



Leveraging Data Science Techniques for Predictive Modeling of Global Skill Penetration Rates

Student: Roatny NUON (M080105)

M-AMS

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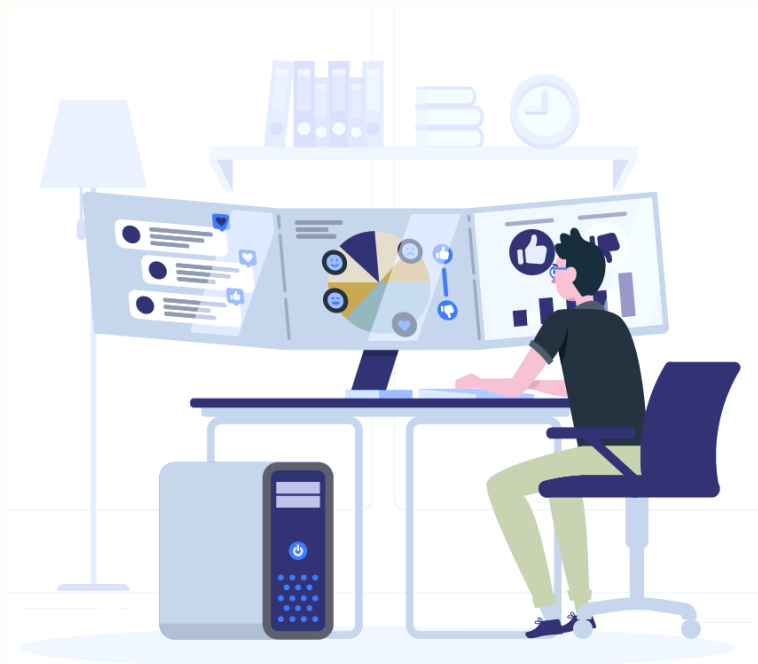
References



01

Introduction

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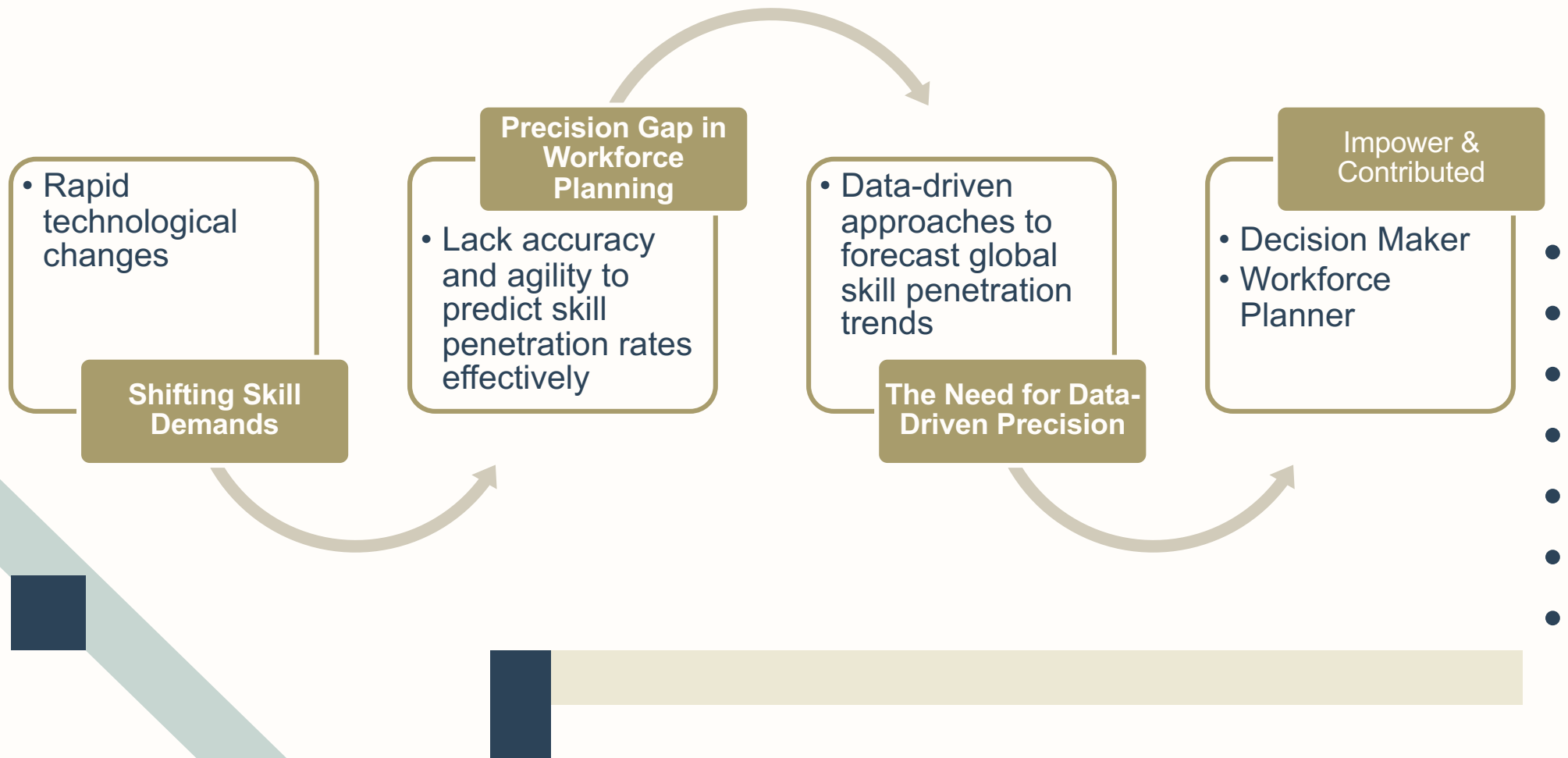


