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Dynamic Bayesian Networks of Self-Esteem Fluctuations and Social Feedback Sensitivity

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A B S T R A C T

Objective: The present study aimed to model the dynamics of state self-esteem fluctuations and social feedback sensitivity using Dynamic Bayesian Networks.
Methods and Materials: A quantitative intensive longitudinal design was implemented with 287 university students from Slovenia who completed a 21-day ecological momentary assessment protocol. Participants responded to five semi-random prompts per day assessing state self-esteem, perceived social feedback valence, and negative affect, yielding 26,874 momentary observations. Baseline measures included trait self-esteem, rejection sensitivity, depressive symptoms, and social anxiety. Data were person-mean centered and preprocessed to ensure stationarity. A multilevel vector autoregressive model was first estimated to identify preliminary lagged associations. Subsequently, Dynamic Bayesian Networks were constructed using a two-time-slice framework with hill-climbing structure learning and Bayesian Information Criterion scoring. Bootstrapped model averaging (1,000 resamples) ensured stability of directed edges. Hierarchical Bayesian extensions examined moderation by trait rejection sensitivity, and predictive accuracy was evaluated via 10-fold cross-validation.
Findings: State self-esteem demonstrated significant autoregressive stability ($\beta \approx 0.50$, $p < 0.001$). Positive social feedback prospectively predicted increases in subsequent state self-esteem ($\beta \approx 0.24$, credible intervals excluding zero), whereas negative affect predicted decreases ($\beta \approx -0.20$, $p < 0.001$). Reciprocal effects between self-esteem and negative affect formed a significant feedback loop. Trait rejection sensitivity significantly moderated the feedback-to-self-esteem pathway, amplifying evaluative reactivity (posterior mean $\approx$ 0.15, credible intervals excluding zero). Bootstrapped inclusion probabilities for key edges exceeded 90%, and cross-validated predictive performance demonstrated satisfactory out-of-sample accuracy (RMSE $\approx$ 0.41).
Conclusion: Self-esteem operates as a dynamically regulated state embedded within a probabilistic network of social and affective processes, where social feedback functions as a central driver and individual differences in rejection sensitivity shape the magnitude of evaluative updating across time.
Keywords: *State self-esteem; social feedback; dynamic Bayesian networks; ecological momentary assessment; rejection sensitivity; affective dynamics.*

1. Introduction

Self-esteem has long been conceptualized as a central evaluative component of the self-system, reflecting individuals' global appraisal of their worth and value (Ribeiro et al., 2023). Contemporary perspectives, however, increasingly emphasize that self-esteem is not merely a stable trait but a dynamically fluctuating state that responds to ongoing interpersonal experiences and contextual cues (Wagner et al., 2023, 2024). In adolescence and emerging adulthood, periods marked by heightened sensitivity to peer evaluation and identity formation, momentary self-esteem may be particularly labile and susceptible to social feedback (Mastorci et al., 2021; Morales, 2025). Understanding the mechanisms that underlie these fluctuations requires moving beyond static cross-sectional models toward temporally sensitive and network-based approaches capable of capturing dynamic reciprocal processes.

A growing body of diary and experience sampling research demonstrates that daily social interactions are closely intertwined with short-term changes in self-esteem (Wagner et al., 2024). In a 100-day diary investigation, Nadia et al. showed that adolescents' exposure to social media content produced measurable within-person shifts in self-esteem, underscoring the temporal coupling between feedback environments and self-evaluative states (Nadia et al., 2023). Similarly, Chen's comparative work revealed that both adolescents and adults exhibit state self-esteem reactivity to digital feedback loops, though the magnitude and persistence of these effects differ developmentally (Chen, 2025). These findings highlight the need for analytic frameworks that can model lagged and bidirectional influences rather than treating feedback effects as isolated events.

