Investigations on Anger Experience with Other Basic Emotions Using Affective Ising Model

Gina Rose N. Tongco-Rosario[1], Christie P. Sio[2] and Jaymar Soriano[1][a]

[1]Department of Computer Science, University of the Philippines Diliman, Quezon City, Philippines
[2]Department of Psychology, University of the Philippines Diliman, Quezon City, Philippines

Keywords: Anger, Anger Experience, Emotion, Affective Ising Model, Computational Psychology, Personality.

Abstract: Understanding individual differences in anger experiences is pivotal for tailored interventions. This study explores the variability in individual anger experiences, focusing on fear, happiness, and sadness as intertwined emotions. A computational approach leveraging the Affective Ising Model (AIM) was performed to analyze discrete emotion pairs to unravel the complex dynamics of how individuals experience anger. By applying the AIM to individual-level data collected through Experience Sampling Methodology (ESM), the study aims to derive parameter estimates that capture the nuanced emotional landscapes of participants. The investigation seeks to elucidate not only how individuals experience anger but also how it interacts with co-occurring emotions, shedding light on the uniqueness of emotional responses. This nuanced understanding can pave the way for personalized interventions. The parameter estimates derived from the AIM will serve as a basis for tailoring interventions, offering targeted strategies aligned with an individual's emotional dynamics. Ultimately, this approach holds promise for shaping more effective and personalized interventions to support emotional well-being.

1 INTRODUCTION

Anger, as a basic emotion, is experienced uniquely by individuals. While traditional approaches have often considered emotions as homogenous responses, recent research demonstrates that people exhibit substantial diversity in how they experience and express anger (Loaiza, 2021; Heylen, et al., 2015). Some individuals might express anger through assertiveness, while others may exhibit withdrawal or aggression. Variability in how individuals experience anger is a complex phenomenon that can significantly impact mental health and well-being. Thus, understanding individual differences in the experience of anger is crucial for developing targeted and personalized interventions to address these varied emotional responses (Hamaker, et al., 2015).

Furthermore, emotions rarely exist in isolation. Fear, happiness, and sadness are closely intertwined with anger, influencing its expression and experience (Panksepp, 2017). Exploring how these discrete emotions interact and co-occur with anger can provide a more comprehensive understanding of an individual's emotional landscape.

Affective Ising Model (AIM) is a powerful tool used in computational psychology to model and understand the dynamics of emotions (Loosens, et al., 2020). This model not only considers the presence of discrete emotions but also their interactions, providing a more nuanced representation of individual emotional experiences. The AIM enables the estimation of parameters for each individual, capturing their unique emotional dynamics. By applying the AIM to individual records of Experience Sampling Methodology (ESM) data, researchers can derive insights into how an individual experiences and transitions between various emotions. ESM are generally considered to be the golden standard (Myin-Germeys, et al., 2018) to study affect dynamics in an ecologically valid manner - a participant’s emotional state is measured repeatedly throughout the day during several days, giving researchers a window into their emotional experiences during their daily lives.

The insights gained from the AIM's parameter estimates can be invaluable in designing interventions

[a] https://orcid.org/0000-0001-9647-5999

Tongco-Rosario, G., Sio, C. and Soriano, J.
Investigations on Anger Experience with Other Basic Emotions Using Affective Ising Model.
DOI: 10.5220/0012470300003657

In *Proceedings of the 17th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2024) - Volume 2*, pages 738-745
ISBN: 978-989-758-688-0; ISSN: 2184-4305

that cater to an individual's specific emotional profile. By understanding how an individual experiences and transitions between emotions, interventions can be personalized to address specific triggers, coping mechanisms, and emotional regulation strategies that align with their unique emotional patterns.

Investigating the individual experience of anger using the AIM, within the context of other emotions, holds the promise of advancing our understanding of emotions and paving the way for personalized interventions aimed at improving mental health and well-being. This approach can revolutionize how we address emotional concerns by tailoring interventions to suit the unique emotional fabric of each individual, thereby fostering more effective and targeted support.

2 AFFECTIVE ISING MODEL

A computational framework for studying the affect dynamics was developed in 2020 (Loosens et al.) The framework coined as the Affective Ising Model (AIM) was inspired by the Ising Model initially used to represent and explain ferromagnetism in statistical mechanics. AIM utilizes a similar concept and applies it to affect states. An individual's emotional landscape consists of stochastic binary neurons grouped into two distinct pools. One pool processes the positive affect while the other, the negative affect. Internally, the neurons are self-exciting. Between pools, mutual excitation or inhibition is present. The contribution of external stimulus is also accounted for in the model. These interactions are depicted in Figure 1.

