Summary

- **Built an end-to-end ML project on AI impact on jobs (2030).**
- **Cleaned and prepared raw data using pandas and NumPy.**
- **Performed EDA with charts and correlation analysis.**
- **Trained 5 supervised ML models for job-risk prediction.**
- **Compared models using accuracy and confusion matrices.**
- **Applied K-Means clustering for unsupervised job grouping.**
- **Used PCA for 3D cluster visualization.**
- **Analyzed feature importance with Random Forest.**

- ## Import all necessary libraries for data analysis and modeling......

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, learning_curve
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.decomposition import PCA
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
plt.style.use("seaborn-v0_8")
K_VAL = 3

from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
import warnings
warnings.filterwarnings("ignore")
```

- ## Did Some Exploratory Data Analysis(EDA)....

- ## Rename columns for consistency.....

In [3]:
```
df.columns = [c.replace(" ", "_") for c in df.columns]
```

- ## Reading dataset using pandas......

In [2]:
```python
df = pd.read_csv("D:\Download\AI_Impact_on_Jobs_2030.csv")
```

- # Did Some Exploratory Data Analysis....

- # Dataset Shape....

In [3]:
```python
print('Shape:', df.shape)
```

```
Shape: (3000, 18)
```

- # Dataset Preview ....

In [44]:
```python
print(df.head())
```

```
             Job_Title  Average_Salary  Years_Experience Education_Level  \
0       Security Guard           45795                28        Master's   
1   Research Scientist          133355                20             PhD   
2  Construction Worker          146216                 2     High School   
3    Software Engineer          136530                13             PhD   
4    Financial Analyst           70397                22     High School   

   AI_Exposure_Index  Tech_Growth_Factor  Automation_Probability_2030  \
0               0.18                1.28                         0.85   
1               0.62                1.11                         0.05   
2               0.86                1.18                         0.81   
3               0.39                0.68                         0.60   
4               0.52                1.46                         0.64   

  Risk_Category  Skill_1  Skill_2  Skill_3  Skill_4  Skill_5  Skill_6  \
0          High     0.45     0.10     0.46     0.33     0.14     0.65   
1           Low     0.02     0.52     0.40     0.05     0.97     0.23   
2          High     0.01     0.94     0.56     0.39     0.02     0.23   
3        Medium     0.43     0.21     0.57     0.03     0.84     0.45   
4        Medium     0.75     0.54     0.59     0.97     0.61     0.28   

   Skill_7  Skill_8  Skill_9  Skill_10  
0     0.06     0.72     0.94      0.00  
1     0.09     0.62     0.38      0.98  
2     0.24     0.68     0.61      0.83  
3     0.40     0.93     0.73      0.33  
4     0.30     0.17     0.02      0.42  
```

- # Dataset Information .....

In [45]:
```python
print("\nDataset info:")
print(df.info())
```

```
Dataset info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 18 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   Job_Title                   3000 non-null   object 
 1   Average_Salary              3000 non-null   int64  
 2   Years_Experience            3000 non-null   int64  
 3   Education_Level             3000 non-null   object 
 4   AI_Exposure_Index           3000 non-null   float64
 5   Tech_Growth_Factor          3000 non-null   float64
 6   Automation_Probability_2030 3000 non-null   float64
 7   Risk_Category               3000 non-null   object 
 8   Skill_1                     3000 non-null   float64
 9   Skill_2                     3000 non-null   float64
 10  Skill_3                     3000 non-null   float64
 11  Skill_4                     3000 non-null   float64
 12  Skill_5                     3000 non-null   float64
 13  Skill_6                     3000 non-null   float64
 14  Skill_7                     3000 non-null   float64
 15  Skill_8                     3000 non-null   float64
 16  Skill_9                     3000 non-null   float64
 17  Skill_10                    3000 non-null   float64
dtypes: float64(13), int64(2), object(3)
memory usage: 422.0+ KB
None
```

- ## Check Missing Values....

In [46]:
```
print("\nMissing values:")
print(df.isnull().sum())
```

```
Missing values:
Job_Title                      0
Average_Salary                 0
Years_Experience               0
Education_Level                0
AI_Exposure_Index              0
Tech_Growth_Factor             0
Automation_Probability_2030    0
Risk_Category                  0
Skill_1                        0
Skill_2                        0
Skill_3                        0
Skill_4                        0
Skill_5                        0
Skill_6                        0
Skill_7                        0
Skill_8                        0
Skill_9                        0
Skill_10                       0
dtype: int64
```

- ## Statistical Summary mean, min, max, and standard deviation......

In [47]:
```
print(df.describe(include="all"))
```

```
                 Job_Title  Average_Salary  Years_Experience Education_Level  \
count                 3000     3000.000000       3000.000000            3000   
unique                  20             NaN               NaN               4   
top      Software Engineer             NaN               NaN     High School   
freq                   175             NaN               NaN             784   
mean                   NaN    89372.279000         14.677667             NaN   
std                    NaN    34608.088767          8.739788             NaN   
min                    NaN    30030.000000          0.000000             NaN   
25%                    NaN    58640.000000          7.000000             NaN   
50%                    NaN    89318.000000         15.000000             NaN   
75%                    NaN   119086.500000         22.000000             NaN   
max                    NaN   149798.000000         29.000000             NaN   

        AI_Exposure_Index  Tech_Growth_Factor  Automation_Probability_2030  \
count         3000.000000         3000.000000                  3000.000000   
unique                NaN                 NaN                          NaN   
top                   NaN                 NaN                          NaN   
freq                  NaN                 NaN                          NaN   
mean             0.501283            0.995343                     0.501503   
std              0.284004            0.287669                     0.247881   
min              0.000000            0.500000                     0.050000   
25%              0.260000            0.740000                     0.310000   
50%              0.500000            1.000000                     0.500000   
75%              0.740000            1.240000                     0.700000   
max              1.000000            1.500000                     0.950000   

       Risk_Category      Skill_1      Skill_2      Skill_3      Skill_4  \
count           3000  3000.000000  3000.000000  3000.000000  3000.000000   
unique             3          NaN          NaN          NaN          NaN   
top           Medium          NaN          NaN          NaN          NaN   
freq            1521          NaN          NaN          NaN          NaN   
mean             NaN     0.496973     0.497233     0.499313     0.503667   
std              NaN     0.287888     0.288085     0.288354     0.287063   
min              NaN     0.000000     0.000000     0.000000     0.000000   
25%              NaN     0.240000     0.250000     0.250000     0.260000   
50%              NaN     0.505000     0.500000     0.500000     0.510000   
75%              NaN     0.740000     0.740000     0.750000     0.750000   
max              NaN     1.000000     1.000000     1.000000     1.000000   

            Skill_5      Skill_6      Skill_7      Skill_8      Skill_9  \
count   3000.000000  3000.000000  3000.000000  3000.000000  3000.000000   
unique          NaN          NaN          NaN          NaN          NaN   
top             NaN          NaN          NaN          NaN          NaN   
freq            NaN          NaN          NaN          NaN          NaN   
mean       0.490270     0.499807     0.499160     0.502843     0.501433   
std        0.285818     0.286050     0.288044     0.289832     0.285818   
min        0.000000     0.000000     0.000000     0.000000     0.000000   
25%        0.240000     0.260000     0.250000     0.250000     0.260000   
50%        0.490000     0.500000     0.490000     0.500000     0.500000   
75%        0.730000     0.740000     0.750000     0.750000     0.740000   
max        1.000000     1.000000     1.000000     1.000000     1.000000   

