

INDUS
INTERNATIONAL
UNIVERSITY

RESEARCH | COLLABORATE | TRANSFORM
FOR A BETTER TOMORROW

Proceedings of International Conference on Multidisciplinary Research: Innovation, Healthcare, Education for Viksit Bharat (ICMR-2026)



INNOVATION



HEALTHCARE



EDUCATION



SUSTAINABLE
DEVELOPMENT



VIKSIT BHARAT

PART

2

Editors

Prof. (Dr.) Punit Goel
Dr. Abu Farah Hoque
Dr. Amit Agrawal
Dr. Sheela Sharma



International Conference On Multidisciplinary Research

Conference Proceedings

Contemporary Perspectives in English Literature,
Sociology, Hindi and Home Science For Viksit Bharat

2026

Organized by

Kalindi Institute of Medical Sciences

Agrasen Mahavidyalaya

Veetranga Research Foundation

In Collaboration with

Wissira Research Lab

Print ISBN: 978-93-7559-048-4

Digital ISBN: 979-8-952358-04-1

Table of Contents

<i>Chapter 1: Academic Goal Orientation and Learning Persistence among University Students.....</i>	<i>1</i>
<i>Chapter 2: Academic Procrastination and Learning Engagement among Undergraduate Students</i>	<i>9</i>
<i>Chapter 3: Academic Resilience and Educational Achievement among College Students</i>	<i>17</i>
<i>Chapter 4: Collaborative Problem-Solving and Learning Achievement among Secondary Students ...</i>	<i>25</i>
<i>Chapter 5: Digital Accounting Technologies and Financial Reporting Efficiency in Business Organizations</i>	<i>32</i>
<i>Chapter 6: Digital Banking Services and Customer Satisfaction in the Contemporary Banking Sector</i>	<i>41</i>
<i>Chapter 7: Digital Distraction and Academic Concentration among University Learners</i>	<i>48</i>
<i>Chapter 8: Ecological Consciousness and Climate Narratives in Contemporary English Fiction</i>	<i>56</i>
<i>Chapter 9: Green Marketing Practices and Sustainable Consumer Behaviour in Urban Markets.....</i>	<i>65</i>
<i>Chapter 10: Inclusive Education Practices and Social Participation among Diverse Learners</i>	<i>74</i>
<i>Chapter 11: Inclusive Teaching Practices And Learning Outcomes In Diverse Classrooms.....</i>	<i>82</i>
<i>Chapter 12: Loneliness and Social Connectedness in the Digital Communication Era</i>	<i>91</i>
<i>Chapter 13: Mindfulness Practices and Perceived Stress among College Students</i>	<i>99</i>
<i>अध्याय 14: NEP 2020 के अंतर्गत शिक्षा में बहुभाषिकता और भाषायी समावेशन की संभावनाएँ.....</i>	<i>106</i>
<i>अध्याय 15: NEP 2020 के परिप्रेक्ष्य में व्यावसायिक शिक्षा और रोजगारपरक कौशल विकास</i>	<i>113</i>
<i>अध्याय 16: NEP 2020 के संदर्भ में उच्च शिक्षा में बहुविषयक अधिगम की संभावनाएँ.....</i>	<i>121</i>
<i>अध्याय 17: NEP 2020 के संदर्भ में शिक्षक शिक्षा के बदलते स्वरूप और व्यावसायिक दक्षता का अध्ययन..</i>	<i>128</i>
<i>अध्याय 18: NEP 2020 के संदर्भ में शिक्षा में प्रौद्योगिकी एकीकरण और डिजिटल समानता की चुनौतियाँ...</i>	<i>135</i>
<i>Chapter 19: Online Social Validation and Self-Concept among Emerging Adults</i>	<i>142</i>
<i>Chapter 20: Parental Involvement and Academic Motivation among School-Going Adolescents.....</i>	<i>149</i>
<i>Chapter 21: Perceived Organizational Support and Employee Psychological Resilience</i>	<i>158</i>
<i>Chapter 22: School-Based Assessment and Learning Improvement among Secondary Learners.....</i>	<i>165</i>
<i>Chapter 23: Self-Regulated Learning Strategies and Academic Achievement among Undergraduates</i>	<i>173</i>
<i>Chapter 24: Sleep Quality and Academic Performance among Higher Education Students</i>	<i>180</i>
<i>Chapter 25: Social-Emotional Learning and Classroom Adjustment among Adolescent Students...</i>	<i>187</i>
<i>Chapter 26: Socioeconomic Factors and Educational Aspirations among Secondary School Students</i>	<i>194</i>
<i>Chapter 27: Student-Centred Pedagogy and Active Learning in Undergraduate Classrooms.....</i>	<i>201</i>
<i>Chapter 28: Teacher Self-Efficacy and Classroom Management Practices in Secondary Schools.....</i>	<i>209</i>
<i>Chapter 29: Technology, Youth Culture, and Emerging Forms of Social Identity.....</i>	<i>218</i>

