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Longitudinal Patterns of Online Activity and Social Feedback Are Associated with Current and Change in Quality of Life in Adult Facebook Users

Davide Marengo * and Michele Settanni

Department of Psychology, University of Turin, Italy
* Correspondence: davide.marengo@unito.it

Abstract: The aim of the study is to explore how sharing status updated and receiving Likes on Facebook, as a form of positive social feedback, correlates with current and perceived changes in Quality of Life (QoL) Sample consisted of 1577 adult Facebook users (76.3% females; 65.9% aged 18-24, 21.9% aged 25-30, 12.3% aged > 30 years old). The study employed a longitudinal approach, collecting Facebook data from adult users over a 12-month period using the Graph API. Data were divided into 12 monthly segments. Two monthly indicators were calculated: the percentage of textual status updates and the average number of Likes per post. Current and perceived changes in Quality of Life (QoL) were administered as self-report measures. The findings indicated a positive correlation between the frequency of textual Facebook posts and current QoL. Furthermore, receiving more Likes was positively associated with a higher current QoL, and perceived improvements in QoL correlated with an increase in Likes over time. The study suggests that online positive social feedback, measured through Likes on Facebook, is associated with both current QoL and perceived improvements in QoL among adult Facebook users. This highlights the potential impact of online social interactions on individual well-being.

Keywords: quality of life; social media; digital traces; structural equation modeling; latent growth modeling

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1. Summary

The advent of social media has radically transformed the way individuals interact and perceive their social environment. Being among the most widely used social media platforms Facebook is expected to play a significant role in shaping these human interactions. Indeed, Facebook, the flagship of Meta, achieved a remarkable milestone by being the first social network to exceed one billion registered accounts; as of fall 2023, its user base exceeds three billion monthly active users [1]. As such, it is paramount to investigate its potential role as factor in users' well-being.

The association between social media use and quality of life (QoL) has been a subject of continuous interest. Research suggests that social media usage is intricately linked to various aspects of psychological well-being. Kross and colleagues [2] found that increased Facebook usage was associated with declines in users' moment-to-moment happiness and overall life satisfaction. Conversely, online social support, particularly positive social feedback on platforms like Facebook, is believed to be a significant factor in influencing users' QoL. A study by Nabi, Prestin, and So [3] indicated that receiving social support online can positively impact emotional well-being. This is further supported by findings that experiencing social support via Facebook is positively associated with users' general well-being [3,4] and users tend to report increased perceived social support and life satisfaction when they believe they had a larger group reading their status updates [5].

Recent studies have utilized objective social media data to explore these relationships further. Marengo and colleagues [6] conducted a study using data mining techniques to evaluate QoL based on multiple indicators of active Facebook usage. This research underscored the potential of leveraging social media data to assess broader life quality indicators, offering a novel perspective

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beyond traditional subjective self-report measures. In a similar way, another study by Marengo and colleagues [7] employed objective data from Facebook to analyze how active use and received Likes correlated with self-esteem and happiness. The authors found that receiving Likes on Facebook was related to an increase in perceived happiness, and that self-esteem mediated this association. Additionally, they found that the more actively users update their profiles and share personal content, such as self-created texts, images, and tags of friends and locations, the more feedback, specifically in terms of Likes, they tend to receive from their online social network. An important aspect of these studies is that by leveraging on objective recording of social media use (as opposed to self-report indicators) they provide a more direct measurement of social media interactions and their impact. Still, these studies employed a cross-sectional data design, limiting the validity of causal inferences.

In turn, longitudinal research employing objective recordings of online activity may provide valuable insights into the dynamic nature of social media interactions and their long-term effects. Utilizing data from three survey waves of the Gallup Panel Social Network Study, the research by Shakya and Christakis [8] examined associations between Facebook activity and real-world social network activity with self-reported physical health, mental health, life satisfaction, and body mass index (BMI). The key findings suggested that increased Facebook use was generally associated with negative impacts on well-being. Specifically, higher engagement with Facebook (Likes clicked, links clicked, status updates) correlated with declines in mental health, life satisfaction, and physical health. Note, the study by Shakya and Christakis [8] found a negative association between Facebook use and well-being but failed to investigate the role of positive social feedback, such as Likes and comments, which in turn may be expected to exert a positive effect.

