Students' Perceptions of Fairness in Assessment: Big Data Mining of Social Media Texts Using Machine learning/AI

Joenathan Halim, Jr
School of Physical and Mathematical Sciences

Asst Prof. Farhan Ali
National Institute of Education

Asst Prof. Rasooli Amirhossein
National Institute of Education

Abstract. Fairness in academic assessment plays a crucial role in shaping students' learning experiences and educational outcomes. This study aims to discover students' perception of fairness in assessment using data analysis and network analysis of Reddit discussions. Through network analysis, we discovered distinct emotional patterns across assessment types to reveal their fairness perception. Our findings provide insights into students' emotional responses to different types of assessments, with implications for educational policy and fairness in evaluation.

Keywords: fairness, data analysis, network analysis

1 INTRODUCTION

Fairness in educational assessment is formally defined as one that ensures all test-takers have an equal opportunity to demonstrate their knowledge and skills, free from bias or irrelevant influences so that test scores are valid for interpretations [6]. Studies have shown that students' perceptions of assessment heavily influence their learning experiences and academic progression [2]. Despite its importance, quantitative insights into student perceptions of assessment remain limited [11]. This study aims to fill the gap in current literature and provide actionable insights for educators and policymakers by conducting big data mining, social network analysis, and statistical inference to uncover students' emotions in their discussions.

We base our approach on the assumption that students' discussions on Reddit reflect authentic emotional and cognitive responses to various types of assessments. For the purpose of this study, assessment types are categorized into three classes based on their stakes: low, medium, and high. Network analysis refers to a framework to identify, analyze, and visualize patterns of statistical association in multivariate data [4].

The scope of this study is limited to English-language Reddit threads about Singapore Exams in primary school to junior college and polytechnic to ensure linguistic and contextual consistency. However, there are inherent limitations to our approach. Reddit users represent a self-selected population and their posts may not reflect the broader student population, despite a large data size. Furthermore, focusing only on Singapore exam setting will limit the generalizability of our findings to other educational systems and cultural contexts.

2 LITERATURE REVIEW

Recent research have shown that perceived fairness and students' personal outcomes, experiences, and emotions are highly linked in the context of educational assessments [5, 10]. For instance, students that have bad exam experience tend to feel more negatively for upcoming exams and later perceive the assessments to be less fair, and vice versa. Hence, the emotional responses triggered by exams have been widely studied because of their impact on performance and well-being [1, 7, 8, 9]. Quantitative analytics techniques have been proven useful to unpack these responses in detail. In education, researchers have long used correlation analysis to link students' emotional states with other factors such as academic performance, perceived course quality, etc. They found out that there is a strong positive correlation between student's happiness and their academic performance, while fear correlated negatively with performance [9]. Similarly with optimism correlated positively to achievements while pessimism show negative correlations to achievements [5].

However, correlation analysis has limitations in capturing the complexity of emotional dynamics. Emotions are often not independent, they fluctuate and co-occur in time. To take into account these dependencies, researchers have proposed network analysis [4]. Network analysis treats individual emotions as nodes in a network and use statistical associations to connect them, highlighting how various emotions interact as a system and which emotion is the central hub for other emotions [1]. A study done by Moeller et al. (2018) illustrates the effectiveness of network analysis for emotions. They revealed that students' feelings across various settings at school are a complex mixture of positive and negative co-occurrences [8]. This kind of insights opens new perspectives on the structure of emotions, discovering which combination of positive and negative emotions yields the best outcome, and understanding these patterns can be crucial information for educators aiming to address emotional needs.

Additionally, network analysis also quantify the notion of centrality of emotion within a network. Centrality is defined as emotions that are most interconnected with others. A high centrality could be a leverage point for intervention or materialization. Recent methodological advances include the use of Gaussian Graphical Models and regularization techniques to estimate emotion networks, ensuring only robust connections are displayed [1]. These techniques help to avoid false positives and interpret complex data more reliably.

