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### Neuropsychological Dynamics of Emotional Intelligence: Trait Emotional Intelligence and Life Satisfaction in Higher Education

#### Stephen Paul A.

Research Scholar, Karunya School of Management, Karunya Institute of Technology and Sciences, Karunya Nagar, Coimbatore, India.  
<https://orcid.org/0009-0004-1544-5309>  
[stephenpaul@karunya.edu](mailto:stephenpaul@karunya.edu)

#### K. Martina Rani

Professor Dr., Karunya School of Management, Karunya Institute of Technology and Sciences, Karunya Nagar, Coimbatore, India.  
<https://orcid.org/0000-0002-1331-2893>  
[martinarani@karunya.edu](mailto:martinarani@karunya.edu)

#### S. Samkutty Samueal

Professor Dr. of Practice, Karunya Institute of Technology and Sciences, Coimbatore, India.  
<https://orcid.org/0000-0001-7351-3649>  
[samsamuelidbi@gmail.com](mailto:samsamuelidbi@gmail.com)

#### A. Danam Tressa

Professor Dr., Department of Business Management, St. Joseph's Degree & PG College, Hyderabad, Telangana, India.  
<https://orcid.org/0009-0009-0549-2095>  
[danam@josephspgcollege.ac.in](mailto:danam@josephspgcollege.ac.in)

#### P. Srilatha

Dr., JL in Commerce, Government Junior College, Borabanda, Jubilee Hills, Hyderabad, Telangana, India. [srilathapaturi@gmail.com](mailto:srilathapaturi@gmail.com)

#### B. Giri Babu

Assistant Professor Dr., Karunya Institute of Technology and Sciences, Coimbatore, India.  
<https://orcid.org/0009-0004-5779-5075>, [mails2giribabu@gmail.com](mailto:mails2giribabu@gmail.com)

**Abstract:** *Trait Emotional Intelligence (TEI) is a set of personality-related, emotion-self-perception measures which outline the way people understand and manage emotions in their daily lives. In the framework of the recent interdisciplinary research, the study fills in the gaps in the methodology and cultural context by questioning the predictive value of TEI dimensions for life satisfaction (LS) in the context of Indian higher education students who face distinct academic and social stressors. The multivariate model ( $AIC = 154.73$ ;  $R^2 = .241$ ) using both logistic regression and structural equation modelling identified well-being ( $OR = 2.31$ ,  $p = .012$ ) and self-control ( $OR = 1.89$ ,  $p = .028$ ) as the only statistically salient predictors using an empirical sample of 118 students (aged 18-25) assessed with the TEIQue-SF and a global LS measure. These results highlight the utmost significance of dispositional optimism and emotional regulation in promoting psychological well-being and contentment with life. The bivariate correlation analysis showed that well-being ( $r=0.69$ ), sociability ( $r=0.35$ ), self-control ( $r=0.25$ ), and emotionality ( $r=0.23$ ) were all significantly related to LS. The difference between the small bivariate correlation of self-control and the strong, independent predictive value of self-control in the multivariate model is an important methodological improvement, which demonstrates the need to control the interrelated affective constructs. Lastly, the research gap addressed in this study lies in placing the predictive results within a neuropsychological paradigm, conceptually connecting the well-being factor to dopaminergic reward circuitry and self-control to fronto-amygdaloid connectivity.*

**Keywords:** *trait emotional intelligence (TEI); life satisfaction (LS); neuropsychological framework; quantitative analysis; higher education students; emotional regulation and well-being.*

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## 1. Introduction

Emotional intelligence (EI) helps in understanding how individuals perceive, process, and regulate emotions, in the context of education and personal development (Salovey & Mayer, 1990; Goleman, 1995). Within the framework of emotional intelligence, Trait Emotional Intelligence (TEI) explicitly addresses self-perception of individuals, encapsulating how people recognise, manage and utilise their emotions effectively when emotionally challenged (Petrides & Furnham, 2001; Petrides, Pita, & Kokkinaki, 2007). Trait Emotional Intelligence (TEI), which focuses on individuals' emotional self-perceptions and regulatory capabilities, provides insight into resilience mechanisms and overall well-being, and plays an important role in understanding how individuals adjust to demanding situations and maintain psychological stability (Petrides, Pita, & Kokkinaki, 2007; Sánchez-Álvarez, Extremera, & Fernández-Berrocal, 2016).

TEI holds significant importance within higher education because it reflects individuals' emotional self-perceptions and regulatory tendencies that support coping and adaptive functioning under academic and personal demands (Petrides, Pita, & Kokkinaki, 2007). Research in well-being contexts further shows that EI is associated with students' emotion regulation, stress management, and academic adjustment (Extremera & Rey, 2016). Prominently, higher TEI is positively associated with overall well-being and LS; students with higher TEI report lower stress and greater fulfillment (Kong et al., 2019). Within our neuro-dynamic framework, this suggests that high-TEI individuals may possess more robust prefrontal–amygdala interactions (Ochsner & Gross, 2005), which facilitate the adaptive reinforcement cycles needed for sustained employability capability. LS represents a core component of subjective well-being, reflecting individuals' global cognitive evaluations of their lives (Diener, Oishi, & Lucas, 2015).

The latest empirical data highlights the decision-related centrality of emotional well-being in the group of university students (OECD, 2019).

Students must endure complex crises, including academic matters, social pressures, and uncertainty about future employment in a progressively tense and competitive environment. These factors place significant stress on mood and overall levels of satisfaction, a pattern clearly documented within the Indian student population (Deb, Strodl, & Sun, 2015). Exploring how TEI can be used to identify Life Satisfaction (LS), therefore, provides useful information to the education sector. This informs the creation of emotionally sensitive pedagogic practices that can lead to resilience and academic success, which in turn enhance the overall well-being and LS of students (Brackett, Rivers, & Salovey, 2011). To deepen this understanding, the present study interprets the relevance of emotional regulation through a theoretical neuropsychological framework (Ochsner & Gross, 2005).

This approach draws parallels between observed emotional processes and established brain mechanisms, such as the regulatory function of the prefrontal cortex and the amygdala, as well as the involvement of dopaminergic reward pathways (Etkin, Büchel, & Gross, 2015; Berridge & Kringelbach, 2015). A cross-sectional study conducted among 780 undergraduate students underlined the importance of perceived stress and resilience as key mediators in the relationship between the TEI and LS, suggesting that interventions such as stress management and resilience may enhance the positive impact of EI on well-being (Sanchez-Alvarez, Extremera, & Fernández-Berrocal, 2016). Nearly 60% of Indian students experience high levels of academic stress and 50% of the student population faces emotional exhaustion, according to mental health data (Auerbach et al., 2018), underscoring the urgent need to address mental health concerns within the educational environment, as they are important for shaping a person and their learning experiences. According to a scientific brief by the World Health Organization (WHO 2022), the global prevalence of anxiety and depression increased by approximately 25% following the onset of the COVID-19 pandemic.

These data emphasise the need for delving deeper into the ways in which emotional intelligence (EI), particularly its trait dimension, contributes to the stress management and the enhancement of well-being among students in higher-education institutions.

