Paths to Global Competitiveness

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Abstract

The study focuses on generating the paths that would model the effects of six predictors on competitiveness. These predictors are innovation, human development, Information and Communications Technology(ICT), Research and Development (R&D), population and education. Data on competitiveness are based on Global Competitiveness Index (GCI). Data on predictors are Global Innovation Index (GII), Human Development Index (HDI), Total Population (TPO), ICT Development Index (IDI), Expenditure on Education(EOE) and Expenditure on R & D (ERD). Multiple regression and path analysis are the statistical tools used to investigate the effects of these six predictors on competitiveness. Sample data are from fifty-eight countries. Stepwise regression and multiple regression have screened out education and the total population, leaving four predictors which are innovation, human development, ICT, and R&D. From these, an initial model was established. It was a simplified model that assumed that all predictors have symmetric relationship that has direct effect on competitiveness. The initial model showed that innovation and human development have more dominant direct effects on competitiveness. It also showed that ICT and R&D have larger indirect effects over the other predictors. Since the initial model lacks a more in-depth relationship among the predictors, an improved design was drawn out of the findings of the first model. The improved model proved that innovation was the most potent predictor and its effect on competitiveness is direct. The second most powerful predictor is ICT, however its effect on competitiveness is indirect. Results also showed the need for ICT to drive innovation and human development to improve competitiveness. R&D can only be seen to contribute to global competitiveness provided that it will drive ICT. Among all predictors, human development has the least effect on competitiveness among the four, but it has direct impact.

Keywords: Research and Development Expenditure; Global Innovation, ICT Development, Path Analysis, Global Competitiveness

1.0 Introduction

Competitiveness can be defined as an aggressive willingness to compete. The key to competitiveness has often been referred to productivity that serves to indicate long-term competitiveness (Ambastha et al, 2004). There are multiple paths to a state of economic prosperity. One worthy basis of prosperity is the nation's capability of producing abundantly. The Global Competitiveness Report from the World Economic Forum ranks countries based on the Global Competitiveness Index(GCI). GCI measures the competence of countries to supply eminent degree of prosperity to citizens. It measures how competitive is the economy of a country. GCI is dependent on how productively a state utilizes obtainable or accessible resources.

Innovation can be defined as a creation of a new device, a process and transforming it into a marketable product or service. Business authors, (Shapiro et al.,2002) pointed out that the central component to succeeding in this constantly changing world is unending innovation. The business sector never ceases reinventing itself. Some institutions created to conduct business induce innovation by influencing internal competition (Shapiro et al.,2002) while others prefer to give employees some incentives(Török et al., 2005). Governments around the world have taken active steps to strengthen their innovation systems. The Global Innovation Index(GII) is a periodic publication that rates economies in terms of their enabling environment to make and create innovations.

Human development has been referred to as the capabilities of people on what they can do and what they can become to pursue a quality life. A decent standard of living, good health, and access to knowledge are essential things that are considered to be valued by everyone. The Human Development Index (HDI) is a composite statistic that rates a nation with values based on the three HDI components namely longevity, education, and income. The origins of the HDI are found in the annual Development Reports of the United Nations Development Programme (UNDP), the World Bank, and UNESCO.

Information and communications technology (ICT) is the integration of telecommunications, computers and audio-visual systems to enable users to access, transmit, store, and manipulate information. The ICT Development Index (IDI) is a value published by the United Nations International Telecommunication Union based on ICT indicators. These indicators are derived from a series of observed facts and are classified into three clusters: access, use, and skills. It is a criterion that is used to compare ICT performance within and across countries and measure the digital divide. For information regarding IDI, data is taken from International Telecommunications Union (ITU) report titled Measuring the Information Society 2012.

Research and Development (R&D) is a combination of fundamental and applied research to find answers to problems or create new goods and knowledge. R&D may result in ownership of intellectual property such as patents. Policy makers are often divided on how much should go to Research and Development. Our society wants to ensure that government spends on the right priorities thus maximizing the return on investment. UNESCO released a data on countries' expenditure on R & D per capita (ERD).

The total population of a country consists of all persons present in the country at the time of the census. United Nations published estimates of countries' total population (TPO). The world population is estimated by the United Nations to be 7.162 billion. China has the largest population. India is the second, and US is third.

Education has been referred to as the gradual process of acquiring knowledge. It is divided into stages such as preschool, primary school, secondary school, college and then post-graduate studies. A right to education, particularly, primary education, has been recognized by some countries. Thus, it is funded by the government. However, some developing countries do not have enough resources for education as shown by UNESCO's data on Government Expenditure on Education (EOD). The data collected is in percentage of Gross Domestic Product (GDP). This data is an indicator on how a country gives importance to education as shown on how they appropriate funds for it.

