International Journal of Basic and Applied Sciences, 14 (6) (2025) 303-312

International Journal of Basic and Applied Sciences

Website: www.sciencepubco.com/index.php/IJBAS
https://doi.org/10.14419/nbbc9625
Research paper

Revisiting The Vocational Outcome Expectations Scale: A Network Psychometric Validation of The Revised Five-Point Likert Version

Patal Kumar Murasing [1] *, Dr. Rajib Chakraborty [2], Dr. Navdeep Singh Raji [3]

[1] Research Scholar, School of Education, Lovely Professional University, Phagwara, Punjab, India
[2] Professor, School of Education, Lovely Professional University, Phagwara, Punjab, India
[3] Assistant Professor, M.K. College of Education, Jalandhar, Punjab, India
**Corresponding author E-mail: navdeep.raji22@gmail.com*

Received: June 27, 2025, Accepted: August 23, 2025, Published: October 17, 2025

Abstract

The revised vocational outcome expectations scale measures the expected outcomes of an individual while pursuing a goal. The original Likert scale-based response categories of this tool are increased from four to five by including the neutral option. The tool is validated on a fresh population of high school students belonging to the North Eastern state of Tripura, India, using the Network Psychometrics approach appropriate for the ordinal data type. The purpose was to improve the quality of the responses obtained from the tool, enhance its psychometric robustness by validating it through a network approach, and increase its cross-cultural validity over a fresh population in a novel context. Data was collected through a stratified random sampling technique from schools representing all eight districts of the Tripura state. The sample size was 568 secondary school students (Boys = 286, Girls = 282). Data analysis was conducted using appropriate packages in R ver. 4.4.2. Exploratory graph analysis revealed a single cluster of the construct, consistent with previous studies, with all nodes displaying robust structural-al consistency of 0.938 within the cluster. Rationale for accepting the estimates of ordinal confirmatory factor analysis, like CFI robust, srmr_bentler, tli. robust and RMSEA. robust, as obtained in this study, is provided along with the statistical details related to the regularized network structure, centrality indices, and edge-weight accuracy. The CS-coefficient is found to be 0.362, indicating acceptable stability of the network. The revised vocational outcome expectations scale is found to be a robust instrument among the population of secondary school students.

Keywords: *Network Psychometrics; Social Cognitive Career Theory; Secondary School Students; Vocational Outcome Expectations; Vocational Outcome Expectations Scale.*

1. Introduction

The high secondary phase of school education is critical in many aspects for the adolescents transiting from school to adulthood, and especially in the context of moving towards joining the workforce of a nation (Skorikov& Vondracek, 2011; Sung & Connor, 2017). A school is the standard social institution where students not only develop their academic identity, but also work on their formative career-related identity, since one of the primary objectives of the school is to prepare students for their future careers through education. In fact, educational and vocational commitments of adolescents feed each other (Negru-Subtirica, Pop, 2017; Negru-Subtirica, Pop &Crocetti, 2017). Owing to its inherently significant nature, adolescence and students belonging to this age group must be the subjects of research in any progressive society. The endeavors in this context can be directed towards making vocational counseling of the adolescent students more scientific and in coherence with the students' educational interests.

One of the vital vocational psychology research variables that plays an important role in the career development of adolescents and young adults is vocational outcome expectations (Vela et al., 2018; Yeh & Borrero, 2012). According to Ali, McWhirter& Chronister (2005), it is rooted in Social Cognitive Theory (Bandura, 1986) and Social Cognitive Career Theory (Lent, Brown & Hackett, 1994) refers to it as "the individuals' expected outcomes when pursuing goals" (Fouad & Guillen, 2006). This variable plays its role in career development by influencing the career-related decisions and their related behaviors in the individuals (McWhirter, Rasheed & Crothers, 2000), and consequently, the efforts should be focused towards those groups and students who struggle the most with career decisions and behaviors because they hail from the marginalized sections, like economically backward regions.

From the perspective of geographical psychology, personality traits of individuals vary from one region to another because of local traditions, culture, and economic conditions. These regional traits are related to important factors like health, politics, and the economy. So, the economic environment and physical geography of a region can help shape the personality traits of its people (Rentfrow et al., 2015). Also, individuals of specific personality traits cluster in certain regions depending on the economic growth prospects of such regions (Garretsen et al., 2019). As a result, the economic backwardness of a region necessitates the placing of efforts to improve the vocational

psychological status of the region's adolescents further. Hence, measurement of variables like vocational outcome expectations is of very high relevance not only to psychologists and vocational counselors, but also to teachers and school administrators.

The 12-item revised vocational outcome expectations scale (McWhirter et al., 2000; Metheny and McWhirter, 2013) is one of the widely used measures of vocational outcome expectations, with its responses recorded in a four-point Likert scaleranging from strongly agree (4) to strongly disagree (1). The selection of an effective Likert scale's options is an important decision to make because it directly influences the adequate and accurate capturing of the essence of a construct and in providing sensible data, especially in survey-based research. These response options must be of a balanced range reflecting the subject's opinions and attitudes in varying degrees. A balanced scale must provide its respondents the opportunity to not only express positive and negative sentiments towards the statement of the item, but also remain neutral if the need be. The inclusion of a neutral option provides a symmetrical range on its both sides, reduces response bias, and also increases the reliability of the collected data. Though the options can vary from four to seven points, a typical Likert scale is structured with five points, ranging from strongly agree (5) to strongly disagree (1), with the neutral option representing the score of 3. Also, the decision of selecting the options in a Likert scale in a balanced manner must be based on ensuring the requirement to capture enough detailed data and keeping the respondent fatigue in check (Koo and Yang, 2025).

Based on the above-discussed rationale, the present study involved the inclusion of the neutral option into the four-point Likert scale structure of the revised vocational outcome expectations scale, making it a five-point Likert scale. There are several studies mentioned in the literature which reported that inclusion of options above three categories, generally improve the psychometric properties of the scale (Preston and Colman 2000; Weng 2004; Lee &Paek, 2014; Finn, Ben-Porath, &Tellegen, 2015; Alwin, Baumgartner, & Beattie 2018; Simms, et al., 2019) with such a benefit reducing when the categories are raised above seven (Lozano, Gargia-Cueto, & Muniz, 2008). The rise in the number of options can aid in capturing the finer differences subjects have while expressing their opinions or attitudes, and also can increase the sensitivity of the tool (Beckstead, 2014).