Background

In today's world, where decisions are increasingly guided by data-driven insights, this research search through into the practical applications of Data Science. Through techniques like data preprocessing, predictive modeling, and interpretation, the study demonstrates how Data Science turns intricate data into actionable wisdom. In parallel, the research aligns seamlessly with Cambodia's developmental vision and mirrors its Sustainable Development Goals (SDGs). Specifically, it contributes to the realization of SDG 9 – Industry, Innovation, and Infrastructure – by predicting skill usage trends across industries, propelling the adoption of innovative technologies. Additionally, it holds the potential to fortify SDG 4 – Quality Education – by spotlighting how Data Science methods amplify workforce training strategies.



Problem Statement



Research Objectives

1. Apply Data Science techniques to preprocess, transform, and analyze text-based World Bank data for predictive modeling of global skill penetration rates.
2. Develop and optimize predictive models using regression algorithms, showcasing the practical integration of machine learning in addressing real-world challenges.
3. Explore correlations between skill penetration trends, economic indicators, and SDG priorities, specifically relevant to Cambodia's development context.
4. Investigate how predictive modeling insights can contribute to the Cambodia Digital Economy and Society Policy Framework's objectives for workforce development and digital transformation.



Scope and Limitation

SCOPE

- The research will utilize the "public_use-skill-penetration" dataset from Word Bank, spanning the years 2015–2019, to predict skill penetration trends using Data Science Techniques.
- Global Perspective: The research will target industries on a global scale, encompassing diverse sectors and regions to capture broad trends in skill demand.

Scope and Limitation

LIMITATION

1.Generalization: The global scope might limit the model's ability to capture nuances specific to individual countries or regions, potentially impacting prediction accuracy at a local level.

2.Assumption of Stationarity: The research assumes that skill penetration trends remain relatively stable over the study period, which might not account for abrupt shifts caused by unforeseen events.

3.External Factors: Economic, political, or social factors that aren't explicitly captured in the dataset might influence skill penetration rates, affecting the model's predictive capabilities.

02

Literature Review

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Literature Reviews-4 papers

Title/Date	Objective	Methodology	Result/Conclusion
<p>"Developing a Machine Learning-based Job Forecasting and Trend Analysis System for Predicting Future Job Markets Using Historical Data."</p> <p>SENTHURVELAUTHAM, S. and SENANAYAKE, N. 2023</p>	<p>Address the gap in understanding of job market trends in the IT field, specifically focusing on roles and skills factors</p> <p>Building Auto-aggressive prediction that predict for various roles and technologies for at least the next 12 months</p>	<p>Data collection: Web scraping, Manually collecting data & Govern. Dataset > 522,180 job listings from the past 24 months in the software industry</p> <p>IF-IDF, ARIMA, LSTM, GRU, SARIMA, Prophet, DeepAR</p> <p>bi-directional LSTM model</p>	<p>Accuracy of 95.71%.</p>
<p>Forecasting unemployment with Google Trends: age, gender and digital divide</p> <p>Rodrigo Mulero and Alfredo Garcia-Hiernaux, 2022</p>	<p>This paper uses time series of job search queries from Google Trends to predict the unemployment in Spain</p> <p>Paper exploits GT time-series data from 2004 to 2018, on a collection of more than 170 search-related items, to predict unemployment figures</p>	<p>Jan. 2004 to Sep. 2018, for a total of 177 monthly observations</p> <p>The data are disaggregated by age and gender groups</p> <p>ARIMA & SARIMA gave result similar. Evaluate model: AIC, RMSE,</p>	<p>RMSE is 14.5% for the youngest unemployed</p>

