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The Evolution of Emotional Displays in Open Source Software Development Teams: An Individual Growth Curve Analysis

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ABSTRACT

Software developers communicate and interact with each other in order to solve complex problems. Such communication often includes emotional displays that have been shown to influence team processes and performance. Yet, little is known about the evolution of team emotional displays. Hence, we investigate a sample of 1121 Open Source Software (OSS) projects from GitHub, using longitudinal data analysis. The results from growth curve analysis shows that the team emotional display decrease over time. This negative linear trend decelerates mid-term as suggested by a positive quadratic trend of time. Such deceleration diminishes toward the end as a negative cubic trend suggests.

KEYWORDS

Team Emotional Display, Growth Curve Analysis, Software Development, Open Source Software

1 INTRODUCTION

Virtual teams enable the recruitment of suitable team members independent of their location [25]. An example are open source software (OSS) development teams that often operate in a virtual environment, while employing technology-mediated means of communication. Such team communication often reflects a multitude of different emotions. Studying such emotions in the context of software development has recently gained the attention of scholars from software engineering (e.g. [14]) and management (e.g. [1]). Existing studies already suggest that emotions influence team processes and outcomes, such as cohesion and performance [6, 17, 22].

While prior investigations often focus on the relationships between emotions and team processes or team outcomes, we lack empirical evidence on antecedents of team emotions. Only few examples exist that investigate the effect of adopting new routines on the development of emotions [7], or the effect of team characteristics on emotional capabilities [1]. Conceptual work suggests the importance of time when investigating team processes and process dynamics [2, 30, 31]. Yet, little empirical research has been done in this regard [3].

Hence, the objective of this study is to investigate time as a variable. Therefore, we require longitudinal data of team emotions. Given that positive emotions are association with successful outcomes [29, 34] and are a central concept in positive psychology investigating the optimal functioning of teams [12], we focus on positive emotions in this study. We benefit from the OSS repository GitHub and the archival project GHTorrent1[1] in order to identify and extract positive emotional displays from 1121 software development projects. We formulate the following research question:

- What is the effect of time on the evolution of positive team emotions in virtual teams?

In this study, we focus on three contributions. First, we investigate temporal dynamics of positive emotional displays in OSS teams. Second, we provide an example of a growth curve analysis, benefitting from OSS repositories in the software engineering domain. Third, we compare three predictive models for the effect of time on team positive emotional displays.

2 BACKGROUND

2.1 Team Emotions

In general, emotions are distinguished between positive and negative emotions. When referring along this dichotomous scale in conjunction with textual analysis, studies also use the term sentiment (analysis). We distinguish the term emotion from moods, i.e. medium-term feelings of which the perceiver is not always aware of, while emotions are short-term feelings that the perceiver realizes [2].

Research in relation to emotions uses dimensional and discrete frameworks in order to classify emotions. Valence-Arousal is an example for a dimensional framework [38], while using individual emotions, such as joy, trust, and surprise would characterize a discrete framework. Plutchik's wheel of emotion reflects both, discrete emotions and their pairs along emotional dimensions [37].

[1] GHTorrent is an archival project for GitHub data (ghtorrent.org).

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Prior studies, suggesting the influence of emotions toward performance, have been conducted in the domain of leadership [46], team research [7, 9], research on individuals [13, 29], and organizational sciences [2]. More so, emotions and their recognition become an important management capability [18]. While few exception exist [1, 7], research on antecedents of emotions and their evolution is limited.

2.2 OSS Teams

OSS development has been of interest to scholars for its openness and emergent behavior. Data about such project teams are often easily accessible due to their open philosophy. Developers contributing to OSS are often highly skilled and highly paid experts during their daytime jobs. Often, they contribute to the OSS community in their limited spare time.

When it comes to interactions within the team, OSS teams tend to use technology-mediated communication [11], limiting the interaction quality. Hence, many physical cues (e.g. mimic) that can reveal and often reflect emotions are not accessible. In addition, OSS team leaders often lack a formal authority structure and rather emerge within community projects.