So, how does a country become competitive? Is it through innovation? Is it through human development? Since we are now in the ICT paradigm shift, can we consider ICT as the prime factor for competitiveness? How about Research and

Development? There were some theories (Kremer, 1993) that claim that population growth will lead to more productivity. Shall the government spend more on education to be more productive? There was evidence that showed education as worthwhile investment and that increases in educational attainment continue to have a substantial impact on productivity (Sweetman, 2002). This paper investigated the effects of innovation, human development, ICT, R&D, population and education on competitiveness.

2.0 Conceptual Framework

Multiple linear regression examines the linear relationships between one continuous response and two or more predictors. The coefficient of determination, denoted by R^2, is one of the criteria used to check whether the model fits the data well. However, in multiple regression, it should not be the only criterion for model selection because R^2 can be made artificially high by simply including too many terms in the model. R^2(adj) is a modified R^2 that has been adjusted for the number of variables in the model. If unnecessary variables are included, then R^2 will become artificially high and R^2 (adj) may get smaller. Significant difference between R^2 and R^2(adj) implies the existence of unnecessary variables in the model. The P-values obtained from multiple regression are used to determine which of the variables have significant interaction effect. The smaller the P-value of a predictor, the more statistically significant is that predictor.

Variables are standardized first before performing the regression. Standardization is used when the variables' raw units are not well-known in a common usage - such as Global Innovation Index. It ignores the variable's disparity in scale of units. The data on EOE are in hundreds while data on HDI is within the range from 0 to 1. Coefficients obtained by multiple regression on standardized variables are called the partial regression coefficients. On the other hand, coefficients obtained using non-standardized variables are known as the concrete regression coefficients. Partial regression coefficients refer to the direct contribution of the individual predictors to the response variable (Akintunde, 2012). They are also considered as the Direct Path Coefficients of the predictors to the response variable. The predictor variable that has the largest partial regression coefficient absolute value can be said to be the most influential to the response variable. This predictor will also have the greatest significance since it will have the smallest P-value. The P-value output in multiple regression is used to determine if the association between the response and the predictor variable is statistically significant. It is done by comparing the P-value with a given Alpha-level. A predictor variable is significant if its P-value is lesser than the assumed alpha-level. A commonly used Alpha level is 0.05.

Before fitting the regression model to all the predictors, stepwise regression is used to screen out predictors not associated with the response variable. Aside from the input variables that are inputted in stepwise regression, it also inputs two values namely Alpha-to-Enter and Alpha-to-Remove. Alpha-to-Enter is the value that determines if any of the predictors not currently in the model should be added to the model. Alpha-to-Remove is the value that determines if any of the predictors in the model should be removed from the model. The values for Alpha-to-Enter and Alpha-to-Remove are both 0.15. Other statistics outputted in stepwise regression are R^2, S, C_p, and PRESS. C_p is called the Mallows' statistic. It is used for assessing how well the model fits the data. PRESS is the sum of squares of the prediction errors. In stepwise regression, the better fit is characterized by smaller S and PRESS, larger R^2, and C_p closer to the number of predictors in the model.

Multiple regression may not be sufficient in the study of the effects of the predictors to the response variable. Direct contribution to the response variable and the indirect effects through other variables to the response variable should also be investigated. It is to this rationale that Path Analysis was conceptualized. Path Analysis or path coefficient method was pioneered by Prof. Sewall Wright (1921). While multiple regression assumes that the values of the predictor variables are independently contributing to the response variable, path analysis assumes that predictor variables are correlating to contribute to the response variable. It provides likely interpretation of the relationships between and within the predictor variables to the response variable. Thus, path analysis is used quantitatively to examine the direct contributions to the response variable and on other predictor variables to the response variable. (Garson_2008) depicted the model in a circle-and-arrow figure in which single-headed arrows indicate influence.

The ISO 3166-1 lists 249 countries in the world. The logic behind the sample size is based on which countries from this list spend more than 100 million dollars annually on research and development and have data on ther variables. Fifty-eight countries were choosen randomly from the list satisfying these conditions.

Variables considered are the Global Competitiveness Index (GCI), Global Innovation Index (GII), Human Development Index (HDI), Total Population (TPO), ICT Development Index(IDI), Expenditure on Education (EOE) and Expenditure on R & D per capita (ERD). GCI was considered as the response variable. The six predictor variables are GII, HDI, TPO, IDI, EOE, ERD.