In view of these findings, the present study aims to extend the current body of research on social media by examining longitudinal patterns of both active Facebook use and online positive social feedback (i.e. received Likes) and their association with current and perceived changes in QoL among adult users. In this way, the present study seeks to contribute to a nuanced understanding of how virtual social interactions on platforms like Facebook can influence an individual's perception of their overall well-being.

2. Materials and Methods

2.1. Procedure and participants

Participants were recruited by disseminating the link to a web app running via web browser online. The web app included a landing page which was used to provide participants with information about the research and collect informed consent. Inclusion criteria for participation in the research were fluency in Italian language, legal age, and a Facebook account. The landing page included a Facebook login button which was used to obtain authorization to collect participants' Facebook passive data (see below). After entering the app using the login button, participants were administered questionnaires assessing demographic characteristics, and study measures. The university institutional review board (n° 88721) approved the research.

The application was disseminated using snowball sampling starting with 10 university students. Data collection took place from March to June 2018. Eventually, the study survey was accessed by Facebook 2998 users. For the present study, analyses were performed on a subsample of 1577 participants which provided researchers with both self-report information about QoL, and Facebook data covering at least 9 months over the considered 12-month period (i.e., participants with missing data for more than 3 months were not included in the sample). The final sample considered consists of 1204 female (76.3%) and 373 males (23.7%), of which 1039 aged 18-24 (65.9%), 345 aged 25-30 (21.9%), and 193 participants aged > 30 years old (12.3%). Of these, 828 participants had a university degree or higher education (52.5%), while 725 had a high-school diploma (46%), and 24 had a middle-school certificate (1.5%).

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2.2. Instruments

2.2.1. Facebook data

Facebook data was collected through the Graph application-programming interface (API). This process involved retrieving users' online status update activities for the 12 months prior to the survey. The data included all posts and their corresponding Likes, which were organized into 12 monthly segments, each covering 30 days, starting from the day participants filled in the survey. For each monthly segment, we calculated two indicators: the percent proportion of textual status updates relative to the total number of total posts, and the average number of "Likes" received per post. Note that the choice to focus on textual status updates as a proportion to the total posts relates to evidence that self-generated textual content may be more strongly related to well-being and positive social feedback than more impersonal posts [7]. Table 1 presents descriptive statistics for each variable at every monthly time point. Please note that in the table, time point 12 coincide with the time when participants provided their self-report QoL assessments. Conversely, timepoint 1 represents the time point furthest from when these self-reports were collected.

Please note that a partial overlap exists between the data examined here and in other published studies by our research group [6,7,9–11].

Table 1. Descriptive statistics for participants' Facebook posts and received Likes.

Timepoint	Variable	Mean	SD	Min	Max	N
1	% Verbal Status updates	54.61	33.72	0	100	1315
2	% Verbal Status updates	55.05	33.63	0	100	1391
3	% Verbal Status updates	54.96	33.71	0	100	1482
4	% Verbal Status updates	55.47	33.09	0	100	1522
5	% Verbal Status updates	54.44	33.66	0	100	1514
6	% Verbal Status updates	54.61	33.48	0	100	1491
7	% Verbal Status updates	54.88	34.28	0	100	1493
8	% Verbal Status updates	54.09	34.33	0	100	1485
9	% Verbal Status updates	53.63	34.52	0	100	1493
10	% Verbal Status updates	52.79	34.94	0	100	1482
11	% Verbal Status updates	52.85	34.43	0	100	1444
12	% Verbal Status updates	53.89	36.73	0	100	1279
1	Average Received Likes	12.22	14.01	0	84.50	1315
2	Average Received Likes	13.52	15.04	0	83.2	1391
3	Average Received Likes	13.48	14.84	0	81.00	1482
4	Average Received Likes	13.09	15.12	0	84.00	1522
5	Average Received Likes	13.22	15.39	0	83.50	1514
6	Average Received Likes	12.25	14.22	0	77.00	1491
7	Average Received Likes	11.93	13.93	0	73.00	1493
8	Average Received Likes	10.79	13.14	0	67.67	1485
9	Average Received Likes	10.43	11.67	0	64.00	1493
10	Average Received Likes	11.61	13.22	0	66.00	1482
11	Average Received Likes	11.31	13.03	0	72.00	1444
12	Average Received Likes	11.30	14.15	0	71.00	1279