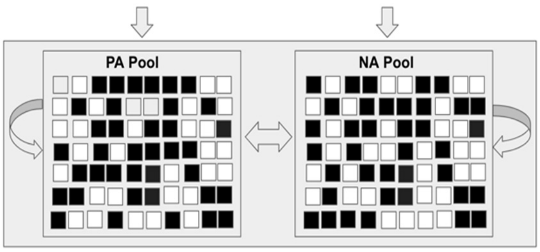


Figure 1: AIM with two pools of neurons. Neurons in each pool are self-exciting. Between pool interaction is also present and each pool may receive an external stimulus.

Define the populations of neurons processing the positive and negative affective states as PA and NA, respectively. Each population consist of N_1 and N_2 stochastic binary neurons. As the neurons change states over time, the average activations also undergo temporal variations, resulting in variations in the affective state. The probability density function (pdf) is given by:

$$p(y) = e^{-\frac{\beta F(y)}{Z}} \quad (1)$$

where $F(y)$ is the free energy function given by

$$F(y) = \sum_{i=1}^{2} \left(-\lambda_i y_i^2 + \theta_i y_i + \frac{N_i}{\beta}\left(y_i ln y_i\right) + \left(1-y_i\right)ln\left(1-y_i\right)\right) + \lambda_{12} y_1 y_2 \quad (2)$$

while Z is the partition function or the normalization constant of the pdf. The parameter β is associated with the inverse temperature in statistical mechanics. Within the AIM framework, the parameter is arbitrary and is assigned a value of 1 for simplicity. Other parameters of the free energy equation are summarized in Table 1.

Table 1: Internal parameters of the AIM.

Parameter	Description
λ_1	strength of self-excitation of PA pool
λ_2	strength of self-excitation of NA pool
λ_{12}	strength of mutual inhibition
θ_1	activation threshold of PA pool
θ_2	activation threshold of NA pool

An individual with a more positive affect has, higher N_{PA} and λ_{PA} (than N_{NA} and λ_{NA}, respectively) and lower θ_{PA} values (than θ_{NA}). A positive value of λ_{12} signifies mutual inhibition between pools while negative values means that both pools excite each other.

The dynamics of the affect states are given by

$$dy_i(t) = -\beta \frac{\partial F}{\partial y} dt + \sqrt{2d} dW_i(t) \quad (3)$$

where $\{W_i(t)\}$ are the associated Wiener processes that are uncorrelated to each other (Verdonck & Tuerlinckx, 2014).

The movement of affect on the energy landscape is given by the diffusion parameter $D = \frac{2}{e(N_i+N_i)^2 \Delta t}$. When D is low, it means that an individual stays longer in that specific affect state.

3 METHODOLOGY

Inside Out Emotion Tracker is an ESM study that was participated in by 109 university students from the Department of Psychology of the University of the

Philippines Diliman. Students were asked to complete an experiential measure of anger and other emotions using their smartphones at multiple random time points per day, across ten days. Before and after the experience sampling task, a global measure of trait anger was administered in a counterbalanced order together with a Filipino Five-Factor inventory (Del Pilar, G., et al., 2016). The research study was approved by the Ethics Review Committee of the University of the Philippines Diliman Department of Psychology. We derive the emotion landscape for the sample. Forty out of 109 satisfy one of the following conditions: (i)high anger duration, (ii)high neuroticism or (iii)low agreeableness. Emotional landscapes from other participants did not have a good fit based on fitness value and landscape plot.

An example of an ESM-based emotion-pair impact data is shown in Figure 2. The happiness impact and anger impact values were calculated based on the participant's responses during the experiment. For each emotion, we determined the emotion impact by multiplying the normalized emotion intensity with the emotion duration. The emotion intensity is on a scale of 1-5 (participants used a five-option scale "not at all" = coded as 1, "a little" = 2; "moderately" = 3; "quite a bit" = 4; "extremely" = 5). The emotion duration is measured for the past hour and is indicated on a sliding scale, anchored on opposing ends by 0% (not at all) and 100% (all the time).

