Towards Measurable Motivation in Software Development

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***Abstract*—Information Technology (IT) experts are feeling the strain of fast-paced, demanding work, and working measures for improved well-being are increasingly being established. One essential element of well-being is motivation. Motivation is critical in order to maintain smoothly working processes and quality in completed tasks. To detect and intercept situations where motivation begins to decrease, we need means to identify changes in motivation. To automatically detect such changes requires ways to measure motivation levels from data at hand. In this study, we present preliminary results towards defining measurable motivational factors. Our approach relies on emotional indicators of motivational change that can be detected automatically from software repositories. Our results show that the emotional content of commit comments and issue texts, extracted using sentiment analysis and emotion detection, is correlated to varying degrees with collaboration and risk metrics. We point to possibilities for future work on more sophisticated measures with more complex data.**

***Index Terms*—motivation, emotions, developer experience, data mining, software development.**

I. Introduction

Working life has undergone a bewildering change in recent years. Adoption of remote work and utilization of software tools for tasks that were previously handled manually or via face-to-face communication, continues to grow. Information Technology (IT) experts are increasingly feeling the pressure of fast-paced work, as 57% of technology company employees report burnout in the United States [1]. The situation could be remedied by ensuring processes and workflows take into account the human factors of software developers, particularly considering motivation. Motivated employees can handle stress better and are also more productive and less prone to errors [2].

On the one hand, motivation at work is tightly linked to tasks. Tasks should be well-mapped to the skills of an employee, while still offering meaningful challenge. Further, there should be the right amount of work given with regard to the time that can be spent for them [2]. Both the contents of the task (what kind of work there is to be done), and the process to complete the task (how the work should be done) impact motivation.

While there are many studies on how to improve software processes regarding prioritizing tasks in teams, handling communication, etc., so far there are few studies on how to incorporate human factors, and particularly motivation of developers as part of the process. Considering individuals on a personal level, emotions have been identified as one of the most central motivators of human behavior. There is strong evidence that experiencing and expressing positive emotions and moods enhances performance at individual, group, and organizational levels [3]. Motivation is altogether a multi-faceted concept. There are extrinsic and intrinsic factors to consider, and different factors have non-trivial relationships. The importance of factors also varies between individuals.

Our long-term goal is to create a model of motivation that, when used with smart methods, can be applied as a tool to improve processes by including factors related to well-being at work. We strive to identify motivational factors in software development tasks that can be automatically extracted and measured from data available on the tasks. This kind of data modeling could enable quick reactions and interventions to correct workflows.

In this study, we take the first steps towards defining factors for this kind of motivational model. We mine data from open-source software repositories. We combine analyses on sentiments and emotions with metrics on software development tasks (complexity of the task, risk level and found collaboration). The preliminary results as revealed in Section IV imply that there are correlations between different task-related metrics and emotions identified from task-related data. While we are still far from a complete measurable model, the results are encouraging and spark discussions on possible research directions. This paper proceeds as follows. In Section II-A we will give background on the concepts of emotion and motivation and go through related work. In Section III we outline the utilized research process and define the metrics we use in the study. In Section IV we give our preliminary results based on collected data and statistical calculations. In Section V-A we reflect how the results can be interpreted considering known theories on emotion and discuss the limitations of the study. Finally, we conclude in Section VI.

II. Background and Related work

A. Emotions and Motivation

Emotions are strong feelings “deriving from one’s circumstances, mood, or relationships with others” [4]. They are

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responses to specific internal and external events [5]. Emotions include psychological and physiological processes, but defining emotion has proven difficult [6] and no final scientific consensus exists. Emotions are intertwined with mood, temperament, personality, disposition, and creativity [7]. Theories of basic emotions give classifications of discrete, measurable, and physiologically distinct emotions. A foundational example is Ekman's theory of basic emotions, which lists six emotions: anger, disgust, fear, happiness, sadness, and surprise [8]. Emotions may also be understood through a multi-dimensional analysis, which often gives rise to a two-factor model consisting of valence ("tone", positive – negative) and arousal ("intensity", passive – energized). These two are not a full explanation of the wide range of emotional experiences that humans can have, but they are theorized to map to an important emotional component called core affect [9].

