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Narcissism and Fame: A Complex Network Model for the Adaptive Interaction of Digital Narcissism and Online Popularity

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This is an extended version of a paper (Jabeen et al., 2019) *that appeared in Complex Networks'19. The new content of this article is a much larger empirical study and an additional focus on the influence of popularity on narcissism, presented along with the analysis of simulation experiments*

List Of Abbreviations and Symbols

AI	Artificial Intelligence
GABA	γ-aminobutyric acid
ACC	Anterior Cingulate Cortex
μ; M	Persistence ; Persistence reification
η; H	Learning rate; Learning rate reification
ω; W	Connection weight
c_Y	Combination function for a state Y
$P_{i,j}$	Combination function parameter reification
ws	World state
ss	Sensory state
srs	Sensory representation state
fs	Feeling state
eval+	Positive evaluation
eval-	Negative evaluation
bs_+	Belief state
striatum	Ventral striatum
PFC	Prefrontal Cortex
es_{happy}	Execution state of happiness
insula	Anterior insula
os	Ownership state
ps	Preparation state
es	Execution state
act	Action
pf	Positive feedback
nf	Negative feedback
anx	Anxiety
sent	Sentiment
eff	Effect / Predicted effect
pop	Popularity
cs	Control state
val	Valuation state
$W_{fs_{love}, bs}$	Omega state for connection $fs_{love} \rightarrow bs+$
$W_{bs, fs_{love}}$	Omega state for connection $bs \rightarrow fs_{love}$
$W_{sat,ins}$	Omega state for connection striatum $\rightarrow$ insula
$W_{fs_{rew}, striatum}$	Omega state for connection $fs_{reward} \rightarrow$ striatum
W_{eval-, ps_a}	Omega state for connection eval- $\rightarrow ps_{act}$
$W_{ps_{act}, srs_{eff}}$	Omega state for connection $ps_{act} \rightarrow srs_{eff}$

$W_{fs_{sent},\, ps_{act}}$	Omega state for connection $fs_{sent} \rightarrow ps_{act}$
postfreqpm	Posting frequency behavior per month
likespm	Average number of likes per month
selfiepm	Number of selfies shared per month
otherpicspm	Number of other pictures per month
hashtagspm	Number of hashtags used per month
pconvspm	Positive conversations per month
nconvspm	negative conversations per month
USER	User name to login
PASSWORD	User's password to login
KPI	Key Performance Indicators
w.r.t	with respect to

Declaration

Availability of data and materials

The data and materials used for analysis and development of results is available here.

Competing interests

The authors declare that they have no competing interests

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Authors' Contribution

Fakhra Jabeen being a Ph.D. student presented the idea and completed the experiments and the project, while Dr. Charlotte Gerritsen and Prof. Dr. Jan Treur being supervisors, designed the study and helped towards completion of the project and producing the final manuscript of the paper.

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Abstract: Social media like Twitter or Instagram play the role of a fertile platforms for self-exhibition and allow their users to earn a good repute. People higher in grandiosity share their contents in a charismatic way and as a result, they are successful in gaining attention from others, which may also influence their responses and behaviors. Such attention and repute enable them to be a trendsetter or a socially recognized maven. In this paper, we present a complex adaptive mental network model of a narcissist to see how popularity can adaptively influence his/her behavior. To analyze and to support behavior showed by our model, we used some key performance indicators from the literature to study the popularity and narcissism of 30 Instagram. The results of the - both computational and empirical - study indicate that our presented computational adaptive network model in general shows the behavior found from the empirical data.

Keywords: *Digital Narcissism, Digital Reputation, Popularity Influence, Complex Network*

1. Introduction

Narcissism reflects a personality trait which relates to a certain cluster of human behaviors, which display self-superiority and self-exhibition. These behaviors mostly relate to entitlement seeking and having a messiah complex. Narcissists need admiration and dwell for their own appearance and achievement, which often leads to lack of empathy for others (Bushman & Baumeister, 1998; Y. Fan et al., 2011). Social media platforms can help narcissists to achieve popularity and have a feeling of worth for themselves, but this can also increase their vulnerability due to the pervasive nature of social media (Bushman & Baumeister, 1998). Different artificial intelligence (AI) techniques were used to detect narcissism from text analysis (Holtzman et al., 2019; Neuman, 2016). There are very limited computational studies addressing these behaviors. Moreover, how popularity can influence such behavior was not studied yet in more depth. Extending the preliminary (Jabeen et al., 2019), the current paper addresses this.

The new level of connectivity through social media, provides a new way to become popular. Therefore, media such as Facebook, Twitter or Instagram can act as new channels for self-promotion of a narcissist. They share proactive materials like selfies (Holtzman et al., 2010), or posts with their lifestyle information, which makes them dominant (Alshawaf & Wen, 2015). Previous studies explained that there is a relationship between narcissism, excessive usage of social media (McCain & Campbell, 2018; Panek et al., 2013) and reward-seeking behavior (Bushman & Baumeister, 1998). In a preliminary version of our work, we presented a complex second-order adaptive network model that explains the reactions of a narcissist in case of positive and negative feedback (Jabeen et al., 2019). However, it is also interesting to see how popularity can influence these reactions; this addition is contributed by the current paper, as is a much more extensive empirical study involving 30 social media profiles.

More specifically, in this paper, in addition to network-oriented computational modeling of narcissist behaviour, we address both empirically and computationally a) how a presumed narcissist earns popularity over time, and b) how popularity can influence his/her behavior. The paper is organized as follows. In Section 2, we discuss the state-of-the-art literature related to narcissistic behaviors, along with popularity over social media. Section 3 presents the method and methodologies applied and the obtained adaptive network model. In Section 4 simulation results are presented. Section 5 discusses how behaviors from real-world relates to the designed computational model, through 30 public Instagram profiles. Section 6 discusses the limitations and future work options of the study and Section 7 concludes the paper.

2. State of the Art Literature

This section presents the related work in two streams: i.e. Firstly, it discusses the psychological and neurological aspects of a narcissistic person and his/her expected behaviors. Secondly, it presents the influence of digital reputation over such behaviors. At the end of the section, AI-based approaches are also discussed, which were used to predict a narcissist.

2.1. Narcissism

Narcissism is characterized by the mythological figure Narcissus, who passionately fell in love with his own reflection (Brummelman et al., 2015). This complex phenomenon of acute concern of self-admiration can be described in terms of psychological, cognitive, and social process.

Psychologically, narcissists show a high tendency for self-admiration and self-presentation (Wang, 2017). A study indicated that there is a strong association between narcissism and reward-seeking behavior (Bushman & Baumeister, 1998). Social media like Instagram is a well-known platform used for self-exhibition (Alshawaf & Wen, 2015). A narcissist may receive a compliment and react with kindness and joy (Moon et al., 2016) as an outcome of reward-seeking behavior (Y. Fan et al., 2011), or a non-empathetic in response to a critic (Bushman & Baumeister, 1998; Y. Fan et al., 2011).

In cognitive neurological sciences, different brain parts interact with each other for an interpretation and response to feedback. For example, the prefrontal cortex (PFC) along with the Anterior Insula and temporal lobe evaluates feedback as a compliment (Olsson et al., 2014). As a result, the Anterior Cingulate Cortex (ACC) along with the ventral striatum show the reward-seeking behavior. Different hormones and neurotransmitters also take part when a person is admired. For example, dopamine is released when a narcissist feels that his target of sharing content is achieved, as (s)he is admired (Daniel & Pollmann, 2014). Similarly, γ-aminobutyric acid (GABA) receptors are activated, due to anxiety, which results from a negative evaluation of a critic (Sun et al., 2016). This negative evaluation leads to a threat to his/her ego as (s)he feels socially rejected (Bushman & Baumeister, 1998). The hippocampus in the brain is affected by psychological stress, which affects, in particular, the memory and the learning capabilities by decreased synaptic plasticity (Schmidt et al., 2013; Sun et al., 2016). This reduction in synaptic plasticity is due to changes in the brain structure caused by stress (Sun et al., 2016). Also, cortisol levels are elevated when a person feels stress (Jauk et al., 2017).

2.2. Popularity

Narcissists use social media excessively, to display their charismatic looks and, by their social skills, they can become social mavens or influencers (Moon et al., 2016). Instagram is an ideal platform for an individual to engage him/herself and to gain more visibility. This process of self-promotion involves the visual appearance of a person with a high number of followers who talk about his/her likability (Holtzman et al., 2010) and, digital reputation is earned (Alshawaf & Wen, 2015). They proactively gear themselves and their followers, to increase the follower likability and engagement (Bernarte et al., 2015). An example of such behavior can be a selfie with lifestyle information (Alshawaf & Wen, 2015), captioned by using hashtags (Page, 2012). Often, they follow limited people and, thus, have a high follower to following ratio, indicating their high influence/popularity (Farwaha & Obhi, 2019)(Garcia et al., 2017). A study also indicated that high numbers of likes can indicate how popular the posts of a person are (Chua & Chang, 2016). High popularity may leave a positive impact and give personal satisfaction (Nesi & Prinstein, 2015; Trent, 1957).

Among AI-based approaches, a study related to machine learning tried to detect narcissism from text, where text as a vector was compared with personality vectors or dimensions resulting patterns of narcissism in psychological dimension (Neuman, 2016). Another textual analysis approach (LIWC) used first-person singular pronouns to detect narcissism (Holtzman et al., 2019). In our previous work, we discussed the vulnerable behavior of a narcissist through a complex network model (Jabeen et al., 2019). Here, we extend our work by studying popularity and its influence on the behavior of a narcissist.

3. Methods and Methodologies and the Obtained Adaptive Network Model

Causal network modeling is a well-known approach in the field of artificial intelligence, which is helpful in making predictions about the behaviors of a person or a real-world scenario. Variables in a causal model, act as basic building blocks to represent the occurrence of an event (e.g. "he graduated"), which leads to behavioral changes in a system or a person (e.g. "he got admission") (Scheines et al., 1991). *Temporal-causal network modeling* distinguishes itself from static causal network modeling, by adding a temporal perspective on causality. In addition, *adaptive* temporal-causal network modeling also addresses that network connections and other network characteristics can change over time. It is applicable to design and simulate a variety of models related to neural, mental, biological, social network, and many other domains. This section describes the adaptive temporal-causal network modeling approach using a multilevel reified network architecture (Treur, 2020), which was used to design our model.

A reified network architecture is a multilevel network architecture, in which a temporal causal network is presented at the base level and the adaptiveness of the network is represented at (higher) reification levels. The ***base level*** contains a causal network representation, specified by a directed graph having 'states' as vertices and, 'connections' as edges between them. To illustrate this, consider a connection: $X \rightarrow Y$. This indicates that state Y is influenced by state X. The *activation level* of Y is computed through a *combination function*, which uses the *aggregated causal impact* by all states including X, from which Y has incoming connections. The *aggregated causal impact* depends on the *connection weights* and the *activation levels* of the incoming states. Therefore, for each state Y we have a:

- **Connection weight $\boldsymbol{\omega}_{X,Y}$**: how strong state X can influence state Y. The magnitude normally varies between 0 and 1, but suppression from a state is specified by a negative connection weight.
- **Speed factor $\boldsymbol{\eta}_Y$**: how fast state Y is influenced by the impact of incoming states. The range is normally between *low*:0 and *high*:1.
- **Combination function $\mathbf{c}_Y$(..)**: used to determine the aggregated impact of all states with incoming connections to Y. Either an existing combination functions can be used like: the identity function, the advanced logistic sum function, and so on, or a custom function can be defined.

The above introduced $\boldsymbol{\omega}_{X,Y}$, $\boldsymbol{\eta}_Y$ and $\mathbf{c}_Y\mathbf{(..)}$ are the *network characteristics* defining a temporal-causal network model. An *adaptive network* model occurs when such characteristics are dynamic and change over time. The adaptiveness of the base level network considered here is represented by ***first-order adaptation principles*** (modeled at level II) and ***second-order adaptation principles*** (modeled at level III). An $\boldsymbol{n}^{\text{th}}$-order adaptive network model is specified by declarative specifications of an $\boldsymbol{n}$+1 leveled network design and can be represented mathematically as shown in Appendix A. Here, it is shown how a (three leveled) second-order reified adaptive network architecture was designed to address the complex adaptive mental network model of a narcissist.

3.1. Level I: the base network level

This section addresses the base network model (Level I) of a narcissist depicting his mental organization by 39 states (Figure 1). A categorical explanation of each state is presented in Table 1. A state can have three types of incoming connections:

- Black arrows for a positive connection with weight values between (0,1].
- Purple arrows for a negative connection with weight values between [-1,0].
- Green arrows show the adaptive connections which lead to an adaptive behavior and will be explained further in Section 3.2.

The model has three inputs from surroundings: ws_{pf}, ws_{nf} and ws_s. State ws_{pf} shows the positive, while ws_{nf} represents the negative feedback from another peer. State ws_s represents the stimulus, for example, the usage of social media. Three output states: es_{happy}, es_{act}, and es_{sent} represent the reaction of a narcissist. State es_{happy} is an outcome when the person receives positive feedback ($ws_{pf} = 1$, $ws_{nf} = 0$) and es_{act} and es_{sent} are the outcomes for a critic received ($ws_{pf} = 0$, $ws_{nf} = 1$).

When a narcissist shares an attractive post (e.g. his/her selfie with an attractive caption) over social media, he often receives different types of feedback from others. A result of feedback like ‘you are awesome’ makes him/her feel happy and loved. Based upon the narcissus mythology, here his/her self-belief (bs+) evaluates such feedback as positive (eval+). Therefore, the mental states related to self-enhancement (PFC; Insula) are activated, along with the reward-seeking states: striatum, feelings of self-love (fs_{love}) and reward (fs_{rew}). The feelings of self-love increase the esteem/self-belief state (bs_{+}) over time, which escalates his or her reward-seeking behavior, making him/her a narcissistic soul.

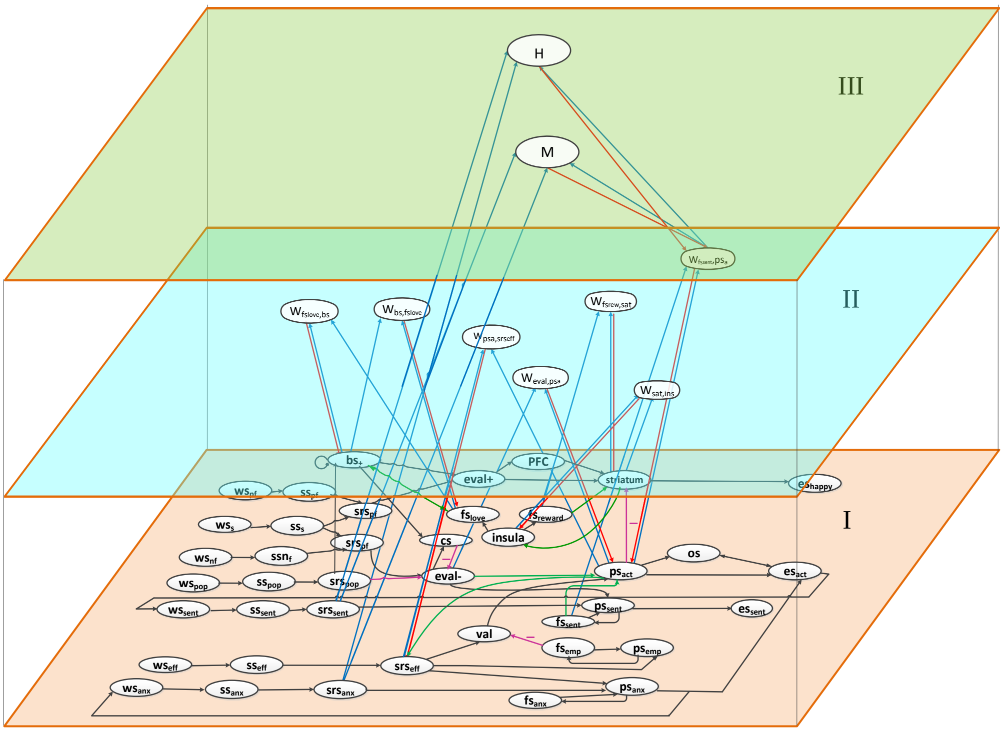

Figure. 1. Reified Second-Order Adaptive Network Architecture for a narcissist person, consisting three levels: base level I, first-order adaptation level II and second-order adaptation level III

A narcissist person usually disagrees to a critic due to high ego/self-belief. So, his/her negative feelings arise when ws_{nf} = 1, which may result in a non-empathetic/negative response. To explain it further, a remark like ‘you are ugly’, will be evaluated (eval-) as negative can provoke a response like ‘go off you loser’. Here, ego/self-belief (bs+) initially tries to suppress this evaluation through control state (cs). However, evaluataion (eval-) is too strong to be suppressed, resulting, a) stimulation of negative sentiments and b) a non-empathic reaction to the peer.

Here, we address two categories of negative sentiments/feelings by the sentiment body loop (ws_{sent}; ss_{sent}; srs_{sent}; fs_{sent}; ps_{sent}; es_{sent}): negative and extreme negative (Ntshangase, 2018). The negative feelings are the low-intensity feelings like: fear, sadness or rejection. While the extreme/very negative feelings, are the ones with a high intensity such as of anger, humiliation, rage or frustration. Action (ps_{act}; es_{act}), is an aggregate result of negative feelings (fs_{sent}), evaluation (eval-) and valuation (val) states. This may result in a response like "back off" or deleting and block that peer. It is be noted, that the valuation state (val) in principle doesn't get activated if the person has empathy (fs_{emp}; ps_{emp}), which is not the case here (as he/she is narcissist (C. Fan et al., 2019). After activation of ps_{act}, the thought process related to ownership state (os) and predicted effect (ws_{eff}; ss_{eff}; srs_{eff}) is also activated, which induces anxiety (ws_{anx};ss_{anx};srs_{anx}; fs_{anx} and ps_{anx}). The body loop of anxiety differs from the body loop of sentiments (Raghunathan & Pham, 1999; Weger & Sandi, 2018), as it can elevate such reactions (es_{act}) along with experience/learning from the actions (ps_{act}).

Popularity (ws_{pop}; ss_{pop}; srs_{pop}) serves as a moderator to these negative feelings. Thus, popularity lowers the negative evaluation (eval-), negative sentiments and feelings of anxiety(Nesi & Prinstein, 2015), so the negative outcomes appear less than before (discussed in Section 3.2).

Table 1. Categorical Explanation of States of Base Network (Level I).

