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Path Analysis for Investigating the Main Factors Behind Chronic Kidney Disease

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ABSTRACT

Kidney failure is a global public health problem, with increasing incidence and prevalence, high costs, and poor outcomes, there is even a substantially higher prevalence of the earlier stages of chronic kidney disease (CKD), with adverse outcomes, including loss of kidney function. Strategies to improve outcomes will require a global effort directed at the earlier stages of CKD. The study's goal is to look at the relationship between factors that causes kidney failure based on creatinine and urea. Data were collected from Delvin pathological laboratory The path analysis method results reveal is underlying mechanism through which statistical tools, as relationship between factors; phosphorus, phosphates, albumin, calcium, glucose, and patient's age, creatinine and urea, which are caused kidney failure issue. The results show arrangement about factors effectiveness and the effects of phosphorus, phosphates, albumin, calcium, glucose, and patient's age are statistically significant as mentioned at section five of the study. This gives the conclusion that kidney failure problem must be more concern.

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1. Introduction

The Kidney failure issue is one of the most important medical problems, because kidney failure is the major and most dangerous phenomenon, which causes loss of life. Kidney disease is a global health problem, affecting over 750 million persons worldwide. [1] In low-income countries where treatment costs need to be paid directly by patients, a month's supply of essential medications for the treatment of chronic kidney disease can cost up to 18 days' wages and the corresponding out-of-pocket costs of dialysis, for acute kidney injury or end-stage kidney disease, are much higher. [9], [11] So to solve this issue several statistical tools exist such as the Path Analysis model which is widely used, e.g., in biomedical, educational, behavioral, and social sciences. Many methods developed to fit Path Analysis.

The basic principles of Path Analysis were developed by a biologist, Sewall Wright, A.M. Kwon, C. Shin, (2016) .it was not developed to discover causal relationships but to test the practical possibility of models developed by the researcher. The statistical methods involved with Path Analysis are methods of testing the appropriateness of a causal model with the use of standardized multiple regression equations.

So that the main objective of the study is to examine the relationship between factors which are caused kidney failure according to creatinine and urea, generally, the study tests the relationship and impacts of phosphorus, phosphates, albumin, calcium, glucose, and patient's age as the indicators (factors) on kidney failure according to creatinine and urea.

2. Materials and Methods

2.1 Types of Variables

A more direct approach to solving these problems is to use a technique called Path Analysis (PA). In several cases, PA has been replaced in recent years by a more complex methodology known as structural equation modeling (SEM), but we'll start with PA because it's easier to understand and forms the foundation for SEM. Despite the fact that both PA and SEM are multiple regression extensions, they heavily rely on path diagrams to visualize what's going on. Most PA and SEM computer applications, in reality, allow you to start with a Path diagram and then let the software work out the rest. So Let's start by drawing a Path diagram of a simple

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multiple regression, such as the three H's leading to faculty performance. each variable is represented by using a rectangle, and each path is represented by a straight line with an arrowhead at one end. Curved lines with arrowheads at both ends connect the predictor variables. the trails are represented by way of instant arrows, while the curved arrows replicate the correlation between the variables. the error term, additionally known as the disturbance term in PA and SEM, is a part of any regression equation and is represented with the aid of a circle with an arrow pointing to the dependent variable (and by extension, part of every PA and SEM diagram).