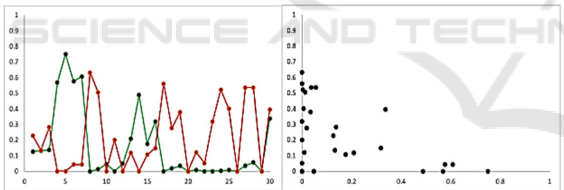


Figure 2: An example of an ESM-derived data consisting of 30 records of a participant's happy-angry emotion impact. Left plot shows the data in sequence while the right plot shows the participant's emotion impact scatter plot from which the emotion landscape is derived.

We use AIM, with each pool representing discrete emotions of fear, sadness, happiness, and anger. The focus is on a basic emotion paired with anger (i.e. fear-anger, sad-anger, happiness-anger, fear/sad/happy-anger). To infer the parameters from data, we used GradientDiffusion (Loosens et al., 2020), a method developed by Loossens et al. This method utilizes the maximum likelihood estimation to derive an individual's affect dynamics in the absence of an external stimulus i.e. solely on the internal system. The implementation is carried out with Julia, a platform known for rapid scientific computing (Bezanson et al., 2017). In many instances, multiple local minima exist and a differential evolution heuristic (Price et al., 2005) is utilized to find the global optimum.

4 RESULTS AND DISCUSSION

From the estimated parameters, we can plot the emotion landscapes given by the free energy function in Equation (1).

4.1 Emotion Landscape and Parameter Values

Figure 3 shows the emotion landscape of an individual for three emotion pairs: (a) afraid-angry, (b) happy-angry, and (c) sad-angry. Each data point represents an emotion impact pair (e.g. afraid, angry) which is the product of one's emotion intensity and duration for a time point). Each emotion pair landscape contains data measured across 30 time points.

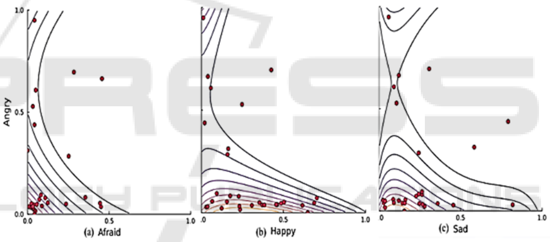


Figure 3: Emotion landscapes of an individual for discrete emotion pairs - (a) afraid-angry, (b) happy-angry and sad-angry emotion pairs.

Among the four emotions, happy (24%) has the highest average emotional impact, followed by sad (21%), angry (13%) and afraid (9%). Among the emotions co-occurring with angry, happy has the lowest activation threshold (θ_i). This signifies that when one's emotion is coupled with anger, it is easiest to activate happiness. Fear activation follows next and then sadness. Once an emotion is activated, the self-excitation strength (λ_i) measures how easy or difficult it is to keep the emotion in an excited state. The strength of mutual inhibition (λ_{12}) measures the interaction between emotion pairs. A positive value indicates that both emotions inhibit each other while a negative value indicates that the emotions excite each other.

Table 2: Internal parameters of the emotion pairs of Figure 2. The subscripts refer to emotion 1 - emotion 2.

Emotion Pair	Parameter Values				
	λ_1	λ_2	λ_{12}	θ_1	θ_2
Afraid-Angry	6.062	12.463	0.010	11.697	15.135
Happy-Angry	0.004	8.137	7.493	2.309	8.597
Sad-Angry	43.885	11.020	0.102	47.903	13.712

Mutual inhibition ($\lambda_{12}>0$) is evident in the case of happy-angry. Sad-angry has minimal mutual inhibition and afraid-angry is almost independent of each other ($\lambda_{12}\sim 0$). The self-excitation strength of emotion-angry pair is lowest with happy-, followed by afraid- and then with sad-.

4.2 Co-Occurring Emotions

Co-occurring emotions are emotions that occur simultaneously, preserving their distinct features such as valence and impact (Harley et al., 2012). These emotional states, like anger and disappointment, are experienced concurrently with one another. In Figure 4 (b1-b3) we can see that happy-angry emotions are co-occurring for all three individuals. The same is observed for sad-angry pair in Figure (c1). For the other emotion pairs, i.e., afraid-angry in Figure 4(a1-a3) and sad-angry in Figure 4(c2-c3), this phenomenon is not apparent. We look at the parameter values for cases in the happy-angry emotion pair. Compared to the other emotion pairs, θi is lowest, λ_{12} is highest, and λ_i is lowest. For sad-angry, we observe bimodality in Figure 4(c1) and in this case the λ_{12} is 0.1 while the rest have λ_{12} ~ 0. This is somehow consistent with anger and fear being on the opposite side of the emotional wheel. Co-occurrences of anger with sadness and happiness have also been reported (Harley et al., 2012) though small.