Kankaras and Capechhi (2025) found that inclusion of a midpoint like neutral in the response options improves the psychometric properties of the scale, and unlike the general perception that the neutral option is used in an invalid manner by the respondents due to their fatigue or to be socially desirable, this study reported that most of the subjects validly use the neutral category. The psychometric properties like total variance explained, reliability level, and eigenvalue rise the most when a psychological scale is of a five-point Likert scale, in comparison to four, six, or seven-point Likert scale (Tekin et al., 2024). Mariano et al. (2024a) reported that the option neutral is a common place and aids in meaningful expression of opinions and attitudes, at least in the school climate domain. They also found that neutral is not an option of choice for the respondents in the face of situations like inadequate information on the topic, indifference, or indecision while replying. They finally suggested inclusion of a neutral option to an already existing four-point Likert scale, to enhance the accuracy of the subject's sentiments and to get better results from the revised tool. Mariano et al. (2024b) also found that there exists a substantial segment of population during survey research which prefer the presence of a neutral response in the scale and its presence is not a representation of any default response category towards the early completion of the data filling or an option meant for selection in case of unsure or non-applicable responses as communicated byKulas, et al. (2008).

According to Smith (2010) cultural considerations also play an important role in the selection of responses of Likert scales. While there are certain cultures where the native subjects show a preference to select extreme categories, there are other cultures that show a tendency to select neutral options as well (Chen et al., 1995).

For ensuring cross-cultural structural validity, the revised vocational outcome expectations scale required revalidation in a fresh population, language, and context, in line with the recommendations of Niles and Harris-Bowlsby (2016). Since the data obtained from a Likert scale based instrument is actually of ordinal data type, the approach of network psychometrics (Constantini et al., 2014), was chosen to validate the revised scale (Johal&Rhemtulla, 2023) with the Weighted Least Squares Mean and Variance Adjusted (WLSMV) estimator applied in place of the Maximum Likelihood (ML) estimator for conducting ordinal data appropriate confirmatory factor analysis (Li, 2016). To learn the basics of network psychometrics, its merits over traditional psychological scale validation techniques like Exploratory factor analysis and Confirmatory factor analysis, and its limitations, the research papers by Borsboom et al. (2021) and Qian et al. (2025) can be studied.

By increasing the response category of the revised vocational outcome expectations scale from four to five, through the inclusion of a neutral option, and by validating it on a fresh population of secondary school students in the Indian context, using a network psychometrics approach, the researchers intended to enhance the scale's cross-cultural and structural validity. The next section of the paper discusses the research design of the study for collecting the data.

2. Methodology

2.1. Population

The justification for selecting the high secondary school students as the population of this study is that adolescent students of Tripura, India, belong to an economically backward northeastern state. According to the latest report of Economic Review (2023-24), released by the Directorate of Economics and Statistics, Government of Tripura, India, the state has a mainly agrarian economy, with over 44% of its people depending on farming and related work for their livelihood. However, cultivable land is limited due to the large forest areas. Because of the state's geographic isolation, it has poor infrastructure, making industrial development slow. As a result, only the unorganized sector dominates the economy. In the context of Tripura, the personality trait of neuroticism, involving anxiety and emotional instability, can influence individuals, especially adolescents, belonging to this region, owing to its economic underdevelopment. Hence, it is very important that the administrators and policy makers have enough research-backed scientific information on the career development-related variables like vocational outcome expectations, handy to them, so that timely and effective interventions can be developed for the state's youth.

2.2. Sample and procedure of data collection

Permission for data collection from schools for the intended research was approved by the Director of Secondary Board Education, Tripura state. The research work was approved by the Institutional Ethics Committee of Lovely Professional University, bearing the reference number LPU/IEC-LPU/2024/2/19. The researcher personally visited the schools of the region and explained the purpose of the visit to the students. The head of the institution and the teacher in the class helped the researcher in the collection of the data during regular

classroom sessions. All students voluntarily participated in the study after being informed of the purpose of the data collection and the anonymity of the data. The sample of the study comprised 568 secondary school students from eight schools representing the eight districts of the Tripura state as part of a stratified random sampling technique. There were 286 boys (50.4%) and 282 girls (49.6%) comprising the sample subjects. 287 (50.5%) students belonged to 11th grade, and 281 (49.5%) belonged to 12th grade. 439 students (77.3%) belonged to the arts stream, 127 students (22.4%) studied sciences, and only two students (0.4%) belonged to the commerce stream. The average age of the subjects was 16.5 years. The physical copies of the questionnaire were finally distributed to the subjects, and they returned the filled forms in 15 to 20 minutes. There were no missing values. Since the tool was administered during regular classroom sessions, the data collection occurred in a naturalistic setting. This enhanced the ecological validity of the study, as participants engaged with the instrument within the authentic context in which the measured constructs are typically experienced. The final sample size after removing the outliers was moderate at 525.

2.3. Instrument

The original scale to measure vocational outcome expectations, developed by McWhirter et al. (2000), contained only six items. Considering the shortness of the scale and addressing the fact that Bandura's (1986) concept of outcome expectations leads to anticipated consequences for a course of action, the revised scale was developed by Metheny & McWhirter (2013) by adding six new items. Two items each from the newly added items represented the three types of outcome expectations as cited by Bandura (1986), namely social outcome expectations, physical outcome expectations, and self-evaluation or satisfaction.

The revised VOE scale (McWhirter et al., 2000; Metheny & McWhirter, 2013) assesses "the individual's level of positive expectations about his/her career choice and his/her belief that his/her actions will lead to a positive result". Participants respond to a four-point scale ranging from strongly agree (4) to strongly disagree (1). In this study, the response category of neutral was also included, and hence the response categories ranged from Strongly Disagree = 1, Disagree = 2, Neutral = 3, Agree = 4, and Strongly Agree = 5. Sample items include, "My career planning will lead to a satisfying career for me," "I have control over my career decisions," and "The future looks bright for me." The mean score is computed with higher scores reflective of higher vocational outcome expectations. McWhirter et al. (2000) reported an estimate of the internal consistency reliability between the items, Cronbach's alpha, of 0.83. Metheny & McWhirter's (2013) study reported the same estimate, as0.93 respectively, for the scale.

