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Comparing Linear Regression to Shrinkage Regression Algorithms using Python: A case study of Internal Shame

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Abstract

Purpose: Internal shame (IS) is a deeply distressing emotional state characterised by avoidance tendencies, diminished self-esteem, and negative self-perception, often accompanied by self-critical thoughts such as self-loathing. It significantly influences an individual's cognitive and emotional processes, shaping self-evaluation and overall functioning. Recent studies have highlighted its prominence as a construct with multifaceted psychological implications, impacted by various psychosocial and emotional factors. This study focuses on examining the determinants of internal shame, including emotional competency, childhood trauma, alexithymia, cognitive flexibility, and distress tolerance, utilising the Explainable Shrinkage Regression Model.

Method: A total of **906** participants (**53.1%** female and **46.9%** male) residing in Tehran were recruited in **2023** through convenience sampling on online platforms. The survey encompassed demographic variables (age and gender)

and psychological assessments, such as measures of childhood trauma, social-emotional competence, internal shame, cognitive flexibility, and distress tolerance. Data analysis employed regression techniques, including Linear Regression, Ridge Regression, Least Absolute Shrinkage and Selection Operator (LASSO), and Elastic Net Shrinkage Regression models. The independent variables included five features: childhood trauma, social-emotional competence, alexithymia, cognitive flexibility, and distress tolerance. The dependent variable was internal shame.
Results: The results indicated that while each model presents its own advantages, Elastic Net regression showed marginally the best performance in prediction of IS having the lowest MSE and highest $\boldsymbol{R^2}$.

Keywords: Internal shame, Regression models, LASSO, Ridge, Elastic Net

1 Introduction

Shame is commonly described as a self-conscious and self-directed moral emotion in which individuals evaluate themselves negatively at a global level rather than focusing on a specific behaviour (Gilbert, 2003; Lear, Lee, Smith, & Luoma, 2022). Experiences of shame are frequently associated with feelings of inadequacy, rejection, helplessness, and a tendency to withdraw from interpersonal interactions (Gilbert, McEwan, Bellew, Mills, & Gale, 2009). In many cases, shame also involves persistent self-criticism and stable negative interpretations of personal worth, which may contribute to enduring emotional distress (Czub, 2013; Duncan & Cacciatore, 2015). Previous literature further distinguishes between internal and external shame. Internal shame refers to negative self-evaluations and perceptions of defectiveness, whereas external shame is related to beliefs about being judged negatively by others (Ferreira, Moura-Ramos, Matos, & Galhardo, 2022; Matos, Pinto-Gouveia, Gilbert, Duarte, & Figueiredo, 2015).

Internal shame has been associated with social withdrawal, persistent self-criticism, impaired self-regulation, and negative self-evaluation processes that may affect broader psychological functioning (Bae, Yoo, & Lee, 2022; Farahani et al., 2023, 2024). Previous findings further suggest that experiences of shame may vary across demographic groups, with some studies reporting higher levels among women and older adults (Aranda, 2015; Ferguson, Eyre, & Ashbaker, 2000; Silfver, 2007; Werbart Törnblom, Werbart, & Rydelius, 2015). Age-related increases in shame have been linked to multiple psychosocial and health-related factors, including reduced autonomy, physical decline, and greater dependence on others in later life (Kashyap, 2022; Wang et al., 2022). Research conducted among elderly populations has additionally shown that both internal and external shame are associated with lower quality of life, psychological

distress, and reduced well-being (Apesoa-Varano, 2019; Crossley & Rockett, 2005; Mantzoukas et al., 2021). Recent theoretical perspectives further emphasize that shame is a dynamic and culturally influenced phenomenon that may evolve across the lifespan and shape psychological well-being in later adulthood (Vanderheiden & Mayer, 2024). Collectively, these findings highlight the importance of supportive interpersonal and healthcare environments when addressing shame-related experiences in older adults.

Psychoanalytic perspectives have long suggested that later life experiences may reactivate unresolved emotional conflicts rooted in earlier developmental periods (Bistoen, Vanheule, & Craps, 2014; Forter, 2007). Within this framework, adverse childhood experiences, including emotional, physical, and psychological abuse, may continue to influence emotional functioning across the lifespan. Dysfunctional attachment relationships characterised by neglect, emotional unavailability, or hostile caregiving environments can interfere with the development of emotional regulation and adaptive psychological capacities in childhood (De Schipper, Tavecchio, & Van IJzendoorn, 2008; O'Connor, Matias, Futh, Tantam, & Scott, 2013). A substantial body of research has further linked childhood trauma to a broad range of difficulties in adulthood, including depression, anxiety, shame, guilt, suicidal ideation, and other maladaptive psychological outcomes (Shahar, Doron, & Szepsenwol, 2015).

Childhood trauma has consistently been identified as an important factor in the development of shame-related experiences (Matos & Pinto-Gouveia, 2010). Early relational environments characterised by neglect, rejection, invalidation, or insufficient emotional support may negatively affect the development of self-worth and emotional security (Dalkılınc, Gultekin, & Guloglu, 2021; Dorahy & Clearwater, 2012; Fowke, Ross, & Ashcroft, 2012). Individuals exposed to such experiences often develop negative self-evaluations, heightened self-criticism, and increased dependence on external approval, which may contribute to persistent feelings of inadequacy and shame (Chan, Hess, Whelton, & Yonge, 2005; Wiechelt & Sales, 2001). In addition, experiences of social exclusion and interpersonal rejection during childhood have been associated with difficulties in identity formation, reduced self-confidence, emotional vulnerability, and withdrawal from social relationships (Platt & Freyd, 2012; Straub, McConnell, & Messman-Moore, 2018; Szentágotai-Tătar & Miu, 2016). These patterns may reinforce long-term cycles of shame, anxiety, and interpersonal sensitivity.

Childhood trauma may also interfere with the development of adaptive emotional regulation processes, reducing an individual's ability to respond effectively to stressful or emotionally demanding situations (Ross, Kaminski, & Herrington, 2019). Such experiences are frequently associated with maladaptive cognitive patterns, including

catastrophising, negative self-appraisal, and persistent self-blame, all of which may contribute to the development of shame-related symptoms (Lee, Scragg, & Turner, 2001; Zhang, Wang, Liu, Wu, & Wang, 2023). Previous studies have further demonstrated that childhood maltreatment is associated with long-term psychological and physical distress, including post-traumatic stress symptoms, internal shame, and emotional difficulties that may persist into adulthood (Healy, Lee, & D'Andrea, 2021; Kealy, Rice, Ogrodniczuk, & Spidel, 2018). Emotional abuse and neglect, in particular, appear to show strong associations with complex trauma-related symptoms and enduring negative self-evaluations (Healy et al., 2021).