4.3 Analysis of Parameter Values

In the succeeding sections we investigate the parameter relationships with emotion impact. This time, we consider a sample of forty individuals.

Activation Threshold. Across emotion pairs, higher anger impact generally means lower anger activation threshold as shown in Figure 5. Lower activation threshold allows for easier and magnified anger experience in an individual. When anger is coupled with all three emotions (afraid, happy or sad), the anger activation threshold is lowest with happiness 72% of the time, followed by sadness at 18% and afraid at 10%. This means that anger is easiest to activate when someone is happy and hardest when one is sad.

With the happy-angry pair, the happiness activation threshold is lower 90% of the time. Happiness is generally easily activated compared to anger. In Figure 6a in terms of magnitude, we see that the activation threshold of happiness is just a fraction of anger and almost zero for very low values of anger impact (inset of Figure 6a). This signifies that one experiences happiness most when anger impact is low.

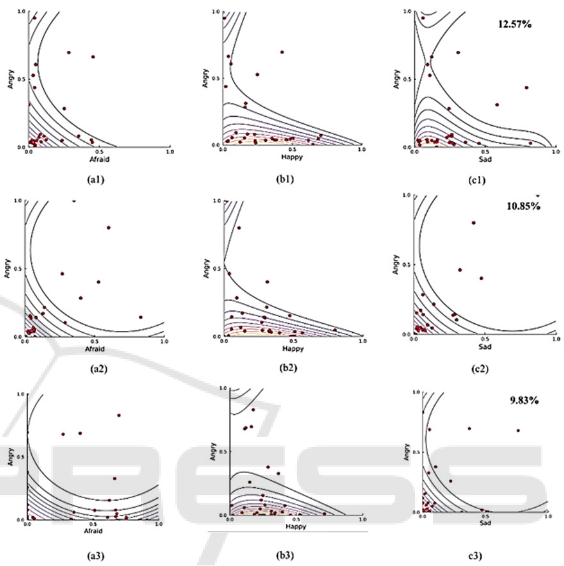


Figure 4: Emotion landscape with co-occurring emotions. Left to right shows the Afraid-Angry, Happy-Angry, Sad-Angry pairs. Top to bottom plots are for decreasing anger impact.

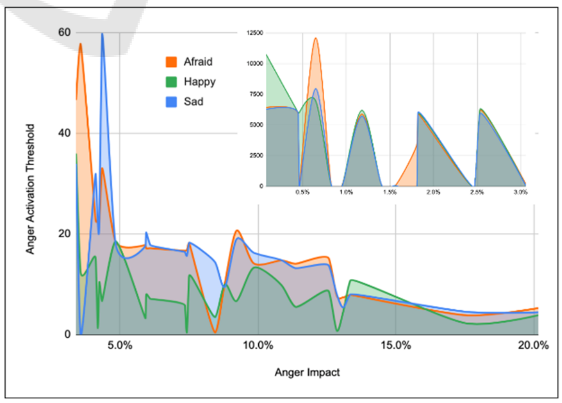
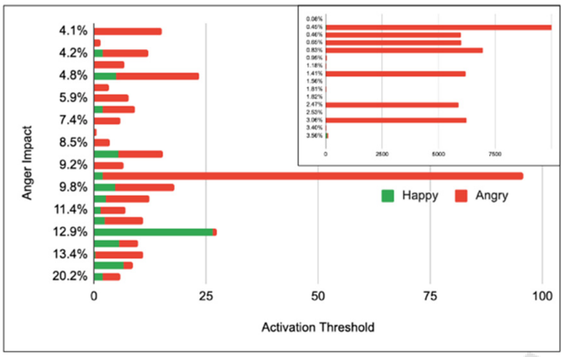
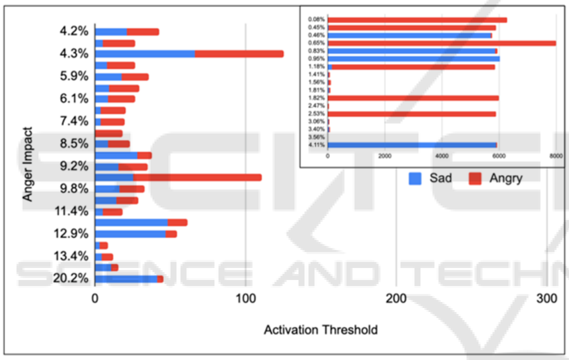


Figure 5: Anger activation threshold and anger impact across emotion pairs.

