

Mind the Gap: On the Relationship Between Automatically Measured and Self-Reported Productivity

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Abstract—To improve software developers’ productivity has been the holy grail of software engineering research. But before we can claim to have improved it, we must first be able to measure productivity. This is far from trivial. In fact, two separate research lines on software engineers’ productivity have co-existed almost in complete isolation for a long time: automated product and process measures on the one hand and self-reported or perceived productivity on the other hand. In this article, we bridge the gap between the two with an empirical study of 81 software developers at Microsoft.

■ **THE TEXTBOOK** definition of productivity is the ratio of the output product over the input effort that made it [1]. While this definition sounds simple, its application to knowledge workers such as software engineers has turned out to be a major challenge [2]—so much so, that even after more than 40 years of work on productivity for software engineers, we still have no generally agreed-upon way to define, let alone measure productivity.

Two main methods on assessing productivity have thus far emerged: 1) The automated measurement of product or process features to assess productivity, such as the lines of code written per day [3], sometimes called traditional

or “objective” productivity measures [4], and 2) the reporting of self-assessed productivity by the software engineers [4], sometimes called self-assessed, self-rated, or self-perceived productivity. Both metrics have distinct benefits and shortcomings. While other metrics such as peer assessment exist, they are much less widely studied.

An advantage of product or process metrics is that they are easy to measure and give seemingly objective results. We refrain from calling them objective, however, because: 1) The choice of which measures to use is itself subjective. 2) The interpretation of a metric such as lines of code per day is problematic and subjective—what about engineers who produce more concise code in the same time, what about that one-liner patch that took a week to debug and fixes a business-

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critical problem? 3) Automatic measures can be gamed [4]. 4) In many cases, automatic measures fail to capture work that happens off-screen, for example, meetings and discussions. Addressing some of these issues, IBM introduced the concept of Function Points in the late 1970s [5]. However, these, too, have drawbacks: they include an element of subjectivity by how one judges “functionality” into the measurement itself.

In the other line of thought on productivity, software developers therefore assess their own productivity instead [6], called self-reported productivity. Self-reported productivity circumvents some of the challenges of automated measures, but it is susceptible to, for example, cognitive biases [4]. In contrast to many automatic measures, its subjectivity also makes it hard to compare across individuals.

We explicitly do not want to claim that one of these two ways to measure productivity is inferior to the other. Both are widely-used measures with their respective advantages and disadvantages. Until now, however, they have existed in almost complete isolation of each other. Bridging the gap between self-reported and automatically measured productivity allows software engineers, managers, and researchers better understand what makes them (feel) productive at work. In this article, we provide the initial steps towards bridging this gap. In particular, we answer the question how self-reported productivity relates to measured productivity.

Data Collection

To gain insight into what drives productivity and its perception, we asked a sample of 1,066 Microsoft Windows developers to participate in a study in which they rated their own productivity daily. We filtered employees to reach out to by their job title being “Software Engineer I,” “Software Engineer II,” or “Senior Software Engineer.” These are the roles where the bulk of programming happens at Microsoft. Of the 1,066 developers, 81 (7.6%) finally participated in our study. Participants reported an average mean of 8 years of professional software development experience (median 6, minimum 1, maximum 26 years), mostly within Microsoft. We wanted make the participant pool as large as possible, so we followed an opportunistic sampling strategy,

allowing every developer who was interested to participate. To further make participation more attractive, we promised a personalized productivity report at the end of the study and raffled three 50\$ Amazon vouchers. During the 5 week study period, developers submitted 1,479 daily productivity ratings in total (out of 2,050 theoretically possible, if everyone submitted every day). However, participants were not required to submit ratings daily, for example because they took a day off.

We enrich these daily ratings with several product and process metrics computed from hundreds of terabytes of data streamed from Microsoft’s internal data store system COSMOS. This included data from the Version Control Systems as well as Windows and IDE usage telemetry. The nature of the IDE telemetry data was comparable, but more abstract than known from other systems, for example WatchDog [7].