           Skill_10  
count   3000.000000  
unique          NaN  
top             NaN  
```

```
freq             NaN
mean        0.493627
std         0.286464
min         0.000000
25%         0.250000
50%         0.490000
75%         0.740000
max         1.000000
```

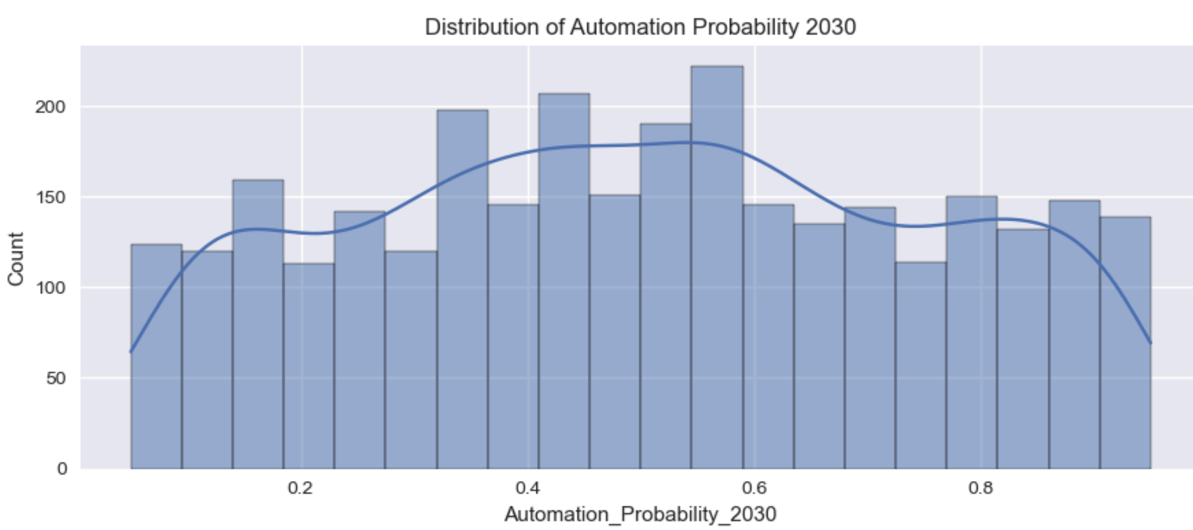
- ## Summary(Risk Category) ....

In [5]:
```
print("\nSummary(Risk Category)")
print(df['Risk_Category'].value_counts())
```

```
Summary(Risk Category)
Risk_Category
Medium    1521
High       740
Low        739
Name: count, dtype: int64
```

- ## Histogram of Automation_Probability_2030.....

In [124]:
```
plt.figure(figsize=(9, 4))
sns.histplot(df["Automation_Probability_2030"], kde=True, bins=20)
plt.title("Distribution of Automation Probability 2030")
plt.xlabel("Automation_Probability_2030")
plt.ylabel("Count")
plt.tight_layout()
plt.show()
```

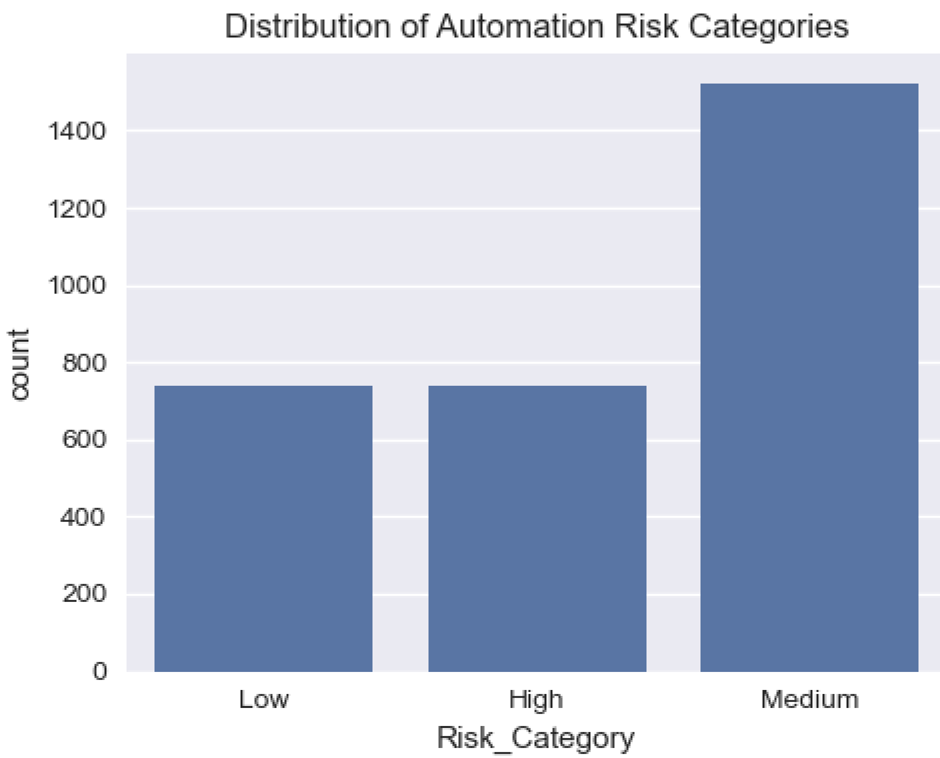


- ## Risk category counts visualization .....

In [125]:
```
print("\nRisk category counts:")
print(df["Risk_Category"].value_counts())
```

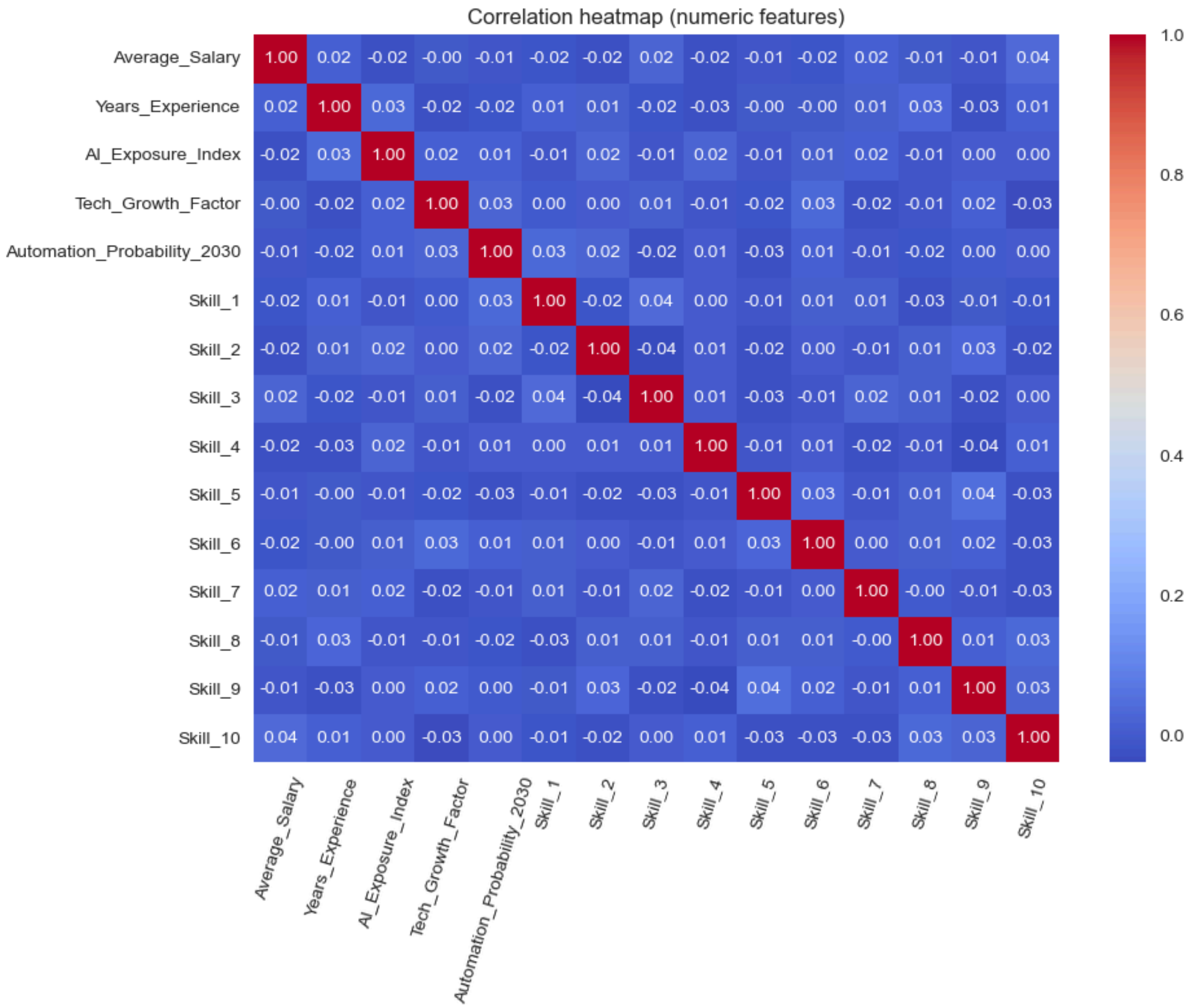
```
plt.figure(figsize=(5,4))
sns.countplot(x="Risk_Category", data=df, order=["Low","High", "Medium"])
plt.title("Distribution of Automation Risk Categories")
plt.tight_layout()
plt.show()
```