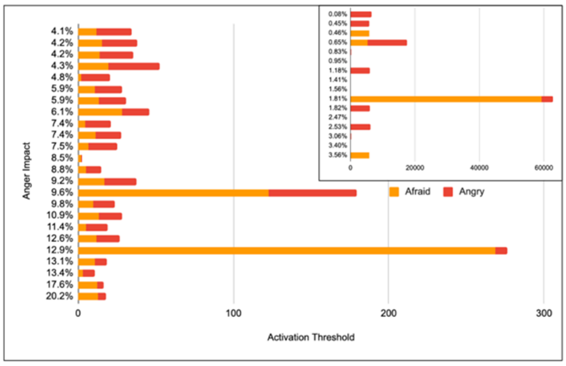
For the sad-angry emotion pair, the activation threshold of sadness is lower 70% of the time which signifies that sadness is easier to experience than anger. Generally at lower anger intensity, sadness is favored (Figure 6b). At higher anger intensity (>12.86%), anger activation thresholds are low which means that in this range anger is easier to activate over sadness. For the Afraid-Angry emotion pair, fear is easier to activate 75% of the time. We can see that at high anger intensity (>12.86%), anger is favored over fear.



(a)



(b)



(c)

Figure 6: Activation Thresholds for (a) Happy-Angry, (b) Sad-Angry and (c) Afraid-Angry landscapes.

Strength of Mutual Inhibition. The strength of mutual inhibition measures the interaction between

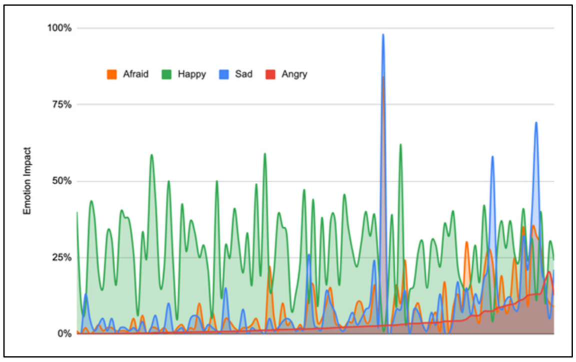


Figure 7: Emotion Impact for fear, happiness, sadness and anger of participants (indexed based on increasing anger impact).

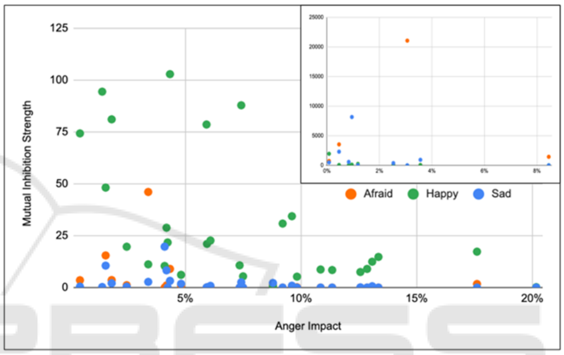


Figure 8: Strength of mutual inhibition of afraid-angry, happy-angry, sad-angry emotion pair.

emotion pairs. A positive value indicates that both emotions inhibit each other while a negative value indicates that the emotions excite each other. Based on our initial look at the emotion impact magnitude, it seems to have a relationship with the strength of mutual inhibition parameters. In Figure 7 we can see that happiness, sadness and then fear ranks from highest to lowest in emotional impact. When we look at the mutual inhibition parameters in Figure 8, we can see that happy- angry are mutually inhibiting for most cases with the magnitude of $|\lambda_{12}| >> 1$. Sad-angry follows this trend of mutual inhibition. Afraid-angry on the other hand is generally independent with $|\lambda_{12}| \sim 0$.

