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Latent Profile Analysis of Secondary School Students on Science Career Commitment in Indian Context

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ABSTRACT

Science Career Commitment is an important construct that determines one's attitude and motivation towards choosing a profession on science. As per the global need for the progress of science and technology, it is essential to encourage young individuals to choose Science, Technology, Engineering and Mathematics (STEM) as career. Hence it is essential to understand students' profile on the basis of science career commitment, so that proper intervention will be designed to meet the need. This study involves a total of 1125 secondary school students (659boys and 466 girls) as sample. Latent Profile Analysis was conducted by using tidy LPA package of R version 4.2.3. the model used in this study were Model 1 and Model 2 with variance and co-variance as equal-zero and varying-varying respectively. The estimands used for the study were AIC, BIC, entropy, BLRT-P value, n-max and n-min etc. Three distinct profiles on science career commitment such as High, Moderate and Low were explored. The objectives and the significance of the study are discussed.

Keywords: Latent Profile Analysis, Science Career Commitment, Secondary school students.

INTRODUCTION

While taking data from a particular group of people, researcher assumed that all the participants may have the same level of the construct to which it is measured, but in reality the participants differ from each other with respect to the measured construct. Also the participants are classified into certain homogenous group called profiles. In a particular profile all the participants are similar to each other with respect to the measured value of the construct but differ from the profile of the other group. These profiles can be explored through a statistical technique called Latent Profile Analysis (LPA), which is developed by (Magnusson and Cairns, 1996; Bergman and El-Khouri, 2003).

This LPA technique enables researcher to explore the hidden psychological factors within the learners. This helps to create profile on the basis of their psychological entities which in turn helps to develop better policies and practices. This LPA method has been used in different domains to analyse profiles of the sample such as person for substance abuse (Cleveland, Collins, Lanza, Greenberg, & Feinberg, 2010; James, McField, & Montgomery, 2013), for self-defence and anti-social behavoiour (Rosato & Baer, 2010), to determine psychosis symptomatology among people (Kibowski & Williams, 2012; Murphy, Shevlin, & Adamson, 2007; Shevlin, Murphy, Dorahy, & Adamson, 2007) and to analyse victimization among peer (Nylund, Bellmore, Nishina, & Graham, 2007).

In this study Latent Profile analysis (LPA) was conducted for Indian secondary school students on their career commitment on science by using Science Career Commitment tool developed by Chemers et al. (2011), and validated in the Indian context, to extract the number of distinct profiles of the participant individuals. The objective of the study is to explore the profiles of secondary school students on the basis of their science career commitment, so that proper interventions could be applied to motivate the young individuals to pursue careers in the field of Science, Technology, Engineering and mathematics (STEM).

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METHODOLOGY

Sample:

Students were selected from the eight schools, affiliated to the Central Board of Secondary Education of three zones such as; North, south and central zones of Odisha, India. A total of 1125 students out of which 659boys and 466 girls, voluntarily participated in the study. All the students received instructions in English throughout their academic life and were fluent in the language. The investigator sought and obtained formal permission from the institution to gather data for her research work having personally visited it. The entire work also received its approval from the Institutional ethics committee, Lovely Professional University, Phagwara, India, bearing reference number LPU/IEC-LPU/2024/2/34.

Statistical Analysis:

Latent Profile Analysis on science career commitment to extract different profiles is conducted by using tidy LPA package of R version 4.2.3. Here variance is set as equal and covariance is zero in case of Model-1 and in model-2 both are taken as varying to estimate profiles. The estimands like, Aikake information criterion(AIC), Bayesian information criterion(BIC), entropy, BLRT-P value, n-max and n-min were estimated to explore the total number of profiles. Graphical presentation of the profiles also taken for analysis.