Literature Reviews-4 papers

Title/Date	Objective	Methodology	Result/Conclusion
<p>Dr. Padmaja Pulicherla et al 2019 J. Phys.: Conf. Ser. 1228 012056</p> <p>"Job Shifting Prediction and Analysis Using Machine Learning"</p>	<p>Designed a predictive model to anticipate the chances of an employee leaving the job</p>	<p>18K data from Analytics Vidhya site Random Forest , XGBoost , CatBoost , LightGBM</p>	<p>CatBoost is the best model with 0.7%</p>
<p>T. V. Huynh, K. V. Nguyen, N. L. T. Nguyen, and A. G. T. Nguyen, "Job Prediction: From Deep Neural Network Models to Applications," 2020</p>	<p>Studying the job prediction using different deep neural network models including Text CNN,Bi-GRU-LSTM-CNN, and Bi-GRU-CNN with various pre-trained word embeddings on the IT job dataset. Input: Given an IT job description collected from the online finding-job sites Output: A predicted job title for this description.</p>	<p>Dataset 10,000 distinct job descriptions, from the online finding-job sites w/ 25 different types of IT-related job. 4 deep neural network models used: TextCNN, two combination models (Bi-GRU-CNN and Bi-GRU-LSTM-CNN) and ensemble mode</p>	<p>In the Bi-GRU-CNN + Glove model, the class "IT Consultant" got largest accuracy of 91.43% and the class "Data Architect" got lowest accuracy of 44.19%</p>



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Data Collection

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Data Background



Type: Secondary Data

LinkedIn Data World Bank.ORG



SIZE

20781 x 7

Includes information about skill group penetration rates across various industries and years.



Features

year, skill group category, skill group name, ISIC section index, ISIC section name, industry name, and skill group penetration rate.



Digital Data for Development

Skill Penetration Dataset

Context

The LinkedIn and World Bank Group collaboration is a prime example of how technology companies can work with development institutions to bring new data and insights to developing countries to address pressing development challenges. The opportunities and challenges presented by the global economy requires the public and private sectors to join forces, share information, share resources, and work towards a common vision to make meaningful, positive and scalable impact.

The dataset underlies the metrics presented on the interactive dashboard of the World Bank Group – LinkedIn partnership. The metrics and data are a product of the partnership and cover industry employment, skill, and migration metrics for over 100 countries. Specifically, the data covers 4 metrics: 1) Industry Employment Shifts, 2) Talent Migration, 3) Industry Skills Needs, and 4) Skill Penetration. LinkedIn and the World Bank Group plan to refresh the data annually at a minimum.

This file contains Skill Penetration data

Details

The Skill Penetration metric looks at how many skills from each of LinkedIn's skill groups (see "Notes" tab) appear among the top 30 skills for each occupation in an industry. For example, if 3 of 30 skills for Data Scientists in the Information Services industry fall into the Artificial Intelligence skill group, Artificial Intelligence has a 10% penetration for Data Scientists in Information Services. These penetration rates are averaged across occupations to derive the industry averages reported. It is likely this metric is best at capturing skill penetration across tradable and knowledge-intensive sectors. For example, it may under-estimate the adoption of AI in Manufacturing, since LinkedIn members are less likely to be in this sector compared to others.