Cognitive flexibility, often described as a key component of psychological resilience, refers to the ability to adapt cognitive and behavioural responses to changing environmental demands (Lackner et al., 2022). Individuals with greater cognitive flexibility are generally more capable of shifting perspectives, regulating emotional responses, and employing adaptive coping strategies during stressful experiences (Kupis et al., 2021; Martinez & Dong, 2020). Cognitive flexibility involves the capacity to modify cognitive and behavioural responses in accordance with changing situational demands and emotional experiences (Farahani et al., 2024; Whittingham & Mitchell, 2023). Individuals with higher levels of cognitive flexibility are generally more capable of adapting to stressful circumstances, considering alternative perspectives, and applying more effective coping strategies when facing interpersonal or emotional challenges (Hayatbini, Knauft, & Kalia, 2021; Wu, Chen, & Jen, 2021). This adaptive processing may reduce rigid negative interpretations of adverse experiences and facilitate more balanced responses to stress, thereby decreasing vulnerability to shame-related reactions (LoSavio, Dillon, & Resick, 2017).

Previous research has linked reduced cognitive flexibility to numerous forms of psychological dysfunction, including depression, anxiety, obsessive-compulsive disorder, aggression, Alzheimer's disease, and shame-related symptomatology (Gruner & Pittenger, 2017; Joseph, Moring, & Bira, 2015; Rai, Krohn, & Pahnke, 2020; Rosa-Alcázar et al., 2020; Sala et al., 2011; Yu, Yu, & Lin, 2020). Although its role in broader psychopathology has been widely examined, the relationship between cognitive flexibility and self-conscious emotions such as shame and guilt has only recently received greater empirical attention.

Existing findings suggest that individuals with higher cognitive flexibility are more likely to reinterpret adverse experiences from alternative perspectives, which may reduce persistent feelings of shame and guilt and promote more adaptive emotional responses (Bem, Strelan, & Proeve, 2021). In contrast, lower levels of cognitive flexibility

have been associated with increased shame, rumination, and maladaptive responses following morally distressing experiences (Cenkner, Usman, & Zalta, 2023). Additional evidence indicates that cognitive flexibility, particularly when accompanied by greater self-compassion, may contribute to lower levels of shame as well as reduced symptoms of depression and anxiety (Mohajeri, Alfooneh, & Imani, 2023). Furthermore, reciprocal associations between shame and cognitive flexibility have also been reported, with elevated shame being linked to poorer performance on measures of cognitive flexibility (Bi, Ma, & Tao, 2022).

Distress tolerance is generally defined as an individual's perceived capacity to withstand negative emotional states and continue goal-directed functioning despite psychological discomfort (Conway, Naragon-Gainey, & Harris, 2021). The construct has been conceptualised broadly within the literature, encompassing tolerance of emotional distress, ambiguity, uncertainty, frustration, and other aversive internal experiences (Arici-Ozcan, Cekici, & Arslan, 2019).

Distress tolerance is theoretically linked to self-regulation processes and may be shaped by factors such as attentional control, emotional appraisal, and responses to psychologically or physically distressing experiences (Farahani et al., 2024; Zvolensky, Vujanovic, Bernstein, & Leyro, 2010). Individual differences in emotional processing appear to influence how effectively distress is managed (Carpenter, Sanford, & Hofmann, 2019). Lower levels of distress tolerance have frequently been associated with maladaptive coping patterns, emotional avoidance, and increased psychological vulnerability when individuals encounter stressful or emotionally demanding situations (Jeffries, McLeish, Kraemer, Avallone, & Fleming, 2016; Lass & Winer, 2020). Conversely, greater distress tolerance has been linked to increased resilience and more adaptive management of adverse emotional experiences (Bayer, Robert-McComb, Clopton, & Reich, 2017).

Previous findings also suggest a close relationship between distress tolerance, shame, and broader psychological functioning. Individuals who are more capable of tolerating ambiguity, failure, and emotional discomfort may be better able to manage shame-inducing situations and respond to them more constructively (Farahani et al., 2023). Research involving adults with intellectual disabilities has demonstrated that both internal and external shame are associated with elevated psychological distress, poorer self-esteem, and difficulties in interpersonal functioning (Clapton, Williams, & Jones, 2018). Similar associations have been observed in studies examining eating disorders and trauma-related conditions. For example, psychological distress and shame have been linked to body dissatisfaction and bulimic symptomatology among women (Bayer

et al., 2017), while internal shame and self-blame have also been identified as important predictors of PTSD symptoms, depression, and anxiety among survivors of sexual violence (Bhuptani & Messman, 2023).

Previous research has also demonstrated important associations between childhood maltreatment, shame, psychological distress, and maladaptive behavioural outcomes, including eating-related psychopathology (O'Loghlen, Galligan, & Grant, 2023). Emotional functioning may play an important role in these relationships, given that difficulties in emotional awareness and regulation are frequently linked to adverse psychological outcomes (D. Preece, Becerra, Robinson, Dandy, & Allan, 2018; Ricciardi, Demartini, Fotopoulou, & Edwards, 2015). Some individuals experience substantial challenges in recognising, interpreting, and verbally expressing their emotional states, which may contribute to emotional ambiguity and reduced emotional clarity (Brewer, Cook, & Bird, 2016; De Berardis et al., 2017).

These emotional-processing difficulties are often discussed within the broader framework of alexithymia and related cognitive-emotional disturbances (Myles & Merlo, 2021; D.A. Preece et al., 2020). Alexithymia is generally characterised by impairments in identifying, analysing, and communicating emotions, together with reduced emotional awareness and limited emotional insight (Hobson, Brewer, Catmur, & Bird, 2019). Such deficits may interfere with adaptive psychological functioning and hinder effective emotional regulation.

Alexithymia has consistently been associated with a range of adverse psychological outcomes and difficulties in emotional functioning (Claesson, Birgegard, & Sohlberg, 2007; Farahani et al., 2024). Individuals with elevated alexithymic traits often experience greater vulnerability to negative affective states and difficulties in regulating emotional responses, particularly due to impairments in identifying and communicating emotions (Matos, Pinto-Gouveia, & Duarte, 2012; Vikan, Hassel, Rugset, Johansen, & Moen, 2010). Such emotional-processing deficits have also been recognised as important contributors to shame-related experiences and broader emotional psychopathology (Seidler et al., 2022).

Previous studies have reported significant associations between alexithymia, shame, guilt, and social anxiety (Cheok & Proeve, 2019). Higher levels of alexithymia have additionally been linked to increased shame and guilt, which may contribute to more severe psychological outcomes, including suicidal ideation and impaired emotional regulation (Rice, Kealy, Oliffe, Treeby, & Ogrodniczuk, 2020; Suslow, Donges, Kersting, & Arolt, 2000). Collectively, these findings suggest that difficulties in emotional awareness and regulation may represent an important mechanism underlying the development and maintenance of internal shame.