2.4. Statistical analysis

Identification of outliers in the data was done using the estimation of the Mahalanobis distance in SPSS Statistics Version. 23.0. Thereafter, the complete data analysis was conducted using the openwareR core team (2016) version. 4.4.2 / RStudio (2020). The statistical analysis followed the workflow of network approaches for multivariate data as outlined by Borsboom et al. (2021), comprising network structure estimation, network description, and network stability analysis. While network structure estimation deals with the construction of the network, network description characterizes its structure, and network stability analysis aids in determining the robustness of the obtained results for replicability in future studies.

Initially, the "EGAnet" package was used for the extraction of the clusters from the obtained data using the default "glasso" method of exploratory graph analysis (EGA). The "LASSO and EBIC" techniques based regularized network structure provided the final network structure. The package "mgm" was used to compute node predictability using R2estimand, and the "qgraph" package plotted the same. The ordinal confirmatory factor analysis using the "WLSMV" estimator was used to estimate the goodness of fit estimates, which are appropriate for ordinal data type scores. The characteristics of the network were estimated through centrality indices plots, the edge weight accuracy confidence interval plot through the comparison of sample and bootstrapped data for 500 iterations. The stability of the network was estimated using a structural consistency exercise using the "bootnet" package and through the estimation of correlation stability CS-coefficient using the "qgraph" package. The results obtained from applying the mentioned statistical techniques on the collected data are presented below, along with their interpretations.

3. Result

3.1. Network structure estimation analysis

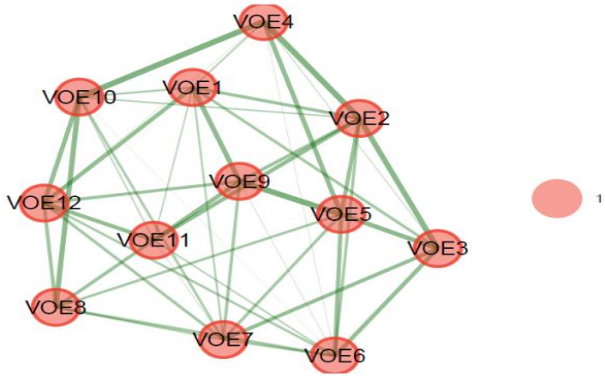

Fig. 1: Network Structure of the Revised Vocational Outcome Expectations Scale Using the Glasso Method on Running Exploratory Graph Analysis (EGA).

To explore the network structure of the scale, an Exploratory Graph Analysis (EGA) was conducted using the graphical least absolute shrinkage and selection operator (glasso) method with the EBICglasso estimator. All 12 nodes of the scale formed a single clustered network. Exploratory Graph Analysis is a method to graphically show which items of a psychological scale are closely related to each other,

forming a group or cluster. The method is computationally carried out using several formulae or estimators, and in the present study, the EBICglasso estimator was used for estimating the number of clusters.

3.2. Estimation of the regularized network structure

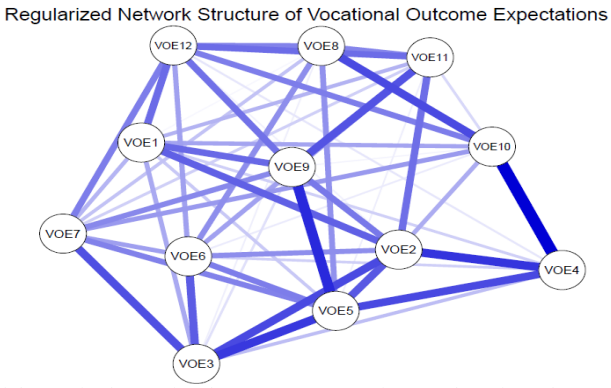

Fig. 2: Regularized Network Structure of the Revised Vocational Outcome Expectations Scale Using Glasso Algorithm with the Extended Bayesian Information Criterion (EBIC) Model Selection Procedure.

A regularized partial correlation network was estimated using the graphical least absolute shrinkage and selection operator (glasso) algorithm with the Extended Bayesian Information Criterion (EBIC) model selection procedure. The codes of Glasso produce models of networks with the weak or poor connections in them removed so that they can be less crowded. The EBIC procedure helps in the selection of the best network model among the lot generated by Glasso (Henry and Ye, 2024). The regularized network structure revealed a sparse but interpretable pattern of connections, indicating that only the most robust associations between items were retained. No spurious correlations were introduced due to the regularization penalty. There were moderate to strong positive partial correlations among several item pairs, suggesting meaningful item interdependencies. No negative edges were found, which implied that the relationships between the items or nodes identified were all positive and directionally consistent with the latent construct. The nodes clustered closely within a single coherent component, supporting the results of Exploratory Graph Analysis (EGA).

3.3. Network structure description analysis

Estimation of Node Predictability

Table 1: Node Predictability

S.No.	Item	R^2
1	VOE1	0.296
2	VOE 2	0.416
3	VOE 3	0.342
4	VOE 4	0.293
5	VOE 5	0.416
6	VOE 6	0.284
7	VOE 7	0.293
8	VOE 8	0.220
9	VOE 9	0.344
10	VOE 10	0.281
11	VOE 11	0.277
12	VOE 12	0.294

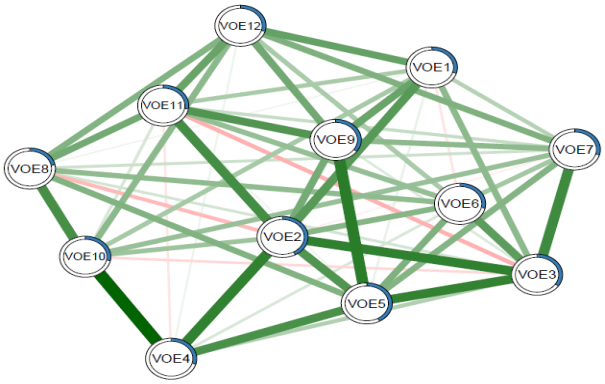

Fig. 3: Node Predictability Plot of the Vocational Outcome Expectations Scale Network.