For more information on the World-Bank Group - LinkedIn Partnership, please visit

linkedindata.worldbank.org

<https://linkedindata.worldbank.org/data>

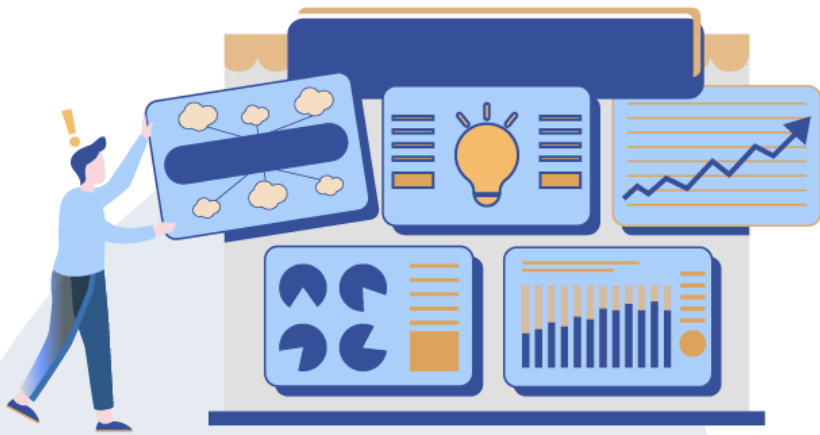
Data Table

	A	B	C	D	E	F	G	H	20750	2019	Tech Skills	Web Develop	J	Information	Broadcast M	0,00453
1	year	skill_group	skill_group	isic_section	isic_section	industry_name	skill_group	penetration_rate	20751	2019	Tech Skills	Web Develop	C	Manufacturi	Industrial Au	0,00435
2	2015	Business Skill	Accounts Pay	M	Professional	Accounting	0,00719		20752	2019	Tech Skills	Web Develop	K	Financial and	Investment M	0,00409
3	2015	Business Skill	Accounts Pay	M	Professional	Law Practice	0,00244		20753	2019	Tech Skills	Web Develop	M	Professional	Photography	0,00406
4	2015	Business Skill	Accounts Pay	M	Professional	Executive Of	0,00222		20754	2019	Tech Skills	Web Develop	R	Arts, enterta	Entertainme	0,00405
5	2015	Business Skill	Accounts Pay	C	Manufacturi	Packaging &	0,00132		20755	2019	Tech Skills	Web Develop	C	Manufacturi	Electrical & E	0,00401
6	2015	Business Skill	Accounts Pay	B	Mining and c	Oil & Energy	0,00132		20756	2019	Tech Skills	Web Develop	R	Arts, enterta	Sports	0,00398
7	2015	Business Skill	Accounts Pay	C	Manufacturi	Printing	0,00128		20757	2019	Tech Skills	Web Develop	C	Manufacturi	Renewables	0,00356
8	2015	Business Skill	Accounts Pay	C	Manufacturi	Machinery	0,00112		20758	2019	Tech Skills	Web Develop	M	Professional	Accounting	0,00354
9	2015	Business Skill	Accounts Pay	K	Financial and	Venture Capi	0,00102		20759	2019	Tech Skills	Web Develop	M	Professional	Legal Service	0,00353
10	2015	Business Skill	Accounts Pay	C	Manufacturi	Plastics	9,40E-04		20760	2019	Tech Skills	Web Develop	M	Professional	Environment	0,00311
11	2015	Business Skill	Accounts Pay	M	Professional	Legal Service	9,20E-04		20761	2019	Tech Skills	Web Develop	M	Professional	Biotechnolog	0,00309
12	2015	Business Skill	Accounts Pay	C	Manufacturi	Textiles	8,30E-04		20762	2019	Tech Skills	Web Develop	M	Professional	Architecture	0,00261
13	2015	Business Skill	Accounts Pay	B	Mining and c	Mining & Me	8,10E-04		20763	2019	Tech Skills	Web Develop	C	Manufacturi	Aviation & A	0,00261
14	2015	Business Skill	Accounts Pay	M	Professional	Mechanical C	7,70E-04		20764	2019	Tech Skills	Web Develop	C	Manufacturi	Automotive	0,00253
15	2015	Business Skill	Accounts Pay	C	Manufacturi	Electrical & E	7,50E-04		20765	2019	Tech Skills	Web Develop	M	Professional	Law Practice	0,00247
16	2015	Business Skill	Accounts Pay	C	Manufacturi	Food Product	7,50E-04		20766	2019	Tech Skills	Web Develop	J	Information	Semiconduct	0,0024
17	2015	Business Skill	Accounts Pay	M	Professional	Environment	7,30E-04		20767	2019	Tech Skills	Web Develop	M	Professional	Mechanical C	0,00226
18	2015	Business Skill	Accounts Pay	C	Manufacturi	Automotive	7,10E-04		20768	2019	Tech Skills	Web Develop	C	Manufacturi	Pharmaceuti	0,00198
19	2015	Business Skill	Accounts Pay	J	Information	Information	6,60E-04		20769	2019	Tech Skills	Web Develop	J	Information	Motion Pictu	0,00194
20	2015	Business Skill	Accounts Pay	M	Professional	Architecture	6,10E-04		20770	2019	Tech Skills	Web Develop	C	Manufacturi	Textiles	0,00192
21	2015	Business Skill	Accounts Pay	C	Manufacturi	Industrial Au	6,00E-04		20771	2019	Tech Skills	Web Develop	M	Professional	Executive Of	0,00184
22	2015	Business Skill	Accounts Pay	C	Manufacturi	Chemicals	5,70E-04		20772	2019	Tech Skills	Web Develop	R	Arts, enterta	Museums &	0,00172
23	2015	Business Skill	Accounts Pay	J	Information	Telecommur	5,50E-04		20773	2019	Tech Skills	Web Develop	C	Manufacturi	Machinery	0,0017
24	2015	Business Skill	Accounts Pay	J	Information	Computer So	5,30E-04		20774	2019	Tech Skills	Web Develop	B	Mining and c	Oil & Energy	0,00168
25	2015	Business Skill	Accounts Pay	M	Professional	Outsourcing/	5,20E-04		20775	2019	Tech Skills	Web Develop	C	Manufacturi	Packaging &	0,00159
26	2015	Business Skill	Accounts Pay	M	Professional	Marketing &	5,10E-04		20776	2019	Tech Skills	Web Develop	B	Mining and c	Mining & Me	0,00147
27	2015	Business Skill	Accounts Pay	M	Professional	Biotechnolog	5,00E-04		20777	2019	Tech Skills	Web Develop	C	Manufacturi	Food Product	0,00144
28	2015	Business Skill	Accounts Pay	R	Arts, enterta	Health, Well	4,90E-04		20778	2019	Tech Skills	Web Develop	C	Manufacturi	Food Product	0,00139
29	2015	Business Skill	Accounts Pay	K	Financial and	Financial Ser	4,80E-04		20778	2019	Tech Skills	Web Develop	C	Manufacturi	Chemicals	0,00139