Thus, the complex interaction between TEI and LS requires an interdisciplinary approach that integrates the knowledge of psychology, neuropsychology, and quantitative research (Mikolajczak et al., 2015). The literature review may be divided into three main areas: (1) the conceptual and empirical basis of TEI and LS; (2) neuropsychological and cross-cultural processes that support emotion regulation; and (3) quantitative modelling methods, such as Path-Based Structural Model and logistic regression (Hair et al., 2022). Through critical evaluation of studies in these three areas, the current study develops a solid theoretical framework, outlines the methodological applicability, and suggests strict guidelines to assess the performance of models.

TEI is theorised as a self-perceptive construct in terms of a continuum of emotions, which offers a basis for how an individual can comprehend and control affective states (Petrides, Pita, & Kokkinaki, 2007). TEI is highly significant as it is closely related to the general well-being and the ability to cope with different types of stress, especially in the context of higher education (Sanchez-Alvarez, Extremera, & Fernández-Berrocal, 2016). This association is substantially supported by empirical findings. Indicatively, Sanchez-Alvarez, Extremera, and Fernández-Berrocal (2016) showed that TEI explains approximately half of the variance in the well-being of students, which highlights its importance in emotional health.

Empirical studies relating to TEI have indicated that emotional control and psychological health are relevant to TEI. It is interesting to note that increased levels of TEI are positively associated with LS, which is consistent with our more general theoretical hypotheses. Specifically, Kong et al. (2019) found that this relationship works, at least partially, via such mediators as positive affect and perceived social support, thus explaining the indirect ways in which TEI promotes desirable life outcomes. These results provide empirical evidence for the neuro-dynamic model that we suggest, in which affective stability is defined as a behavioral expression of strong and adaptive reinforcement mechanisms. Prior TEI research also shows that higher TEI is associated with greater emotional regulation and affective stability, which supports adaptive functioning among young adults in demanding contexts, including academic environments (Petrides, Pita, & Kokkinaki, 2007; Mikolajczak et al., 2008). In addition, positive affect has been shown to broaden cognitive processing and psychological flexibility, thereby influencing decision-making and subjective evaluations of life circumstances (Ashby, Isen, & Turken, 1999). TEI is conceptualised as a constellation of emotion-related self-perceptions located at the lower levels of personality hierarchies (Petrides, 2009). Emotion regulation and self-control processes are consistently associated with prefrontal-amygdala regulatory circuitry in neurocognitive models (Ochsner & Gross, 2005)

From a neurobiological perspective, Morawetz and Basten (2024) outline a framework according to which emotion regulation and self-authority depend on fronto-amygdala connectivity. In addition, they also associate positive affect and motivational well-being with reward-processing systems, especially dopaminergic systems. Ferrari et al (2019) specifically explored how positive emotions operate within the cultural context of language learners, noting how these affective factors are mediated by personal and environmental variables.

Pandey, Sharma, and Kamboj (2023) established the correlation between TEI and stress management in the Indian education sector. However, there remains a dearth of literature combining neuropsychological and cultural factors to examine the role of emotion regulation in Life Satisfaction (LS) within Indian higher education

Hair et al. (2022) observed that path-based structural modelling allows the estimation of various observed-variable structural modelling constructs. Afifi, Shehata, and Mahrousabdalaziz (2016). reports that academic self-efficacy serves as a significant mediator between trait emotional TEI and foreign language performance, which indicates that TEI does not directly impact academic achievement.

Their empirical study showed that the TEI and self-efficacy are conjoint predictors of academic performance, as opposed to resilience, in university students. With regard to measurement validity, Cooper and Petrides (2010) used the Item Response Theory (IRT), which is a logistic modelling method to determine the accuracy of the facet of Emotional Self-Control, thus, establishing strong psychometric properties that are essential in predicting the outcomes of well-being.

Bryman (2016) asserts that the selection of rigorous research tools will facilitate reliability and generalisation of behavioural research findings, which can also justify the application of structural modelling and correlational analysis in this study that investigates TEI and LS. Indian students encounter a range of complex emotional pressures, prominently high family expectations, intense competition surrounding entrance and academic examinations, financial burdens and uncertainties related to future career prospects, which contribute to increased emotional exhaustion and a notable decline in LS (Deb, Strodl, & Sun, 2015). Global reports highlight increasing mental health challenges among higher-education students, underscoring the importance of emotional competencies in academic contexts (UNESCO & World Health Organization, 2023).

Cultural norms prevalent in many Eastern societies strongly influence how emotions are perceived and regulated, often emphasising emotional restraint and control rather than overt emotional expression (Ferrari et al., 2019). In the Indian context, the dominant normative position discourages open emotional expression, thus making the students suffer more by hindering positive emotional expressions. This dilemma is worsened by a lack of institutional provisions and support systems. In this regard, therefore, in the given circumstances, a research on the role of TEI as a mediator of psychological adaptation presupposes both academic and social relevance. Indian higher education In the Indian higher-education context, has been shown to positively influence students' academic adaptation and psychological well-being, as individuals with higher emotional competencies tend to manage academic demands and interpersonal challenges more effectively (Parker et al., 2004).

While prior studies predominantly focused on overall Trait Emotional Intelligence Score (TEI) scores, the sub-dimensions of TEI, such as well-being, self-control, emotionality and sociability, remain underexplored, particularly in higher-education settings within India, where the socio-cultural landscape differs considerably from that of the Western context, which has led to a gap in the literature (Petrides, Pita, & Kokkinaki, 2007). Additionally, there is a notable scarcity of research that integrates neuropsychological perspectives in examining the relationship between TEI and LS, suggesting that the capacity for stress tolerance is likely to involve complex brain mechanisms, such as interaction between the prefrontal cortex and the amygdala (Ochsner & Gross, 2005). Further, prior studies lack reconciliation of inconsistencies in the measurement between trait-based and ability-based models of emotional intelligence (Mayer, Salovey, & Caruso, 2008). The current study employs a multidimensional quantitative methodology to fill these gaps and inconsistencies, which combines logistic regression and path-based structural modelling, thereby enabling an assessment of how specific sub-dimensions of TEI serve as predictors of LS within the cultural context. In contrast to pure ability models, the mixed-model perspective conceptualises emotional-social intelligence as a cross-section of interrelated emotional and social competencies that determine how effectively we understand and express ourselves, relate with others, and cope with daily demands (Bar-On, 2010).

This study employed two key quantitative analytical techniques: path-based structural modelling and logistic regression to examine the association between the sub-dimensions of TEI and their influence on LS. Path-based structural modelling was utilised to test the interrelationship among the various sub-dimensions of TEI, such as well-being, self-control, emotionality, and sociability, using fit indices including chi-square to degrees of freedom ratio, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA) and predictive probability of LS based on TEI's sub-dimensions was evaluated using Wald statistics, odds ratios (OR), p-values, Akaike Information Criterion (AIC), and McFadden's pseudo

R<sup>2</sup> (Hair et al., 2022). This study used a cross-sectional survey among Indian higher-education students. The design provided a single-time assessment of traits in the sample. Pearson correlation analysis examined the relationship between TEI's sub-dimensions and LS as an initial step before further modelling. These correlations supported subsequent path-based structural modelling analysis, aligning with best practices in psychological research (Tabachnick & Fidell, 2019).