Prior studies in the context of OSS investigate team diversity [35, 44], innovation [28], and social influence [40]. However, emotions within such teams received little attention. Existing studies are rather descriptive, suggesting distributed teams have more positive content [15], and analyze nine open source projects in order to derive a sentiment analysis technique in the context of software development [21].

2.3 Time

Time is central to evolutionary variables and hence, plays an important role in theory development. While prior studies tend to take measures at a specific point in time in order to investigate cause and effect chains, they ignore the role of time in their models entirely. Time is often a subtle elements in prior calls for future research, such as change in management [36], or dynamics in team processes [26, 27], or dynamics of well-being [41]. While time can be considered a contextual factor (e.g. [47]), using longitudinal data analysis it becomes a focal point of the investigation [36].

3 RESEARCH METHOD

We follow a data driven approach toward the analysis of the data in response to our research question [5]. Thus, we first sample and collect data from the repository. We explore the data and its variables. Where needed, we modify and transform the data before developing and testing new models.

3.1 Sampling and Data Collection

When sampling the data, we define clear inclusion and exclusion criteria in order to sample active projects. Thus, we include projects with more than 50 comments in total, removing projects with little activity [23].We exclude projects that are either redundant, inactive or incomplete. Inactive projects have less than 2 commits per month, less than 24 commits in total, less than 6 developers, less than 6 months of activity [44]. Incomplete projects missed more than 25% of committer information or missed more than 25% lines of code.

The data was extracted from GHTorrent, complemented with data from the GitHub API and summarized on a monthly basis. This summarization and aggregation on the project team level allows us to draw meaningful conclusions, while relying on multiple data points. As a result, we identify 1121 projects that suffice criteria for further data analysis. We compare variables with statistics reported from prior studies [42, 43, 45].

3.2 Variables

All variables result from data processing of GHTorrent and GitHub data. The variables are aggregated on a monthly basis, forming the team average (e.g. emotions per sentence in comments), or the team sum (e.g. team size considers all participants until the end of the month). Descriptive statistics are presented in Table 1.

Table 1 - Descriptive statistics of the data set (N=1121).

Variable	Mean	SD
Team Positive Emotional Display	0.045	0.053
Project Month	27.790	22.442
Leader Positive Emotional Display	0.183	0.155
Communication Frequency	6.772	13.244
Network Density	0.152	0.177
Project Team Size	93.820	285.773
Number of Commits	173.300	221.735
Lines of Code	20110.6	134509.8

Time plays an important role in the development and contagion of emotions. Emotions form and change over time. Hence, we document and aggregate emotional displays by the team members of the sampled projects. We compare projects by their relative date in order to maintain temporal dynamics.

For the extraction of emotional displays, we calculate individual scores for each project team. These scores are calculated relative to the number of sentences per comment and aggregated on a monthly basis. We consider a developer as a team member, when he/she commits to a project. We extract positive and negative emotional displays using the Syuzhet R package, as it has been evaluated in prior research studies and builds on Plutchik's wheel of emotions [19, 33, 37], which is a balanced framework with 4 positive and 4 corresponding negative emotions. While sentiment analysis tools in their default settings can lead to negative results [20], we considered negations and domain specific aspects, such as the identification of error messages [48].

Table 2 - Intercorrelation Matrix.

	Variable	1		2		3		4		5		6		7		8		9	10
1	TPED	1.00																	
2	Time	-0.30	**	1.00															
3	Time^2	-0.07	**	0.69	**	1.00													
4	Time^3	-0.13	**	0.72	**	0.95	**	1.00											
5	LOC	0.02		-0.03	**	-0.01		-0.02	**	1.00									
6	Commits	-0.01		0.11	**	0.05	**	0.06	**	0.21	**	1.00							
7	Comments	0.46	**	-0.20	**	-0.05	**	-0.10	**	0.04	**	0.13	**	1.00					
8	PTS	-0.16	**	0.29	**	0.22	**	0.22	**	0.00		0.40	**	-0.11	**	1.00			
9	ND	0.56	**	-0.38	**	-0.12	**	-0.18	**	-0.02	**	-0.15	**	0.47	**	-0.22	**	1.00	
10	TLPED	0.26	**	0.00		0.01		0.01		-0.01		-0.03	**	-0.02	**	0.00		0.00	1.00