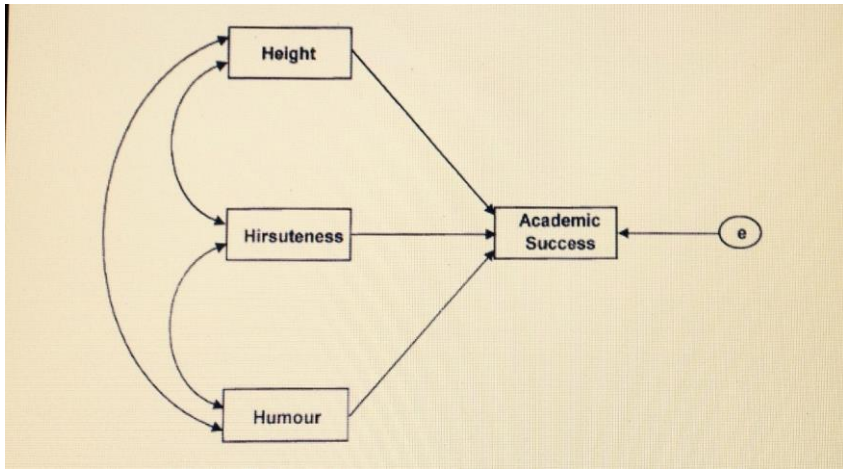

Figure (2-1): Path Analysis model

We don't talk about "independent" and "dependent" variables in PA or SEM. Exogenous variables and endogenous variables are the terms we use instead. The exogenous variable has paths leading from it but none leading to it (we don't count the curved arrows since they're only representing correlations between the variables and aren't considered paths). The three Hs are thus exogenous variables. An endogenous element, likewise, has at least one direction to it. As a result, head injury will be classified as an endogenous variable. Note also that all endogenous variables have an error term tacked on, which corresponds to the assumption in multiple regression that the dependent variable is measured with some degree of error GBD, (2015).

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2.2 Background of Path Analysis

in the 1910s and Nineteen Twenties, a biologist named Sewall Wright added the fundamental principles of path analysis Hoyle, R. H. (Ed.), (2012). It became created to assess the purposeful feasibility of the researcher's fashions, not to find out causal relationships. consistent with Wright (1921), "the technique can be used to locate the logical implications of a few unique hypotheses in regard to them in situations in which the causal relations are unknown." “even though the phrase may be lacking, the principle for which it stands continues to have huge foreign money. Jha V. (2013) said in a discussion of the clinical community's understanding of causation.

2.3 The procedure of path evaluation

path evaluation statistical approaches are essentially techniques of verifying the correctness of a causal model the usage of standardized more than one regression equations. one of the essential drawbacks of no experimental techniques, as with every non-experimental procedure, is the absence of manage and consequent incapacity to deal with all variables in a given system. the consequences can only be used as approximations to causality, so hopes for definitive causal rationalization must now not be entertained presently the power of the technique is impressing many individuals, but the frequency of its use is regularly growing.

the use of traditional correlation and a couple of regression techniques, the causal relationships amongst variables can most effective be inferred. these strategies frequently show proof of important relationships, however while correctly the use of path evaluation to check a theoretical model, it's far possible to as a minimum postulate causal linkages amongst a set of variables. in order to “correctly” use K.A. Bollen (2016), suggest that the following four assumptions have to be met:

1- linear relation among variables.
2- residual correlation equal to zero.
3- there is a one-way causal flow.
4- variables measure are interval scale.

Also Kishore SP (2011) has developed a six – step sequence in the application of PA that will:

1. Develop a causal model.
2. Establish a pattern of associations among the sequence's variables.

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3.Depict a path diagram.

4. evaluate the basic model's path coefficients.

5. Test for “goodness of fit” with the basic model.

6. Interpret the result.

2.4 Causality and Model Building

Before we go any further, let's clear up same misconceptions. People used to believe that they could use PA to prove causality because of all those single-headed arrows; in reality, it was once referred to as causality evidence

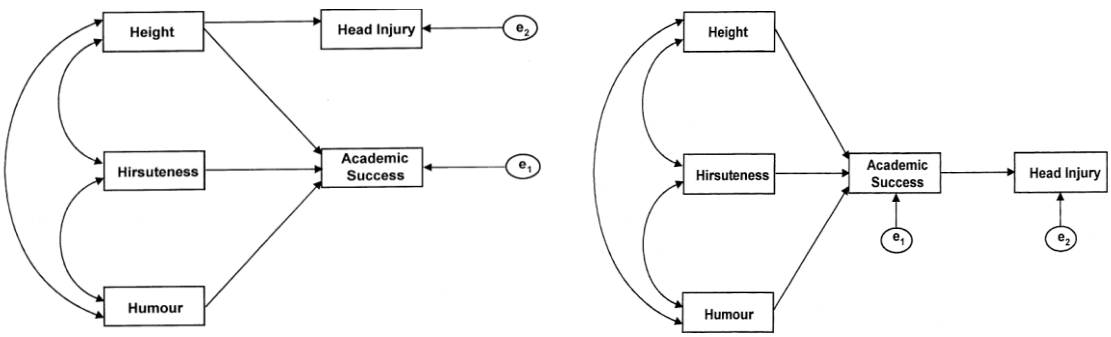

Figure (2-2): Causality and Model Building of path analysis

The second misconception is the PA may be used to develop theoretical models. Model-testing procedures such as PA and SEM are not model-development procedures. Our models have to be based on concept, knowledge, or even hunches at all times, Robert M. Brenner (2018)