Self-Excitation Strength. Once an emotion is activated, the self-excitation strength measures how easy or difficult it is to keep the emotion in an excited state. First, we look at the self-excitation strength of anger when coupled with other emotions (see Figure 9). As the self-excitation strength of anger decreases, the anger impact increases across all emotions. For

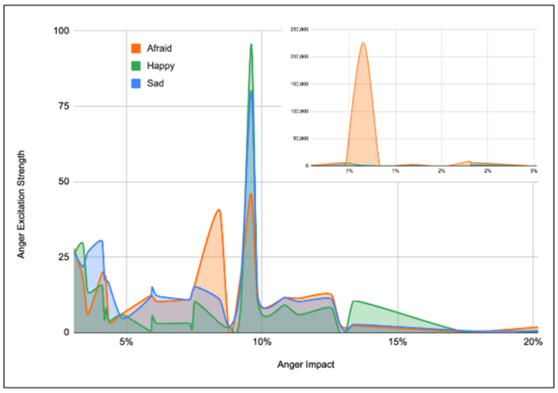


Figure 9: Anger self-excitation strength with afraid-, happy- and sad- anger pairs for increasing anger impact. Inset shows anger impact from 0%-3%.

anger in this range (anger impact > 10%), we see an indirect relationship between the self-excitation strength and emotion impact. Lower λ_i signifies that the emotion is felt for longer. It is also evident that anger self-excitation strength is generally reduced when coupled with happiness.

In the succeeding subsections we delve deeper for each emotion pair.

Afraid-Angry Self-Excitation Strength. Figure 10 shows the self-excitation strength with anger impact for afraid-angry. We consider two cases for this emotion pair to. One is when $\lambda_{Afraid} < \lambda_{Angry}$ (Figure 11a) and $\lambda_{Afraid} > \lambda_{Angry}$ (Figure 11b).

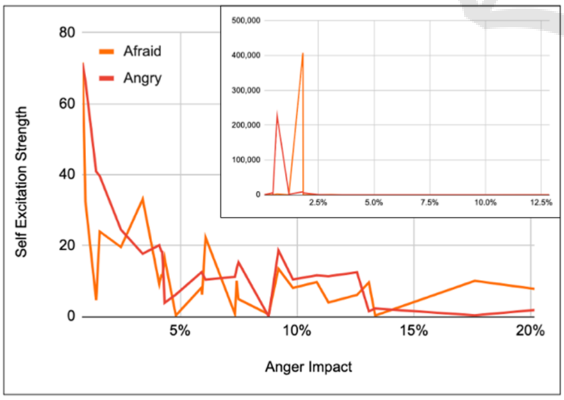


Figure 10: Self-excitation strength of afraid-angry emotion pair. Inset shows cases with higher λ_i values.

Figure 11a shows 62.5% of the population, where $\lambda_{Afraid} < \lambda_{Angry}$. We stipulate that for this scenario (case a), the afraid emotion impact is higher. This is generally true. However, there are six out of the twenty five cases where anger emotion impact is higher (Figure 11a inset). For Case b, when anger has lower self-excitation strength (Figure 11b), afraid generally has the higher emotion impact. There are five of the fifteen cases where anger has the higher emotion impact (Figure 11b-inset). For afraid-angry emotion pair, the hypothesis that lowers self-excitation strength leads to higher emotion impact holds true sixty percent of the time.

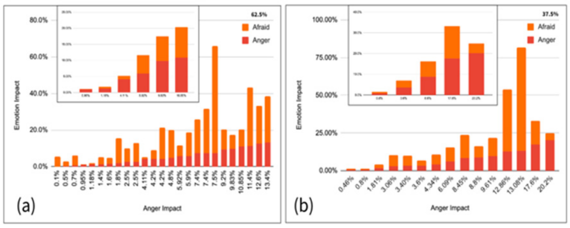


Figure 11: Self-excitation strengths for (a) Afraid < Angry and (b) Afraid > Angry landscapes.

Happy-Angry Self-Excitation Strength. Figure 12 shows the self-excitation strength for happy-angry pair. We test the same hypothesis that lower λ_i means higher emotion impact for that emotion. For this scenario, happiness self-excitation strength is lower so we expect higher happiness impact.

We show the two cases in Figure 13. First, we check the case when happiness has the lower self-excitation strength which holds for 85% of our population. Again, generally, happy impact is higher than anger impact except for the seven out of the thirty four cases (Figure 13a inset) where the reverse is true. When angry has the lower self-excitation strength, only one out of the six cases disagree with the hypothesis. For the happy-anger pair, our hypothesis holds true 67% of the time.