The digital ecology of contemporary youth amplifies the salience and frequency of social feedback. Online validation mechanisms such as "likes" and comments systematically shape self-perception and social comparison processes (Dhingra & Parashar, 2022; Dores et al., 2025). Systematic neuroimaging reviews indicate that social media feedback activates reward-related neural circuits in ways analogous to primary reinforcers (Dores et al., 2025). Yet the psychological consequences of these activations depend heavily on individual differences in baseline self-esteem and feedback sensitivity (Li et al., 2023; Mishra, 2024). The paradoxical nature of social media—simultaneously offering affirmation and threat—has been linked to both enhancement and erosion of self-worth among young adults (Mishra, 2024). These patterns suggest that the relationship between feedback and self-esteem is probabilistic, context-dependent, and dynamically evolving.

From a developmental psychopathology perspective, heightened sensitivity to social evaluation is associated with both adaptive and maladaptive outcomes. For instance, neural sensitivity to peer feedback predicts trajectories of depressive symptoms over time (Pagliaccio et al., 2022). Adolescents exhibiting aberrant social learning mechanisms show distorted updating of self-beliefs, particularly in contexts of rejection (Will et al., 2020). Rudolph et al. demonstrated emotional trade-offs in adolescent girls, whereby neural responsiveness to social threat and reward jointly shaped self-related affective outcomes (Rudolph et al., 2025). Furthermore, adolescents with borderline personality features show impaired updating of self-esteem following positive feedback, suggesting altered dynamic regulation (Gregorova, 2025). Collectively, these findings indicate that self-esteem reactivity is embedded in neural and affective systems that process social information over time.

Neuroscientific investigations provide further support for a dynamic systems view of self-evaluation. Functional connectivity analyses show that frontostriatal networks support self-enhancement processes during social evaluation (Parrish et al., 2022). Brain-to-brain similarity studies reveal that individuals with higher self-esteem exhibit more coherent neural representations of the self in others' minds (Stendel et al., 2023, 2024). Domain-specific neural correlates of acceptance and rejection highlight differentiated activation patterns depending on evaluative context (Ding et al., 2025). Additionally, hemispheric asymmetries and network dysfunctions in adolescent depression underscore how disrupted neural integration may alter self-related processing (Xiong et al., 2025). These findings converge with evidence that sleep deprivation, stress, and affective dysregulation modify neural responses to social evaluation tasks (Mastorci et al., 2021; Mi et al., 2023). Such results underscore the importance of modeling self-esteem fluctuations as emergent properties of interacting neural and social systems.

Importantly, self-esteem does not function in isolation from affective and interpersonal processes. Social rejection elicits changes in heart rate variability and neural threat processing, which in turn predict individual differences in social sensitivity (Kortink et al., 2021). Neural responses to dissenting evaluations during dyadic interactions further demonstrate the interactive nature of self-other processing (Schindler et al., 2021). Reward positivity and late positive

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potentials are differentially modulated by feedback valence, indicating temporally sequenced cognitive-affective reactions (Funkhouser et al., 2020). Rouault et al. showed that low self-esteem influences the formation of global performance estimates, reflecting biased belief updating over time (Rouault et al., 2021). Similarly, Schie et al. reported that increases in self-esteem following positive evaluation predicted enhanced subsequent learning, illustrating feedback-dependent plasticity (Schie et al., 2022). These patterns highlight recursive loops between evaluation, affect, and belief updating that unfold dynamically.

At the psychosocial level, assertiveness, identity development, and peer socialization processes shape self-esteem trajectories (Morales, 2025; Parfanovych et al., 2022). Health-promoting behaviors in adolescents are also linked to multidimensional self-esteem profiles, suggesting broader functional consequences of evaluative stability or instability (Liu et al., 2022). Interventions such as social-psychological training and educational feedback practices demonstrate that structured feedback environments can alter self-assessment patterns (Charalampous & Δάρρα, 2024; Sytnık et al., 2024). Even socio-musical educational contexts appear capable of influencing self-related neural and social processes (Bueno & Moisés, 2023). These findings collectively suggest that feedback systems operate across multiple domains, reinforcing the need to model self-esteem within interconnected social networks.