Daily Email Probes. At the heart of the study was a daily intervention with an email (a) asking study participants to self-assess their productivity for the day, depicted in **Figure 1**. Participants could choose when they wanted to receive these emails, with the intention that they could reflect on productivity at the end of their workday. We maximized usability of the emails for multiple email clients. In particular, we focused on mobile devices so developers could rate their day for example during their commute. Figure 1 (left) shows an example email of how developers rated their productivity on a five star scale. We picked this scale for familiarity with popular other rating systems such as Amazon’s or Airbnb’s. We also wanted to keep the cognitive load small so that they would not need to differentiate between a 7 or an 8 star rating for a day. Clicking on a star would register the rating and bring participants to a web page (Figure 1, right), on which they could further specify 17 attributes for a day or enter an attribute of their own. Separate research found that these pre-defined attributes distinguish a good from a bad day for a developer [8], such as “*I did not sleep well,*” “*I had fewer interruptions than usual,*” or “*I had more meetings than usual.*”

Windows Telemetry. With participants’ consent, we collected application usage data from

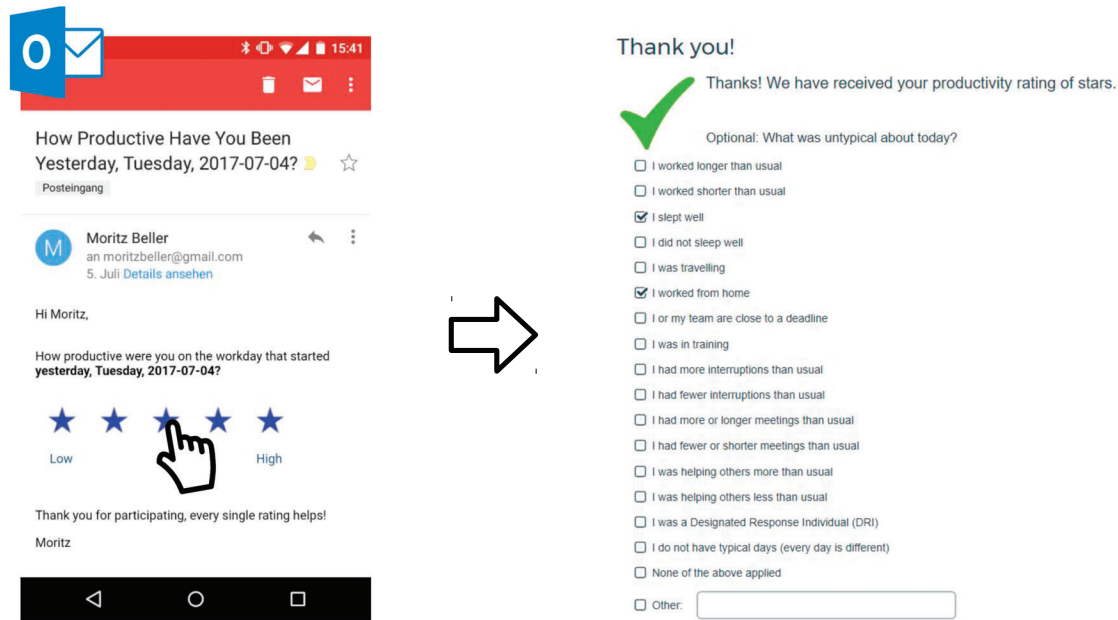


Figure 1. Once a developer rated their productivity in the daily email probe (left), they could enter additional attributes for the day, such as “I slept well” and “I worked from home” (right).