2 Materials and methods

To evaluate the relative contribution of the predictors of IS, three shrinkage regression algorithms were applied. These procedures help overcome multi-collinearity and overfitting and are extensions of the ordinary least squares approach. The data was analyzed within the Python programming environment, which has been proven very useful for practical application of psychological research (Kovač, Ratković, Farahani, & Watson, 2024). Recent studies have also applied machine learning regression approaches to model internal shame using similar psychological predictors (Kovač, Ratković, Farahani, & Watson, 2025).

Regression analysis stands as a pivotal statistical tool, employed to discern patterns and relationships within the collected data. This approach rigorously analyze how dependent variables change in response to alterations in one or more independent variables, offering insights into both the strength and nature of these associations. By fitting the data to a regression model, it enables to predict trends and forecast outcomes, thereby providing a robust statistical framework for testing our hypotheses.

Ridge regression, also known as Tikhonov regularization, is commonly applied in situations involving multicollinearity among predictor variables (Hoerl & Kennard, 1970). Although ordinary least squares estimates remain unbiased under multicollinearity, increased variance in the estimated coefficients may reduce the stability and reliability of the model. By introducing a penalty parameter, λ, Ridge regression imposes a constraint on the size of the coefficients, thus reducing model complexity and preventing over-fitting. The parameter λ is crucial in this method as it controls the amount of shrinkage, and the larger λ implies the greater shrinkage. Ridge regression is particularly effective in situations with high collinearity, but selecting an appropriate λ is essential for balancing bias and variance (Hastie, Tibshirani, & Friedman, 2001).

LASSO regression, introduced by Tibshirani (1996), is a linear regression method that employs shrinkage. Where Ridge regression shrinks coefficients but never fully sets them to zero, LASSO regression can both shrink coefficients and reduce some to zero, facilitating feature selection in datasets with numerous features. LASSO introduces a penalty term to the loss function, equivalent to the absolute value of the coefficients' magnitude, with the penalty strength governed by a tuning parameter, λ. This characteristic makes it particularly useful for eliminating redundant or less significant variables, thus simplifying the model and enhancing interpretability.

Elastic Net regression, a hybrid of Ridge and LASSO regression, incorporates penalties from both methods to regularize regression models (Zou & Hastie, 2005). This approach is especially beneficial when dealing with multiple correlated features, as

it merges the properties of both, LASSO and Ridge regressions. Elastic Net regression encourages group effects in correlated variables like Ridge regression and maintains the feature selection property of LASSO regression. A central component of Elastic Net regression is the mixing parameter λ, representing the overall regularization strength, which balances the $L1$ and $L2$ regularization. This balance allows the model to combine feature selection and multicollinearity management, making it highly effective for high-dimensional data where LASSO regression might be inconsistent and Ridge regression might not provide sufficient regularization.

2.1 Method

The study sample consisted of 906 participants residing in Tehran during 2023, including 53.1% women and 46.9% men. Participants were recruited through online platforms using a convenience sampling approach. Prior to participation, all individuals received information regarding the aims of the study, study procedures, confidentiality, and the voluntary nature of participation. Electronic informed consent was obtained before data collection began. To protect participant privacy, all responses were anonymized and stored using identification codes rather than personally identifiable information. Data were maintained on secure encrypted servers with restricted access in accordance with established data protection and confidentiality standards. Participants were additionally informed of their right to discontinue participation at any stage without consequences.

The study included demographic variables (age and gender) together with measures of childhood trauma, social-emotional competence, alexithymia, cognitive flexibility, distress tolerance, and internal shame. Shrinkage-based regression methods, including LASSO, Ridge, and Elastic Net regression, were applied to examine predictors of internal shame (IS). Childhood trauma, social-emotional competence, alexithymia, cognitive flexibility, distress tolerance, and age were entered as predictor variables, whereas IS was specified as the dependent variable. For model evaluation, the dataset was randomly divided into training (70%) and testing (30%) subsets.

Model performance was further evaluated using 5-fold cross-validation. Under this procedure, the dataset was partitioned into five subsets of approximately equal size. During each iteration, four subsets were used for model training and the remaining subset was used for validation. The process was repeated until each subset had served once as the validation set, after which performance estimates were averaged across folds to obtain a more stable assessment of model generalisability.

Model accuracy was assessed using the coefficient of determination (R^2). The training score reflected predictive performance on the training dataset, whereas the cross-validation score represented the average R^2 obtained across validation folds. Together, these indicators provided insight into the predictive performance and generalisation capacity of the regression models.

2.2 Measures

2.2.1 Childhood Trauma Questionnaire (CTQ)

The Childhood Trauma Questionnaire (CTQ) (Bernstein et al., 2003) is a self-report measure commonly used to assess experiences of childhood abuse and neglect in both adolescent and adult populations. The instrument contains five subscales assessing Emotional Abuse, Physical Abuse, Sexual Abuse, Emotional Neglect, and Physical Neglect, with each dimension represented by five items. Responses are provided on a 5-point Likert scale ranging from *Never true* (0) to *Very often true* (4), and higher scores reflect greater exposure to childhood maltreatment (Farahani et al., 2023).

The CTQ consists of 28 items in total, including 25 items assessing abuse and neglect experiences and an additional 3 items intended to identify potential minimization or denial of childhood adversity. Previous research reported satisfactory psychometric properties for the instrument, with Cronbach's alpha coefficients ranging from 0.78 to 0.95 across the five subscales (Bernstein et al., 2003). Concurrent validity estimates based on therapist evaluations of childhood trauma ranged between 0.59 and 0.78 (Bernstein et al., 2003).

Evidence supporting the reliability of the CTQ has also been reported in Iranian samples. For example, Ebrahimi (2013) found Cronbach's alpha coefficients ranging from 0.81 to 0.98 across the subscales. In the present study, Cronbach's alpha values ranged between 0.83 and 0.89, indicating satisfactory internal consistency.

2.2.2 Social Emotional Competence Questionnaire

The Social Emotional Competence (SEC) questionnaire, originally developed by Zhou and Ee (2012), assesses key dimensions of social and emotional functioning, including self-awareness, social awareness, self-management, relationship management, and responsible decision-making (Farahani et al., 2023; Zhou & Ee, 2012). The instrument contains 25 items rated on a six-point Likert scale ranging from *fully disagree* (1) to *fully agree* (6). Example items include statements such as "if someone is sad, angry, or happy, I know what they are thinking." Previous research has supported the psychometric adequacy of the questionnaire. For example, Emamgholivand, Kadivar, and

Sharifi (2019) reported satisfactory content, face, and criterion validity, together with Cronbach's alpha values above 0.70, indicating acceptable internal consistency. In the present study, the Cronbach's alpha coefficient for the SEC questionnaire was 0.76.