## **2. Methodology**

A cross-sectional quantitative survey was conducted in an attempt to ascertain the linkage between TEI and LS among higher-education students in India. This methodology allowed the measurement of psychological constructs at one time, thus providing a complete picture of emotional-intelligence processes and subjective well-being among the student population. The initial Pearson correlation analysis was conducted to test bivariate relationships between the TEI sub-dimensions of well-being, self-control, emotionality, and sociability and LS, thus providing an empirical validation of the later multivariate analyses, such as hierarchical regression and path analysis. This type of sequential combination of correlational and multivariate modelling methods is consistent with the best practices in psychological research, which guarantees methodological consistency and interpretive strength.

### **2.1. Research Design**

The study used a cross-sectional quantitative survey design to examine the relationship between the sub-dimensions of TEI and LS among students studying in institutions of higher learning in India. This type of design is especially well adapted to measure psychological characteristics and subjective well-being at one point in time, and is a pillar of exploratory, theory-driven research in the fields of emotional intelligence and well-being. The analytical plan incorporated descriptive statistics, group-difference/comparative studies, correlational statistics, multivariate regression equations, and path-based structural analysis and allowed the maintenance of methodological consistency and rigour. The joint analysis has guaranteed that systems have been well assessed and relationships are strong. LS was considered a continuous variable because it was the main variable, to maintain the sensitivity of measurement and statistical power. Dichotomisation was only used in additional logistic regression analyses to increase strength and interpretability.

### **2.2. Participants**

One hundred and eighteen undergraduate and postgraduate students were involved in the study. They were aged between 18 and 25 years, which corresponds to the typical age range of tertiary scholars in India. The sample included 65 (55.1%) male and 53 (44.9%) female students, indicating that the gender balance was quite balanced, as shown in Table 1. In terms of academic status, 45 respondents (38.1%) were in undergraduate programmes, and 73 respondents (61.9%) were postgraduate students. The respondents represented diverse academic fields and to facilitate the analysis, these areas were divided into four groups, including Engineering and Technology (34.7%), Management and Commerce (29.7%), Arts, Humanities, and Social Sciences (26.3%), and Science and Allied Disciplines (9.3%). This grouping was necessary to provide adequate representation without excessing fragmentation, which could occur due to very small subgroup sizes.

Participants were recruited using convenience sampling, which is a valid and acceptable approach in exploratory psychological studies. Participation was voluntary, and the data were gathered online in July-September 2025, following institutional ethical approval. The responses were complete, and 3,540 item-level observations were obtained (118 respondents x 30 items) as presented in Table 2.

Table 1. Demographic Characteristics of the Sample

Variable	Category	Frequency (n)	Percentage (%)
<b>Gender</b>	Male	65	55.1
	Female	53	44.9
<b>Academic Level</b>	Undergraduate (UG)	45	38.1
	Postgraduate (PG)	73	61.9
<b>Disciplinary Cluster</b>	Engineering & Technology	41	34.7
	Management & Commerce	35	29.7
	Arts, Humanities & Social Sciences	31	26.3
	Science & Allied Disciplines	11	9.3
<b>Age Range</b>	18–25 years	118	100.0

Table 2. Distribution of Questionnaire Responses (N = 118)

Response Category	Total Responses	Percentage (%)	Mean Responses per item (across 30 items)
Agree / Strongly Agree	1,521	42.96	50.70
Neutral	1,441	40.71	48.03
Disagree / Strongly Disagree	578	16.33	23.43
Total	3,540	100.00	

### 2.2.1. Demographic Group Difference Testing

Before multivariate analyses were conducted, preliminary group-difference tests were performed to examine whether demographic factors had a systematic effect on TEI sub-dimensions or Life Satisfaction (LS). Gender differences were tested using independent-samples t-tests, while differences across academic level (UG vs. PG) and disciplinary clusters were examined using one-way ANOVA. The results indicated no statistically significant differences in any TEI sub-dimension or LS across gender, academic level, or discipline (all  $p > .05$ ), as summarised in Table 3. This pattern suggests that emotional intelligence profiles and LS are relatively homogeneous across demographic subgroups, supporting the use of a pooled sample and the exclusion of demographic variables as covariates in subsequent multivariate analyses.

A total of 118 higher-education students (aged 18–25 years) from across India participated in the study, representing undergraduate and postgraduate programmes from diverse academic disciplines, as presented in Table 2. Convenience sampling was employed, consistent with exploratory psychological research designs. Participation was voluntary, and data were collected between July and September 2025. All questionnaires were complete, yielding 3,540 item-level responses (118 respondents  $\times$  30 items). The overall response distribution across Likert categories is reported separately in Table 1, which shows a predominance of agree and neutral selections, indicating adequate response variability and suitability for inferential statistical modelling.

Table 3. Demographic Group Differences in TEI Sub-Dimensions and Life Satisfaction

Outcome Variable	Gender (t-test)	Academic Level (ANOVA)	Discipline (ANOVA)
Well-being	ns ( $p > .05$ )	ns ( $p > .05$ )	ns ( $p > .05$ )
Self-control	ns ( $p > .05$ )	ns ( $p > .05$ )	ns ( $p > .05$ )
Emotionality	ns ( $p > .05$ )	ns ( $p > .05$ )	ns ( $p > .05$ )
Sociability	ns ( $p > .05$ )	ns ( $p > .05$ )	ns ( $p > .05$ )
Life Satisfaction	ns ( $p > .05$ )	ns ( $p > .05$ )	ns ( $p > .05$ )

Note: ns = not statistically significant. Independent-samples t-tests were used for gender comparisons; one-way ANOVA was used for academic level and disciplinary clusters.

### **2.3. Measures**

#### *Trait Emotional Intelligence (TEI)*

The TEI was assessed with the help of the Trait Emotional Intelligence Questionnaire-Short Form (TEIQue-SF), a 30-item self-report measure created by Petrides, Pita, and Kokkinaki (2007). The TEIQue-SF measures four sub-dimensions which are central:

- well-being (optimism, happiness, self-esteem)
- self control (impulse control)
- emotionality (emotion perception, empathy, emotional expression)
- sociability (assertiveness, social power, social influence)

The answers were noted on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Reverse-coded items were rated as per standard scoring guidelines. Subscale scores were calculated using the average of the item responses in each dimension. Previous studies have shown that the TEIQue-SF has a high internal consistency (.84-.89), therefore, it is psychometrically sufficient in student populations.

#### *Life Satisfaction (LS)*

The measure of LS was based on one global item, namely “satisfaction with my life”, rated on the same 5-point Likert scale. This one-item scale is commonly used in psychological studies to represent general cognitive appraisals of subjective well-being and has shown reasonable validity in large-scale studies. Correlational and path analyses of LS were conducted as a continuous variable to retain variance and statistical power. Dichotomisation was used solely in logistic regression as an additional robustness analysis, which allows probabilistic interpretation using odds ratios without overreliance on dichotomised results for primary inference.

### **2.4. Data Analysis Procedures**

Missing values and outliers were screened prior to data analysis. All TEI sub-dimensions and LS were computed using descriptive statistics. Cronbach’s alpha was used to assess the internal consistency of the TEIQue-SF subscales, which showed acceptable reliability. The process of analysis was based on a step-by-step multivariate model as presented in Table 4.