3.0 Research Design and Methods

Standardization of data is done first. Standardized data is obtained by subtracting the mean from the individual value and dividing the result by the standard deviation. Stepwise regression and multiple regression are then performed to test which among the six predictors are not associated with the response variable GCI, thus to be screened out. A matrix of direct effects of the remaining variables is constructed. It contains the coefficients computed from simple regression between variables. This matrix is also called the observed correlation matrix. A matrix consisting of R^2 (Pearson Correlation) and a Matrix plot are also generated. An initial model is established. In this model we connect GII, HDI, ERD and IDI directly to GCI. It is a simplified model where its longest paths are just of length 2. A reproduced correlation

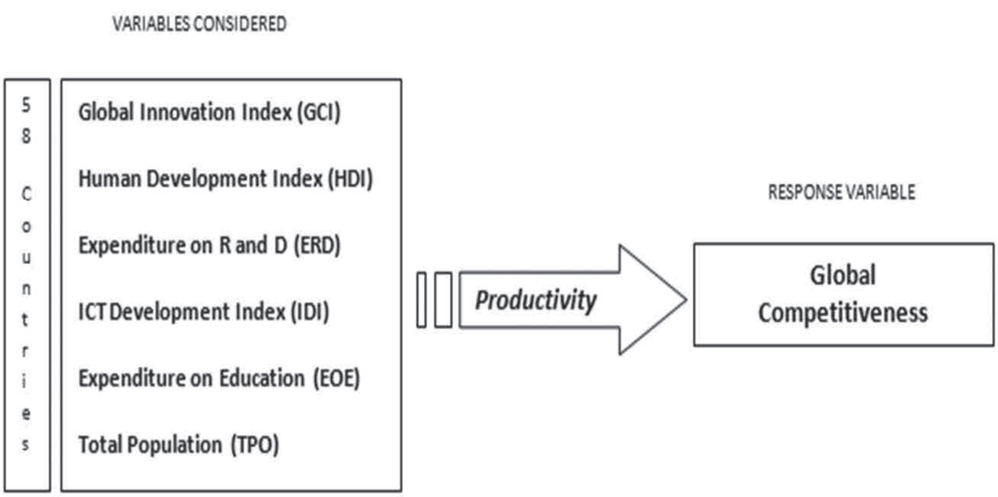

Figure 1: The predictors and the response variable

between each variable is calculated through path decomposition. A reproduced correlation matrix is generated and compared to the observed correlation matrix. The reproduced correlation is said to be consistent with the observed data if only a few reproduced correlations differ from the observed correlation by more than 0.05. An improved model is proposed based on the total direct and indirect effects of the initial model. A more profound investigation is done by rearranging the diagram such that the longest path is four as compared to the first diagram that has the longest path of 2. Reproduced correlation matrix is generated again in the improved model and compared with the observed correlation matrix. Conclusion was then drawn out of the initial model and the improved model.

4.0 Results and Discussion

The table below gives the top 5 highest and lowest for each variable in the available data. At a glance, it is observed that Switzerland and Korea have the higher rank while Ethiopia is at the bottom.

Data from different sources are then standardized. The standardized values are then subjected to stepwise regression with GCI versus GII, HDI, ERD, EOE, TPO and IDI. In stepwise regression computation, default values for Alpha-to-Enter and Alpha-to-Remove was used which are both 0.15. Below is the output of Stepwise Regression.

```
 Alpha-to-Enter: 0.15  Alpha-to-Remove: 0.15

Response is   GCI    on  6 predictors, with N =   58

    Step            1         2         3         4
Constant  1.113E-151.825E-151.927E-153.807E-15

GII             0.870     1.254     1.085     1.048
T-Value         13.18      8.88      6.82      6.84
P-Value         0.000     0.000     0.000     0.000

IDI                       -0.43     -0.47     -0.90
T-Value                   -3.02     -3.39     -4.03
P-Value                   0.004     0.001     0.000

ERD                                  0.24      0.33
T-Value                              2.09      2.80
P-Value                             0.041     0.007

HDI                                            0.42
T-Value                                        2.39
P-Value                                       0.020

S               0.498     0.466     0.452     0.433
R-Sq            75.61     79.08     80.66     82.54
R-Sq(adj)       75.17     78.32     79.58     81.23
C-p              18.8      10.4       7.7       4.1
PRESS         14.8302   13.2253   12.9907   11.9116
R-Sq(pred)      73.98     76.80     77.21     79.10
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Figure 2: Stepwise Regression: GCI versus GII, HDI, ERD, EOE, TPO, IDI

At Step 1, GII has p-value = 0. GII is the first predictor to be entered into the model since it has the smallest p-value less than 0.15 (the alpha-to-enter value). At Step 2, IDI has the smallest p-value less than 0.15, so it is the second predictor to be

Table 1: Top 5 Highest and Top 5 Lowest for each variable

	GCI	GII	HDI	ERD	IDI	EOE	TPO
Highest	Switzerland	Switzerland	Norway	Korea, Rep.	Korea, Rep.	Denmark	China
2nd Highest	Singapore	United Kingdom	Australia	United States	Sweden	Iceland	India
3rd Highest	Finland	Sweden	Switzerland	Japan	Iceland	New Zealand	United States
4th Higest	Germany	Finland	Netherlands	Luxembourg	Denmark	Sweden	Indonesia
5th Highest	Netherlands	Netherlands	United States	Sweden	Finland	Norway	Brazil
5th Lowest	Greece	Morocco	South Africa	Peru	Indonesia	Romania	Slovenia
4th Lowest	Uruguay	Indonesia	Vietnam	Vietnam	Philippines	Singapore	Latvia
3rd Lowest	Argentina	Philippines	Morocco	Algeria	Algeria	Turkey	Estonia
2nd Lowest	Serbia	Ethiopia	India	Indonesia	India	Peru	Luxembourg
Lowest	Ethiopia	Algeria	Ethiopia	Ethiopia	Ethiopia	Philippines	Iceland

entered into the model. At Step 3, ERD is introduced into the model and lastly at Step 4 is HDI. After Step 4, no predictors outside the model have p-values less than 0.15, and no predictors in the model have p-values greater than 0.15. For this reason, no predictors can be entered into or removed from the model.

In the output, S and PRESS decrease from step 1 to step 4, R^2 increase from step 1 to step 4, and C_p becomes closer to the number of predictors in the model that is 4. Together, these statistics indicate that the step 4 model, containing the predictors GII, IDI, ERD, and HDI, provides the better fit for the data. Thus, EOE and TPO will be excluded. This result is also supported by the regression analysis output for GCI versus the six predictor variables, as follows:

```
The regression equation is
GCI = 0.0000 + 1.07 GII + 0.466 HDI + 0.358 ERD + 0.0521 EOE - 0.0466 TPO
         - 1.03 IDI

Predictor        Coef     SE Coef        T        P
Constant      0.00000     0.05740     0.00    1.000
GII            1.0676      0.1694     6.30    0.000
HDI            0.4662      0.1865     2.50    0.016
ERD            0.3577      0.1221     2.93    0.005
EOE           0.05208     0.07188     0.72    0.472
TPO          -0.04660     0.07040    -0.66    0.511
IDI           -1.0272      0.2569    -4.00    0.000

S = 0.4372      R-Sq = 82.9%      R-Sq(adj) = 80.9%
```

Figure 3: Regression Analysis: GCI versus GII, HDI, ERD, EOE, TPO, IDI

The P-values of EOE and TPO are comparatively large. Stepwise regression result indicates that government expenditure on education and the total population has nothing to do with global competitiveness. The move is supported by their large P-values.

In addendum, it can be observed from the top 5 highest and lowest table that there is no common country in top 5 largest GCI and top 5 highest EOE. The same holds true for those with the 5 least in GCI and EOE. There is also no common country among the top 5s of GCI and TPO.

For this reason, EOE and TPO will be dropped from among the predictor variables considered. Only the predictors GII, HDI, ERD, and IDI are considered.

Dropping EOE supports the theory by (Ping,2005) that education can only influence productivity growth by stimulating technological progress and increasing the efficiency. The influence depends on the sector in which people work and varies furthermore with education levels. Education, however shows positive implications for future productivity growth (Sweetman, 2002), thus Government should continue investing in education.

4.1 Observed Correlation

Observed correlation matrix contains all the direct effect path coefficients between two variables. These are obtained using simple linear regression between the two variables.

Table 2: Observed Correlation Matrix

	ERD	IDI	GII	HDI	GCI
ERD	1	0.80112	0.85307	0.69403	0.79211
IDI		1	0.89967	0.93999	0.70091
GII			1	0.83631	0.86953
HDI				1	0.67899
GCI					1

Let Dpredictor, response denotes the direct effect path coefficients between the two variables. Below is the matrix plot of all the variables.

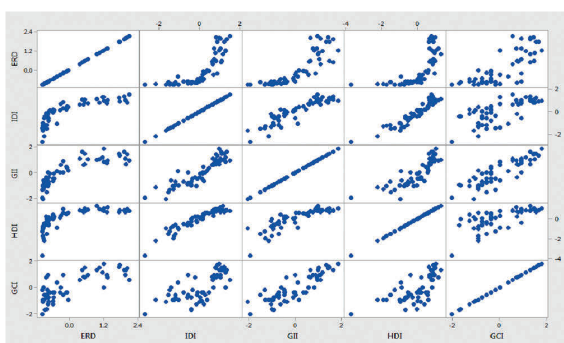


Figure 4: Matrix Plot of ERD, IDI, GII, HDI, GCI vs. ERD, IDI, GII, HDI, GCI

The Pearson Correlation between the variables are presented in the table below.

Table 3: R^2 , Pearson Correlation, in Percentage

	ERD	IDI	GII	HDI	GCI
ERD	100	64.2	72.8	48.2	62.7
IDI	64.2	100	80.9	88.4	49.1
GII	72.8	80.9	100	69.9	75.6
HDI	48.2	88.4	69.9	100	46.1
GCI	62.7	49.1	75.6	46.1	100

4.2 Initial Model

GII, HDI, ERD, and IDI are found to be statistically significant in the regression of GCI. In the initial model, directed edge from each of the four significant predictors to GCI was drawn. All predictors are assumed to have symmetric relationship with each other so bidirectional edges are drawn to each other.

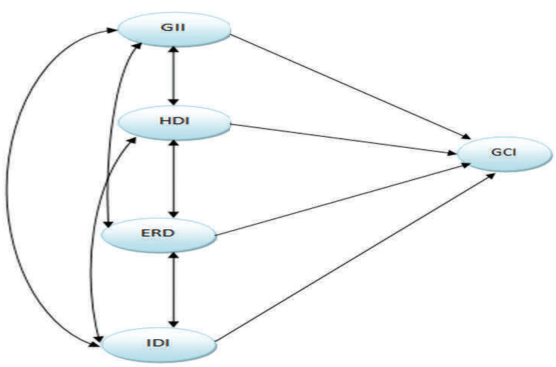


Figure 5: The Initial Model

Multiple Regression is performed between GCI and the remaining predictors GII, HDI, ERD, and IDI. Below is the regression analysis output.