2.2.3 Internal Shame Scale

The Internal Shame Scale (ISS), developed by Cook (1993), is a self-report instrument designed to assess experiences of internal shame and self-evaluative tendencies. The scale consists of 30 items distributed across two dimensions related to shame and self-esteem. Responses are recorded using a five-point Likert scale ranging from *never* (0) to *always* (4). Higher scores reflect greater feelings of inadequacy, inferiority, loneliness, and negative self-evaluation, whereas lower scores are associated with more positive self-perceptions and higher self-confidence.

Previous studies have reported satisfactory psychometric properties for the ISS. Cook (1993) reported Cronbach's alpha coefficients of 0.94 for the shame-related dimension and 0.90 for the self-esteem dimension. In an Iranian validation study, Rajabi and Abbasi (2011) found an overall Cronbach's alpha coefficient of 0.90, with values of 0.89 for men and 0.91 for women. In the current study, Cronbach's alpha coefficients ranged from 0.88 to 0.91, indicating good internal consistency.

2.2.4 Cognitive Flexibility Questionnaire

The Cognitive Flexibility Questionnaire (CFI) is a concise 20-item self-report tool developed by Dennis and Vander Wal (2010) to assess an individual's cognitive flexibility, particularly their ability to challenge and replace dysfunctional thoughts with more adaptive ones (Farahani et al., 2023). Each item is rated on a five-point Likert scale ranging from *strongly disagree* (1) to *strongly agree* (5). The CFI evaluates three dimensions of cognitive flexibility: a) the willingness to perceive difficult situations as manageable; b) the capacity to identify multiple interpretations of life events and human behavior; and c) the ability to generate alternative solutions for challenging circumstances. The CFI is employed in both clinical and non-clinical contexts to monitor progress in cognitive-behavioral therapy aimed at addressing mental health issues (Dennis & Vander Wal, 2010). Its convergent validity with the Martin and Robin Cognitive Flexibility Scale has been reported at 0.75. The scale also demonstrated strong internal consistency, with a Cronbach's alpha coefficient of 0.90 for the total score and 0.87, 0.89, and 0.55 for the subscales. In Iran, the CFI has shown suitable convergent and concurrent factor validity. Unlike the original scale, which yielded two factors, the Persian adaptation identified three distinct factors: perception of

controllability, perception of alternative options, and perception of justification of behavior (Kohandani & Abolmaali Alhosseini, 2017). In this research, Cronbach's alpha coefficients for the CFI ranged between 0.81 and 0.87, confirming its reliability in measuring cognitive flexibility.

2.2.5 Distress Tolerance Scale

The Distress Tolerance Scale (DTS), developed by Simons and Gaher (2005), is a self-report measure designed to assess an individual's perceived ability to tolerate and manage emotional distress. The instrument evaluates several dimensions of distress tolerance, including tolerance of negative emotional states, attentional absorption by distress, cognitive appraisal of emotional discomfort, and behavioural efforts to regulate distress. The scale consists of 15 items grouped into four subscales related to emotional distress tolerance, absorption, appraisal, and regulation.

Responses are recorded on a five-point Likert scale ranging from *strongly disagree* (1) to *strongly agree* (5), with higher scores indicating greater distress tolerance. Previous studies reported Cronbach's alpha coefficients of 0.72, 0.82, 0.78, and 0.70 for the respective subscales, while the overall scale demonstrated an internal consistency coefficient of 0.82. In an Iranian validation study, Azizi (2010) reported a Cronbach's alpha coefficient of 0.67 together with a test–retest reliability coefficient of 0.79. In the present study, Cronbach's alpha values ranged between 0.82 and 0.88, indicating satisfactory reliability.

2.2.6 Toronto Alexithymia Scale

The Persian version of the Toronto Alexithymia Scale (TAS-20) (Bagby, Parker, & Taylor, 1994) was used to assess alexithymic traits. Permission for the use of the TAS-20 in the present study was obtained from the copyright holder. The instrument consists of 20 items rated on a five-point Likert scale ranging from 1 (*completely disagree*) to 5 (*completely agree*). The scale includes three dimensions: Difficulty Identifying Feelings (DIF), Difficulty Describing Feelings (DDF), and Externally Oriented Thinking (EOT). Total alexithymia scores are calculated by summing responses across all subscales.

Previous studies have reported satisfactory psychometric properties for the TAS-20. Tull, Medaglia, and Roemer (2005) reported Cronbach's alpha coefficients of 0.83, 0.77, and 0.73 for the DIF, DDF, and EOT subscales, respectively, with an overall internal consistency coefficient of 0.82. Evidence supporting the reliability of the Persian adaptation has also been reported in Iranian samples, with Cronbach's alpha coefficients

of 0.82, 0.75, and 0.72 for the respective subscales and 0.81 for the total scale (Besharat, 2007). In the current study, Cronbach's alpha coefficients ranged between 0.79 and 0.83.

2.3 Analysis Method

In our research, we employed advanced regression techniques: Ridge, LASSO, and Elastic Net regression to analyze and interpret our data with a high degree of precision. Ridge regression is applied to help mitigate potential multicollinearity in the dataset, contributing to more stable coefficient estimates by introducing a modest penalty on their magnitude. LASSO regression, on the other hand, is instrumental for both variable selection and regularization, aiding in enhancing the model's prediction accuracy and interpretability by shrinking coefficients towards zero. Elastic Net regression, combining the features of both Ridge and LASSO, is deployed to capitalize on their respective strengths, particularly in scenarios where multiple correlated predictors exist. These regression techniques are pivotal in our approach, allowing us to rigorously examine the relationships between the IS and independent variables, and to ensure that our models are both robust and free from overfitting. The severity of the shrinkage in all three models is determined by a shrinkage parameter, the higher the value of the shrinkage parameter the more the regression estimates are reduced nearer to, and in some cases eventually reach, zero.

2.4 Performance Evaluation

To evaluate model performance, four commonly used metrics were considered: Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2).

MSE represents the average squared difference between observed values (y_i) and predicted values ($\widehat{y}_i$), as defined in Equation 1:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2\,. \tag{1}$$

MAE quantifies the average absolute deviation between predicted and observed values:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{y}_i|. \tag{2}$$

MAPE expresses prediction error as a percentage of the observed values:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \widehat{y}_i}{y_i}\right| \times 100\%. \tag{3}$$

The coefficient of determination (R^2) was used to estimate the proportion of variance in internal shame explained by the regression models:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2}, \tag{4}$$

where $\overline{y}$ denotes the mean of the observed values and n represents the total number of observations.

