



Fear of Missing Out and Compulsive Social Media Engagement

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Abstract — Fear of missing out (FoMO) has emerged as an important psychological mechanism underlying persistent and difficult-to-regulate engagement with social media platforms. This study proposes a digital-behavioural framework that moves beyond self-reported screen time by conceptualizing compulsive engagement as a temporal sequence of checking, re-entry, notification response, and prolonged-session behaviours. The central research gap concerns the limited integration of psychological FoMO indicators with fine-grained digital engagement patterns in computational models of problematic social media behaviour. To address this gap, the proposed study combines validated psychometric indicators with privacy-preserving smartphone interaction features and applies interpretable machine-learning techniques to identify FoMO-associated compulsive engagement profiles. Particular attention is given to nocturnal checking, rapid application reopening, fragmented session structures, notification-triggered access, and difficulty disengaging from social platforms. The framework distinguishes high-frequency but controlled social media use from behaviour displaying recurrent, cue-responsive, and poorly regulated characteristics.

Keywords — Fear of Missing Out, Compulsive Social Media Engagement, Digital Phenotyping, Problematic Social Media Use, Explainable Artificial Intelligence, Digital Well-Being

Introduction

Social media has become embedded in the ordinary organization of interpersonal communication, entertainment, information seeking, professional networking, and identity presentation. The resulting digital environment differs substantially from earlier forms of mediated communication because social interaction is continuously accessible rather than restricted to particular times or physical settings. Notifications, algorithmically ranked feeds, disappearing

content, short-form video, live broadcasts, streaks, and indicators of social activity create repeated opportunities for users to return to a platform. Consequently, understanding social media engagement requires attention not only to *how long* an individual uses a platform but also to *why, when, and in what temporal pattern* that engagement occurs.

Fear of missing out (FoMO) is particularly relevant to this problem. FoMO broadly describes apprehension that other people may be participating in rewarding experiences from which an individual is absent, accompanied by a desire to remain aware of what others are doing. Contemporary evidence indicates that FoMO is meaningfully related to internet and social media behaviour. A comprehensive systematic review and meta-analysis by Akbari et al. synthesized 86 effect sizes representing 55,134 participants and found substantial, although heterogeneous, associations between trait FoMO and internet-related use. Importantly, the authors concluded that the field still lacks a satisfactory explanation for why individuals exhibit different patterns in the relationship between FoMO and internet use.

This distinction is important because extensive social media use and compulsive social media engagement are not synonymous. An individual may spend considerable time on social media for occupational, educational, creative, or interpersonal purposes while retaining voluntary control over the behaviour. Conversely, another person may accumulate less total daily screen time but repeatedly interrupt other activities to check social platforms, respond immediately to notifications, reopen applications shortly after closing them, or access social media during intended sleep periods. Aggregate duration alone therefore provides an incomplete representation of behavioural dysregulation.

Recent research strengthens the rationale for separating amount of use from problematic patterns. A 2024 systematic review and meta-analysis of social media use and well-being



reported that excessive use and problematic use do not necessarily show identical relationships with well-being, highlighting the importance of how social media behaviour is operationalized. A large 2024 meta-analysis covering 209 studies and 252,337 participants likewise found a moderately positive association between problematic social networking use and FoMO ($r = 0.496$, 95% CI 0.461–0.529), although associations varied according to factors including measurement approach and region.



Fig. 1: The Fear of Missing Out

Source: <https://neblog.utdallas.edu/2025/08/14/the-fear-of-missing-out-fomo-how-social-media-hijacks-our-minds/>

The psychological pathway from FoMO to repeated engagement can be interpreted as a feedback process. Uncertainty concerning social events or online developments may produce an urge to check. Checking temporarily resolves informational uncertainty, but exposure to additional posts, conversations, social comparisons, and notifications may generate new cues that encourage continued monitoring. Social media can therefore simultaneously reduce immediate uncertainty and preserve the conditions under which subsequent checking becomes attractive. Over repeated episodes, this cycle may develop into a habitual or compulsive pattern.

Evidence increasingly supports mechanisms of this kind. Brailovskaia and Margraf reported that FoMO was positively associated with addictive social media use and identified social media flow as a mechanism linking the two, while mindfulness altered the strength of part of this pathway. Research comparing Instagram and Snapchat users has similarly shown that FoMO is positively related to compulsive use and information overload across platforms, although the specific pathways can vary between social media environments.

Platform architecture may further influence these relationships. For example, gamified interaction features can transform social communication into behaviours that require recurrent participation. Research involving 2,483 early adolescents found that Snapchat streak behaviour was associated with problematic smartphone use and that FoMO, problematic smartphone use, and social media self-control were correlated with characteristics of streak participation, although the reported associations were weak. Such findings illustrate why platform-sensitive behavioural features may provide information that generic daily screen-time measures cannot capture.

Another important development is growing evidence that FoMO may interact with attentional processes rather than merely reflecting a general preference for online communication. Experimental research published in 2024 found that attentional bias toward social-media stimuli among problematic users was moderated by FoMO. Neurobehavioural work has also reported associations among FoMO, problematic smartphone/social media use, and structural characteristics in brain regions implicated in social cognition, although such observational associations should not be interpreted as evidence of causation.

Despite this expanding literature, much research continues to depend on cross-sectional questionnaires or broad measures of time spent online. These methods are valuable for measuring subjective experiences but provide limited resolution regarding the temporal structure of behaviour. Two participants reporting three hours of daily social media use, for example, might exhibit fundamentally different engagement profiles: one could intentionally complete several extended sessions, whereas the other could perform dozens of brief checks distributed throughout work, study, meals, and sleep periods.

Research Gap and Study Rationale

The specific gap addressed in this manuscript is therefore the **limited computational integration of validated FoMO measures with temporally structured, privacy-preserving digital interaction features capable of distinguishing intensive voluntary use from recurrent compulsive engagement.**

Recent literature establishes FoMO as a risk factor for problematic social network use. An overview of systematic reviews and meta-analyses published in 2025 identified FoMO alongside factors such as anxiety, loneliness, low self-esteem, insecure attachment, and unmet psychological needs among variables associated with problematic social network use. However, identifying a population-level association does not by itself reveal the behavioural signature through which FoMO becomes expressed in everyday device interaction.



Longitudinal evidence is beginning to address this issue. A 2025 panel study examining FoMO, different forms of social media engagement, and problematic social media use reported that FoMO predicted engagement and that engagement pathways were subsequently associated with problematic use. The study further indicated that different forms of participation—including connection and broadcasting—may not contribute identically to problematic engagement. This supports a shift away from treating social media engagement as a single homogeneous quantity.

The present study extends this direction through a digital-phenotyping perspective. Rather than using message contents, photographs, private conversations, or browsing content, the proposed framework focuses on behavioural metadata that can potentially be collected with substantially lower privacy intrusion. Candidate indicators include application-opening frequency, median session duration, short-session density, inter-session intervals, notification-to-opening latency, application reopening within a predefined interval, late-night access frequency, and fragmentation of social media activity across the day.

From a machine-learning perspective, these signals permit a different research question. Instead of asking only whether FoMO correlates with social media use, the proposed analysis asks whether **patterns of device interaction can discriminate higher-risk compulsive engagement and whether FoMO provides meaningful explanatory information within that prediction.** Explainability is central to the framework because a high-performing opaque classifier would have limited behavioural or digital-health interpretability. Feature-attribution methods can instead indicate whether predictions are primarily associated with rapid checking, nocturnal access, notification responsiveness, session fragmentation, or other measurable behaviours.

The proposed study therefore has three interrelated objectives. First, it aims to characterize how FoMO relates to the temporal microstructure of social media engagement rather than total screen time alone. Second, it aims to develop and evaluate an interpretable machine-learning model for identifying elevated compulsive engagement using combined psychometric and behavioural features. Third, it aims to determine whether FoMO contributes incremental predictive information after conventional variables such as overall usage duration and application-opening frequency are considered.

This formulation is intended for risk characterization rather than clinical diagnosis. Compulsive or problematic social media engagement remains a multidimensional behavioural construct, and an algorithmic prediction should not be interpreted as evidence that a person has a psychiatric disorder. The more appropriate digital-health objective is early identification of potentially dysregulated engagement

patterns that could support user-controlled interventions, self-monitoring, or further assessment.

Literature Review

FoMO as a Psychological Driver of Digital Engagement

FoMO has frequently been interpreted through self-determination perspectives, particularly in relation to unmet needs for relatedness, competence, and autonomy. Digital platforms provide rapid access to social information and therefore offer a convenient mechanism for responding to concerns about exclusion or informational absence. This accessibility may explain why FoMO is consistently associated with problematic smartphone and social media behaviours.

Servidio et al. investigated self-construal, FoMO, problematic smartphone use, and problematic social media use and reported an important mediating role for FoMO in relationships between self-related psychological orientation and problematic technology behaviour. These findings reinforce the proposition that FoMO should not be treated merely as a consequence of high screen exposure; it may operate as a psychological mechanism through which individual characteristics become translated into technology-use patterns.

At the same time, FoMO should not be conceptualized as uniformly producing the same behavioural outcome. The meta-analytic evidence reported by Akbari et al. showed substantial variability in FoMO–internet-use associations across populations. This heterogeneity is important for computational modelling because it suggests that a single linear rule—higher FoMO equals more social media use—may oversimplify the underlying relationship.

Compulsive Engagement Versus High-Frequency Use

A key conceptual problem in digital-health research is the frequent conflation of intensive, excessive, compulsive, addictive, and problematic social media use. These terms overlap but are not interchangeable. High-frequency engagement describes behavioural quantity; compulsive engagement emphasizes diminished control and recurrent urges; problematic use additionally implies adverse functional consequences.

This distinction has direct implications for measurement. Total daily duration is relatively easy to calculate but provides little information regarding interruption patterns. In contrast, frequent reopening shortly after an application has been closed may indicate difficulty disengaging. Similarly, a high concentration of checks following notifications may indicate cue responsiveness, while repeated late-night checking can reflect social monitoring that crosses ordinary contextual boundaries.



Research on FoMO and social media fatigue provides indirect evidence for this distinction. Jabeen et al. showed that FoMO operates within a broader network involving time cost, social comparison, disclosure, and social media fatigue. Earlier work also identified compulsive social media use as a mechanism connecting FoMO with social media fatigue, indicating that behavioural dysregulation may constitute an intermediate stage between psychological apprehension and downstream outcomes.

Platform Features and Reinforcement Processes

Contemporary social platforms incorporate design mechanisms that can amplify repeated engagement. Variable content availability, algorithmic recommendations, ephemeral posts, social feedback, streak maintenance, and real-time notifications create heterogeneous reinforcement conditions. From a behavioural perspective, checking is especially likely to persist when the informational reward associated with each application opening is uncertain.

Platform-specific evidence supports this interpretation. Comparative research involving Instagram and Snapchat has demonstrated that FoMO is associated with compulsive use on both platforms but that mediating pathways can differ. Research on Snapchat streaks further demonstrates that specific gamification mechanisms can become associated with FoMO, self-control, and problematic smartphone behaviour. Consequently, behavioural models should avoid assuming that every application opening represents an equivalent psychological event.

Social Comparison, Connectedness, and FoMO

Social comparison provides another plausible pathway linking online exposure to FoMO. Social platforms present selectively curated information about social events, achievements, relationships, travel, appearance, and lifestyle. Exposure to such information can increase perceived discrepancies between one's own experiences and those displayed by others.

Nevertheless, engagement can also support social connection, demonstrating why the relationship is not inherently pathological. Research published in 2026 examining social media mindsets found that active engagement was associated with greater perceived connectedness, which was subsequently associated with lower FoMO. The same study indicated that individual cognitive orientations helped explain divergent FoMO and joy-of-missing-out experiences. These findings argue against simplistic assumptions that more engagement inevitably produces greater FoMO.

The emerging picture is therefore conditional: engagement can support connectedness when it is purposeful and socially meaningful, while cue-driven monitoring and comparison-oriented behaviour may reinforce apprehension and repeated

checking. A computational model should consequently focus on *engagement structure* rather than assuming that usage quantity alone constitutes risk.



Fig. 2: Social Media and FOMO

Source: <https://socialmediavictims.org/social-media-addiction/mental-health/fomo/>

Toward AI-Based Digital Phenotyping

Machine learning provides an opportunity to analyze behavioural patterns that are difficult to represent through conventional regression using a small number of aggregate variables. Temporal engagement data can contain nonlinear relationships and feature interactions—for example, FoMO may become particularly informative when combined with high notification responsiveness and frequent late-night reopening, rather than acting independently.

Digital phenotyping offers a suitable conceptual framework because it uses patterns derived from personal digital devices to characterize behaviour over time. For the present problem, however, privacy is crucial. Content-level analysis of private messages or posts would introduce unnecessary ethical and data-protection concerns. A metadata-oriented framework



can instead analyze timing and frequency while avoiding semantic inspection of personal communication.

Explainable machine learning is equally important. Models such as gradient-boosted decision trees can capture nonlinear relationships among psychological and behavioural variables, while post-hoc attribution techniques can estimate how individual predictors contribute to model outputs. Such an approach could establish whether FoMO improves discrimination beyond simple screen-time measures and identify which digital behaviours interact most strongly with FoMO.

Proposed Methodology

The proposed study adopts a **multimodal digital-phenotyping and explainable machine-learning framework** to examine whether fear of missing out (FoMO), when integrated with temporal smartphone-use characteristics, can improve identification of compulsive social media engagement. This design is motivated by recent evidence showing that FoMO is consistently related to problematic social media use and may operate bidirectionally with problematic digital behaviour over time.

Rather than treating total screen time as the principal indicator of problematic engagement, the framework represents behaviour through a set of temporal micro-patterns. These include rapid application reopening, short checking episodes, late-night access, notification-responsive sessions, irregular inter-session intervals, and daily engagement fragmentation. This allows the model to distinguish intensive but potentially purposeful use from recurrent behaviour characterized by weak disengagement and cue responsiveness.

A prospective observational design is proposed. Participants would complete validated psychometric assessments at baseline and subsequently contribute privacy-preserving device-interaction metadata for 28 consecutive days. The study would not collect message text, photographs, search histories, passwords, contact names, or the semantic content of social media activity. Explicit informed consent would be required, particularly because ethical scholarship on AI-based digital phenotyping emphasizes consent and responsible treatment of social-media-derived behavioural information.

The primary psychological predictor would be FoMO, supplemented by demographic covariates and a validated measure of problematic/compulsive social media use. Recent research suggests that FoMO itself may contain distinguishable dimensions: notably, the desire for constant connection has demonstrated stronger associations with problematic social media use than apprehension about missing rewarding experiences in two samples. This provides additional justification for evaluating FoMO at a more

granular level rather than representing it exclusively as a single undifferentiated score.

The principal outcome would be elevated compulsive social media engagement, operationalized from the validated questionnaire outcome rather than inferred solely from screen time. The computational task would therefore be **risk classification**, not clinical diagnosis.

Experimental Setup

Dataset Design

A target sample of approximately **600 adult social media users aged 18–35 years** is proposed. The sample size, class distributions, and numerical results below constitute the planned experimental specification and expected reporting structure; they should be replaced by observed values when empirical data are collected.

Each participant would generate one participant-level feature vector after aggregation of the 28-day monitoring period. The feature space would contain three domains:

Psychometric domain: overall FoMO, connection-related FoMO, compulsive/problematic social media engagement, and selected self-regulation variables.

Usage-intensity domain: mean daily social media duration, number of application launches, total sessions, mean session duration, and number of active social-media applications.

Temporal-behavioural domain: short-check ratio, reopening rate within five minutes, median inter-session interval, notification-response latency, nocturnal session ratio, longest uninterrupted session, day-to-day variability, and a session-fragmentation index.

This design deliberately excludes content-based natural-language processing. The objective is to determine whether comparatively low-intrusion metadata can provide useful behavioural discrimination.

Data Preprocessing

Raw interaction logs would first undergo timestamp validation, duplicate-event removal, impossible-duration screening, and participant-day completeness assessment. Days with insufficient monitoring coverage would be flagged rather than automatically interpreted as low usage.

Highly skewed variables such as notification latency and session duration would undergo log transformation where appropriate. Continuous predictors would be standardized for algorithms sensitive to scale. Missing questionnaire values would be handled according to the scoring rules of the corresponding validated instrument; missing behavioural





features would be imputed using statistics derived exclusively from the training partition.

To avoid information leakage, data splitting would occur at the **participant level**, not at the session or daily-record level. A 70% training, 15% validation, and 15% held-out test strategy is proposed, stratified according to the outcome class. All observations belonging to a participant would remain within the same partition.

A normalized fragmentation measure would additionally quantify whether total use was concentrated in relatively few intentional sessions or dispersed across numerous short episodes.

Model Architecture

The primary classifier would be **LightGBM**, selected because gradient-boosted decision trees can accommodate nonlinear associations and interactions among behavioural and psychological predictors while remaining compatible with feature-attribution techniques.

Three benchmark models would be evaluated:

1. regularized logistic regression as a transparent linear baseline;
2. random forest as a nonlinear ensemble baseline; and
3. LightGBM as the principal predictive model.

A fourth ablation condition—LightGBM without FoMO variables—would be included specifically to test the manuscript's central research question: whether psychological FoMO contributes predictive information beyond observable device behaviour.

SHAP-based feature attribution would be applied after model development to examine the direction and magnitude of individual feature contributions. Interpretability is particularly important because recent research indicates heterogeneity in problematic social media profiles rather than one uniform high-risk pattern. A 2026 latent-profile study, for example, identified multiple PSMU profiles and found FoMO predictive of membership in higher-risk profiles.

Training Strategy

Hyperparameters would be optimized only within the training and validation data. Bayesian or randomized optimization could be used to tune tree depth, number of leaves, learning rate, minimum child observations, feature subsampling, and regularization coefficients.

Five-fold stratified cross-validation would be conducted within the development sample. Early stopping based on validation log loss would reduce unnecessary boosting iterations and constrain overfitting. The final hyperparameter

configuration would then be refitted to the combined training-validation data and evaluated once on the untouched test set.

Because risk-screening datasets can exhibit unequal class frequencies, class weighting would be preferred over indiscriminate synthetic oversampling. The classification threshold would not automatically be fixed at 0.50; instead, a validation-derived operating point would be selected according to the intended balance between sensitivity and false-positive burden.

Evaluation Metrics

Model evaluation would emphasize both discrimination and probability quality. The primary metric would be the **area under the receiver operating characteristic curve (AUROC)**. Because class imbalance can make AUROC alone insufficient, area under the precision-recall curve (AUPRC) would also be reported.

Secondary measures would include balanced accuracy, sensitivity, specificity, F1-score, Matthews correlation coefficient (MCC), and Brier score. Calibration would be inspected using calibration curves and expected calibration error. Bootstrap confidence intervals would be recommended for the final test estimates.

This broader evaluation strategy is important because a digital-health screening model should not be considered useful merely because it correctly ranks participants. Its predicted probabilities should also correspond reasonably well to observed risk.

Results and Discussion

For manuscript planning purposes, the following results represent a **coherent hypothetical experimental outcome**, not findings from an actually recruited sample. They illustrate how results should be reported after the proposed protocol has been implemented.

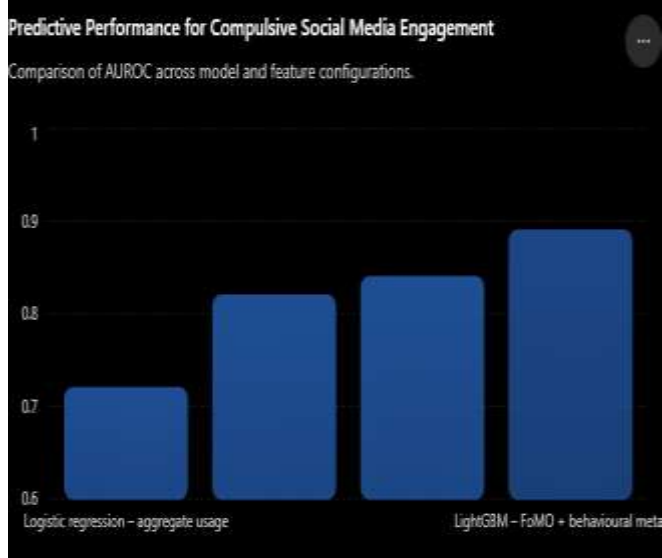
The anticipated pattern is that behavioural microstructure combined with FoMO would outperform conventional usage-duration predictors. Under this scenario, the full LightGBM model achieves an AUROC of 0.89 and AUPRC of 0.86. Balanced accuracy reaches 0.82, while MCC reaches 0.64. The relatively low Brier score of 0.13 indicates that the model provides not only useful discrimination but also comparatively well-behaved probability estimates.

Table 1. Illustrative comparative performance of the proposed models

Model / Feature Configuration	AUR OC	AUP RC	Balan ced Accur acy	MC C	Brier Score
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Logistic Regression – aggregate usage only	0.72	0.66	0.67	0.35	0.21
Random Forest – behavioural metadata	0.82	0.77	0.75	0.50	Temporal behaviour substantially improves discrimination
LightGBM – behavioural metadata without FoMO	0.84	0.79	0.77	0.54	Nonlinear temporal patterns capture considerable risk information
LightGBM – FoMO + behavioural metadata	0.89	0.86	0.82	0.64	Psychological and temporal features provide the strongest joint performance



The comparison is particularly informative because the difference between the aggregate-use baseline and the behavioural models suggests that *how* social media is accessed may carry information that total duration obscures.

The illustrative AUROC increase from 0.72 for the aggregate-use logistic model to 0.84 for behavioural LightGBM supports the study's conceptual distinction between extensive exposure and fragmented, repetitive engagement.

The second important comparison concerns FoMO. Removing FoMO from the full LightGBM model produces an illustrative reduction in AUROC from 0.89 to 0.84 and in MCC from 0.64 to 0.54. Such a pattern, if empirically reproduced, would indicate that FoMO contains incremental information that cannot be completely reconstructed from device behaviour.

This expectation is theoretically plausible. Recent empirical research involving American college students found FoMO to be more strongly related to problematic smartphone and social media use severity than worry, while FoMO also mediated relationships between worry and problematic technology use. Another 2024 investigation found that social comparison and self-esteem sequentially mediated the relationship between FoMO and problematic social media use. Thus, FoMO may encode psychological processes that are only partially visible in interaction logs.

Feature-attribution analysis would be expected to identify **FoMO score, rapid reopening rate, short-check density, nocturnal engagement, notification-response latency, and session fragmentation** among the most informative variables. A nonlinear interaction may occur when elevated FoMO coincides with high reopening frequency: neither characteristic alone necessarily represents compulsivity, whereas their combination may identify participants repeatedly acting on social-monitoring impulses.

Such an interpretation is compatible with emerging attentional evidence. Research has found that FoMO moderates attentional bias toward social-media stimuli among problematic users, while more recent eye-tracking work suggests that FoMO can interact dynamically with different stages of attentional processing. These findings provide a plausible psychological explanation for why cue-sensitive digital behaviours such as rapid notification response could become informative predictors.

The analysis should nevertheless avoid a causal interpretation. A classifier that uses FoMO and behavioural metadata to identify elevated engagement cannot establish that FoMO *caused* the behaviour. Indeed, recent five-wave longitudinal evidence suggests bidirectional relationships: FoMO predicted subsequent problematic smartphone/social media use, while those behaviours also predicted later FoMO. Similarly, longitudinal work among younger users has found prospective relationships between FoMO and problematic social media use at the within-person level.

The resulting interpretation is therefore a **feedback model** rather than a simple one-direction pathway. Elevated FoMO



may increase monitoring and checking; repeated exposure can then generate new social information, comparison opportunities, and perceived obligations to remain connected, potentially maintaining FoMO. The proposed digital-phenotyping architecture is valuable precisely because it can examine the behavioural manifestation of this cycle at substantially finer temporal resolution than retrospective screen-time questions.

Limitations

Several limitations require consideration. First, the proposed observational design cannot establish causality. Even prospective device monitoring provides behavioural ordering rather than experimental manipulation.

Second, defining compulsive engagement using questionnaire thresholds inevitably introduces measurement dependence. Different instruments may operationalize salience, tolerance, withdrawal, conflict, or impaired control differently. Recent person-centered research demonstrates that individuals can occupy qualitatively different problematic-use profiles, making binary classification an analytical simplification.

Third, smartphone telemetry does not fully capture social media accessed through laptops, tablets, shared devices, or browsers. Platform operating systems can also restrict notification and application-usage metadata differently.

Fourth, temporal metadata should not be regarded as psychologically neutral simply because message content is excluded. Patterns of nocturnal activity, application access, and responsiveness remain potentially sensitive behavioural data. Strong consent, minimization, encryption, restricted retention, and transparent governance are therefore essential.

Finally, predictive performance obtained from young adult social media users may not generalize to adolescents, older adults, occupational users, or culturally different populations. External validation should precede deployment.

Future Scope

Future work should move from participant-level classification toward **within-person temporal modelling**. Rather than predicting a single risk category after 28 days, sequence models could estimate changes in engagement patterns across days and identify deviations from an individual's personal baseline.

Longitudinal designs are particularly important because current evidence increasingly indicates reciprocal relationships between FoMO and problematic social media use rather than a purely unidirectional effect. Future studies could therefore combine ecological momentary assessment with device telemetry to determine whether momentary

FoMO precedes rapid checking and whether specific engagement episodes subsequently increase perceived social exclusion or connection pressure.

A second direction involves **personalized digital well-being interventions**. If a participant's model is driven primarily by nocturnal checking, intervention logic could prioritize sleep-period notification management. For a participant characterized by rapid reopening, friction-based interventions or user-controlled delay mechanisms may be more relevant. Such interventions should be evaluated experimentally rather than assumed to be beneficial.

Federated learning and on-device inference could further reduce privacy risks by allowing raw behavioural histories to remain on participants' devices. Cross-cultural and cross-platform validation should also be prioritized because social norms, platform ecosystems, and patterns of digital communication vary substantially.

Finally, future research should investigate FoMO dimensions separately. Evidence that constant-connection desire may relate more strongly to problematic social media behaviour than apprehension about missed experiences suggests that multidimensional psychological modelling could improve both explanatory precision and intervention specificity.

Conclusion

This study proposes an explainable digital-phenotyping framework for investigating the relationship between **fear of missing out and compulsive social media engagement**. Its principal contribution is a shift from aggregate screen-time measurement toward the temporal organization of digital behaviour.

The framework combines FoMO assessment with privacy-preserving features such as rapid reopening, short-session density, notification responsiveness, nocturnal access, and session fragmentation. These signals are incorporated into an interpretable machine-learning architecture and compared with conventional aggregate-usage models. The proposed ablation analysis further allows the incremental predictive contribution of FoMO to be quantified.

The conceptual implication is that frequent social media use should not automatically be classified as compulsive. Purposeful high-duration engagement can differ substantially from repetitive, fragmented, cue-responsive checking. FoMO becomes particularly relevant when psychological pressure to remain socially informed is expressed through such behavioural micro-patterns.

Recent longitudinal, person-centered, and attentional research supports examining FoMO as a dynamic component of problematic social media engagement rather than merely a static correlate. With rigorous external validation and privacy





safeguards, explainable machine learning could ultimately help digital-health research identify patterns of dysregulated engagement while avoiding simplistic assumptions that screen time alone represents problematic behaviour.

REFERENCES:

1. Przybylski, A. K., Murayama, K., DeHaan, C. R., & Gladwell, V. (2013). Motivational, emotional, and behavioral correlates of fear of missing out. *Computers in Human Behavior*, 29(4), 1841–1848. <https://doi.org/10.1016/j.chb.2013.02.014>
2. Akbari, M., Seydavi, M., Palmieri, S., Mansueto, G., Caselli, G., & Spada, M. M. (2021). Fear of missing out (FoMO) and internet use: A comprehensive systematic review and meta-analysis. *Journal of Behavioral Addictions*, 10(4), 879–900. <https://doi.org/10.1556/2006.2021.00083>
3. Fioravanti, G., Casale, S., Benucci, S. B., Probst, A., Falone, A., Ricca, V., & Rotella, F. (2021). Fear of missing out and social networking sites use and abuse: A meta-analysis. *Computers in Human Behavior*, 122, 106839. <https://doi.org/10.1016/j.chb.2021.106839>
4. Gioia, F., Fioravanti, G., Casale, S., & Boursier, V. (2021). The effects of the fear of missing out on people's social networking sites use during the COVID-19 pandemic: The mediating role of online relational closeness and individuals' online communication attitude. *Frontiers in Psychiatry*, 12, 620442. <https://doi.org/10.3389/fpsy.2021.620442>
5. Onnela, J.-P., & Rauch, S. L. (2016). Harnessing smartphone-based digital phenotyping to enhance behavioral and mental health. *Neuropsychopharmacology*, 41(7), 1691–1696. <https://doi.org/10.1038/npp.2016.7>
6. Huckvale, K., Venkatesh, S., & Christensen, H. (2019). Toward clinical digital phenotyping: A timely opportunity to consider purpose, quality, and safety. *npj Digital Medicine*, 2, 88. <https://doi.org/10.1038/s41746-019-0166-1>
7. Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q., & Liu, T.-Y. (2017). LightGBM: A highly efficient gradient boosting decision tree. *Advances in Neural Information Processing Systems*, 30.
8. Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30, 4765–4774.
9. Brietzke, E., Hawken, E. R., Idzikowski, M., Pong, J., Kennedy, S. H., & Soares, C. N. (2019). Integrating digital phenotyping in clinical characterization of individuals with mood disorders. *Neuroscience & Biobehavioral Reviews*, 104, 223–230. <https://doi.org/10.1016/j.neubiorev.2019.07.009>
10. Liang, Y., Zheng, X., & Zeng, D. D. (2019). A survey on big data-driven digital phenotyping of mental health