```
The regression equation is
GCI = 0.0000 + 1.05 GII + 0.423 HDI + 0.326 ERD - 0.901 IDI

Predictor      Coef   SE Coef      T      P
Constant    0.00000   0.05690   0.00  1.000
GII          1.0479    0.1532   6.84  0.000
HDI          0.4228    0.1766   2.39  0.020
ERD          0.3263    0.1165   2.80  0.007
IDI         -0.9007    0.2237  -4.03  0.000

S = 0.4333     R-Sq = 82.5%     R-Sq(adj) = 81.2%
```

Figure 6: Regression Analysis GCI versus GII, HDI, ERD, IDI

GII, HDI, and ERD are positively correlated with GCI since they have positive coefficients. Only IDI is negatively related, that is, its increase will decrease GCI.

Below is the order according to decreasing absolute values of the regression coefficients:

1.0479 for GII
-0.9007 for IDI
0.4228 for HDI
0.3263 for ERD

GII, IDI, HDI, ERD is the order according to which predictor variable has the most potent relationship to GCI. With the assumption that Alpha level is 0.05 in this regression analysis, it can be concluded that these four predictor variables are statistically significant since their P-values are lesser than 0.05.

R^2 is 82.5%. R^2(adj) is 81.2%, thus a decrease of 1.3% if unnecessary variables are added to the model. A difference of 1.3% is small enough to imply that there are no unnecessary variables. The four variables GII, IDI, HDI and ERD are all necessary variables. This result strengthened the conclusion of our stepwise regression.

Let $P_{predictor,\ response}$ denotes the beta values for a regression.

Therefore for the regression GCI versus GII, HDI, ERD, IDI; the beta values are:

$$P_{GII,\ GCI} = 1.0479$$
$$P_{HDI,\ GCI} = 0.4228$$
$$P_{ERD,\ GCI} = 0.3263$$
$$P_{IDI,\ GCI} = -0.9007$$

A path decomposition starts by exhaustively listing the routes. The longest path in this model has a length of 2. An example path of length 2 is IDI, GII, GCI, that is, there are two edges from IDI to GCI in this route.The path ERD, IDI has length equals to 1.

Let $C_{START, DESTINATION}$ denote reproduced correlation.

For example, to compute for $C_{ERD, GII,}$ the paths are those which start at GII and ends at GCI are considered. These are the paths:

GII GCI
GII HDI GCI
GII ERD GCI
GII IDI GCI

Thus:

$C_{GII, GCI} = P_{GII, GCI} + D_{GII, ERD} P_{ERD, GCI} + D_{GII, HDI} P_{HDI, GCI} + D_{GII, IDI} P_{IDI, GCI}$

$= 1.0479 + 0.85307 \times 0.3263 + 0.83631 \times 0.4228 + 0.89967 \times -0.9007$

$= 1.0479 + 0.27835674 + 0.35359187 + -0.81033277$

$= 0.86951584$

The observed correlation and the reproduced correlation of the initial model are placed adjacently to each other in the excel sheet where computation of the difference between their corresponding entries was shown in the third matrix below. In cell B19, the formula =B3-B11 was entered and copied to the remaining cells in the matrix. It can be seen that no entry in the Difference matrix is greater than 0.05. The result tells us that all our path coefficients are significant at the 0.05 level. Therefore, the path model that was established in the initial model is consistent with the observed data.

Table 4: Initial Model Difference of Observed Correlation and Reproduced Correlation

	A	B	C	D	E	F
1	Observed Correlation					
2		ERD	IDI	GII	HDI	GCI
3	ERD	1	0.80112	0.85307	0.69403	0.79211
4	IDI		1	0.89967	0.93999	0.70091
5	GII			1	0.83631	0.86953
6	HDI				1	0.67899
7	GCI					1
8						
9	Reproduced Correlation					
10		ERD	IDI	GII	HDI	GCI
11	ERD	1	0.80112	0.85307	0.69403	0.79209915
12	IDI		1	0.89967	0.93999	0.70089742
13	GII			1	0.83631	0.86951584
14	HDI				1	0.67898225
15	GCI					1
16						
17	Difference					
18		ERD	IDI	GII	HDI	GCI
19	ERD	0	0	0	0	0.00001085
20	IDI	0	0	0	0	0.00001258
21	GII	0	0	0	0	0.00001416
22	HDI	0	0	0	0	0.00000776
23	GCI	0	0	0	0	0