2.5 path analysis model types

All of our models are based totally on our comprehensive knowledge and thorough understanding of the theories. these can be as easy or as complex as required; we've proven only a handful of the various alternatives to be had. Because we know that endogenous variables have error terms associated with them we won’t bother to draw them, in A Should Look familiar; it shows a simple regression type of model with two exogenous (X1 and X2) and one endogenous (Y) variable. B shows a mediated model, in which Y modifies the effect of X on Z.

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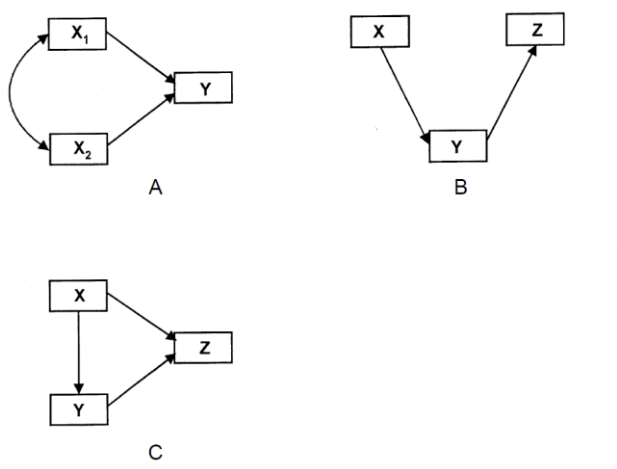

Figure (2-3): path analysis type

C is a bit extra complex combining elements of the two preceding models. X has a direct effect on variable Z, Y and y turn effects Z. Jha V. (2013)

2.6 Direct and Indirect Effects

Path Analysis has the aim of determining the "direct" and "indirect" effects of one variable on another. Estimate coefficient values of path form variable to another by using these equations bellow:

$$RP = r_0$$

$$\begin{bmatrix} r_{11} & \cdots & r_{1j} \\ \vdots & \ddots & \vdots \\ r_{i1} & \cdots & r_{ij} \end{bmatrix} \begin{bmatrix} P_{01} \\ \vdots \\ P_{0i} \end{bmatrix} = \begin{bmatrix} r_{10} \\ \vdots \\ r_{i0} \end{bmatrix}$$

Where:

r_{ij} : is a correlation between X_i and X_j , and can be calculated it as follows:

$$r_{ij} = \frac{\sum X_i X_j * \frac{\sum X_i \sum X_j}{n}}{\sqrt{\sigma_{X_i} * \sigma_{X_j}}}$$

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P_{0i} : direct effect for X_{i} on Y

r_{i0} : correlation among X_{i} and Y

$\mathrm{r_{ij}} * P_{0j}$: effect for X_{i} on Y according to X_{j}

Now let we have three independent variables with one dependent variable, can be write these equations above on the figure bellow as:

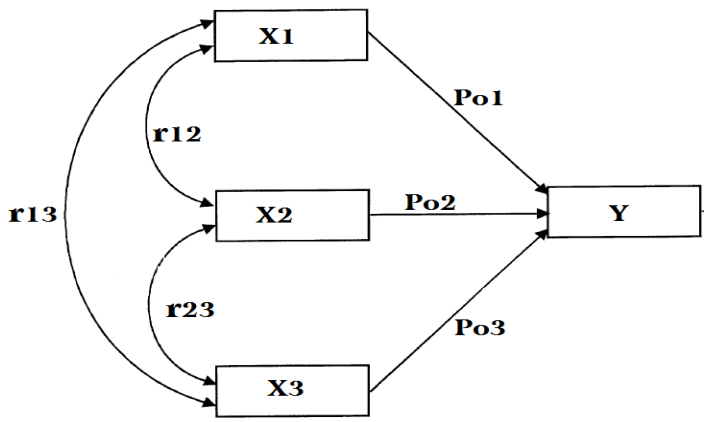

Figure (2-4): direct effect and correlation of Path Analysis

We can determine coefficient of determination as follows:

$$R^2_{0(i)} = \sum P_{0i}\, r_{i0}$$

to illustration above can be rewrite the coefficient of determination formula as:

$$R^2_{0(i)} = P_{01}r_{10} + P_{02}r_{20} + P_{03}r_{30}$$

$$\text{And } P^2_{0u} = 1 - R^2_{0(i)}$$

Where: P^2_{0u} is an quantity of residual.

