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Research Article

Remodeling the knowledge economy growth concept using machine learning analysis

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ABSTRACT
Traditional econometric models are now considered to be weak in measuring economic activities in line with new economic realities. The consequence is inaccurate forecasts and growing concerns for predicting impact and timely macroeconomic policy interventions. The purpose of this study was to identify features that expedite knowledge economy driven growth and create a machine learning model that addresses the methodological weaknesses of econometric models in assisting lagging economies drive a knowledge economy-based transition. A naïve bayes model was designed and implemented based on a small dataset from the Organisation of Economic Development and Corporation (OECD) members' Science and Technology Indicators (STIs) and World Bank Gross National Income (GNI) per capita growth rates from 44 countries (OECD and non-OECD countries). The initial dataset had observations over 4 years (2015-2018). The formulated model had an F1 score of 85% at its peak which was satisfactory based on the size of the dataset. The results from the study indicate that economies targeting sustainable high growth are continuously going to rely on the capacitation of business research. Transitioned economies in the last two decades have experienced negative growth rates in basic research with more focus being made towards applied and experimental research. In addition, there is need for the business sector to collaborate with government, with the former conducting much of the gross research in an economy.

Keywords: Knowledge economy, machine learning, OECD, R&D.

INTRODUCTION
Most economies lagging in growth are faced with a challenge of determining the course of action to take to facilitate wealth creation that upgrades social development. Economies that are striving to uplift citizens from poverty for example, Sub-Saharan Africa economies are desperate for economic models that will achieve the most rapid growth over the shortest period. For economies looking for growth, the context of development has structurally changed, with some researchers concluding that the "passage from poor to rich nations has been kicked away" (Chang, 2003). For example, the current forerunners were sustained by free trade agreements (Mason and Shetty, 2019) which now have a different implication. This research is focused on creating a new growth model that addresses the shortcomings of traditional economic theory in measuring and evaluating realities under the new economy. The methodological weaknesses of economic theory in explaining relationships is also explored with an alternative approach established based on machine learning models. The research takes a machine learning approach in modelling a possible pathway to growth based on observing the relationships of the knowledge-based growth strategies taken by the Organisation of Economic Corporation and Development (OECD) countries. The study attempts to discard the assumptions in traditional economic theory which present challenges of modelling economy at all levels. The new economic relationships have not been adequately documented as for example measuring growth is foregoing a lot of unmeasured value characterized by the knowledge and digital economies (Bean, 2016; Watanabe et al., 2018). The approach will help governments in the future to limit economic assumptions which are no longer in existence.

MATERIALS AND METHODS
The reality of growth in economics is being broadly classified into the forerunners and the latecomers (Cavallini et al., 2016; Lee and Melerba, 2019). There is clarity on which country falls under what category but there is no consensus on the path to be taken by countries that are lagging. The models are unclear on which approach to take and the context of executing the individual country priorities as each economy is different from the other. The near consensus has put the knowledge economy under spotlight as a potential catalyst to transformation. Evidence from forerunners demonstrate knowledge economy sustained

growth observed over the last several decades. One branch of economics (evolutionary economics) has focused more on the processes of learning backed capacity building (Constantine, 2017) and how this has facilitated the progress of economies which were previously significantly behind the economic and technological frontiers. Most of these processes have been proved to be backed by layers of innovation systems; which have been either regional innovation systems or broad national innovation systems (Yoon and Park, 2016; Pique, Berbegal-Mirabent and Erzkowitz, 2018). The evolution of the capacity building has also occurred with many variations in the different economies. Latecomers were observed to have been late entrants in areas where significant specializations in the international production chains had been at advanced levels (Bean, 2016). The existing chains did not deter the growth of the late entrants as these economies identified niches that helped to create and sustain competitive advantages that narrowed the time to catch up in some cases and propelling others to frontrunners (Brem and Radziwon, 2017; Lee and Marleba, 2019).