3 METHODOLOGY

3.1 DATASET

We collected data from a Reddit community forum called "r/SGExams", totaling to 38921 Reddit posts. The dataset is about student life in Singapore, ranging from preliminary school all the way to university and postgraduate school. Having collected the data, we filtered it using regular expression to extract posts that contain our keywords ensuring they are related to our topic. Our main focus is Singapore exams for primary school all the way to junior college and polytechnic, which include PSLE, O levels, A levels, weighted assessments, quizzes, midterm exam, finals exams, and so on.

3.2 DATA ANALYSIS

With the filtered data, each post is then categorized into three groups according to their weightage: low, medium and high stakes. Additionally, we defined 27 emotion categories to label each of the posts, where one posts could have zero or more emotion labels. To classify each posts, we created a list of keywords for each of the emotion label by utilizing a word embedding model (GloVe Wiki-Gigaword-300) to extract the top 20 words with closest semantic distance to each label. Once the dataset is curated, we plotted the pearson correlation matrix to analyze the correlation of each emotion labels for each exam stake. We also constructed a network analysis using the bootnet package in R via glasso with EBIC for model selection and laid out using the Fruchterman-Reingold algorithm for each exam stake to analyze the co-occurrences and centrality of different emotions. Similarly, we repeat the pipeline for Pekrun emotion labels with different set of keywords [3].

4 RESULT & DISCUSSION

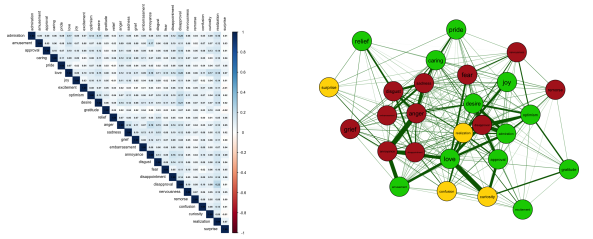
4.1 PEARSON CORRELATION & NETWORK ANALYSIS

Figure 1 shows the pearson correlation matrix and network analysis for the emotion labels across different exam stakes. Inspection of the raw Pearson matrices shows that emotions tend to rise and fall together, but the strength and selectivity of these co-fluctuations shifts with perceived stakes. Low-stakes tests already exhibit a pronounced "like-with-like" structure: positive emotions (e.g., joy–love $r = 0.27$; pride–optimism $r = 0.24$) and negative emotions (e.g., anger–annoyance $r = 0.25$; grief–sadness $r = 0.32$) cluster tightly, whereas cross-valence links are generally weak (¡ 0.10). Under medium stakes the average correlation coefficient drops, most visibly within the negative block and between neutrals (confusion, surprise) and the rest of the matrix, indicating a partial decoupling or compartmentalisation of affect. High-stakes exams, by contrast, are accompanied by a broad uplift in coefficients: not only do within-valence associations strengthen (e.g., fear–nervousness $r = 0.35$; joy–excitement $r = 0.29$), but several mixed-valence pairs (notably desire–fear and pride–fear, both approximately 0.20) also intensify, suggesting that positive drive and threat are simultaneously amplified when much is on the line. Collapsing across all stakes reproduces this composite picture, with the largest coefficients in the same positive-positive and negative-negative sub-matrices and moderate ties bridging desire, fear and pride, underscoring their central motivational role.

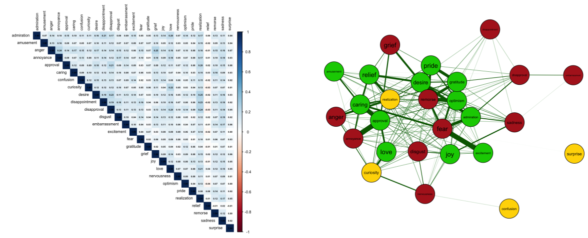
The multivariate network was created using the glasso algorithm and laid out using the Fruchterman-Reingold algorithm. The nodes were color coded to indicate different emotions, green nodes represents positive emotions, yellow nodes represent neutral emotions, and red nodes represent negative emotions. Meanhwile, the edges are color coded to represent the connection. Green edges indicate positive connection, while red edges represent negative correlation, with edge thickness reflecting the connection strength [4].