<i>Chapter 30: Technology-Enhanced Teaching and Classroom Participation among Undergraduate Learners</i>	<i>225</i>
अध्याय 31: उच्च शिक्षा में कृत्रिम बुद्धिमत्ता आधारित शिक्षण से अकादमिक सहभागिता का मूल्यांकन	233
अध्याय 32: उच्च शिक्षा में शैक्षिक नेतृत्व और शिक्षक नवाचार संस्कृति के मध्य संबंध	240
अध्याय 33: गृह विज्ञान और वस्त्र विज्ञान के संदर्भ में पर्यावरण-अनुकूल परिधान चयन एवं उपभोक्ता जागरूकता का अध्ययन	247
अध्याय 34: मनोविज्ञान के परिप्रेक्ष्य में सकारात्मक पालन-पोषण और किशोर मानसिक लचीलापन का प्रभाव	254
अध्याय 35: विद्यालयी शिक्षा में शिक्षक भावनात्मक बुद्धिमत्ता और कक्षा प्रबंधन प्रभावशीलता का अध्ययन .	261
अध्याय 36: विधायी कानून के अंतर्गत साइबर अपराध नियंत्रण और व्यक्तिगत डेटा संरक्षण का समकालीन अध्ययन	267
अध्याय 37: शिक्षा में खेल आधारित अधिगम द्वारा विद्यार्थियों की संज्ञानात्मक सहभागिता का विकास.....	273
अध्याय 38: शिक्षा में परियोजना आधारित अधिगम द्वारा समस्या समाधान कौशल के विकास का विश्लेषण .	281
अध्याय 39: सोशल मीडिया का युवा पीढ़ी की हिंदी भाषा पर प्रभाव.....	288
अध्याय 40: हिंदी साहित्य में पर्यावरण चेतना और प्रकृति विमर्श का अध्ययन.....	294

List of Contributors

Ch.	Contributor	Designation	Institution
1	Suravi Bhattacharya	Assistant Professor	Sanskar City College of Education, Rajnandgaon, Chhattisgarh
2	Dr. Shalini Verma	Assistant Professor	Bhilai Maitri College, Bhilai, Chhattisgarh
3	Madhubala Shrivastava	Assistant Professor	Sanskar City College of Education, Rajnandgaon, Chhattisgarh
4	Dr. Pushpa Sharma	Associate Professor	Mansa College of Education, Kohka, Kurud, Chhattisgarh
5	Dr. Ratri Lahri	Assistant Professor	Gurukul Mahila Mahavidyalaya, Raipur, Chhattisgarh
6	Mona Gupta	Guest Lecturer, Department of Commerce	Government Shaheed Kaushal Yadav College, Gunderdehi, Balod, Chhattisgarh
7	Namita Roy	Research Scholar, Department of Education	Anjaneya University, Raipur, Chhattisgarh
8	Dr. Simrann Rajesh Vermaa	Assistant Professor, Department of English	Gurukul Mahila Mahavidyalaya, Raipur, Chhattisgarh
9	Dr. Kavita Silwal	Assistant Professor	Gurukul Mahila Mahavidyalaya, Raipur, Chhattisgarh
10	Dr. Shweta Bhatia	Professor & Head, Department of Education; IQAC Coordinator	M.J. College, Kohka, Bhilai, Chhattisgarh
11	Dr. Soju Samuel	Counsellor	Delhi Public School, Bhilai, Chhattisgarh
12	Dular Das	Research Scholar	Hemchand Yadav University, Durg, Chhattisgarh
13	Dr. Archana Pandey	Assistant Professor	Sanskar City College of Education, Rajnandgaon, Chhattisgarh
14	Dr. Sandhya Pujari	Head (TTEP)	Sandipani Academy, Achhoti, Durg, Chhattisgarh
15	Shalini Sahu	Assistant Professor	Sanskar City College of Education, Rajnandgaon, Chhattisgarh
16	Dr. Manju Sahu	Associate Professor	M.J. College, Kohka, Bhilai, Chhattisgarh
17	Mrs. Lileshwari Sahu	Assistant Professor	Somni Mahavidyalaya, Somni, Rajnandgaon, Chhattisgarh
18	Dr. Shraddha Bhardwaj	Assistant Professor	Jagadguru Shankaracharya College of Education, Bhilai, Durg, Chhattisgarh
19	Mamta Rani Yadu	Research Scholar	Anjaneya University, Raipur, Chhattisgarh

International Conference On Multidisciplinary Research

20	Dr. Sumita Singh	Assistant Professor, Department of Education	St. Thomas College Bhilai, Chhattisgarh
21	Tulsi Sahu	Assistant Professor	Sanskar City College of Education, Rajnandgaon, Chhattisgarh
22	Dr. Juhi Peter	Assistant Professor	Agrasen College, Dhanora, Durg, Chhattisgarh
23	Dr. Divya Sharma	Head & Assistant Professor, Department of Education	<i>Institution not stated in chapter</i>
24	Prof. (Dr.) Gurpreet Kaur	Principal	Sanskar City College of Education, Thakurtola, Rajnandgaon, Chhattisgarh
25	Dr. Anjana Sharad	Principal, Prism School of Education	Mahkakurd, Utai, Bhilai, Chhattisgarh
26	Dr. Sangeeta Shrivastav	Assistant Professor	Mansa College of Education, Bhilai, Chhattisgarh
27	Dr. Ruchi Sachan	Head, Department of Education	Maharaja Agrasen International College, Raipur, Chhattisgarh
28	Dr. Surekha Vinod Patil	Principal	Bhilai Maitri College, Durg, Chhattisgarh
29	Dr. Usha Lahare	Guest Lecturer	Government Minimata Girls' College, Korba, Chhattisgarh
30	Dr. Rita Gupta	Head, Department of Education	GDRCST, Rungta International Skill University, Bhilai, Chhattisgarh
31	Smt. Anupama Ambast	Assistant Professor	CTE, Raipur, Chhattisgarh
32	Smt. Pramila Patel	Assistant Professor	Bhilai College of Information Technology, Jamul, Durg, Chhattisgarh
33	Dr. Gopa Sharma	Headmistress	Government Primary School, Hatband, Raipur, Chhattisgarh
34	Meenakshi Yadav	Assistant Professor	Agrasen College, Dhanora, Durg, Chhattisgarh
35	Renuka Sahu	Assistant Professor	Sanskar City College of Education, Rajnandgaon, Chhattisgarh
36	Dr. Atul Kumar Soni	Assistant Professor	Pt. Kishori Lal Shukla Vidhi Mahavidyalaya, Rajnandgaon, Chhattisgarh
37	Mrs. Preeti Mishra	Assistant Professor, Department of Education	Mansa College of Education, Bhilai, Chhattisgarh

International Conference On Multidisciplinary Research

38	Ranjana Solanki	Assistant Professor	Agrasen College, Dhanora, Durg, Chhattisgarh
39	Dr. Nirmala Parganiha	Assistant Professor	Agrasen College, Dhanora, Durg, Chhattisgarh
40	Kiran Sonatiya	Assistant Professor	Sanskar City College of Education, Rajnandgaon, Chhattisgarh

Chapter 19: Online Social Validation and Self-Concept among Emerging Adults

Mamta Rani Yadu

Research Scholar

Anjaneya University

Raipur, Chhattisgarh

Abstract— Online social platforms increasingly transform interpersonal approval into visible and quantifiable signals such as likes, reactions, comments, shares, and follower counts. For emerging adults, repeated exposure to these metrics may influence not merely momentary self-esteem but the organization, stability, and clarity of the broader self-concept. The present study proposes a digital-behavioral framework for examining how dependence on online social validation relates to self-concept clarity among individuals aged 18–29 years. A central research gap is identified in the limited integration of psychological self-report measures with computational indicators derived from validation-seeking behavior and simulated social-feedback responses. The proposed framework conceptualizes validation dependence as a multidimensional construct involving approval monitoring, feedback sensitivity, comparative engagement, and emotional reactivity to insufficient feedback. Machine-learning analysis is subsequently designed to determine whether these combined behavioral and psychological indicators can distinguish relatively stable from validation-contingent self-concept profiles.

Keywords— Online social validation, Self-concept clarity, Emerging adulthood, Social media, Machine learning, Digital mental health

Introduction

Social media has altered the architecture of interpersonal evaluation. Approval that was historically communicated through conversation, facial expression, social inclusion, or other contextual signals can now be expressed through numerical and persistent indicators. Likes, reactions, comments, reposts, views, and follower counts make social evaluation visible, comparable, and repeatedly accessible. For emerging adults, whose identities may still be undergoing substantial educational, occupational, relational, and personal development, these feedback mechanisms create an environment in which evaluations from others can become intertwined with evaluations of the self.

The psychological importance of online feedback cannot be reduced to the amount of time spent using social media. Two individuals with comparable daily usage may have substantially different experiences. One may primarily use digital platforms for communication and information exchange without attaching substantial personal significance to engagement statistics. Another may repeatedly monitor reactions, modify self-presentation according to anticipated approval, compare engagement counts with peers, or interpret unexpectedly weak feedback as evidence of social inadequacy. Consequently, the

psychological meaning assigned to online feedback may be more informative than exposure duration alone.

Empirical evidence provides a basis for this distinction. Using objective Facebook behavioral data from 2,349 users, Marengo et al. found that profile activity and personal-content sharing were associated with the amount of positive feedback received and that received likes were connected with perceived happiness through self-esteem. Their findings demonstrate that measurable online feedback can participate in psychological processes rather than functioning merely as a superficial platform statistic. Earlier experimental work similarly demonstrated that the relationship between positive social-media feedback and self-esteem can depend on individual psychological resources, including purpose in life.

More recent experimental evidence strengthens the argument that the quantity of social feedback can affect emerging adults. Xiao et al. studied 1,007 undergraduate students using an experimental social-media paradigm in which participants received different levels of likes. Participants receiving fewer likes showed lower self-esteem, reduced meaningful existence, and fewer positive emotions; some effects were stronger among individuals reporting greater shyness or previous cybervictimization. These findings indicate that numerical social signals can acquire sufficient psychological salience to influence immediate self-related and emotional states.

However, self-esteem and self-concept are not interchangeable. Self-esteem primarily concerns evaluative feelings about personal worth, whereas self-concept encompasses the organized knowledge, attributes, beliefs, roles, and representations through which individuals understand who they are. An individual can experience temporary changes in self-esteem without experiencing substantial restructuring of the self-concept. Conversely, chronic dependence on external evaluation may potentially make self-definition less internally coherent even when average self-esteem appears relatively adequate.

Self-concept clarity is therefore especially relevant. It concerns the extent to which beliefs about oneself are clearly defined, internally consistent, and relatively stable. Digital environments may influence this clarity through what can be described as a recursive feedback process. A user constructs a digital representation of the self, observes audience reactions, interprets those reactions, modifies subsequent presentation, and receives another round of evaluation. Over repeated cycles, externally rewarded representations may become disproportionately influential in determining which personal attributes are displayed, emphasized, or regarded as socially valuable.

Developmental research provides additional grounds for investigating this mechanism. A behavioral and neuroimaging study involving adolescents and young adults found associations between social-media use, reflected peer judgments, and aspects of self-concept processing. Participants with greater social-media use demonstrated smaller differences between their own self-ratings and how they believed peers would evaluate them, illustrating the potential relevance of perceived audience evaluation to self-representation. Although that investigation extended only to age 21 at baseline and was not designed specifically around validation dependence, it provides evidence that digitally mediated peer evaluation deserves consideration in models of self-concept development. The present manuscript consequently distinguishes **online social validation exposure** from **online social validation dependence**. Exposure refers to encountering or receiving indicators of approval. Dependence refers to the degree to which individuals use those indicators to regulate self-evaluation, emotional state, or subsequent self-presentation. This distinction addresses a conceptual limitation in studies that treat the number of likes received as equivalent to their psychological influence. Ten likes may have negligible significance for one person and considerable self-evaluative significance for another.

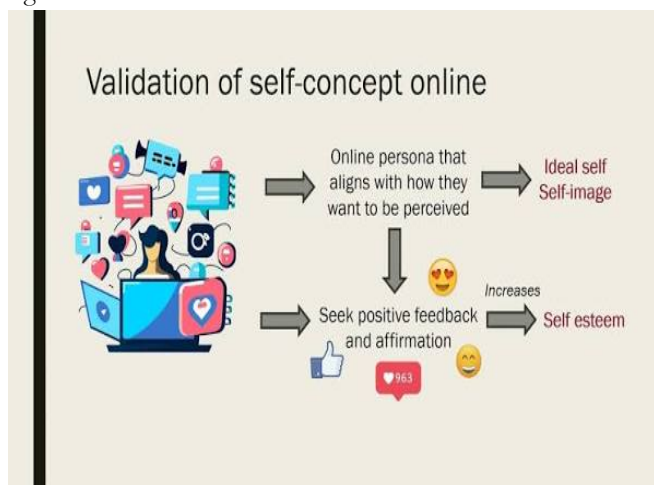


Fig. 1: Validation of Self Concept

Source: <https://www.youtube.com/watch?v=5PGGagWZOWQ>

Research Gap

Existing research has established relationships among social-media feedback, self-esteem, emotional responses, happiness, and perceived social inclusion. Experimental studies have also demonstrated that manipulated feedback can alter short-term psychological responses. Nevertheless, three methodological issues remain important.

First, much of the literature concentrates on **self-esteem or immediate affective outcomes rather than self-concept clarity**. This leaves unresolved whether dependence on digital approval corresponds with the organization and stability of self-knowledge rather than merely transient feelings of personal worth.

Second, online validation is frequently represented by a single indicator—most commonly likes. Contemporary social validation is multidimensional. Users encounter reaction

counts, comments, views, follower changes, response latency, comparison with peer engagement, and perceived discrepancies between expected and actual feedback. A multidimensional representation may therefore capture validation sensitivity more effectively than raw engagement counts.

Third, traditional linear statistical models may insufficiently represent heterogeneous and nonlinear patterns. The psychological consequences of validation are unlikely to increase uniformly with every additional like or comment. Effects may depend on baseline self-concept, expectations, comparison tendencies, emotional reactivity, and behavioral monitoring. Machine-learning methods provide a complementary means of identifying interactions and nonlinear combinations without assuming that every predictor operates independently or linearly.

The distinctive research gap addressed in this study is therefore the **absence of an integrated computational framework that combines multidimensional online-validation dependence, feedback-reactivity indicators, and psychological measures to model self-concept clarity among emerging adults**.

Accordingly, the principal objective is to investigate whether self-concept profiles can be computationally differentiated using patterns of online validation dependence rather than general social-media use alone. A secondary objective is to determine which behavioral dimensions—such as feedback monitoring, approval-based self-presentation, social comparison, or emotional sensitivity to low engagement—contribute most strongly to model predictions. This approach positions machine learning as an analytical instrument for psychological pattern recognition rather than as a substitute for psychological theory.

The study is guided by the expectation that stronger dependence on external digital validation will correspond with lower self-concept clarity, particularly when validation dependence co-occurs with frequent comparison and high emotional reactivity. It is further anticipated that nonlinear models will reveal heterogeneous profiles that conventional exposure-based measures may obscure.

Literature Review

Online Social Feedback as a Psychological Signal

Social validation can be conceptualized as information indicating acceptance, recognition, interest, or approval from other people. Digital platforms have operationalized such information through explicit engagement features. These mechanisms are distinctive because they quantify social response and permit users to compare their feedback with that received by others.

Sociometer-based interpretations provide one explanation for why these indicators matter psychologically. If self-esteem partly responds to perceived relational value, visible indicators of acceptance can temporarily affect self-evaluation. Burrow and Rainone demonstrated this principle through observational and experimental studies in which positive Facebook feedback was associated with self-esteem, while purpose in life reduced sensitivity to that feedback. This moderating effect is

theoretically important because it demonstrates that feedback does not exert uniform influence. Internal psychological resources can modify the extent to which external approval becomes self-relevant.

Research using objective digital data has provided complementary evidence. Marengo et al. avoided exclusive reliance on participants' recollections of online behavior by examining Facebook profile activity and received likes. Positive feedback was associated with happiness, with self-esteem functioning as part of the explanatory pathway. The study illustrates the value of integrating behavioral traces with psychological variables—a principle extended in the proposed methodology of the present investigation.

Insufficient Validation and Emotional Reactivity

The absence or relative scarcity of positive feedback may also carry psychological meaning. Rather than interpreting engagement in absolute terms, users can evaluate their feedback against expectations and the apparent popularity of peers. Consequently, perceived under-validation may operate as a discrepancy signal: the response received differs from the response anticipated.

Recent experimental research provides particularly relevant evidence. Xiao et al. randomly exposed young adults to different quantities of likes and observed significantly lower self-esteem among participants assigned to receive fewer likes. Lower-feedback participants also reported weaker meaningful existence and fewer positive emotions. Importantly, vulnerability was not homogeneous: shyness and previous cybervictimization intensified some negative responses.

This heterogeneity supports the present manuscript's decision to avoid a simple deterministic proposition that "fewer likes cause poorer self-concept." The theoretically meaningful construct is feedback sensitivity. An individual's response to the discrepancy between anticipated and received validation may provide substantially more information than the raw number of reactions.

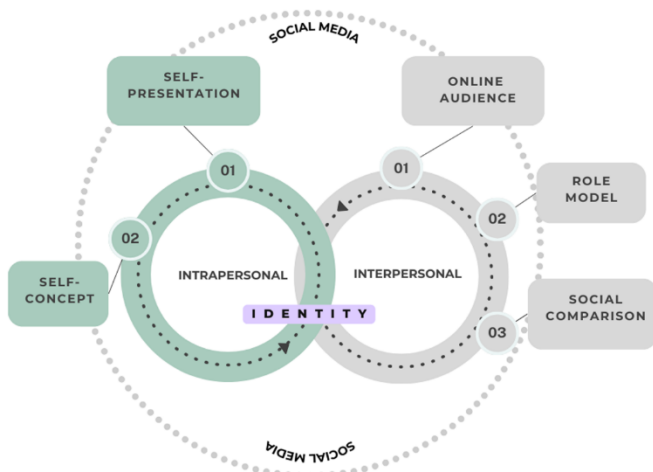


Fig. 2: Social media: a digital social mirror for identity development during adolescence

Source: <https://link.springer.com/article/10.1007/s12144-024-05980-z>

Earlier experimental work on selfie posting likewise indicates that psychological effects vary according to the outcome assessed and the timing of measurement. In a seven-day

intervention involving participants aged 16–25, Coulthard and Ogden reported different patterns for appearance and face satisfaction, while the intervention did not produce a general effect on self-esteem or mood. Such findings caution against treating social-media feedback as a universally positive or negative exposure.

From Self-Esteem to Self-Concept

A substantial portion of social-validation research examines self-esteem because it provides a sensitive indicator of perceived worth. Yet emerging adulthood involves broader identity-related processes. People must integrate academic abilities, employment aspirations, relationships, physical characteristics, personal values, social roles, and future identities into reasonably coherent representations of themselves.

Online environments complicate this process because self-presentation is both editable and observable. Users can selectively publish attributes likely to attract favorable responses. When particular presentations receive disproportionately high engagement, those attributes may become reinforced. Over time, a feedback-dependent individual may increasingly answer the implicit question "Who am I?" using evidence derived from "What receives approval?"

The distinction has methodological implications. An immediate reduction in self-esteem following weak engagement does not necessarily indicate low self-concept clarity. Conversely, repeatedly adapting one's digital identity to external approval could theoretically produce uncertainty even when short-term self-esteem remains high. The present framework therefore treats self-concept clarity as the central outcome while retaining validation-related affective processes as explanatory features.

Research examining neural and behavioral mechanisms of social-media use supports greater attention to reflected self-appraisal. In a longitudinal study of 150 adolescents and young adults, social-media use was examined alongside self-ratings and participants' estimates of how peers would rate them. Greater use was associated with smaller differences between self-evaluations and anticipated peer evaluations, alongside differences in medial prefrontal cortex activity during self-related processing. Although these findings cannot establish that social validation causes self-concept change, they demonstrate that perceived peer evaluation and self-processing can be empirically connected.

Social Comparison and Algorithmically Visible Popularity

Social comparison represents another mechanism connecting online validation with self-concept. Social-media platforms expose users not only to others' content but also to visible indicators of how audiences respond to that content. Comparison can therefore occur simultaneously at the level of appearance, achievement, lifestyle, and social popularity.

For emerging adults, this environment may encourage comparative self-appraisal. A user can evaluate whether a peer appears more attractive or successful while simultaneously observing that the peer's content attracts greater engagement. Quantified popularity may consequently function as an additional cue suggesting which identities or attributes receive social reward.

The important distinction is again between availability and dependence. Social comparison is possible without substantially modifying self-definition. Risk may become greater when comparative information is repeatedly internalized as evidence of personal adequacy. Thus, the proposed model treats comparison orientation and validation dependence as interacting constructs rather than assuming that exposure automatically produces adverse psychological outcomes.

Proposed Methodology

The study adopts a **multimodal predictive-analytic design** to examine whether dependence on online social validation can predict variations in self-concept clarity among emerging adults. Unlike approaches that use daily social-media duration as the principal exposure variable, the proposed framework models the psychological significance assigned to digital feedback. The analytical unit is therefore not simply platform use but the combination of feedback monitoring, approval sensitivity, social comparison, validation-contingent self-presentation, and emotional reactions to discrepancies between expected and received engagement.

The primary outcome variable is **self-concept clarity (SCC)**, operationalized using the 12-item Self-Concept Clarity Scale developed by Campbell et al. The original instrument conceptualizes SCC as the extent to which beliefs about oneself are clearly and confidently defined, internally consistent, and temporally stable. Higher scores indicate a more coherent and stable self-concept after appropriate reverse scoring.

A composite **Online Validation Dependence Index (OVDI)** is proposed specifically for the present study. Rather than treating likes as an isolated predictor, the OVDI consists of four domains: feedback-monitoring intensity, approval-contingent self-evaluation, comparative engagement sensitivity, and behavioral adaptation following weak feedback. Items are rated on a five-point response format. Because the OVDI is a newly proposed research measure, its dimensional structure would require empirical validation before substantive interpretation.

Participants are emerging adults aged 18–29 years who report active use of at least one social-media platform during the preceding six months. A target sample of **480 participants** is proposed to provide sufficient observations for model development and held-out evaluation. Recruitment would use stratified sampling across university students, employed young adults, and individuals in transitional education or employment settings to avoid restricting emerging adulthood to undergraduate populations.

Participation would require informed consent. Direct identifiers, private messages, passwords, contact lists, and raw personal posts would not be collected. Behavioral indicators would be self-reported or voluntarily generated through controlled study tasks. The protocol should receive institutional ethics approval before data collection.

Experimental Setup

Dataset Construction

The proposed dataset contains three feature families.

The first family comprises **psychological variables**, including SCC score, validation dependence, social-comparison

orientation, perceived importance of online approval, and emotional response to weak engagement.

The second comprises **behavioral indicators**, such as estimated frequency of checking engagement after posting, time to first feedback check, frequency of editing or deleting poorly performing posts, attention to follower changes, and frequency of comparing one's engagement with that of peers.

The third comprises **feedback-discrepancy variables** generated through controlled hypothetical social-media scenarios. Participants indicate the number of reactions they would normally expect for standardized posting scenarios and report their likely affective response when hypothetical engagement is substantially below, near, or above expectation. This permits calculation of an **Expected–Received Validation Discrepancy (ERVD)** without manipulating participants' real social-media accounts.

The dataset would contain approximately 25–35 candidate predictors after demographic and behavioral coding. Age and broad participant-status variables would be retained primarily for adjustment and subgroup analysis rather than treated as psychologically meaningful determinants by default.

Preprocessing

Preprocessing would begin with range checks, duplicate-response screening, attention checks, and assessment of completion time. Records failing predefined data-quality criteria would be excluded before model fitting.

For multi-item measures, scoring would follow the specifications of the original instruments. The SCC Scale consists of 12 items rated on a five-point response scale, with multiple reverse-keyed items. The original scale and its psychometric foundation were reported by Campbell et al. in *Journal of Personality and Social Psychology*.

Missing numerical values would be imputed using training-set medians when the amount of missingness remains below a predefined acceptable threshold. Categorical variables would be encoded without imposing artificial ordinal relationships. Continuous predictors used by scale-sensitive algorithms would be standardized using parameters estimated exclusively from the training partition.

To prevent information leakage, the complete preprocessing pipeline—including imputation, scaling, feature selection, and hyperparameter optimization—would be fitted inside the training folds rather than before cross-validation.

The primary outcome would be treated continuously in regression analysis. A secondary classification analysis would divide participants into lower-clarity and higher-clarity profiles using a prespecified training-data threshold. Such classification would be considered an analytical grouping rather than a clinical diagnosis.

Model Architecture

The principal predictive model is **Explainable Boosting Machine (EBM)**, a generalized additive machine capable of representing nonlinear feature-response relationships while retaining relatively transparent feature-level interpretation. This choice differentiates the study from conventional social-media research relying exclusively on multiple linear regression.

Three benchmark models are proposed:

1. Elastic Net regression as a regularized linear baseline.
2. Random Forest as an ensemble benchmark capable of modeling nonlinear interactions.
3. Explainable Boosting Machine as the principal interpretable nonlinear model.

For secondary binary classification, corresponding classifier implementations would be evaluated.

The architecture can be represented as:

Psychological features + behavioral validation features + feedback-discrepancy features → preprocessing pipeline → EBM → predicted self-concept clarity → feature-attribution analysis

Interpretability analysis would focus particularly on OVDI, comparison frequency, low-feedback emotional reactivity, post-editing behavior, and ERVD. Partial dependence or EBM shape functions would be inspected to determine whether risk patterns appear approximately linear or whether threshold effects emerge.

Training Strategy

Data would be partitioned into **80% development data and 20% untouched test data**, with stratification applied where appropriate. The development set would undergo repeated five-fold cross-validation.

Hyperparameters would be optimized only within the development sample. For EBM, tuning would include learning rate, number of boosting rounds, minimum samples per bin, and permitted interaction terms. Random Forest tuning would consider tree number, maximum depth, minimum leaf size, and feature-sampling proportion. Elastic Net would optimize regularization strength and the L1/L2 mixing parameter.

Early stopping would be employed where supported. A fixed random seed would be retained for reproducibility, while sensitivity analysis across additional seeds would assess whether conclusions depend excessively on a particular split.