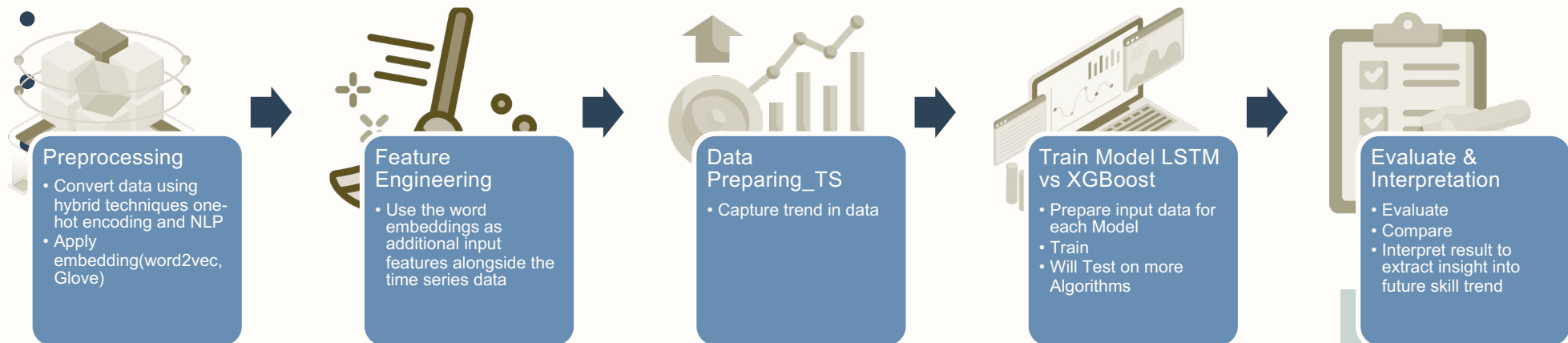
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Methodology

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How to achieve Predictive Task