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2.2.2. Quality of Life measures

We administered a specifically devised 8-item instrument assessing participants' current state and perceived change in general QoL during the previous year. The instrument assesses general QoL, and three specific components of QoL, namely psychological, physical, and social QOL; these components have been identified as key by the World Health Organization when performing surveys assessing QoL [12]. Participants' current QoL state was measured using four items: 1) "How would you rate your physical health?" (Physical QOL); 2) "How would you rate your mental health?" (Psychological QOL); 3) "How satisfied are you with your personal relationships?" (Social QOL), 4) "How would you rate your quality of life?" (General QOL). Participants answered each question using a 5-point Likert scale (1-Very poor, 2-Poor, 3-Acceptable, 4-Good, 5-Very good). Then, we assessed participants' perceived change in QoL during the last 12 months. Again, we administered 4 items: 1) "Compared with a year ago, how would you rate your physical health?" (Physical QOL); 2) "Compared with a year ago, how would you rate your mental health?" (Psychological QOL); 3) "Compared with a year ago, how satisfied are you with your personal relationships?" (Social QOL), 4) "Compared with a year ago, how would you rate your quality of life?" (General QOL). Participants answered each question using a 5-point Likert scale (1-Much worse, 2-Worse, 3- About the same, 4-Better, 5-Much better).

2.3. Data analysis

First, a Confirmatory Factor Analysis (CFA) model was estimated including two latent constructs: current perceived QoL and perceived change in QoL. QoL was indicated by observed variables measuring current states of physical health, mental health, social QoL and general QoL (QoL). Correspondingly, perceived change in QoL was indicated by variables assessing perceived changes over the past year in these same domains. Given the expected local dependency among variables assessing similar aspects of QoL; to account for this effect, correlations between error components of items assessing the same component were allowed within the model. A conceptual diagram for the CFA model is represented in Figure 1, panel *a*. In the figure, dashed lines indicate covariance between latent factors.

To model the longitudinal association between verbal status updates and received Likes, we used as an auto-regressive latent trajectory model with structure residuals (ALT-SR) [13]. A conceptual diagram for the model is represented in Figure 1, panel *b*. In the context of Facebook data, the ALT-SR model allowed us to model between-person associations among more stable components of user's activity and received Likes (e.g., mean levels, growth rates), while also modeling reciprocal associations between these variables as they manifest within individuals over time. In the figure,, *x1-x12* and *y1-y12* represent objective indicators of posting activity (i.e., percent of verbal status updates) and positive feedback (i.e., average received Likes) for the 12 consecutive time points (i.e., 12 months). Note that in the figure, variables at time point 12 reflect participants' Facebook activity during the month prior the self-report QoL assessments. Conversely, time point 1 represents the time point furthest from when these self-reports were collected (i.e., 12 months earlier).