Traditional economic theory assumes existing relationships as a starting point of interpreting economic phenomena. Researchers have agreed that most of the limitations given are because of complex relationships explained by a few independent variables evaluated over a very limited time span (Makridakis et al., 2018; Haraguchi et al., 2019). The interpretations of these models are only as good as the assumptions themselves sometimes resulting in ignorance being exercised when the patterns in data are observed in isolation (Jung et al., 2018). Machine learning models potentially can be an alternative to measuring economic phenomena and forecasting growth. There is still however insufficient focus on these learning models and on restricted estimation horizons (Mullainathan and Spiess, 2017).

Traditional economics in assisting growth in Africa has been subject of great debate almost the same as a similar debate in South East Asia in the 1980s. For example, Behuria and Goodfellow (2019) have castigated Rwanda's growth strategy which they suggest defies traditional economic principles of linked growth. On the contrary, this is the same verdict given by the first World Bank missions to South Korea and Singapore in the 1960s as the teams accounted the status quo as not having the same ideals as that in the west; the individualistic and profit centred narrative to drive the growth (Vu, 2013). What followed was economic growth which was far much faster than had been observed for any other economies in history. This dynamic has been credited to dynamic policies which were contrary to all known economic conventions then. The models have however created problems of their own. For example; South Korea has 75% of its GDP being contributed by a few companies yet the minority Small to Medium Enterprises (SMEs) are contributing to the largest share of job creation (Betz et al., 2015). Specifically, there is a recommendation for a traditional industrialisation led growth matched with human capital development (ibid). Human capital development in this regard encompasses the knowledge transfer aspect necessary to facilitate innovation.

The aim of this research is to develop a supervised machine learning model to assist struggling economies to ascertain the knowledge based leapfrogging strategies to employ to accelerate economic growth. The strategies were formulated from existing frameworks which attempt to conceptualize the underlying economic agent relationships. In pursuit of achieving the development of this model, the following are the key research objectives which were used to guide the research:

- To identify the critical success factors that enable leapfrogging strategies to expedite and sustain knowledge economy led growth.
- To design a supervised machine learning model for predicting economic growth appropriate for economies at different stages of development.
- To evaluate the performance of the model based on appropriate measures.

The data collection strategy for the study is given in Table 1.1. The research was narrowed down to macrolevel Triple Helix observations. This was not limited to activities observed in countries with formal National Innovation Systems. More elaborate details of the data collection strategy are as given in the table which follows.

Table 1: Data collection techniques

Data	Type of data	Approach
Factors to be used	Secondary data	The content analysis was used to establish the key variables to be considered.
Data sets for the model building and validation	Secondary data	OECD Science and Technology Indicators (STIs) for 44 OECD and Non-OECD member countries. An additional 2 aggregated observations for Europe's group of 28 and Group of 15 countries were also

		considered. The data were observations from 2015 to 2018. The data was relevant as an economic development state is measured per year and thus the growth strategies are forecasted over time. The STI indicators also measure the Triple Helix agent capacities, relationships, and activities.
Dependent variable (GNI Growth Rate / GNI Growth Class)	Secondary data	GNI qualifies the economic development state. Data was obtained from The World Bank Data site.

The Cross-Industry Process for Data Mining was applied as the data mining method. This method was considered because it is regarded as applicable across domains and is neutral across industries (Palacios et al., 2017). Economies are made of different industries and growth measures an aggregation of economic activities by varying industries, thus requiring an industry neutral factor assessment for the model to work.

RESULTS

The initial data exploration was carried out on Microsoft Excel and SAS Studio. The summary of the data showed that 2018 had the most observations with missing data. Thus, cases with less than 60% of data, were excluded as these did not have enough measures to make meaningful conclusions against them. For example, imputing 50% of missing data on a single case implies that most of the more than half of its target variable would be explained by imputations from other cases. There is thus less value contributed by such on observation on the overall scope of the research.

Initial missing values assessment

Table 1.2 below gives a summary of missing values in the dataset per year. This summary was essential as it helped map the best approach to take in the project. The considered approach needed to minimize the amount of excluded data given that the dataset was already small.