```
Risk category counts:
Risk_Category
Medium    1521
High       740
Low        739
Name: count, dtype: int64
```



- # Correlation heatmap for numeric features........

In [57]:
```
numeric_cols = df.select_dtypes(include=[np.number]).columns
plt.figure(figsize=(10, 8))
corr = df[numeric_cols].corr()
sns.heatmap(corr, annot=True,fmt='.2f', cmap="coolwarm")
plt.title("Correlation heatmap (numeric features)")
plt.xticks(rotation=73)
plt.tight_layout()
plt.show()
```



- ## Encode the target variable (Risk_Category) into numerical labels......

In [8]:
```python
label_encoder = LabelEncoder()
df["Risk_Category_Encoded"] = label_encoder.fit_transform(df["Risk_Category"])
```

- ## Separates input features (X) and the target variable (y).......

In [9]:
```python
feature_cols = [c for c in df.select_dtypes(include=[np.number]).columns
                if c != "Risk_Category_Encoded"]

X = df[feature_cols]
y = df["Risk_Category_Encoded"]
```

- ## Split data into training 80% and testing 20% sets.......

In [10]:
```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y)
```

- ## Training testing Shape.....

In [17]:
```
print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
print("y value counts:\n", y.value_counts())
```

```
X_train shape: (2400, 15)
X_test shape: (600, 15)
y value counts:
 Risk_Category_Encoded
2    1521
0     740
1     739
Name: count, dtype: int64
```

- ## Standardize all numerical features using StandardScaler......

In [13]:
```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

model_results = {}
trained_models = {}
```

- ## Starting Unsupervised Analysis: K-Means & PCA....

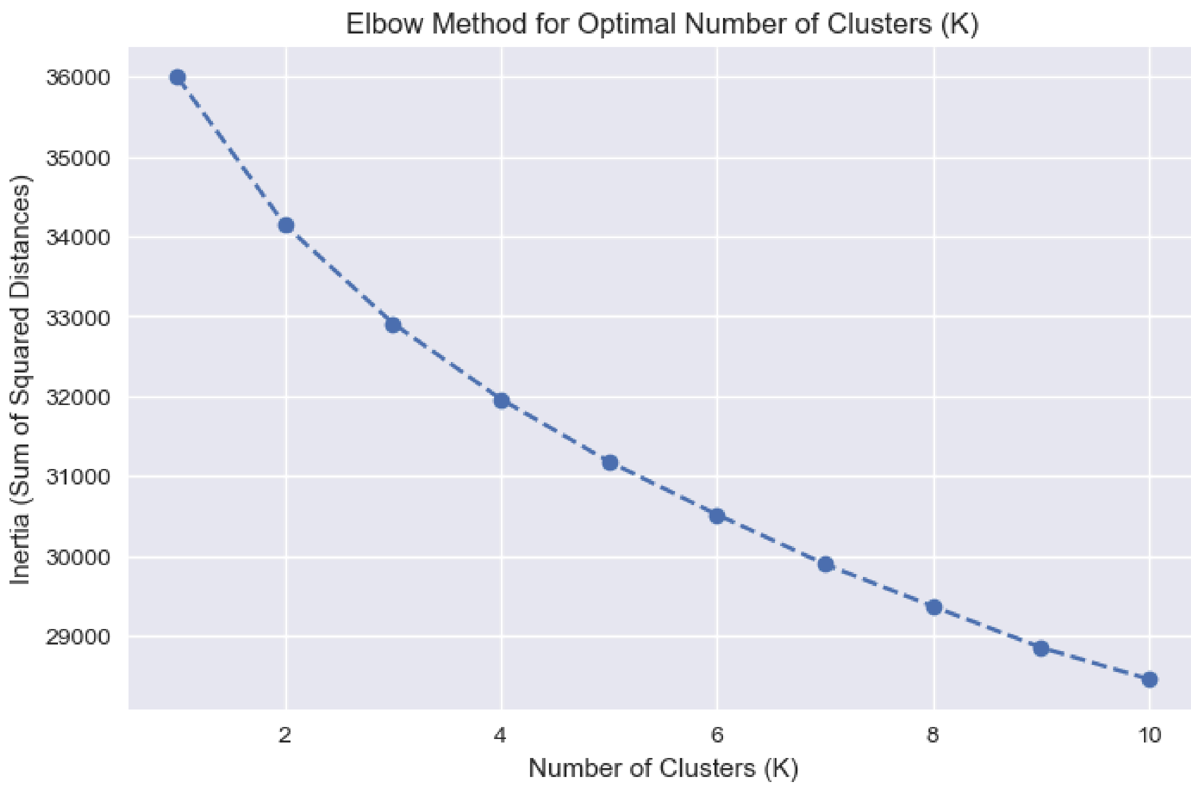
- ## Elbow Method for Optimal Clusters....

In [68]:
```
print("--- Starting Unsupervised Analysis: K-Means & PCA ---")
inertia_values = []
max_k = 10
# Test K from 1 to max_k
for k in range(1, max_k + 1):
    # Use X_train_scaled as K-Means is distance-based
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    kmeans.fit(X_train_scaled)
    inertia_values.append(kmeans.inertia_)
```