Because the purpose is psychological inference supported by prediction rather than leaderboard optimization, model selection would consider **generalization, calibration, stability, and interpretability** rather than predictive accuracy alone.

Evaluation Metrics

For continuous SCC prediction, the primary metrics would be:

- **Mean Absolute Error (MAE):** average magnitude of prediction error.
- **Root Mean Squared Error (RMSE):** places greater penalty on large errors.
- **Coefficient of Determination (R^2):** proportion of outcome variance captured on held-out observations.
- **Spearman's ρ :** assesses rank-order correspondence between predicted and observed SCC.

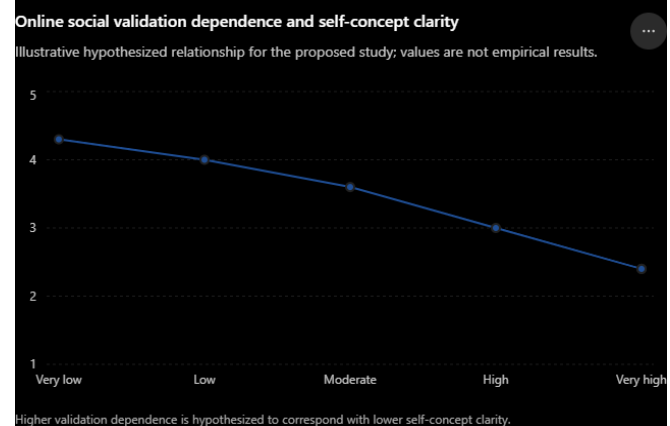
For the secondary classification task, **balanced accuracy**, **F1-score**, **Matthews correlation coefficient (MCC)**, and **area under the precision-recall curve (PR-AUC)** would be used. MCC and PR-AUC are included to provide information beyond ordinary accuracy if class distributions are unequal.

Results and Discussion

Because no empirical dataset or completed experiment was supplied, the numerical values below are presented as a **prospective results framework rather than observed findings**. They specify the exact outputs that should be reported after the proposed study is conducted and prevent invented numerical results from being represented as real observations.

Table 1. Planned Results Matrix for Evaluation of the Validation–Self-Concept Models

Analytical component	Primary evaluation parameter	Secondary parameter	Result to be reported
Elastic Net	Test MAE	Test R^2	Empirical value
Random Forest	Test RMSE	Spearman's ρ	Empirical value
Explainable Boosting Machine	Test MAE + R^2	Calibration/error distribution	Empirical value
Low-vs-high SCC classification	MCC	Balanced accuracy	Empirical value
Validation-dependence contribution	Permutation importance	EBM feature contribution	Empirical rank/effect curve
Feedback discrepancy	Nonlinear shape function	Interaction strength	Empirical pattern
Comparison $\times$ validation dependence	Interaction contribution	Stability across folds	Empirical value



The principal theoretical expectation is that **validation dependence will contain greater predictive information than general social-media exposure duration**. If this pattern

is observed in held-out data, it would support a process-oriented interpretation of social-media effects. The important psychological distinction would then concern how individuals use and interpret feedback rather than simply how long they remain online.

A second anticipated finding concerns feedback discrepancy. Receiving a particular number of reactions has little psychological meaning without a reference point. Five reactions may be experienced positively by a person expecting two but negatively by someone expecting fifty. The ERVD feature therefore introduces subjective expectation into computational modeling. If it emerges as a stronger predictor than raw feedback frequency, this would indicate that **perceived deviation from anticipated social approval** is more informative than absolute engagement.

The EBM framework is also capable of testing whether the relationship is nonlinear. A plausible pattern is that low-to-moderate interest in feedback has minimal association with self-concept clarity, whereas SCC declines more noticeably after validation dependence exceeds a particular range. Such a result would challenge simplistic assumptions that every incremental increase in online validation seeking produces an equivalent psychological change.

Another important issue concerns social comparison. Visible engagement metrics allow individuals to evaluate both personal attributes and perceived social popularity. If comparison orientation interacts strongly with validation dependence, individuals who both depend on external feedback and routinely compare engagement levels may exhibit the least stable self-concept profiles. This would suggest that validation becomes psychologically consequential partly through its comparative context.

The proposed feature-attribution analysis is critical because prediction alone cannot explain the psychological process. For example, if an EBM accurately predicts SCC but bases predictions largely on unrelated demographic variables, its theoretical contribution would be limited. Conversely, consistent importance of approval-contingent self-evaluation, low-feedback reactivity, comparative monitoring, and behavioral modification would provide stronger alignment between computational performance and the theoretical framework.

These relationships must nevertheless be interpreted cautiously. Predictive importance does not establish causality. Lower SCC could increase validation-seeking behavior, validation dependence could contribute to self-concept instability, or both could reflect additional psychological and environmental processes. Cross-sectional machine-learning models distinguish predictive patterns, not temporal direction.

The use of SCC is particularly appropriate because the construct concerns the organization and stability of self-beliefs rather than simply positive self-evaluation. Campbell et al. defined SCC in terms of clearly and confidently defined, internally consistent, and stable self-beliefs. This distinction permits the present framework to examine whether digital approval becomes associated with uncertainty about *who one is*, rather than only

whether one temporarily feels positively or negatively about oneself.