Categories		References
Stimulus states:		*"the representation of the world external to the body can come into the brain only via the body itself"* (Damasio 2010)
ws_i	World state. i = stimulus (s); positive / negative feedback (pf/nf)	
ss_i	Sensory state. i = stimulus; pf / nf	
srs_i	Representation state j = pf / nf	
Attribution / evaluation states:		*"Narcissism involves states for self-enhancement and mentalizing."* (Olsson et al., 2014)
eval+	Positive evaluation of feedback	
eval-	Negative evaluation of feedback	

Happiness related states: **bs_+** Self-belief state **striatum** Ventral Striatum : brain part **PFC** Prefrontal Cortex: brain part **fs_{reward}** Feeling state of reward (Amygdala) **fs_{love}** Feeling state self-love (Amygdala) **es_{happy}** Execution state of happiness **insula** Anterior Insula : brain part	*"fMRI studies show activations at or near dopaminergic midbrain nuclei and the VS that correlate with both reward expectation and reward prediction errors…"*(Daniel & Pollmann, 2014)
Sentiment related action states: **os** Ownership state **ps_{act}** Preparation state of action **es_{act}** Execution state of action	*"mind is informed of the actions taken .. the feeling associated with the information signifies that the actions were engendered by our self."* (Damasio 2010)
Body Loops: Sentiment (sent) and Anxiety (anx): **ws_i** World state i=sent / anx **ss_i** Sensor state i= sent / anx **ps_i** Preparation state of i = sent / anx **fs_i** Feeling state i = sent / anx **es_{sent}** Execution state of sentiment)	*"The as-if body loop hypothesis entails that the brain structures in charge of triggering a particular emotion be able to connect to the structures in which the body state corresponding to the emotion would be mapped."* (Damasio, 2012)
Predicted Effect of Action: **ws_{eff}** World state of effect **ss_{eff}** Sensor state of effect **srs_{eff}** Representation state of effect	*"They need to know that this person will listen to their fears, take them seriously and do something"*(Elliott 2002)
Control states: **cs** Control state **val** Valuation state	*"the survival intention of the eukaryotic cell and the survival intention implicit in human consciousness are one and the same".* (Damasio, 2012)
Popularity **ws_{pop}** World state of effect **ss_{pop}** Sensor state of effect **srs_{pop}** Representation state of effect	*"popularity moderated … depressive symptoms."* (Nesi & Prinstein, 2015)

3.2. Level II and III: the adaptation levels

The reified network architecture used for our network model has two adaptation levels represented by first- (Level II) and second-order (Level III) adaptation (see Figure 1). The first-order adaptation level (Level II) relates to the ability to learn/adapt certain behavior(s) by experience over time (for example: with age) known as *neuroplasticity* or *hebbian plasticity/hebbian learning*. In this case, connections in the base network appear not to be fixed in terms of their weights and may change over time (shown by green arrows at Level I). In our model, this change is due on hebbian learning principle, modeled by seven reification states: '**W**-states' at Level II (also see Table 2). The second-order adaptation level (Level III) addresses adaptation of **W**-states, which represents *plasticity of neuroplasticity* or *metaplasticity* (Robinson, Harper, and McAlpine 2016; Schmidt et al. 2013). It is modeled by adaptive persistence factor μ and adaptive learning rate η by reification states **M** and **H** respectively at Level III. This shows how synaptic transmission can be influenced and controlled by other factors, for example, through hormones or neurotransmitters (Robinson et al., 2016; Treur, 2020, Ch. 4).

Table 2. Explanation of States in Level II and III.

States per Level		References
Level II (Plasticity / Omega states):		*1 – 4: Potentiation in the striatum depends not only on strong pre- and postsynaptic activation … reward prediction … modify behavior.*(Daniel & Pollmann, 2014)
1. $\mathbf{W}_{fs_{love}, bs}$	For $fs_{love} \rightarrow bs$	
2. $\mathbf{W}_{bs, fs_{love}}$	For $bs \rightarrow fs_{love}$	
3. $\mathbf{W}_{sat,ins}$	For striatum $\rightarrow$ insula	
4. $\mathbf{W}_{fs_{rew}, striatum}$	For $fs_{reward} \rightarrow$ striatum	*5 – 7: Presynaptic somatodendritic 5-HT1… people with a high level of aggression, there is a greater density … with impulse control.*(de Almeida et al., 2015)
5. $\mathbf{W}_{eval-, ps_a}$	For eval- $\rightarrow ps_{act}$	
6. $\mathbf{W}_{ps_{act}, srs_{eff}}$	For $ps_{act} \rightarrow srs_{eff}$	
7. $\mathbf{W}_{fs_{sent}, ps_{act}}$	For $fs_{sent} \rightarrow ps_{act}$	
Level III (Meta-Plasticity):		*Damage to neurons in hippocampal CA3 area and microstructure of synapse indicates that anger… harms plasticity ....* (Sun et al., 2016)
H	Speed factor for $\mathbf{W}_{fsang,psa}$	
M	Persistance factor for $\mathbf{W}_{fsang,psa}$	

In Figure 1, the inter-level interactions are represented by two types of arrows: red (downward) and blue (upward). The red arrows show the specific causal impact from reification states to a certain state, while the blue arrows are used to create and represent the dynamics of the reification states on the higher levels. For illustration, consider when a person receives negative feedback, (s)he reacts (ps_{act}; es_{act}) after having a negative sentiment about the feedback (connection: eval- $\rightarrow$ ps_{act}). The way of reacting after such a feeling is learnt from personal experience. This can be modeled by hebbian learning at Level II. To model Hebbian learning, reification state $\mathbf{W}_{eval-,ps_{act}}$ receives an impact from the pre-synaptic and post-synaptic states, i.e. eval- (relating to stress-related cortisol levels) and ps_{act}; this $\mathbf{W}_{eval-,ps_{act}}$ in turn affects the post-synaptic state ps_{act}, making it a form of circular causation. Similarly, when a positive feedback is evaluated (fs_{reward} relating to dopamine release), this affects $\mathbf{W}_{fs_{rew},striatum}$, with respective pre-synaptic (fs_{reward}) and post-synaptic (striatum) states. A similar pattern of interlevel connections can be observed for Level III. Here, metaplasticity states **H** and **M** receive input from the pre-synaptic (srs_{sent};

srs_{anx}) and post-synaptic (ps_{act}) states, represented in Fig. 1 by blue upward arrows. These states are related to meta-adaptation, which controls (red arrows from **M** and **H** to $\mathbf{W}_{fs_{sent}, ps_{act}}$) the learning and the speed of the state $\mathbf{W}_{fs_{sent}, ps_{act}}$ at Level II (Schmidt et al., 2013; Sun et al., 2016).

A network model can be simulated using the reified network engine designed in MATLAB, by providing a declarative specification in form of role matrices. A role matrix is a compact specification by the concept of the role played by a state (Treur, 2020, Ch. 9). For example, base network matrix (**mb**) enlists all the states with incoming connections to any state. Similarly, connection weight matrix (**mcw**) and speed matrix (**ms**) provide the connection weights and speed factor for each state. The combination function weight (**mcfw**) and combination function parameter matrix (**mcfp**) specify combination functions with their weights, and parameters respectively. Role matrices provide a declarative specification of the adaptive network model. The full specification of the adaptive network model in terms of role matrices can be found online (Jabeen, 2020).

4. Simulation Experiments

By simulation experiments the dynamics of the designed adaptive network model can be explored through simulating real-world scenarios. In this section, we present different simulations. First, we will see the two reactions of a narcissist i.e. a happy reaction or a reaction expressing annoyance. Second, we will see how a person gains popularity over social media and how it will influence both of his/her reactions. Third, we will see how a person reacts, when (s)he loses popularity. Therefore, this section is divided into two subsections a) reactions to a feedback and b) influence of popularity on the reactions.

4.1. Reactions to feedback

Here, we present our two scenarios; i.e. with: a) a positive reaction or, b) a negative reaction, along with few example tweets of Donald Trump, who is studied as a 'narcissistic', and to have a 'messiah complex' (Nai, 2019).

4.1.1. Reacting a Positive Feedback

Social media like Facebook, Twitter, or Instagram is a platform, where self-confidence of a narcissist speaks by itself (Moon et al., 2016; Wang, 2017). For example, the following tweet of Trump:

> "…my two greatest assets ... mental stability and being, like, really smart … I went from VERY successful businessman, to top TV Star…." (Tweeted: 1:27 PM – Jan 6, 2018)

Figure 2 shows the simulation results; here the horizontal axis shows the time scale and, the vertical axis shows the dynamic state values ([0,1]) over time. As positive feedback is received (ws_{pf} = 1), the state eval+ (purple) is activated, which in turn activates the state PFC (golden) around time point $t \approx 5$ - 10. These two activations along with bs+ (brown), activate the self-rewarding behavior through the striatum state (green-dotted). This activates insula (orange) at t ≈ 12, indicating a self-thinking process. The self-thinking process, boosts the feelings of self-love fs_{love} (dark-brown) and self-reward fs_{reward} (pink), at time point $t \approx 10$. As a result, (s)he expresses gratitude, with such an expression.

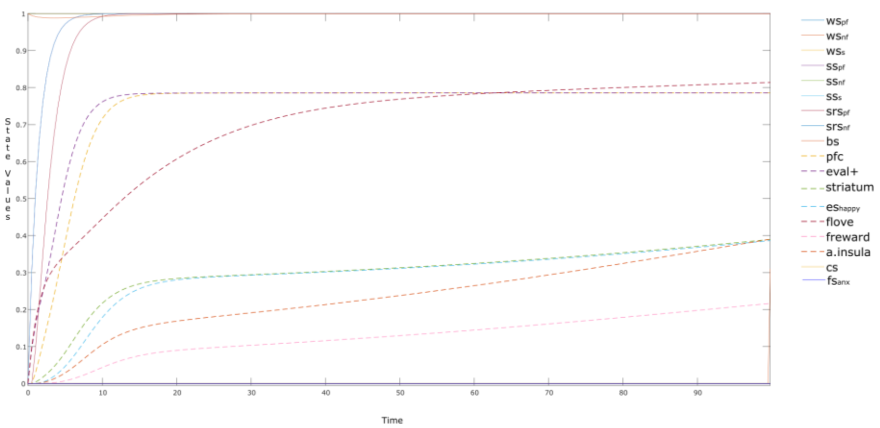

Figure. 2. Simulation of the model when ws_{pf} = 1 and ws_{nf} = 0: reaction is cheerful/happy.

4.1.2. Reaction a Negative Feedback

While observing a negative feedback of another person, a narcissist can react negative or extreme negative. ***Negative reactions*** may include an expression of sadness, fear, disgust, etc. While ***extreme negative*** reactions express negative feelings with a stronger intensity and can be expressed through anger, hostility, etc. (Ntshangase, 2018). For example, let's consider another tweet of Trump, where he doesn't seem to feel pleasure from another peer, i.e.:

> "what kind of lawyer would tape a client? So sad! is this a first, never heard of it before? Why was the tape so abruptly (cut)....too bad" (Tweeted: 2:34 PM – July 25,2018)

Or, let's take an example like,

> "… world class loser, Tim O`Brien, who I haven't seen or spoken … knows NOTHING about me … wrote a failed hit piece book…" (Tweeted: 6:20 AM – Aug 8,2019) (Folley, 2019)

Figure 3 and 4, shows the simulation results. Certain behavior (e.g. videotaping and cutting in between without any notification) is evaluated as negative, thus eval- ( ) gets activated at time point t ≈ 10-15. This stimulates the negative sentiments (fs_{sent} , ps_{sent}), along with the re-action states (bright green : ps_{act}; es_{act}) at t ≈ 20 - 25 . Also, the body loop of sentiments is activated (ws_{sent} ; ss_{sent} ; srs_{sent} ; ps_{sent}; fs_{sent} and es_{sent}: clustered by) around time point t ≈ 20. This action provokes self-conscious behavior (os) on the basis of some past memories (: ws_{eff} ; ss_{eff} and; srs_{eff}) resulting in anxiety (ws_{anx}; ss_{anx}; srs_{anx}; fs_{anx}; and ps_{anx}: clustered by). As the person doesn't have empathy (: ps_{emp}), also anxiety intensifies the action (es_{act}) state. Here, it can be observed, that although self-rewarding states are low (values = 0.03 at time t = 0 – 10), the feeling of self-love fs_{love} ( ) continues to grow after t = 100, intensifying the self-belief/ego (black dotted), indicating his love for himself only grows with the period of time. Figure 4 shows a similar behavior, with higher intensity shown by a body loop of sentiments in red.

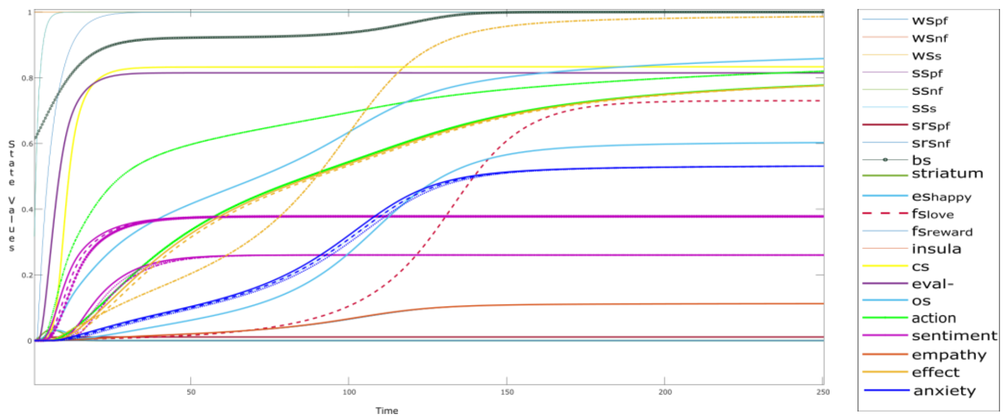

Figure. 3. Simulation of the model when $ws_{pf} = 0$ and $ws_{nf} = 1$: reaction is negative.

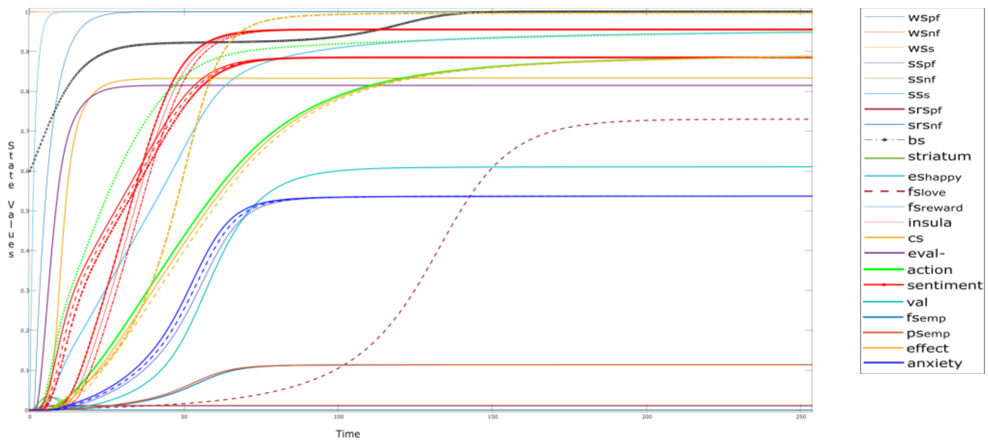

Figure. 4. Simulation of the model when $ws_{pf} = 0$ and $ws_{nf} = 1$: reaction is extreme negative.

4.2. Influence of popularity on reactions during feedback

In this section, we address two behaviors of a narcissist: i.e. a) how (s)he reacts when (s)he is not popular and b) how does the popularity influence his/her behavior.

4.2.1. When the person is not popular

Section 4.1 explains the reactions of a narcissist upon a positive or a negative feedback (Figure 3, 4). Here, we combined them (Figure 5), to address a) behavior without popularity and hebbian learning (described further in Section 4.3). Here, $ws_{pop} = 0$, and the episodes with white background are the episodes whenever a *positive feedback* is observed, for example, the first episode has duration of time points $t = 0 - 100$. In contrast, the episodes with colored background show the episodes with *negative feedback*, for example, during time points t = 100 – 200. The length of duration and order of occurrences can be interchanged or overlapped, but for the purpose of simplicity, we kept them non-overlapping and with equal intervals. Interestingly, learning from different levels of intensities can be observed through two similar episodes. For example, negative response/action (: ps_{act};es_{act}) in earlier episodes is lower (t = 100-200) than later episode (t = 300 – 400). Similarly, anxiety (: ws_{anx}; ss_{anx}; srs_{anx}; fs_{anx}; ps_{anx}) also increases with each episode.

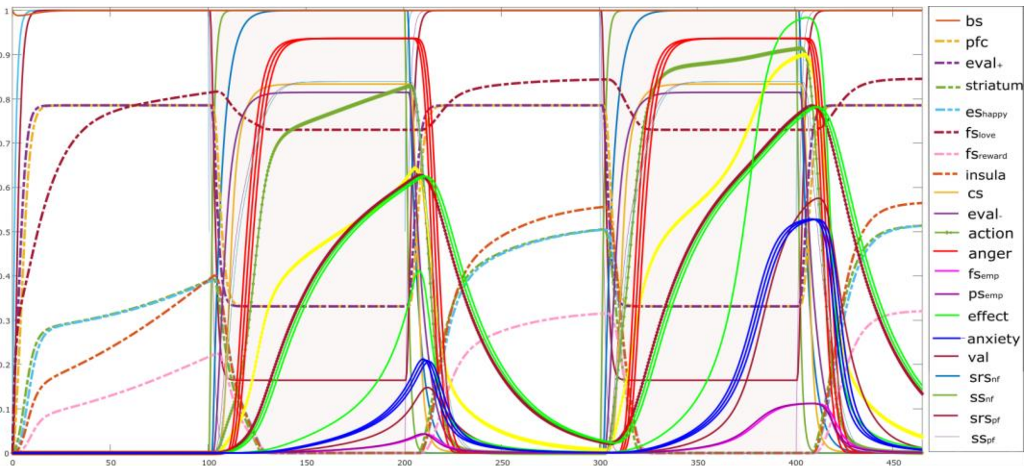

Figure. 5. Simulation of the model with alternative episodes of ws_{nf} = 1 or ws_{pf} = 1: no popularity

4.2.2. When the person gains popularity

Popularity is not earned overnight, but narcissists who aim to become social maven or influencers often choose tactics related to self-grandiosity and socialization. For example, they use an excess of social media to share their selfies and have a high number of likability and followers (Chua & Chang, 2016; Folley, 2019; Page, 2012). Popularity influences the behaviors and the symptoms related to depression (Nesi & Prinstein, 2015), and anxiety are reduced (Trent, 1957).

This ongoing process is shown in Figure 6. For simplicity, only the most important curves are presented in the figure. A person starts to earn popularity ( ) by sharing posts, at time point t = 450. This popularity gain lowers the intensity of the negative feelings (fs_{sent}: - - -, es_{sent}: , anxiety:), which were high before t < 450, with no popularity. Here it is to be noted that the popularity of a person is 0 for the minimum and 1 for the maximum.