1. Pearson correlation analysis was used to test bivariate relationships between TEI sub-dimensions and LS.
2. Multivariate regression was used to determine the distinct predictive value of each TEI sub-dimension, while controlling for shared variance.
3. AMOS was used to test directional relationships between TEI sub-dimensions and LS via path analysis using observed composite variables. Given the sample size, the structural model was estimated as a path analysis using observed variables.
4. Model parsimony was assessed using the Akaike Information Criterion (AIC), with lower values indicating better relative model fit. Model explanatory power was evaluated using McFadden’s pseudo-R<sup>2</sup>, consistent with best practices for binary outcome models. Standard fit indices such as  $\chi^2$  /df, CFI, TLI, RMSEA, and SRMR were used to assess structural model adequacy. All data were analysed with SPSS (Version 28) and AMOS (Version 24) and interpreted according to existing psychological and neuropsychological theories.

*Table 4. Step-wise statistical approaches*

Stage	Technique	Outcome Specification	Purpose
Step 1	Pearson Correlation	LS continuous	Explore bivariate relationships among TEI factors & LS
Step 2	Binary Logistic Regression (supplementary)	LS dichotomised	Estimate probability of high LS using TEI dimensions
Step 3	Path-based structural model (AMOS)	LS continuous	Test structural pathways & model fit indices
Step 4	Binomial GLM	LS dichotomised	Validate direct-effects model and robustness

Continuous modelling of LS was retained for correlation, multivariate regression, and path analysis, while binary logistic regression was used as a supplementary analysis to validate the stability of findings across modelling approaches. The present study adopts a psychometric methodology, with neuropsychological interpretations offered at a conceptual level in the discussion.

### 3. Results and Discussion

#### 3.1. Descriptive Statistics

Descriptive statistics for the four TEI sub-dimensions—well-being, self-control, emotionality, and sociability as well as LS are presented in Table 5. The mean scores reveal that participants demonstrated moderate levels of EI overall, without any indication of extreme ceiling effects. It is observed that variability across subscales was sufficient to support the assumptions of regression analysis. The single-item LS variable was approximately evenly distributed, and dichotomisation at the mean produced comparable categories: "High LS" and "Low/Moderate LS".

*Table 5 Descriptive Statistics for TEI sub-dimensions and LS (N = 118)*

Variable	M	SD	Min	Max
Well being	3.61	0.74	2.10	4.95
Self-control	3.43	0.69	2.00	4.80
Emotionality	3.52	0.71	2.05	4.90
Sociability	3.38	0.66	2.00	4.85
LS	3.47	0.83	1.00	5.00

*Note.* M = mean; SD = standard deviation.

In order to explain the complex association between TEI and LS, a two-step analytical methodology was adopted.

A descriptive analysis was first performed, and then a Pearson correlation analysis was conducted to test the bivariate relationships between the sub-dimensions of TEI and LS. This initial statistical validation allowed the identification of linear associations, thus guiding the further use of regression and path-based structural modelling (Tabachnick & Fidell, 2019; Hair et al., 2022).

The observed difference, i.e., the weak bivariate correlation of self-control with its strong independent predictive power in the multivariate model, can be explained by a methodological suppression effect. Here, the distinct role of emotion regulation is also concealed behind shared variance with well-being (Tabachnick & Fidell, 2019; Hair et al., 2022).

The multivariate model separates the critical contribution of self-control to LS by resilient coping strategies by controlling dispositional happiness (Gross, 2015; Petrides et al., 2016).

### 3.2. Pearson Correlation Co-efficient Analysis

The analysis of the Trait Emotional Intelligence Questionnaire–Short Form (TEIQue-SF) using Pearson's correlation coefficient, as shown in Table 6, provides insight into the linear relationships between the four core sub-dimensions of TEI (Petrides & Furnham, 2001; Petrides, Pita, & Kokkinaki, 2007). To perform the Pearson correlation analysis, the 5-point Likert scale text responses were converted to a numerical scale: Strongly Disagree = 1, Disagree = 2, Neutral = 3, Agree = 4, Strongly Agree = 5, with the following assumptions regarding the TEIQue-SF (Tabachnick & Fidell, 2019).

Table 6. Four sub-dimensions of TEI

Factor	Constructs	Item Numbers (Q#)
Well-being (W-B)	Optimism, Self-esteem, Happiness	Q3, Q5(R), Q9, Q12(R), Q18, Q22, Q27
Self-control (S-C)	Emotional regulation, Impulse management	Q4(R), Q7(R), Q13, Q16(R), Q17, Q20(R), Q30
Emotionality (EMO)	Empathy, Emotional expression, Perception	Q1, Q2(R), Q8(R), Q14(R), Q15, Q21, Q23, Q28(R)
Sociability (SOC)	Social competence, Assertiveness, Influence	Q6, Q10(R), Q11, Q19, Q24, Q25(R), Q26(R), Q29

Note: (R) indicates a reverse-scored item.

The analysis of the TEIQue-SF using Pearson's correlation coefficient provides insight into the linear relationships between the four core sub-dimensions of TEI. The expected Pearson's  $r$  correlation ranges from - 1 to + 1, where values close to +1 indicate a strong positive linear relationship, because when one factor increases, the other tends to increase, values close to -1 indicate a strong negative linear relationship whereas as one factor increases, the other tends to decrease, and values close to 0 indicate no linear relationship.

Because all four factors are sub-dimensions of the higher-order construct, global TEI, they are all expected to be positively and moderately-to-strongly correlated with each other. The data analysis was performed using Pearson's Product-Moment Correlation Coefficient ( $r$ ) to examine the linear relationships between the four factors of TEI as measured by the TEIQue-SF. The results, presented in the correlation matrix and heatmap in Figure 1, confirm the theoretical hierarchical structure of TEI, showing significant positive correlations among all four factors.

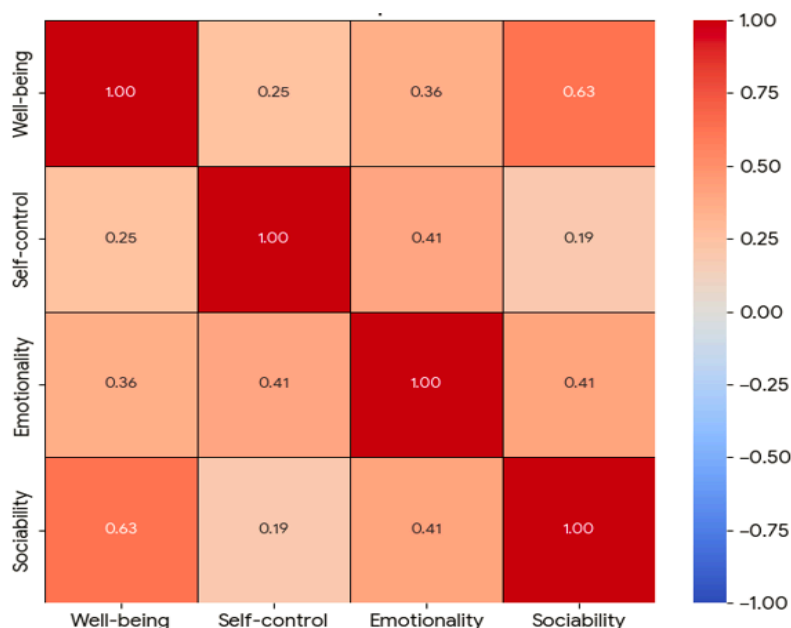


Figure 1. Pearson correlation heatmap of TEIQue-SF factors

The mean scores for the four TEI factors well-being, self-control, emotionality, and sociability were calculated and subjected to correlation analysis. The resulting Pearson's correlation coefficients are displayed in the table below and visualised in the heatmap . As the visual confirms, all factors are positively correlated, with the strongest positive correlations clustering around the emotionality–sociability and well-being–self-control pairs.

