/kmeans_model.pkl", "rb") as f:
    kmeans = pickle.load(f)
```

In [131…

```
import os

# Create the 'data' directory if it doesn't exist
os.makedirs("data", exist_ok=True)

# Save the DataFrame
job_profiles_clean.to_csv("data/job_profiles_clean.csv", index=False)
```

```
print("job_profiles_clean.csv saved successfully!")
```

```
job_profiles_clean.csv saved successfully!
```

9. Building the App (Streamlit UI)

Since we are deploying a career recommender system, Streamlit is ideal for interactive UI with sliders for RIASEC, education level, and skill selectors.

9.1 Deplyoment

This project is deployed and accessible live via Streamlit Cloud. **SmartPath Personalized Career Recommender SmartPath Personalized Career Recommender**

Explore the app, get your recommended career paths, and interact with insightful dashboards instantly!

Summary

This project demonstrates how data science can bridge the gap between self-assessment and real-world labor market opportunities. By combining RIASEC psychological profiling with skills and educational alignment, we created a hybrid scoring system to recommend the most suitable careers.

The system:

- Accepts user input via a simple interface
- Calculates cosine similarity between user RIASEC scores and job profiles
- Measures skill and education alignment
- Returns and ranks the top job matches
- Provides actionable visual summaries and downloadable/exportable results

---

Project Conclusion: Career Clarity Made Easy

The SmartPath Career Engine offers a **data-driven and intuitive approach** to career exploration. By integrating personal interests, educational background, and relevant skills, the tool provides tailored recommendations that bridge the gap between self-knowledge and labor market insights.

Key Takeaways:

- Top job recommendations aligned with personal RIASEC profiles

- Visual breakdown of skill, education, and interest matching
- Highlighted “skill gaps” for future learning
- One-click CSV download or email delivery for your results

Whether you're a student, job seeker, or career coach, this engine offers a **powerful starting point** for making informed, personalized career decisions.

Explore. Learn. Match. Thrive.

Recommendations & Next Steps

For Users:

- Focus on jobs with high **hybrid similarity** for better fit
- Use the skill gap insights to prioritize learning or upskilling
- Consider additional education pathways if education mismatch is high

For Developers:

- Integrate real-time job market APIs (e.g., LinkedIn, Glassdoor)
- Expand skill taxonomy to include soft skills and industry-specific tools
- Build a Streamlit or Gradio dashboard for live demo access
- Add chatbot integration for a conversational recommendation experience

For Institutions or Career Coaches:

- Deploy for student guidance or employee reskilling programs
- Extend for marginalized groups with tailored career roadmaps

---

Future Improvements

- Resume parsing for auto-input
- Personalized career roadmap prediction
- Geo-localized job relevance
- Full user authentication (Streamlit + Firestore)
- Advanced skill gap analysis using embeddings

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This work reflects a growing commitment to applying data science in empowering youth, career clarity, and digital transformation in Africa.

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Final Note

"SmartPath isn't just a project, it's a mission to democratize data-driven career guidance for youth across Africa and beyond. Powered by Data Science, AI, and open data, we're unlocking opportunities and building futures, one youth at a time."