The diagram below illustrates the comparison of the direct effect to GII on GCI and the total indirect effect of GII on GCI. The path with the solid arrow means direct effect, and the indirect paths are those with dashed arrows.

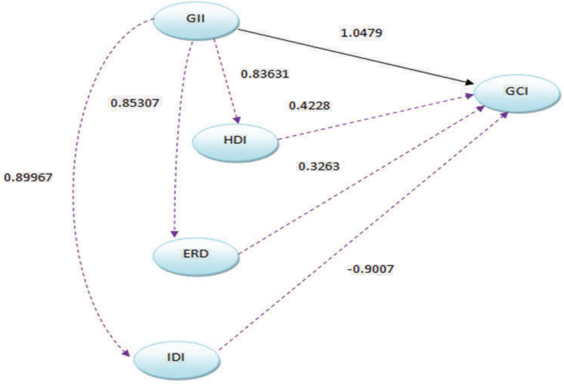


Figure 7: Direct versus indirect effects of GII on GCI

Direct effect of GII on GCI = 1.0479
Indirect effect of GII via HDI on GCI
= 0.4228 x 0.83631 = 0.35359187
Indirect effect of GII via ERD on GCI
= 0.3263 x 0.85307 = 0.27835674
Indirect effect of GII via IDI on GCI
= -0.9007 x 0.89967 = -0.81033277
Total indirect effects of GII on GCI
= 0.35359187 + 0.27835674 + -0.81033277
= -0.17838416

This table summarizes the reproduced correlation computation and indirect effects computation.

Outcome	Determinant	Direct	Indirect	Total
GCI (Variance is 82.5%)	GII	1.0479	-0.17838416	0.86951584
	HDI	0.4228	0.25618225	0.67898225
	ERD	0.3263	0.46579915	0.79209915
	IDI	-0.9007	1.60159742	0.70089742

It can be observed that:

- the direct effect of GII on GCI is greater than its indirect effects;
- the direct impact of HDI on GCI is higher than its indirect effects;
- the indirect impact of ERD on GCI are greater than its direct effect; and
- the indirect effects of IDI on GCI are greater than its direct effect.

The predictor with the largest total effect on GCI was GII (0.86951584). The remaining predictors arranged according to decreasing effect on GCI are ERD (0.792099153), IDI (0.700897421) and HDI(0.678982245). This model explained approximately 82.5% in GCI. GII (1.0479) and HDI (0.4228) have direct effects on GCI. ERD (0.46579915) has larger effect on GCI indirectly through other predictors; and positively through GII (0.89393205) and HDI (0.29343588). Similarly, IDI (1.60159742) has more significant indirect effect on GCI – the two most significant values were through GII (0.94276419) and HDI (0.39742777).

The full diagram of the initial model, Figure 5, includes all the possible paths from the predictor variables to the response variable.

The diagram below, referred as the reduced diagram, shows only the paths from the predictors of the response variable that have the dominant values.

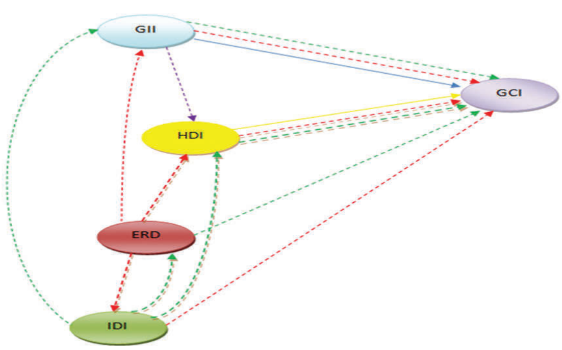


Figure 8: Reduced Diagram

In the diagram, direct effects are represented by solid arrows while indirect effects are in dashed arrows. The blue arrow represents the direct impact of GII on GCI; while the yellow arrow represents the direct effect of HDI on GCI. The three red paths from ERD to GCI represent the indirect effects of ERD on GCI. The three green paths represent the indirect effects of IDI on GCI.

4.3 Improved Model

The initial model lacks in it a more in-depth relationship between the predictors. A model is established based on the findings of the Initial Model.

The Path Diagram is constructed based on the reduced diagram of the initial model. GII and HDI are two predictor variables that have the direct effect on GCI. Directed edges from GII to GCI; and from HDI to GII was drawn. ERD has lesser direct impact to GCI but will have a positive indirect impact to GCI through GII and HDI. Directed edges from ERD to GII and from ERD to HDI was drawn. Also, since IDI will have greater indirect effect to GCI through GII and HDI, directed edges are drawn from IDI to GII, and from IDI to HDI. To come up with a simpler path diagram, the indirect impact of IDI via ERD on GCI is not considered since it has the least value of the indirect effects of IDI on GCI. Double-headed arrows are drawn between ERD and IDI to factor in the relationship between these two predictor variables. Below is the Path Diagram.

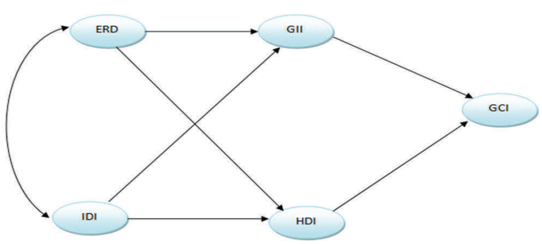


Figure 9: Reproduced Model

Based on the Path Diagram, the following three regression analysis was performed.