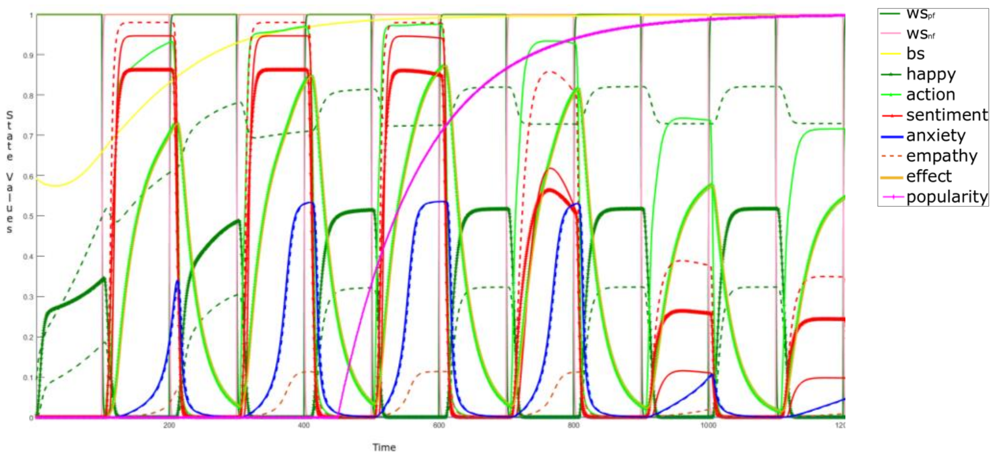

Figure. 6. Simulation of alternative episodes of $ws_{nf} = 1$ or $ws_{pf} = 1$:with popularity gain

4.2.3. When the person loses popularity

Popularity is not static always, and it is natural that a person can gain/lose popularity over time. The reason can be variation of looks, trends, and so on (Polhemus, 2011). As a result, narcissists' vulnerability may lead to negative reactions.

Figure 7 shows, when a person loses/tends to lose popularity, how different feedbacks can influence him/her. First, it can be observed in the duration of $t = 1800$ – 1900,when a positive feedback is received ($ws_{pf} = 1$), the person feels rewarded and loved (fs_{love} and fs_{reward}:), so he is happy (es_{happy}:). However, in this scenario, his esteem (bs:) and fs_{love} are already high, so there is no further learning in the self-rewarding behavior. The reason is that (s)he is aware of his/her self-worth. Second, when a disliking behavior or a critic is observed, (s)he flares up, which activates the negative sentiments (sentiment = es_{sent}: ; action = es_{act}:) and anxiety () for t > 2100. Here, it is to be noted that predicted effect shows the same behavior due to hebbian learning of ($srs_{eff} \rightarrow ps_{act}$).

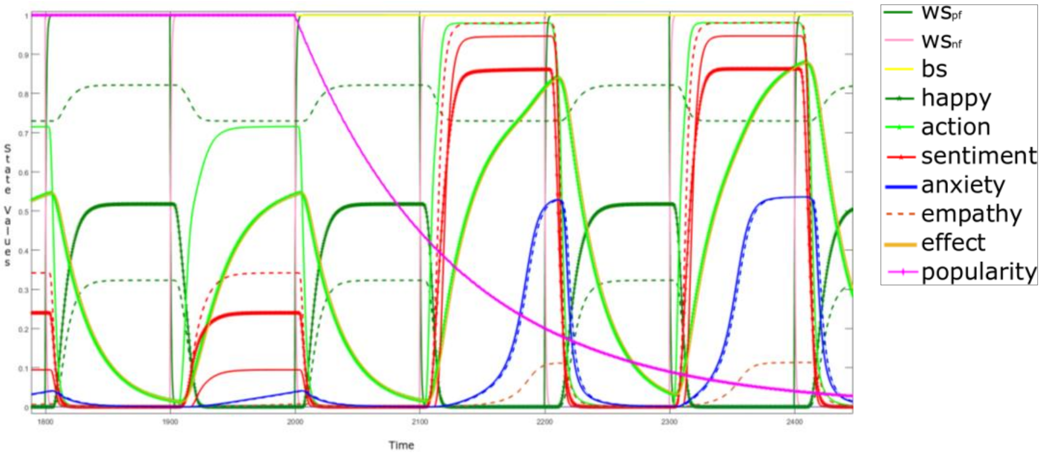

Figure. 7. Simulation of alternative episodes of ws_{nf} = 1 or ws_{pf} = 1.with popularity loss.

4.4. Exhibition of learning experience in the model

In this section, we discuss the influence of hebbian learning on the Levels II and III. Previously, we saw the complex learning behavior over time (in episodes). For example, in the second episode of positive feedback (t = 200 to 300), the reward-related states (striatum, fs_{reward}, fs_{love}, insula) are elevated more than the first episode (t = 0 to 100) in Figure 5. Similar behavior is observed when negative feedback is received. Here, we can observe the underlying behavior of hebbian learning (Figure 8) at other levels: Level II for plasticity (**W**-states) and Level III for metaplasticity (**M** and **H**). For example, consider $\mathbf{W}_{eval-,psa}$ (blue), the initial value of the state is 0.2. During each negative episode the value is increased, so during t = 300 to 400 the value is increased almost from 0.5 to 0.76. Similarly, $\mathbf{W}_{psa,srs_{eff}}$ is raised compared to the previous episode showing the learning behavior (Sun et al., 2016). However, it can also be observed that due to metaplasticity, the state $\mathbf{W}_{fs_{sent},psa}$ (colored background) was not much raised between two episodes due to **M** and **H** states (dotted) (Sun et al., 2016).

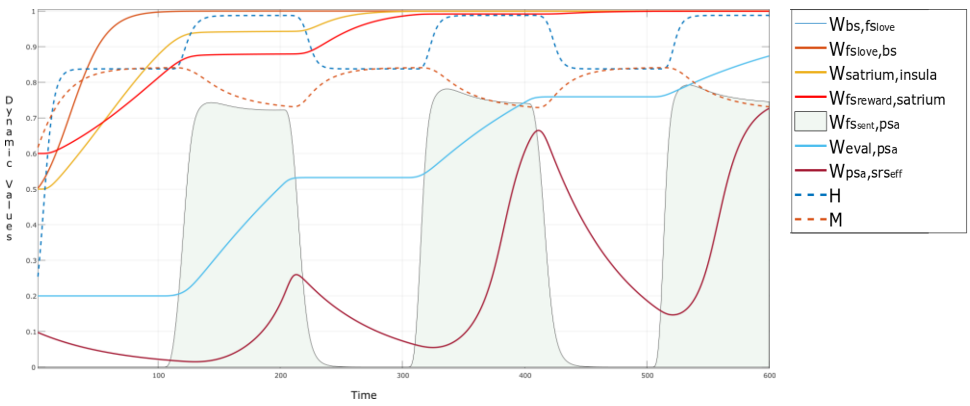

Figure. 8. Effects of plasticity (W states) and metaplasticity for $W_{fs_{sent},psa}$ (M and H)

Figure 9 reflects how popularity influence states at Level II and Level III. Here, we can see that the learning in **W**-states related to negative evaluation, action, and sentiments start to reduce after $t > 450$. This is an effect of popularity gain, also we see same behavior for the metaplasticity-related states **M** and **H**. This behavior would be vice versa when a person loses popularity.

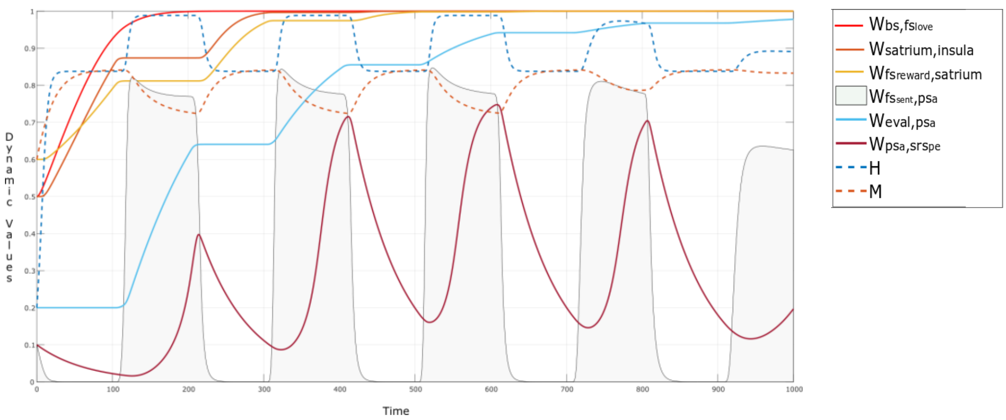

Figure. 9. Effects of plasticity (W states) and metaplasticity (M and H) under influence of popularity

5. Analysis of Simulation Experiments with Reference to Real-World Data

In this section, we analyze the behavior of our adaptive network model in relation to gathered empirical/real-world data. To accomplish this, we analysed thirty random public Instagram profiles, with presumably some extent of narcissistic traits, in line with literature such as (Chua and Chang 2016, Folley 2019, Page

2012). We compared the behaviors found there to our simulation experiments discussed in the previous section.

5.1. Materials and Methods

Social media like Twitter or Instagram offer an environment where people tend to share their information, emotions and opinions to get feedback from others. We chose Instagram because: i) its users have more tendency towards narcissism (Moon et al., 2016), and ii) different types of reactions can be observed in the form of conversations. These profiles were selected using the following criteria:

i) the participants had at least shared 60 posts and

ii) they tend to share their selfies.

To examine the behavior of the model in correlation with the Instagram data, we used the following hypotheses through few key performance indicators (KPIs) were obtained (see Table 3):

a) *Narcissism/Grandiose Exhibition*
   i. Narcissistic people tend to share their selfies more frequently.
   ii. On appreciation, they feel happy and proud but react negatively otherwise.
b) *Popularity*
   i. They gain popularity through particular behaviors, for example, self-presentation, or by using hashtags (Utz et al., 2012).
   ii. They have a high number of followers or friends (Utz et al., 2012)
   iii. More popularity can influence their behaviors:
      a) They engage more to seek admiration. (Paramboukis et al., 2016)
      b) their depression/anxiety is reduced (Nesi & Prinstein, 2015; Trent, 1957).

Table 3. KPIs to measures for popularity and narcissism along with their relevant literature

KPI	Explanation	Reference
Grandiose Exhibition:		
selfiepm/ otherpicspm	how many selfie/other pictures shared per month	"Categories emerged .. on Instagram. *Personal promotion, brand promotion, and sponsored promotion .. increase their popularity*… digital reputations" (Alshawaf & Wen, 2015)
postfreqpm	frequency of sharing posts per month	"narcissists have more Facebook friends and *tend to post more provocative material*" (Bernarte et al., 2015)
pconvsspm; nconvspm	how many positive and negative conversations per month	"The relation between narcissism and *disagreeableness increases* when self-esteem is taken into account" (Holtzman et al., 2010)

Popularity:		
followerspm	how many followers per month	"Instagram Leaders … have *more followers than they are following"* (Farwaha & Obhi, 2019; Utz et al., 2012)
likespm	how many likes per month	We chose *the number of "likes" as the index of popularity* of a post (Zhang et al., 2018)
htagspm	count the number of posts which had one or more hashtags (boolean)	"… use hashtags to make their *professional identity searchable* … promote their identity as affiliated.. wider professional field" (Farwaha & Obhi, 2019, p. 2012)

Figure 10 briefly describes the algorithm used to formulate the results for the addressed KPIs. First, we extracted basic data of a profile from Instagram (steps 1-4). Second, we extracted data for each post in relation to its duration (5-7). Later, for every month, we extracted the posting frequency, the average number of likes, the selfie count, the number of posts which used hash tags, and the positive and negative conversations (8-13).

Algorithm used to formulate the KPIs

Input: The name of the Instagram user

Output: KPIs values: followerspm; likespm; postfreqpm; selfiepm; otherpicspm ; hashtagspm; pconvsspm; nconvspm

```
1   insta = instantiate instaloader
2   login(insta,USER,PASSWORD)
3   profile = getprofileofuser (insta,user)
4   followerspm = extractfollowers (profile)
5   since = date(dd,mm,yyyy)
6   until = date(dd,mm,yyyy)
7   posts = get_sorted_posts_within_duration (profile,since, until)
8   for each month:
9       postfreqpm = countpostspm(posts)
10      likespm = averagenoof_likes_pm(posts)
11      selfiepm = find_selfies_pm(posts)
        otherpicspm = find_nonselfies_pm(posts)
12      hashtagspm = getpostswithhashtagspm(posts)
13   nconvspm = extract_negative_conversations(posts)
```

Figure. 10. Algorithm showing steps to extract data for KPIs

For selfie recognition, we used the KNN classifier with face encodings (Adam, 2016) with the minimum threshold of 0.4. Moreover, for sentiment analysis, we used the combination of two classifiers: the IBM Watson tone analyzer and the Vader Sentiment Analyzer. The Watson tone analyzer was able to identify three types of sentiments: Cheerful, Negative, and Strong Negative. ***Cheerful emotions*** were related to happy/neutral reactions: joy, positive analytical. By positive analytical, we mean a neutral/positive discussion with an audience (maybe by telling a product name). This was computed by looking into the sentiment of the previous comment, and based upon its score, it was considered as a non-negative reply (as telling about herself and her products will make her feel happy about herself). The ***negative emotions*** were related to sadness or fear, while ***extreme negative*** meant anger, which is a negative feeling with strong intensity (Ntshangase, 2018). It can be an outcome of humiliation, annoyance or hostility. If the IBM Tone Analyzer does not detect any tone (for example, “Nice” without “.”), theVader sentiment analyzer was used. It can detect three type of sentiments: positive, negative, and neutral (Hutto & Gilbert, 2014), which were also used in our prior work (Jabeen et al., 2019). Table 4 shows some example conversations in terms of feedback ‘F’ and reply ‘R’, as analyzed by the Watson tone analyzer and the Vader sentiment analyzer.

Table 4. Conversation examples with sentiments

Type	Feedback/Reply	Sentiment
F	It looks hella face tuned	Neutral
R	you look hella negative	Negative
F	Well I think you look gorge! So happy for your family during this time	Joy
R	thank you!	Joy
F	You need to blend you highlight a bit more	Neutral
R	No I want to blind you so you piss off my page	Anger

5.2. Results and Discussion

In this section, we will discuss our results from relevant to deviant cases in relation to the simulation experiments presented in Section 4. Each section will discuss the KPIs of popularity with reference narcissism (Table 3), i.e.: a) number of followers per month, b) the average number of likes obtained per month, and c) hashtag usage. The obtained results for all 30 considered profiles can be found in Appendix B.

5.2.1. Followers

Different studies indicate a ‘followers to following ratio’ (ff) and the number of followers (f) as a measure of popularity of a profile (Farwaha & Obhi, 2019; Garcia et al., 2017). In our analysis, we used the number of followers to study behaviors in relation with popularity and narcissism. Therefore, we distributed the 30 extracted profiles in three groups with respect to the number of followers (Figure 11). The first group consists of 5 of the 30 profiles (more than 50K), the second group had 9 profiles (between 10K – 50K), and our third group has 16 profiles (less than 10K).

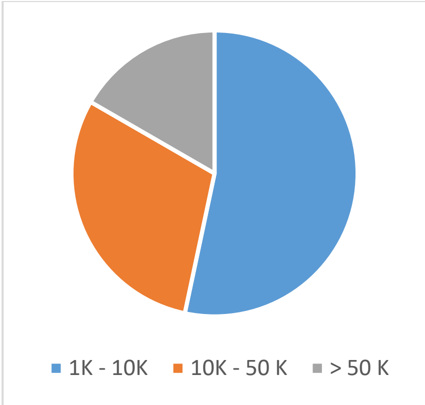

Figure. 11. Distribution of the participants of our study with respect to the number of followers

The collected data was analyzed using a measurement of time in months. It was observed that all users tend to post on a regular basis. As every profile tends to share different numbers of posts per month, we took the average of data per month, like posts/selfies per month by a user. It was observed that most participants tend to share more posts with selfies each month over a period of time (See Appendix B for the selfies ratio of each user). This can be an indication of self-love. For example: in Figure 12, P3:CB has a high ratio of followers to following (followers :262000, following: 609), indicating this person is popular. Figure 12-a shows a normalized distribution of the number of posts, average likes, hashtags, and followers per month. We can see an increase in posting frequency along with the average number of likes and number of followers. We can also see the trendlines indicating a linear increase in the average numbers of likes and the number of followers. This is also addressed by a user like:

“I don't think that looks nice but the media say it was pretty, so people started following that and they got a lot of likes for it…” (Chua & Chang, 2016)

In Figure 12-b, we can see some correlation between sharing selfies and average likes and thus the number of followers in a month. High variations were also observed between the average number of selfies and the number of followers (see Appendix B). Therefore in section 5.2.2 we will discuss our analysis with respect to the average likes as well.

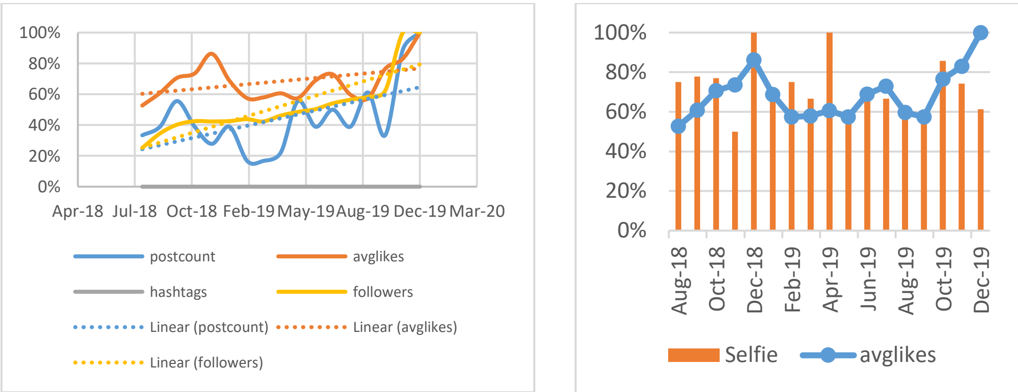

Figure. 12. a) Posting frequency in relation with the popularity related KPIs. b) Selfie sharing with average number of likes over time

During the conversation analysis, it was observed that 11 out of the 30 profiles actively responded to their followers. Figure 13 shows the distribution of participants with respect to their total response rate (= $\frac{\sum conv}{total\ posts}$), with values like:

$$Response\ rate\ (p) = \begin{cases} high; & value \geq 0.75, \\ medium; & value > 0.5\ and < 0.75 \\ low & \end{cases}$$

On the one hand, it was observed that 5:14 users in the category of <10K followers, and 3:9 users in 10K-50K actively responded to their followers. While on the other hand in the more than 50K category, all users (5:5) actively participated in conversations. In other words, 13 participants participated into the conversations more proactively (Bernarte et al., 2015) .

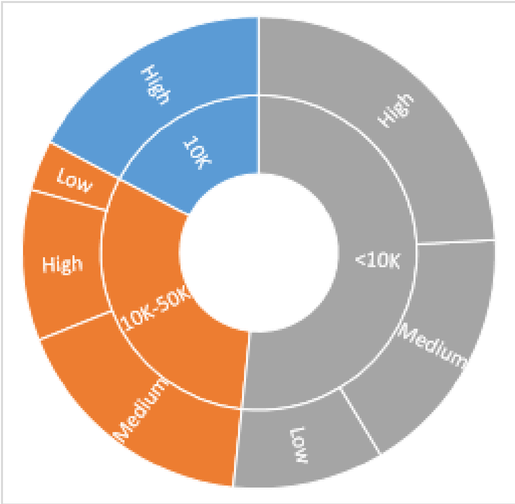

Figure. 13. Average responses per post with respect to the followers' distribution

An overall observation of conversations and sentiment analysis, people tend to respond more in a positive or neutral manner (Joy, positive analytical and Positive) than a negative manner (Anger, Fear, Sadness, Negative). Another interesting pattern was that most users with a low number of followers had more cheerful comments than negative ones. This truly doesn't relate to our simulations (i.e., negative behaviors have higher intensity with low/less popularity). However, we can assume that they didn't get critics most of the time, another possible reason can be to attract more followers or friends, or they were naïve on Instagram. With reference of the number of followers, there was no significant variation observed for negative or positive conversations (See Appendix B).