RESULTS

Results of Latent Profile Analysis with R codes:

1. Data Import from the file

2. > library(tidyLPA)

3. > install.packages("dplyr")

4. > library(dplyr)

5. > library(haven)

6. > SCC_1125 <- read_sav("SCC_1125.sav")

7. > View(SCC_1125)

```
> SCC_1125%>%select(SCC)%>%single_imputation() %>% estimate_profiles(1)

tidyLPA analysis using mclust:

Model Classes AIC     BIC     Entropy prob_min prob_max n_min n_max

1     1       3066.38 3076.43 1.00    1.00     1.00     1.00  1.00

BLRT_p

> SCC_1125%>%select(SCC)%>%single_imputation() %>% estimate_profiles(2)

tidyLPA analysis using mclust:

Model Classes AIC     BIC     Entropy prob_min prob_max n_min n_max

1     2       2573.05 2593.15 0.95    0.97     0.99     0.18  0.82

BLRT_p

0.01

> SCC_1125%>%select(SCC)%>%single_imputation() %>% estimate_profiles(3)

tidyLPA analysis using mclust:
```

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Model Classes AIC BIC Entropy prob_min prob_max n_min n_max

1 3 2425.97 2456.13 0.89 0.88 0.98 0.16 0.63

BLRT_p

0.01

> SCC_1125%>%select(SCC)%>%single_imputation() %>% estimate_profiles(4)

tidyLPA analysis using mclust:

Model Classes AIC BIC Entropy prob_min prob_max n_min n_max BLRT_p

1 4 2430.00 2470.21 0.61 0.00 0.98 0.00 0.63 1.00

Model Classes AIC BIC Entropy prob_min prob_max n_min n_max BLRT_p

2 3 2336.853 2377.058 0.57 0.69 0.89 0.09 0.65 0.01

> SCC_1125 %>% select(SCC)%>%single_imputation() %>% estimate_profiles(1:3, variances = c("equal", "varying"), covariances = c("zero", "varying"))%>%compare_solutions(statistics = c("AIC", "BIC"))

Compare tidyLPA solutions:

Model Classes AIC BIC

1 1 3066.379 3076.430

1 2 2573.046 2593.148

1 3 2425.972 2456.125

2 1 3066.379 3076.430

2 2 2498.575 2523.703

2 3 2336.853 2377.058

Best model according to AIC is Model 2 with 3 classes.

Best model according to BIC is Model 2 with 3 classes.

An analytic hierarchy process, based on the fit indices AIC, AWE, BIC, CLC, and KIC (Akogul & Erisoglu, 2017), suggests the best solution is Model 2 with 3 classes.

> SCC_1125%>%select(SCC)%>%single_imputation() %>% estimate_profiles(3)%>%plot_profiles()

Latent Profile Analysis:

Table 1

Model	Classes	AIC	BIC	Entropy	Prob_min	Prob_max	n-min	n-max	BLRT_P
1	1	3066.38	3076.43	1.00	1.00	1.00	1.00	1.00	-
	2	**2572-05**	**2593.15**	**0.95**	**0.97**	**0.99**	**0.18**	**0.82**	**0.01**
	3	**2425.97**	**2456.13**	**0.89**	**0.88**	**0.98**	**0.16**	**0.63**	**0.01**
	4	2430.00	2470.21	0.61	0.00	0.98	0.00	0.63	1.00

Interpretation: According to AIC and BIC value model 1 is the best model with classes 2 and 3. But the value of BIC and AIC are lowest i.e. 2425.97 and 2456.13 respectively, for the class with profiles 3, in the most popular model 1. The goodness of fit between the model and the data is very significant with p-value less than 0.05 at 0.01of the estimand BLRT p-value for this class 2 & 3. As in class 3 of model 1, the value of AIC and BIC values are lowest so, it provides a reasonable fit to the model. Class 3 contains with its profiles termed as the high SRL, and the low SRL. For rest of the classes, the p-value is non-significant and hence they are not considered for further analysis.

The entropy of class 3 is 0.89, which means that 89 percent of the cases of total 1125, that is 1001 cases, were properly classified into their most probable profile. 88 percent of the cases belonging to the lowest profile could be properly classified under this category as the Prob min is 0.88. Since Prob_max is 0.98, it means that 98 percent cases belonging from the higher profile were properly classified into its respective category. The number of cases in the lowest profile is 180 as the n-min is 0.16. The number of cases in the highest profile is thus 709, since the n-max is 0.63.