Table 2: Missing value summary per year

Year	Number of observations	More than 20% missing values per observation	Percentage of total observations in that year
2015	46	1	2%
2016	46	7	15%
2017	46	3	7%
2018	46	24	52%

The summary given in the table above shows that 52% of individual country observations recorded in 2018 had at least 20% missing of variables with missing values data. Quickly deleting this data would imply that a lot of observations would not be included in the research. An alternative approach was taken to allow for the 2018 observations to be further observed after feature engineering. Thus, the initial dataset for 2017 and 2018 would be used to determine which features where to be used for the model development stage. After these were established, then an additional model would be created (as a cross validation including the 2018 data adjusted for missing values based on the critical features). This stage therefore was critical in ascertaining the Training, and Testing dataset split. Further aggregation criterion was therefore explored to enable more informed summaries of the dataset. These would also enable multi-level data imputation criterion by ensuring that the adopted imputation methods preserved the nature of other relationships which are observed in cases like the ones needing imputation (van Buren, 2012; Grund, et al., 2016).

The regional split

The individual observations were first subdivided into three regions. The first region constituted the EU-15 countries as at May 2004. These countries included: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and United Kingdom. The second grouping comprised the EU-28 OECD member countries. These included: Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia and Slovenia. The last bloc comprised the rest of the countries whose data is documented by OECD which were grouped as "Rest of the World". These countries include non-EU OECD members (Iceland, Switzerland and Norway), International OECD Members (Australia, Chile, Japan, Israel, New Zealand, South Korea and the United States) and lastly non-OECD countries (Argentina, China, Russia, Singapore, South Africa and Taiwan). The respective regionalization of the data helped in carrying out the initial data exploration as well as aggregation of the data. Analyzing the data from countries would complicate the descriptive analysis as there would be many data points and over different years. From Figure 4.1, after making the first deletions on the cases with more than 50% of unobserved data, the retained datasets had forty-three cases for 2015, forty-one cases for 2016, forty-four cases for 2017 and thirty-three cases for 2018. In total 161 observations were retained. The regional constitution of the data was almost consistent except for 2018 data. The data in 2018 reduced many countries falling under the Rest of the World category (dropped to almost 17%) being the least compared to the other years where this category had the highest contribution in 2016 and 2017. This data distribution in a way retains the various model employed in pursuing growth aspirations by different countries which was an essential element in ensuring the attainment of the project objectives.