Motivation is often defined as the explanation behind why people initiate, continue, or terminate a certain behavior at a particular time [10]. The stronger the motivational state, the more likely that it influences behavior. Content theories of motivation aim to describe what goals always or usually motivate people. For example, according to Herzberg's two-factor theory, certain workplace factors result in job satisfaction and are thus motivators, while hygiene factors are those that lead to dissatisfaction if absent, but do not produce satisfaction in themselves [11]. The two-factor theory has been the basis for other theories that consider motivation in the workplace, such as the Job Characteristics Theory, a theory of work design that seeks to enrich work by affecting motivational outcomes [12].

Emotion can be seen as a driving force behind motivation [13], and high or low motivation is often associated with specific emotions. Emotion is a crucial part of the motivational processes and can be used as an indicator of those processes.

B. Related work

Beecham et al. [14] found several motivating and de-motivating factors for software engineers. However, the study does not mention any technique to calculate them or what kind of data the factors could be based on.

Sharp et al. [15] developed an enhanced model for motivation by using the concepts of Beecham et al. [14] and several existing models, such as the Job Characteristics Model (Theory) [12]. The enhanced version considers individual characteristics in addition to other software engineering characteristics. The contextual factors here denote the work setting, i.e., the external environment like leadership, company's performance, and so on.

An empirical study on how the motivational model applies in practice has been conducted in Pakistan [16], where the Hofstede Cultural Dimension Model was taken into account to understand the results. Authors highlight the need to include culture when interpreting motivational factors.

Graziotin et al. [17] proposed an approach to find factors that create unhappiness among software developers. The factors listed for unhappiness can be considered as de-motivators, and matches with the de-motivating factors provided by Beecham et al. [14]. However, Graziotin et al. [17] did not provide a way to measure these factors either.

Ortu et al. [18] implemented an approach to store the issue details from issue tracking systems like Jira. This approach can be used to further extract details related to the issue that are relevant in motivation mining. While the study mentioned issue fixing time as one of the factors that affect emotion, as well as motivation of a developer, it did not show how it can be measured. Ortu et al. later added an emotional classification to the extracted data set [19]. However, the emotion is decided manually and there is no sentiment analysis in the approach. No detailed study has been made to elaborate the process of extracting motivational factors.

Utilizing techniques to mine software repositories, Mäntylä et al. [20] have studied how time pressure and productivity could be deduced. With similar data, Graziotin et al. [21] show that unhappiness is tied to low motivation and repetitive tasks, among other factors. While these studies link repository mining and motivation, they do not yet reveal how the nature of tasks affect motivation. Similarly to Ortu et al. [19], we have fetched issue, commit, and contribution details for each developer, but go further by also extracting different metrics from the issue and commit details. We have used the set of motivational and de-motivational factors as defined by Beecham et al. [14], and the approach of Sharp et al. [15] is further considered in understanding the outcome.

III. Research Process

The general problem we are trying to solve is *What task-related factors motivate software experts?* Since our first step to investigate this focuses on open-source software development, we are specifically looking into the following research questions (RQs):

- RQ1: What are the factors in software development tasks that impact the motivation of a developer?
- RQ2: What factors can be measured?
- RQ3: What kind of relationships are there between different factors?

The research process to answer these questions proceeded as follows. We perused the literature to learn about existing motivational studies on software development (background for RQ1). We listed found motivators and de-motivators and categorized them to measurable and non-measurable (initial step for RQ2). In the following, we will give details on how we collected data from open-source software repositories (Section III-A) and what metrics we developed for measuring motivational factors (based on literature and available data) (Section III-B).

