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# Factors Affecting Whether College Students Go Back to School after Suspension

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***Abstract :*** *The present study investigated factors that might affect college students going back to school after being suspended in Taiwan based on the institutional research data of KS University. Results showed that the grades, enrolled department, entrance method, academic performance and the interaction between grades and enrolled department are the factors that significantly affect whether college students go back to school after being suspended in Taiwan. Juniors were the college students with the lowest ratio of those going back to school after being suspended. College of applied human ecology (department 2) showed the lowest ratio of students going back to school compared to other departments. Students who applied through direct application showed a higher ratio of going back to school than those entering based on the unified exam. Students with lower academic performance had a higher ratio of going back to school. Interaction effect also indicated that students with the lowest ratio of going back to school were juniors from College of applied human ecology.*
***Keywords -*** *Factors; Back to school; Suspension; Linear information model; Institutional research*

## I. Introduction

Student suspension or withdrawal has become an import issue for private colleges in Taiwan. Fig. 1 shows the flow chart of student suspension and withdrawal and the results in Taiwan.

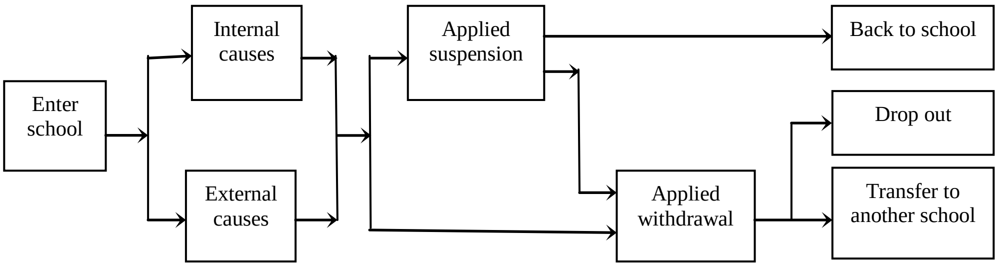


Fig. 1. Flow chart for student suspension and withdrawal and the results

To better understand the circumstances, Hung et al. [1] constructed a conceptual model (Fig. 2) based on a literature review to reveal the real (internal) causes of suspension and withdrawal of college students in Taiwan.

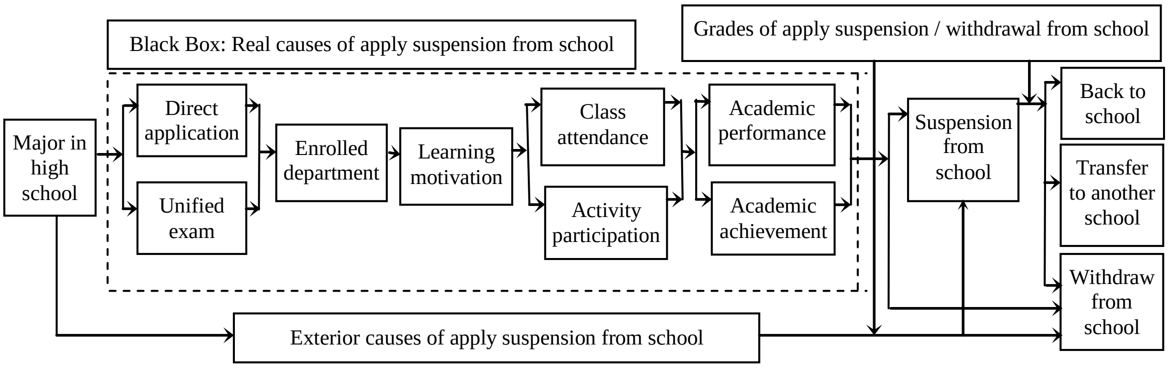


Fig. 2. Model of suspension and withdrawal from school in Taiwan

Hung et al. [2] verified the conceptual model which they proposed based on institutional research (IR) data and indicated that the conceptual model (Fig. 3) can actually reflect the current situation in Taiwan.

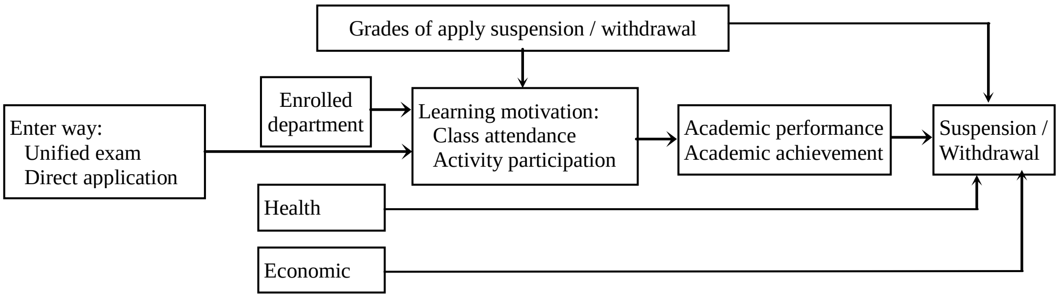


Fig. 3. Significant path coefficients for suspension and withdrawal

However, their results only indicate the significance coefficients of the path between the factors rather than recognizing the impact of each individual factor on suspension or withdrawal. Therefore, Hung et al. [3] employed a logistic regression (LR) method associated with information geometry to analyze the data. Results showed that the class attendance and interaction between class attendance and academic performance significantly affect college students' suspension and withdrawal in Taiwan.

As a result, if the students can go back to school after being suspended, then the impact of suspension is slight. Therefore, to understand the factors that affect whether college students go back to school after being suspension is also an important issue. Thus, the present study investigated the factors related to this issue.

The basic theory of the geometrically supported LR analysis method (linear information model, LIM) [4-7], which characterizes the geometry of the association between categorical variables, was introduced by Hung et al. [3]. Therefore, the present study directly analyzes IR data by employing LIM.

## II. Practical Data Analysis

An IR was conducted to evaluate the status of college students in KS University who were suspended from school from 2010-2014. We examined how various factors affected predictions of whether students would go back to school after being suspended by using a LIM model.

Based on data likelihood decomposition, an information approach supported by geometry theory for selecting the main and interaction effects of the predicting variables is introduced to LR analysis.

### 4.1. Data And Codes

In the IR data of KS University, a nominal variable is used to define the status of the response variable (back to school=1 and withdrawal=2), denoted by R=1 and 2. Seven predictors, each coded as "1 to 2 or 1 to 5" are used. Thus, the data consist of a multivariate contingency table of seven variables, having 800 cells and a total count of 1,657. Table I lists the codes of the seven prediction variables and the response variable, and their descriptions.

Table I. List of codes and descriptions of the variables

| Variable | Code | Description |
|---|---|---|
| Entrance method | EM, $x_1$ | 1: direct application; 2: unified exam. |
| Living city | LC, $x_2$ | 1: Tainan city; 2: other cities. |
| Gender | GE, $x_3$ | 1: Male; 2: Female. |
| Enrolled department | ED, $x_4$ | 1: college of creative media;<br>2: college of applied human ecology;<br>3: college of information technology;<br>4: college of business and management;<br>5: college of engineering. |
| Class attendance | CA, $x_5$ | 1: number of class absence < 5; 2: others. |
| Academic performance | AP, $x_6$ | 1: average scale > 60; 2: others. |
| Grade | GR, $x_7$ | 1: applied suspension at first grade;<br>2: applied suspension at second grade;<br>3: applied suspension at third grade;<br>4: applied suspension at fourth grade;<br>5: applied suspension after fourth grade. |
| Result | R | 1: back to school; 2: withdrawal. |

**4.2. Classical LR Analysis**

Table II shows the association between R (result) and each individual prediction variable.

Table II. Association between R and each individual factor

| | | Result | | Ratio of going back to school |
|---|---|---|---|---|
| Variable | Code | back to school | withdrawal | |
| EM, $x_1$ | 1 | 686 | 60 | 91.96% |
| | 2 | 747 | 164 | 82.00% |
| LC, $x_2$ | 1 | 511 | 62 | 89.18% |
| | 2 | 922 | 162 | 85.06% |
| GE, $x_3$ | 1 | 911 | 130 | 87.51% |
| | 2 | 522 | 94 | 84.74% |
| ED, $x_4$ | 1 | 277 | 27 | 91.12% |
| | 2 | 169 | 53 | 76.13% |
| | 3 | 230 | 36 | 86.47% |
| | 4 | 295 | 50 | 85.51% |
| | 5 | 462 | 58 | 88.85% |
| CA, $x_5$ | 1 | 673 | 128 | 84.02% |
| | 2 | 760 | 96 | 88.79% |
| AP, $x_6$ | 1 | 1062 | 196 | 84.42% |
| | 2 | 371 | 28 | 92.98% |
| GR, $x_7$ | 1 | 178 | 17 | 91.28% |
| | 2 | 227 | 24 | 90.44% |
| | 3 | 223 | 77 | 74.33% |
| | 4 | 415 | 47 | 89.85% |
| | 5 | 389 | 59 | 86.83% |

A full model for the case of using seven predictors $\{x_1, x_2, \ldots, x_7\}$ for the result $R$ is:

$I(\{x_1,x_2,x_3,x_4,x_5,x_6,x_7\},R)$
$= 7\ x_i$
$+21\ x_ix_j$
$+35\ x_ix_jx_k$
$+35\ x_ix_jx_kx_l$
$+ 21\ x_ix_jx_kx_lx_m$
$+ 7\ x_ix_jx_kx_lx_mx_n$
$+ 1\ x_ix_jx_kx_lx_mx_nx_o$…………………………………………………………………………………….(1)

The full model of classical LR analysis for equation (1) would include 7 main effects, 21 two-order interactions, 35 three-order interactions, 35 four-order interactions, 21 five-order interactions, 7 six-order interactions, and 1 seven-order interaction. It would take a very long time to obtain the full model results; furthermore, the full model results would be too complex to interpret.

If we select the factors one by one, it would still be too complex to calculate the relationship between the seven prediction variables and the response variable because any variable of the seven prediction variables can be coded as $x_1$, $x_2$, …, and $x_7$. In this case, there would be 5,040 (7!) combinations that need to be calculated. Thus, selecting variables efficiently for the LR model is clearly the major problem.

Thus, classical LR analysis methods usually assume that the high-order interactions are insignificant. However, this approach might neglect some significant high-order interactions and lead to incorrect interpretation.

Therefore, reducing items without missing significant interactions is very important, especially for significant high-order interactions.

**4.3. LIM Analysis**

A basic approach is to eliminate redundant predictors and to test LR models that can be interpreted using the least number of significant interaction terms. A straightforward extension of the MI identities in (1) to high-way tables is examined for IR data analysis in this study. An extension of the first equation of (1) to the case of using seven predictors $\{x_1,x_2, \ldots,x_7\}$ for the response variable R is:

$I(\{x_1,x_2,x_3,x_4,x_5,x_6,x_7\},R)$
$= I(R,x_1|x_7,x_6,x_5,x_4,x_3,x_2)$
$+ I(R,x_2|\ x_7,x_6,x_5,x_4,x_3)$
$+ I(R,x_3|x_7,x_6,x_5,x_4)$
$+ I(R,x_4|x_7,x_6,x_5)$
$+ I(R,x_5|x_7,x_6)$
$+ I(R,x_6|x_7)$

$+ I(R,x_7)$…………………………………………..……….……………………..…..….……..(2)

Identity (2) is constructed by the rule of selecting the first least significant ($7^{th}$ order) conditional MI (CMI) term, then selecting the least significant $6^{th}$ order CMI term, and continuing until reaching the last $2^{nd}$ order CMI term $I(R,x_6|x_7)$. Table III shows the calculation of the decomposition of identity (2) for each variable.

Table III. Calculation of the decomposition of identity (2)

| Variable | $I(R,x_i\|x_j,\ldots)$ | | | $Int(R,x_i,x_j,\ldots)$ | | | $I(R,x_i\|\|x_j,\ldots)$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | Likelihood ratio | *df* | *Sig.* | Likelihood ratio | *df* | *Sig.* | Likelihood ratio | *df* | *Sig.* |
| EM, $x_1$ | 249.132 | 400 | 1.000 | 209.988 | 399 | 1.000 | 39.144 | 1 | 0.000 |
| LC, $x_2$ | 107.578 | 400 | 1.000 | 102.479 | 399 | 1.000 | 5.099 | 1 | 0.024 |
| GE, $x_3$ | 122.624 | 400 | 1.000 | 116.319 | 399 | 1.000 | 6.305 | 1 | 0.012 |
| ED, $x_4$ | 290.952 | 640 | 1.000 | 274.615 | 636 | 1.000 | 16.337 | 4 | 0.003 |
| CA, $x_5$ | 130.776 | 400 | 1.000 | 130.718 | 399 | 1.000 | 0.058 | 1 | 0.810 |
| AP, $x_6$ | 85.923 | 400 | 1.000 | 70.406 | 399 | 1.000 | 15.517 | 1 | 0.000 |
| GR, $x_7$ | 350.337 | 640 | 1.000 | 293.222 | 636 | 1.000 | 57.115 | 4 | 0.000 |

The efficient way to select an initial sequence of variables is according to the significance level of the main and interaction term based on MI and CMI. Therefore, identity (2) is updated as:

$$
\begin{aligned}
& I(R,\{x_1,x_2,x_3,x_4,x_5,x_6,x_7\}) \\
& \quad = Int(R,x_1,\{x_2,x_3,x_4,x_5,x_6,x_7\}) \\
& \quad + I(R,x_1|| x_2,x_3,x_4,x_5,x_6,x_7\}) \\
& \quad + Int(R,x_2,\{x_3,x_4,x_5,x_6,x_7\}) \\
& \quad + I(R,x_2||\{x_3,x_4,x_5,x_6,x_7\}) \\
& \quad + Int(R,x_3,\{x_4,x_5,x_6,x_7\}) \\
& \quad + I(R,x_3||\{x_4,x_5,x_6,x_7\}) \\
& \quad + Int(R,x_4,\{x_5,x_6,x_7\}) \\
& \quad + I(R,x_4||\{x_5,x_6,x_7\}) \\
& \quad + Int(R,x_5,\{x_6,x_7\}) \\
& \quad + I(R,x_5||\{x_6,x_7\}) \\
& \quad + Int(R,x_6,\{x_7\}) \\
& \quad + I(R,x_6||\{x_7\}) \\
& \quad + Int(R,x_7) \ldots\ldots (3)
\end{aligned}
$$

**4.4. Determine Initial Sequence Of Factors**

Table III showed factor GR is the most significant factor. Therefore, the GR factor is first entered into the LR model. Then repeating the calculation procedure (Appendix Table I-VI), the factor ED is entered into the LR model secondly, followed by EM, AP, CA, LC and GE. When the entry sequence of the variables is determined, the next problem is the selection of a proper LR model.

Table IV. Sequential decomposed CMI components of identity (2)

| MI, CMI Terms | $I(R, X_{(t)}\|R^{(t)}\backslash X_{(t)})$ | | | $Int(R, X_{(t)}\|R^{(t)}\backslash X_{(t)})$ | | | $I(R, X_{(t)}\|\|R^{(t)}\backslash X_{(t)})$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | CMI | *df* | *Sig.* | Interaction | *df* | *Sig.* | Partial Asso. | *df* | *Sig.* |
| $I(R,x_7\|x_1,x_2,x_3,x_4,x_5,x_6)$ | 350.337 | 640 | 1.000 | 293.222 | 636 | 1.000 | 57.115 | 4 | 0.000 |
| $I(R,x_4\|x_1,x_2,x_3,x_5,x_6)$ | 175.374 | 128 | 0.003 | 147.474 | 124 | 0.074 | 27.900 | 4 | 0.000 |
| $I(R,x_1\|x_2,x_3,x_5,x_6)$ | 72.643 | 16 | 0.000 | 42.703 | 15 | 0.000 | 29.940 | 1 | 0.000 |
| $I(R,x_6\|x_2,x_3,x_5)$ | 34.666 | 16 | 0.004 | 17.302 | 15 | 0.301 | 17.364 | 1 | 0.000 |
| $I(R,x_5\|x_2,x_3)$ | 9.130 | 4 | 0.058 | 2.595 | 3 | 0.458 | 6.535 | 1 | 0.011 |
| $I(R,x_2\|x_3)$ | 7.281 | 2 | 0.026 | 1.668 | 1 | 0.197 | 5.613 | 1 | 0.018 |
| $I(R,x_3)$ | 2.510 | 1 | 0.113 | - | - | - | - | - | - |

**4.5. Selection Of A Proper LR Model**

An LR model is constructed from identity (2) using the hierarchical set of variable parameters {$x_7$, $x_4$, $x_7x_4$, $x_1$, $(x_7x_4)x_1$, $x_6$, $(x_7x_4x_1)x_6$, $x_5$, $(x_7x_4x_1x_6)x_5$, $x_2$, $(x_7x_4x_1x_6x_5)x_2$, $x_3$} as identity (4).

$$
\begin{aligned}
& \text{Logit}(R|\{x_6,x_7,x_5,x_1,x_3,x_4,x_2\}) \\
& \quad = 1.886^* \\
& \quad - 0.823\ _{(x_{7=3})}{}^* \\
& \quad - 0.747\ _{(x_{4=2})}{}^* \\
& \quad + 2.285\ _{(x_{7=3},x_{4=1})}{}^* \\
& \quad - 1.055\ _{(x_{1=1})}{}^*
\end{aligned}
$$

$- 1.538\ x_7x_4x_1$
$- 0.970\ _{(}x_{6=1)}$*
$- 13.401\ x_7x_4x_1x_6$
$- 0.083\ x_5$
$+ 13.824\ x_7x_4x_1x_6x_5$
$+ 0.419\ x_2$
$- 14.280\ x_7x_4x_1x_6x_5x_2$
$+ 0.644\ x_3$……………………………………………………..…………………………………(4)

## III. Results

Analysis of results shows only the main effect of $x_7$, $x_4$, $x_1$, $x_6$ and interaction of $x_7x_4$ reached a statistical level of significance ($p<0.01$), indicating that grades, enrolled department, entrance method, academic performance and interaction between grades and enrolled department significantly affect the ratio students going back to school after being suspended.

Grades ($x_7$) significantly affect the ratio students going back to school after suspension. Table V shows juniors ($x_{7=}3$) had the lowest ratio of students going back to school. In contrast, freshman ($x_{7=}1$) showed the highest ratio of students going back to school.

Table V. Effect of grades on ratio of going back to school after suspension

| Grade | Result | Number of students | Ratio of going back to school |
|---|---|---|---|
| 1 | back to school | 178 | 91.28% |
| | withdrawal | 17 | |
| 2 | back to school | 227 | 90.44% |
| | withdrawal | 24 | |
| 3 | back to school | 223 | 74.33% |
| | withdrawal | 77 | |
| 4 | back to school | 416 | 89.85% |
| | withdrawal | 47 | |
| 5 | back to school | 389 | 86.83% |
| | withdrawal | 59 | |

Enrolled department ($x_4$) significantly affects the ratio of students going back to school after suspension. Table VI shows department 2 resulted in the lowest ratio of students going back to school. In contrast, department 1 had the highest ratio of students going back to school.

Table VI. Effect of enrolled department on ratio of going back to school after suspension

| Enrolled department | Result | Number of students | Ratio of going back to school |
|---|---|---|---|
| 1 | back to school | 277 | 91.12% |
| | withdrawal | 27 | |
| 2 | back to school | 169 | 76.13% |
| | withdrawal | 53 | |
| 3 | back to school | 230 | 86.47% |
| | withdrawal | 36 | |
| 4 | back to school | 295 | 85.51% |
| | withdrawal | 50 | |
| 5 | back to school | 462 | 88.85% |
| | withdrawal | 58 | |

Entrance method ($x_1$) significantly affects the ratio of students going back to school after suspension. The students who entered the school by direct application ($x_1$=1) had a higher ratio of students going back to school than those who entered via the unified exam ($x_1$=2).