telemetry built into internal development builds of Microsoft Windows. This resulted in detailed data on how much time developers spent in different applications on their machines. Many developers at Microsoft use a desktop workstation as well as a notebook; our telemetry gathers information from both and identifies that they come from the same employee. This state-of-the-art internal telemetry framework includes features such as automatic detection of inactivity [7]. Similar to previous work at Microsoft [9], we categorized applications into a set of different classes, aiming to have at least the 90th percentile of observed applications grouped into classes. This means that in less than 5% of applications, we would report time in a non-standard application spent as “Other” when it really should be in one of the pre-defined categories. For example, we classified Microsoft Outlook and Mozilla Thunderbird into the email class and Visual Studio, Eclipse, vim, emacs, and many others into the coding class, but an exotic code editor only used by one developer might be miss-labeled as other. This also bears the risk of misclassification if a developer uses emacs to do their emails, since we would always label it as “coding”. However, we anecdotally

know that such cases are rare in the tightly-integrated Microsoft ecosystem. Moreover, the classification was done by a member of the Windows developers sub-group that we studied, so they are familiar with the typical tools and processes. We then aggregated the amount of time spent in each application class for every day. This way, we ended up with *time spent on pure coding, debugging, code reviewing, testing, and other development tasks*. Moreover, we also incorporated the *time spent on emails, in the browser, and other applications*. The *total active time* summarizes the overall time spent active in front of the computer for all applications. Monitoring developers’ application usage bears potential privacy risks. Therefore, respecting developers’ privacy was paramount in this study. We designed and adhered to an ethics board approved study protocol with early anonymization and did not store developers’ personalized reports.

Other data sources. Other data sources included the code review and version control systems at Microsoft. From them, we extracted how many check-ins developers did in merged pull requests and how many code reviews they

performed per day. Moreover, we extracted all meetings and events from their public Outlook calendars. We aggregated this information only for the days developers took part in our study, summarizing the duration of all events in the calendar the developer accepted as the number of meetings in a day, the cumulative meeting time, and whether the day was part of a meeting spanning multiple days.

Modeling Self-Reported Productivity

The main goal of this study is to understand whether, and if so, which automatically measurable factors could describe self-reported productivity. To this aim, once we had collected all data, we started a step-wise process of building and refining linear models with the self-reported productivity score as a dependent variable and combinations of telemetry and other data as the independent variables. We chose linear models because they are the most basic form of modeling and the easiest to understand. To get an initial overview of relationships, we checked our data for the presence of cross-correlations. In the following, we describe the results of the different models we built in terms of the variance of the productivity score we could explain with them (the so-called R^2 value). Explained variance is the standard metric to evaluate how well a model fits the data—a perfectly fit linear model would, given the input of our independent variables such as telemetry, always predict the correct productivity score for any given day and developer.

- 1) We started the modeling process with a model containing only the coding time component from telemetry. Explaining 7% of the variance we observed in the data, this simple model gave us an easy-to-understand baseline over which to improve. While we did not have lines of code measurements available, a slightly more complex model with it and the developers' seniority at Google explained only 1.7% of self-reported productivity [4].
- 2) As a next step, we added all other application telemetry data, improving the explained variance by a relatively small 2 percentage points. This hints at the fact that coding time might be the most relevant

predictor among time spent in different applications.

- 3) From previous studies on productivity we know that rating behavior differs tremendously between individuals [6], [9], [10]. Consequently, adding a baseline intercept for every developer (their User ID) made a large difference in the variance the model was able to explain, to now 34%. This intercept allows the model to adapt to different rating behavior among participants—assume one developer's average rating might be 2.5, while another's might be 4 stars.
- 4) Adding meeting data from developers' calendars did not further increase the model's explanatory power. As a result, we left it out in our best-fit model attempt.
- 5) For the final model, we added the day attributes developers submitted, shown in **Table 1**. The table presents all features with their coefficients, with the day attributes in the lower half. Many of the day attributes in the model represent orthogonal pairs, e.g., "I slept well" and "I did not sleep well." Traveling has by far the largest negative effect on self-reported productivity (down by one point), followed by being a "designated response individual," having many interruptions, and a bad sleep. On the plus side, it seems to be the case that antithetical partners, for example having a good night's sleep or fewer interruptions than usual, can (almost) entirely make up for a bad day. "Designated response individual" is "Microspeak" [11] for "being on-call." It seems natural that developers lower their reported productivity when expecting to deal with urgent unforeseen issues. There might be many reasons for why the attribute "I worked from home" (Figure 1, right) did not emerge as significant in the final model, from an averaging effect in the population (some might prefer it, others not) to the fact that it might simply make no difference. We originally included many more team-related attributes (see Figure 1, right) but they turned out to be insignificant in the final model.