The relationship among the terminology and the chart is pretty clear, but the connection to causal inference more problematic: Moosa MR, (2016)

Direct and indirect effects can be found in causal relationships among variables. Direct causal effects are those that occur when one variable causes another. When one or more factors moderate the relationship between two variables, indirect effects emerge. The magnitude of the indirect effects is determined by taking the product of the path coefficients along the path way between the two causally related

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variables. As a result, in a path model, the total indirect effect between two variables equals the sum of the products of each indirect impact, Moosa MR, al. (2016)

2.7 Goodness of fit

We have different type of theories about which variables or directions to use in the path model. calculating theories may be compared by estimating different path models and comparing goodness of fit statistics to check one better matches the correlation matrix in the observed data. Alternative hypotheses can be merged into a single path model, and we can determine which pathways are more important by comparing the relative intensity of different pathways within the same path model, Raykov, T (2006)

A variety of goodness of fit and competing path models are used to assess model fit and evaluate competing path models. A range of fit statistics are produced by several computer algorithms often used to estimate path models. Although there is some disagreement about which tests are the best to use, it is generally recommended that when testing model fit, we look at more than one fit statistic. There is a plethora of fit indexes, as well as a plethora of debates about them. Issues with all interventions include the following: Although certain parts of the data which fit poorly, the overall fit is appropriate. Doesn't imply that it's theoretically important, Hseyin E, (2007), The predictive strength of the X2 test should not be indicated. Is a badness of fit index, and in general, is comparing your model to one that would perfectly fit the data? (a just- identified model). df = difference between the number of parameters and correlations used to estimate them, sample covariance/correlation matrix vs. replicated in this situation, you don't want to be rejected.

If you do, it suggests you need to add some variable to the model. The problem with this approach entails all the same issues of any test of statistical significance. Sample size, assumptions etc. Furthermore, one cannot accept a null hypothesis from an NHST approach. Thought that doesn’t stop a lot of people. Root mean square residuals the name implies a kind of average residual between the fitted and original covariance matrix Like covariance itself, hard to understand its scale Standardized (regarding the correlation matrix), Eshima Nobuoki, (2001).

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*Goodness of Fit Index, Adjusted GFI*1Kind of like our R^2 and adjusted R^2 for the structural model world, but a bit different interpretation It is the percent of observed covariance explained by the covariance implied by the model R^2 in multiple regression deals with error variance whereas GFI deals with error in reproducing the variance-covariance matrix, which takes into account the number of parameters being estimated Incremental fit indices bentlers Norm Fit Index, Non- Norm FI (Tucker-Lewis Index), and CFI (NFI adjusted for sample size) test the model against an independence model E.g. 80% would suggest the model fits the data 80% better Others Akaike Information Criterion, Bayesian Information Criterion Good for model comparison1, can work for non-nested models .

3. Data Analysis and Results

3.1 Data Description:

The data set for this study was gathered from the dlvin pathological laboratory and consists of 153 observations. The individuals were chosen from all submitted records during the period of 2018-2019.The data search was done automatically due to the lack of manual. Eight variables were summarized as below. The descriptions of these variables are stated as in the below:

3.2 Variables of the study

3.2.1 Response variable:

The main response variable is the creatinine the sub-response variable is urea, which is scale variable in nature.

3.2.2 Explanatory variables:

For the explanatory variables (independent variables), all variables are scale variable. That is means they do not identifier such as some of the nominal variables have several levels and there should be an identifier (number: 1, 2, 3…), they are: age, calcium, phosphorus, phosphates, glucose, and albumin.