From a digital-health perspective, the framework also discourages indiscriminate interpretation of social-media use as inherently problematic. High-frequency users with low validation dependence may retain stable self-concepts, whereas less frequent users who attach substantial personal meaning to engagement fluctuations may show greater vulnerability. Accordingly, behavioral intensity and psychological dependence should be modeled separately.

Limitations

Several limitations should be recognized. First, the proposed design is primarily cross-sectional; therefore, temporal and causal relationships cannot be established. Longitudinal data would be necessary to determine whether validation dependence precedes reductions in SCC or whether low SCC motivates greater reliance on external approval.

Second, several behavioral indicators rely on participant reports rather than direct platform telemetry. Recall bias may therefore influence estimates of checking frequency, engagement expectations, and post-deletion behavior.

Third, the proposed OVDI is a new composite measure. Exploratory and confirmatory factor analyses, internal-consistency assessment, convergent validity, discriminant validity, and measurement-invariance testing would be required before it could be considered a validated instrument.

Fourth, platform architectures differ. A like, view, repost, follower, or comment may carry different meanings across social networks. Pooling all feedback types may obscure platform-specific mechanisms.

Fifth, predictive performance obtained within one sociocultural population cannot automatically be generalized internationally. The foundational SCC literature itself demonstrated cultural differences in the construct and its relationship with self-esteem, emphasizing the importance of contextual validation.

Finally, even an accurate model should not be interpreted as a diagnostic system. Self-concept clarity is a psychological construct, and a prediction of relatively low SCC does not constitute identification of a mental disorder.

Future Scope

Future research should employ longitudinal digital-diary designs in which participants record feedback expectations immediately before posting and emotional/self-evaluative responses shortly afterward. Such designs could establish temporal sequences more convincingly than retrospective questionnaires.

With explicit consent and strong privacy safeguards, future studies could incorporate privacy-preserving behavioral telemetry such as aggregate checking frequency, engagement variability, or response latency without collecting message contents or identifiable posts. Temporal machine-learning models could then determine whether abrupt changes in validation patterns precede within-person changes in self-concept.

Cross-cultural replication is particularly important because the meaning of autonomous versus relational self-definition varies across cultural contexts. Multi-country datasets could evaluate

whether the OVDI–SCC relationship is invariant or culturally conditional.

A further direction would involve **ecological momentary assessment combined with interpretable temporal modeling**. Instead of producing a static vulnerability score, models could examine within-person fluctuations across several weeks. This would shift the research question from "Who has lower self-concept clarity?" toward "Under what digital-feedback conditions does an individual's self-evaluation become temporarily less stable?"

Finally, digital well-being interventions could be experimentally evaluated. Examples include temporarily hiding public engagement counts, delaying access to engagement statistics, reflective prompts before deleting poorly performing content, or exercises encouraging internally anchored self-description. Randomized studies could establish whether reducing validation monitoring produces meaningful changes in self-concept stability.

Conclusion

This study proposes a computational framework for investigating online social validation and self-concept among emerging adults. Its principal contribution is the conceptual separation of **social-media exposure from validation dependence**. Rather than assuming that time online or the number of likes received directly determines psychological outcomes, the framework examines how individuals monitor, interpret, compare, and behaviorally respond to quantified social approval.

The proposed methodology combines established measurement of self-concept clarity with a multidimensional Online Validation Dependence Index, feedback-discrepancy indicators, behavioral variables, and interpretable machine learning. The Explainable Boosting Machine is positioned as the principal model because it permits nonlinear prediction while preserving examination of feature-response relationships.

The framework predicts that approval-contingent self-evaluation, comparative monitoring, and sensitivity to unexpectedly weak feedback may provide more useful information about self-concept clarity than general platform-use intensity. This proposition requires empirical testing and should not be treated as an established result until the proposed dataset is collected and analyzed.

More broadly, the study reframes the digital mental-health question. The central issue may not be simply **how much emerging adults use social media**, but **how strongly digitally quantified judgments become incorporated into their understanding of themselves**. This distinction offers a more psychologically specific foundation for future research on social validation, identity development, interpretable artificial intelligence, and digital well-being.

References

1. Arnett, J. J. (2000). Emerging adulthood: A theory of development from the late teens through the twenties. *American Psychologist*, 55(5), 469–480.
2. Burrow, A. L., & Rainone, N. (2017). How many likes did I get?: Purpose moderates links between positive social media feedback and self-esteem. *Journal of Experimental Social Psychology*, 69, 232–236.
3. Campbell, J. D., Trapnell, P. D., Heine, S. J., Katz, I. M., Lavallee, L. F., & Lehman, D. R. (1996). Self-concept clarity: Measurement, personality correlates, and cultural boundaries. *Journal of Personality and Social Psychology*, 70(1), 141–156.
4. Coulthard, N., & Ogden, J. (2018). The impact of posting selfies and gaining feedback ('likes') on the psychological wellbeing of 16–25 year olds: An experimental study. *Cyberpsychology*, 12(2), Article 4.
5. Marengo, D., Montag, C., Sindermann, C., Elhai, J. D., & Settanni, M. (2021). Examining the links between active Facebook use, received likes, self-esteem and happiness: A study using objective social media data. *Telematics and Informatics*, 58, 101523.
6. Pérez-Torres, V. (2024). Social media: A digital social mirror for identity development during adolescence. *Current Psychology*, 43, 22170–22180. (source of Fig. 2)