5.2.2. The Average number of Likes

In this section, we analyze the behavior of Instagram users with respect to an increase/decrease in the average number of likes. As per hypothesis, a user seeks the opportunity of self-promotion to get compliments or likes (Holtzman et al., 2010; Paramboukis et al., 2016; Zhang et al., 2018). As addressed by an Instagram user:

> "It makes me happy, ... I think, to me is you are cool, you're pretty, so you get a lot of likes." (Chua & Chang, 2016)

In relation to grandiose self-exhibition, we looked into the selfie ratio, mostly it was observed, that participants have a higher tendency of getting likes if they share selfies (Figure 12-b; Appendix B). To investigate it further, we took each profile and computed the pearson correlation coefficient between the number of selfies and the average number of likes shared per month by:

$$corr_p = \frac{\sum(selfie - \overline{selfie})(likes - \overline{likes})}{\sqrt{\sum(selfie - \overline{selfie})^2 \sum(likes - \overline{likes})^2}}$$

where,

$corr_p$ = correlation value of a profile

$\overline{selfie}$ and $\overline{likes}$ are the sample means of selfies and average number of likes in the duration of data collected.

It was observed that most of the profiles had a positive correlation between the two variables, however there were 6 out of 30 profiles, for which this correlation was low (>-0.1). Figure 14 shows the distribution of users with respect to their relation/correlation values where:

$$relation_{(selfie,likes)} = \begin{cases} high; & corr_p > 0.5, \\ medium; & corr_p > 0.3 \; and < 0.5 \\ low; & corr_p < 0.29 \end{cases}$$

Here, 12 users (40%) showed a weak linear relationship, while 18 people showed moderate to strong positive relationships (moderate: 7; high: 11). This explains the behavior that people tend to share their selfies more often as they may find this as an opportunity for approval and likability from their followers (Chua & Chang, 2016).

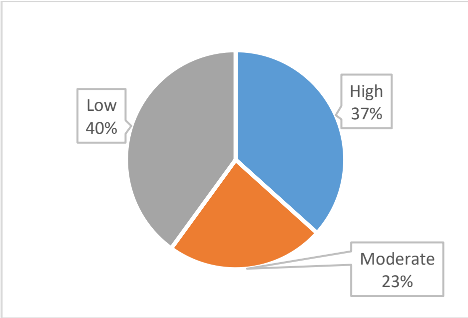

Figure. 14. Distribution of participants with respect to correlation values between selfies and average likes

While looking into the reactions of the users, we studied the extracted sentiments in the context of the average number of likes. Mostly, it was observed that in all profiles the users were mostly happy when they received more likes than otherwise. To make an explicit conclusion, we normalized each sentiment also in conversations. Therefore, a sentiment score per month was assigned through:

$$sent(t) = \frac{sent\_score(t)}{\sum sentiments(t)}$$

where

sent_score(t) = the individual score of a sentiment in a month *t* and,

$\sum sentiments(t)$ = total sentiments found within a month *t*.

sent(t) = a value of a sentiment in range of [0,1].

Here, it is to be noted that possible sentiments are the ***cheerful*** (Joy/Positive, Positive Analytical, Neutral), the ***negative*** (Fear, Sadness, Negative) and the ***extreme negative*** (Anger) sentiments. For example, if in a month *t*, the sentiments of a user are: Joy = 2, Sadness = 1, and Negative = 1, then *sent_score* for each in the month *t* are: Joy = 0.5, Sadness = 0.25 and Negative = 0.25. This implies that during conversations in month *t*, the user was 50% filled with ‘Joy’ and 25% for the rest of two. Similarly, we normalized the average number of likes for each month by dividing average likes obtained in a month by maximum likes received by a user in the duration of extracted data, resulting in a value between [0,1].

We manually analyzed all profiles for the similarities and differences, mostly positive conversations were observed showing personal satisfaction (Nesi & Prinstein, 2015). However, in negative responses/reactions few interesting patterns were observed. For example in Figure 15 when average number of likes of P2:LV are decreased (June 18, December 18, February 19 and so on) we can observe negative conversations (sadness: green, negative = maroon or anger: silver). Also, positive conversations can be seen when (s)he gets more likes. A similar pattern can be observed for P24:LJ, P30: AB and so on (Appendix B).

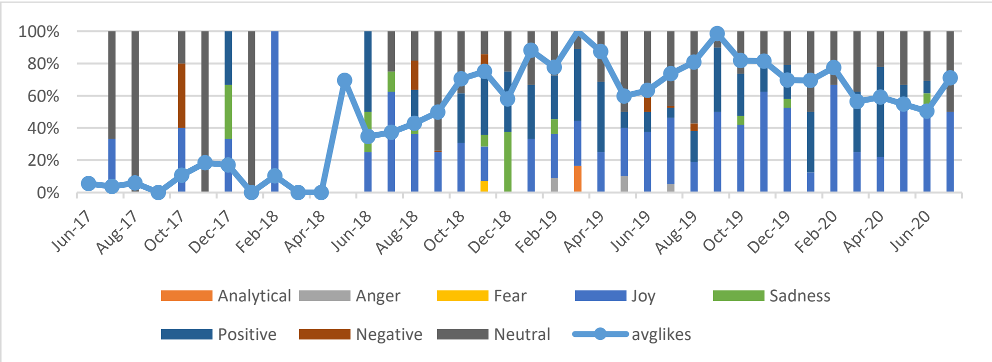

Figure. 15. Relation between the sentiments and the average number of likes (normalized) over time

This can be considered as the behavior of a person being similar to the behavior we modeled in Section 3, shown in Figure 1, (which models the reactions over a feedback as a cheerful response or a negative reply). Also, when a person gets popular (more average likes), then negative expressions are reduced. Here, it is to be noted that in February 18, there are few sudden drops in the average number of likes and conversations. This is possible, because this user did not share any post in this duration (Figure 16).

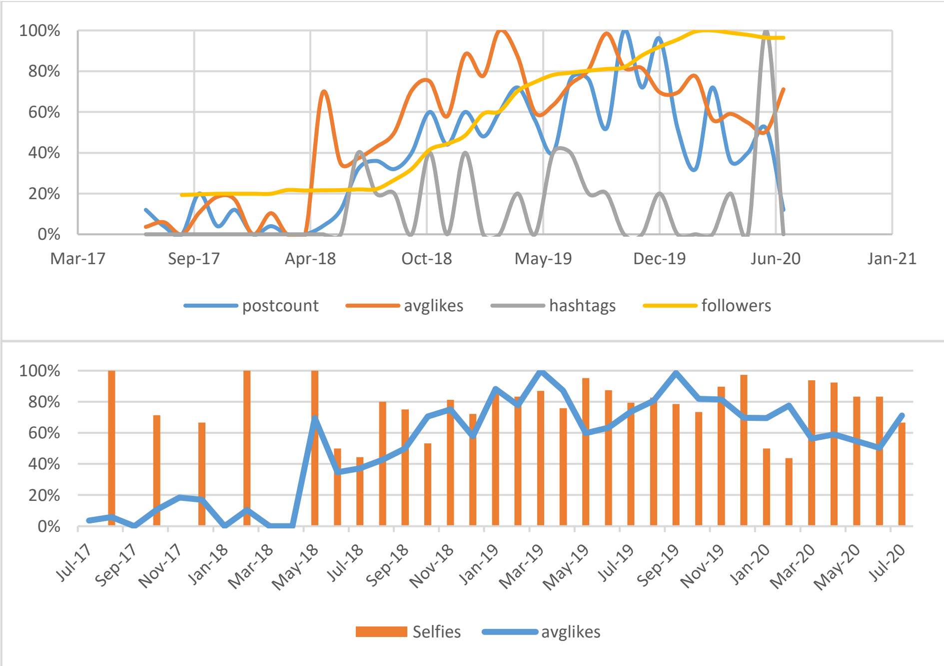

Figure. 16. Sharing behaviors of P2 with average number of likes over time

For other profiles, we observed further variations in the behaviors in comparison to the designed model. However, we can use a notion of 'most of the times' to generalize their behaviors. What we mean to say here is that although in August 18 P2:LV received more likes, we can still see some negative sentiments, but most of the time the person showed behavior similar to our model.

Table 5. Results showing which profiles are mostly aligned with the simulation results.

Aligned profiles			Only positive profiles			Non-aligned profiles			Total
P2	P3	P4	P8	P17	P18	P1	P6	P7	
P5	P9	P12	P25	P28		P10	P11	P13	
P15	P16	P24				P14	P19	P20	
P27	P29	P30				P21	P22	P23	
						P26			
12 = 40%			5 = 16.66%			13 = 43.33%			30 = 100%

Table 5 enlists the profiles which reflected the indicated behavior most of the time, as well as the profiles which responded positively, and the rest which act more like outliers and show more variations from our simulation experiments. These fluctuating behaviors can be due to multiple reasons like: difference in personalities, their current popularity and time. For example, P10 or P20 seems to be less popular (less number of likes), during the whole time for which data was collected, resulting in fluctuating behavior.

We also tried to look through the patterns of hashtags, however, we were unable to see any patterns in relation to the behaviors, except most of the profiles used hashtags to gain visibility. In conclusion from Table 5, we saw that almost 60% of the profiles showed behaviors similar to our model, i.e. a narcissist is overwhelmed with joy when they get positive feedback and otherwise. Also, increase in popularity lead to happy reactions with a decrease in negative conversations. In Section 6, limitations and future work of the study are discussed.

6. Limitations and Future work

The Watson analyzer is pretty accurate, also the Vader sentiment analysis gives a high accuracy in sentiment detection and classification (Hutto & Gilbert, 2014). However, during the conduction of the study, it was observed that classifiers identified a few responses as negative, although they were positive (*'fierce as fuck 🔥'*) or (*'fuck!! love you'*). Although we adapted sentiment analysis as per needs of Instagram contents, though, it still can be validated further. Moreover, during selfie detection and analysis, many pictures that were taken from the back or were incomplete (without face), were categorized as others. Improvements in the two can help to improve the results and study further. We haven't used textual analysis approaches to study narcissism in the text, as they require natural language processing with longer texts, whereas in Instagram bibliography is the known as most long text, but it is not intended for this type of analysis. Also, we encountered messages which didn't have any text but just emojis like '♥♥' or '💋💋'.

Furthermore, in this study, almost all of the profiles in the dataset were presumed as narcissists. However, the authors didn't have their NPI scores or knew them personally. To make our work more concrete, it would be nice to investigate it more, for example, why do they have fluctuating behaviors and their relationship to the personality traits of a narcissist. So, as future work, we aim to set an experiment, which involves studying a person in relevance to his/her NPI score, sensitivity, and overall mood of a person to see this in relation to narcissism. This will help us to study behaviors with the understanding of narcissism in relation to personality traits in more detail. We also aim to study surrounding people like friends and family, who interact to a person with such behaviors.

7. Conclusion

In this paper, we presented a complex adaptive mental network model, which addresses the adaptive cognitive processes of a narcissist. Moreover, it explains his or her behavior and reactions, when (s)he receives positive or negative feedback. As his/her personality is vulnerable, to an ego-threatening message it is responded in a negative way, especially when popularity is low. In addition to our prior work, we saw how popularity can influence such a person's behavior. It was studied in how far when reward-seeking behavior blends with an increase in popularity, the negative reactions are reduced. In order to compare our adaptive network model with empirical data, we extracted and analyzed data from 30 public profiles. Both from our simulation experiments and from the empirical analysis we observed that popularity acts as a moderator for a person with narcissistic traits. Thus our model indeed displays the real-world behavior of a narcissist, concerning the expression of emotion under the influence of increase/decrease in popularity.

In future work, we aim to incorporate different psychological measures like NPI score, sensitivity, or mood, to monitor narcissists. Moreover, we aim to design an automated system that can support a narcissist by counseling if he is highly vulnerable.

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Appendix

A. Numerical relevance of the model

The mathematical representation of a reified network architecture in terms of its network characteristics can be explained as follows (Treur, 2020):

1. At every time point t, the activation level of state Y at time t is represented by $Y(t)$, with the values between [0,1].
2. The single impact of state X on state Y at time t is represented by $\mathbf{impact}_{X,Y}(t) = \omega_{X,Y}\, X(t)$; where $\omega_{X,Y}$ is the weight of connection $X \rightarrow Y$. All single impacts for a given state Y are aggregated by a combination function $\mathbf{c}_Y(..)$; see below.
3. Specific states are used to model specific types of network adaptation, where network characteristics such as connection weights and combination functions are dynamic. For example, $\mathbf{W}_{X,Y}$ represents an adaptive connection weight $\boldsymbol{\omega}_{X,Y}(t)$ for the connection $X \rightarrow Y$, while $\mathbf{H}_Y$ represents an adaptive speed factor $\boldsymbol{\eta}_Y(t)$ of state Y. Similarly, $\mathbf{C}_{i,Y}$ and $\mathbf{P}_{i,j,Y}$ represent adaptive combination functions $\mathbf{c}_Y(.., t)$ over time and their parameters, respectively. Combination functions are built as a weighted average from a number of basic combination functions $\mathrm{bcf}_i(..)$ from a library, which take parameters $P_{i,j,Y}$ and values V_i as arguments. For adaptive network models in which network characteristics are dynamic as well, the universal combination function $\mathbf{c^*}_Y(..)$ used for any state Y is defined as:

$$\mathbf{c^*}_Y(S,C_1,\ldots,C_m,P_{1,1},P_{2,1},\ldots,P_{1,m},P_{2,m},V_1,\ldots,V_k,W_1,\ldots,W_k,W)=W+S[C_1\mathrm{bcf}_1(P_{1,1},P_{2,1},W_1V_1,\ldots,W_kV_k) + \ldots +C_m\mathrm{bcf}_m(P_{1,m},P_{2,m},W_1V_1,\ldots,W_kV_k)] \,/\, (C_1+\ldots+C_m) - W]$$

where at time t:

- variable S is used for the speed factor reification $\mathbf{H}_Y(t)$
- variable C_i for the combination function weight reification $\mathbf{C}_{i,Y}(t)$
- variable $P_{i,j}$ for the combination function parameter reification $\mathbf{P}_{i,j,Y}(t)$
- variable V_i for the state value $X_i(t)$ of base state X_i
- variable W_i for the connection weight reification $\mathbf{W}_{Xi,Y}(t)$
- variable W for the state value $Y(t)$ of base state Y.

4. Based on the above universal combination function, the effect on any state Y after time Δt is computed by the following *universal difference equation* as:

$$Y(t+\Delta t) = Y(t) + [\mathbf{c}^*_Y(\mathbf{H}_Y(t), \mathbf{C}_{1,Y}(t), \ldots, \mathbf{C}_{m,Y}(t), \mathbf{P}_{1,1}(t), \mathbf{P}_{2,1}(t), \ldots., \mathbf{P}_{1,m}(t), \mathbf{P}_{2,m}(t), X_1(t), \ldots, X_k(t), \mathbf{W}_{X_1,Y}(t), \ldots, \mathbf{W}_{X_k,Y}(t), Y(t)) - Y(t)]\, \Delta t$$

which also can be written as a *universal differential equation*:

$$\mathbf{d}Y(t)/\mathbf{d}t = \mathbf{c}^*_Y(\mathbf{H}_Y(t), \mathbf{C}_{1,Y}(t), \ldots, \mathbf{C}_{m,Y}(t), \mathbf{P}_{1,1}(t), \mathbf{P}_{2,1}(t), \ldots., \mathbf{P}_{1,m}(t), \mathbf{P}_{2,m}(t), X_1(t), \ldots, X_k(t), \mathbf{W}_{X_1,Y}(t), \ldots, \mathbf{W}_{X_k,Y}(t), Y(t)) - Y(t)$$

B. Dataset

The large table below enlists the data collected from the 30 Instagram profiles. The first and the third column have the information like the profile ID, their name initials, their number of followers (f) and current followers to following ratio (f/f). Here it is to be noted that to keep the anonymity of results, each profile is assigned ID in a pattern like PXX. The second and fourth column consist of the increase/decrease in frequency

a. of posts, followers, average number of likes and hash tags
b. ratio between selfies and other pictures
c. sentiments related variations

These data were extracted and studied over a period of time for each profile s indicated. Note that this compares to simulation results for the model designed in Section 3 aiming at a single person and his/her related behavior.