3 Results and Discussion

3.1 Data Summary

Table 1 presents descriptive statistics for all study variables, including the mean, standard deviation (Std), minimum (Min), quartiles (Q1 -Q3), median (Q2), and maximum (Max) values. The analysed predictors included emotional competence (EC), distress tolerance (DIST), cognitive flexibility (CFL), alexithymia (ALEX), and childhood trauma (TRAU), while internal shame (IS) was treated as the outcome variable.

Table 1: Descriptive statistics of the dataset

Metric	**EC**	**DIST**	**CFL**	**ALEX**	**TRAU**	**IS**
Mean	73.85	18.06	70.75	43.32	55.17	78.08
Std	10.08	8.71	10.01	10.58	7.63	13.66
Min	37.00	9.00	10.00	18.00	39.00	51.00
Q1	68.00	12.00	66.00	36.00	51.00	68.00
Q2	75.00	15.50	72.00	43.00	53.00	76.00
Q3	81.00	22.00	77.00	51.00	57.00	86.00
Max	95.00	75.00	91.00	75.00	95.00	118.00

Figure 1 displays the Pearson correlation coefficients between the EC, DIST, CFL, ALEX, TRAU, and the IS values. It illustrates both the strength and direction of the linear relationship between IS values and the evaluated inputs, with coefficients ranging from -1 to $+1$. The Pearson correlation matrix indicates moderate pairwise associations among the independent variables. The highest absolute correlation between predictors is 0.49 (EC and CFL), which does not suggest strong linear dependency. While the

heatmap provides an initial overview of inter-variable relationships, multicollinearity was not inferred solely from pairwise correlations. This implies that we can more confidently assess the individual impact of each variable on the dependent variable IS and that each one contributes distinct information to the model. Hence, there is no need to reduce the number of independent variables to address multicollinearity.

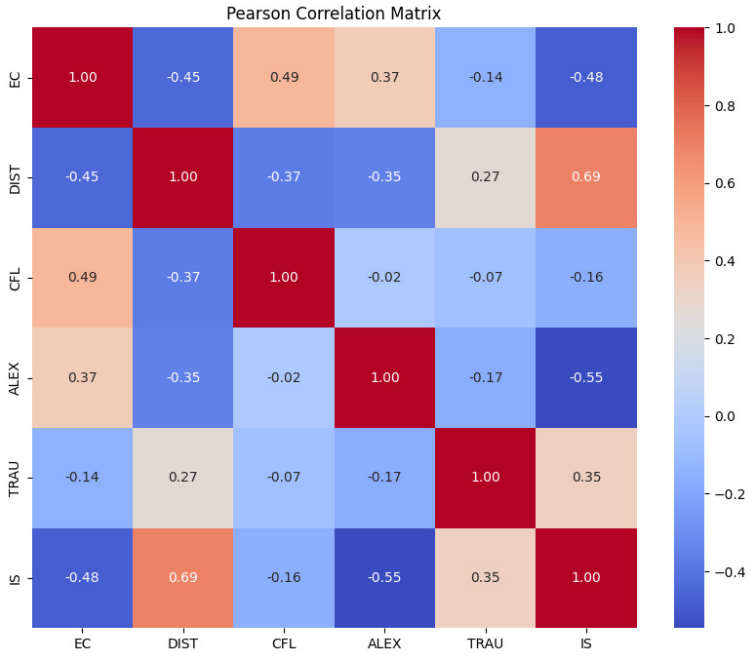


Fig. 1: Pearson correlation values

The correlation matrix supports these findings, showing notable correlations between several pairs of predictors. For instance, there is a strong positive correlation between IS and DIST (0.69), and a moderate negative correlation between IS and ALEX (-0.55). These correlations indicate that changes in one predictor are associated with significant changes in another, which can distort the interpretation of individual predictor effects in a standard regression model.

Prior to model estimation, outliers were identified and removed using the Interquartile Range (IQR) method (Q1 = 0.25 quantile, Q3 = 0.75 quantile, threshold = $1.5\times$ IQR). The regression models were subsequently trained on the filtered dataset.

3.2 Regression Model

The baseline multiple linear regression model was estimated using ordinary least squares (OLS), with EC, DIST, CFL, ALEX, and TRAU entered simultaneously as predictors of IS. The Analysis of Variance (ANOVA) is displayed in Table 2. The overall regression model is highly significant, with an F-value of 221.34 and a P-value of 0.00. All independant variables (EC, DIST, CFL, ALEX, TRAU) are significant in the model, with P-values of 0.00 and high F-values (ranging from 21.25 to 328.19), indicating that each variable significantly contributes to the model. The adjusted sum of squares for each variable indicates the amount of variability in the dependent variable IS that is accounted for by that variable. The adjusted sum of squares is the highest for the predictor DIST (22759).

The model's standard error S, indicating the average distance that the observed values fall from the regression line, is 8.32756. The R^2 value is 63.14%, meaning approximately 63.14% of the variability in the dependent variable can be explained by the model, while the adjusted R^2 is 62.86%, providing a more accurate measure for models with multiple variables. The predicted R^2 of 61.58% suggests that the model predicts new observations with a similar level of accuracy. In summary, the regression model explains a significant portion of the variance in the dependent variable, with each predictor variable contributing significantly and high R^2 values indicate a good fit.

Table 2: Analysis of variance

Source	**DF**	**Adj. Sum of squares**	**Adj. Mean Square**	**F-Value**	**P-Value**
Regression	5	76749	15349.8	221.34	0.00
EC	1	2794.80	2794.80	40.30	0.00
DIST	1	22759.30	22759.30	328.19	0.00
CFL	1	1473.40	1473.40	21.25	0.00
ALEX	1	6164.00	6164.00	88.88	0.00
TRAU	1	2297.40	2297.40	33.13	0.00
Error	646	44799	69.30		
Lack-of-Fit	310	44799	144.50	*	*
Pure Error	336	0.00	0.00		
Total	651	121548			

Summary of the regression analysis is displayed in Table 3. The coefficients in the regression model represent the estimated effects of each predictor on IS. For example, the coefficient for EC is -0.2669, indicating that for each unit increase in EC, IS is expected to decrease by 0.2669 units, assuming other variables are held constant. The standard error (SE) of each coefficient, such as 0.0420 for EC, indicates the precision

of these estimates. The T-Values are test statistics used to determine the significance of each coefficient. Higher absolute values suggest greater significance, and DIST has the greatest significance in the model (18.12). The P-Values are near zero for all predictors, indicating their statistically significant contributions to the model. VIF values, displayed in the last column, are all below 2 implying that there is no significant multicollinearity among the predictors.