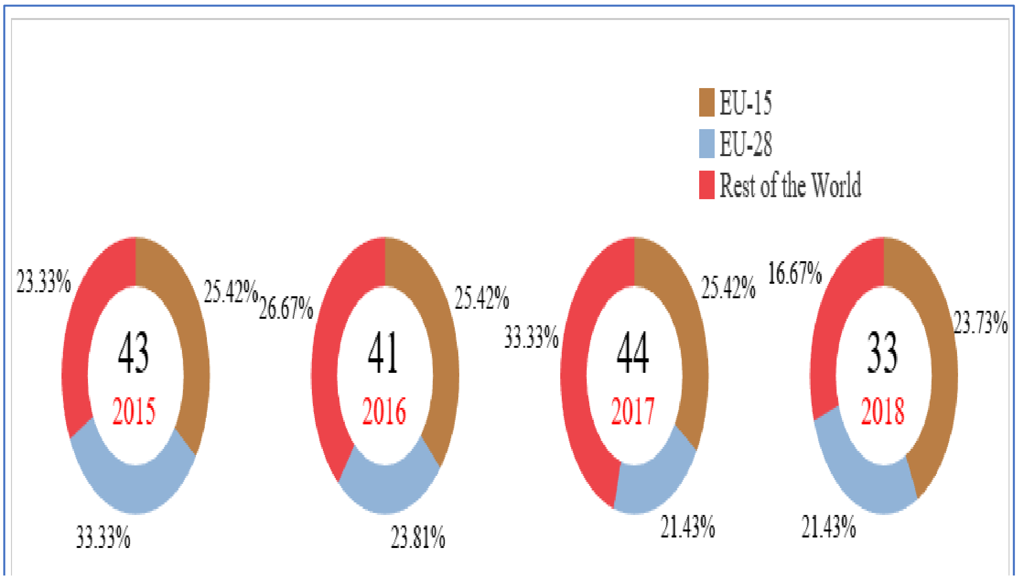

Fig.1: Regional breakdown of observed data

The different states of economic development

The second objective of the research required a perspective that narrowed down on strategies appropriate to different stages of development. Investigating this aspect thus meant that a clear distinction had to be made to demarcate the development state of each case so that differences would be clear and observable. The dataset provided two possible development states. On one hand was a transitioned economy and the other hand being a developed economy. The countries were split into two classes. The first classes comprised countries which have been high income countries for the last two decades. The second class broadly classified all classes which transitioned into a new state of development over the past decade or leapfrogged from being low medium countries in the last 25 years. The class definitions used a different data summary from the World Bank which documents all transitioned economies using the Atlas method. Figure 1.2 shows that on average, there has been varying activities in the knowledge economies between 2015 and 2018. Whilst there has been a negative growth in HERD in 2016 (of -5.38%), BERD had a general upward growth except in 2018 where growth slowed down to 4.92%. The average GNIs have also been on a general upward trend, again with an exception in 2018 where the growth rate dropped to 2.93% from a peak of 3.27% in 2017. However, across the years, the average represented countries have maintained a consistent 40:60 ratio for the high income and the transition economies respectively.