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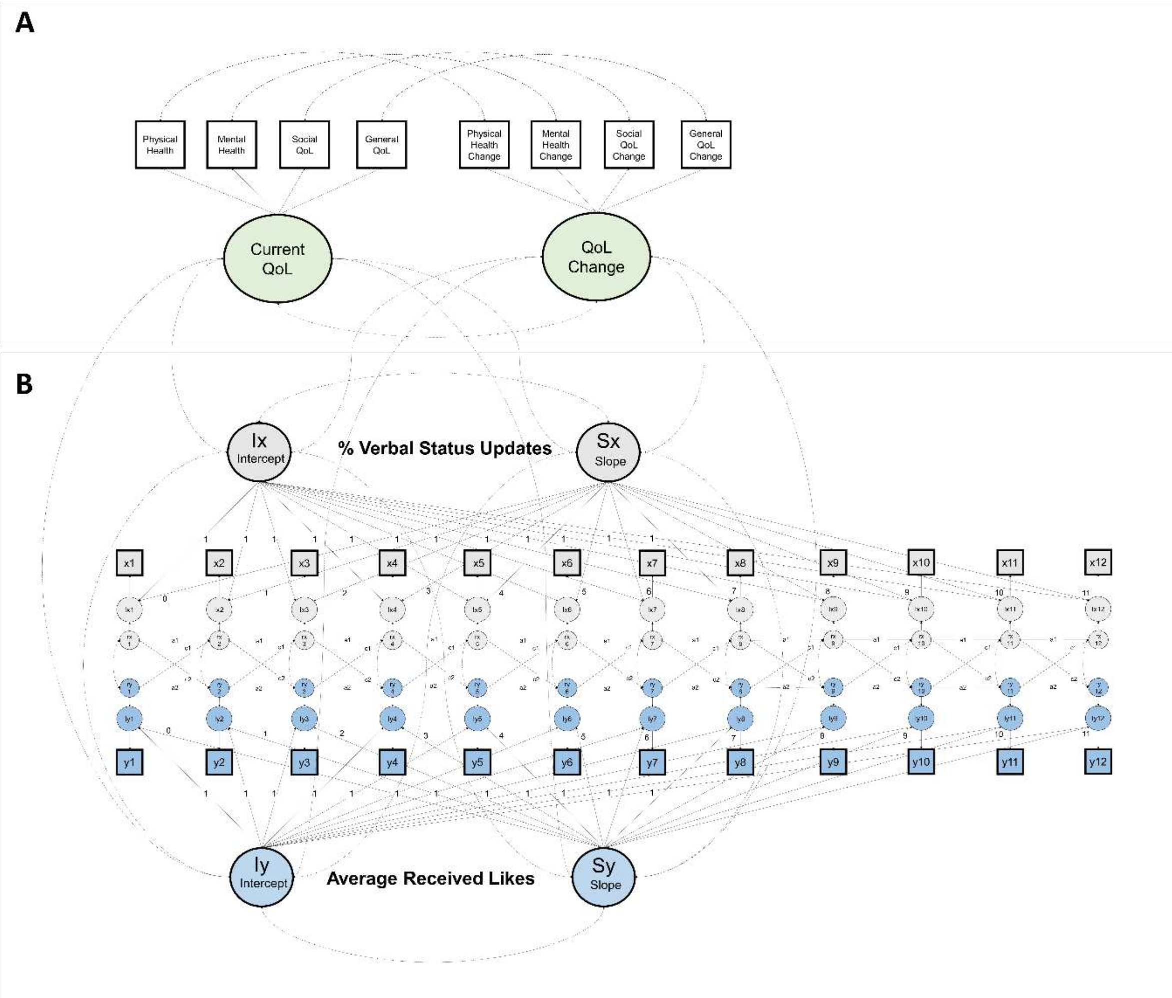

Figure 1. Conceptual Diagrams for the Tested Models: a) Correlated-factor CFA model of Perceived Current QOL and QOL change; b) Auto-Regressive Latent Trayectory Model with Structure Residuals for the association between Verbal Status Updates (%) and Average Received Likes over 12 months of Facebook Activity.

One advantage of the ALT-SR over traditional auto-regressive cross-lag models is that we can capture variance that does not change (i.e., the intercept parameters, *Ix*, and *Iy*), the variance that changes over the course the considered period (i.e., the slope parameters, *Sx* and *Sy*). Additionally, the model includes within-person autoregression paths (*a1-a2*) and cross-lagged paths (*c1-c2)* between residuals allowing us to determine the time-varying links between propensity to verbal activity on Facebook and receiving Likes across consecutive time points. Note that in our study these cross-lagged paths were constrained to be the same across time points to capture an overall tendency over the consider 12-months period.

Finally, the models were combined in a single model to explore correlations between the latent variables representing current perceived QoL and perceived change in QoL and both intercept and slope indicators of user's verbal posting activity and received Likes. In Figure 1, these latent correlations are represented by dashed lines linking the two models in panel *a* and *b*.

To establish model fit of the tested models we compute the following available model fit statistics: the comparative fit index (CFI) [14] and the Tucker–Lewis Index (TLI) [15] measures of incremental model fit, the root mean square of approximation (RMSEA). Based on commonly used thresholds for model fit statistics in structural equation modeling [16,17] we consider values of CFI > 0.95, TLI > 0.95, and RMSEA < 0.05 as indication of good model fit, while CFI and TLI > 0.90, and RMSEA < 0.08, as indication of acceptable fit.