Across all four networks, exam stakes influenced both the density and structure of students' affective co-activation patterns. A consistent, tightly interconnected core of positive emotions—particularly desire, love, pride, joy, caring, and relief—remained stable across contexts. However, the broader network architecture followed a U-shaped trajectory: emotional connectivity declined at medium stakes but increased markedly under high-stakes conditions. Medium-stakes assessments were characterized by the peripheral drift of neutral emotions (e.g., confusion, surprise) and the emergence of inhibitory links between positive and negative states, suggesting a deliberate compartmentalization of emotions to preserve cognitive focus. In contrast, high-stakes exams generated a densely interconnected network, with social-approach emotions (e.g., caring, gratitude, admiration) becoming central and strongly co-occurring with threat-related states (e.g., fear, grief). This pattern suggests that high-pressure situations evoke complex, multiplex emotional responses that are not exclusively negative and may be mitigated by feelings of social connectedness. The persistent coupling of desire and fear across all conditions highlights its function as a motivational core, while the variable centrality of social emotions suggests that interventions promoting peer support may be particularly beneficial in high-stakes evaluative contexts.

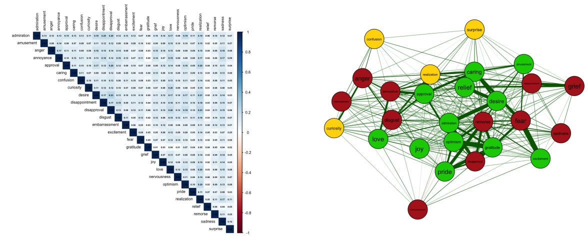
Taking into account both pearson correlation and network analysis, the zero-order correlations and the partial-correlation (glasso) networks converge on three key insights: (i) a stable, densely interconnected core of positive emotions is present in every context, providing an affective buffer; (ii) medium-stakes assessments are affectively “looser”, with both methods showing the lowest mean connectivity and the greatest segregation of neutral states, consistent with strategic narrowing of emotional bandwidth; and (iii) high stakes re-entangle the system, as rising correlations translate—once shared variance is controlled—into a thick web of unique links, especially between motivational approach (desire, pride) and avoidance (fear, grief) nodes. The glasso models additionally reveal inhibitory (red) edges that the Pearson matrices cannot detect, clarifying that some apparent independence at the zero-order level actually reflects active suppression among emotions when resources are strained. Thus, while Pearson correlations map the overall volume of shared affect, network analysis pinpoints the specific channels through which emotions co-activate or inhibit one another; the joint evidence paints a nuanced picture of exam-related affect that oscillates from moderately cohesive (low stakes), to selectively pruned (medium stakes), to highly multiplex (high stakes).



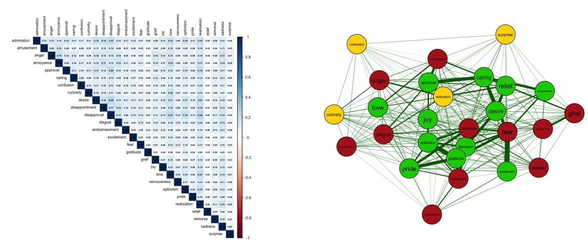
a) Pearson Correlation Matrix for low stakes exams b) Network Analysis for low stakes exams



c) Pearson Correlation Matrix for medium stakes exams d) Network Analysis for medium stakes exams



e) Pearson Correlation Matrix for high stakes exams f) Network Analysis for high stakes exams



e) Pearson Correlation Matrix for all exam stakes f) Network Analysis for all exams stakes

Figure 1: Results for each assessment stakes

4.2 STATISTICS

As seen in Table 1, positive emotions dominated the affective landscape, accounting for roughly 57% of all coded instances, with neutral states comprising about 18% and negative states the remaining 25%. The single most frequently expressed emotion was disapproval (54%), followed closely by love (46%), curiosity (43%), and optimism (42%), indicating that students oscillated between self-critical evaluation and approach-oriented engagement even before valence filtering. Mid-range frequencies clustered around appraisal-related states such as realization (29%), approval (29%) and desire (28%), while social uplifts like admiration (25%) and gratitude (24%) were also prominent, underscoring the interpersonal texture of the exam context. In contrast, relief-type recovery emotions were vanishingly rare (relief approximately 0.3%) and other low-base-rate states included remorse, pride, embarrassment, and surprise (¡ 3%), suggesting that the testing window captured anticipatory tension more than post-outcome reactions. Importantly, the positive-neutral-negative distribution remained remarkably stable when the sample was split by stakes, yet specific emotions shifted: approach-avoidance blends such as desire, admiration, and disapproval increased as stakes rose, whereas confidence signals like optimism and epistemic neutrals (confusion, surprise) tapered, hinting at a motivational tightening and reduced cognitive slack under greater evaluative pressure.