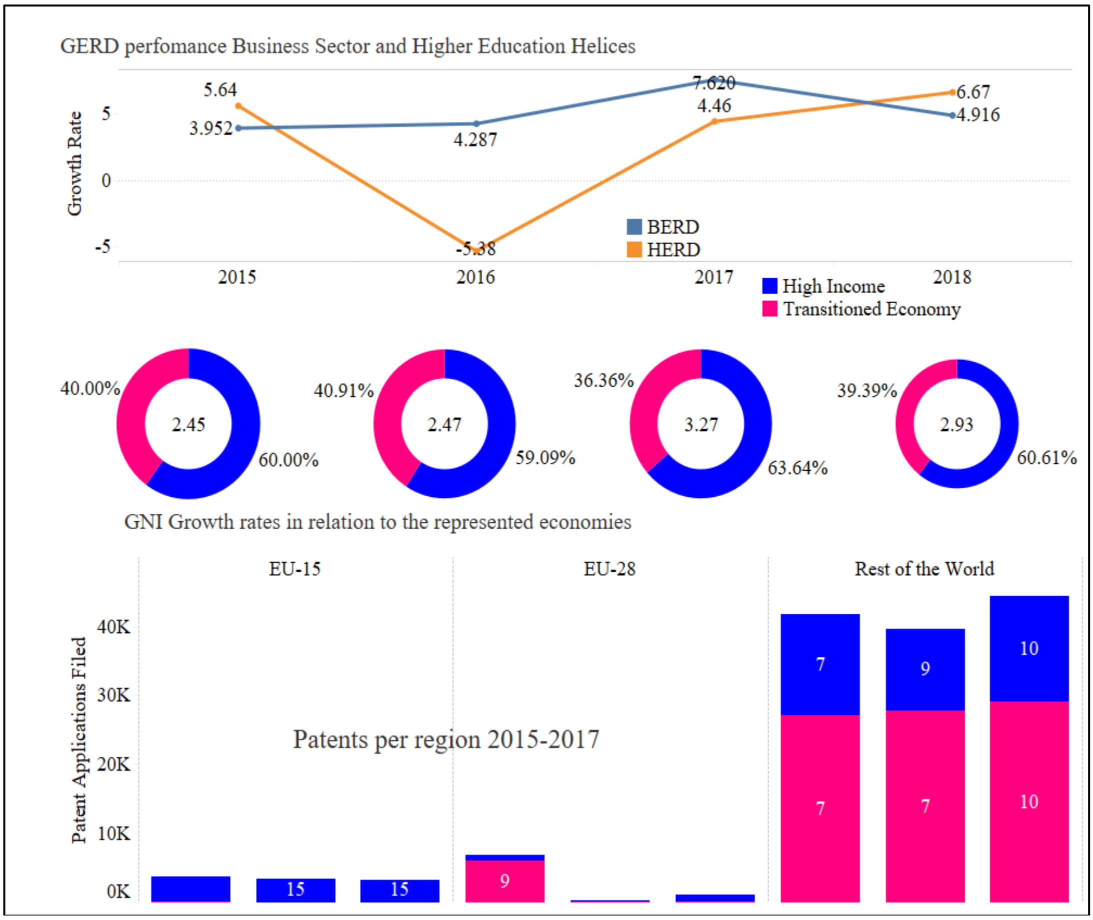

Fig.2: KE activities across countries at different levels of development

When the development state is considered in respect with the number of protected innovations, only economies outside of the European Union are driving their growth from new inventions as portrayed by the high number of filed patents. The number of patents also shows that the race for new innovations by the rest of the world is almost balanced between transitioned economies and developed economies. On the contrary, the EU15 economies are having fewer innovations. In 2015, several EU-28 economies had a good run of inventions. Clearly these differences indicate that varying approaches are being taken to drive economic growth as knowledge transfer is being carried out for new products (as represented by patent applications) or to facilitate adoption of new technologies. The later approach only drives output and operational efficiencies without necessarily creating new products and services. As far as this research is concerned, these differences further justify a need to further explore the nature of these relationships and how they relate to economic transformation. The use of these technologies however can be described in terms of whether these documented economies are adopting an export led economic transformation or otherwise.

The knowledge economy and economic models export led transformation

The earlier revealed weaknesses of GDP and GNI per capita as measures of economic welfare can be depicted from the following descriptions. Despite the weaknesses, the two still provide insightful information on economic performance. An export led economy has a lot of its income obtained from local businesses with foreign interests thus, accruing a lot of income from capital and human resources deployed in other economies. This is one aspect of GNI that helps differentiate it from the GDP based measure. In a way the GNI per capita assists in showing this focus of economic activity. Figure 1.3 provides a comparison of the GDP and GNI per capita indicators in comparison with the knowledge economy activities and Gross Expenditure on Research Development changes.