<table>
<tr><th>Profile:
Initials
F
f/f</th><th>a. Popularity
b. Selfie Ratio
c. Percentage Reactions with respect to average number of Likes</th><th>Profile:
Initials
F
f/f</th><th>a. Popularity
b. Selfie Ratio
c. Percentage Reactions with respect to average number of Likes</th></tr>
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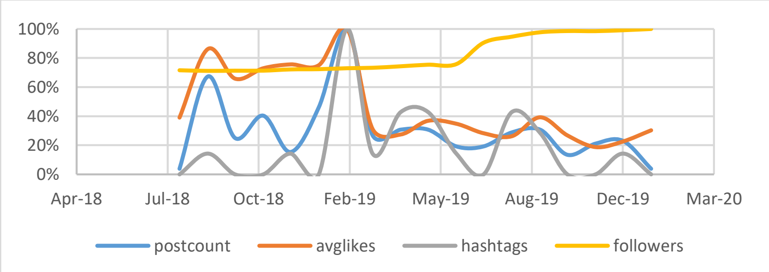
2547.4</td><td>

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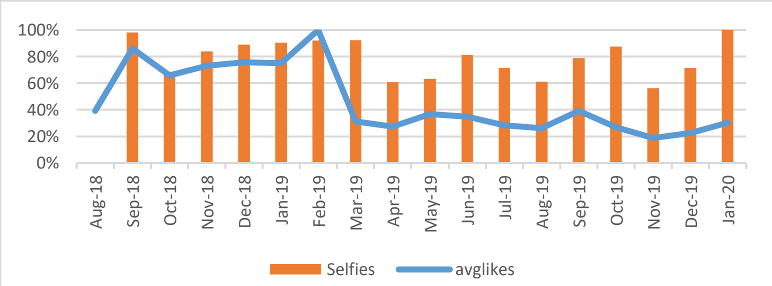

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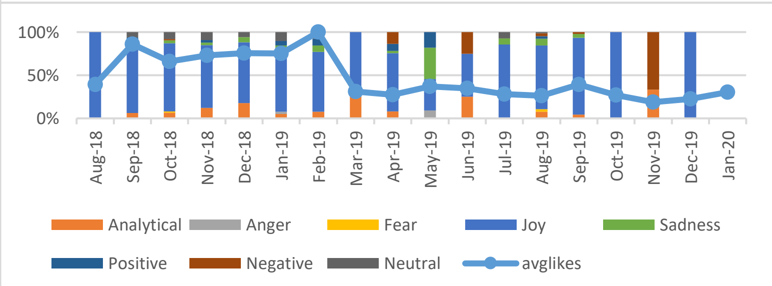

c.</td><td>P2:
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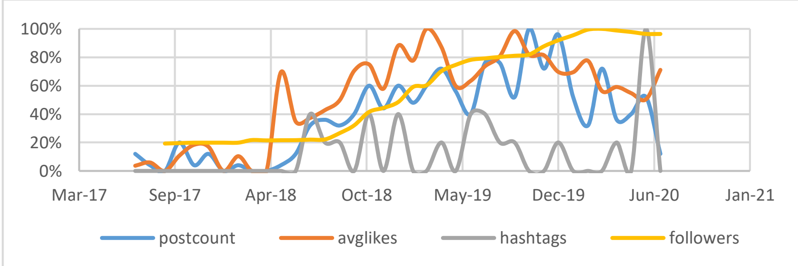
854.6</td><td>

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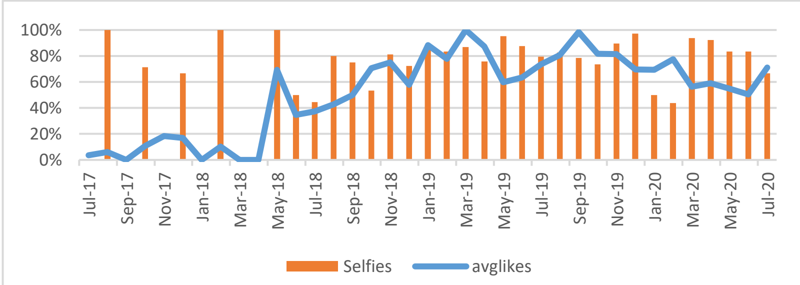

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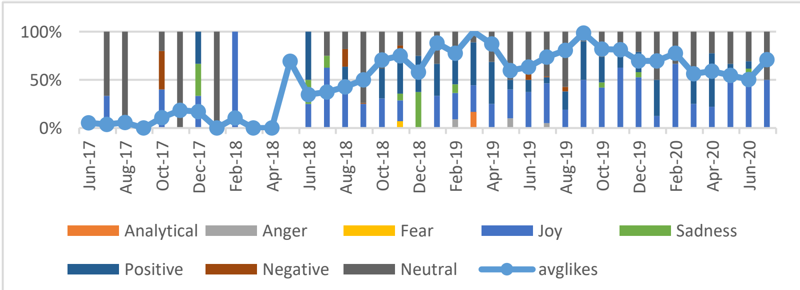

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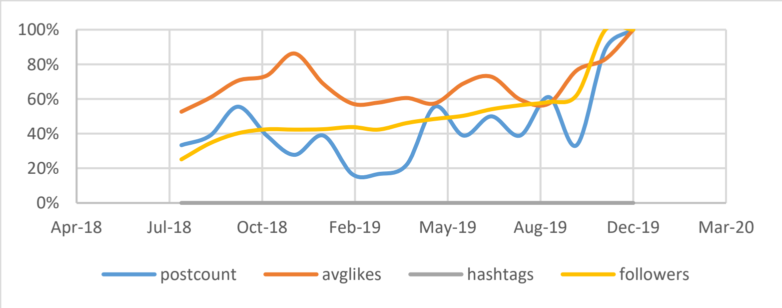

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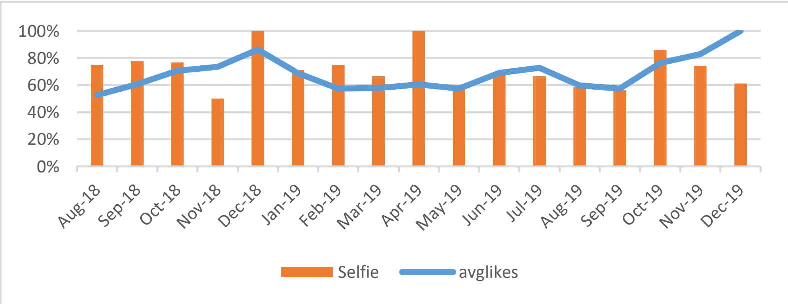

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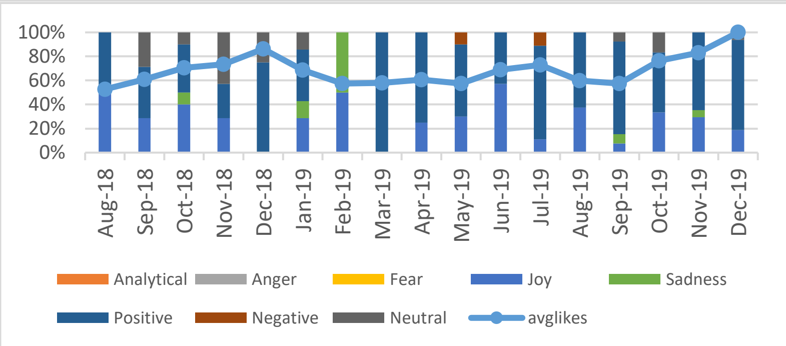

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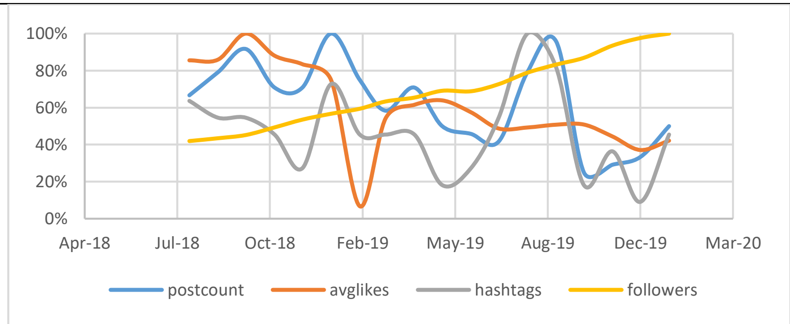

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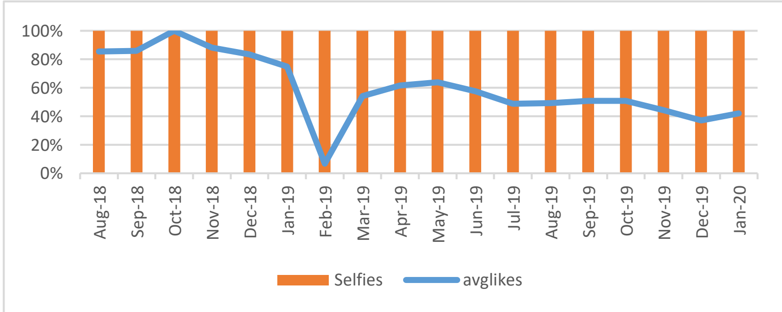

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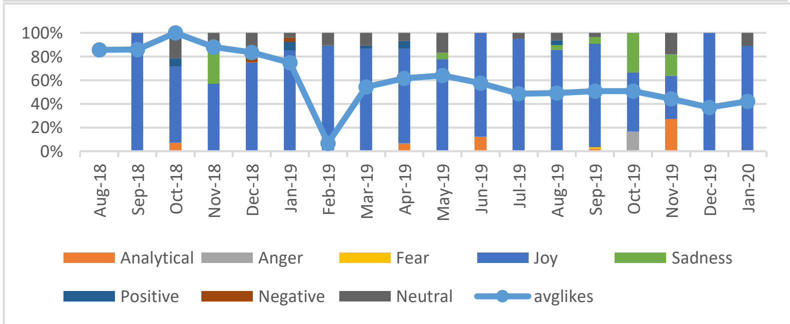

c.

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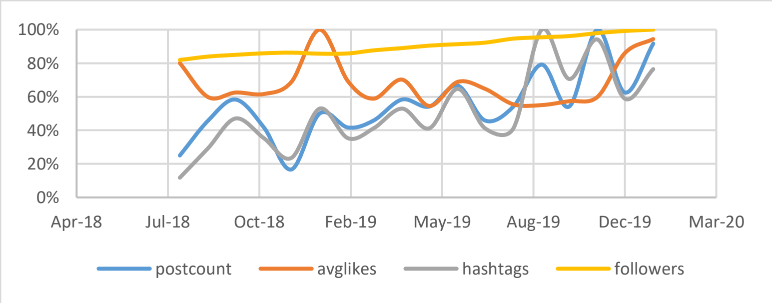

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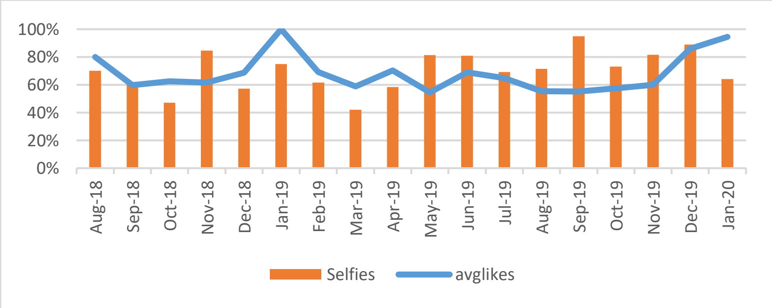

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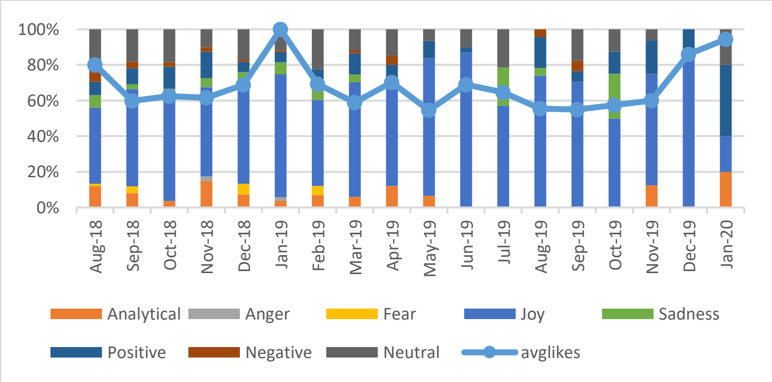

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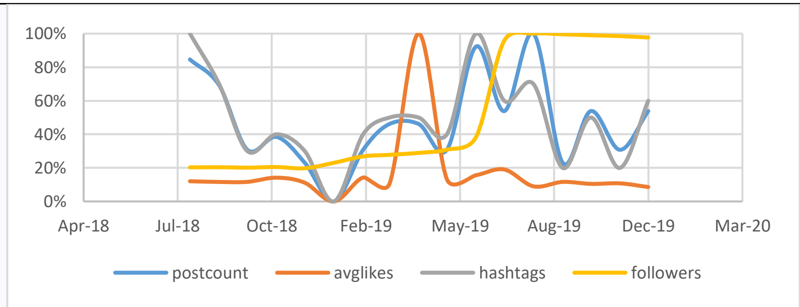

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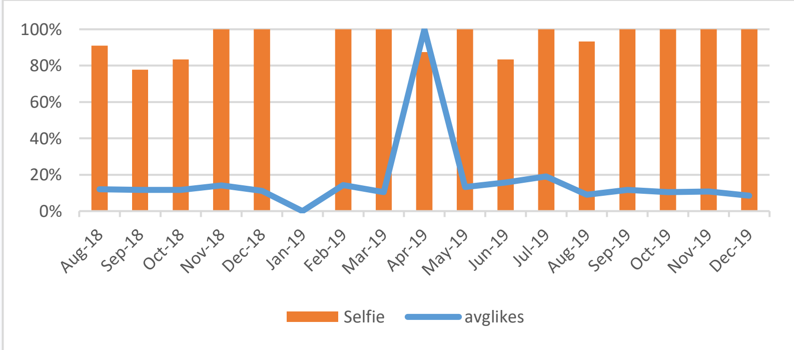

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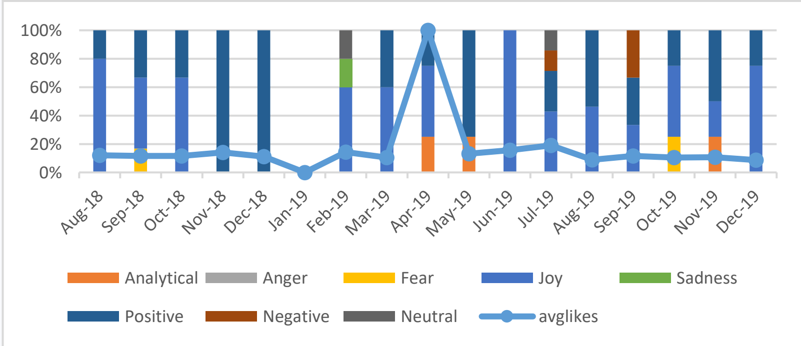

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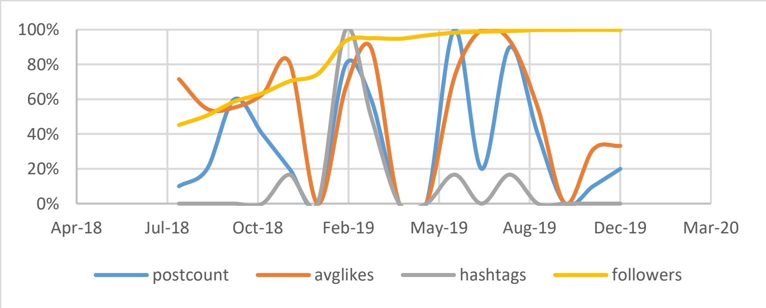

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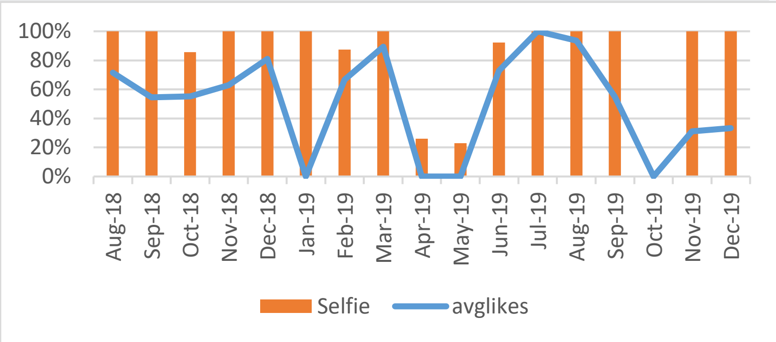

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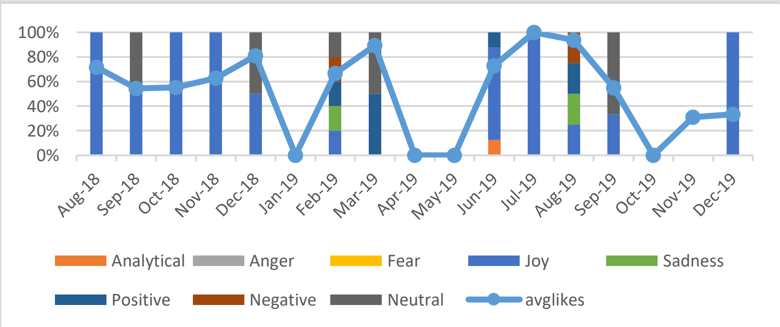

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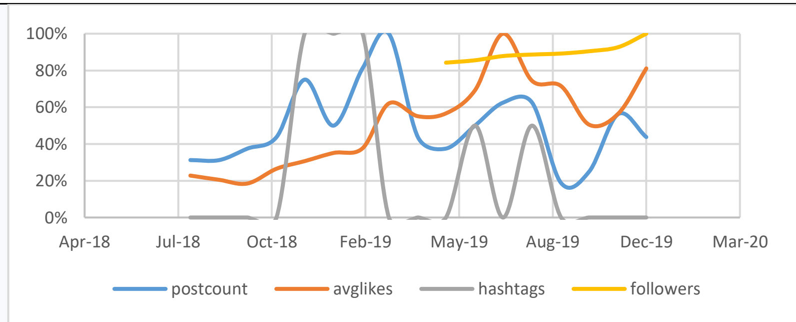

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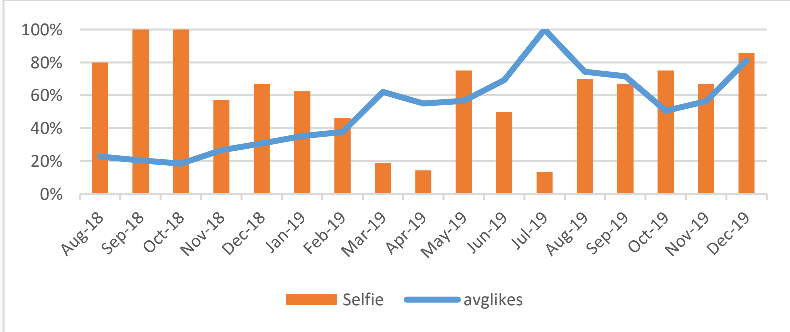

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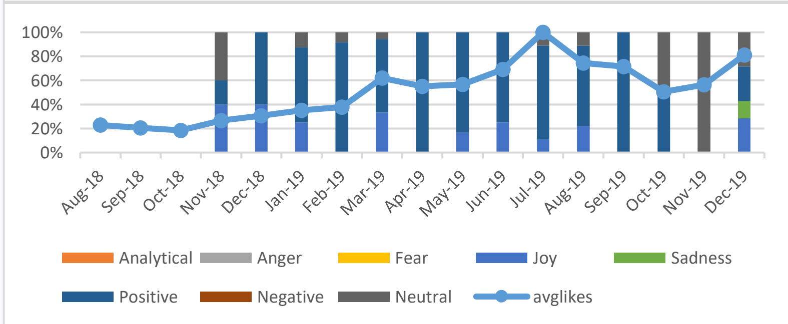

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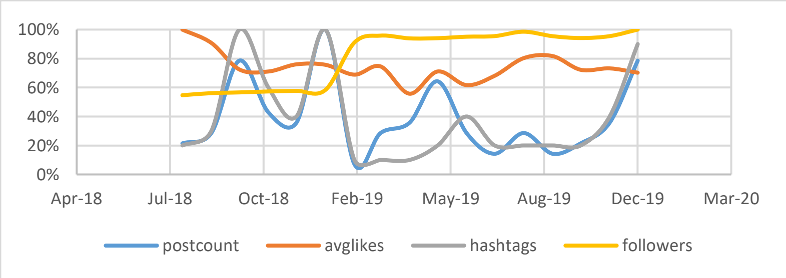

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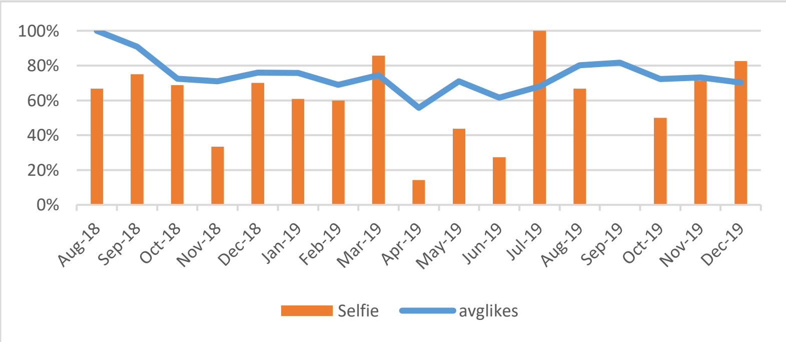