Note: TPED = Team Positive Emotional Display; LOC = Lines of Code; PTS = Project Team Size; ND = Network Density; TLPED = Team Leader Positive Emotional Display. * p<.05; ** p<0.01

We also extracted emotional display scores for each team leader. We considered a person to be the team leader based on the number of commits, centrality in the social graph, and whether or not the person was the first committer [4]. In addition, we extracted the number of comments per project month and the network density based on their communication network each month. We also consider relevant control variables on a monthly basis: project team size, number of commits, and lines of code. We use standardized scores for all variables in our analysis. The intercorrelation matrix is presented in Table 2.

3.4 Data Analysis

Growth curve analysis (GCA) [32] is used to analyze the team positive emotional display data from GitHub projects of 1 month to 120 months. We employ individual GCA [32, 39] in order to estimate our models and analyze the effect of time on the evolution of emotional displays. Individual GCA allows the analysis of longitudinal change using structural equation modelling [8]. In contrast to other longitudinal data analysis approaches (e.g. repeated measures), GCA provides different benefits [8, 39]. First, it facilitates a hierarchical (multilevel) analysis. This allows the analysis of group and subject variables in the same model. Second, GCA works with fewer assumptions (e.g. assumption of homogeneity of regression slope, assumption of independence) and performs better with missing data [10]. Third, GCA can fit different functional forms (polynomials) to time-dependent data. We use akaike information criterion (AIC) and bayesian information criterion (BIC) as goodness of fit indicators. Given the similarity of model 2-4 we also report the chi-squared (χ^2) test results.

4 MODEL SPECIFICATION

We use r for our data transformation and analysis. In order to estimate our models, we use the lme4 package[2]. Following prior guidelines [8, 39], we first develop an unconditional model to estimate the any mean differences in team positive emotional displays. Second, we formulate an unconditional growth curve linear model. Our third and fourth model expand the linear model with quadratic and cubic polynomials. The fifth model builds on prior results in order to develop a conditional model investigating other predictors (leader positive emotional display, number of comments, and project density). Table 3 presents an overview of the models, while Table 4 presents a nested comparison of all models. We use development project as our grouping variable.

The unconditional growth curve model captures individual changes over time within the project [8, 39]. We fit linear, quadratic, and cubic trends to explain the trajectory of changes over time in the repeated measures. Since these models measure within-individual changes, they are referred to level-1 models. The conditional model investigates changes between projects and thus is referred to as level-2 model [8]. By introducing additional predictors as explanatory variables, we can investigate differences between projects. In , level-1 models capture the effect of time within projects, while level-2 models capture variation in intercept and slope across projects [32]. We provide exemplary visualizations of unconditional linear, quadratic, and cubic trends, as well as an example for a conditional linear trend (Figure 1).

[2] The lme4 package analyses mixed-effect models (http://lme4.r-forge.r-project.org).

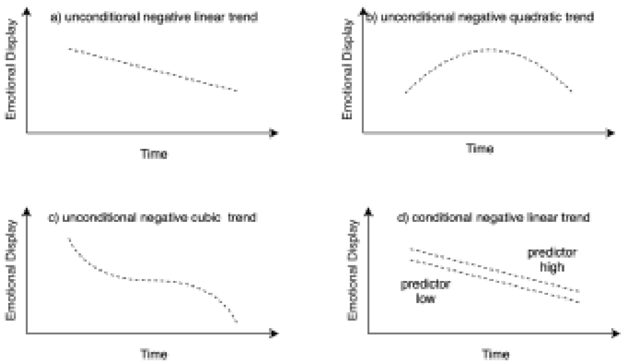

Figure 1 - Exemplary visualizations of unconditional and conditional negative trends.