Table 1. The features and their coefficient values making up the final productivity model.

Feature	Coefficient
Telemetry Coding time	0.18
Telemetry Review time	0.18
Telemetry Other time	0.09
User ID	[-0.93; 1.45]
I was traveling	-0.93
I was a designated response individual	-0.46
I had more interruptions than usual	-0.49
I had fewer interruptions than usual	0.58
I slept well	0.31
I did not sleep well	-0.38
I worked longer than usual	0.24
I worked shorter than usual	-0.35
I had more or longer meetings than usual	-0.26
I had fewer or shorter meetings than usual	0.23
None of the above applied	-0.32

With this final model including day attributes, we were able to explain almost half (47%, i.e. $R^2 = 0.47$) of the variance in the observed data. This final model has a good fit for a concept as complex as productivity [12]. Capturing more would likely be over-fitting, as the automatic measurements that serve as input to the model simply do not capture all important aspects of productivity, such as off-screen work, nor do they give insight into the quality of the on-screen work, such as the difficulty of a task. With an average of 18.3 ratings per developer (User ID), over-fitting of the model is a concern. We thus performed a reduction of our regressed model, keeping only coefficients that had a statistically significant impact on the model when left out.

Post-Study Survey

One week after the study period, we sent personalized reports to developers to give them insights into their productivity ratings and general application use. In the reports, we created a set of visualizations fusing productivity ratings with automatically measured product and process. Every developer received a customized report. Our aim was to test the visualizations for a possible future productivity dashboard that Microsoft planned to deploy in its Windows development groups. To assess the effectiveness of the reports and visualizations, we launched a post-study survey together with the reports. Participants first saw their personalized report and afterwards could fill out the short survey. This survey was filled out

by 47 participants (58.0% of all participants). The sidebar depicts the layout of the productivity reports and summarizes developers' opinions of the visualizations.

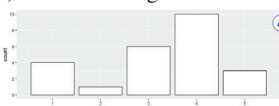
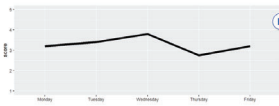
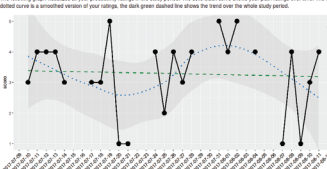
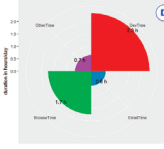

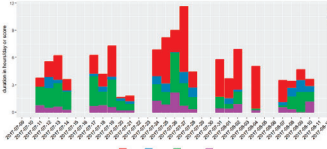
Besides the visualizations, we were also interested in how the participants perceived the study in general. Three quarters of participants would continue to rate their productivity to get an updated report like the one we send them at the end of the study, every week. All of the participants in the survey either liked (91.2%) the daily rating emails or were at least neutral (8.2%) toward them. Only 4.4% found the emails at the end of their personal work day disruptive. The free text participants could enter about the study anecdotally confirmed this, with participants writing "I found it interesting to have this natural point of the day where I would reflect on how the day went. I started keeping a little work journal because of it." Most developers (71.8%) agreed or strongly agreed to the statement that they learned something new from the report. The majority of developers (89%) were interested in participating in future studies on productivity. We take this as a strong sign that they not only enjoyed participating in the study, but that it provided tangible benefits to them. Enjoying the study and taking part in the non-mandatory post-study survey, though, might be correlated—making these findings susceptible to the volunteer bias.