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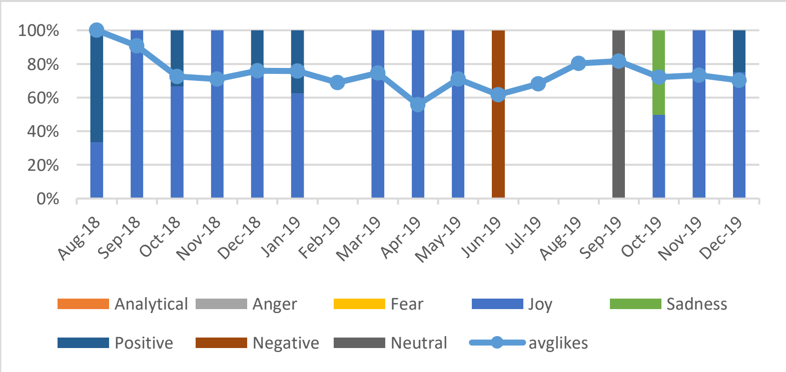

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P10:
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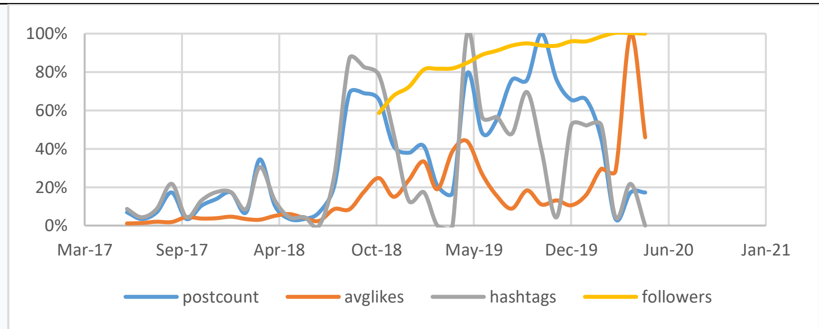
4.95



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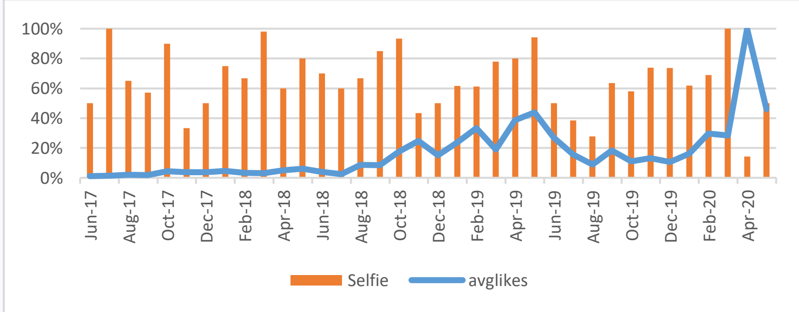

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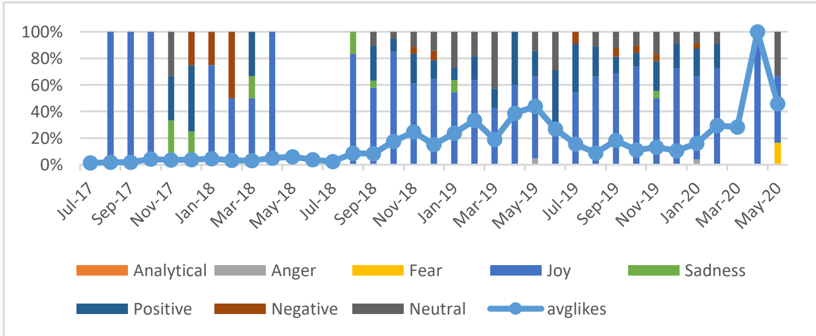

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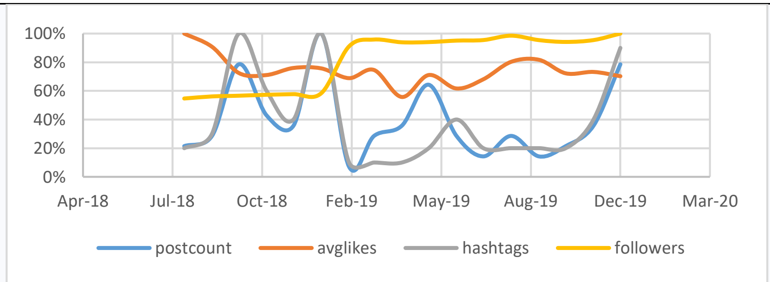

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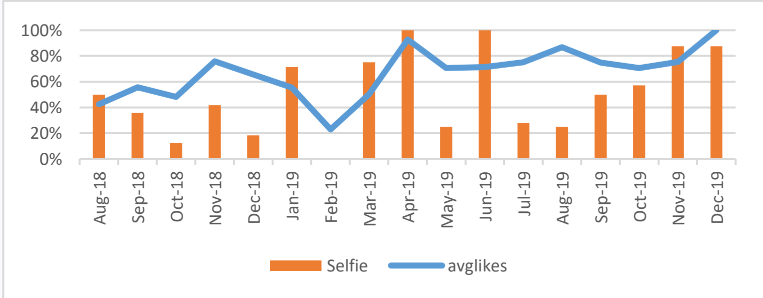

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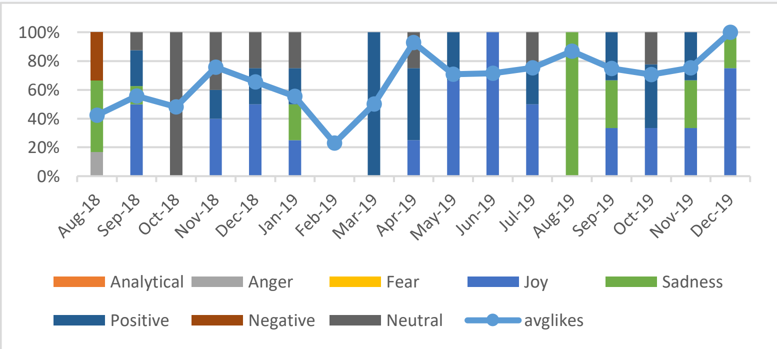

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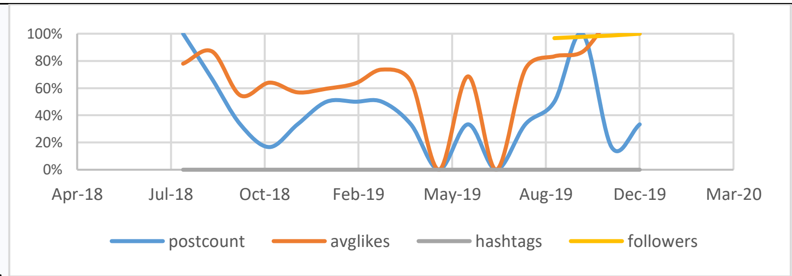

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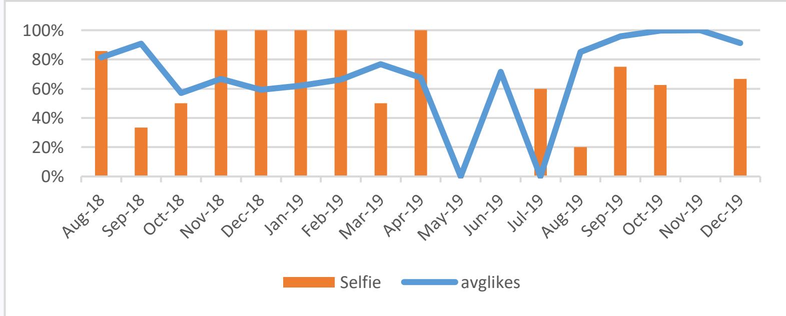

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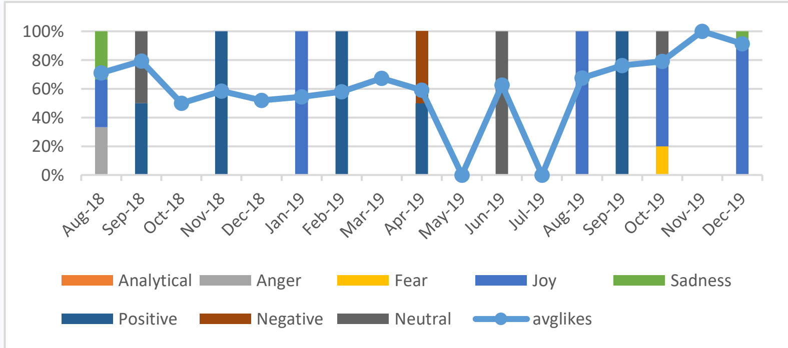

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SB
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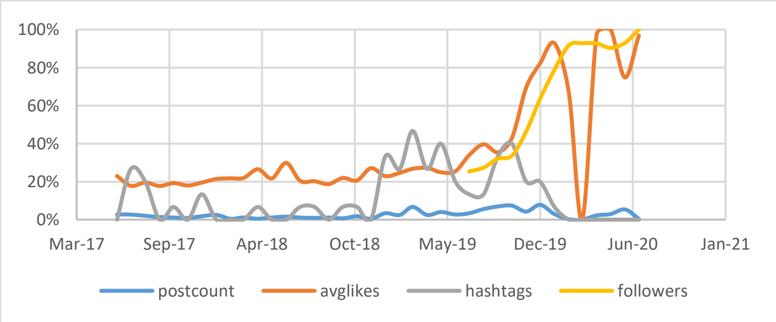

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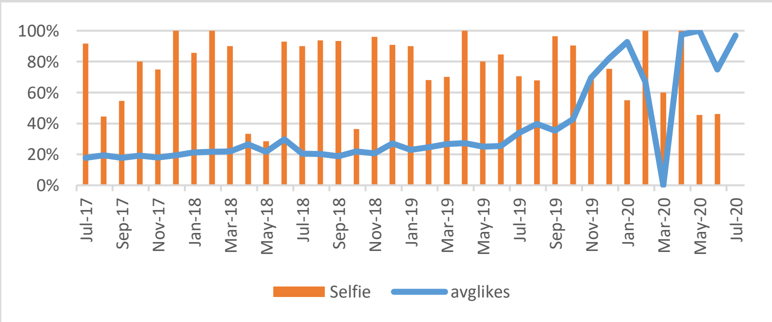

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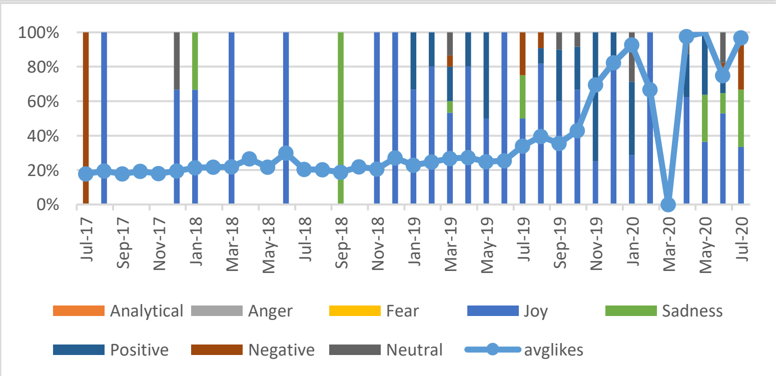

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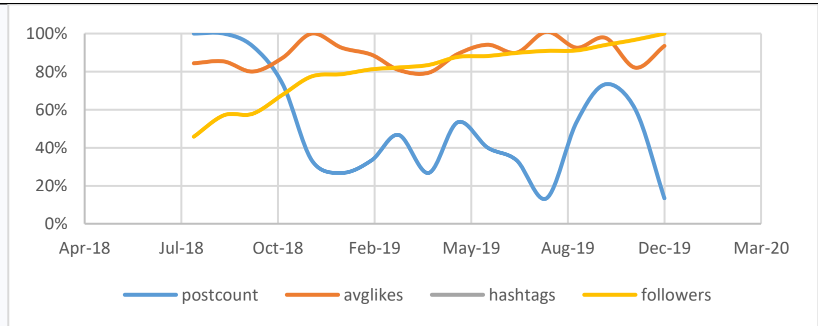
P14:
MB
10486
7.13



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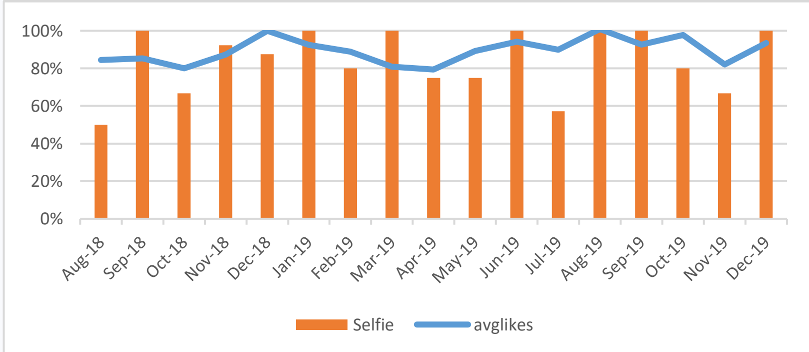

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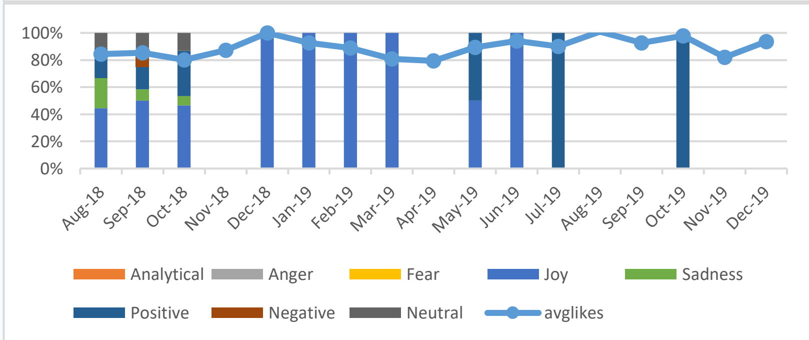

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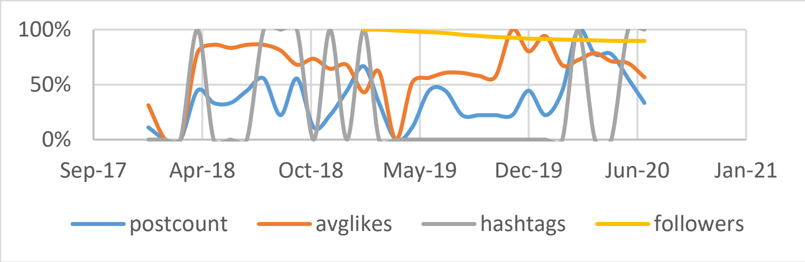
P15:
FC
9600
10.6



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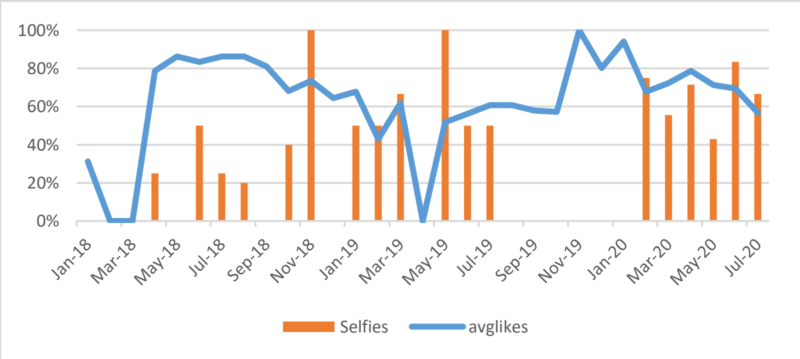

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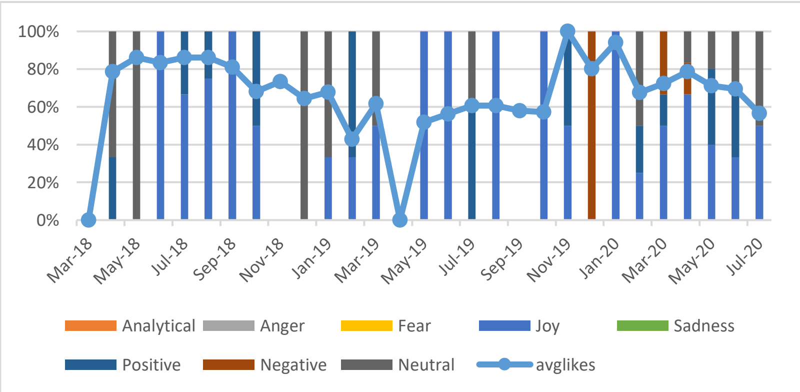

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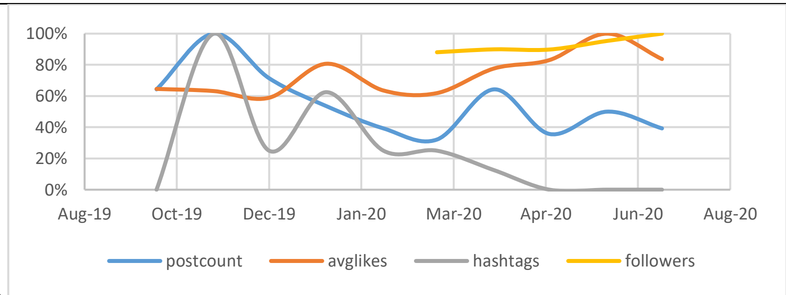
P16:
NL
8439
1.97



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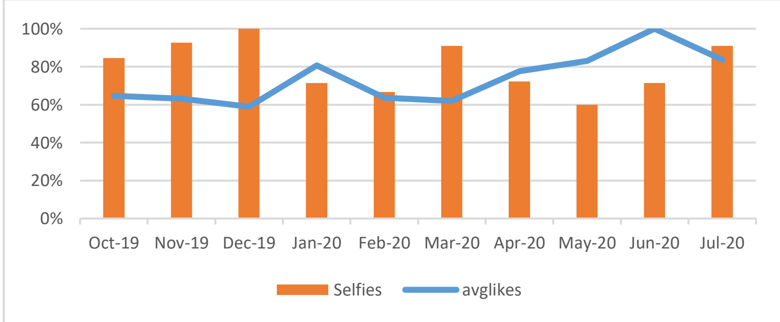