```
--- Starting Unsupervised Analysis: K-Means & PCA ---

1. Running Elbow Method to find optimal K...
```

Visualize the Elbow...

In [69]:
```
# Visualize the Elbow Method
plt.figure(figsize=(8, 5))
plt.plot(range(1, max_k + 1), inertia_values, marker='o', linestyle='--')
plt.title('Elbow Method for Optimal Number of Clusters (K)')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Inertia (Sum of Squared Distances)')
plt.grid(True)
plt.show()
print("")
```



- ## Clustering,PCA & Validation...

In [88]:
```
K_VAL = 3
kmeans_val = KMeans(n_clusters=K_VAL, random_state=42, n_init='auto')
cluster_labels = kmeans_val.fit_predict(X_train_scaled)

# Validation: Compare Clusters to True Risk Categories
comparison_df = pd.DataFrame({
    'True_Risk_Category_Encoded': y_train,
    'KMeans_Cluster': cluster_labels
})
cross_tab = pd.crosstab(comparison_df['True_Risk_Category_Encoded'], comparison_df['K

print(f"Cluster Alignment (K={K_VAL}):")
print(cross_tab)
print("\n")
```

```
--- Unsupervised Analysis: Step 2 (Clustering, 2D PCA & Validation) ---
Cluster Alignment (K=3):
KMeans_Cluster              0    1    2
True_Risk_Category_Encoded
0                         104  260  228
1                         323  113  155
2                         412  380  425
```

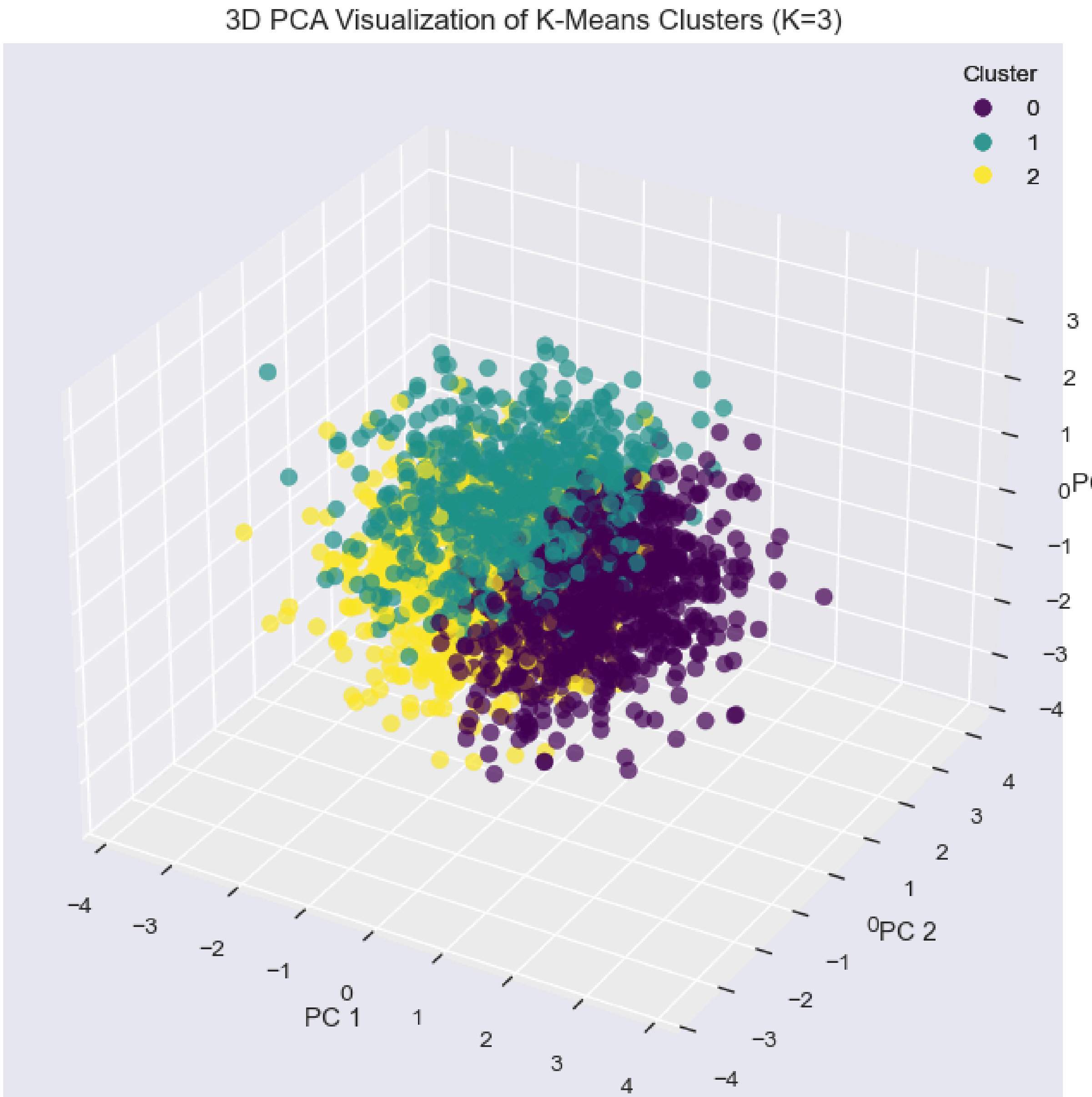
- ## Perform Principal Component Analysis (PCA) to reduce dimensions...

In [91]:
```
# 2. Dimensionality Reduction with PCA
pca = PCA(n_components=3, random_state=42)
X_pca = pca.fit_transform(X_train_scaled)

explained_variance = pca.explained_variance_ratio_.sum()
print(f"Variance Explained by 3 PCs: {explained_variance:.2%}")
```

```
Variance Explained by 3 PCs: 22.32%
```

- ## Visualization for K-Means clusters in a 3D scatter plot...

In [92]:
```
# 3. Create 3D Visualization
pca_df = pd.DataFrame(data=X_pca, columns=['PC1', 'PC2', 'PC3'])
pca_df['KMeans_Cluster'] = cluster_labels
pca_df['KMeans_Cluster'] = pca_df['KMeans_Cluster'].astype('category')

fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(111, projection='3d')

scatter = ax.scatter(pca_df['PC1'], pca_df['PC2'], pca_df['PC3'],
                     c=pca_df['KMeans_Cluster'].cat.codes,
                     cmap='viridis',
                     s=50,
                     alpha=0.7)

ax.set_title(f'3D PCA Visualization of K-Means Clusters (K={K_VAL})')
ax.set_xlabel('PC 1')
ax.set_ylabel('PC 2')
ax.set_zlabel('PC 3')
legend1 = ax.legend(*scatter.legend_elements(), title="Cluster")
ax.add_artist(legend1)
plt.show()
print("")
```



- **supervise Learning: Define a reusable function to train, predict, and evaluate model performance......**

In [41]:
```
def evaluate_model(name, model, X_tr, y_tr, X_te, y_te):
    model.fit(X_tr, y_tr)
    y_pred = model.predict(X_te)
    acc = accuracy_score(y_te, y_pred)
    model_results[name] = acc
    trained_models[name] = model
    print("=" + name + "=")
    print("Accuracy:", round(acc, 4))
    print(classification_report(y_te, y_pred, target_names=label_encoder.classes_))