A. Data collection

We used the PyGitHub library (supporting Python v3+) to extract data from GitHub. Issue details from 35 GitHub repositories were extracted, following the approach of Rath et al. [22]. A total of 26566 issue comments from closed issues were collected. We further collected 6520 commits from these closed issues. Out of these, we selected only those issues and

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commits where the *same developer* had both *commented* on the issue and *committed* the code, so that we could focus on the data provided by the software developer actually performing a certain task (committing the code that resolved the issue). We particularly wanted to focus on the developer performing the task in order to get a clear view of task-related motivational factors, which is our main interest.

As a result, our final dataset has 1069 records (issue and commit pairs), with data from 139 individual developers, ranging from 2015 to October 2021. Based on labels used in the repositories, issues are categorized into five main categories: Bug, Documentation, Enhancement, Feature and Others. In the category "Others", all type of issues that do not belong any of the four categories mentioned are considered. For sentiment analysis, we used TextBlob, and for identifying emotions from text, we used Text2Emotion.

B. Metrics for Motivation

Beecham et al. [14] list 21 motivators and 15 de-motivators that are particular for software engineers. We categorized these into measurable and non-measurable based on an estimation of whether we could calculate a numerical value for the factor. Factors that would have required information from organizational policies, personal skills, etc. were at this stage categorized as non-measurable. For the measurable motivators we examined what kind of data we were able to get from GitHub, and created a mapping between the motivators and available data. Ultimately, we were able to formulate metrics for three motivators, given in Table I. Figure 1 further illustrates what kind of data from issues and commits was used with which tools and metrics.

We recognize that categorizing the factors is problematic. Had we had access to organizational data, other factors could have been labeled as "measurable" as well. Further, as this is the first iteration, the suggested metrics are simple. For example, for collaboration we might envision more complicated formulae, taking into account past connections or collaboration across different projects. The limitations of data, metrics and scope are further discussed in Section V-C.

The defined metrics are based on literature. Lines Of Code (LOC) is commonly used to determine the size and the complexity of software. For example, Nystedt and Santos [23] and Tashtoush et al. [24] describe LOC as one of the approaches in complexity calculation of a software. In addition, we take into account the number of files involved in changes, demonstrating how contained (or not) the changes are to a specific part of code. Together, lines of code and number of files are combined for our complexity metric (1). We categorized complexity as high, if it is larger than the average complexity in the specific category of issues (Bug, Documentation, Enhancement, Feature or Others), and as low, if it is below average of the specific category.

Beecham et al. [14] list collaboration as one of the motivational factors that affects software engineers when they are working in a team projects. In our collaboration metric (2), we count as collaborators those who (in addition to the developer pushing the commit) are tagged to comments or marked as assignees, commenters or commit authors to an issue. We then subtract those who have only been mentioned, but show no active participation in the issue.

Finally, Raphael [25] names delivery time or completion time as one of the profound risks in any agile software development project. Based on this, we calculate risk (3) based on how much the completion time of an issue deviates from the average. If the completion time for an issue is greater than the average completion time for the same issue category, the risk is high, otherwise risk is low. We recognize that calculating risk in this hindsight fashion has its limits.

TABLE I
METRICS FOR MOTIVATIONAL FACTORS.

Motivational factor	Related data	Formula
Technically challenging work (Complexity of tasks)	Number of files, number of files changed, number of lines changed	$Ci = nL * nF$ (1), Ci = Complexity of an issue at code level, nL = Number of changed lines (in commit), nF = Number of changed files (in commit)
Participation/ Involvement/ Working with others	Information on assignee, commenter, commit author	$CS = CL - ML$ (2), CS = Collaboration Score, CL = Number of collaborators, ML = Number of mentions
Risk/Risk related to project delivery time	Completion time of issues	R_i = High, if $Ct_i > Avg(Ct)$, R_i = Low, if $Ct_i < Avg(Ct)$ (3), R_i = Risk of an issue, Ct_i = Completion time of an issue