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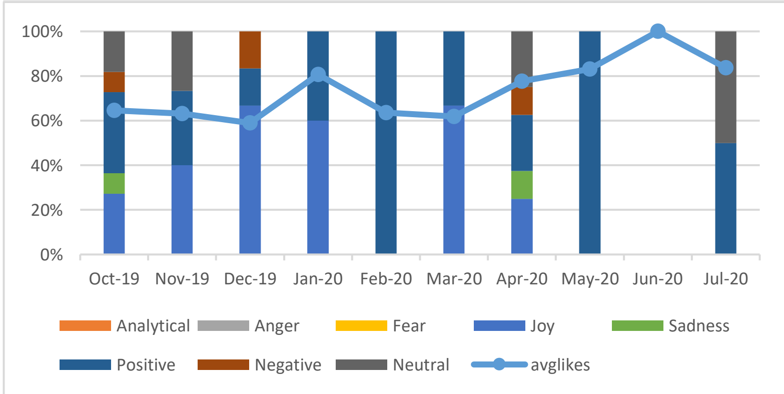
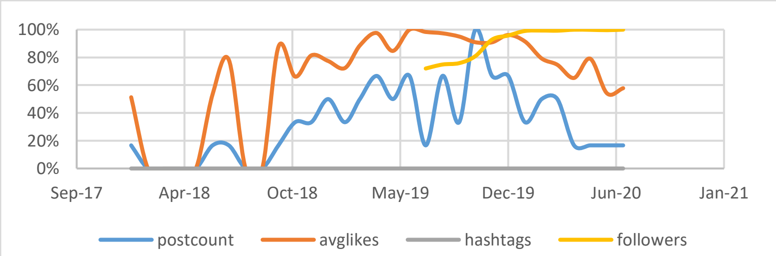
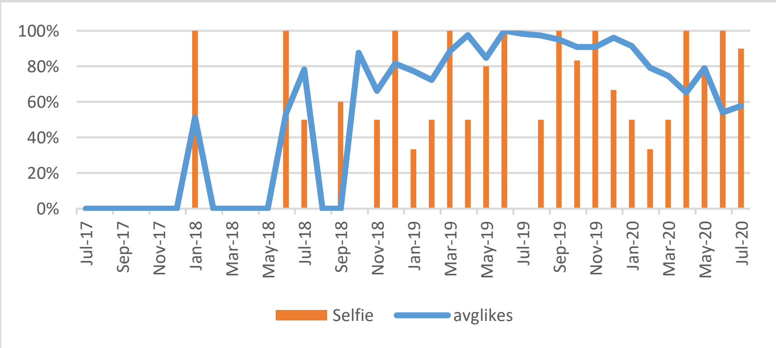
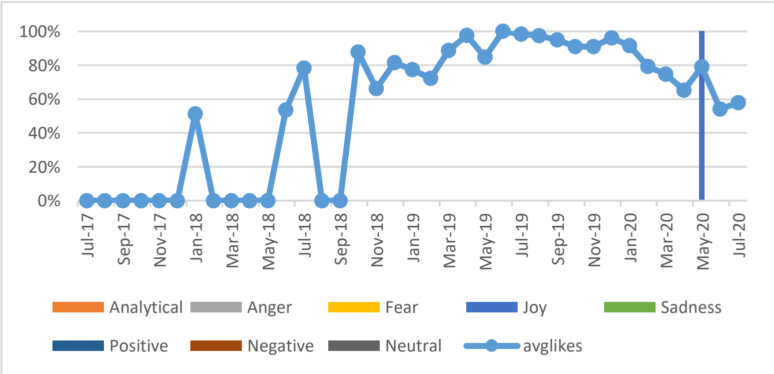
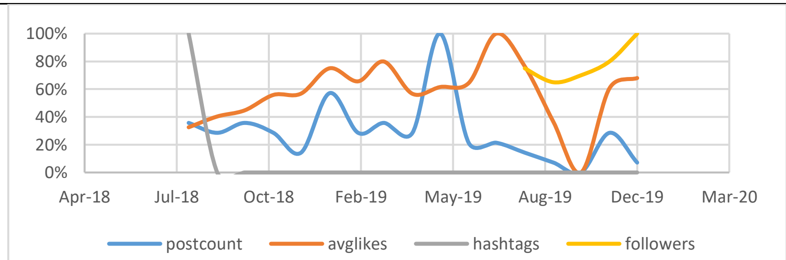
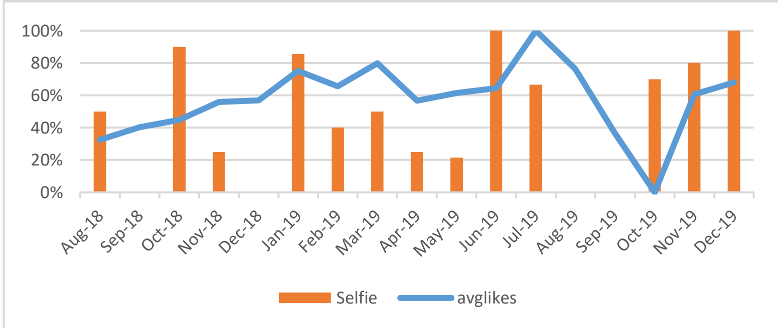
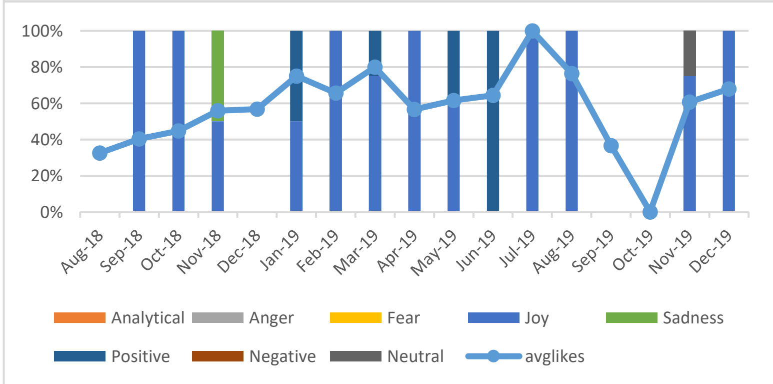
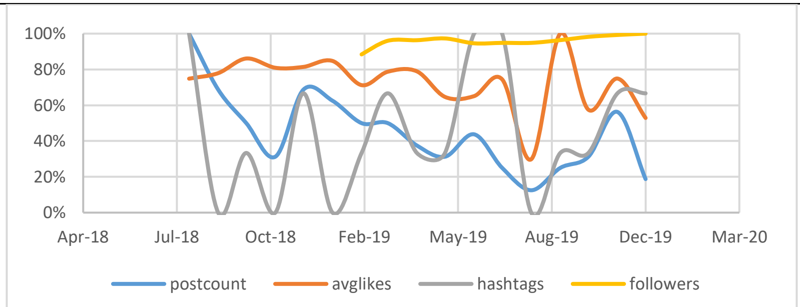


c.

P17: SM 8400 8.5	 a.  b.  c.	P18: TR 8079 16.16	 a.  b.  c.

P19:
EL
7748
3.97



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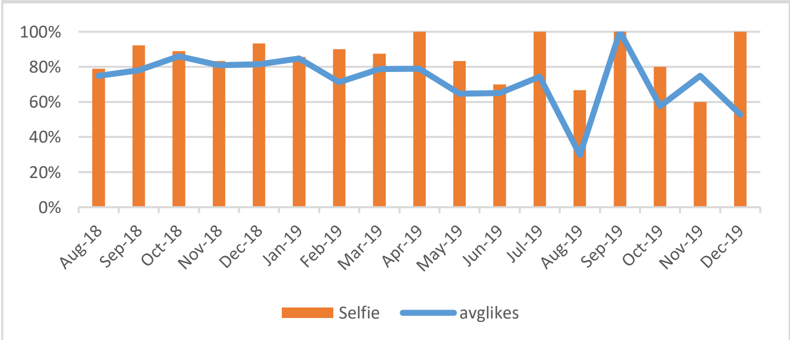

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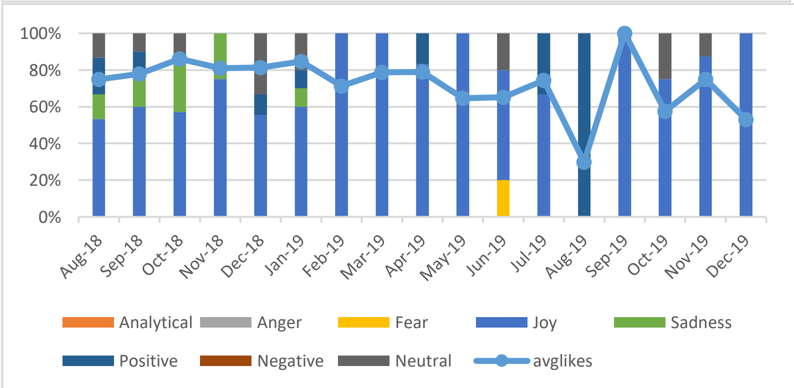
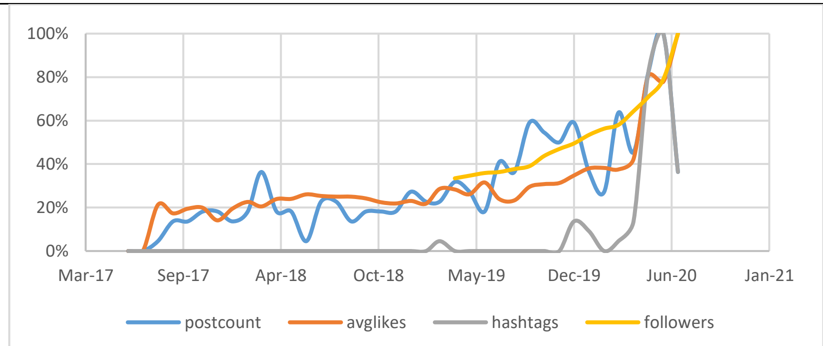


c.

P20:
S
5800
6.66



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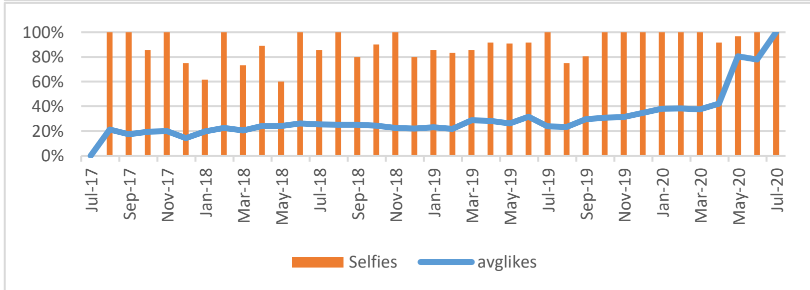

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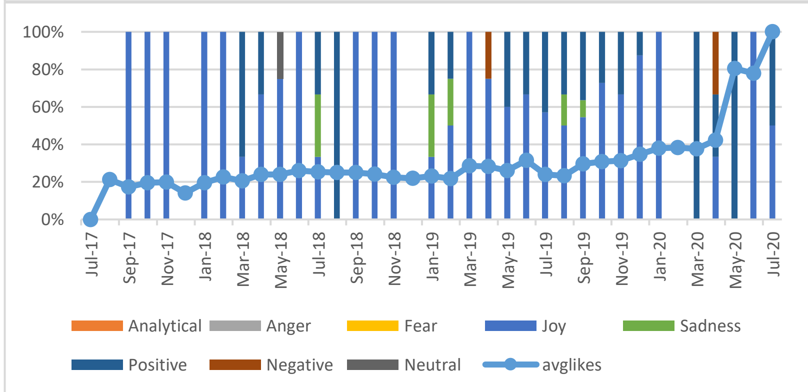

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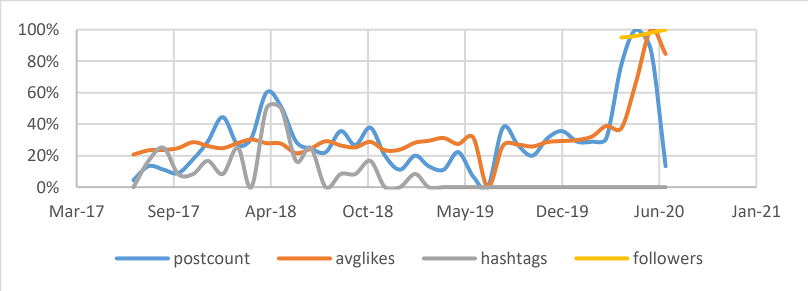
P21:
KS
4740
3.78



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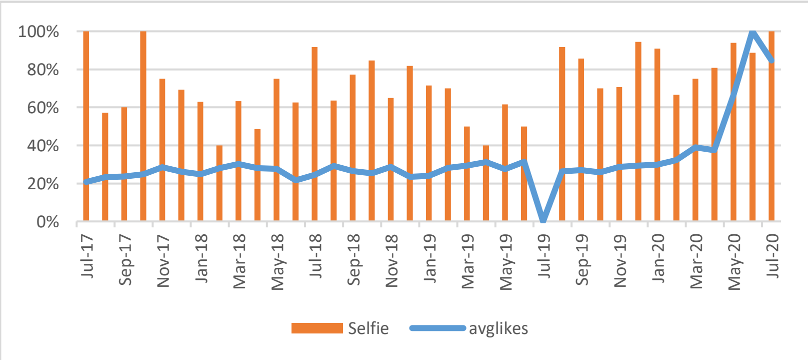

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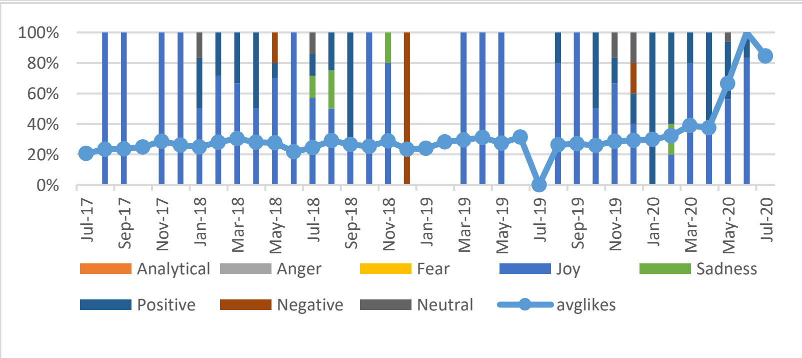

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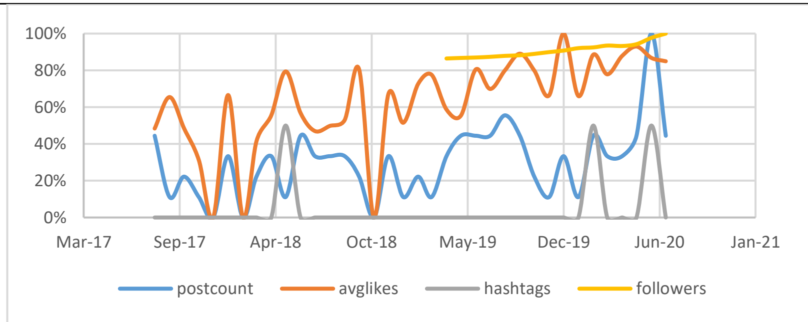
P22:
EZ
4300
3.32



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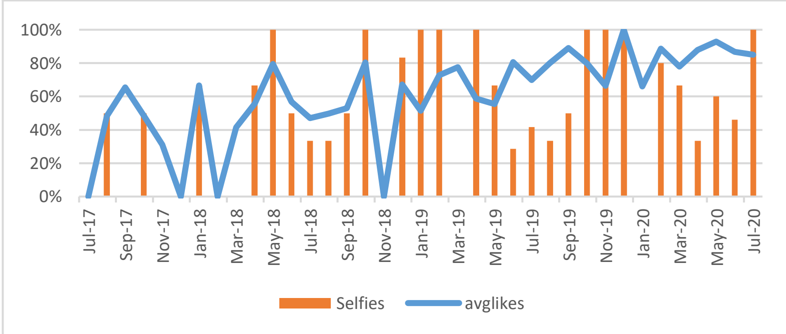