4.1 Unconditional Model

Our first model identifies the variance of team positive emotional displays independent of time. We find that intraclass correlation coefficient (ICC) is 0.47, suggesting 47% of the variation in team positive emotional display is due to inter-team differences. This supports the use of individual GCA [39].

Table 3 –Model Specification and overview.

Model Specification
Model 1 – Unconditional Mean Model
Model 2 – Unconditional Linear Growth Curve Model
Model 3 – Unconditional Quadratic Growth Curve Model
Model 4 – Unconditional Cubic Growth Curve Model
Model 5 – Conditional Model – Adding Predictors

Table 4 –Nested model comparison.

Model	df	AIC	ΔAIC	BIC	ΔBIC
Model 1	3	59741	-	59765	-
Model 2	6	55768	3973	55816	3949
Model 3	7	55648	120	55705	111
Model 4	8	55426	222	55491	214
Model 5	32	36877	18549	37125	18366

4.2 Unconditional Growth Model

Our second model forms the linear model, as it investigates the individual variation over time. More specifically, we find a negative linear trend of time (β= -0.91, SE = 0.042, $p < 0.01$), indicating the decrease of team positive emotional display with project duration.

When adding polynomial terms, we first investigate a quadratic influence of time. For model three, we find a significant negative linear trend of time (β = -0.83, SE = 0.040, $p < 0.01$) and a positive quadratic trend of time (β = 0.22, SE = 0.019, $p < 0.01$). Hence, the team positive emotional display decreases with project duration, whereas the negative growth rate decelerates mid-term. Yet, the deceleration caused by the quadratic trend is smaller than the overall negative linear trend. Since the quadratic term increase the model fit (ΔAIC=120, ΔBIC= 111, $\Delta\chi^2$= 121.59, p<0.01), we retain the term in future models.

Our fourth model finds a significant negative linear trend of time (β = -0.59, SE = 0.039, $p < 0.01$), a significant positive quadratic trend of time (β = 0.59, SE = 0.031, $p < 0.01$), and a negative cubic trend of time (β = -0.43, SE = 0.028, $p < 0.01$). Here, we find that the team positive emotional display decreases with project duration (linear trend). This negative trend decelerates mid-term (quadratic trend), yet the deceleration diminishes toward the end (cubic trend). The cubic trend further increases the model fit (ΔAIC=222, ΔBIC= 214, $\Delta\chi^2$= 223.99, p<0.01) and hence, we retain the term for future models.

4.3 Conditional Growth Model

In our fifth model, we add predictor variables that may explain variance in team positive emotional display over time. We add leader positive emotional display, number of comments, and density of the project's communication network. In addition, we control for number of commits, number of developers, and lines of code changed. Judging by the AIC and BIC the model provides better predictive power (ΔAIC=18549, ΔBIC= 18366, p<0.01).

We find a significant direct negative effect for project team size (β = -0.13, S E = 0.027, $p < 0.01$), a non-significant effect for lines of code (β = 0.01, SE = 0.006, $p = 0.26$), and significant direct positive effects for all other variables and controls (p<0.01). The results suggest significant interaction effects between the variables number of commits (β = -0.03, SE = 0.012, $p < 0.05$), number of developers (β = 0.25, SE = 0.045, $p < 0.01$), network density (β = 0.09, SE = 0.025, $p < 0.01$), and leader emotional displays (β = -0.15, SE = 0.008, $p < 0.01$) with the linear trend.

For the interaction with the quadratic trend, we find significant effects for lines of code (β = 0.05, SE = 0.019, $p < 0.05$), number of commits (β = 0.05, SE = 0.025, $p < 0.05$), number of comments (β = -0.10, SE = 0.027, $p < 0.01$), number of developer (β = -0.27, SE = 0.052, $p < 0.01$), network density (β = 0.20, SE = 0.033, $p < 0.01$), and leader positive emotional display (β = 0.21, SE = 0.018, $p < 0.01$).

When analyzing the cubic trend, we find significant interactions with number of comments (β = 0.20, SE = 0.051, $p < 0.01$), number of developers (β = 0.14, SE = 0.030, $p < 0.01$), network density (β = -0.44, SE = 0.065, $p < 0.01$), and leader emotional display (β = -0.14, SE = 0.021, $p < 0.01$).