Node predictability measures the extent of variance in a node that is explained by all the other nodes surrounding it, in terms of the estimand R2. Nodes 2 and 5 emerge as the most important elements in the network with 41.6% of their variance explained by the nodes surrounding them, as shown in Table 1 numerically and in fig.3 graphically. Node 8 is the weakest element of the network, with 22.0% of its variance explained by the nodes surrounding it.

3.4. Estimation of centrality indices

The characteristics of the network structure are described with the help of the estimands, like Centrality indices like strength, closeness, betweenness and expected influence are graphically shown below:

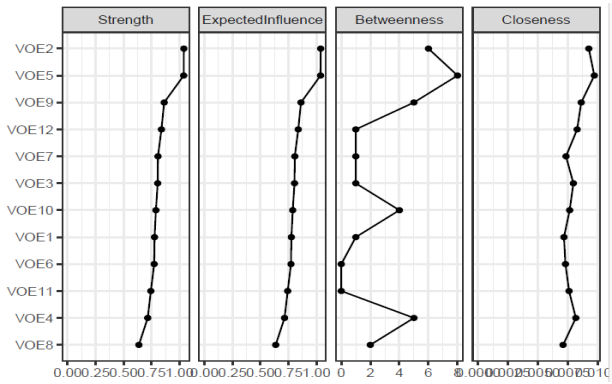

Fig. 4: Centrality Indices Plot of the Vocational Outcome Expectations Construct.

As mentioned in the node predictability table, nodes 2 and 5 are the strongest elements of the network with respect to their strength and expected influence over other nodes with which both nodes are directly connected. These two nodes are also the vital elements of the network when indirect connections between the nodes inis seen through closeness estimation. Node 5 is an important element that comes between the connections of many other nodes in the network.

3.5. Estimation of ordinal confirmatory analysis

Table 2: Network Loadings of the Vocational Outcome Expectations Network

S.No.	Node	Loading
1	VOE1	0.65
2	VOE 2	0.74
3	VOE 3	0.63
4	VOE 4	0.6
5	VOE 5	0.73
6	VOE 6	0.63
7	VOE 7	0.64
8	VOE 8	0.56
9	VOE 9	0.69
10	VOE 10	0.62
11	VOE 11	0.62
12	VOE 12	0.66

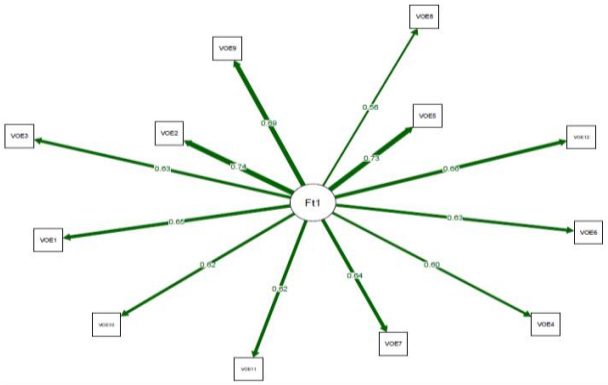

Fig. 5: Network Loadings Plot of the Vocational Outcomes Expectations Scale.

Table 3: Goodness of Fit Estimation based on Network Loadings

S.No.	Estimand for df=54.0	Benchmark of the Estimand	Standard ML-based Estimate	Robust WLSMV-based Estimate	Remark on Goodness of Fit
1	CFI	0.95	0.990	0.901	Good
2	TLI	0.95	0.987	0.87	Acceptable
3	RMSEA	0.08	0.051	0.094	Good
4	SRMR	0.05	0.054	0.042	Acceptable

The goodness of fit estimates of the network, when the data is assumed to be of interval type, is considered under the maximum likelihood (ML) estimator, are excellent with CFI=0.990, TFI=0.987, RMSEA=0.051, and SRMR=0.054. But, the data obtained from Likert point scales are of an ordinal data type and hence required the weighted least square mean and variance adjusted (WLSMV) estimator for conducting the confirmatory analysis of the network. In this context, for a degree of freedom 54.0, the CFI.robust = 0.901, TFI.robust=0.87, RMSEA.robust=0.042, and SRMR_bentler=0.094. While the degree of freedom df independent estimates of CFI.robust

and SRMR_bentler are acceptable, the df dependent TLI.robust and RMSEA.robust estimates are slightly off-track. Such disagreements are common when the degree of freedom df is low at 54 (Xia and Yang, 2019) and the estimator is WLSMV for ordinal data. Also, both TLI and RMSEA are sensitive to model complexity, apart from being sensitive to a low degree of freedom. Overall, the network structure's validity is confirmed by the ordinal empirical data

3.6. Network structure stability analysis

Estimation of the Structural Consistency of the Network Nodes:

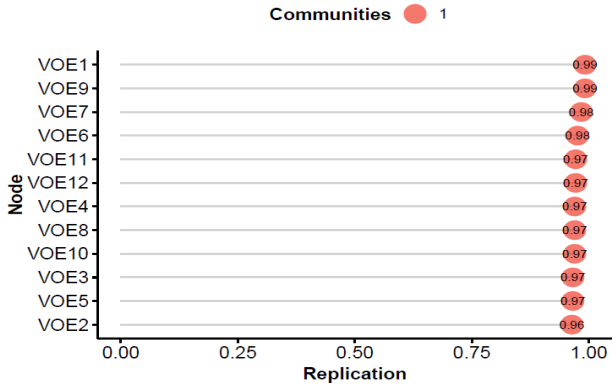

Fig. 6: Structural Consistency of the Vocational Outcome Expectations Network Nodes.

All nodes strongly loaded on the vocational outcome expectations cluster retained their intactness when compared in the 500 iterated bootstrapped samples. Overall, the structural consistency is estimated to be 0.938. It implies that out of the total 500 bootstrappings conducted, the nodes of the network formed a single cluster nearly 470 times, showing 93.8% consistency in the structure. Only 25 times, or 0.05%, did the nodes display a two-cluster structure, and only 6 times did the nodes form a three-cluster network structure. While nodes 1 and 9 loaded 99% of the time on the network, node 2 loaded the least, 96% of the time on the single clustered network, indicating strong structural stability of the network node-wise. Bootstrapping is a technique that involves the generation of multiple datasets by randomly reordering the rows of the original input data provided by the researcher (Efron, 1979) for mimicking data multiplicity.