The corresponding regression equation is given by Equation 5 showing that the dependent variable IS is predicted based on a linear combination of the variables EC, DIST, CFL, ALEX, and TRAU, along with a constant term.

$$IS = 70.31 - 0.2669EC + 0.8263DIST + 0.1845CFL - 0.3381ALEX + 0.2564TRAU \tag{5}$$

The model shows that IS is influenced positively by DIST, CFL, and TRAU, and negatively by EC and ALEX, with all relationships being statistically significant. A

Table 3: Regression analysis summary

Term	**Coefficient**	**SE Coefficient**	**T-Value**	**P-Value**	**VIF**
Constant	70.31	4.55	15.45	0.000	
EC	-0.2669	0.0420	-6.35	0.000	1.69
DIST	0.8263	0.0456	18.12	0.000	1.48
CFL	0.1845	0.0400	4.61	0.000	1.51
ALEX	-0.3381	0.0359	-9.43	0.000	1.35
TRAU	0.2564	0.0446	5.76	0.000	1.08

comprehensive picture of the Ridge regression model's performance on test data is presented in Figure 2, indicating its ability to learn from data, the accuracy of its predictions, the distribution of its errors, and how its coefficients are affected by regularization.

Figure 2a shows the paths of the coefficients as a function of the regularization parameter (λ), plotted on a logarithmic scale. Each line represents a different coefficient in the regression model. As λ increases, the coefficients shrink towards 0, which is the effect of Ridge regularization. Coefficients stabilize after a certain value of λ, which implies that the model has reached a point where additional regularization does not significantly change the weights of the features in the model.

The learning curve for Ridge regression is displayed in Figure 2b and illustrates the model's performance over time as more training examples are used. The red line represents the training score, showing how well the model fits the training data. It

starts high and decreases slightly, indicating that as more data is introduced, the model becomes less overfitted to the training set. The green line represents the cross-validation score, showing how well the model generalizes to unseen data. This line increases as more data points are added, showing that the model benefits from more data and generalizes better with a larger training set. The shaded areas around each line show the variability of the scores (Mean-Std, Mean+Std), with a wider area indicating more variation in the model's performance.

Prediction error plot comparing the predicted values to the actual values is displayed in Figure 2c. Most points seem to be close to the line presenting perfect predictions, though there is some deviation, especially for higher values, indicating potential areas for model improvement.

Residuals Plot for Ridge Regression, shown in Figure 2d, provides a visual diagnostic of the model's performance by plotting the residuals (the differences between observed values and model predictions) against the predicted values. The residuals are spread around the horizontal axis without a distinct pattern, suggesting that the variance is relatively stable across predicted values. Most residuals are concentrated around zero, indicating generally accurate predictions, though some outliers, particularly at higher predicted values, suggest occasional deviations from the model's accuracy.

As for the analysis of the Ridge regression model, four diagnostic plots of the LASSO regression model were examined to assess model performance and feature selection efficacy. A comprehensive view of the LASSO regression model's performance on test data, from how it handles regularization and variable selection to its predictive accuracy and the consistency of its errors across the range of predictions are presented in Figure 3. The coefficient path plot (Figure 3a) reveals that as the regularization parameter increased, a convergence of coefficients towards 0 is observed, reflecting LASSO's inherent feature selection capabilities - particularly notable is the stabilization of coefficients at higher λ values, indicating the threshold beyond which model complexity reduction does not significantly enhance performance. The learning curve plot (Figure 3b) illustrates the performance of the model as the size of the training data increases. The training score starts relatively high at approximately 0.7 but decreases slightly and stabilizes around 0.65 as more training examples are added. The cross-validation score shows a steady increase, stabilizing around 0.6 with more training data. The persistent gap between the training and cross-validation scores indicates a certain degree of overfitting. The prediction error (Figure 3c) shows a generally good predictive performance with data points closely aligning with the line of perfect prediction, even though with a slight deviation at higher values. The residuals plot (Figure 3d) displays

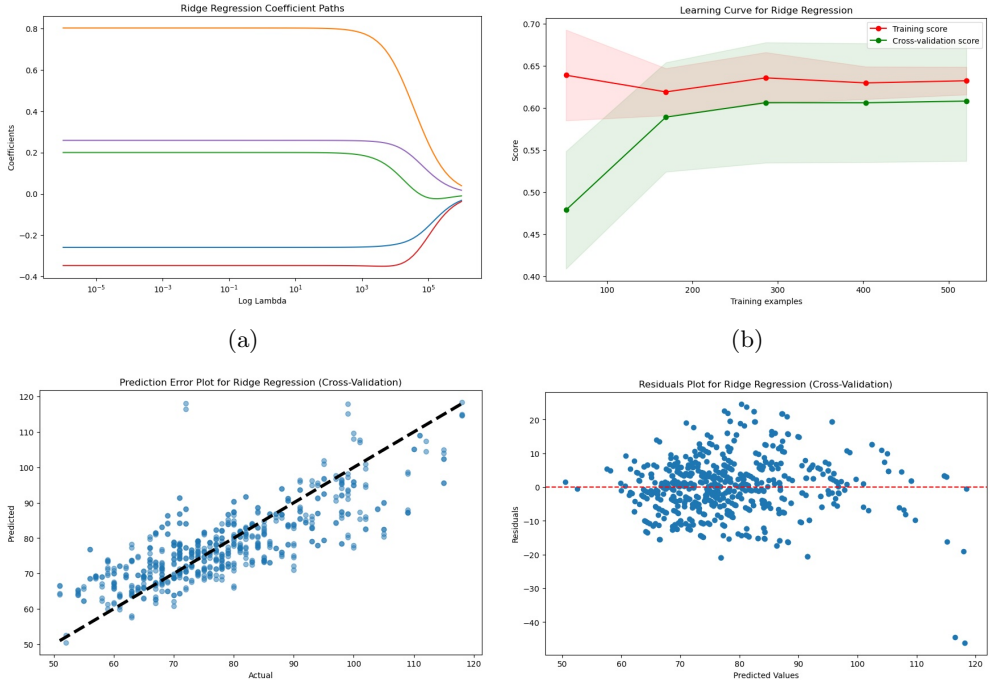


Fig. 2: Ridge regression plots (a) Coefficient paths (b) Learning curves (c) Prediction error (d) Residuals

a random scatter of residuals around the zero line without a clear pattern, indicating no systematic errors, although the spread hints at potential variance in predictive accuracy across the range.