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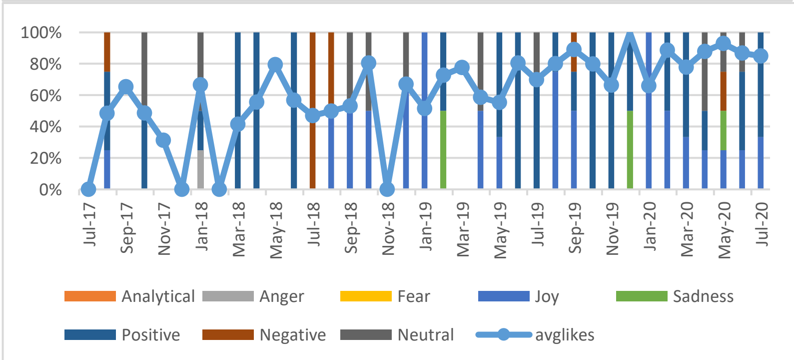
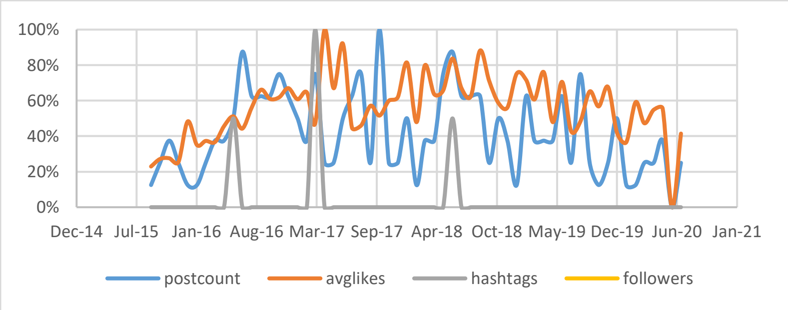
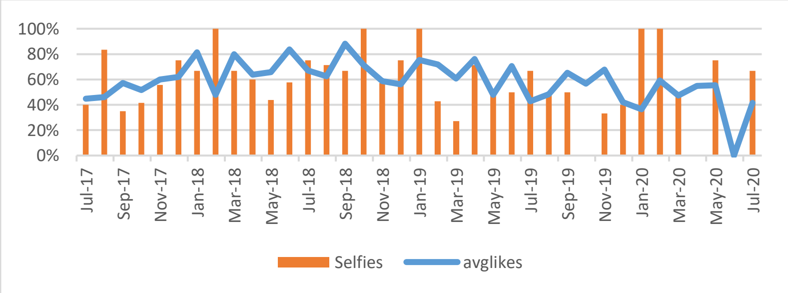
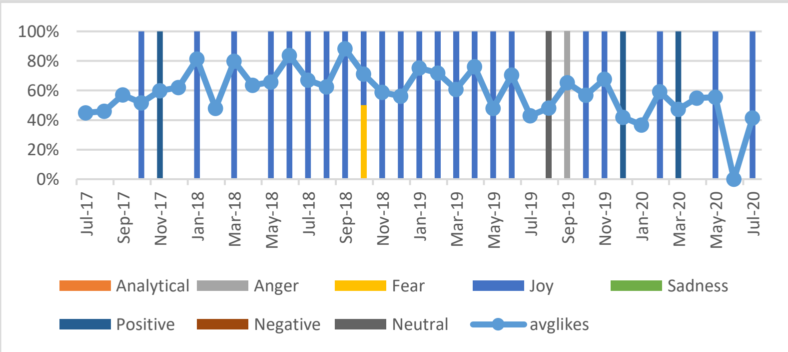
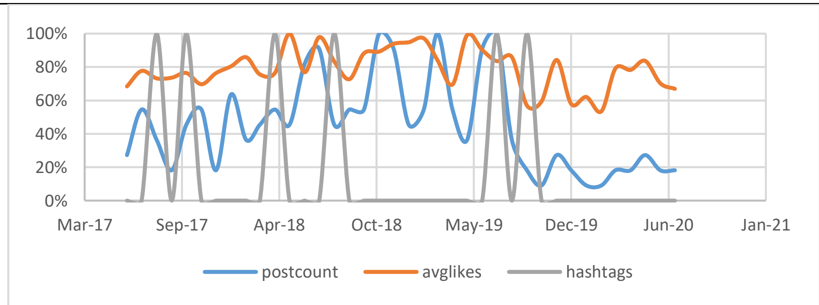
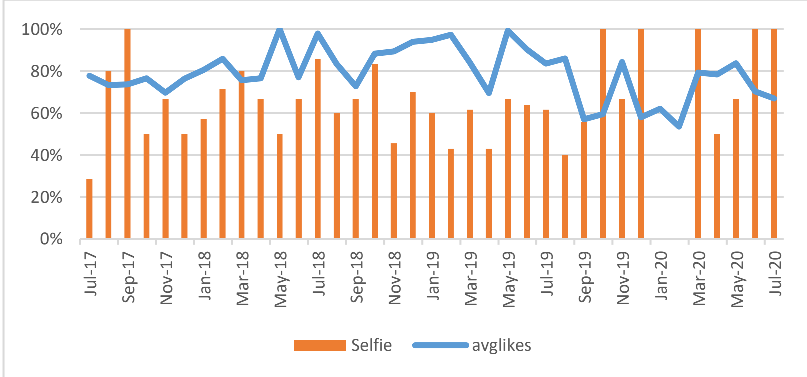
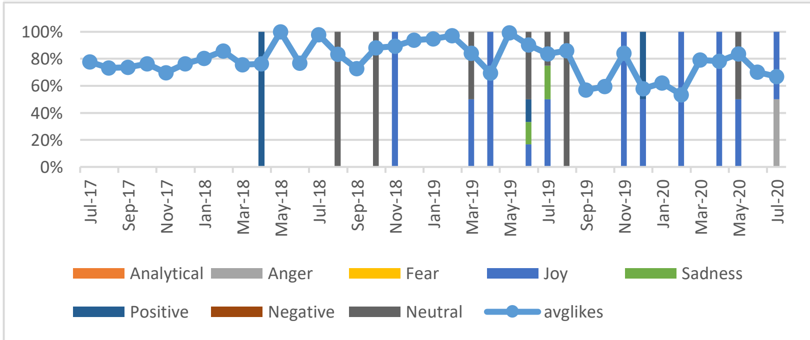
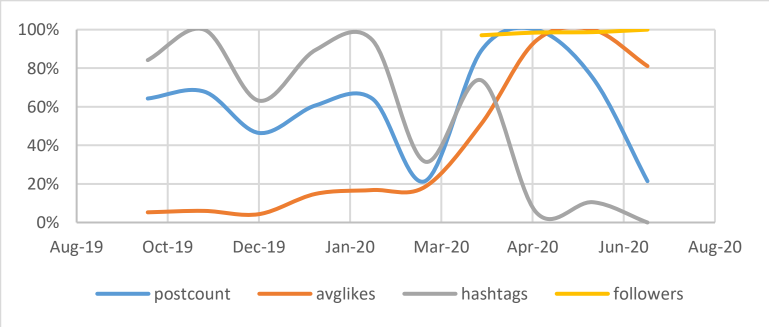


c.

P23: OM 4100 3.75	 a.  b.  c.	P24: KL 3632 4.11	 a.  b.  c.

P25:
LJ
3200
2.58



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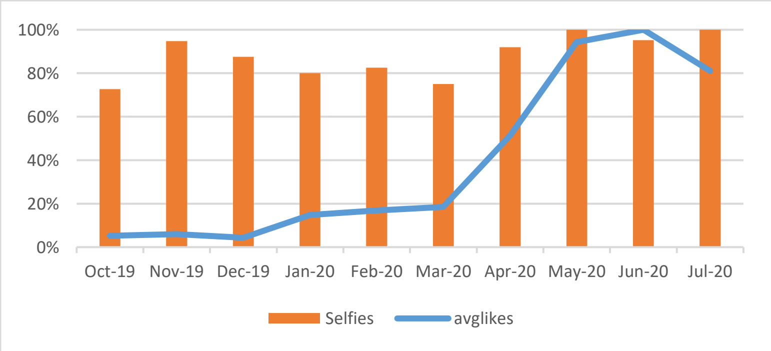

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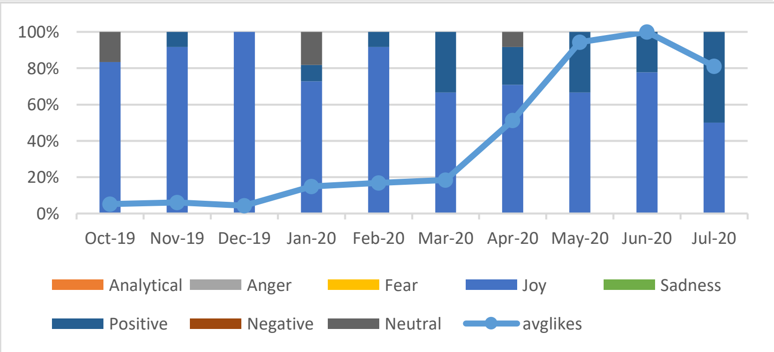
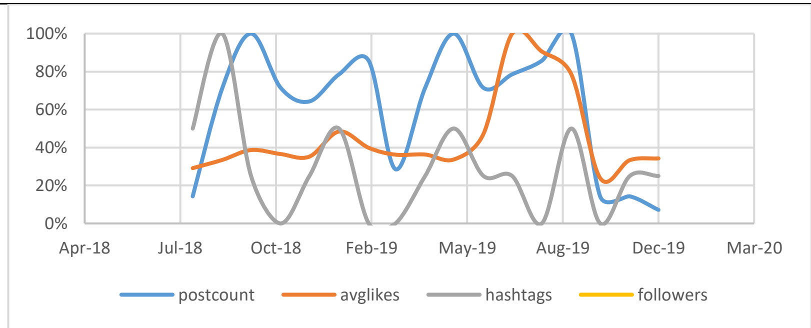


c.

P26:
SS
3174
4.78



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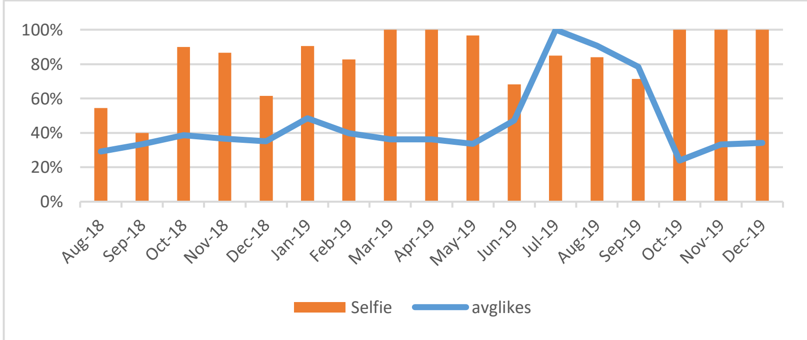

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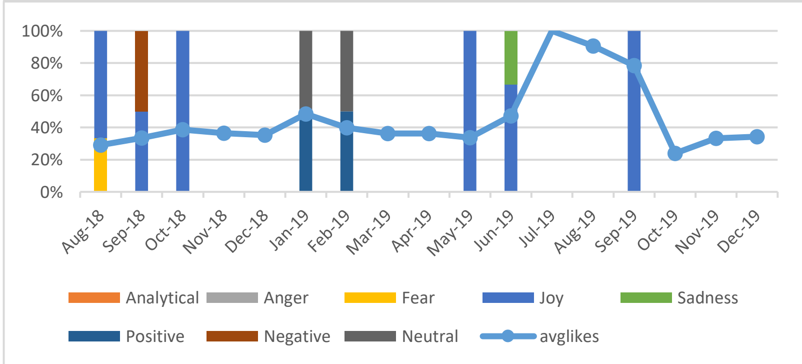
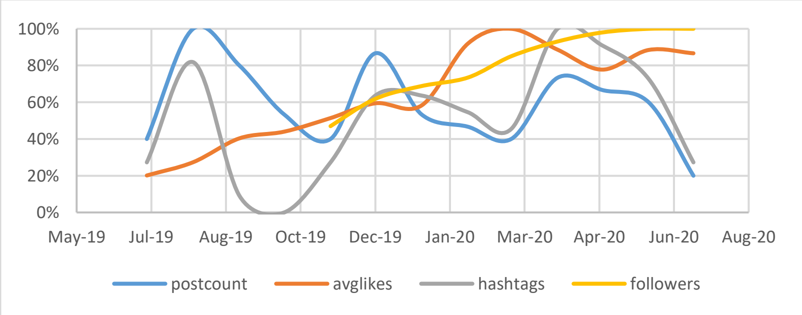


c.

P27:
KLI
3169
5.93



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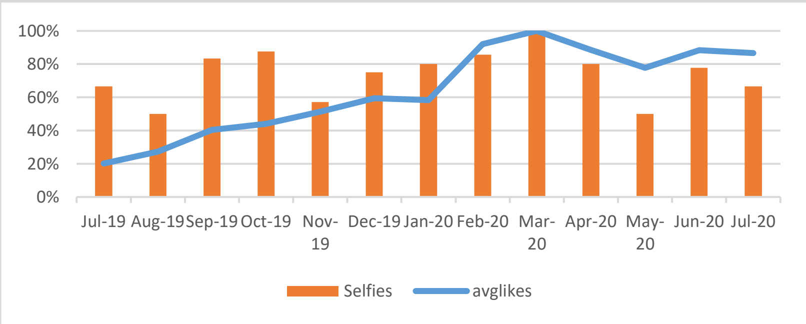

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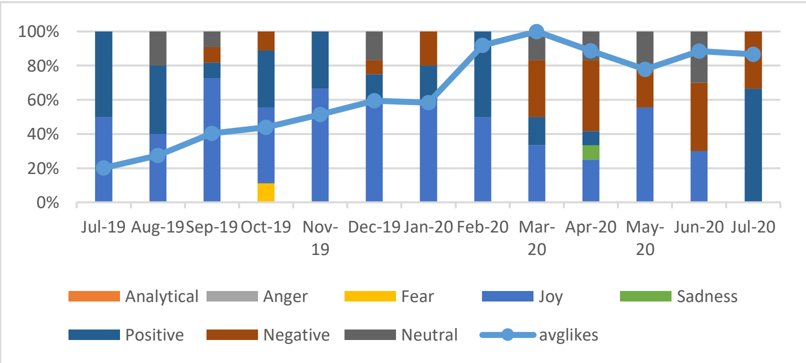
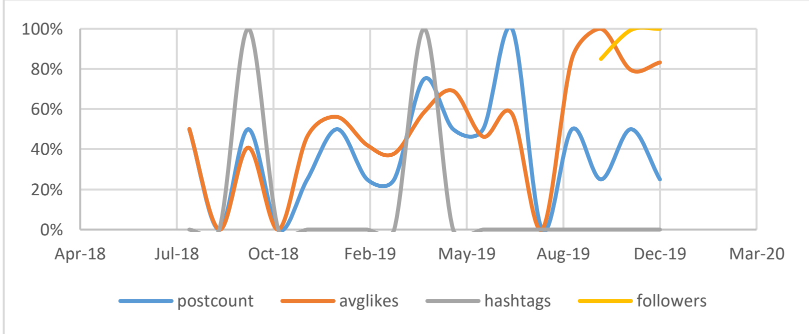


c.

P28
EB
3094
2.85



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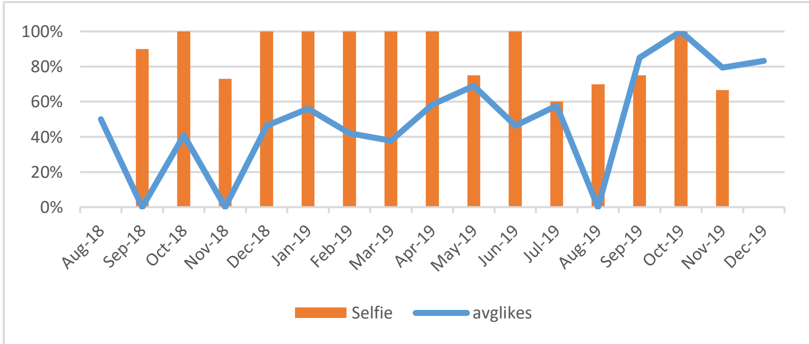

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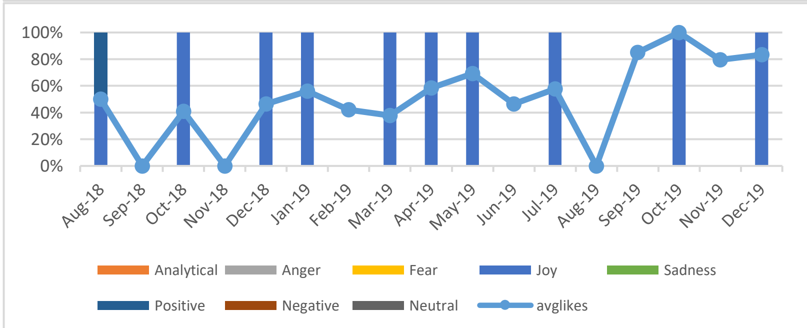
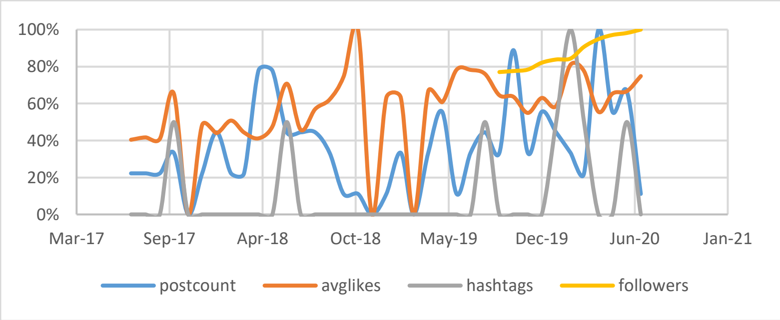


c.

P29:
AT
2845
2.5



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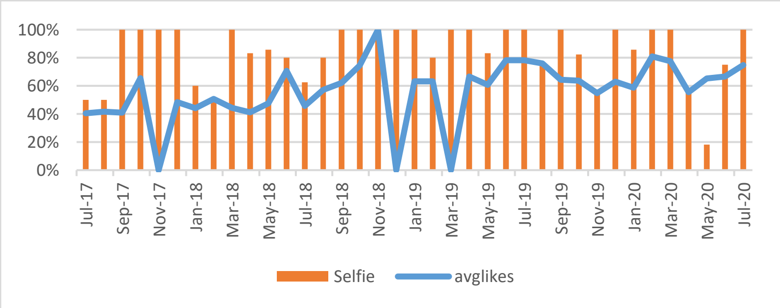

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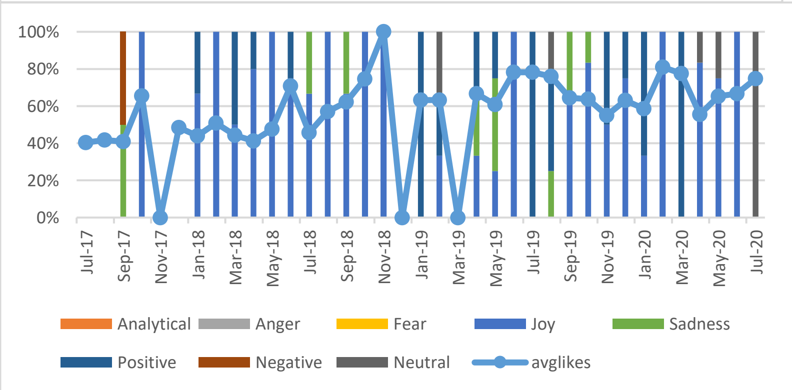

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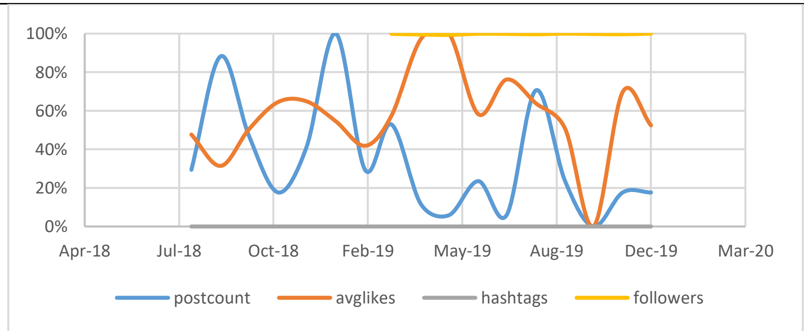
P30:
AB
1534
1.91



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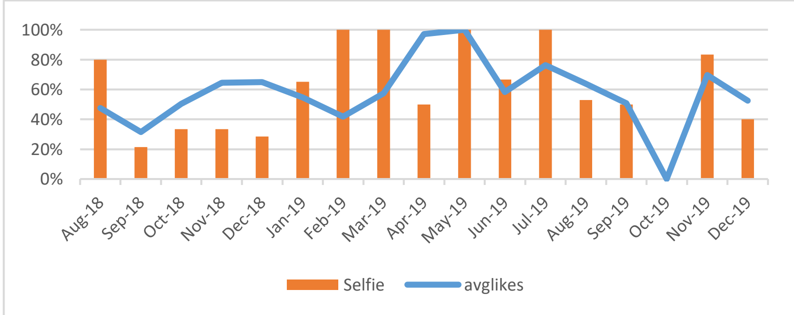

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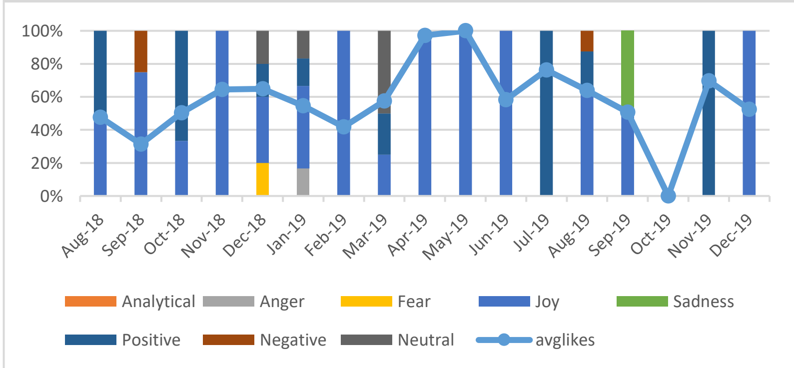

c.