    # Confusion matrix
    cm = confusion_matrix(y_test, y_pred)
```

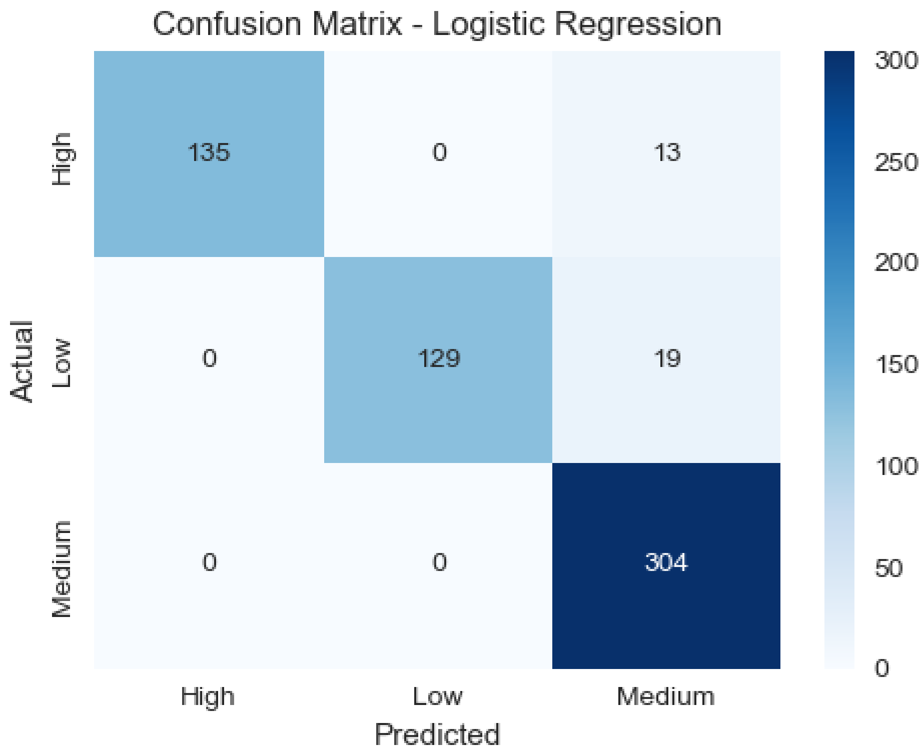
```
    plt.figure(figsize=(5,4))
    sns.heatmap(
        cm,
        annot=True,
        fmt="d",
        cmap="Blues",
        xticklabels=label_encoder.classes_,
        yticklabels=label_encoder.classes_
    )
    plt.title("Confusion Matrix - " + name)
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.tight_layout()
    plt.show()
    print()
    return model, acc
```

- **Logistic Regression Predictions**
- **Logistic Regression Accuracy And**
- **Confusion Matrix, f1-score for Logistic Regression ...**

In [67]:

```
# Logistic Regression
log_reg = LogisticRegression(max_iter=1000, C=0.0084,)
log_reg, log_acc = evaluate_model(
    "Logistic Regression", log_reg, X_train_scaled, y_train, X_test_scaled, y_test
)
print("Final Logistic Regression accuracy:", log_acc)
```

```
=Logistic Regression=
Accuracy: 0.9467
              precision    recall  f1-score   support

        High       1.00      0.91      0.95       148
         Low       1.00      0.87      0.93       148
      Medium       0.90      1.00      0.95       304

    accuracy                           0.95       600
   macro avg       0.97      0.93      0.95       600
weighted avg       0.95      0.95      0.95       600
```

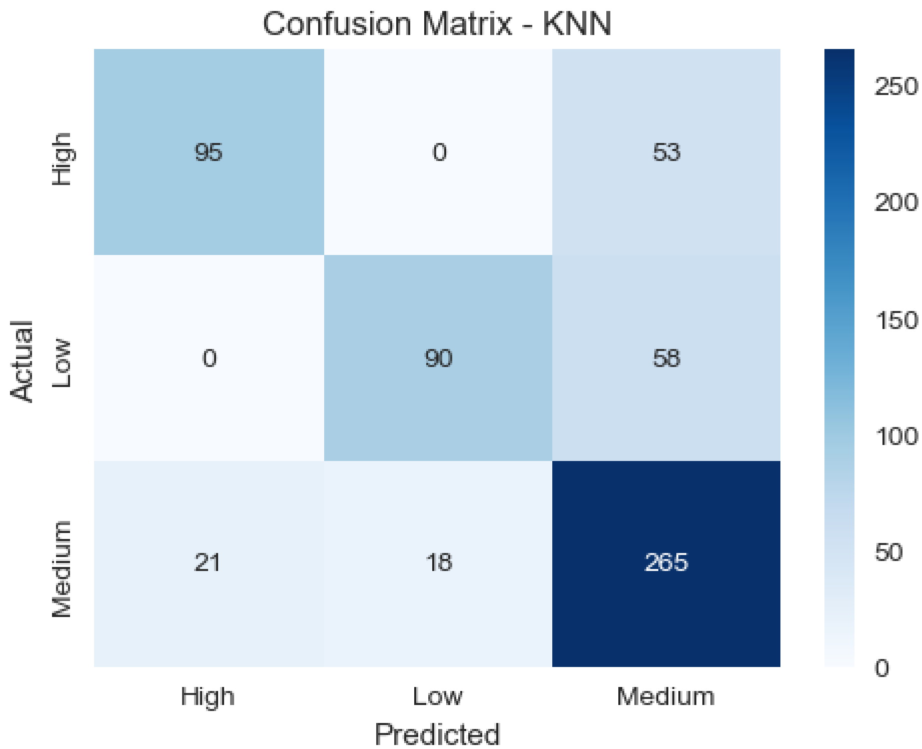