```
The regression equation is
GCI = 0.0000 + 1.00 GII - 0.160 HDI

Predictor      Coef     SE Coef       T       P
Constant    0.00000     0.06496    0.00   1.000
GII          1.0037      0.1195    8.40   0.000
HDI         -0.1604      0.1195   -1.34   0.185

S = 0.4947     R-Sq = 76.4%     R-Sq(adj) = 75.5%
```

Figure 10: Regression Analysis: GCI versus GII, HDI

```
The regression equation is
GII = - 0.0000 + 0.369 ERD + 0.604 IDI

Predictor      Coef     SE Coef       T       P
Constant   -0.00000     0.05032   -0.00   1.000
ERD         0.36942     0.08481    4.36   0.000
IDI         0.60372     0.08481    7.12   0.000

S = 0.3832     R-Sq = 85.8%     R-Sq(adj) = 85.3%
```

Figure 11: Regression Analysis: GII versus ERD, IDI

```
The regression equation is
HDI = - 0.0000 - 0.165 ERD + 1.07 IDI

Predictor      Coef     SE Coef       T       P
Constant   -0.00000     0.04366   -0.00   1.000
ERD        -0.16476     0.07359   -2.24   0.029
IDI         1.07198     0.07359   14.57   0.000

S = 0.3325     R-Sq = 89.3%     R-Sq(adj) = 88.9%
```

Figure 12: Regression Analysis: HDI versus ERD, IDI

Let $P_{\text{Predictor Variable, Response Variable}}$ denotes the beta values for the three regression above.

Therefore,

$P_{GII, GCI} = 1.0037$

$P_{HDI, GCI} = -0.1604$

$P_{ERD, GII} = 0.36942$

$P_{IDI, GII}$ = 0.60372
$P_{ERD, HDI}$ = -0.16476
$P_{IDI, HDI}$ = 1.07198

In the path diagram, the direct effect between ERD and IDI is taken into consideration. From the table on Direct Effect Path Coefficient Matrix, $D_{ERD,IDI} = D_{IDI,ERD} = 0.80112$.

For example, to compute for $C_{ERD,GII}$, the paths are those which start at ERD and ends at GII are considered. These are the paths:

ERD, GII
ERD, IDI, GII

Thus:

$$C_{ERD, GII} = P_{ERD, GII} + D_{ERD, IDI} P_{IDI, GII}$$
$$= 0.36942 + 0.80112 \times 0.60372$$
$$= 0.8530721664$$

The observed correlation and the reproduced correlation of the improved model are placed adjacently to each other in the excel sheet where the difference between their corresponding entries in the third matrix below was computed.

Table 5: Difference between Observed and Reproduced Correlation of the Reproduced Model

Observed Correlation

	ERD	IDI	GII	HDI	GCI
ERD	1	0.80112	0.85307	0.69403	0.79211
IDI		1	0.89967	0.93999	0.70091
GII			1	0.83631	0.86953
HDI				1	0.67899
GCI					1

Reproduced Correlation

	ERD	IDI	GII	HDI	GCI
ERD	1	0.80112	0.853072166	0.694024618	0.744906985
IDI		1	0.89966975	0.939987469	0.752224538
GII			1	0.823875809	1.0037
HDI				1	-0.1604
GCI					1

Difference

	ERD	IDI	GII	HDI	GCI
ERD	0	0	-2.1664E-06	5.3824E-06	0.047203015
IDI	0	0	2.496E-07	2.5312E-06	-0.051314538
GII	0	0	0	0.012434191	-0.13417
HDI	0	0	0	0	0.83939
GCI	0	0	0	0	0

In the Difference matrix only two entries are greater than 0.05, that is, only two reproduced correlations are significantly different from the observed. The improved model can still be considered to be consistent with the observed data.

Table 6: Computed Direct and Indirect Effect of the Reproduced Model

Origin	Path	Value	Total	Effect
ERD	ERD,GII,GCI	0.37078685		
	ERD,HDI,GCI	0.02642750		
	ERD,IDI,GII,GCI	0.48544168		
	ERD,IDI,HDI,GCI	-0.13774905	0.744906985	Indirect
IDI	IDI,GII,GCI	0.60595376		
	IDI,HDI,GCI	-0.17194559		
	IDI,ERD,GII,GCI	0.29704476		
	IDI,ERD,HDI,GCI	0.02117160	0.752224538	Indirect
GII	GII,GCI	1.00370000	1.0037	Direct
HDI	HDI,GCI	-0.16040000	-0.1604	Direct