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3.3 Testing the linear relationship between the explanatory variables and the response variable:

To check the nature of the relationship between the explanatory variables and response variable, it is needed to draw the plot between explanatory variables as whole and the response variable as follows in figure (3-1):

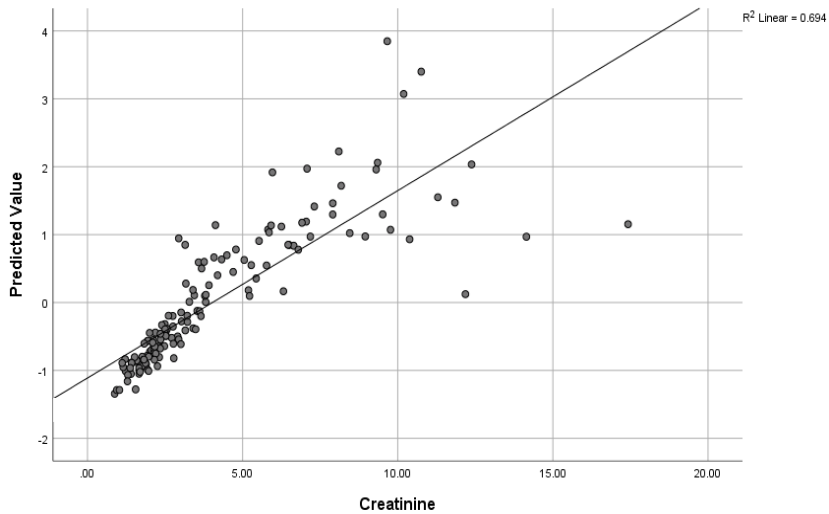

Fig (3-1): Relationship between observation and predictive value for the response variable

It is obvious from figure above that the explanatory variables that included in the model have a linear relationship. Because the linear relationship if their existence, appears near the straight line that represents the best line which was fitted the data, in this case of the previous figure, the points are spread around the best straight line which was fitted the data, which means that the relationship between the response variable and every variable of the explanatory variables included in the model have linear relationship. Also, the above figure shows that the relationship between the observation values for the response variable and the expected values is the linear relationship; this means that the linear relationship assumption in this model between the explanatory variables and the response variable is actually achieved.

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3.4 Testing the homogeneity of variance across levels of explanatory variables:

To check homogeneity of variance, the residuals and response variable was plotted as shown in figure (3-2):

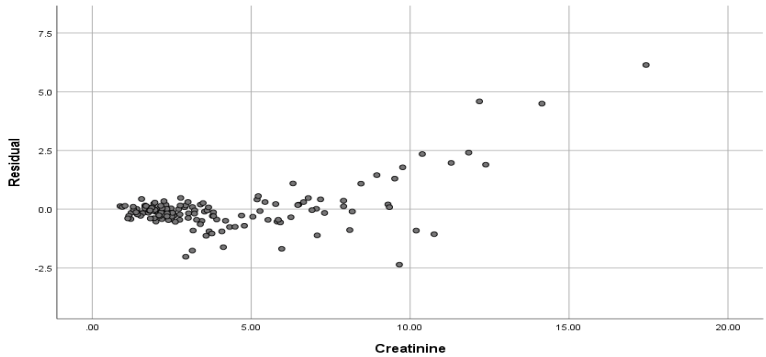

Figure (3-2): Relationship observation values to the response variable and the residual standard values

Is clear from the above figure that the residuals randomly spread and homogeneity in accordance with the values of the observation values of the response variable, this means that the homogeneity assumption in this model about variance is actually achieved. This means homogeneity of variance is met.

3.5 Goodness of fit results:

The Chi-square tests the null hypothesis that the over identified (reduced) model fits the data as well as does a just-identified (full) model.

Table (3-1): Goodness of fit Measurements

Measurements	Values
Chi-square (p-value)	12.003 (0.62)
χ2 / d.f	1.98
RMSEA	0.0127
NFI	0.93
CFI	0.95
IFI	0.96
GFI	0.95