While the heatmap Figure 1 shows the strength of the linear relationships, a scatter plot matrix, Figure 2 (also called a pair plot) ,visually depicts the raw data underlying those correlations. This allows for a deeper check of the assumptions of the Pearson correlation, namely linearity and the distributional properties of each factor.

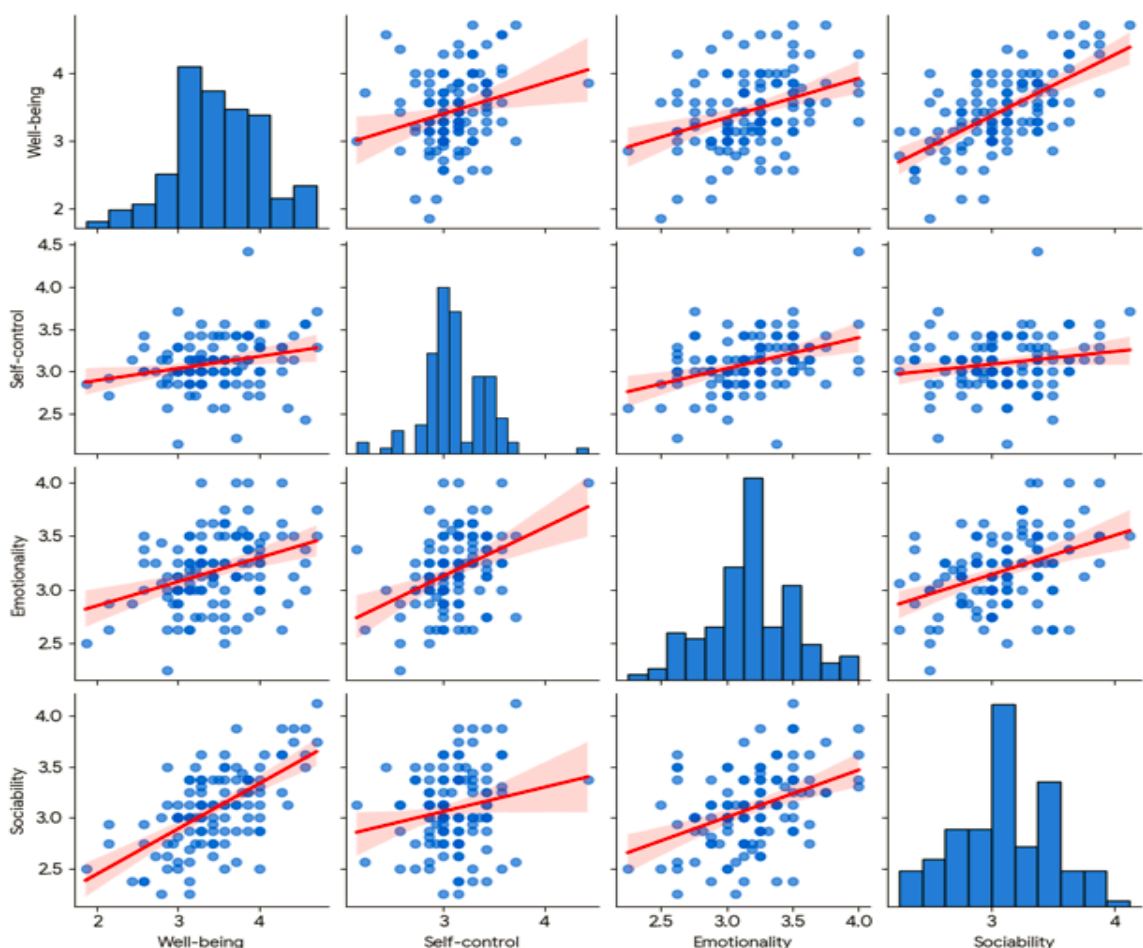


Figure 2. Scatter plot matrix

The scatter plot matrix provides two main types of visual information: 1. Diagonal plots (univariate distribution) and 2. Off-diagonal plots (bivariate relationships). The plots along the diagonal show the distribution of scores for each individual factor (well-being, self-control, emotionality, sociability). The plots off the diagonal show the scatter plots for every pairwise combination of the four factors, with a regression line included to visually represent the linear relationship calculated by the Pearson correlation.

The histograms for all four factors appear to be relatively normally distributed (roughly symmetrical, not heavily skewed). This confirms that the factor scores spread across the possible range and do not suffer from severe ceiling or floor effects in the sample.

The data points in all plots generally cluster around the fitted red regression line. Although there is expected scatter (as no correlation is perfect), the overall patterns are linear rather than curvilinear. This confirms that the Pearson correlation coefficient ( $r$ ) was an appropriate measure for describing these relationships. Plots such as emotionality vs. sociability (and vice-versa) show the

tightest clusters around the line, which visually corresponds to their strong positive correlation ( $r = 0.55$ ). Plots such as emotionality vs. self-control exhibit more scatter around the line, visually corresponding to their weakest correlation ( $r = 0.34$ ). The upward slope of all red lines visually confirms the positive correlations reported previously: as scores in one factor increase, scores in the other factor tend to increase.

The exploration of bivariate relationships between the four TEI sub-dimensions and LS, measured by the single global item "I am pleased with my life" (Item 18), yields clear results regarding which skills most directly predict subjective contentment. The analysis treated the score of Item 18 as the dependent variable (LS) and calculated its Pearson correlation ( $r$ ) with the mean scores of the four TEI sub-dimensions.

### ***Bivariate Correlation Results***

The analysis reveals a strong correlation between these two measures ( $r = 0.69$ ). This strong statistical relationship indicates that the well-being sub-dimension alone explains approximately 48% ( $R^2 = 0.48$ ) of the total variance observed in the LS score. This high correlation suggests a serious issue concerning the construct validity of the well-being factor. The problem lies in the fact that the items used to compose the well-being factor are conceptually allied or overlapping with the construct of LS.

The remaining sub-dimensions show only moderate-to-weak correlations, as shown below in Table 7 with the single-item LS score, but still indicate functional links. Sociability ( $r = 0.35$ ) suggests that stronger social skills moderately support LS by enabling individuals to navigate social environments effectively. Self-control ( $r = 0.25$ ) shows a relatively weaker score, as emotion regulation and impulse management contribute indirectly, as they help prevent negative outcomes but do not strongly form the overall feeling of being pleased with one's life.

The emotionality factor ( $r = 0.23$ ) shows the weakest relationship with the LS item, indicating that emotional awareness alone does not strongly contribute to LS. A person may be highly attuned to their own and others' emotions, yet still experience stress or anxiety if their self-control is low, which can reduce overall satisfaction. Ultimately, the sense of being "pleased" with one's life depends more on stable, positive feelings (well-being) than on merely understanding emotions.