```
Final Logistic Regression accuracy: 0.9466666666666667
```

- ## KNN Predictions
- ## KNN Accuracy
- ## Confusion Matrix, f1-score for KNN

In [43]:
```
# KNN
knn = KNeighborsClassifier(n_neighbors=7)
knn, knn_acc = evaluate_model(
    "KNN", knn, X_train_scaled, y_train, X_test_scaled, y_test
)
```

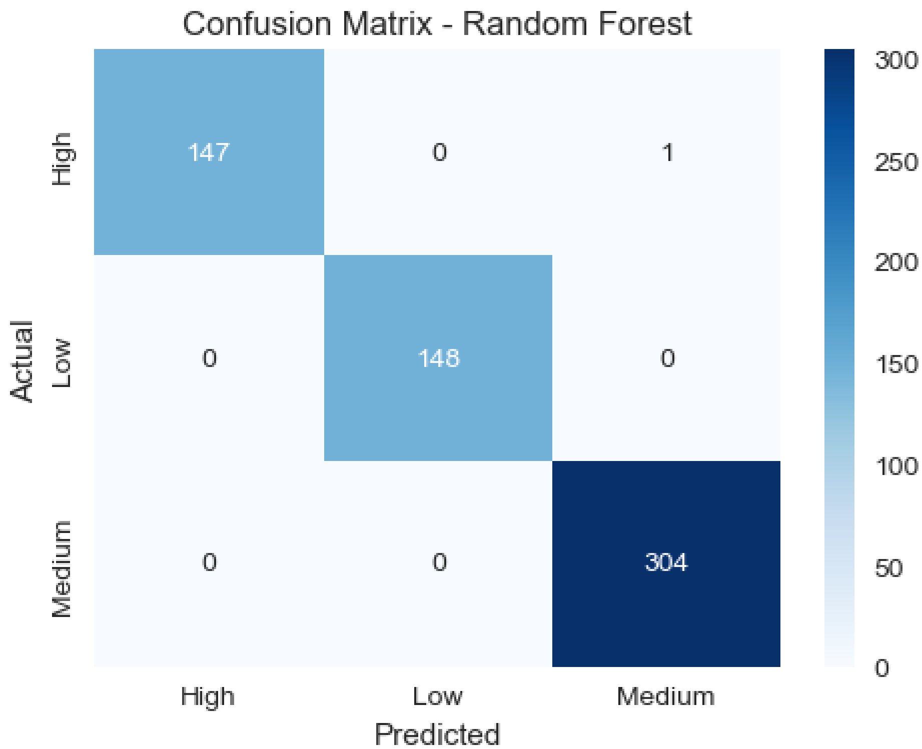
```
=KNN=
Accuracy: 0.75
              precision    recall  f1-score   support

        High       0.82      0.64      0.72       148
         Low       0.83      0.61      0.70       148
      Medium       0.70      0.87      0.78       304

    accuracy                           0.75       600
   macro avg       0.79      0.71      0.73       600
weighted avg       0.76      0.75      0.75       600
```



- **Random Forest Predictions..**
- **Random Forest Accuracy..**
- **Confusion Matrix, f1-score for Random Forest..**

In [75]:
```
# Random Forest (no scaling needed)
rf = RandomForestClassifier(
    n_estimators=150, max_depth=3, random_state=42
)
rf, rf_acc = evaluate_model(
    "Random Forest", rf, X_train, y_train, X_test, y_test
)
```

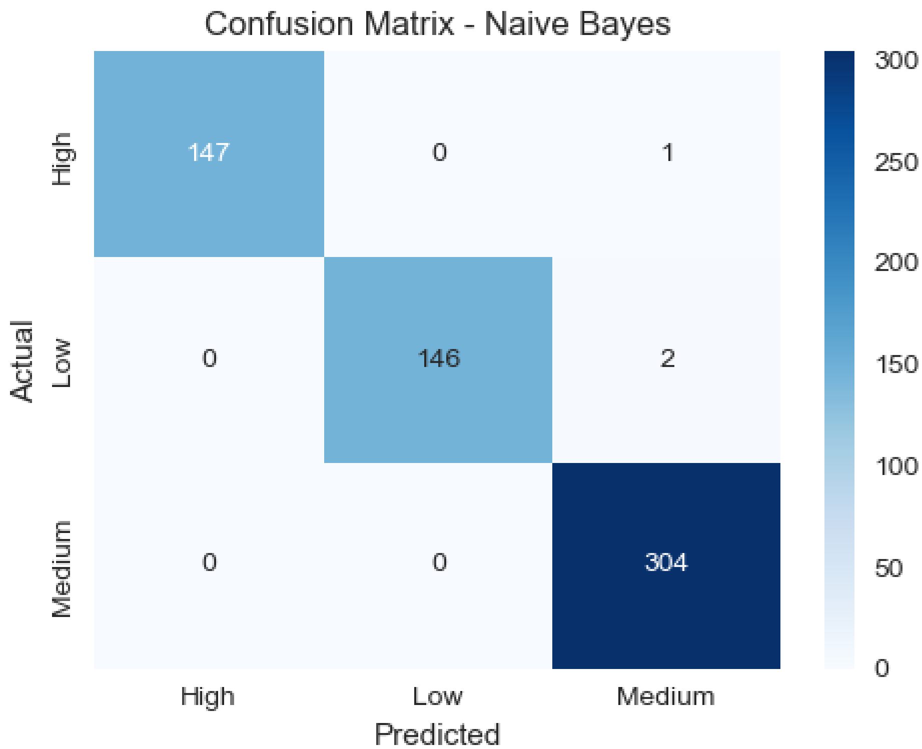
```
=Random Forest=
Accuracy: 0.9983
              precision    recall  f1-score   support

        High       1.00      0.99      1.00       148
         Low       1.00      1.00      1.00       148
      Medium       1.00      1.00      1.00       304

    accuracy                           1.00       600
   macro avg       1.00      1.00      1.00       600
weighted avg       1.00      1.00      1.00       600
```



- ## Naive Bayes Model Training
- ## Naive Bayes Predictions
- ## Naive Bayes Accuracy, confusion matrix and f1-score

In [45]:
```
# Naive Bayes
nb = GaussianNB()
nb, nb_acc = evaluate_model(
    "Naive Bayes", nb, X_train_scaled, y_train, X_test_scaled, y_test
)
```

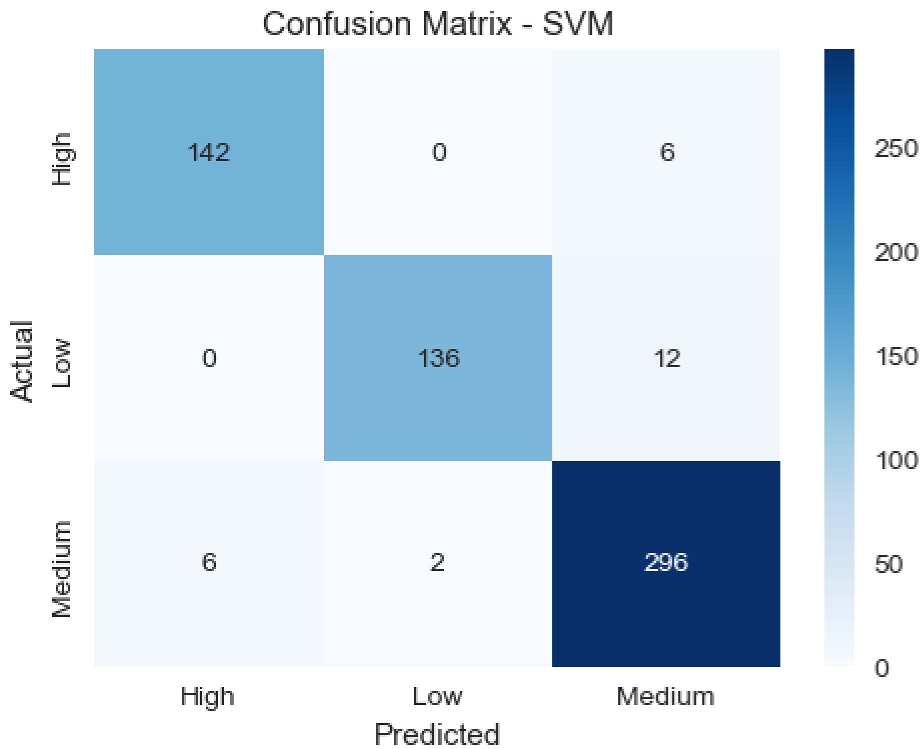
```
=Naive Bayes=
Accuracy: 0.995
              precision    recall  f1-score   support