Conclusion

This study is an initial step toward bridging the gap between two lines of thought on productivity: automated measures and self-reported productivity. With a simple model, we were able to explain almost half of the variance contained in self-reported productivity when expressed as automatic product and process measures. The step-wise model fit confirmed that establishing an individual baseline for rating behavior is crucial. Time spent coding emerged as an important factor for developers' self-reported productivity, as did day attributes such as being able to work with(out) interruptions or sleep quality. While we need more studies in different contexts to generalize the findings, our results should at least make organizations aware of the large conceptual discrepancy between self-reported and measured

SIDEBAR: Visualizations in the Productivity Reports

At the end of the study, each participant received a personal productivity report consisting mainly of the visualizations A-F below. In a post-study survey, we then assessed the effectiveness of the visualizations. The table below depicts an exemplary visualization and the percentage of respondents who agreed that the respective visualization is easy to understand (Easy), taught them something new (New), and was actionable (Act). The cells are color-coded on a gradient from pure green, denoting full agreement, over orange (50%) to red (0%), denoting no agreement. As the color distribution shows, overall, our visualizations tended to be easy to understand, but relatively lower in actionability. The visualizations of ratings by weekday (B) and application usage by category (D, E) received the highest scores for easy understanding (85% and higher); novelty was rated higher for the chart that included the whole study cohort as a comparison (E) than the non-comparative variant (D). This goes in line with 64% of study participants agreeing that “comparisons with the whole developer population helped me better understand my own values.” Actionability was below 50% across the board and the highest for visualizations (D) and (E) at around 45%. This highlights both a common problem with visualizations [13] and a need to design more actionable visualizations in future reports.

Visualization Name	Easy	New	Act
(A) Overall Ratings: distribution of the ratings a participant submitted 	Not surveyed—purpose was for participants to cross-check data		
(B) Ratings per Weekday: average productivity rating per weekday 	95.4%	52.3%	23.2%
(C) Ratings over Time: daily productivity ratings over time with trend lines 	59.1%	40.9%	18.2%
(D) Application Usage: polar chart of the developer's average active time across four app categories (dev, browsing, email, other) 	86.4%	61.4%	47.7%
(E) Application Usage Comparison: polar chart of all other developers 	86.3%	74.4%	44.2%
(F) Application Usage Over Time: daily active time in app categories 	65.9%	45.4%	25.0%

productivity. Another important consideration is that optimizing for individual productivity is different from optimizing for team productivity, which might be an ultimately more important metric for organizations.

A natural extension of our work would be to include measures such as biometrical data of developers (for example, to quantify whether they indeed had a good sleep). Since our study ran only for the course of five weeks and to ease interpretation of the models, we performed cross-sectional data analysis, disregarding differences in time. In the future, more complex linear mixed models could enhance the regression analysis.

Reflecting on our visualizations, we learned that developers preferred easy-to-grasp visualizations with one clear focus. They seemed to enjoy a new, unexpected perspective on well-understood data (such as the weekday chart). Too much detail turned out to be counter-intuitive, even on the insightfulness of a visualization. By contrast, a comparison with other developers seems to increase the overall value of a visualization, but measures need to be taken to preserve the individual's privacy and not to use this comparative data for performance evaluation, for which it is not suitable. We initially worried whether our daily emails would be perceived as disruptive. The opposite was the case: developers largely embraced them.

Because the study showed that *Coding time* was the most dominant process measure on self-reported productivity, Microsoft started investigating to make it a key metric for some of its development teams, including installing interventions for its developers to increase their coding time. Finally, most developers learned something new from the study and almost all would participate in a future study. If by nothing else, the sheer process of reflecting on their productivity helped developers be more productive.

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THREE KEY INSIGHTS

- The more time software developers can spend on coding, the higher they rate their produc-

tivity.

- Traveling had the single largest negative impact on self-reported productivity. Quality of sleep and interruption-free work were important, but the weekday was not (no “Friday effect”).
- The sheer process of reflecting on their productivity seemingly helped software engineers be more productive.

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