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Table (3-1) explains seven fit model measurements which are; Chi-square, Chi-square over d.f., root mean square error of approximation (RMSEA), normed-fit index (NFI), comparative-fit index (CFI), incremental-fit index (IFI), goodness of fit index (GFI). The non-significant Chi-square indicates that the fit between our over identified model and the data is not significantly worse than the fit between the data and the just-identified model. While one might argue that non significance of this Chi-square indicates that the reduced model fits the data well, the relative chi-square (χ2 / d.f), is an index of how much the fit of data to model has been reduced by dropping one or more paths. One rule of thumb is to decide you have dropped too many paths if this index exceeds 2 or 3, but in this case this measure is equal to 1.98, the root mean square error of approximation (RMSEA), is an index of the amount by which the estimated variances and covariance differ from the observed variances and covariance. Smaller is better, which is equal to 0.0127, the Normed Fit Index (NFI) is equal to 0.93, that is simply the difference between the two models' chi-squares divided by the chi-square for the independence model, the values of 0.9 or higher indicate good fit, the Comparative Fit Index (CFI) in the current study is 0.95, which uses a similar approach (with a noncentral chi-square) and is said to be a good index for use even with small samples. It ranges from 0 to 1, like the NFI, and 0.95 (or 0.9 or higher) indicates good fit, although, the IFI value of 0.9 or higher indicate good fit, in this study is equal to 0.96. Finally, the GFI, the goodness of fit index is equal to 0.95, tells us what proportion of the variance in the sample, this should exceed 0.9 for a good model.

3.6 Direct and Indirect value:

The figure (3-3) explains all direct and indirect effects such as the following below:

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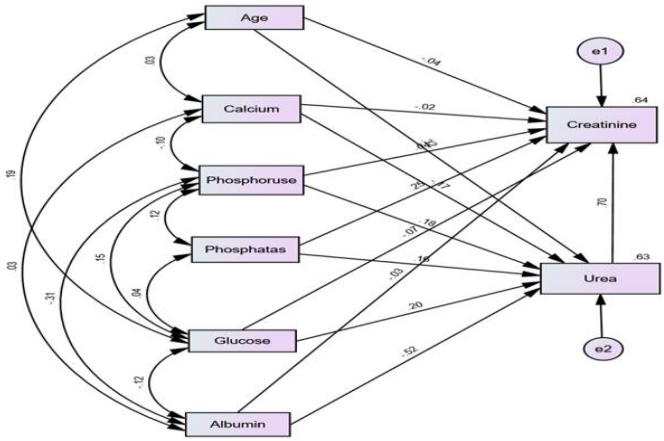

Figure (3-1): Structure of Path Analysis model

From figure (3-1) can be determine the changes of creatinine and urea as functions of effects of each age, calcium, phosphorus, phosphates, glucose, and albumin, and all direct effects are shown from the figure.

Table (3-2): parameters estimation of regression weights model

Variables			**Estimate**	**S.E.**	**C.R.**	**P**
Urea	<---	Age	-0.166	0.317	4.086	0.000
Urea	<---	Calcium	0.176	0.852	-2.148	0.032
Urea	<---	Phosphorus	0.156	2.294	2.129	0.033
Urea	<---	Phosphates	0.199	0.043	2.012	0.044
Urea	<---	Glucose	-0.523	0.108	2.498	0.012
Urea	<---	Albumin	0.043	6.833	-6.439	0.000
Creatinine	<---	Phosphorus	-0.032	0.093	0.503	0.615
Creatinine	<---	Albumin	-0.041	0.345	-0.305	0.760
Creatinine	<---	Age	-0.067	0.014	-0.463	0.643
Creatinine	<---	Glucose	0.252	0.004	-0.808	0.419
Creatinine	<---	Phosphates	-0.022	0.002	3.162	0.002
Creatinine	<---	Calcium	0.702	0.035	-0.279	0.780
Creatinine	<---	Urea	-0.166	0.005	5.564	0.000

From table (3-2) can be note that the effects of each of (age, calcium, phosphorus, phosphates, glucose, and albumin) are statistically significant on the urea, the

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value of Critical Ratio test of each them are equal to (4.09, 2.15, 2.13, 2.01, 2.50, 6.44) respectively, with p-values (0.000, 0.032, 0.033, 0.044, 0.012, 0.000) respectively, which are less than the statistical level (alpha = 0.05), that is means there are statistically significant effect of each of them (age, calcium, phosphorus, phosphates, glucose, and albumin) on the urea, and the amount of these effects are (-0.166, 0.176, 0.156, 0.199, -0.523, 0.043) respectively. Although, the effects of each of (phosphates, and urea) are statistically significant on the creatinine, the value of Critical Ratio test of each them are equal to (3.162, and 5.56) respectively, with p-values (0.002, 0.000) respectively, which are less than the statistical level (alpha = 0.05), that is means there are statistically significant effect of each of them (phosphates, and urea) on the creatinine, and the amount of these effects are (-0.022, -0.166) respectively.