        High       1.00      0.99      1.00       148
         Low       1.00      0.99      0.99       148
      Medium       0.99      1.00      1.00       304

    accuracy                           0.99       600
   macro avg       1.00      0.99      0.99       600
weighted avg       1.00      0.99      0.99       600
```



- **Support Vector Machine (SVM) Model Training...**
- **Support Vector Machine (SVM) Predictions....**
- **Support Vector Machine (SVM) Bayes Accuracy...**

In [46]:
```
# SVM
svm_clf = SVC(kernel="rbf", C=1.0, gamma="scale", probability=True, random_state=42)
svm_clf, svm_acc = evaluate_model(
    "SVM", svm_clf, X_train_scaled, y_train, X_test_scaled, y_test
)
```

```
=SVM=
Accuracy: 0.9567
              precision    recall  f1-score   support

        High       0.96      0.96      0.96       148
         Low       0.99      0.92      0.95       148
      Medium       0.94      0.97      0.96       304

    accuracy                           0.96       600
   macro avg       0.96      0.95      0.96       600
weighted avg       0.96      0.96      0.96       600
```

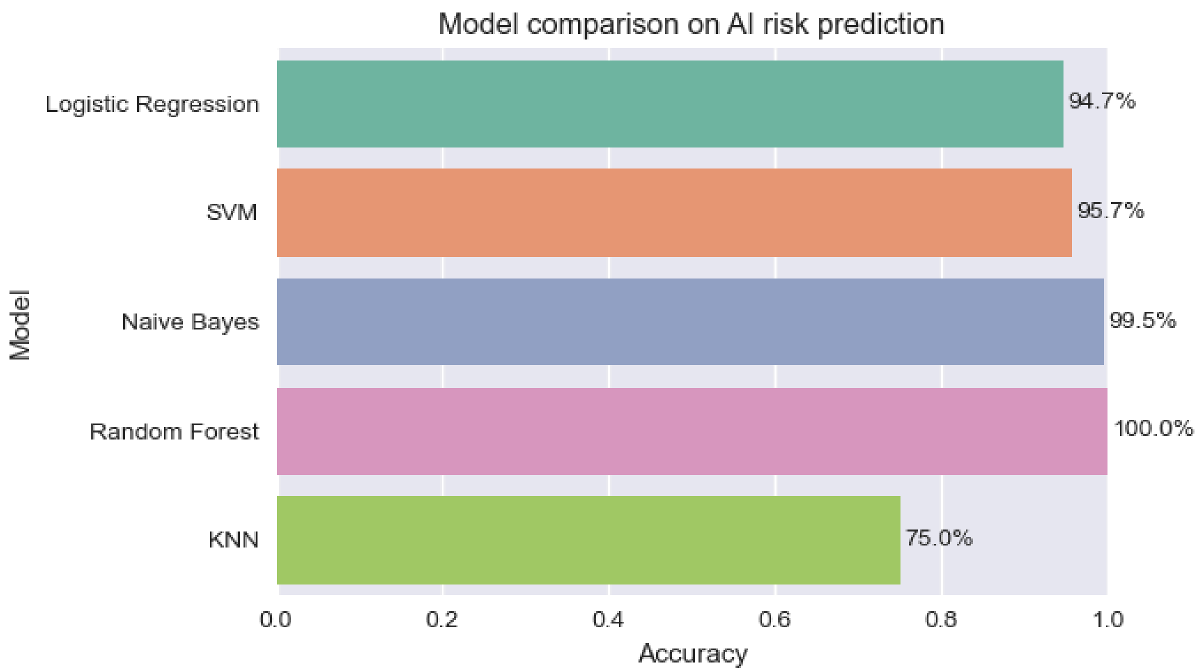


- ## Model Performance Summary Table visualization.....

In [47]:
```
print("Model accuracies summary:")
for name, acc in model_results.items():
    print(name + ":", round(acc, 4))
```

```
Model accuracies summary:
Logistic Regression: 0.9467
SVM: 0.9567
Naive Bayes: 0.995
Random Forest: 1.0
KNN: 0.75
```

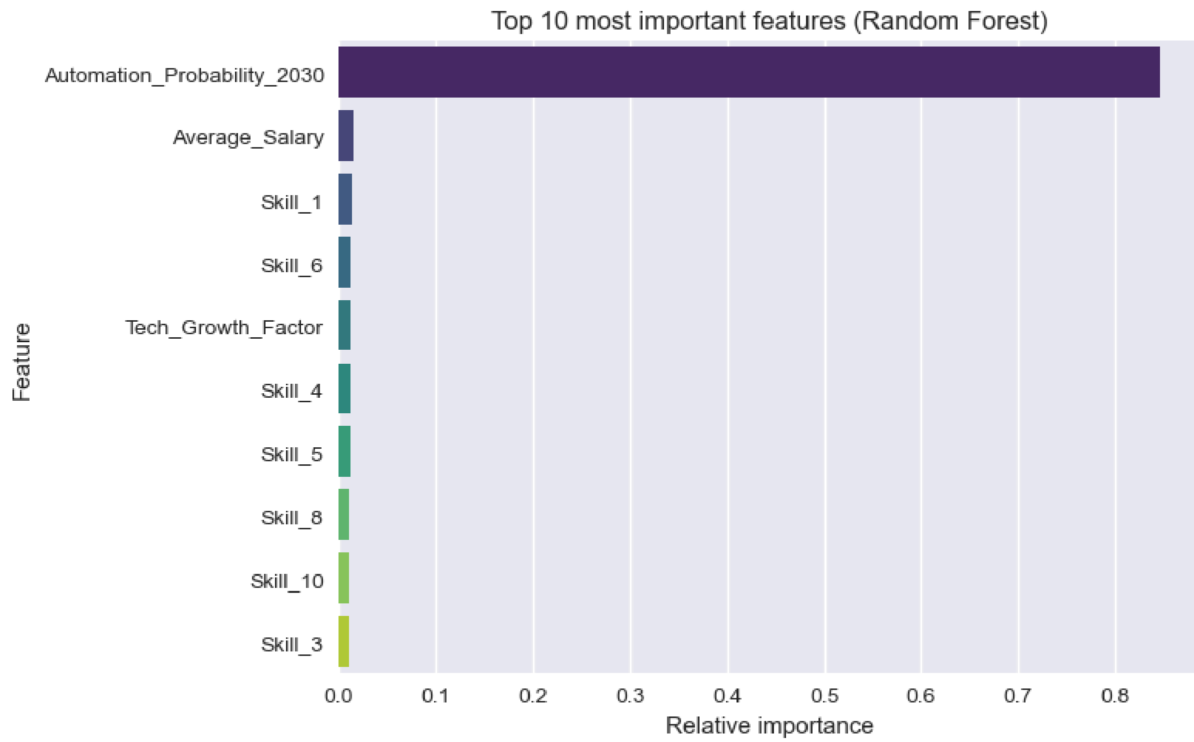
In [48]:
```
plt.figure(figsize=(7, 4))
model_names = list(model_results.keys())
accuracies = [model_results[m] for m in model_names]
sns.barplot(x=accuracies, y=model_names, palette="Set2")
for i, v in enumerate(accuracies):
    plt.text(v + 0.005, i, str(round(v * 100, 1)) + "%", va="center")
plt.xlim(0, 1)
plt.xlabel("Accuracy")
plt.ylabel("Model")
plt.title("Model comparison on AI risk prediction")
plt.tight_layout()
plt.show()
```



- ## Feature importance from Random Forest....

In [69]:
```
# Feature importance from Random Forest
importances = rf.feature_importances_
feat_names = X.columns
feat_imp = list(zip(feat_names, importances))
feat_imp_sorted = sorted(feat_imp, key=lambda x: x[1], reverse=True)[:10]
feat_labels = [f[0] for f in feat_imp_sorted]
feat_values = [f[1] for f in feat_imp_sorted]
```

In [27]:
```
plt.figure(figsize=(8, 5))
sns.barplot(x=feat_values, y=feat_labels, palette="viridis")
plt.title("Top 10 most important features (Random Forest)")
plt.xlabel("Relative importance")
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```