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Note that in the analyses, gaps in Facebook activity were considered missing by design, and thus plausibly compatible with the missing-at-random data assumption (see Table 1 for information about the amount of data available at each wave). To retain all available data in the analyses, model estimation was performed by using full information maximum likelihood (FIML) estimator in Mplus [18]. FIML treats all observed predictors as a single-item latent variable; therefore, each individual contributes to the data they have available at each time point to the likelihood function and no individuals are removed from the analysis through listwise deletion. Under the assumption that data are missing completely at random (MCAR), our estimates and SEs are unbiased by the missing data [19]. Note that to ensure robustness of standard errors to non-normality, all analyses were performed using a bootstrap approach with 1000 samples to compute 95% confidence intervals of the parameters.

3. Results

3.1. Model fit

The CFA model testing the two latent QoL factors—current state and perceived change in QoL—demonstrated acceptable fit. The chi-square goodness-of-fit test was significant ($\chi 2$ (15) = 81.89, p < .001), an expected outcome in large samples. RMSEA was 0.053 with a 90% confidence interval ranging from 0.042 to 0.065, indicating an adequate but not excellent fit. The CFI and TLI values were 0.978 and 0.959, respectively, both surpassing the conventional threshold for acceptable fit, while the SRMR was 0.030, well below the .08 cut-off. The positive correlation between the two QoL factors was strong (r = 0.612), suggesting a notable relationship between current QoL and perceived changes over time. The diagram in Figure 2 provides a visualization of the tested model. Note that all parameters in the figure are significant at p<.01.

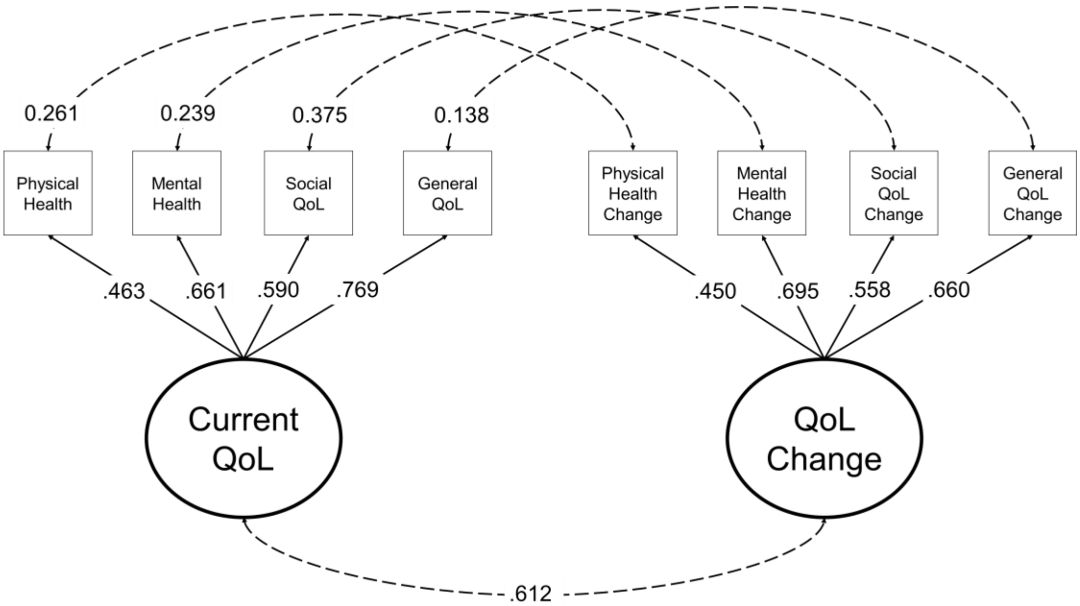

Figure 2. *CFA* model of Perceived Current QOL and QOL change: Standardized factor loading estimates and latent correlations.