Table VII. Effect of entrance method on the ratio of going back to school after suspension

| Entrance method | Result | Number of students | Ratio of going back to school |
|---|---|---|---|
| 1 | back to school | 686 | 91.96% |
| | withdrawal | 60 | |
| 2 | back to school | 747 | 82.00% |
| | withdrawal | 164 | |

Academic performance ($x_6$) significantly affects the ratio of students going back to school after suspension. The students with better academic performance ($x_1$=1) had a lower ratio of going back to school than those with lower academic performance ($x_1$=2). This result comes into conflict with our exceptions and might result from it being harder for students with poor academic performance students to transfer to another school. Therefore, they tend to come back to school after being suspended when they fail to transfer.

Table VIII. Effect of academic performance on the ratio of going back to school after suspension

| Academic performance | Result | Number of students | Ratio of going back to school |
|---|---|---|---|
| 1 | back to school | 1062 | 84.42% |
| | withdrawal | 196 | |
| 2 | back to school | 371 | 92.98% |
| | withdrawal | 28 | |

The interaction effect between grades and enrolled department significantly affects the ratio of students going back to school after suspension. Table IX shows the association between grades and the enrolled department. Table IX indicates that college of applied human ecology (department 2) resulted in lowest ratio of junior students going back to school; in contrast, college of creative media (department 1) had the highest ratio of senior students going back to school.

Table IX. Association between grades and enrolled department with R

| | | Result | Enrolled department | | | | |
|---|---|---|---|---|---|---|---|
| | | | 1 | 2 | 3 | 4 | 5 |
| Grade | 1 | back to school | 40 | 21 | 22 | 39 | 56 |
| | | withdrawal | 2 | 4 | 3 | 3 | 5 |
| | 2 | back to school | 54 | 30 | 53 | 46 | 44 |
| | | withdrawal | 3 | 6 | 6 | 2 | 9 |
| | 3 | back to school | 51 | 44 | 25 | 46 | 57 |
| | | withdrawal | 3 | 29 | 4 | 24 | 15 |
| | 4 | back to school | 64 | 41 | 62 | 77 | 172 |
| | | withdrawal | 2 | 5 | 10 | 8 | 22 |
| | 5 | back to school | 68 | 33 | 68 | 87 | 133 |
| | | withdrawal | 17 | 9 | 13 | 11 | 9 |

## IV. Conclusions

Although there are many factors that might affect whether college students go back to school after suspension, however, the present study found that grades, enrolled department, entrance method, and academic performance significantly affect the ratio of students going back to school after being suspended. Furthermore, the interaction between grades and enrolled department also significantly affects the ratio of students going back to school after suspension.

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Appendix Table I. Calculation of decomposed after deleted GR

| Factor | $I(R,x_i\|xj,\ldots)$ | | | $Int(R,x_i,x_j,\ldots)$ | | | $I(R,x_i\|\|x,\ldots)$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | Likelihood ratio | *df* | *Sig.* | Likelihood ratio | *df* | *Sig.* | Likelihood ratio | *df* | *Sig.* |
| EM, $x_1$ | 146.113 | 80 | 0.000 | 121.088 | 79 | 0.002 | 25.025 | 1 | 0.000 |
| LC, $x_2$ | 64.869 | 80 | 0.990 | 58.964 | 79 | 0.955 | 5.905 | 1 | 0.015 |
| GE, $x_3$ | 97.351 | 80 | 0.091 | 95.065 | 79 | 0.105 | 2.286 | 1 | 0.131 |
| ED, $x_4$ | 175.374 | 128 | 0.003 | 147.474 | 124 | 0.074 | 27.900 | 4 | 0.000 |
| CA, $x_5$ | 104.522 | 80 | 0.034 | 104.040 | 79 | 0.031 | 0.482 | 1 | 0.488 |
| AP, $x_6$ | 60.832 | 80 | 0.946 | 44.593 | 79 | 0.999 | 16.239 | 1 | 0.000 |