IV. PRELIMINARY RESULTS

In Tables II and IV, we present results concerning the complexity metric. Considering our categorization between high and low complexity, there were 116 high complexity issues and 950 low complexity issues. Note that for some commits the comment field is blank, thus the percentages do not sum to 100%, as no emotion could be detected for blank fields. Also for some issues (commits) complexity was zero, in which cases they were discarded. We can clearly see from Table II that there are distinct differences between the emotions expressed in issue comments (usually utilized discussing the task with others in the community) and commit comments (usually used to summarize the solution). While already 40.5% of all high complexity issues were found Happy, in commit comments the percentage went up to 66.4%. Yet, for low complexity issues, the portion of Happy comments was similar for both issue comments and commit comments. A distinct difference between issues and commit comments is also found in texts expressing Surprise – there are some of such in issues, but none in commits. Finally, looking at the distribution of emotions, Happy is clearly the dominant emotion for both high and low complexity tasks and both in issues and commits.

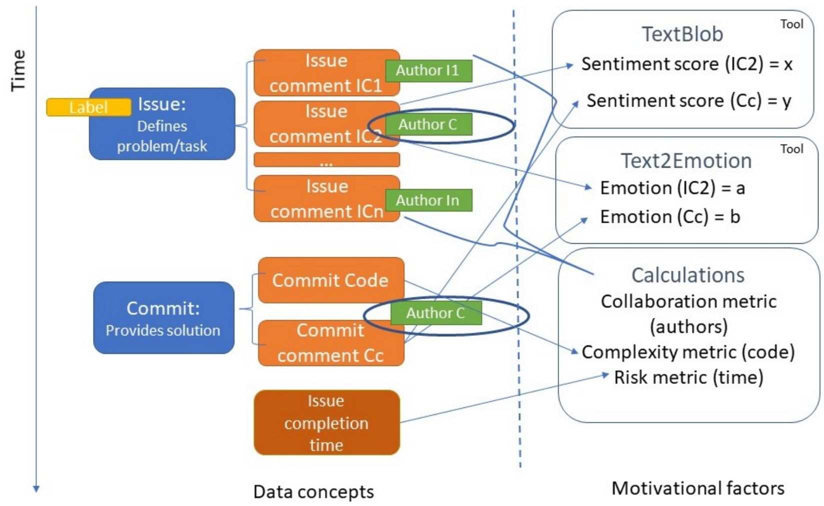

Fig. 1. Conceptual model of data collected for the study, analysis tools used to collect and process the data, and metrics extracted based on the raw data as indicators of motivational factors.

The second-most common emotion varies greatly. For issues, there is an equal amount of comments categorized as Sad or Fear for both high and low complexity issues. For low complexity issues, there is also a similar amount of issue comments labeled as Angry, while for high complexity issues Angry is very rarely found. For commit comments, on the other hand, Angry is clearly the second most commonly found emotion both for high and low complexity tasks, Fear and Sad being more seldom found.

Conducting a multinomial regression test for statistical significance showed that data source (issue or commit) was statistically significant in explaining the found emotion ($p = 0.00$), while level of complexity was not ($p = 0.065$).

In Table IV, we give the average complexity and completion time of issues by category. The used categories are gained by labels used in the mined projects. While four labels (Feature, Enhancement, Bug, Documentation) were consistently used in all repositories, other labels varied greatly, and have been combined under ”Others”. Here we can see that features have the highest complexity and highest completion time – though we should note the very low number of features (4). Bugs have the lowest complexity, and are on the lower end of used time to complete. Documentation may intuitively seem surprisingly complex, but this may be explained via systematic documentation involving small changes across multiple files.

In Table III, we summarize emotions found in high and low risk issues. In total we found 265 high risk issues and 804 low risk issue. The results are very similar to those in complexity, particularly regarding the differences between issues and commits. and the high percentage of Angry found in commits compared to issues. There are further similarities in how the percentage of ”Happy” is much higher in high risk issues than commits made for high risk issues, while for low risk issues, the percentage of ”Happy” comments is similar for issues and commits. However, contrary to complexity, conducting a multinomial regression test for statistical significance showed that both the data source (issue or commit) ($p = 0.00$) and the risk level ($p = 0.009$) were statistically significant in explaining the found emotion. Considering how similar the results intuitively appear, this prompts us to reconsider the method for categorization of complexity.