3.7. Estimation of the network's edge-weights accuracy

The accuracy of the ordering of the edges of the network for a 95% confidence interval obtained through the comparison of these orderings in the sample and bootstrapped data is graphically shown below:

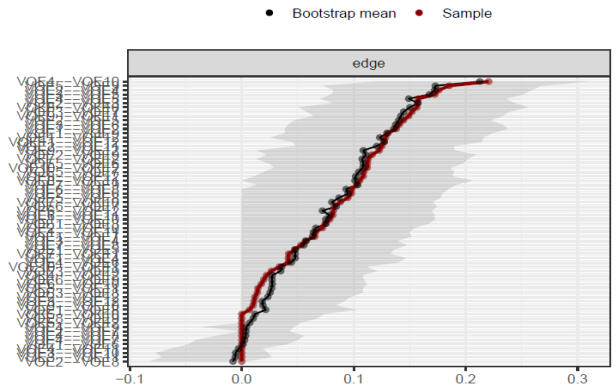

Fig. 7: Edge Weight Accuracy Confidence Interval Plot of the Vocational Outcome Expectations Construct.

From Figure 7, we observe that the lower bound of the confidence interval is -0.1 and its upper bound is 0.1, and hence the value zero is within this interval, indicating a non-significant result obtained from the edge weight accuracy estimation exercise. This non-significant result indicates that there is not much difference between the ordering of the edges, in decreasing order of their strength, obtained from the sample data and the bootstrapped (Efron, 1979) data. Hence, the ordering of these edges in the network can be expected to be replicable in future studies. The edge connecting node 4 with node 10 is the strongest in the network. Node 2and node 8formthe the weakest edge of the network.

3.8. Estimation of correlation-stability CS coefficient of the network

The stability of the network can be graphically and quantitatively studied through the correlation stability plot and the Correlation-stability CS coefficient, as discussed below:

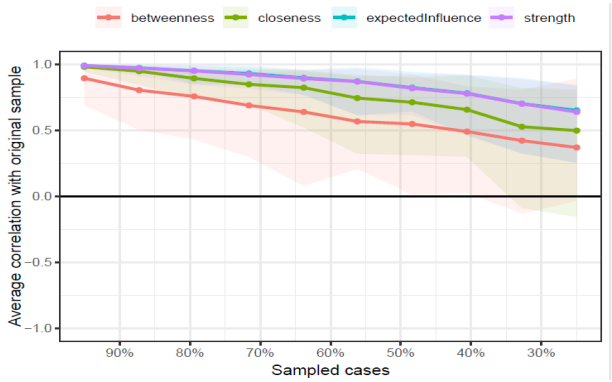

Fig. 8: Correlation Stability Plot of the Vocational Outcome Expectations Construct.

There is a steady decline in the correlation between the network structure obtained for complete data, from 525 sample subjects (100% cases), and the structure of the network obtained on reducing the sample size by 10% successively, computed under the "case-dropping" technique, since the obtained CS-coefficient is 0.362, which is however above the minimum acceptable benchmark of 0.25-0.5 (Epskamp and Fried, 2018), indicating an acceptable estimation of the entire network's stability.

4. Discussion

The revised VOE scale (McWhirter et al., 2000; Metheny & McWhirter, 2013), comprising of four-point Likert scale response categories, was extended to the standard five-point Likert scale categories through the inclusion of the neutral option in the scale. The scale was validated using Network Psychometrics (Golino &Epskamp, 2016; Golino & Demetriou, 2017), an approach that is superior to the traditional psychological scale validation approaches of Exploratory factor analysis, Confirmatory factor analysis, and Cronbach's alpha estimation for reliability. The adopted approach is also appropriate considering the ordinal data type scores obtained from Likert scale-based questionnaires used for survey-based cross-sectional descriptive research design studies require polychoric correlation and WLSMV estimator, instead of the Pearson Product-Moment correlations and maximum likelihood (ML) estimator for conducting exploratory, confirmatory, and reliability analysis (Xia & Yang, 2018; Christensen et al., 2020).

By increasing the response category of the scale through data granularity, the measurement sensitivity of vocational outcome expectation in the targeted population is improved. Such exercises are taken up relatively less frequently and can contribute to better measurement of the variable, not only in the context of the studied sample but also while administering the tool in secondary school adolescents across India. It is expected that this development can further the research of applied career psychology among teaching practitioners. Measurement of vocational outcome expectations in secondary school students, specific to Science, Technology, Engineering, and Mathematics (STEM) related careers can have vital educational implications, paving the way for school-industry cooperation in the near future, which can improve the quality of STEM education in the country in general.

The scale was originally developed for the United States sophomores (McWhirter et al., 2000) and later revised to be administered to college students (Metheny & McWhirter, 2013). The present study not only validated the scale for a homogeneous population of secondary school students, but also proved the exercise of adding new items to the original scale, based on Bandura's (1986) concept of outcome expectations, to be valid by obtaining a single cluster network structure of the construct, which also indicates the seamless integration of the revised scale's items, specific to outcomes related to the career decision making process, with the original six items of the scale, thus forming a system of dynamically interacting components. Extension of the validity of the scale on a completely fresh population in a different culture improves the ecological validity of the scale, indicating another contribution in applied career psychology.

The scale's factor structure was validated on Turkish undergraduates (Isik, 2014) and Latino undergraduates of the United States (Vela et al., 2018) as well. In each of these studies, the scale was found to be unidimensional, though estimated using the traditional approaches of scale validation in its four-point Likert scale response format. The scale in the form of a network structure is also estimated to be unidimensional or single-clustered. All estimates of the network describing its characteristics and stability are found to be robust enough to report improvement in the overall psychometrics of the revised vocational outcome expectations scale. According to Qian et al. (2025), network psychometrics has been applied in several disciplines like social psychology (Dalege et al., 2016), personality psychology (Aunger et al., 2025), mathematics education (Stella, 2022), science education (Biswal and Chakraborty, 2025), and psychopathology (Briganti et al., 2024; Ramos-vera et al., 2023). However, its usage was found to be relatively less in fields like marketing, creativity, entrepreneurship, and youth development, since the details of this approach are not widely known to researchers. The present study extended the application of network psychometrics to validate a tool of critical career psychology variables on youth and established the unidimensional structure of the construct using a robust approach, hence suggesting a development made in computational psychometrics and data science, especially using open software like R/RStudio.