Table 2 Summary of the Specification of Model 1 and Model 2

Model	Classes	AIC	BIC	Entropy	Prob_min	Prob_max	n-min	n-max	BLRT_P
1	**3**	**2425.97**	**2456.13**	**0.89**	**0.88**	**0.98**	**0.16**	**0.63**	**0.01**
2	**3**	**2336.853**	**2377.058**	**0.57**	**0.69**	**0.89**	**0.09**	**0.65**	**0.01**

The above table in Table 2 shows the comparison of class 3 of Model 1 and model 2. From the result obtained in the statistical analysis, it is found that the class 3 of Model 1 has lowest value of AIC and BIC and is also significant, as BLRT_P value is 0.01 but if we compare with class 3 of Model 2 data, it is found that this model contains lowest value of AIC, BIC and entropy as compared to Model 1 class 3 value. It is also found that Model 2 class 3 is significant as BLRT_P value is 0.01. Hence Model 2 class 3 is found to be the best model.

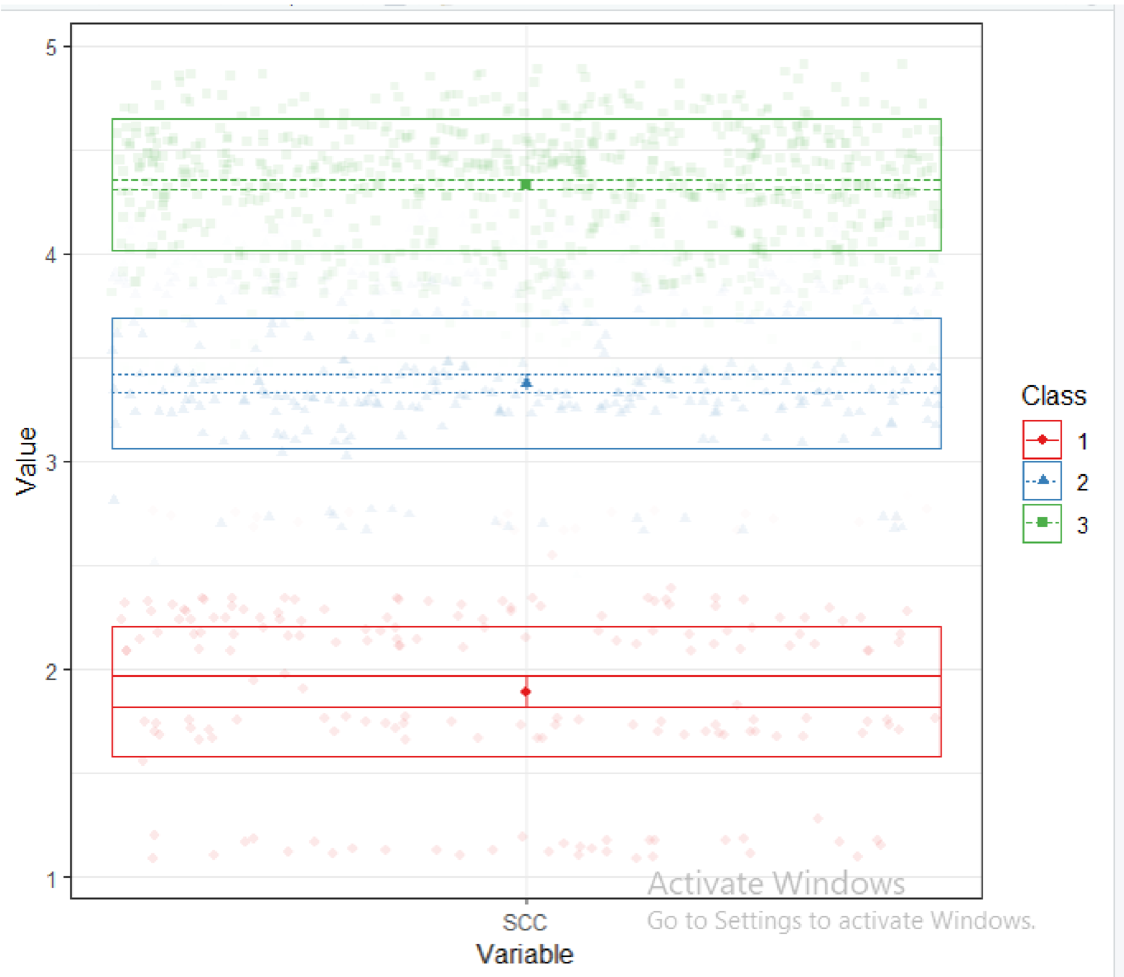

Figure 1. Latent Profile Analysis plot on Science Career Commitment (SCC) of Secondary school students

Interpretation:

The above graph shown in Fig 1 represents the Latent Profile Analysis(LPA) graph on Science Career Commitment(SCC) of secondary school students. The x-axis represents the variable SCC and the y-axis represents the numerical values which were measured. This graph shows three classes such as; class 1 (Red colour), class 2(Blue colour) and class 3(Green Colour). Class1 ranges in between 1.5 to 2.5, class 2 ranges between 2.5 to 3.5 and class 3 ranges between 4 to 5. This shows that class 3 contains highest value of distribution of data on science career commitment. This analysis shows that three distinct groups of profiles such as on the basis of their commitment to science career such as, high, moderate and low science career commitment.