Finally, in Table V we have mapped collaboration values to emotions. Interestingly, issues and commit comments labeled as Happy have the lowest collaboration score on average, while highest collaboration scores are found on issues as Angry or Sad, and both issues and commits labeled as Fear.

V. Discussion

A. *Reflections*

In both issues and commits of both high and low complexity, Happy was the dominant emotion. This is consistent with prior research on software developer happiness [21]. As an emotional component of motivation, happiness could be both an outcome of successful goal attainment and an antecedent that increases the likelihood of purposeful action. It is not surprising that the Happy emotion appears frequently in the data: happy developers more likely create comments.

However, looking more closely at the data, more high-complexity commit comments were Happy than high-complexity issues, while for low complexity commits and issues, Happy comments were about the same. We speculate that this may be an outcome of goal attainment: when a developer completes a high-complexity task, their emotional state tends toward happiness and this is reflected in how the commit message turns out. In issues, happiness is not as strongly represented because the matter is still under discussion and the developer has not yet reached closure on the task. Similarly, low-complexity tasks do not result in a sense of achievement of the same magnitude as high-complexity tasks. That there were some occurrences of Surprise in issues but none in commits

TABLE II
EMOTIONS BY COMPLEXITY

Emotion	Source	Complexity category	Count	Percentage (per complexity category)
Happy	Issue	High	47	40.5%
		Low	458	48.2%
	Commit comment	High	77	66.4%
		Low	479	50.4%
Sad	Issue	High	27	23.3%
		Low	200	21%
	Commit comment	High	8	6.9%
		Low	89	9.3%
Surprise	Issue	High	13	11.2%
		Low	50	5.3%
	Commit comment	High	-	
		Low	-	
Fear	Issue	High	27	23.3%
		Low	220	23.2%
	Commit comment	High	4	3.4%
		Low	88	9.3%
Angry	Issue	High	2	1.7%
		Low	22	23.2%
	Commit comment	High	26	22.4%
		Low	265	27.9%

TABLE III
EMOTIONS CATEGORIZED BY RISK LEVEL

Emotion	Source	Risk level	Count	Percentage
Happy	Issue	High	131	49.4%
		Low	377	46.9%
	Commit comment	High	166	62.7%
		Low	391	48.6%
Sad	Issue	High	55	20.8%
		Low	172	21.4%
	Commit comment	High	9	3.4%
		Low	88	10.9%
Surprise	Issue	High	20	7.5%
		Low	43	5.3%
	Commit comment	High	-	
		Low	-	
Fear	Issue	High	54	20.4%
		Low	193	24.0%
	Commit comment	High	21	8.0%
		Low	73	9.1%
Angry	Issue	High	5	1.9%
		Low	19	2.4%
	Commit comment	High	67	25.3%
		Low	224	27.9%

TABLE IV
AVERAGE COMPLEXITY AND COMPLETION TIMES

Issue category	Count	Avg. complexity	Avg. completion time (hours)
Feature	4	204995	288
Enhancement	77	3642	216
Bug	114	1100	187
Documentation	288	24840	179
Others	556	6454	257

TABLE V
COLLABORATION

Emotion	Source	Count	Average collaboration score
Happy	Issue	508	1.274
	Commit comment	557	1.540
Sad	Issue	227	1.978
	Commit comment	97	1.701
Surprise	Issue	63	1.873
	Commit comment	-	
Fear	Issue	247	1.968
	Commit comment	94	1.915
Angry	Issue	24	1.958
	Commit comment	291	1.732

is probably a reflection of the ongoing nature of the former and closure in the latter.

The second-most common emotion varied greatly among high- and low-complexity issues and commit comments. The Angry emotion was the second-most common one for high- and low-complexity commit comments, while it was rarely found in high-complexity issue comments. This emotion may be related to getting stuck (commenting in issues) or feeling that work performed by oneself or others is inadequate (commenting in both issues and commits).