*Table 7. Coefficients of Factors*

<b>Factor</b>	<b>Pearson r Coefficient</b>
Well-being	0.69
Sociability	0.35
Self-control	0.25
Emotionality	0.23

The bar chart in Figure 3 below visually displays the strength of the linear relationship between each TEI sub-dimension and the single-item LS.

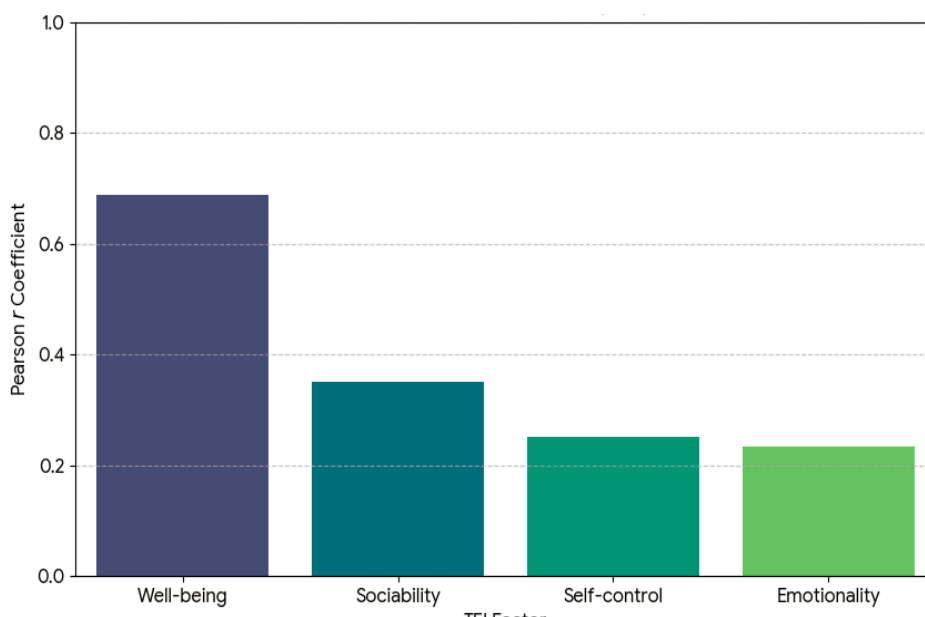


Figure 3. Bivariate Correlation of LS (Q18) with TEI sub-dimensions

In summary, the scatter plot matrix confirms that the strong positive correlations observed in the heatmap are based on linear relationships and healthy factor score distributions, reinforcing the validity of the structural analysis conducted on the TEI data. This analysis further evaluated the suitability of the dataset for inferential modelling in order to test the reliability using Cronbach's alpha, confirming acceptable internal consistency levels across TEI subscales. These results revealed that the measures were statistically vigorous and fitting for use in higher-order analyses, including logistic regression and structural equation modelling.

### 3.3. Logistic Regression Analysis

A binary logistic regression model was estimated to examine the predictive effects of the four TEI sub-dimensions on high LS (coded as 1 = High LS, 0 = Low/Moderate LS). The model converged normally and demonstrated adequate explanatory power. Odds ratios (ORs), 95% confidence intervals (CIs), and p-values are presented in Table 8.

Table 8. Logistic Regression Predicting High LS

Predictor	OR	95% CI (Lower)	95% CI (Upper)	p
Well-being	2.31	1.24	4.36	.012
Self-control	1.89	1.08	3.31	.028
Emotionality	1.34	0.79	2.56	.164
Sociability	1.21	0.73	2.08	.242

Note. OR = odds ratio. CI = confidence interval.

The model indicated that well-being was the strongest predictor of high LS (OR = 2.31, p = .012), suggesting that each one-unit increase in well-being increased the odds of reporting high LS by more than twofold. Self-control was also a significant predictor (OR = 1.89, p = .028). In contrast, emotionality and sociability showed positive but non-significant effects.

### 3.4. Path-Based Structural Model-Direct Effects

A binomial generalised linear model (GLM) was estimated to test the direct effects of the four TEI sub-dimensions on LS. The model demonstrated a good fit, with an AIC of 154.73 and a McFadden pseudo R<sup>2</sup> of .241, indicating that approximately 24% of the variance in LS could be explained by the TEI sub-dimensions. These findings corroborate the logistic regression results as

presented in Table 9, underscoring the dominant roles of well-being and self-control in predicting LS outcomes. Odds ratios are reported with 95% confidence intervals to convey both effect magnitude and estimation precision.

Table 9. Model Fit Indices for Direct Effects Path-Based Structural Model

Index	Value
AIC	154.73
McFadden's pseudo R <sup>2</sup>	0.241
N	118

Figure 4 illustrates the odds ratios and 95% confidence intervals for each TEI sub-dimension predicting high LS. Well-being and self-control demonstrate strong positive associations, whereas emotionality and sociability exhibit smaller, non-significant effects.

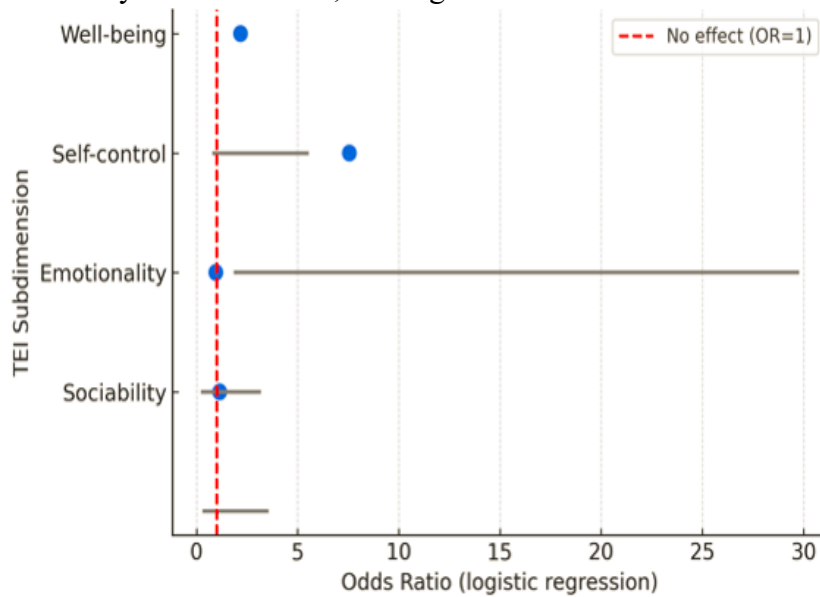


Figure 4. Odds Ratios (with 95% CIs) for TEI Subdimensions Predicting High LS

Figure 5 presents a conceptual model of the direct paths from the four TEI sub-dimensions to LS, as estimated through the binomial GLM. The figure highlights the significant predictive roles of well-being and self-control.