Table (3-3): Total, Direct, and Indirect effects

Effects	**Variables**	Creatinine	Urea
Direct Effects	Phosphates	0.252	0.156
	Phosphorus	0.043	0.176
	Albumin	-0.032	-0.523
	Calcium	-0.022	-0.166
	Glucose	-0.067	0.199
	Age	-0.041	0.321
	Urea	0.702	0.000
Indirect Effects	Phosphates	0.11	0.000
	Phosphorus	0.123	0.000
	Albumin	-0.367	0.000
	Calcium	-0.117	0.000
	Glucose	0.14	0.000
	Age	0.225	0.000
	Urea	0.000	0.000
Total Effects	Phosphates	0.362	0.156
	Phosphorus	0.166	0.176
	Albumin	-0.399	-0.523
	Calcium	-0.139	-0.166
	Glucose	0.073	0.199
	Age	0.184	0.321
	Urea	0.702	0.000

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Table (3-3) explain all effects, it is noted that the (phosphorus, phosphates, albumin, calcium, glucose, age and urea) have a direct effect on the creatinine by amount (0.252, 0.043, -0.032, -0.022, -0.67, -0.041, 0.702) respectively, that is means, when (phosphorus, phosphates, and urea) go up by 1 standard deviation, creatinine goes up by (0.252, 0.043, 0.702) standard deviations respectively, and when (albumin, calcium, glucose, age) go up by 1 standard deviation, creatinine goes down by (0.032, 0.022, 0.67, 0.041) standard deviations respectively.

while the indirect effects of each mentioned variables on the creatinine are equal to (0.11, 0.123, -0.367, -0.117, 0.14, 0.255, 0.000) respectively, that is means, when (phosphorus, phosphates, glucose, age) go up by 1 standard deviation, creatinine goes up by (0.11, 0.123, 0.14, 0.255) standard deviations respectively, and when (albumin, calcium) go up by 1 standard deviation, creatinine goes down by (0.367, 0.117) standard deviations respectively.

Although, the variables (phosphorus, phosphates, albumin, calcium, glucose, and age) have a direct effect on the urea by amount (0.156, 0.176, -0.523, -0.166, 0.199, 0.321) respectively, that is means, when (phosphorus, phosphates, glucose, and age) go up by 1 standard deviation, urea goes up by (0.156, 0.176, 0.199, 0.321) standard deviations respectively, and when (albumin, calcium) go up by 1 standard deviation, urea goes down by (0.523, 0.166) standard deviations respectively.

4. Results and Conclusions

The results show arrangement about factors effectiveness and the effects of phosphorus, phosphates, albumin, calcium, glucose, and patient's age are statistically significant on the urea, the effect of glucose on the urea is greatest effect. Beside the negative direct effect of this factor, it may be concluded that this result concerning the direct effect of this factor comes from the fact that the less glucose lead to more improve urea and less kidney failure issue, while the effect of albumin on the urea is smallest effect. In addition, the effects of factors phosphates and urea are statistically significant on the creatinine which is caused kidney failure problem, the each mentioned factor have a direct effect on creatinine and urea, whenever the factors have an indirect effect on the creatinine only. This gives the conclusion that kidney failure problem must be more concern.

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تحليل المسار لتحري في العوامل الرئيسية وراء مرض الكلى المزمن

الملخص:
تظهر النتائج الترتيب حول فعالية العوامل وآثار الفوسفور والفوسفات والألبومين والكالسيوم والجلوكوز وعمر المريض ذات دلالة إحصائية كما هو مذكور في القسم الخامس من الدراسة .وهذا يعطي الاستنتاج بأن مشكلة الفشل الكلوي يجب أن تكون أكثر قلقا.

شیکردنەوەی ریکاری (path analysis) بۆ دۆزینەوەی هۆکارە سەرەکیەکانی نەخوشی گورچیلە

پـوختـه:
ئەنجامەکان دەریدەخات ریزبەندی کاریگەری و هۆکاری فسفور و فوسفات و ئەلبومین و کالسیوم و گلوکوز و تەمەنی نەخوش ئاماژەی ئامارین وەك لە بەشـــی پێنجی تۆژینەوەکەدا ئاماژەی پێکراوە . ئەمەش بۆمان دەردەخات کە دەبێت زیاتر نیگەران بین بۆ نەخۆشی لەکارکەوتنی گورچیلە.