Appendix Table II. Calculation of decomposed after deleted GR and ED

| Factor | $I(R,x_i\|xj,\ldots)$ | | | $Int(R,x_i,x_j,\ldots)$ | | | $I(R,x_i\|\|x,\ldots)$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | Likelihood ratio | *df* | *Sig.* | Likelihood ratio | *df* | *Sig.* | Likelihood ratio | *df* | *Sig.* |
| EM, $x_1$ | 72.643 | 16 | 0.000 | 42.703 | 15 | 0.000 | 29.940 | 1 | 0.000 |
| LC, $x_2$ | 26.710 | 16 | 0.045 | 23.024 | 15 | 0.084 | 3.686 | 1 | 0.055 |
| GE, $x_3$ | 41.234 | 16 | 0.001 | 31.844 | 15 | 0.007 | 9.390 | 1 | 0.002 |
| CA, $x_5$ | 39.901 | 16 | 0.001 | 39.068 | 15 | 0.001 | 0.833 | 1 | 0.361 |
| AP, $x_6$ | 34.666 | 16 | 0.004 | 17.302 | 15 | 0.301 | 17.364 | 1 | 0.000 |

Appendix Table III. Calculation of decomposed after deleted GR, ED and EM

| Factor | $I(R,x_i\|xj,\ldots)$ | | | $Int(R,x_i,x_j,\ldots)$ | | | $I(R,x_i\|\|x,\ldots)$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | Likelihood ratio | *df* | *Sig.* | Likelihood ratio | *df* | *Sig.* | Likelihood ratio | *df* | *Sig.* |
| LC, $x_2$ | 13.564 | 8 | 0.094 | 9.560 | 7 | 0.215 | 4.004 | 1 | 0.045 |
| GE, $x_3$ | 20.145 | 8 | 0.010 | 14.450 | 7 | 0.044 | 5.695 | 1 | 0.017 |
| CA, $x_5$ | 10.376 | 8 | 0.240 | 10.326 | 7 | 0.171 | 0.050 | 1 | 0.823 |
| AP, $x_6$ | 34.019 | 8 | 0.000 | 13.368 | 7 | 0.064 | 20.651 | 1 | 0.000 |

Appendix Table IV. Calculation of decomposed after deleted GR, ED, EM and AP

| Factor | $I(R,x_i\|xj,\ldots)$ | | | $Int(R,x_i,x_j,\ldots)$ | | | $I(R,x_i\|\|x,\ldots)$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | Likelihood ratio | *df* | *Sig.* | Likelihood ratio | *df* | *Sig.* | Likelihood ratio | *df* | *Sig.* |
| LC, $x_2$ | 6.323 | 4 | 0.176 | 2.531 | 3 | 0.470 | 3.792 | 1 | 0.051 |
| GE, $x_3$ | 5.611 | 4 | 0.230 | 2.446 | 3 | 0.485 | 3.165 | 1 | 0.075 |
| CA, $x_5$ | 9.130 | 4 | 0.058 | 2.595 | 3 | 0.458 | 6.535 | 1 | 0.011 |

Appendix Table V. Calculation of decomposed after deleted GR, ED, EM, AP and CA

| Factor | $I(R,x_i\|xj,\ldots)$ | | | $Int(R,x_i,x_j,\ldots)$ | | | $I(R,x_i\|\|x,\ldots)$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | Likelihood ratio | *df* | *Sig.* | Likelihood ratio | *df* | *Sig.* | Likelihood ratio | *df* | *Sig.* |
| LC, $x_2$ | 7.281 | 2 | 0.026 | 1.668 | 1 | 0.197 | 5.613 | 1 | 0.018 |
| GE, $x_3$ | 4.167 | 2 | 0.125 | 1.668 | 1 | 0.197 | 2.499 | 1 | 0.114 |

Appendix Table VI. Calculation of decomposed after deleted GR, ED, EM, AP, CA and LC

| Factor | $I(R,x_i\|xj,\ldots)$ | | | $Int(R,x_i,x_j,\ldots)$ | | | $I(R,x_i\|\|x,\ldots)$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | Likelihood ratio | *df* | *Sig.* | Likelihood ratio | *df* | *Sig.* | Likelihood ratio | *df* | *Sig.* |
| GE, $x_3$ | 2.510 | 1 | 0.113 | - | - | - | - | - | - |