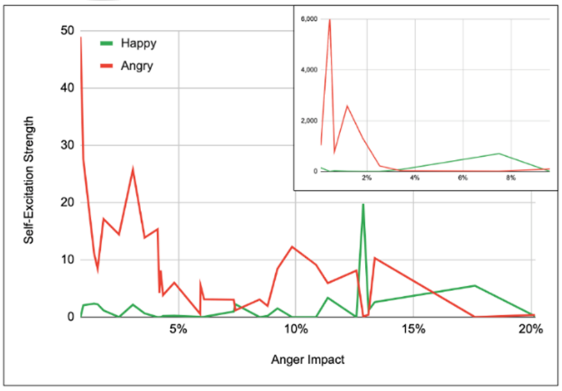


Figure 12: Self-excitation strength of happy-angry pair.

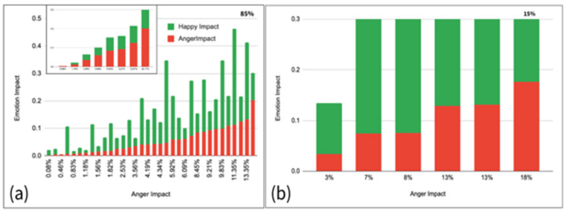


Figure 13: Self-excitation strengths for (a) Happy < Anger and (b) Happy > Anger landscapes.

Sad-Angry Self-Excitation Strength. Figure 14 shows the self-excitation strength for the sad-angry pair. Generally we observe that sadness has the lower λ_i. Again we analyze the two cases and show them in Figure 15 (a & b). For case a, sad has the lower λ_i for 65% of the sample. Generally, sadness will have the higher emotion impact for this scenario. We find however, that twelve of the twenty two samples have anger impact higher than sad impact (Figure 15 a inset). For case b, there are six of the fourteen cases where the reverse of our hypothesis occurs. In the case of sad-angry pair, our hypothesis is true for only 42.5% of the time. Across emotion pairs, the self-excitation strength relationship and contribution to emotion impact varies.

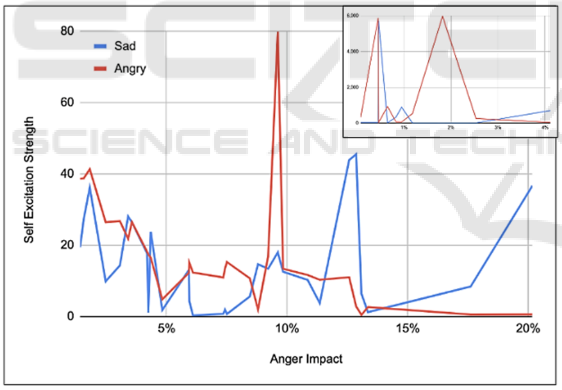


Figure 14: Self-excitation strengths of sad and angry and corresponding strength of mutual inhibition.

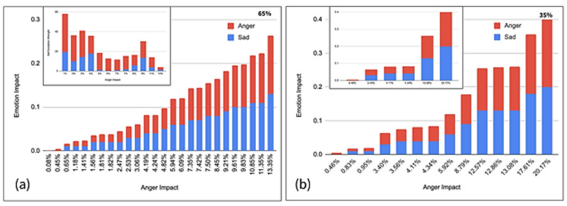


Figure 15: Self-excitation strengths for (a) Sad < Anger and (b) Sad > Anger.

Based on our investigations, we find the following emotion process. An emotion is first activated. Lower activation threshold allows for easier emotion activation. Once activated, the interplay between the pools contribute to the sustained emotional experience measured by the emotional impact. A positive value of strength of mutual inhibition represents two pools mutually inhibiting each other. The self-excitation strength of an emotion coupled with the mutual excitation contributes to the emotion impact.

Across emotion pairs, higher anger impact generally means lower anger activation threshold. Lower activation threshold allows for easier and magnified anger experience in an individual. As the self-excitation strength of anger decreases, the anger impact increases across all emotions. For anger in this range (anger impact > 10%), we see an indirect relationship between the self-excitation strength and emotion impact. When we look at the mutual inhibition parameters, we can see that happiness and anger are mutually inhibiting for most cases with the magnitude of $|\lambda_{12}| >> 1$. Sadness follows this trend of mutual inhibition. Fear on the other hand is almost independent of anger $|\lambda_{12}| \sim 0$.

5 CONCLUSIONS

We demonstrated a computational framework of understanding individual anger experience using Affective Ising model. By performing maximum likelihood of discrete emotion-pair landscapes, we derived insights regarding how an individual experiences anger differently as it co-occurs with other basic emotions namely fear, sadness, and happiness.