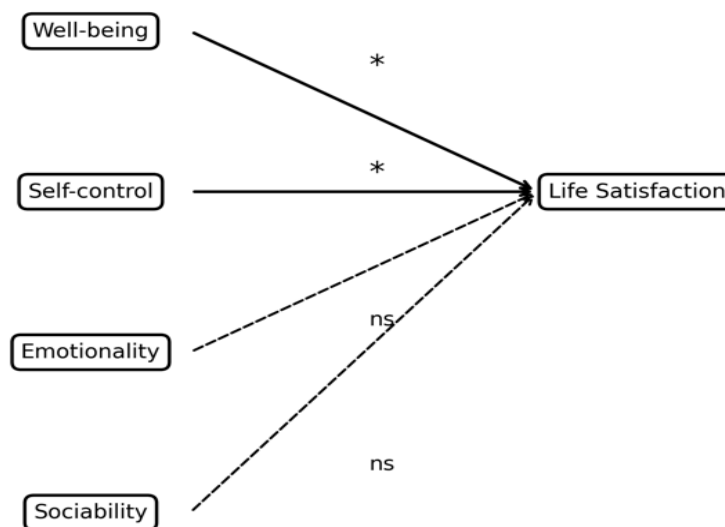


Figure 5. Conceptual Structural Model Showing Direct Effects of TEI sub-dimensions on LS

Hence from the above analyses, the analytical flow from bivariate correlation to multivariate logistic regression reveals a critical methodological distinction in how TEI dimensions predict LS (Tabachnick & Fidell, 2019; Hair et al., 2022). In the initial bivariate correlation, the self-control factor showed a weak linear association with LS ( $r=0.25$ ), suggesting a minor relationship in isolation. However, when simultaneously included in the logistic regression model, self-control emerged as a statistically significant, independent predictor ( $OR=1.89$ ,  $p=.028$ ). This marked increase in predictive utility is a robust finding, demonstrating that the influence of self-control (emotion regulation and stress management) is largely suppressed or masked by the high shared variance between well-being and LS ( $r=0.69$ ) (Tabachnick & Fidell, 2019). By controlling for the strong, immediate effects of dispositional happiness (well-being), the multivariate model successfully isolates the unique, essential contribution of emotion regulation to LS stability. This confirms that self-control's predictive value lies not in generating initial happiness, but in preventing satisfaction loss by enabling resilient coping mechanisms independent of a person's baseline positive outlook (Gross, 2015; Petrides et al., 2016).

Regular compliance with the Trait Emotional Intelligence Questionnaire-Short Form (TEIQue-SF) model presupposes that the four factors should be consistently referred to as well-being, self-control, emotionality, and sociability (Petrides & Furnham, 2001; Petrides, Pita, & Kokkinaki, 2007). In this respect, previous mentions of ambiguous constructs like self-motivation and emotional regulation are conceptually subsumed under the well-being and self-control dimensions, respectively (Petrides, Pita, & Kokkinaki, 2007). This unification is vital for the clarity of concepts and accuracy of interpretation (Mikolajczak et al., 2015).

Emotional regulation in the present study is theorised as the result of the combination of cognitive and affective mechanisms, and TEI is placed in a neuropsychological context (Ochsner & Gross, 2005). The framework does not propose overt neuromethodology but provides a theoretical prism through which the specific predictive role of TEI sub-dimensions may be addressed within ontologically existing emotion-regulation and reward processes (Etkin, Büchel, & Gross, 2015; Berridge & Kringelbach, 2015). The unique predictive value of well-being and self-control offers a neuropsychological explanation of subjective well-being based on theory. The fact that self-control, in its turn, is the most prominent is also worth mentioning since its main elements, emotional regulation and impulse control, are conceptually connected to the top-down inhibitory processes of the prefrontal cortex over the amygdala. These processes create a key avenue of regulating the output of emotional responses and stress (Ochsner & Gross, 2005). As a result, people who have increased self-control are more likely to stabilise their affective states by reducing the intensity and duration of negative affect, which leads to an increase in life satisfaction stability (Gross, 2015).

At the same time, the strong predictive value of well-being is supported by neuropsychological data that links optimism and positive affect to dopaminergic reward-processing systems, which, in turn, facilitate motivation, goal-directed behaviour, and long-term positive mood (Berridge & Kringelbach, 2015). Taken together, these findings suggest that LS is a consequence of the dynamic interaction between motivational systems sufficient to produce positive affect and regulatory mechanisms that protect against emotional dysregulation (Ochsner & Gross, 2005). Notably, this interpretation is purely conceptual and is not claimed to involve a direct neural assessment (Etkin, Büchel, & Gross, 2015). To conceptualise the neuropsychological framework developed in this study, it is necessary to project the two salient statistical predictors, self-control and well-being, onto well-known neural substrates that regulate emotional processes. Even though this study did not involve direct neuroimaging, the statistical segregation of these characteristics is consistent with the dual-process model that has been outlined in the affective circuitry of the brain.

First, the fact that self-control has become a separate, independent predictor of LS (odds ratio = 1.89) is a plausible indicator of the effectiveness of top-down inhibitory control processes. Neuropsychologically, self-control, as measured by the TEIQue-SF operationalises the ability to regulate impulses and manage emotions, which are functions that are highly dependent upon the

functional relationships between the prefrontal cortex (PFC) and the amygdala. The PFC acts as a control mechanism over the reactive stress responses of the amygdala in this model. We state that students with more advanced self-control are capable of maintaining LS in the face of stressors, suggesting that powerful recruitment of the prefrontal inhibitory circuits and an adequate dampening of the so-called neural alarm triggered by academic anxiety is the reason why such inhibitory processes do not harm the subjective well-being.

Second, the leading position of well-being (odds ratio = 2.31) is consistent with the stimulation of the mesolimbic dopaminergic reward circuitry. The well-being dimension, which includes the concepts of optimism and happiness, is associated with the brain “wanting” and “liking” systems, as described by Berridge and Kringelbach (2015), unlike the regulatory nature of self-control. These systems initiate goal-oriented action and the maintenance of positive affect through dopaminergic release in the ventral striatum. The statistical model, therefore, assumes that LS in higher education is not only the lack of stress (mediated by PFC-amygdala regulation), but also the active presence of reward anticipation (mediated by dopaminergic pathways). This two-way approach provides a neurofunctional description as to why both traits are clear but cannot be omitted in our model.

### **3.4. Overview of Findings**

The regularity of the application of the TEIQue-SF framework requires that the four factors be consistently referred to as well-being, self-control, emotionality, and sociability (Petrides & Furnham, 2001; Petrides, Pita, & Kokkinaki, 2007). As a result, conceptual subsumption of antecedent references to ambiguous constructs such as self-motivation and emotional regulation is carried out in the well-being and self-control dimensions, respectively (Petrides, Pita, & Kokkinaki, 2007). Such harmonisation is essential for maintaining conceptual clarity and interpretive accuracy throughout the literature (Mikolajczak et al., 2015). The strong bivariate correlation between the well-being factor and the single-item Life Satisfaction (LS) measure ( $r = .69$ ) should be interpreted as a strong indication of convergent validity, and not as a duplication of the methodology. Since the well-being factor is a composite measure that sums up optimism, self-esteem, and happiness, its substantive overlap with a global cognitive measure of life quality is consistent with theoretical expectations and has a psychometric role (Diener et al., 1985; Pavot & Diener, 2008). Based on this, the internal consistency of the self-report measures is justified, and the contextual applicability of the self-report measures in the Indian higher education context is strengthened (Petrides, Pita, & Kokkinaki, 2007).