4.3 Additional Analysis

We explored also the use of orthogonal polynomials, as presented in prior studies [32]. We compared two models including our predictors and the control variables lines of code and number of commits. A comparison of the model using orthogonal polynomials (AIC = 37853, BIC = 38125) with the model using non-orthogonal polynomials (AIC = 36919, BIC = 37136) suggests a better fit of the latter.

5 DISCUSSION

Overall, the results show significant effects of time on the evolution of team positive emotional display within OSS teams. We distinguish between an unconditional model, and three unconditional growth models that investigate linear, quadratic, and cubic trends of time on team positive emotional display. Further, we develop a conditional model by adding common predictors from the literature in order to improve the model fit.

5.1 Time-Dependency of Emotions

When investigating unconditional growth models, we find a significant negative linear trend. Prior studies suggest that emotions are the result of relationships that may deteriorate over time [24]. Hence, the inception of a project is a positive event that causes positive emotional displays. With time, these positive emotional displays become less and lesser, and thus reduce with time.

In addition, we find a positive quadratic trend of time toward team positive emotional display. Therefore, the prior negative trend decelerates in time. Prior studies suggest that past emotional experiences influence future emotional experiences [16]. Therefore, the team may notice the decline in positive emotional displays and remembers prior positive experiences. The memory and reminiscence of more positive times leads to the deceleration of the negative trend.

The results also suggest a significant negative cubic effect of time on team positive emotional display. Here, past emotional experiences continue. The team learns that the negative trend did not reverse, but merely decelerate and hence, the motivation behind the positive quadratic trend diminishes.

5.2 The Influence of Additional Predictors

We find significant direct positive effects of number of comments, network density, and leader positive emotional display, as well as for the control variable number of commits in the linear model. The control variable project team size has a signification direct negative effect on team emotional displays, indicating lower overall displayed positive emotions for the smaller projects relative to the larger projects. We explain the insignificant effect of lines of code by the fact that these variables have not yet been jointly tested in a single model.

When analyzing the interaction of the additional predictors with the linear trend of time, the stronger effect of number of developers supports the prior negative effect. Meaning that project teams that increase in size experience a stronger negative trend of emotional display over time. We also find a stronger negative effect of leader positive emotional display over time. This suggests that teams with highly positive emotional leaders decrease less in their team’s positive emotional display over time.

The results also suggest strong positive interactions between network density, and leader positive emotional display with the quadratic effect of time. Therefore, positive leaders and closely connected teams are better equipped to decelerate the negative linear trend over time.

The interaction of the cubic trend with number of comments, and project team size show stronger positive effects, while the interactions of the cubic trend with density and leader emotional display show stronger negative effects. The positive interaction effects of number of comments and project team size suggest that more comments and larger teams continue to experience a stronger decrease of team positive emotional display toward the end. The negative interaction effects of leader positive emotional display and network density however, suggest that positive leaders and denser project teams experience less decrease of team project positive emotional displays toward the end.

6 CONCLUSION

Using data from 1121 GitHub projects, we extract emotional displays for OSS project teams using a natural language processing toolkit. We apply longitudinal data analysis in order to understand the effect of time toward the evolution of team positive emotional display. The results show a negative linear trend, indicating that the positive emotional displays reduce over time. While a positive quadratic effect of time decelerates this trend mid-term, a negative cubic trend suggests that the decrease of team positive emotional display continues toward the end.

Overall, this study provides three key contributions:

- Investigation of the temporal dynamics of positive emotional displays in OSS teams.
- An example application of longitudinal data analysis toward a larger data set from an OSS repository.
- Comparison of different predictive models related to the effect of time on team positive emotional display.

While effects of positive emotions have been documented by prior research, e.g. in positive psychology, future research should also include the analysis of negative emotions in order to provide a holistic picture. Hence, the development of a joint mixed effect model that considers positive and negative emotional displays using seemingly unrelated regression can help us to better understand the evolution and effects of emotional displays in the future.

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