The Elastic Net regression model's performance on test data was methodically evaluated through a series of plots, providing an overall view of its predictive capabilities and the behavior of its parameters (Figure 4). The Elastic Net regression coefficient paths (Figure 4a) illustrate the impact of regularization on the feature coefficients across different values of the logarithm of λ, where each trajectory represents a coefficient's shrinkage towards 0, underscoring the dual regularization effect inherent in Elastic Net regression. As the penalty increases, the coefficients approach and eventually settle at 0, a characteristic that aids in feature selection and model complexity reduction. The learning curve for Elastic Net regression (Figure 4b) reveals the model's response to increasing training data, with the training score and the cross-validation score converging, although with a persistent gap that indicates a mild overfitting to the training set. The prediction error for Elastic Net regression (Figure 4c) shows a

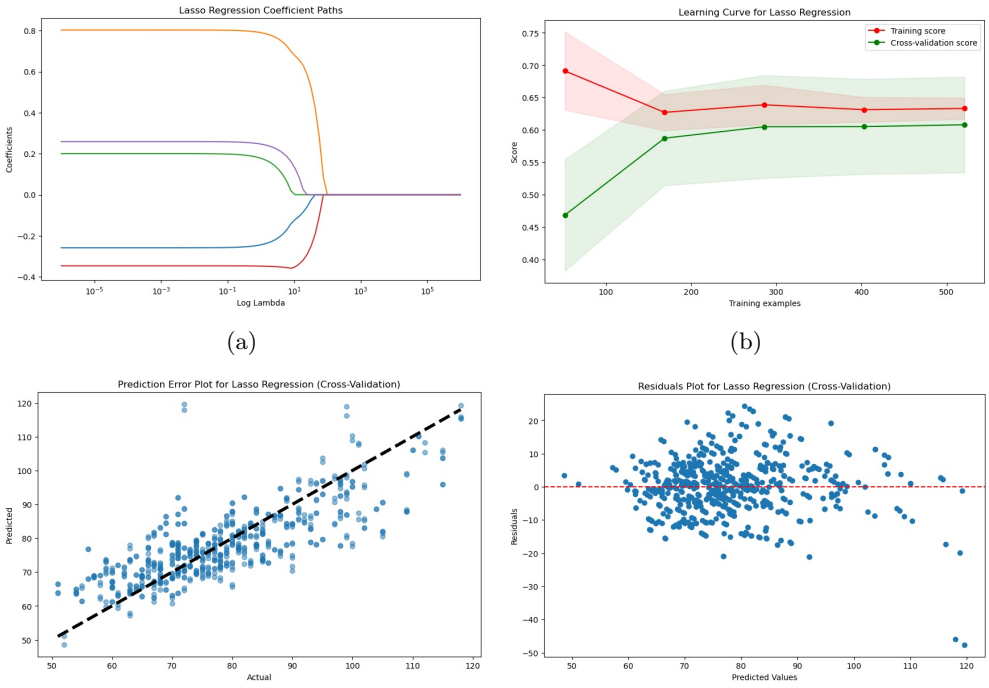


Fig. 3: LASSO regression plots (a) Coefficient paths (b) Learning curves (c) Prediction error (d) Residuals

clustering of points along the line representing good predictions, but with some scatter away from the line at higher value ranges. This denotes a strong predictive accuracy across the majority of the data, with some exceptions. The residuals plot for Elastic Net regression (Figure 4d) provides insight into the discrepancies between observed and predicted values. The lack of discernible pattern or systematic deviation from the horizontal line at zero residual value indicates a satisfactory model fit. However, the spread of the residuals indicates varying accuracy across different levels of predicted values, suggesting areas where the model's predictive performance could potentially be improved.

The performance evaluation results of three different regression models: Ridge, LASSO, and Elastic Net regression models are presented in Table 4. Each model employs a different approach to regularize linear regression, aiding in mitigating issues like overfitting and multicollinearity. For the Ridge regression model, a high optimal λ value of 2154.4347 suggests significant penalization of large coefficients to control overfitting. In contrast, the LASSO regression model shows an optimal λ of

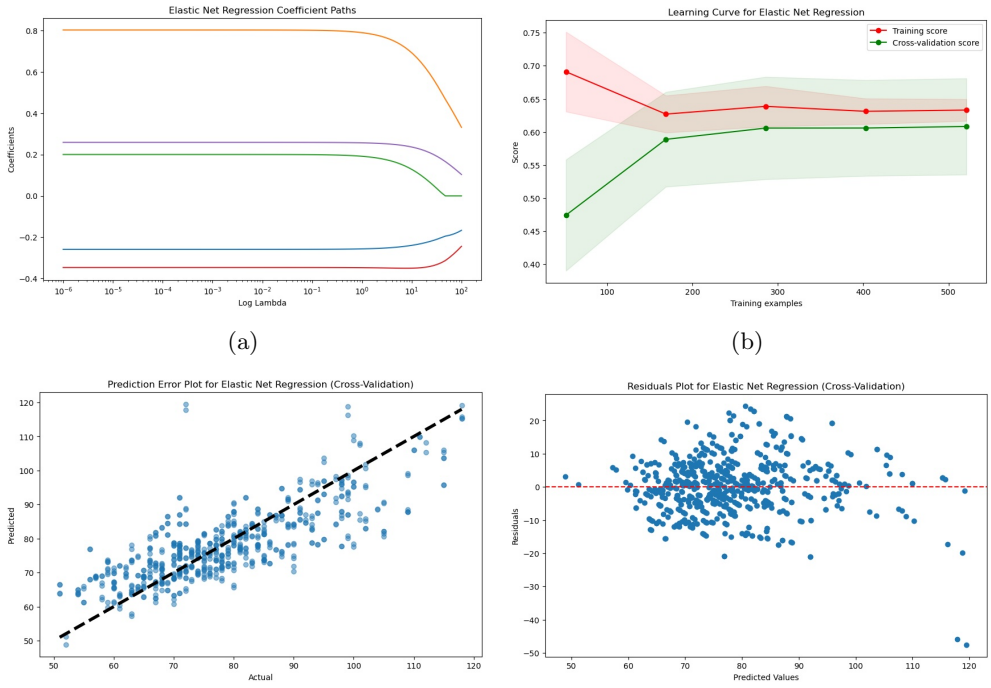


Fig. 4: Elastic Net regression plots (a) Coefficient paths (b) Learning curves (c) Prediction error (d) Residuals

1e-6, indicating no regularization and behaving similarly to standard linear regression. The Elastic Net regression model, with an optimal λ of 1.6681, provides a balance between the two, combining elements of both Ridge and LASSO regression models. The Elastic Net regression model records the lowest MSE at 71.6515, followed closely by Lasso (71.6575) and Ridge regression model (71.7167), showing marginal differences in performance. In terms of MAE, the differences among the models are minimal, with both LASSO and Elastic Net regression models leading in accuracy (6.3901). The Elastic Net regression model has an optimal $L1$ ratio of 0.1. This ratio determines the balance between $L1$ and $L2$ regularization techniques (characteristic of LASSO and Ridge regression, respectively). An $L1$ ratio of 0.1 in Elastic Net regression implies a preference towards $L2$ regularization, but with a small $L1$ component. All three models exhibit similar MAPE values, indicative of comparable accuracy across the models. Elastic Net regression model has the highest R^2 value (61.5651), implying a slightly superior fit compared to the other models.