The ALT-SR model used to extract latent intercept and slope indicators for verbal status updated and average received Likes on Facebook showed excellent fit across all indices ($\chi 2$ (280) = 581.48, p < .001, with a particularly low RMSEA of 0.026 (90% CI [0.023, 0.029]), and high CFI and TLI both at 0.980 and 0.980, respectively, with an SRMR of 0.029.

Integrating the two models, the final model also showed excellent fit, indicating that our hypothesized model is consistent with the observed data ($\chi 2$ (475) = 857.86, p < .001; RMSEA = 0.023 [0.020, 0.025]; CFI = 0.979; TLI = 0.978; SRMR = 0.029).

3.2. Longitudinal patterns of online activity on Facebook and links with QoL dimensions

Mean values of intercept and slope scores for verbal status updates and average received Likes and latent correlations with both current QoL and perceived QoL change are shown in Table 2. Results of the final model indicate that in our data, the slopes for both verbal status updates and average received Likes had decreasing trend over time. Specifically, the slope for verbal status updates indicates that the proportion of text-based status updates gradually declines as time progresses (S*x* = -0.186; 95% C.I. [-0.317, -0.061]). Similarly, the slope for average received Likes shows a reduction in the number of likes received per post over the course of the observation period (S*y* = -0.195; 95% C.I. [-0.248, -0.136]). This pattern suggests a changing dynamic in user behavior and interaction on the platform during the studied timeframe.

Looking at latent correlations between indicators of Facebook activity, a strong positive correlation between the overall tendency for verbal expression on Facebook and average received Likes (r = 0.489, 95% CI [0.431, 0.539]), suggesting that more verbal users tend to receive more feedback. Furthermore, the slope of verbal status updates showed a positive relationship with the increase in received Likes over time (r = 0.301, 95% CI [0.024, 0.596]), indicating that users who increase their verbal posting activity may perceive an enhancement in their social feedback.

Current QoL was positively associated with the intercept parameter for both average received Likes (r = 0.196, 95% CI [0.127, 0.269]) and verbal posting activity (r = 0.093, 95% CI [0.024, 0.163]), although this latter association was quite weak. In turn, perceived QoL change was positively with the temporal increase in Likes across the 12 time points (r = 0.175, 95% CI [0.047, 0.319]), suggesting that users experiencing an improvement in QoL also showed an increase (or a lower decline) in received Likes compared to users that perceived a worsening or stability in QoL over the previous year.

Finally, we report on results emerging from autoregression paths (*a1-a2*) and cross-lagged paths (*c1-c2)* between residuals of the ALT-SR model. These autoregression and cross-lagged paths can provide insight into how time-specific changes in verbal status updates and average received Likes impact the same variables measured at the next time point. We only found a significant autoregression effect, indicating that time-specific increases in verbal status updates activity tend to carry on to the following time point (a1 = 0.036, 95% CI [0.011, 0.064]). Estimated parameters for the final model are reported in full in the supplementary materials.

Table 2. Mean values of intercept and slope scores for Verbal Status Updates and Average Received Likes and latent correlations with current and perceived change in QoL**.**

	Mean	Current QoL	QoL Change
% Verbal Status Updates – Intercept (Ix)	55.321 [54.009, 56.761]	.093 [.024, .163]	.067 [-.003, .136]
% Verbal Status Updates – Slope (Sx)	-0.186 [-0.317, -0.061]	-.027 [-.150, .108]	.011 [-.117, .139]
Avg. Received Likes – Intercept (Iy)	13.150 [12.504, 13.779]	.196 [.127, .269]	.054 [-.023, .124]
Avg. Received Likes – Slope (Sy)	-0.195 [-0.248, -0.136]	-.031 [-.163, .084]	.175 [.047, .319]

[1] Values in bracket are 95% confidence intervals (1000 bootstrap samples).