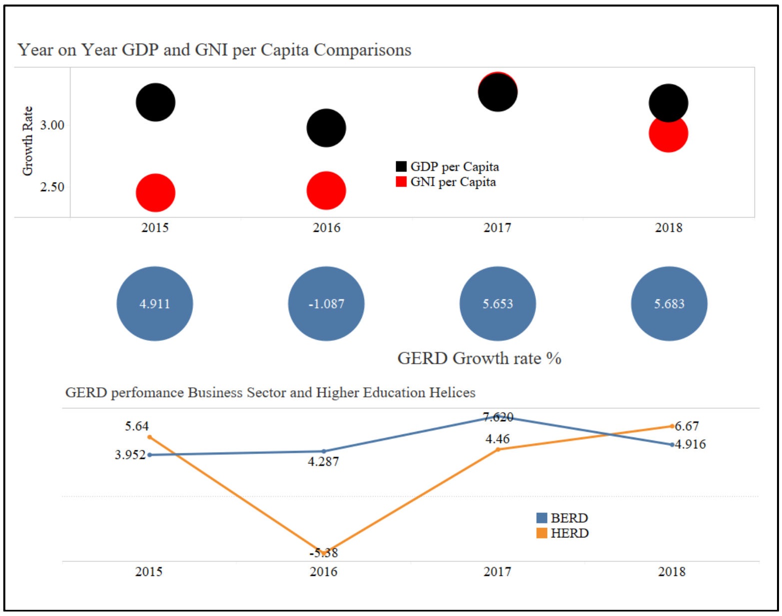

Fig.3: GNI and GDP growth in terms of KE activities

The gap between GDP and GNI per capita has been narrowing over the years. In 2017, GNI was marginally greater than GDP. It was noted that BERD was at its peak growth thus possibly driving the income potential produced by the knowledge economy at firm level. This in turn improved the GNI for the whole economy. The GERD during this same year was relatively high as well implying that the overall knowledge economy's activity was high during this year. The GDP and GNI discrepancy over the years can also help explain that new products and services are accessible without necessarily redeploying the resources across geographical boundaries. Instead, companies can develop and enhance processes and have production occurring in a different economy as well delivery made straight from the manufacturer to the end user through platforms. Such services offered over platforms sometimes are difficult to account for in GDP changes though they are driven by extensive knowledge transfer of technologies that enhance business processes. This is another example that helps in objective 1 which seeks to explain the leapfrogging strategies which can employed to fast track growth. Whenever GERD has been having growth, in the cases of 2015, 2016 and 2018; this has also translated to positive GNI and GDP growth through the relationship between the growth indicators is not obvious.

This also supports an interest to establish observations by earlier researchers on the need to establish the fastest growth path for new industries in short periods (Huff, 1995; Lee, 2007).

The Naïve Bayes classifier algorithm employs conditional probabilities to assign the most likely class. The structure of the Naïve Bayes algorithm assigns one parent to each variable. Thus, critical requirement for all predictors to be independent of each other. In addition, the Naïve Bayes model assumes that all independent variables follow a Gaussian distribution (normal distribution) which give the basis of using probability distributions to calculate the class predictions. The model makes an estimate to classify X to class C in each dataset based on the existing information in the dataset. Thus, the Probability of assigning an observation X to C is based on a Hypothesis H (which is an assumed relationship based on the dataset and source of evidence). The citation P(H/X) denotes the probability of observation X given the conditions known to exist in the Hypothesis supported by H. The same P(H/X) is also known as the posterior probability characterizing (conditioned) on X. The model has been observed to be very efficient despite the independence assumption and has been utilized to use econometric growth based on existing and known economic relationships (Karaca and Cattani, 2018). The Naïve Bayes however to an extent is naïve because of the nonexistence of absolute independence in predictors. In addition, the normality assumption is also justified by the test of skewness with most of the independent variables which are normally distributed. These two factors thus justified the use of Naïve Bayes as an appropriate model for consideration. The dataset was split into Training and Testing data. The two splits were preferred based on the size of the dataset (Raschka, 2018; Kim, 2009). Stratified sampling was used to enable the representation of the data which is appropriate for a classification model as was employed in this research. The general code used is given in the figure below.

```
#Stratified sampling
set.seed(123)
split = sample.split(df$Growth_class, SplitRatio = 0.7)
train_nom = subset(df, split == TRUE)
test_nom = subset(df, split == FALSE)
```

Fig.4: Screenshot of the code for sampling

The split was based on the target variable Growth_class to ensure that the classes represented. A ratio of 70:30 was also considered to be appropriate based on the size of the dataset and the training implications anticipated during the model formulation process. The stratified sample was checked for proportional representation so that the modelling would be consistent and affect the learning to be inclined to a better estimation of one class compared to the other.

```
> #checking the class distribution
> prop.table(table(dg$Growth_class))

        H         S 
0.5153846 0.4846154 
> 
> set.seed(123)
> split = sample.split(dg1$Growth_class, SplitRatio = 0.7)
> train_ohe = subset(dg1, split == TRUE)
> test_ohe = subset(dg1, split == FALSE)
> prop.table(table(train_ohe$Growth_class))

        0         1 
0.4835165 0.5164835 
> prop.table(table(test_ohe$Growth_class))

        0         1 
0.4871795 0.5128205 
> 
```