Table 4: Ridge, LASSO, and Elastic Net regression model evaluation results

Performance Metric	**Ridge Regression**	**LASSO Regression**	**Elastic Net Regression**
Optimal λ	2154.4347	1e-6	1.6681
MSE	71.7167	71.6575	71.6515
MAE	6.411	6.3901	6.3901
MAPE	8.3851	8.3575	8.3573
R^2	61.5301	61.5619	61.5651
$L1$ ratio			0.1

Although the optimal lambda for LASSO regression is very close to zero ($1e-6$), indicating a minimal regularization effect, penalized regression models such as LASSO, Ridge, and Elastic Net were considered to enhance model stability and generalization performance. These techniques help control potential coefficient variability and reduce overfitting, particularly in the presence of moderate correlations among predictors. As a result, they contribute to more robust and reliable predictive performance.

While this study primarily evaluates statistical metrics, such as accuracy and cross-validation scores, the findings hold significant implications for understanding and modeling internal shame. The strong predictive relationships identified for distress tolerance, cognitive flexibility, and internal shame highlight their potential as intervention targets. For instance, enhancing distress tolerance through mindfulness-based stress reduction or emotion regulation training may empower patients to better cope with chronic pain. Interventions designed to improve cognitive flexibility, such as cognitive-behavioural therapy, could help patients reframe negative thoughts associated with pain, reducing its emotional and physical impact. Addressing IS through self-compassion or acceptance-based therapies could mitigate the psychological distress that exacerbates pain.

The findings of our study have significant real-world applications, particularly in psychological and clinical settings. By identifying key predictors of IS, such as childhood trauma, cognitive flexibility, distress tolerance, and alexithymia, practitioners can better tailor interventions to address these underlying factors. For instance, therapeutic programs could focus on enhancing cognitive flexibility and distress tolerance to help individuals manage shame-related emotions more effectively. Additionally, the use of advanced regression models, such as Elastic Net and LASSO, provides a framework for clinicians and researchers to develop predictive tools for identifying individuals at higher risk of experiencing IS, enabling early intervention and personalized treatment strategies. These insights also have broader implications for designing prevention programs, particularly in vulnerable populations, by addressing the long-term psychological

impacts of childhood trauma and fostering resilience through targeted emotional and cognitive skill-building.

4 Conclusions

In this paper, three regression models: Ridge, LASSO, and Elastic Net regression were applied to predict the values of IS. Each of these models is a variation of linear regression that incorporates different techniques to regularize or constrain the model, which can help in dealing with issues like overfitting and multicollinearity. Although all evaluated models demonstrated satisfactory performance, Elastic Net regression achieved the most favourable overall results, yielding the lowest MSE and the highest R^2 values.

We have identified factors which have strong associations, both taken individually and together, with IS, namely EC, DIST, CFL, ALEX and TRAU. We hope that in identifying these related characteristics that this will help in furthering understanding and conceptualising of IS and lead to improved treatments for the significant numbers of people whose lives have been blighted by this condition.

The findings of this paper provide valuable insights into the application of advanced regression techniques in psychological research. The slight edge of the Elastic Net regression in this context suggests a promising direction for future research in similar domains, where model interpretability and predictor selection are crucial. Considering the high VIF values observed in our analysis, which indicate significant multicollinearity, it is crucial to employ regression techniques that can mitigate this issue. Penalized regression models, such as Lasso, Ridge, and Elastic Net, are particularly suited for this purpose. These models enhance the stability of coefficient estimates, which improves the robustness and interpretability of the model. Consequently, this ensures more reliable and insightful predictions.

The Ridge, LASSO, and Elastic Net regression methods were employed due to their strengths in handling multicollinearity, performing feature selection, and preventing overfitting in datasets with correlated predictors. Ridge regression stabilizes coefficient estimates through L2 regularization, making it suitable for multicollinearity, whereas LASSO regression applies L1 regularization, allowing less informative coefficients to be reduced to zero and thereby facilitating feature selection. Elastic Net regression combines these strengths, offering a balance between feature selection and multicollinearity management, particularly useful when predictors are highly correlated.

While alternative models such as Random Forests, Support Vector Machines (SVM), or Neural Networks can be considered, they were not selected due to the specific goals of

this study. Random Forest and SVM models are valuable at modelling non-linear relationships but lack the interpretability needed for understanding predictor importance in psychological research. Neural Networks, although powerful, were deemed unsuitable due to the relatively small dataset size and the study's focus on feature importance rather than purely predictive performance. The selected regression models align with the study's emphasis on interpretability and the need to manage multicollinearity while ensuring robust predictions.

Although recruitment through social media enabled access to a large pool of participants, reliance on convenience sampling may have reduced the representativeness of the sample and introduced selection-related biases. Future research could benefit from combining alternative recruitment procedures, including stratified or probability-based sampling methods, in order to ensure broader demographic coverage. Integrating online recruitment with offline data collection, such as community-based outreach or face-to-face survey administration, may also help minimise biases associated with exclusively digital participation. Such methodological adjustments could strengthen the generalizability and ecological relevance of findings related to internal shame and associated psychological constructs.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Ethics approval and consent to participate

This observational study was conducted in accordance with the ethical standards of the institutional research committee and the principles outlined in the Declaration of Helsinki and its subsequent amendments. Ethical approval for the study was obtained from the Ethics Committee of Tarbiat Modares University, Tehran, Iran (Approval No. IR.MODARES.REC.1401.197). All procedures involving human participants complied with relevant institutional and national ethical guidelines. Prior to participation, individuals received information regarding the aims of the study, study procedures, confidentiality, and the handling of personal data. Electronic informed consent was obtained from all participants before completion of the survey.

Author Contributions

NK: Conceptualization, Investigation, Formal analysis, Methodology, Software, Visualization, Writing - review & editing. HF: Conceptualization, Investigation, Data curation, Methodology, Validation, Writing - original draft, Project Administration. KR: Conceptualization, Formal analysis, Writing - original draft, Validation, Writing - review & editing. PW: Conceptualization, Investigation, Methodology, Validation, Writing - review & editing, Funding. All authors have read and agreed to the published version of the manuscript.

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Consent for Publication

Not Applicable.

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Data Availability Statement

The datasets and software used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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