An Angry emotion is seen as moderate to high on the arousal dimension, and in terms of motivation may thus be a driver for action. Fear is also often seen as moderate to high on arousal, which is visible in somewhat higher occurrence in both high- and low-complexity issues. In commit comments, however, we did not see Fear nor Sad emotions. For Fear, this could be due to the valence dimension of the emotion: fear is not conducive to creativity and action, and is motivationally more likely to result in withdrawal or self-regulation. A similar explanation could be plausible in the case of Sad emotions, which is found more in issues and less in commits.

Beecham et al. [14] and Sharp et al. [15] list a number of external signs or outcomes showing the level of motivation among software engineers. These include retention, productivity, project delivery time, absenteeism, and project success. Whereas these signs are on the project and organizational levels, our findings address motivation on the individual level. Project and organizational indicators typically react to changes slowly or even completely after the fact, as in retention and project success. Motivation, measured via emotional indicators visible in actual work products or by-products is a more direct view into the individual and collaborative processes. They may also provide more direct means of understanding what it is about software engineers' work that is motivating and de-motivating and open paths toward acting upon motivational changes based on emotional expressions in work artifacts.

B. Addressing research questions

Looking into both the quantitative results as well as our reflections on them, we address our research questions.

RQ1: What are factors in software development tasks that impact the motivation of a developer? Examining the literature in the field revealed a number of extensive studies, listing both motivators and de-motivators for software engineers. Based on our quantitative data, there is (varying) correlation between identified measurable elements and the identified emotions in tasks. The risk of missing a deadline, i.e., the time it takes to complete a task, was shown to have statistical impact on the emotion found. While the level of complexity using our categorization between high and low complexity was not found significant, there were indications that a more fine-grained view of complexity could produce significant results.

RQ2: What factors can be measured? Utilizing data from GitHub and comparing it with the motivators and de-motivators found in literature, we have identified complexity of task, collaboration/teamwork, risk of delay, emotion and sentiment as measurable factors. More factors could be identified with more sophisticated data mining approaches or additional data sources.

RQ3: What kind of relationships are there between different factors? While our data prompts discussion on the relationship between different motivational factors, more work is required to properly understand them. We are currently performing a qualitative study to further understand and validate our quantitative findings, as well as experimenting with clustering algorithms to discover relationships between the factors.

C. Limitations

As we are presenting preliminary results, we acknowledge a number of limitations. First, we need more sophisticated methods to enhance the existing metrics. A particular concern is how the metrics can be either generalized or re-focused into other contexts where the primary work products are not code, but rather the manipulation of other kinds of artifacts.

Secondly, the question of transferability remains open . These results pertain to software developers in Open Source Software projects. To what extent they can be generalized to software engineers in other contexts, remains an open question.

Finally, the study results contain some uncertainty in attributing the detected emotions. We did not attempt to separate emotions attributed to the individual situation of each participant, to the task itself, to the tools used, or to the collaborative environment. We also could not distinguish the precise motivational role of each emotion expression. For instance, in the case of Anger, we did not separate between anger that increased emotion and resulted in action from anger as an expression after such an action (e.g., having fixed an issue, a person's commit message may express anger about the issue or its underlying reasons). However, it was not an aim of this study to reach that level of attribution; we aimed to examine associations between tasks and motivation-indicating emotions on a more general level.

VI. Conclusions

Our vision is to address a very complex, multi-faceted problem: identifying motivational factors in software development work and creating smart ways to intervene when motivation drops; and introducing more sensitivity to human factors into software processes and workflows. Our preliminary results are a stepping stone towards finding a measurable model of motivational factors. Our findings give positive indications that we can translate motivational factors into measurable metrics, and find statistically significant relationships between task-related metrics and experienced emotions. More work is needed to fine-tune metrics (more data, qualitative validation) and particularly to understand the causality between task and emotion (e.g., feelings impacting task duration or vice versa). Further work is also needed to have a larger dataset, enabling a broader statistical analysis, as well as complementing it with a qualitative study. We hope to inspire discussions and research openings in this direction by releasing the preliminary results on our vision. Some possible avenues would be to investigate how digitization or transferability of tasks affects the emotions of developers.

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