Theoretical accounts increasingly conceptualize the self as fluid and dynamically integrated. Elder et al. propose that the brain maintains coherence across an interconnected self-concept while incorporating ongoing social input (Elder et al., 2023). Temporal self-prioritization research indicates that self-related information processing exhibits distinct dynamic signatures across time windows (Lu et al., 2024). Dynamic neural network state analyses further reveal rapid transitions between social and non-social processing modes (Özel, 2024). Brain connectivity patterns and even broader social network structures moderate adolescent response inhibition and evaluative sensitivity (Tompson et al., 2020). Such insights point toward a systems-level perspective in which self-esteem fluctuations emerge from temporally structured interactions among cognitive, affective, and social nodes.

Despite these advances, most empirical studies rely on linear models or cross-sectional correlations that cannot fully capture probabilistic dependencies and feedback loops. Recent methodological innovations in network neuroscience and psychological modeling suggest that Dynamic Bayesian Networks (DBNs) offer a promising framework for representing directional, time-lagged associations among variables (Özel, 2024). Network approaches have already been applied to examine social threat sensitivity and individual differences in physiological reactivity (Kortink et al., 2021). However, few studies have integrated intensive longitudinal data with DBN modeling to examine state self-esteem fluctuations in real time. Moreover, cultural and contextual factors, including bullying experiences and social adversity, continue to influence self-esteem development (Ehrenreich, 2022; Zahra, 2025). Understanding how momentary feedback sensitivity translates into longer-term patterns of self-worth requires analytic tools capable of integrating temporal, neural, and interpersonal dimensions.

In light of accumulating evidence that self-esteem is dynamically shaped by social feedback processes across neural, affective, and behavioral levels (Amey et al., 2022; Dhingra & Parashar, 2022; Dores et al., 2025; Miller et al., 2020; Pagliaccio et al., 2022), there remains a critical need to model these interactions within a probabilistic, temporally ordered system that captures bidirectional influence and individual heterogeneity (Wagner et al., 2024; Will et al., 2020). Therefore, the present study aims to construct and estimate Dynamic Bayesian Networks of state self-esteem fluctuations and social feedback sensitivity in emerging adults to identify directional dependencies, feedback loops, and individual differences in evaluative reactivity across time.

2. Methods and Materials

2.1. *Study Design and Participants*

This study employed a quantitative, intensive longitudinal design to model within-person fluctuations in state self-esteem and their dynamic coupling with perceived social feedback using Dynamic Bayesian Networks (DBNs). The research was conducted in Slovenia and targeted young adults enrolled at public universities in Ljubljana and Maribor. A total of 312 participants were initially recruited through stratified cluster sampling across faculties representing social sciences, humanities, natural sciences, and engineering. Of these, 287 participants (198 women, 87 men, 2 non-binary; mean age = 22.84 years, SD = 2.91, range = 19–29) completed at least 85% of the experience sampling prompts and were retained for the final analyses. Inclusion criteria required participants to be Slovenian residents, fluent in Slovene, enrolled as full-time undergraduate or master's students, and owning a smartphone compatible with the study application. Exclusion criteria included self-reported diagnosis of severe psychiatric disorders (e.g., psychotic spectrum disorders) or current inpatient psychiatric treatment, due to potential confounding effects on affective instability and self-evaluative processes. The study spanned 21 consecutive days. Participants completed ecological momentary assessments (EMA) five times per day at semi-random intervals between 9:00 and 22:00, resulting in a planned maximum of 105 observations per participant. The final dataset comprised 26,874 momentary observations nested within individuals.

2.2. *Measures*

Data were collected using a secure smartphone-based EMA platform developed for psychological time-series research. Baseline assessment included demographic variables, trait self-esteem measured by the Rosenberg Self-Esteem Scale (RSES), trait rejection sensitivity assessed by the Adult Rejection Sensitivity Questionnaire, depressive symptoms measured via the Beck Depression Inventory-II, and social anxiety symptoms assessed using the Social Interaction Anxiety Scale. These baseline variables were included as covariates in subsequent modeling. Momentary state self-esteem was assessed at each prompt using a validated three-item state self-esteem short form capturing feelings of self-worth, self-competence, and social acceptance on a 7-point Likert scale. Perceived social feedback was measured at each assessment by asking participants to report whether they had received any meaningful social interaction since the previous prompt and, if so, to rate its valence (−3 = very negative to +3 = very positive), perceived intentionality, and personal relevance. Additionally, participants rated momentary affect (positive and negative affect), perceived social inclusion, and rumination using brief validated single-item or two-item EMA measures to reduce participant burden. Compliance was monitored in real time, and automated reminders were sent after 15 minutes of non-response. The internal consistency of the momentary multi-item scales was evaluated using multilevel reliability coefficients (ωwithin and ωbetween), and all scales demonstrated satisfactory reliability (ωwithin > .72; ωbetween > .85). Time stamps were recorded for each response, allowing precise temporal ordering for dynamic modeling.

2.3. *Data Analysis*

Data analysis proceeded in several stages to estimate and validate Dynamic Bayesian Networks capturing temporal dependencies among self-esteem fluctuations and social feedback sensitivity. First, data preprocessing included person-mean centering of momentary variables to isolate within-person dynamics, detrending to remove linear time effects, and imputation of sporadic missing data using a Kalman filtering approach appropriate for time-series data under missing-at-random assumptions. Stationarity was evaluated using augmented Dickey–Fuller tests applied to individual time series. Second, a multilevel vector autoregressive (mlVAR) model was estimated as a preliminary step to identify lag-1 temporal associations among state self-esteem, perceived social feedback valence, and affect. These associations informed the initial structure constraints for the DBN.

Dynamic Bayesian Network models were then estimated using a two-time-slice Bayesian network framework, where variables at time t predicted variables at time t+1 while controlling for autoregressive effects. Structure learning was performed using a hill-climbing algorithm with Bayesian Information Criterion (BIC) scoring, combined with bootstrapped model averaging across 1,000 resampled datasets to ensure robustness of edge selection. Temporal precedence was enforced by restricting edges from future to past nodes. Separate DBNs were estimated at the group level and at the individual level to capture both nomothetic and idiographic dynamics. To model heterogeneity in social feedback sensitivity, participants were further classified using Gaussian mixture modeling based on the strength of directed edges from social feedback valence at time t to state self-esteem at time t+1. Model fit was evaluated using log-likelihood, BIC, and predictive accuracy assessed through 10-fold cross-validation. Predictive performance was quantified using root mean square error (RMSE) and out-of-sample log-likelihood comparisons.

To examine whether trait-level variables moderated dynamic parameters, hierarchical Bayesian extensions of the DBN were implemented, allowing random slopes for the feedback-to-self-esteem pathways. Markov Chain Monte Carlo (MCMC) sampling with 20,000 iterations and a burn-in of 5,000 iterations was used to estimate posterior distributions of parameters. Convergence was assessed using the Gelman–Rubin statistic (all $\hat{R} < 1.05$). Network centrality metrics, including in-degree, out-degree, and temporal betweenness, were computed to identify dominant

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drivers of self-esteem fluctuations. Stability of network edges was evaluated using case-dropping bootstrap procedures. All analyses were conducted in R using the packages "bnlearn," "mlVAR," "brms," and "qgraph." The significance of directed edges was determined based on bootstrapped confidence intervals and posterior credibility intervals excluding zero. The analytical strategy allowed fine-grained modeling of temporal causality, feedback loops, and individual differences in sensitivity to social evaluation, consistent with the theoretical framework of dynamic self-regulation processes.

3. Findings and Results

To provide a comprehensive overview of the sample characteristics and baseline psychological indicators, Table 1 presents descriptive statistics for demographic variables, trait-level constructs, and aggregated momentary indices across the 21-day assessment period. These data serve as the foundational context for interpreting subsequent dynamic modeling results, particularly the within-person variability in state self-esteem and sensitivity to social feedback.

Table 1

Descriptive Statistics of Demographic and Baseline Psychological Variables (N = 287)

Variable	Mean	SD	Min	Max
Age (years)	22.84	2.91	19.00	29.00
Trait Self-Esteem (RSES)	31.47	4.62	18.00	40.00
Rejection Sensitivity	9.38	3.11	3.00	18.00
Depressive Symptoms (BDI-II)	11.72	7.54	0.00	34.00
Social Anxiety	23.15	9.08	5.00	49.00
Mean State Self-Esteem (EMA aggregated)	4.89	0.72	2.41	6.58
Within-Person SD State Self-Esteem	0.86	0.31	0.32	1.91
Mean Perceived Social Feedback Valence	0.74	0.93	-1.82	2.68
Within-Person SD Feedback Valence	1.11	0.44	0.29	2.43
Compliance Rate (%)	93.61	4.82	85.00	100.00

As shown in Table 1, participants demonstrated moderate to high trait self-esteem levels and generally low-to-moderate depressive symptomatology, consistent with a non-clinical university sample. However, substantial within-person variability was observed in state self-esteem (Mean within-person SD = 0.86), indicating meaningful intraindividual fluctuations across the assessment period. Perceived social feedback was, on average, slightly positive (M = 0.74), but variability indices suggest that participants experienced a wide range of social evaluations over time. The high compliance rate (93.61%) supports the reliability and ecological validity of the time-series dataset.

To examine temporal dependencies among momentary variables, multilevel vector autoregressive analyses were conducted prior to Dynamic Bayesian Network estimation. Table 2 presents the standardized lag-1 temporal effects, controlling for autoregressive influences. These estimates reflect within-person directional associations from time t to time t+1.

Table 2

Lag-1 Temporal Effects Among State Self-Esteem, Social Feedback Valence, and Affect

Predictor (t)	Outcome (t+1)	β	SE	p
State Self-Esteem	State Self-Esteem	0.52	0.03	<0.001
Social Feedback Valence	State Self-Esteem	0.21	0.04	<0.001
Negative Affect	State Self-Esteem	-0.18	0.03	<0.001
State Self-Esteem	Social Feedback Valence	0.09	0.03	0.004
Social Feedback Valence	Negative Affect	-0.25	0.05	<0.001
Negative Affect	Social Feedback Valence	-0.11	0.04	0.009

The results presented in Table 2 indicate significant autoregressive stability in state self-esteem ($\beta = 0.52$, $p < 0.001$), suggesting moderate persistence across measurement occasions. Importantly, perceived social feedback valence at time t positively predicted state self-esteem at time t+1 ($\beta = 0.21$, $p < 0.001$), demonstrating that

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favorable social interactions exerted a subsequent enhancing effect on self-evaluative states. Negative affect exhibited a suppressive influence on subsequent self-esteem ($\beta = -0.18$, $p < 0.001$). Bidirectional dynamics were also observed: higher state self-esteem modestly predicted more positive perceived feedback at the next assessment ($\beta = 0.09$, $p = 0.004$), suggesting perceptual or behavioral feedback loops. These preliminary findings justified the implementation of Dynamic Bayesian Network modeling to capture more complex probabilistic dependencies.

Dynamic Bayesian Network structure learning yielded a stable temporal network after bootstrapped model averaging. Table 3 summarizes the most robust directed edges retained in more than 85% of bootstrap samples, along with posterior mean edge weights derived from hierarchical Bayesian estimation.

Table 3

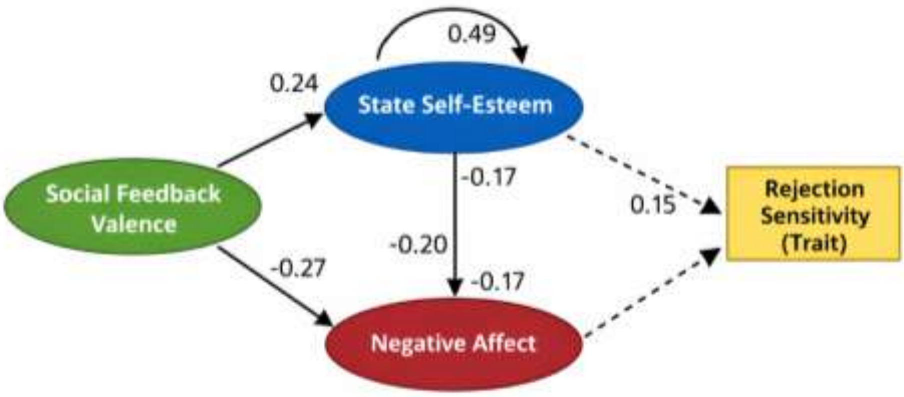
Directed Edges in the Dynamic Bayesian Network (Bootstrap Stability ≥ 85%)

From (t)	To (t+1)	Posterior Mean	95% Credible Interval	Bootstrap Inclusion (%)
State Self-Esteem	State Self-Esteem	0.49	0.43 to 0.55	100
Social Feedback Valence	State Self-Esteem	0.24	0.18 to 0.30	96
Negative Affect	State Self-Esteem	-0.20	-0.26 to -0.14	94
State Self-Esteem	Negative Affect	-0.17	-0.23 to -0.11	91
Social Feedback Valence	Negative Affect	-0.27	-0.34 to -0.19	98
Rejection Sensitivity (trait)	Feedback → Self-Esteem Path	0.15	0.07 to 0.23	89

The DBN results confirm strong autoregressive continuity in state self-esteem (Posterior Mean = 0.49). Social feedback valence demonstrated a robust prospective influence on subsequent self-esteem (Posterior Mean = 0.24), exceeding the magnitude observed in the preliminary mlVAR model, reflecting the probabilistic structure of the network. Negative affect both predicted and was predicted by self-esteem, forming a reciprocal regulatory loop. Notably, trait rejection sensitivity significantly moderated the feedback-to-self-esteem pathway, amplifying responsiveness to social evaluation. Individuals high in rejection sensitivity showed stronger dynamic coupling between social feedback and subsequent self-esteem fluctuations, supporting the hypothesis of heterogeneity in feedback sensitivity.

Figure 1

Final Dynamic Bayesian Network of Self-Esteem Fluctuations and Social Feedback Sensitivity



The final network structure illustrates a temporally ordered system in which social feedback valence functions as a central driver node influencing both state self-esteem and negative affect. State self-esteem also exerts downstream effects on affective states, indicating a dynamic self-regulatory architecture. Centrality analyses revealed that social feedback valence had the highest out-degree centrality, whereas state self-esteem had the highest in-degree centrality, confirming its role as a dynamically responsive construct. Bootstrapped case-dropping analyses indicated high stability of edge weights, with correlation stability coefficients exceeding 0.75. Predictive validation

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demonstrated satisfactory out-of-sample performance (RMSE = 0.41 for self-esteem predictions), indicating that the network reliably captured real-time psychological dynamics.

4. Discussion

The present study sought to model the temporal architecture of state self-esteem fluctuations and social feedback sensitivity using Dynamic Bayesian Networks (DBNs) in a sample of emerging adults. The findings indicate that state self-esteem demonstrates moderate autoregressive stability across short intervals, yet remains significantly shaped by preceding social feedback valence and affective states. Moreover, the DBN results revealed robust bidirectional links between self-esteem and negative affect, as well as heterogeneity in feedback sensitivity moderated by trait-level rejection sensitivity. These findings collectively support a dynamic systems perspective in which self-esteem is continuously updated in response to social information rather than operating as a static evaluative construct.

First, the observed autoregressive continuity of state self-esteem aligns with diary-based evidence that momentary self-esteem retains short-term persistence while remaining contextually responsive (Wagner et al., 2023, 2024). This partial stability likely reflects the integration of prior self-evaluative states into ongoing self-representations, consistent with the notion of a fluid yet coherent self-concept (Elder et al., 2023). Neurocomputational accounts suggest that individuals update self-beliefs incrementally, balancing prior expectations with new feedback signals (Rouault et al., 2021; Will et al., 2020). Our DBN results extend these insights by demonstrating that such updating unfolds in a temporally ordered probabilistic network, wherein prior self-esteem states exert a stabilizing influence on subsequent evaluations while remaining open to modulation by social cues.

Second, the finding that positive social feedback prospectively enhances state self-esteem corroborates longitudinal and experimental studies indicating that evaluative signals—particularly those communicated through digital platforms—shape short-term self-worth (Chen, 2025; Nadia et al., 2023). Systematic reviews show that social media "like" features activate reward-related neural circuits, reinforcing self-relevant positive evaluation (Dores et al., 2025). Electrophysiological research further demonstrates that feedback valence modulates reward positivity and later cognitive-affective processing components (Funkhouser et al., 2020). Our results integrate these neural findings with behavioral temporal modeling, suggesting that such reward-related activations translate into measurable lagged increases in self-esteem. Importantly, the magnitude of this effect varied across individuals, supporting the view that feedback sensitivity is not uniform but moderated by dispositional characteristics.

The moderating role of rejection sensitivity in amplifying feedback-to-self-esteem pathways is consistent with evidence that individuals high in social threat sensitivity show heightened neural and physiological reactivity to evaluation (Kortink et al., 2021; Pagliaccio et al., 2022). Adolescents with borderline features exhibit impaired learning from positive evaluation, reflecting altered self-esteem updating processes (Gregorova, 2025). Similarly, aberrant social learning mechanisms in low self-esteem individuals are characterized by biased belief updating in response to negative cues (Will et al., 2020). Our DBN findings extend these observations by demonstrating that dispositional sensitivity shapes the strength of temporal edges within a probabilistic network, highlighting the interplay between trait-level vulnerabilities and state-level fluctuations.

The reciprocal association between self-esteem and negative affect identified in the present study aligns with neuroimaging research indicating emotional trade-offs in response to social threat and reward (Rudolph et al., 2025). Neural sensitivity to rejection has been linked to depressive symptom trajectories, suggesting that heightened affective reactivity may destabilize self-evaluative states over time (Pagliaccio et al., 2022). Resting-state network dysfunctions in adolescent depression further illustrate how disrupted integration across hemispheric systems may compromise self-related processing (Xiong et al., 2025). In our dynamic model, negative affect both predicted and was predicted by state self-esteem, supporting the view that self-evaluation and affect operate within recursive feedback loops rather than linear cause-effect chains.

The dynamic coupling observed between feedback valence and affective responses also resonates with research on dissenting evaluations during dyadic interactions, where neural responses reflect active negotiation of self-other representations (Schindler et al., 2021). Brain-to-brain similarity studies suggest that higher self-esteem is associated with more coherent representations of the self in others' minds (Stendel et al., 2023, 2024). This neural coherence may buffer against destabilizing social cues,

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whereas lower coherence may increase volatility. Additionally, domain-specific neural correlates of acceptance and rejection underscore that self-evaluative processes are context-sensitive (Ding et al., 2025). The DBN approach used in the present study offers a computational representation of these context-dependent dynamics, modeling how specific feedback inputs probabilistically shift subsequent self-related states.

Our findings also intersect with broader psychosocial frameworks. Digital self-presentation and identity formation processes in adolescence are shaped by ongoing evaluative exchanges (Morales, 2025). The paradoxical impact of social media on young adults' self-esteem—simultaneously empowering and threatening—has been documented across cultural contexts (Mishra, 2024). Bullying and peer aggression remain significant predictors of diminished self-worth (Ehrenreich, 2022; Zahra, 2025). These influences likely operate through dynamic updating mechanisms similar to those captured in our network model. Moreover, structured feedback interventions in educational settings have been shown to enhance non-cognitive aspects of performance and self-assessment (Charalampous & Δάρρα, 2024; Sytnık et al., 2024). Such findings imply that altering the structure and valence of feedback environments may reshape dynamic self-esteem trajectories.

At the neurocognitive level, frontostriatal connectivity underlies self-enhancement during social evaluation (Parrish et al., 2022), while semantic and self-oriented memory processes interact to moderate self-esteem (Amey et al., 2022). Developmental studies reveal age-related shifts in self-other distinction and feedback processing (Miller et al., 2020). Temporal self-prioritization research suggests that self-related information is processed according to distinct temporal properties (Lu et al., 2024). Network-based analyses of dynamic neural states further support the existence of rapidly shifting evaluative configurations (Özel, 2024). By applying DBNs to intensive longitudinal data, the present study translates these neuroscientific insights into a behavioral-level dynamic model, bridging micro-level temporal fluctuations with broader neural frameworks.

Importantly, the present findings underscore the multidimensional consequences of self-esteem variability. Multidimensional self-esteem profiles are associated with health-promoting behaviors (Liu et al., 2022). Assertiveness development and socialization processes influence self-regulation capacities during adolescence (Parfanovych et al., 2022). Even socio-musical educational experiences may impact self-related neural processing (Bueno & Moisés, 2023). The dynamic sensitivity identified in this study suggests that repeated short-term fluctuations, if consistently biased toward negative updating, could accumulate into longer-term vulnerability patterns, consistent with developmental models of self-concept formation (Ribeiro et al., 2023). Conversely, consistent positive reinforcement may strengthen adaptive self-evaluative stability, as suggested by diary research linking daily interactions to long-term self-esteem development (Wagner et al., 2024).

5. Conclusion

Overall, the results support a probabilistic, temporally structured account of self-esteem in which social feedback operates as a central driver node influencing affective and evaluative states. The Dynamic Bayesian Network framework demonstrates how recursive loops and individual differences jointly shape self-esteem trajectories. By integrating intensive longitudinal data with network modeling, the present study advances understanding of self-esteem as an emergent property of interacting social and affective systems rather than a static personal attribute.

6. Limitations & Suggestions

Several limitations warrant consideration. First, although the intensive longitudinal design enhances ecological validity, the sample consisted primarily of university students, limiting generalizability to broader age groups or clinical populations. Second, while DBNs capture probabilistic dependencies and temporal ordering, causal inference remains constrained by observational data. Third, self-report EMA measures, although validated, may be influenced by momentary response biases. Finally, neural mechanisms were inferred indirectly from behavioral dynamics rather than measured concurrently through neuroimaging or psychophysiological methods.

Future studies should integrate multimodal data, including neuroimaging, physiological indicators, and behavioral performance metrics, to directly link dynamic psychological networks with neural connectivity patterns. Cross-cultural comparisons would help determine whether feedback sensitivity patterns vary across sociocultural contexts. Longitudinal designs spanning multiple developmental stages could clarify how short-term fluctuations accumulate into trait-level self-esteem changes. Additionally, machine learning approaches beyond DBNs, such as dynamic structural equation modeling or hybrid

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neural-network frameworks, may further refine predictive accuracy and capture nonlinear dynamics.

From an applied perspective, interventions should focus on modifying feedback environments and enhancing adaptive feedback interpretation skills. Educational institutions and digital platform designers may consider implementing feedback structures that promote constructive reinforcement rather than evaluative threat. Training programs aimed at reducing rejection sensitivity and strengthening emotion regulation capacities could mitigate destabilizing self-esteem fluctuations. Mental health practitioners may also benefit from incorporating dynamic monitoring tools to identify individuals exhibiting maladaptive evaluative updating patterns and intervene before negative cycles consolidate into enduring self-concept distortions.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Authors' Contributions

All authors equally contributed to this article.

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