According to social cognitive career theory (SCCT; Lent, Brown, & Hackett, 1994, 2000), the vocational outcome expectations are a cognitive variable that provides the basis for the formation of career interests and goals in adolescents. Its revised scale in the present form emerges as a robust instrument to measure this vital career development variable, suitable for administration on Indian secondary school students, showing improved psychometrics in its five-point Likert scale version. The new version is expected to capture finer distinctions in the subjects' responses to the statements of vocational outcome expectations, enhance the overall precision of the scale, and increase the total variance explained of the construct.

With its improved psychometric robustness, the scale can now be employed to conduct latent profile analysis studies to categorize the secondary school students, belonging to diverse cultures and boards, into homogeneous groups based on their vocational outcome expectations scores more accurately, allowing for the development of effective and tailored interventions to promote it at the school level. Such exercises can not only streamline the career or vocational selection of young adolescents but also place the school-industry partnership on a scientific footing.

Moreover, the latest version of the scale is expected to reduce any possibility of displaying ceiling or floor effects (McHorney & Tarlov, 1995) whenever it is administered in any study with a sample size of more than 50. When the data collected from a psychological scale shows the existence of these effects, it means that the scale does have extreme items. The extreme items in a scale help in the identification of subjects with low or high scores of any construct measured. Lack of such items in the scale also indicates its poor content validity. When this effect is found in any study, it indicates that the existing items of the measuring scale are not capable of separating subjects belonging to the extreme groups of the construct, reducing the scale's reliability as well. These effects have a benchmark of 15 %. If the extreme scores of the subjects are more than the mentioned benchmark, these effects are said to exist in a study (Terwee et al., 2007).

4.1. Limitations and future suggestions

Though the sample size was moderate, the data were collected from the sample subjects who are culturally distinct and belong to a geographically isolated north-eastern state of India. This aspect of the study limits national representativeness owing to cultural diversities prevailing in different regions of the country. Future studies must replicate the validation exercise for secondary school students from other states of the country and also belonging to other school boards, and extend the scale's applicability to the STEM careers context. Data was collected purely using the questionnaire instrument, which is well documented in the literature to introduce social desirability and subjective bias (Lu, Li, & Li, 2025). Future studies can adopt a mixed-method design and incorporate interviews and classroom observations to gain further insights into the construct.

5. Conclusion

The present study improved the psychometric properties of the revised vocational outcome expectations scale by increasing its response categories through the inclusion of a neutral option. It also validated the displayed the superiority of the network psychometrics approach in validating psychological scales with ordinal data type scores. The reported advancement is expected to make the process of career/vocational selection more scientific and objective at the secondary school level.

Funding Statement

The authors did not receive any funding for this study.

Conflict of Interest Disclosure

The authors have no conflict of interest to declare.

Ethical Approval

Permission for data collection from secondary schools was approved by the Director of Secondary Board Education, Tripura state. The Institutional Ethics Committee (IEC) of Lovely Professional University approved the work through its reference number LPU/IEC-LPU/2024/2/19.

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

References

[1] Aunger, R., Gallyamova, A., & Grigoryev, D. (2025). Network psychometric-based identification and structural analysis of a set of evolved human motives, *Personality and Individual Differences*, 233, 112921, ISSN 0191-8869, https://doi.org/10.1016/j.paid.2024.112921.
[2] Ali, S. R., McWhirter, E. H., & Chronister, K. M. (2005). Self-efficacy and vocational outcome expectations for adolescents of lower socioeconomic status: A pilot study. *Journal of Career Assessment*, 13, 40-58. https://doi.org/10.1177/1069072704270273.
[3] Alwin, D. F., Baumgartner, E. M., & Beattie, B. A. (2018). "Number of Response Categories and Reliability in Attitude Measurement." *Journal of Survey Statistics and Methodology*, 6(2), pp. 212-239.https://doi.org/10.1093/jssam/smx025.
[4] Bandura, A., & National Inst of Mental Health. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall, Inc.
[5] Briganti G, Scutari M, Epskamp S, Borsboom D, Hoekstra RHA, Golino HF, Christensen AP, Morvan Y, Ebrahimi OV, Costantini G, Heeren A, Ron J, Bringmann LF, Huth K, Haslbeck JMB, Isvoranu AM, Marsman M, Blanken T, Gilbert A, Henry TR, Fried EI, McNally RJ. Network analysis: An overview for mental health research. *Int J Methods Psychiatr Res*. 2024 Dec;33(4):e2034. https://doi.org/10.1002/mpr.2034.
[6] Beckstead, J.W. (2014). On measurements and their quality. Paper 4: Verbal anchors and the number of response options in rating scales. *International Journal of Nursing Studies*. 51, 807–814.https://doi.org/10.1016/j.ijnurstu.2013.09.004.
[7] Borsboom, D., Deserno, M.K., Rhemtulla, M., Epskamp, S., Fried, E.I., McNally, R.J., Robinaugh, D.J., Perugini, M., Dalege, J., Costantini, G., Isvoranu, A, Wysocki, A.C., van Borkulo, C. D., van Bork, R., & Waldrop, L.J.(2021). Network analysis of multivariate data in psychological science. *Nature Reviews Methods Primers*. 1, 58 (2021). https://doi.org/10.1038/s43586-021-00055-w.
[8] Biswal, S. & Chakraborty, R. (2025). Validation of Science Career Commitment Model for Secondary School Students: Role of Self-Efficacy, Motivation, Engagement and Identity through Network Analysis, *Journal of Applied Bioanalysis*, 11(3), p. 34-43. https://doi.org/10.53555/jab.v11i3.218.