There are four indirect routes from ERD to GCI and four indirect routes from IDI to GCI. The outcome of primary interest was GCI. The predictor with the largest overall effect on GCI was GII (1.003). The remaining predictors of GCI arranged according to decreasing overall effect are IDI (0.75222454), ERD(0.74490698) and HDI(-0.1604). GII and HDI have direct effects on GCI; while ERD and IDI have an indirect impact on GCI through GII and HDI. Among these four predictors of GCI, only HDI has the negative impact to GCI. This model explained approximately the 76.4% of the variance in GCI. The primary predictor of GII was IDI(0.89966975) closely followed by ERD(0.85307217). The direct effect of IDI(0.60372) on GII is greater than its indirect effects. But ERD(0.48365217) has more significant indirect effect on GII. Approximately 85.8% of the variance of GII was explained by the model. IDI(0.93998747) is the primary predictor of HDI, and this is because IDI(1.07198) has substantial direct effect on HDI. ERD(0.85878462) has more significant indirect effect on HDI. Approximately, 89.3% is explained by this model.

5.0 Conclusion

The four significant predictors of competitiveness considered in this paper are innovation, human development, ICT, and R&D. The initial model and the improved model proved that innovation is the most potent predictor to competitiveness. This result validates that an innovation-driven economy is one that has the most potential for international competitiveness.

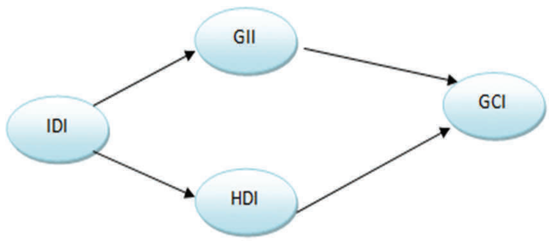
Innovation and human development have the direct effect on competitiveness while ICT and R&D will contribute to the competitiveness indirectly through innovation and human development. These results formalize and confirm that ICT and R&D cannot be a strategy in itself but an enabling technology that can become a powerful source of competitiveness advantage.

Comparing ICT and R&D as predictors of innovation and human development, ICT has larger total effect on innovation than R&D. It also has more substantial overall impact on human development than R&D. Comparing what contributes to the overall impact of ICT and R&D to innovation and human development, ICT has more significant effects (than indirect effects) to innovation and human development. R&D has more significant indirect effects on innovation and human development, than direct effects. That is, R&D can contribute more to innovation and human development through ICT.

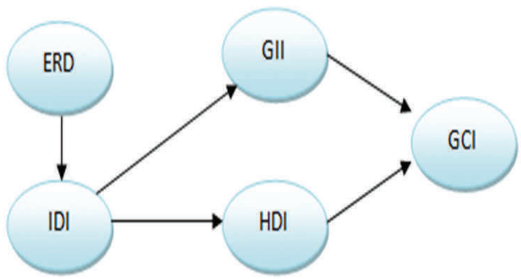
According to the improved model, the predictors to competitiveness arranged according to decreasing significance are innovation, ICT, R&D, and human development. Based on the paths, key points can be identified:

1. In order to improve competitiveness, the focus should be on innovation. It has a direct effect on competitiveness.

2. ICT should be focused next to innovation. But the action plan should be that ICT should drive innovation and human development to improve competitiveness.



3. R&D can only be seen to contribute to global competitiveness, provided that it will drive ICT.



4. Human development is the least predictor to competitiveness among the four. But it has direct effects.

An elaborate and systematic plan of action should be put forward by policy makers, business leaders and the academe to advance and enhance international competitiveness based on this path analysis.

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