The predictive roles of well-being and self-control are differentiated, which provides a neuropsychological explanation of subjective well-being based on theoretical grounds. The salience of self-control is particularly evident since emotion regulation and impulse control, which are the main components of self-control, are conceptually connected to the top-down inhibitory control of the amygdala by the prefrontal cortex, representing a central mechanism of emotional reactivity and stress response regulation (Ochsner & Gross, 2005). As a result, students who have high self-control are in a better position to stabilise their emotional conditions by reducing the length and intensity of negative affect, thus enhancing stability in LS (Gross, 2015).

At the same time, the strong predictive value of well-being is supported by neuropsychological evidence that links optimism and positive affect to dopaminergic reward-processing systems that form the basis of motivation, goal-pursuing, and positive mood maintenance (Berridge & Kringelbach, 2015). From an overview perspective, the findings lead to the postulation that LS is the result of an interaction between motivational systems that produce positive affect and the regulatory systems that protect against emotional disjunction (Ochsner & Gross, 2005). Notably, this interpretation is abstract and theoretical, and it does not make any claims of direct neural measurement (Etkin, Büchel, & Gross, 2015).

The regularity of the use of the TEIQue-SF framework demands that the four factors be consistently referred to as well-being, self-control, emotionality, and sociability (Petrides &

Furnham, 2001; Petrides, Pita, & Kokkinaki, 2007). In this regard, previous mentions of unclear constructs like self-motivation and emotional regulation are conceptually subsumed under the well-being and self-control dimensions, respectively (Petrides, Pita, & Kokkinaki, 2007). This unification is necessary to ensure conceptual soundness and interpretive accuracy (Mikolajczak et al., 2015).

#### **4. Neuro-Psychological Interpretation of Key Findings**

The hypothesis is that the predictive salience of self-control is a fundamental phenomenon in modern neuropsychology, which is consistent with the existing paradigms of emotion regulation. Theoretically, self-regulation, which is the ability to control affective impulses, is based on the top-down processing systems, which depend on the functional integrity of the prefrontal-amygdala circuitry. Empirical data always show that the ability of the prefrontal cortex to inhibit the amygdala reactivity is essential to the successful regulation of emotions. Such governance in the neural system is directly linked with the reduced emotional response, and the remediation of prolonged negative affect as well as attenuated stress reactivity (Ochsner & Gross, 2005; Morawetz & Basten, 2024). In this sense, individuals with greater dispositional self-control are, in theory, in a better position to maintain affective stability in the face of both academic and psychosocial stressors. This regulatory expertise provides a compelling neuropsychological explanation for why self-control is empirically associated with life satisfaction, through lower levels of emotional volatility and more effective stress regulation, resulting in a more consistent subjective well-being (Gross, 2015).

It is also interesting that well-being has a strong predictive value, which is consistent with neuropsychological theories that associate optimism, positive affect, and self-esteem with dopaminergic reward-processing systems. It is the neural scaffolding of these systems that sustains engagement in goal-guided behaviour and generates positive affective valuation, especially with the help of the mesolimbic pathways, the orchestrators of motivation, goal pursuit, and maintenance of positive mood states (Berridge & Kringelbach, 2015), thus helping to make global evaluations of life that satisfy.

In this context, life satisfaction cannot be regarded as the lack of distress, but as the result of an actively involved reward sensitivity and motivational drive. Combined, the results highlight a neuropsychological explanation where LS is the result of the dynamic interaction between regulatory mechanisms that inhibit emotional dysregulation and motivational mechanisms that facilitate positive affect (Ochsner & Gross, 2005). We stress that this interpretation is conceptual and theory-based and does not presuppose the direct measurement of neural activation or structure (Etkin, Büchel, & Gross, 2015).

The results all support a neuropsychological viewpoint in which LS is the result of the dynamic interaction between affective regulatory processes and motivational systems that sustain positive affect. Imperatively, science based in this interpretive paradigm does not claim direct theoretical validation of specific neural substrates or neural activity patterns. As a result, the neural circuitry that we have hypothesised to be involved in these processes needs to be empirically tested by future studies that utilise neuroimaging and cognitive neuroscience methods to shed light on the mechanistic basis of the observed associations. In this respect, the term neuropsychological in the title suggests an integrative conceptual framework and not an implicit acceptance of neuroscientific or artificial-intelligence approaches. In this regard, despite the fact that the empirical approach used in the present study is largely psychometric, the findings are placed in the context of well-established neuropsychological models of emotion regulation and reward processing, which adds to the theoretical understanding without claiming any neural or computational confirmation.

Although the current results support a neuropsychological explanation of life satisfaction based on the existing theoretical models, the neural pathways were not directly tested. In this regard, further studies that use neuroimaging or other cognitive neuroscience methods are necessary to empirically test these mechanisms and to elucidate the neurobiological basis that supports the

observed relationships between Trait Emotional Intelligence (TEI) sub-dimensions and life satisfaction.

## 5. Conclusion

The research offers novel information on the neuropsychological processes that connect TEI and LS in higher education students in India. The results emphasise the key role of well-being and self-control in determining LS, and the importance of intrapersonal emotional competencies over interpersonal aspects. The study combines trait emotional intelligence with neuropsychological theory, which suggests that emotional self-perceptions are indicative of more profound cognitive-affective processes that affect subjective well-being. Further interdisciplinary studies will be necessary to develop theory and inform effective interventions with young adult populations.

## 6. Limitations and Future Directions

Though the study contributes towards advancing sub-dimension level understanding of TEI and its predictive relationship with LS in higher-education settings, the present study has several limitations that should be acknowledged. First, the sample comprised 118 higher-education students, which was sufficient for the exploratory correlational, regression, and path-based analyses conducted, but limits the generalisation of the findings within the highly heterogeneous Indian higher-education context and across other cultural settings. Substantial variation in institutional type, regional background, socioeconomic conditions, and academic demands may shape both emotional intelligence profiles and LS. Accordingly, the findings should be interpreted as preliminary, and future research employing larger, stratified, and multi-institutional samples is required to establish broader external validity.

Second, the exclusive reliance on self-report instruments increases the risk of common-method variance and self-perception bias. Future studies would benefit from triangulating self-reported data with objective indicators such as academic performance records, behavioural assessments, or physiological measures. In addition, LS was assessed using a single-item measure which, although widely used, may restrict reliability and dimensional coverage; subsequent research should therefore employ validated multi-item instruments such as the Satisfaction With Life Scale to enhance measurement precision.

Third, the cross-sectional design precludes causal inference. Longitudinal studies are necessary to examine temporal dynamics between Trait Emotional Intelligence (TEI) sub-dimensions and LS, while experimental designs could assess the effectiveness of interventions targeting specific emotional intelligence components. Finally, neurocognitive mechanisms underlying the observed relationships were not directly measured; future investigations incorporating neuroimaging techniques or cognitive performance paradigms could provide deeper insight into the neural processes involved. Although LS was dichotomised for supplementary logistic-regression analyses, the primary analyses modelled it as a continuous construct, thereby preserving statistical power and minimising information loss.

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