[9] Chen, C., Lee, S.Y., & Stevenson, H.W. (1995). Response style and cross-cultural comparisons of rating scales among East Asian and North American students. *Psychol. Sci*., 6, 170–175.https://doi.org/10.1111/j.1467-9280.1995.tb00327.x.

[10] Costantini, G., Epskamp, S., Borsboom, D., Perugini, M., Mõttus, R., Waldorp, L. J., & Cramer, A. O. J. (2014). State of the aRt personality research: A tutorial on network analysis of personality data in R. *Journal of Research in Personality*. https://doi.org/10.1016/j.jrp.2014.07.003.

[11] Christensen, A. P., Golino, H., & Silvia, P. J. (2020). A Psychometric Network Perspective on the Validity and Validation of Personality Trait Questionnaires. *European Journal of Personality*. https://doi.org/10.1002/per.2265.

[12] Dalege, J., Borsboom, D., Van Harreveld, F., Van den Berg, H., Conner, M., & Van der Maas, H. L. (2016). Toward a formalized account of attitudes: The Causal Attitude Network (CAN) model. *Psychometric Review*, 123(1), 2.https://doi.org/10.1037/a0039802.

[13] Economic Review of Tripura Report 2023-24, Directorate of Economics and Statistics, Government of Tripura, Agartala, https://ecostat.tripura.gov.in.

[14] Efron, B. (1979). "Bootstrap Methods: Another Look at the Jackknife." *Ann. Statist*. 7 (1) 1 – 26. https://doi.org/10.1214/aos/1176344552.

[15] Epskamp, S., & Fried, E. I. (2018). A tutorial on regularized partial correlation networks. *Psychological Methods*, 23(4), 617–634. https://doi.org/10.1037/met0000167.

[16] Efron, B. (1979). Bootstrap methods: another look at the jackknife. *The Annals of Statistics*, 7(1), 1–26.https://doi.org/10.1214/aos/1176344552.

[17] Fouad, N. A.,& Guillen, A. (2006). Outcome expectations: Looking to the past and potential future. *Journal of Career Assessment*, 14, 130-142.https://doi.org/10.1177/1069072705281370.

[18] Finn, J. A., Ben-Porath, Y. S., &Tellegen, A. (2015). "Dichotomous Versus Polytomous Response Options in Psychopathology Assessment: Method or Meaningful Variance?" *Psychological Assessment*, 27(1), pp. 184-193.https://doi.org/10.1037/pas0000044.

[19] Garretsen, H., Stoker, J. I., Soudis, D., Martin, R., &Rentfrow, J. (2019). The relevance of personality traits for urban economic growth: making space for psychological factors.*Journal of Economic Geography*, 19(3), 541-565. https://doi.org/10.1093/jeg/lby025.

[20] Golino, H.F, Epskamp, S. (2016). Exploratory graph analysis: A new approach for estimating the number of dimensions in psychological research. *PLoS ONE*, 12(6): e0174035. https://doi.org/10.1371/journal.pone.0174035.

[21] Golino, H.F., &Demetriou, A., (2017). Estimating the dimensionality of intelligence like data using Exploratory Graph Analysis, *Intelligence*, https://doi.org/10.1016/j.intell.2017.02.007.

[22] Henry, T.R. & Ye, A. (2024). The effects of omitted variables and measurement error on cross sectional network psychometrics models, *Advances in Psychology*, https://doi.org/10.56296/aip00011.

[23] Isik, E. (2014). Psychometric Properties of Vocational Outcome Expectations Scale inTurkishUndergraduate Students. 3rd Internatonal Counseling and Education Conference, ICEC.

[24] Johal, S. K., &Rhemtulla, M. (2023). Comparing estimation methods for psychometric networks with ordinal data. *Psychological Methods*, 28(6), 1251–1272. https://doi.org/10.1037/met0000449.

[25] Koo M, &Yang S-W. (2025). Likert-Type Scale. *Encyclopedia*. 5(1):18. https://doi.org/10.3390/encyclopedia5010018.

[26] Kankaraš, M., Capecchi, S. (2025). Neither agree nor disagree: use and misuse of the neutral response category in Likert-type scales. *Metron,* 83, 111–140 (2025). https://doi.org/10.1007/s40300-024-00276-5.

[27] Kulas, J. T., Stachowski, A. A., & Haynes, B. A. (2008)."Middle Response Functioning in LikertResponses to Personality Items." *Journal of Business and Psychology*, 22(3), pp. 251-259.https://doi.org/10.1007/s10869-008-9064-2.

[28] Lent, R. W., Brown, S. D., & Hackett, G. (1994). Toward a unifying social cognitive theory of career and academic interest, choice, and performance. *Journal of Vocational Behavior*, 45(1), 79–122. https://doi.org/10.1006/jvbe.1994.1027.

[29] Lent, R. W., Brown, S. D., & Hackett, G. (2000). Contextual supports and barriers to career choice: A social cognitive analysis. *Journal of Counseling Psychology*, 47, 36–49.https://doi.org/10.1037/0022-0167.47.1.36.

[30] Li, C.H.,(2016). Confirmatory factor analysis with ordinal data: Comparing robust maximum likelihood and diagonally weighted least squares. *Behavior Research Methods*, 48, 936–949. https://doi.org/10.3758/s13428-015-0619-7.

[31] Lu, H., Li, X., & Li, K. (2025). Adaptation and Validation of the Scale for Chinese Preschool Teachers' Self-Efficacy (SCPTSE): Based on Classical Test Theory and Item Response Theory. *Behavioral Sciences*, 15(6), 741. https://doi.org/10.3390/bs15060741.

[32] Lee, J., &Paek, I. (2014). "In Search of the Optimal Number of Response Categories in a Rating Scale." *Journal of Psychoeducational Assessment*, 32(7), pp. 663-673.https://doi.org/10.1177/0734282914522200.

[33] Lozano, L. M., García-Cueto, E., &Muñiz, J. (2008). "Effect of the Number of Response Categories on the Reliability and Validity of Rating Scales." *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences*, 4(2), pp. 73-79.https://doi.org/10.1027/1614-2241.4.2.73.

[34] McWhirter, E. H., Rasheed, S. & Crothers, M. (2000). The effects of high school career education on social-cognitive variables. *Journal of Counseling Psychology*, 47, 330-341. https://doi.org/10.1037/0022-0167.47.3.330.