Discussion

The present study aimed to expand the understanding of the association between online positive social feedback on Facebook and perceived changes in Quality of Life (QoL) among adult users. Consistent with prior research [2–7], our study emphasizes the interconnectedness of online social interaction and individuals' well-being. Notably, a positive correlation was observed between the frequency of verbal expression in Facebook status updates and the number of Likes received, indicating that more expressive users tend to receive more feedback. Additionally, an increase in verbal status updates over time was linked to a perceived enhancement in social feedback, highlighting the potential impact of increased engagement on received support. Furthermore, the study revealed that users with a higher current quality of life also received more Likes on their posts, suggesting a connection between positive social feedback and well-being. Lastly, individuals who perceived a temporal increase in Likes also perceived an improvement in their quality of life, underscoring the dynamic relationship between online social interactions and subjective well-being. Thus, while earlier studies highlighted the potential adverse effects of increased Facebook use on subjective well-being, our findings suggest a more nuanced picture. The positive association between receiving Likes (a form of online social feedback) and enhanced perceived QoL aligns with the idea that not all that happens on social is necessarily detrimental. This supports findings indicating that certain forms of online engagement, like receiving Likes on social media, can influence an individual's sense of well-being [4,7].

The innovative use of objective social media data in our research methodology echoes recent trends in the field [6–8]. By analyzing real-time interactions and feedback on Facebook, we could capture the immediate effects of online social support on QoL. This approach offers a more direct and dynamic measurement of social media interactions, overcoming some limitations of self-reported data which can be subject to recall bias and subjective interpretation.

However, the longitudinal design of our study revealed that the relationship between Facebook activity and QoL is not static but evolves over time. This finding is in line with Shakya and Christakis's observation of the long-term effects of Facebook use on various aspects of well-being [8]. Unlike Shakya and Christakis's study [8], which found a general negative correlation between Facebook use and well-being, our study highlights the positive impact of specific types of Facebook interactions, particularly receiving likes, on perceived QoL over time.

This study has strengths. The use of a large sample size and the separation of the methods for data collection for Facebook interactions and self-reported QoL measures, we improved the robustness of our numerical results and reduced the risk of biases that could arise from using a common method for studied variables.

The sample selected in our study is also a source of limitation. The gender distribution indicates a strong prevalence of young and female participants, and as such, may have not fully captured the variability that is observed in the broader population, thus limiting generalizability of results.

Another limitation of our study, as with many others in this field, is the reliance on self-reported measures of QoL. Despite our integration of objective Facebook data, the subjective nature of QoL assessment may still influence the results. Another notable limitation is the approach to assessing changes in QoL. Instead of measuring QoL longitudinally, our study relied on participants' perceptions of change in their QoL. This method may not accurately capture the true trajectory of QoL changes over time, as it depends on individual subjective recall and interpretation. Perception-based measures can be influenced by various factors, including current mood, recent events, and individual biases, which might not accurately reflect actual changes in QoL. For instance, an individual's current state of well-being could disproportionately influence their perception of past well-being, known as the current-state bias [20]. A more robust approach for future studies could be to assess QoL at multiple time points, as done in previous research of this kind [8] thus providing a more objective and temporal perspective of how QoL evolves in relation to social media use. This longitudinal method would allow for a clearer understanding of the directionality and causality of the relationship between Facebook activity and QoL. Furthermore, while our study leverages objective data from Facebook, complementing this with additional objective measures of well-being, such as physiological indicators, could provide a more comprehensive understanding of the impact of social media on QoL.

To conclude, our study presents evidence of a positive association between Facebook activities and Quality of Life (QoL) in adult users. It reveals that more frequent verbal expression in Facebook updates and a higher number of Likes received correlate with better QoL. The study also observes that individuals who perceive an increase in Likes report an improvement in QoL. This contributes a new perspective to the understanding of social media's impact on well-being, suggesting potential positive aspects contrary to previous research.

Declaration of AI and AI-Assisted Technologies in the Writing Process

While composing this document, the author(s) employed OpenAI's ChatGPT 4 for assistance with grammar and spelling checks, as well as to enhance the clarity and readability of the text. After the utilization of this AI tool, the author(s) meticulously reviewed and modified the content where necessary. The author(s) assume full responsibility for the final content of this publication.

Authors Contributions: DM and MS jointly conceptualized the study. Both authors were involved in data collection, curation, and development of the methodology. DM took the lead in analyzing the data, creating visual representations, and drafting the manuscript. MS provided critical revisions that significantly improved the manuscript. All authors read and approved the final manuscript.

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Conflicts of Interest: The authors declare that they have no competing interests relevant to the content of this article.

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