While the approach may be promising, the study is hoped to be validated in consultations with psychologists and clinicians. The study shall be extended to include external excitations that are hypothesized to be events or situations experienced by individuals that could critically affect their mental health state and could be the reason for transitioning to a multimodal emotion landscape. With this computational approach, it may be possible to reverse engineer an individual's mental health state by providing appropriate interventions. Once fine-tuned the framework may be utilized to create an anger software aimed at anger emotion diagnosis and management.

The study considered a sample size which can be extended to cover the general population. AIM is a simplified representation of emotion dynamics and does not include representation of culturally specific emotions. Parameter estimation challenges, absence of biological factors, and limited incorporation of external influences contribute to its realism constraints. Despite these limitations, it remains valuable, and researchers should acknowledge its constraints while considering complementary approaches for a more comprehensive understanding of emotional processes.

ACKNOWLEDGEMENTS

G. Tongco-Rosario would like to acknowledge the ERDT Program of the DOST-SEI for her scholarship and other grants.

C. Sio would like to thank the participants in the Inside Out Emotions Tracker survey, Ms. Grazianne-Geneve Mendoza for her assistance in the ESM study and the Philippine Social Science Center for their support in funding the data collection phase through the Research Award Program.

REFERENCES

Bezanson, J., Edelman, A., Karpinski, S., & Shah, V. B. (2017). Julia: A fresh approach to numerical computing. SIAM review, 59(1), 65-98.

Graham, S., Depp, C., Lee, E. E., Nebeker, C., Tu, X., Kim, H. C., & Jeste, D. V. (2019). Artificial intelligence for mental health and mental illnesses: an overview. *Current Psychiatry Reports*, 21, 1-18.

Hamaker, E. L., Ceulemans, E., Grasman, R. P. P. P., & Tuerlinckx, F. (2015). Modeling affect dynamics: State of the art and future challenges. *Emotion Review*, *7*(4), 316-322.

Harley, J., Bouchet, F., and Azevedo, R. (2012). Measuring learners' co-occurring emotional responses during their interaction with a pedagogical agent in MetaTutor, in Lecture Notes in Computer Science, Vol. 7315, Intelligent Tutoring Systems, eds S. A. Cerri, W. J. Clancey, G. Papadourakis, and K. Panourgia (Berlin; Heidelberg: Springer-Verlag), 40–45.

Hauser, T. U., Skvortsova, V., De Choudhury, M., & Koutsouleris, N. (2022). The promise of a model-based psychiatry: building computational models of mental ill health. *The Lancet Digital Health*, 4(11), e816-e828.

Heylen, J., Verduyn, P., Van Mechelen, I., & Ceulemans, E. (2015). Variability in anger intensity profiles: Structure and predictive basis. Cognition and Emotion, 29(1), 168-177.

Houben M, Vansteelandt K, Claes L, Sienaert P, Berens A, Sleuwaegen E, et al. Emotional switching in borderline personality disorder: A daily life study. *Personality Disorders: Theory, Research, and Treatment*. 2016;7(1):50–60.

Loaiza, J. R. (2021). Emotions and the problem of variability. Review of Philosophy and Psychology, 12(2), 329-351.

Loosens, T., Mestdagh, M., Dejonckheere, E., Kuppens, P., Tuerlinckx, F., & Verdonck, S. (2020). The Affective Ising Model: A computational account of human affect dynamics. *PLoS Computational Biology*, *16*(5), e1007860.

Myin-Germeys, I., Kasanova, Z., Vaessen, T., Vachon, H., Kirtley, O., Viechtbauer, W., & Reininghaus, U. (2018). Experience sampling methodology in mental health research: new insights and technical developments. *World Psychiatry*, *17*(2), 123-132.

Panksepp, J. (2007). Neurologizing the psychology of affects: How appraisal-based constructivism and basic emotion theory can coexist. Perspectives on psychological science, 2(3), 281-296.

Price, K. V., Storn, R. M., & Lampinen, J. A. (2005). The differential evolution algorithm. *Differential evolution: a practical approach to global optimization*, 37-134.

Spruijt-Metz, D., Hekler, E., Saranummi, N., Intille, S., Korhonen, I., Nilsen, W., & Pavel, M. (2015). Building new computational models to support health behavior change and maintenance: new opportunities in behavioral research. *Translational Behavioral Medicine*, 5(3), 335-346.

Verdonck, S., & Tuerlinckx, F. (2014). The Ising Decision Maker: a binary stochastic network for choice response time. *Psychological review*, *121*(3), 422.