Fig.5: Verifying the consistency of representation after stratified sampling

The consistency of representation was verified by checking that the datasets proportionality of classes was maintained as in the original dataset. The figure above shows that the consistency was attained with Class 0 and Class 1 (Slow Growth and High Growth) maintained at around 48.5: 51.5. It was only in a correctly represented split that modelling would be carried out. An iterative process was carried out to throughout the model formulation process with additional data exploration, to understand causality patterns where necessary. Some of the models such as (ben1) has sensitivity to the structure of the data much more than model 1. This therefore would influence the overfitting potential of the model. The model utilized the Training/Test cross validation. This was because a small dataset was used in the study thus partitioning data into 3 sets would leave only a small test set to be utilized in the evaluation. To ascertain the model performance, the error and accuracy measures were used to evaluate model performance. However additional measures were selectively utilized in certain cases to analyse in detail specific observations- for example classification error. Most economic forecasts have been observed to have Mean Absolute Errors of around 1. The model evaluation would therefore be based on k-fold validation which helps give a balance of the tradeoff between the overfitting and underfitting biases associated with smaller datasets.

DISCUSSIONS

The initial data analysis revealed that most transitioned economies are the ones attaining the highest growth. Though the data was based on comparative STIs observed over 3 years, the model supported the same findings as the descriptive analysis. The conditional probability of the different economic states is given by figure 1.6 below.

```
$`Atlas_Wealth_State.Transitioned Economy`
                        Atlas_Wealth_State.Transitioned Economy
train_ohe$Growth_class      [,1]      [,2]
                       0 0.3181818 0.4711553
                       1 0.4893617 0.5052912
```

Fig.6: Economy state and growth relevance

The figure above shows that:
P(*High growth/Transitioned economy))* = 51%
(The probability that an economy will attain a high growth given that it is a transitioned economy).
This therefore indicates that the transitioned economies have been attaining the Higher Growth. The observed trend is however consistent with the fact that for any economy to transition, it must perform much better than the global economy at the least. If it is coming from a low GNI per capita zone, double digits are easily attainable as the percentage growth is calculated over a lower value. This also indicates that there is a difference in what drives growth between a transitioned economy and a high developed economy.

In terms of the features impacting growth, the nature of research has varying impact. For example, Basic research does not have significant impact on economic development. This was shown by a negative mean growth rate being a better estimate of the high growth economies. On the contrary, the slow growth economies, have higher growth rates in basic expenditures.

```
$Basic_RD_pcnt__GDP
                      Basic_RD_pcnt__GDP
train_nom$Growth_class        [,1]      [,2]
                     0  0.09535766 1.0933049
                     1 -0.03659372 0.9816977
```

Fig.7: Basic R&D's role in driving economic change

The high growth economies have experienced reduced or negative growth in their investment in Basic Research and Development. This is demonstrated by the mean growth rate of -3.65% for countries eventually attaining high growth. This therefore means that applied research better drives growth compared to basic research. Thus, knowledge acquired needs to have a particular use. Another noted observation has been the switch of the funding and research performance roles. The high performing economies have the business sector funding most of all research which includes government research. In addition, the business sector is also performing the research. Government and business are identically performing for 59.36% of government research. This indicates an equal collaborative effort by both sectors towards knowledge creation and consumption. This is contrary to the previous assertions where, the government's role was limited to enforcing contracts (Leydesdorff and Meyer, 2013) and policy assistance (Pique, et al., 2018). These findings also suggest a model different to that which drove the success of South Korea, a model characterised by intense university-industry collaboration (Yoon, 2015). This statistic reveals the new collaborative role of the business sector and the government sector as essential in the KE ecosystem.

```
$GERD_pcnt_pfmd_by_BS
                        GERD_pcnt_pfmd_by_BS
train_ohe$Growth_class     [,1]     [,2]
                       0 58.93477 16.09201
                       1 59.35745 15.49272

$GERD_pcnt_pfmd_by_Gvt
                        GERD_pcnt_pfmd_by_Gvt
train_ohe$Growth_class     [,1]     [,2]
                       0 58.93477 16.09201
                       1 59.35745 15.49272
```

Fig.8: The business sector's vital role in the knowledge economy

However, it is possible that the business sector is the one influencing the applied research being carried out by the government as it seeks to protect itself or its innovations as was observed in the knowledge originator function played by government laboratories in the Silicon Valley innovation system (Pique et al., 2018). This can justify the increased business' interest in collaboration efforts with government. In addition, government research allows for access of knowledge by small entities who otherwise cannot afford to invest much in the knowledge generation processes. As such government research enhances the spill over of knowledge transfer for enhanced productivity and value creation by all players. Such capacitation also explains why now business enterprise research account for more than 50% of the overall research personnel almost in all the OECD member countries. These observations seem to support the suggestion by (Pique et al., 2018) that innovation ecosystems evolve as these mature. This however cannot be identified in its truest sense as this study aggregated at a macro level the innovative ecosystems thriving on the knowledge economy.