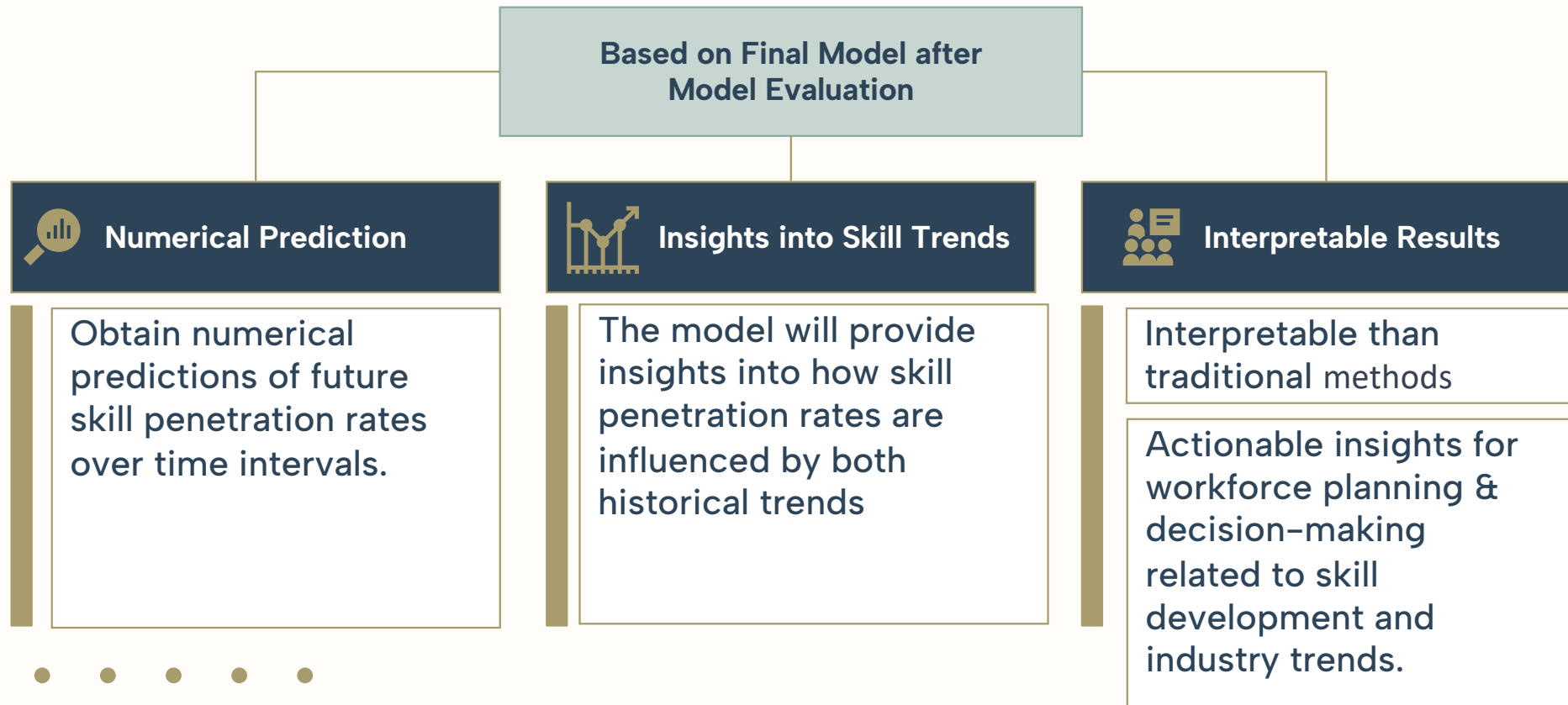
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Expected Result

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Expected Result



References

SENTHURVELAUTHAM, S. and SENANAYAKE, N. 2023 "Developing a Machine Learning-based Job Forecasting and Trend Analysis System for Predicting Future Job Markets Using Historical Data"

Mulero and Alfredo Garcia-Hiernaux, 2022, Forecasting unemployment with Google Trends: age, gender and digital divide

Dr. Padmaja Pulicherla et al 2019 J. Phys.: Conf. Ser. 1228 012056 "Job Shifting Prediction and Analysis Using Machine Learning"

T. V. Huynh, K. V. Nguyen, N. L. T. Nguyen, and A. G. T. Nguyen, "Job Prediction: From Deep Neural Network Models to Applications," 2020

Data source: <https://linkedindata.worldbank.org/data>





Thank You!

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