DISCUSSION

This study examined the latent classes among secondary school students on science career commitment Indian context. Different estimands such as; AIC, BIC, entropy, BLRT_P value, n-max and n-min were assessed by using tidy LPA package of R studio version 4.2.3. The availability of free software such as R studio version 4.2.3 make the analysis easier and availability of tidyLPA package expedite the latent profile analysis in different domains to explore the profiles of the sample involved in the study. With the analysis of the data, two distinct models such as Model 1 and Model 2 were developed. Model 2 with class 3 was found to be the best model with lowest value of AIC and BIC.

CONCLUSION

The objective of this study to find out the different profiles of secondary students with respect to their science career commitment. This study put a light that we can address the heterogeneity rather take as homogeneous group. These findings enable educationist and policy makers to develop intervention programmes and more engaging curriculum to provide more vibrant STEM education to the students at secondary level and lead the country with science and technology based. This study has both policy and educational implications.

Ethics Statement:

The entire work was conducted as per the guidelines to be followed during data collection in Ph.D. works as laid down by the Institutional ethics committee, Lovely Professional University, Phagwara, India, with its approval for the same, bearing reference number *LPU/IEC-LPU/2024/2/34*

Author Contributions:

First author gathered the data, conducted data analysis and wrote the manuscript and the third author supervised the entire study.

Conflict of Interest Statement:

The authors declare no conflict of interest.

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REFERENCES

[1] Bergman, L. R., & El-Khouri, B. M. (2003). A Person-Oriented Approach: Methods for Today and Methods for Tomorrow. New Directions for Child and Adolescent Development, 2003(101), 25–38.

[2] Chemers, M. M., Zurbriggen, E. L., Syed, M., Goza, B. K., & Bearman, S. (2011). The role of efcacy and identity in science career commitment among under- represented minority students. Journal of Sociological Issues, 67, 469–491.

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[3] Cleveland, M. J., Collins, L. M., Lanza, S. T., Greenberg, M. T., & Feinberg, M. E. (2010). Does individual risk moderate the effect of contextual-level protective factors? A latent class analysis of substance use. Journal of Prevention & Intervention in the Community, 38, 213- 228.

[4] James, S., McField, E.S., & Montgomery, S.B. (2013). Risk factor profiles among intravenous drug using young adults: A latent class analysis (LCA) approach. Addictive Behaviors, 38, 1804-1811.

[5] Kibowski, F. & Williams, G. (2012, May). Can latent classes of childhood trauma predict latent classes of psychosis-like experiences? Secondary data analysis using a nationally representative subsample of the NCS-R. Paper presented at the annual conference of the British Psychological Society Northern Ireland Branch, Killadeas, Northern Ireland.

[6] Magnusson, D., & Cairns, R. B. (1996). Developmental science: Toward a unified framework. Cambridge, England: Cambridge University Press.

[7] Murphy, J., Shevlin, M., & Adamson, G. (2007). A latent class analysis of positive psychosis symptoms based on the British Psychiatric Morbidity Survey. Personality and Individual Differences, 42, 1491-1502

[8] Nylund, K., Bellmore, A., Nishina, A., & Graham, S. (2007). Subtypes, severity, and structural stability of peer victimization: What does latent class analysis say? Child Development, 78, 1706-1722.

[9] R Studio Team, RStudio: Integrated Development for R. RStudio, Inc., Boston, MA, URL http://www.rstudio.com/, 2023.

[10] Shevlin, M., Murphy, J., Dorahy, M. J., & Adamson, G. (2007). The distribution of positive psychosis-like symptoms in the population: a latent class analysis of the National Comorbidity Survey, Schizophrenia Research, 89, 101-109.