The business sector has now consistently been increasing its investment in research and development, which is most likely aligned to applied and experimental research. The increase therefore is not affected by whether an economy experiences a GDP contraction or not as it drives the business output and new product offerings at a micro level. BERD therefore is sustaining research activity through funding and performance. The consistent involvement of business sector sustains the creation and growth of capacity which streamlines innovation and technological transfer where its most needed. Government research allows for access of knowledge by small entities who otherwise cannot afford to invest much in the knowledge generation processes. As such government research enhances the spill over of knowledge transfer for enhanced productivity and value creation by all players. Such capacitation also explains why now business enterprise research account for more than 50% of the overall research personnel almost in all the OECD member countries. These observations seem to support the suggestion by (Pique et al., 2018) that innovation ecosystems evolve as these mature.

The study employed the Naïve Bayes model based on its known simplicity and surprisingly efficiency in most studies. The model formulation process revealed the sensitivity of the NB to several factors. The NB is sensitive to the feature arrangement. Rearranging the features improved the training performance from 60% to more 80%. This is consistent with the observations of functionally dependent features which were employed in this model (Rish et al., 2001). Rearranging the features in a way, moderates the impact of highly correlated features thus deterring the impact of a possible weak extreme case performance NB model created in this study had a satisfactory performance.

The study observed the improved performance of the NB model because of including one categorical predictor. This particular predictor enabled an additional effect to be observed from a one hot encoding transformation which however resulted in an overfitted model (performance of 96% to 98% compared to 66% on the test data) on a naïve_bayes function with a configured kernel density regulation and a fair performance on a generalised NB model based on the e1071 library (non-kernel function). There is a possibility that with additional feature engineering and a larger dataset the model could have been further enhanced. The small dataset used in this regard thus limited the potential experimentation that could have enriched the observation of the NB development and possible new findings on its behaviour in predicting economic phenomena. The previous discussion pointed to possible weaknesses that the small data set employed in this study potentially limited the depth of the experimentations carried out in this study. However, the model had overall satisfactory performance. This is demonstrated by the several metrics summarised in Table 3.

Table 3: The NB model performance summary

	Error	Specificity	Sensitivity	F1 score
Model 1	0.28	0.81	0.65	0.72
Model 2	0.25	0.78	0.75	0.75
Model 3	0.29	0.71	0.71	0.71

Many domains expect an F1 score of 80% on small datasets (Cassidy, 2020). The developed model attained an F1 score of 85% at its peak. This score illustrates that the model created in the project had an acceptable performance associated with good models on small datasets (Cassidy, 2020). This also shows that the NB was consistent in predicting the implications of GNI per capita growth rate and possible economic transitions based on STI indicators.

CONCLUSION

The aim of this research was to develop a supervised machine learning model to enable battling economies consider a knowledge-economy led economic transformation. The strategies were formulated from existing frameworks which attempt to conceptualise the underlying economic agent relationships characterising the modern economy. The initial objectives set at the beginning of the study focused on three issues. The first aspect focused on identifying the critical success factors that enable leapfrogging to expedite and sustain knowledge economy led growth. The second aspect looked at developing a supervised machine learning model for predicting economic growth appropriate for economies at different stages of development. The last objective was aimed at evaluating the performance of the model based on appropriate measures. After analysing the key weaknesses of the traditional approaches to measuring the economy, growth was then contextualised in light if the new economic realities. Parallels were also drawn of the transition of economies in Asia as well as European economies.

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