[35] Metheny, J. &McWhirter, E. H. (2013). Contributions of social status and family support to college students' career decision self-efficacy and outcome expectations. *Journal of Career Assessment*, 21, 378–394. https://doi.org/10.1177/1069072712475164.

[36] Stella, M. (2022). Network psychometrics and cognitive network science open new ways for understanding math anxiety as a complex system, *Journal of Complex Networks*, 10(3), cnac012, https://doi.org/10.1093/comnet/cnac012.

[37] Mariano, L.T., Phillips, A., Estes, K., & Kilburn, M.R. (2024a). Should survey likert scales include neutral response categories: Evidence from a randomized school climate survey, Working Paper, RAND Corporation.

[38] Mariano, L.T., Phillips, A., Estes, K., & Kilburn, M.R. (2024b). Examining the inclusion of neutral response categories using an item response theory approach: Analysis of a randomized survey of teachers, Working Paper, RAND Corporation.

[39] Negru-Subtirica, O., & Pop, E. I. (2017). Reciprocal Associations between Educational Identity and Vocational Identity in Adolescence: A Three-wave Longitudinal Investigation. *Journal of Youth and Adolescence*, 47(4), 703–716. https://doi.org/10.1007/s10964-017-0789-y.

[40] Negru-Subtirica, O., Pop, E. I., &Crocetti, E. (2017). Good omens? The intricate relations between educational and vocational identity in adolescence. *European Journal of Developmental Psychology*, 15(1), 83–98. https://doi.org/10.1080/17405629.2017.1313160.

[41] Niles, S. G. & Harris-Bowlsby, J. (2016). *Career development interventions* (5th ed.). Boston, MA: Pearson.

[42] Preston, C. C., & Colman, A. M. (2000). "Optimal number of response categories in rating scales: reliability, validity, discriminating power, and respondent preferences." *ActaPsychologica*, 104(1), pp. 1-15. https://doi.org/10.1016/S0001-6918(99)00050-5.

[43] Qian, M., Wang, X., & Dai, S. (2025). Psychometric Network Analysis and Dimensionality Assessment: A Software Review. *Education Sciences*, 15(5), 555. https://doi.org/10.3390/educsci15050555.

[44] Rentfrow, P. J., Jokela, M., Lamb, M. E. (2015) Regional personality differences in Great Britain. *PLoS One*, 10: e0122245.https://doi.org/10.1371/journal.pone.0122245.

[45] RStudio Team (2020). RStudio: Integrated Development for R. RStudio, PBC, Boston, MA URL http://www.rstudio.com/.

[46] Ramos-Vera, C., Rosa Franco, V., Vallejos Saldarriaga, J., & Serpa Barrientos, A. (2023). Psychometric Networks and Their Implications for the Treatment and Diagnosis of Psychopathologies. *IntechOpen*. https://doi.org/10.5772/intechopen.105404.

[47] Sung, C., & Connor, A. (2017). Social-cognitive predictors of vocational outcomes in transition youth with epilepsy: Application of social cognitive career theory. *Rehabilitation Psychology*, 62(3), 276–289. https://doi.org/10.1037/rep0000161.

[48] Skorikov, V. B., &Vondracek, F. W. (2011). Occupational identity. In S. J. Schwartz, K. Luyckx, & V. L. Vignoles (Eds.), *Handbook of identity theory and research* (pp. 693–714). New York, NY: Springer.https://doi.org/10.1007/978-1-4419-7988-9_29.

[49] Simms, L. J., Zelazny, K., Williams, T. F., & Bernstein, L. (2019). "Does the Number of Response Options Matter? Psychometric Perspectives Using Personality Questionnaire Data." *Psychological Assessment*, 31(4), 557-566.https://doi.org/10.1037/pas0000648.

[50] Smith, T.W. (2010). Surveying across nations and cultures. In Handbook of Survey Research, 2nd ed.; Marsden, P.V., Wright, J.D., Eds.; Emerald Group: Bingley, UK, pp. 733–763.
[51] Tekin, M., Toraman, C. & Kosan, A.M.A. (2024). How many grades of response categories does the commitment to the profession of medicine scale provide the most information?*International Journal of Assessment Tools in Education*, 11(3), 524-536.https://doi.org/10.21449/ijate.1400157.
[52] Terwee, C.B., Bot, S.D., de Boer, M.R., van der Windt, D.A., Knol, D.L., Dekker, J., Bouter, L.M., de Vet, H.C. (2007). Quality criteria were proposed for measurement properties of health status questionnaires. *Journal of Clinical Epidemiology*.60(1):34-42. Epub 2006 Aug 24. PMID: 17161752.https://doi.org/10.1016/j.jclinepi.2006.03.012.
[53] Vela, J. C., Karaman, M. A., Smith, W. D. & Hinojosa, Y. (2018). An examination of the structure of the vocational outcome expectations scale with latina/o students. *UluslararasıTürkçeEdebiyatKültürEğitimDergisi, 7*(4), 2733-2746.https://doi.org/10.7884/teke.4272.
[54] Weng, L. J. (2004). "Impact of the Number of Response Categories and Anchor Labels on Coefficient Alpha and Test-retest Reliability." *Educational and Psychological Measurement*, 64(6), pp. 956-972. https://doi.org/10.1177/0013164404268674.
[55] Xia, Y., & Yang, Y. (2018). The Influence of Number of Categories and Threshold Values on Fit Indices in Structural Equation Modeling with Ordered Categorical Data, *Multivariate Behavioral Research*, 53:5, 731-755, https://doi.org/10.1080/00273171.2018.1480346.
[56] Xia, Y., & Yang, Y. (2019). RMSEA, CFI, and TLI in structural equation modeling with ordered categorical data: The story they tell depends on the estimation methods. *Behavior Research Methods*, 51(1), 409–428. https://doi.org/10.3758/s13428-018-1055-2.
[57] Yeh, C. J. &Borrero, N. E. (2012). Evaluation of a health careers program for Asian American and Pacific Islander high school students. *Journal of Multicultural Counseling and Development*, 40, 227-239.https://doi.org/10.1002/j.2161-1912.2012.00020.x.