Table 1: Comparison of Emotions by Stake Filters (Percentages)

Emotion	All Stakes	Low Stakes	Medium Stakes	High Stakes
disapproval	54.24%	43.68%	56.06%	60.80%
love	46.17%	39.63%	49.02%	49.81%
curiosity	43.37%	40.07%	43.64%	45.49%
optimism	41.58%	33.80%	47.98%	45.16%
realization	29.26%	22.75%	30.40%	33.30%
approval	28.58%	22.57%	29.57%	32.32%
desire	27.66%	20.25%	27.01%	32.74%
admiration	25.20%	19.04%	25.66%	29.17%
gratitude	23.67%	19.27%	24.40%	26.41%
amusement	13.03%	10.92%	11.59%	14.78%
excitement	12.50%	8.72%	12.46%	15.02%
disappointment	12.44%	9.23%	12.85%	14.46%
annoyance	9.33%	7.39%	9.55%	10.55%
fear	8.55%	6.62%	9.08%	9.70%
confusion	8.44%	6.64%	10.99%	9.02%
nervousness	7.68%	5.80%	10.16%	8.32%
disgust	7.24%	5.30%	6.82%	8.62%
sadness	5.98%	4.22%	5.64%	7.22%
grief	4.73%	3.74%	4.95%	5.32%
anger	4.47%	3.40%	4.60%	5.15%
joy	3.97%	2.66%	3.52%	4.95%
caring	3.80%	2.99%	4.13%	4.43%
surprise	2.90%	2.25%	3.13%	2.89%
embarrassment	2.71%	2.17%	2.91%	3.06%
pride	2.70%	2.04%	3.43%	3.16%
remorse	2.39%	1.88%	2.52%	2.94%
relief	0.27%	0.19%	0.30%	0.32%

5 CONCLUSION

Leveraging nearly 39 000 Reddit posts from r/SGExams, this work demonstrates that large-scale social-media mining combined with correlation and network modelling can surface nuanced patterns in students' affective responses to assessment. Three robust insights emerged. First, a tightly knit hub of approach-oriented positive emotions (desire, love, pride, joy, caring, relief) persists across all assessment contexts, signalling an underlying motivational "buffer" against stress. Second, medium-stakes assessments exhibit the least emotional connectivity—neutral feelings drift to the periphery and inhibitory links appear—suggesting that students deliberately compartmentalise affect to conserve cognitive resources when a test is important but not decisive. Third, when stakes escalate, the affective system re-entangles: social-approach emotions become central and co-activate with threat-related states, producing highly multiplex blends of desire, pride, fear and grief. These high-stakes patterns imply that pressure does not merely amplify negativity; it also intensifies prosocial bonding and approach motives, highlighting peer support as a potential lever for fostering perceived fairness.

Educationally, our findings extend fairness research beyond psychometric validity to the lived emotional ecology of testing. Designers of assessment systems might:

a) calibrate medium stakes to preserve the cognitive "sweet spot" where emotions are neither overwhelming nor inert;

b) embed social or collaborative elements in high-stakes settings to harness the naturally rising prosocial impulses; and

c) monitor the desire–fear nexus as an early indicator of maladaptive stress, intervening before it crystallises into chronic anxiety or disengagement.

Methodologically, this study affirms the value of emotion networks for complementing zero-order correlations: network edges uncovered unique inhibitory and facilitative channels invisible to traditional metrics. The pipeline—keyword expansion via word embeddings, regularised Gaussian Graphical Models, and stake-stratified comparison—offers a scalable template for future affective-learning analytics.

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