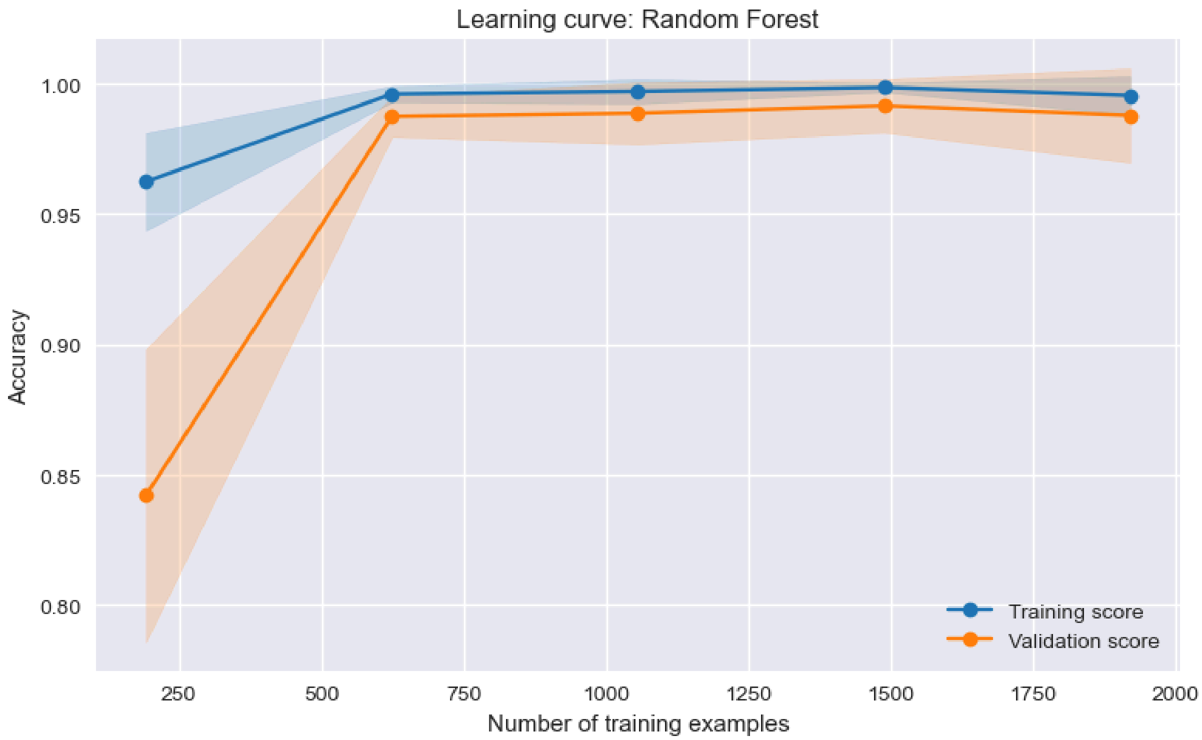


- # visualize the Learning Curve for the best model (Random Forest)....

In [76]:
```
best_model_name = max(model_results, key=model_results.get)
best_model = trained_models[best_model_name]
print("Best model by accuracy:", best_model_name)

#  Choose correct feature representation
if best_model_name in ["Logistic Regression", "Random Forest", "KNN", "Naive Bayes",
      X_curve = X_train_scaled
else:
     X_curve = X_train

train_sizes, train_scores, test_scores = learning_curve(
    best_model,
    X_curve,
    y_train,
    cv=5,
    train_sizes=np.linspace(0.1, 1.0, 5),
    scoring="accuracy",
    n_jobs=-1
)

train_mean = np.mean(train_scores, axis=1)
train_std = np.std(train_scores, axis=1)
val_mean = np.mean(test_scores, axis=1)
val_std = np.std(test_scores, axis=1)

plt.figure(figsize=(8, 5))
plt.plot(train_sizes, train_mean, "o-", color="tab:blue", label="Training score")
plt.fill_between(train_sizes, train_mean - train_std,
```

```
                 train_mean + train_std, alpha=0.2, color="tab:blue")
plt.plot(train_sizes, val_mean, "o-", color="tab:orange", label="Validation score")
plt.fill_between(train_sizes, val_mean - val_std,
                 val_mean + val_std, alpha=0.2, color="tab:orange")

plt.title("Learning curve: " + best_model_name)
plt.xlabel("Number of training examples")
plt.ylabel("Accuracy")
plt.legend(loc="best")
plt.tight_layout()
plt.show()
```

```
Best model by accuracy: Random Forest
```



- ## model testing ....

In [33]:

```
# Create a dictionary for a new job profile (e.g., "Machine Operator")
new_job_data = {
    'Average_Salary': [45000],
    'Years_Experience': [10],
    'AI_Exposure_Index': [0.40],
    'Tech_Growth_Factor': [0.15],
    'Automation_Probability_2030': [0.92],  # Critical for High Risk
    'Skill_1': [0.15], # Low for Cognitive Skills
    'Skill_2': [0.25],
    'Skill_3': [0.85], # High for Manual/Repetitive Skills
    'Skill_4': [0.20],
    'Skill_5': [0.70],
    'Skill_6': [0.35],
    'Skill_7': [0.20],
    'Skill_8': [0.10],
    'Skill_9': [0.50],
```

```
    'Skill_10': [0.90]
}
new_job_df = pd.DataFrame(new_job_data)
```

In [36]:
```
new_job_scaled = scaler.transform(new_job_df)
prediction_encoded = best_model.predict(new_job_scaled)
predicted_risk = label_encoder.inverse_transform(prediction_encoded)

print(f"Input Automation Probability: {new_job_data['Automation_Probability_2030'][0]
print(f"The Predicted AI Risk Category for the new job is: {predicted_risk[0]} ")
```

```
Input Automation Probability: 0.92
The Predicted AI Risk Category for the new job is: High
```

In [ ]: