What Happens to All These Hackathon Projects? – Identifying Factors to Promote Hackathon Project Continuation

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Time-based events, such as hackathons and codefests, have become a global phenomenon attracting thousands of participants to hundreds of events every year. While research on hackathons has grown considerably, there is still limited insight into what happens to hackathon projects after the event itself has ended. While case studies have provided rich descriptions of hackathons and their aftermath, we add to this literature a large-scale quantitative study of continuation across hackathons in a variety of domains. Our findings indicate that a considerable number of projects get continued after a hackathon has ended. Our results also suggest that short- and long-term continuation are different phenomena. While short-term continuation is associated with technical preparation, number of technologies used in a project and winning a hackathon, long-term continuation is predicated on skill diversity among team members, their technical capabilities in relationship to the technologies and their intention to expand the reach of a project. Moreover, we found intensive short-term activity to be associated with a lower likelihood of long-term project continuation.

CCS Concepts: • **Human-centered computing → Empirical studies in collaborative and social computing**.

Additional Key Words and Phrases: Hackathon; Project Sustainability; Project Continuation; Social Computing

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1 INTRODUCTION

Time-based events, such as hackathons and codefests, have garnered increased interest from researchers and practitioners in recent years [64]. During such events participants typically form teams and engage in intensive collaboration to complete a project that is of interest to them [55]. Hackathons[1] have been adopted in a variety of domains such as small-medium size enterprises [39], large corporations [31, 53, 59], (higher) education institutions [25, 37, 56], civic engagement groups [28, 29, 43], (online) communities [2, 16] and others.

[1]We will use the term hackathon as a substitute for aforementioned events throughout the remainder of this article.

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There is an increasing body of research around hackathons in particular in the HCI and CSCW communities since such events require individuals to collaborate while developing a technical artifact which is of core interest to these communities [9, 24, 53, 67]. Most existing work however focuses on the event itself covering aspects such as how teams self-organize [67], how to support newcomers [52], how to deal with diverse audiences [22], how to encourage participation [64], how to organize events for specific communities [33, 54] and how to organize a hackathon [6, 55]. Whether and how projects get continued after an event has ended and which aspects might be associated with continuation has received limited attention beyond studies on single events in the context of entrepreneurship [13, 33] and corporations [53] so far. This is surprising since hackathons are typically organized with specific goals in mind such as creating new and innovative technology [6, 62], tackling civic, environmental and public health issues [3, 5, 18, 32, 57, 65], spreading knowledge [23, 42, 50] and expanding communities [48, 64]. Most of these goals arguably require follow up activities after an event has ended in order to come to fruition and prior work has shown that most hackathon projects do not get continued despite participants' individual continuation intentions [7]. Existing work moreover mainly focuses on in-depth studies of a small number of teams participating in a specific hackathon that takes place in a specific domain which is not sufficient to develop an understanding of how different aspects can contribute to project continuation after an event has ended. To develop this understanding and to provide suggestions for organizers and participants to foster project continuation it is necessary to develop a larger scale overview of these aspects that covers a large variety of different teams participating in multiple hackathons in different domains.

It is important to note that not all hackathons are designed with continuation intentions in mind. Beyond the fact that there is evidence for project continuation, we argue though that neglecting the potential for project continuation is a missed opportunity. Organizers and participants invest considerable resources to prepare for and run hackathons or to participate in them developing interesting and innovative prototypes. It thus appears worthwhile to assess project continuation, to explore aspects that may affect continuation and to identify means to promote it. Moreover, participants might come to events with their own goals in mind that are not necessarily aligned with the goals of the organizers [46]. These participant goals might consequently involve project continuation even if the event is not specifically designed with continuation in mind.

In this work we thus study collaborative practices around the development of technology in a setting – co-located hackathons – during which participants collaborate face-to-face. Related to project continuation we particularly focus on technical continuation activities since hackathons typically encourage producing prototypes or demonstrations, which require post-hackathon technical work if an actual product or feature is to be produced. This necessity has been discussed in various contexts including corporate [53], entrepreneurial [12] and civic hackathons [11]. Our study thus focuses on a setting where co-located collaboration is likely followed by online activity. In particular, we aim to answer the following two research questions:

RQ$_1$. *Do hackathon projects get continued after the event has ended?*

RQ$_2$. *Which aspects may be associated with technical project continuation?*

To address them, we conducted an archival analysis of the hackathon database Devpost[2]. Devpost is used by corporations, universities, civic engagement groups and others to advertise events and attract participants, thus mainly covering hackathons that are open for anyone to participate. Our aim was to use Devpost as a basis to explore if – and how – projects get continued and to derive aspects that can potentially be associated with project continuation. Our findings

[2]https://devpost.com/

indicate that more than one third of all hackathon projects demonstrate some form of continuation activity after the hackathon itself has ended. However, continuation rapidly deteriorates after the first few days and only about 5% of all projects are continued for more than 5 months. Moreover, our findings suggest that short- and long-term continuation are different phenomena. On one hand, our findings suggest that technical preparation activities prior to a hackathon, the number of technologies a team uses to create a project and winning one of the few prizes at a large event can be positively associated with short-term continuation. On the other hand, skill diversity and skill matching among team members and their intention to expand their project's reach can support continuation in the long run. Our analysis also provides indication that intensive short-term activity can be detrimental to long-term continuation.

The contribution of this paper is twofold. First, we present insights into the continuation of hackathon projects beyond singular events indicating that there is technical continuation activity. Second, we identify aspects that are associated with short- and long-term project continuation thus providing suggestions for organizers and participants of time-based social computing events on how to prepare, conduct and follow up on an event to foster project continuation after it has ended.

2 HACKATHON PROJECT CONTINUATION

We draw on the theory of collaboration by open superposition (COSP) [35] to develop our hypotheses. COSP explains how all-volunteer open source developers, with limited time and diverse motivations, manage to create software. The central idea is that volunteer developers have only their own limited effort to invest. They will not take on a task until sufficient progress has been made on the project that their own volunteer effort is sufficient to complete their task in an acceptable time. We adapt this theory to the hackathon context by noting that a team is likely to continue to invest effort post-hackathon only if the effort available after an event has ended is sufficient to achieve a team goal. Thus, continuation should be more likely 1) if the team makes more progress during the hackathon, leaving less to be completed afterwards (section 2.1), and 2) motivation for continuation is high, meaning that the team is likely to be willing to invest more effort post-hackathon (section 2.2).

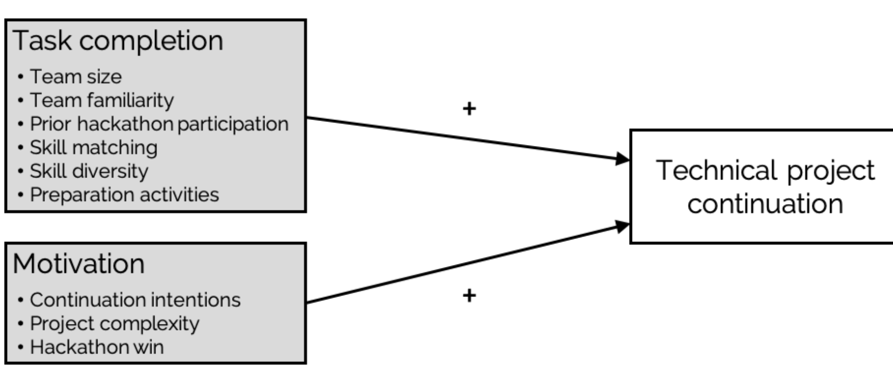

Fig. 1. Aspects related to task completing and motivation that might influence technical project continuation.

2.1 Task completion

Prior work by Nolte et al. [53] in the context of corporate hackathon discussed the connection between team efficiency and project continuation after an event has ended [53]. Teams that work together efficiently during a hackathon can be expected to develop a more mature prototype which in turn can make it easier to continue working that prototype after an event has ended. One aspect that has been linked to team efficiency is the number of team members. However, reported findings in different contexts appear to be contradictory. Larger teams have been found to be more efficient in the context of research teams by Wallmark et al. [69] while Staas et al. [60] found the opposite to be true for organizational teams. The short duration of a hackathon nonetheless appears to favor smaller teams since the coordination effort can be expected to be lower for smaller teams [60].

H_1. *Small teams will be positively associated with technical project continuation.*

In addition to team size, work on team performance also suggests that team familiarity – prior interactions between team members – can improve coordination and efficiency [27] thus leaving less complex work to be done post-hackathon.

H_2. *Team familiarity will be positively associated with technical project continuation.*

We expect prior hackathon participation of team members to be positively associated with efficiency and the ability to judge the potential and viability of project ideas. Individuals that have previously participated in hackathons are familiar with the setting which allows them to e.g. avoid typical hackathon pitfalls such as attempting projects that cannot feasibly be completed during the short duration of an event.

H_3. *Team members' prior participation in hackathons will be positively associated with technical project continuation.*

Nolte et al. [53] argued that skill matching – a fit between a teams' skills and technical project requirements – can support them to cope with technical challenges of a project. This can allow them to develop a polished prototype during a hackathon, which in turn can make it easier to continue working on the prototype after the event itself has ended.

H_4. *Fit between a teams' skills and project requirements will be positively associated with technical project continuation.*

Teamwork during a hackathon is not only about efficiently carrying out a project though. At the core of most hackathons is for teams to develop innovative ideas and artifacts [3, 39, 70]. Scholars have pointed out that team diversity can be beneficial for tasks that require creativity and innovation in the context of software development [26] and organizational teams Jackson et al. [36]. By team diversity we specifically refer to individual team members having different skills which can be expected to have a positive impact on teams and their projects in this context.

H_5. *Skill diversity within a team will be positively associated with technical project continuation.*

Finally, research indicates that preparation activities prior to the hackathon – such as discussing a project idea or setting up a common development environment – can promote project continuation in the context of civic [33] and corporate hackathons [53]. This is reasonable since preparation activities might make it easier for participants to cope with challenges during a hackathon thus allowing them to attempt more complex projects and reach a more mature project state, which in turn can promote post-event continuation.

H_6. *A teams' preparation activities prior to a hackathon will be positively associated with technical project continuation after a hackathon.*

2.2 Motivation

Prior research on continuation behavior after a hackathon [7, 33, 53] discussed the potential influence of a teams' continuation intentions which can be perceived as an indicator for motivation. Indeed, the relationship between intentions and behavior has been extensively studied in various other contexts most notably as part of the theory of planned behavior [1]. Intentions have also been specifically discussed related to continuation behavior in the context of research on psychology, health [8] and information systems [4].

H$_7$. *A teams' continuation intentions related to their project will be positively associated with technical project continuation.*

Another aspect that has been found to promote project continuation in both scientific [41], corporate [53] and civic hackathons [33] is whether a hackathon project is a direct extension of an existing technical artifact e.g. a product of a corporation. This aspect can however be perceived as not particularly relevant for this study, since hackathon organizers typically encourage participants to develop innovative ideas and prototypes [3, 39, 70] rather than stick to existing products or services. Moreover, in the case of corporate hackathons, it is unlikely that external participants will have detailed insight into the main product lines.

The technical complexity of a project can also be expected to have an effect on project continuation. On the one hand, projects that require the use of a large number of different technologies can be difficult to complete which, can have a negatively influence on project continuation due to frustration among participants. On the other hand, using different technologies can spark interest, serving as motivation for participants to continue working on their project after a hackathon. Referring back to the innovative nature of hackathons, we argue that attempting a complex project will serve as a motivation for teams to continue working on it after an event has ended.

H$_8$. *The complexity of a teams' project will be positively associated with technical project continuation.*

Finally, it is common for many hackathons that teams compete for prizes during the course of an event [19, 50, 63]. These prizes are typically awarded based on the project that a team has worked on. Such prizes can motivate participants to attend an event and continue working on their project after the hackathon has ended.

H$_9$. *A teams' project winning a prize at a hackathon will be positively associated with technical project continuation.*

3 METHODOLOGY

To answer our research questions and address the corresponding hypotheses, we conducted an archival analysis of the Devpost hackathon database. In this section, we elaborate on the details of the setting (section 3.1), the data contained in Devpost (section 3.2) and the conceptualization of aspects that are potentially associated with project continuation (section 3.4) including a coding scheme we developed to study continuation intentions (section 3.3). Then, we outline the analysis procedure (section 3.5).

3.1 Setting

The data used in this work was collected from the online hackathon database Devpost which contains information about hackathons across the globe. Most of the hackathons contained in Devpost are organized in a university context but Devpost also contains information about hackathons that are organized by corporations[3], civic engagement groups[4] and others. While most of the events are open for public participation, the main target group for most events are university and high school students and young professionals. Participation in hackathons is voluntary and everyone can propose project ideas that are of interest to them. Some hackathons however require

[3]https://t-mobile-iothack.devpost.com/
[4]https://suncode2018.devpost.com/

project ideas to be directed towards a specific theme such as health[5], sustainable energy[6], specific technologies[7] or others. In order to work on a project idea, participants have to form a team. Teams can form and exchange ideas before or during the hackathon. Most hackathons have a competitive element but there are also events that do not include prizes. During competitive events, projects are typically evaluated by a panel of experts using predefined evaluation criteria that are announced prior to or at the beginning of the hackathon. It is common for competitive hackathons to have multiple prizes that are awarded based on expert judgment and sometimes also on a popular vote.

Devpost contains information about hackathons, projects and participants (see Fig. 2 for an overview) which organizers and participants curate themselves. Devpost does not check for data accuracy. Organizers typically enter information about hackathons including time, date, theme and prizes prior to the event for promotional purposes. Participants can create project profiles including textual descriptions of their project, a link to the GitHub repository they used as a code base for the hackathon, a list of technologies they report to be relevant for their project, a textual description of future plans and information about a potential prize they won during the hackathon. In addition, participants can also create personal profiles, link them to the projects they participated in and report on their technical skills.

3.2 Data

The dataset we used for this work was collected on May 11th, 2018 and it contains data of 73 hackathons during which 1912 participants worked on 592 unique projects. The hackathons in this dataset took place during one month, from April 11th to May 11th, 2018. The dataset represents a snapshot of Devpost at this point in time. We focused our analysis on hackathons that took place during the last month before our data collection to reduce noise caused by the fact that organizers and participants can change this information at any point in time. We will treat self-reported variables such as individual participants skills as perceived skills because we presume that they reflect the perception of the individuals that entered the data into Devpost.

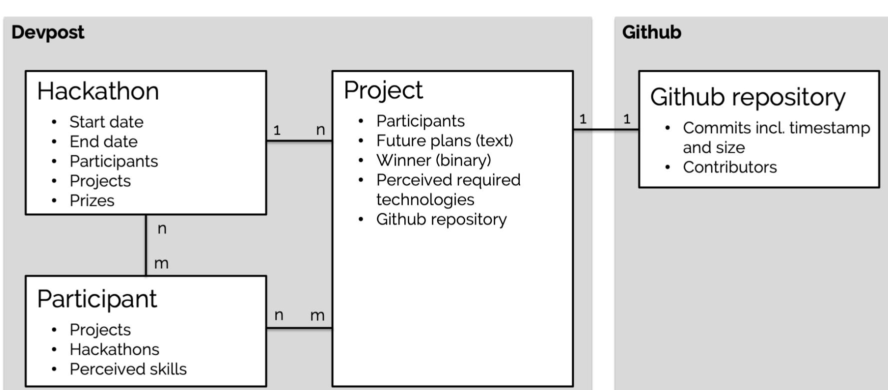

Fig. 2. Variables contained in the analyzed dataset.

We focus on individual projects as the unit of analysis. Each project can only be submitted to one hackathon, but each hackathon can host multiple projects (connection between *hackathon* and

[5]https://uon-i2n-aged-care-hack.devpost.com/
[6]https://suncode2018.devpost.com/
[7]https://idt-unchained-hackathon-6199.devpost.com/

project in Fig. 2). Projects are conducted by a team of participants. Each participant can be part of multiple projects and can join multiple hackathons. It is also possible for participants to work on multiple projects during the same hackathon. For each project the dataset contains information about the team that works on it (*participants* in the box *project* in Fig. 2) and a list of technologies that are required to complete it as identified by the team itself (*perceived required technologies*). The dataset also contains information about whether a project won a prize at a hackathon (*winner*) and a written statement by the team about their *future plans* for their project. Each project can be linked to a single GitHub *repository*. Apart from information about who participated in a hackathon and which projects were conducted as part of it, the dataset also contains information about hackathon *prizes* and information about the day the hackathon started (*start date*) and ended (*end date*). In addition to projects and hackathons, the dataset also contains information about individual participants including which hackathons they participated in, which project teams a participant was a part of and her/his *perceived skills*. Perceived technologies and perceived participant skills can be matched because Devpost uses the same set of keywords (e.g. Python, Node.js, R and others) for both fields.

Additionally, we collected information about activities related to projects before and after a hackathon using the GitHub API[8] (connection between *project* and GitHub *repository* in Fig. 2). The data collected from GitHub includes information about commits including timestamps, contributors and commit size. We focus our analysis on commits as a means to capture technical continuation of projects. The data from GitHub was collected six months after the initial data collection from Devpost (November 2018) to ensure a sufficient time frame for continuation activities to unfold.

From the raw dataset we only included projects that were conducted during collocated hackathons because we expect that collaborating on a project while being at the same place at the same time is significantly different from collaborating online. Moreover, we excluded projects that were part of a hackathon with less than three projects and ten participants to ensure sufficient information for our analysis. Finally, we excluded projects and participants that were lacking any of the aforementioned information, such as perceived required technologies and perceived skills, to ensure comparability between individual data points.

3.3 Studying continuation intentions

To be able to study continuation intentions based on our dataset we developed and applied a coding scheme (Table 1) to each project's description of *future plans* (Fig. 2). We first distinguished between positive (code 1a) and negative (code 1b) intentions while also considering the absence of concrete intentions related to the continuation of a hackathon project (code 1c). Moreover, prior work also indicates that continuation intentions might be directed at different follow-up activities. These include technical continuation activities [7] as well as activities related to expanding the reach of a project by attracting funding [53] or expanding the user base of a project e.g. in the context of a community [33]. We thus distinguish between technical continuation intentions (codes 2a and 2b) and intentions to expand the reach of a project (code 2c). We also distinguish between finishing the technical development of a team's project as it was intended during the hackathon (code 2a) and adding new features (code 2b) because teams with either or both of these intentions might exhibit different continuation behavior.

[8] https://developer.github.com/v3/

Code	Description
1a	**Concrete continuation intentions** related to a team's project (e.g. *"we definitely want to improve performance"*).
1b	Concrete statements that a team does **not intend to continue** their project (e.g. *"we have no plans for the further development"*).
1c	**No concrete continuation intentions** stated related to a team's project (e.g. *"graduate in a few years"*).
2a	Future plans related to **finishing the technical development** of a project as the team intended during the hackathon (e.g. *"finish the chat and database"*).
2b	Future plans related to **adding features or integrating the project into a larger (eco-)system** (e.g. *"add in a feature to take YouTube links as an input"* or *"integrate the application with twilio"*).
2c	Future plans related to **expand the user base, acquire funding for their project or turn it into a startup** (e.g. *"we plan on submitting it to the Google Play Store"* or *"continue as a startup"*).

Table 1. Coding scheme to study project continuation intentions.

3.4 Operationalization of concepts

For our research purposes, we developed team-level operationalizations for the aspects we previously identified from existing literature (Fig. 1 in section 2) based on our dataset (Fig. 2). We discuss each of the analyzed aspects in the following starting with technical project continuation activity as the outcome variable followed by team and project related aspects.

Technical project continuation. We assessed project continuation based on commit activity in a linked GitHub repository after the end date of a hackathon. In order to account for the fact that even active projects are not likely to show daily commit activity we adapted a common measure from research on open source communities [68] by considering a project to be active if it shows commits during the last month our dataset covers (month 5). We thus considered any project which shows commits later than 5 months after a hackathon as active (or else, continued) and all remaining projects as inactive (or else, discontinued). We also included three different aspects related to a project's activity on GitHub during the first 6 days after a hackathon. The decision for this time frame was based on an initial descriptive analysis of the dataset which we will discuss in the following (section 3.5). We included the **frequency of activities** by calculating the average number of activities per project during the aforementioned time span because it can reasonably be expected that continuous activity shortly after a hackathon has ended might be associated with long-term continuation activity. We also included the **number of contributors** per project and the **average commit size** as additional facets of continued GitHub activity. We included both aspects in our analysis because it can be expected that a larger contributor base can foster long-term continuation and that smaller commits can indicate minor corrections or polishing activities while larger commits can point towards major changes. Average commit size in this context refers to the number of files that were affected (added, modified or deleted) per commit divided by the number of commits during the aforementioned span of 6 days after the hackathon. We chose to use this particular metric because there is evidence that it is comparable to other activity metrics such as added/deleted lines [30].

Team size. The size of a team is represented by the number of participants in a project (*participants* in *project* in Fig. 2).

Team familiarity. The obtained dataset does not allow us to study all potential aspects of team familiarity such as participants working in the same company, students taking common courses or participants being familiar with each other through e.g. common social activities. We thus focus on their **common hackathon participation** by adapting a measure proposed by Newman [51] for networks of scientists. For each hackathon team (*participants* in *project* in Fig. 2), we iterate over all possible combinations of pairs (dyads) of team members to ensure that we capture both ties within and between subgroups of that team. Then, for each of these pairs we identify prior instances where they were part of the same team within a hackathon. For each identified prior instance, we divide the size of the pair (2) by the size of the team this pair was a part of to account for the potential effect that a pair might become more familiar with each other in a smaller than a larger team. Adding up all coexistence calculations of a team represents the final metric for common hackathon participation.

Prior hackathon participation. We assess the prior hackathon participation of a team by summing up the number of hackathons that each individual team member has participated in prior to a hackathon before dividing it by the number of team members.

Skill matching. To assess the fit between perceived participant skills and technical project requirements, we compare the skills perceived by each participant in a team (*perceived skills* in Fig. 2) and the perceived technologies required for a project (*perceived required technologies* in Fig. 2). For each participant we divide the number of perceived skills that s/he has in common with the perceived required technologies by the number of all perceived required technologies. Summing up these individual scores, we then divide the result by the number of participants to arrive at a normalized score for each team.

Skill diversity. To assess skill diversity within a team, we calculate the similarity of perceived team skills and then reverse the result by subtracting it from one. To arrive at a team level measure, we create the union of all perceived skills of all team members. Using this union as a basis we then calculate the overlap of each individual team member with the overall perceived skills of the entire team and divide the result of this calculation by the size of the union of all perceived team skills. Adding up all scores for each team, we then divide the results by the number of team members to arrive at a normalized team measure.

Continuation intentions. We included a separate binary variable for each of the previously discussed codes for a teams' continuation intentions (section 3.3) into our model. If a team e.g. voiced positive continuation intentions related to finishing the technical continuation of a project the variables for the codes 1a and 2a would receive a score of 1 while all other code related variables would receive a score of 0.

Preparation activities. To assess preparation, we focus on technical preparation because our dataset does not cover other preparation activities. It also appears reasonable to specifically focus on technical preparation since this aligns to the focus of our study which is on technical project continuation after a hackathon has ended. For this variable we calculate the number of activities related to a GitHub repository prior to a hackathon.

Technical complexity. We define the technical project complexity as the number of technologies participants perceive to be required to complete it (*perceived required technologies* in Fig. 2).

Winning. For this aspect we consider two different measures. First, we consider winning as a **binary** variable. Each project that won a prize at a hackathon receives a score of 1 while all other projects receive a score of 0. Second, we calculate a **weighted average** based on the number of prizes that were awarded during hackathon in relationship to the number of participating teams for each winning team. Therefore, we divide the number of prizes per hackathon (*prizes* in Fig. 2) by the number of participating teams (*projects* in Fig. 2). We reverse the calculated result by subtracting it from one to arrive at a weighted score for each winning team. The score of non-winning teams is 0. The aim of this measure is to account for the assumption that winning one of the very few prizes at a large hackathon might serve as a stronger motivation for a team to continue their project than winning one of the many prizes at a small hackathon.

3.5 Analysis procedure

We first asked two coders to independently apply the previously discussed coding scheme (Table 1) to each team's stated future plans to analyze their continuation intentions. Afterwards we assessed the inter coder agreement through Cohens-Kappa [14] (Table 5 in appendix A.1). Following the guidelines by Landis and Koch [40] we found substantial (0.61 - 0.80) to almost perfect agreement (0.81 - 1.00) scores for all codes making them suitable for further analysis.

In order to gain insight into project activities after a hackathon, we first summarized the number of commits per project. We found that 35.30% of all projects in our dataset had at least one commit after the hackathon had ended (Fig. 3). This number dropped rapidly to 17.06% by day 6 after the hackathon and continued declining to 3.55% after 5 months. The average number of commits (orange line in Fig. 3) declined even more rapidly starting with an average of 1.78 commits per day to 0.36 commits by day 6 to 0.04 commits per day by month 5. Projects that showed continuation activity had more than 2 contributors on average (average number of contributors = 2.72, SD = 1.16, Table 2) while commits affected 4 files on average (average commit size = 4.05, Table 2) but the relatively large standard deviation (SD = 23.73, Table 2) points towards a large disparity between commit sizes among the projects that showed continuation activity.

These findings suggest that most hackathon projects do not show any continuation activity in terms of commits to connected GitHub repositories. Moreover, they suggest that for the majority of projects, the after-hackathon activity only lasts for six days (one week) after the end of an event. In order to explore potential differences between this observed short- and long-term project continuation behavior, we divided the data into two parts: a) projects that show commit activity only within the first week after the hackathon (day 1 to day 6) and b) projects that continued to show commit activity to the connected GitHub repository after the first week after the hackathon (from day 7 to 5 months). For the first part, we used logistic regression to model project continuation and for the second part, we used survival analysis. Using these two modeling techniques is common for survival analysis e.g. in the context of open source projects [58, 68].

We thus followed the following three-step analytical approach:

(1) We carried out a descriptive analysis in order to summarize and gain a better understanding of the dataset and to assess if hackathon projects get continued after the event has ended thus answering $\mathbf{RQ}_1$ (section 4.1);
(2) We carried out a logistic regression analysis in order to model short-term project continuation (until day 6 after the hackathon ending) and to identify aspects that can be associated with project continuation directly after a hackathon, thus contributing to answering $\mathbf{RQ}_2$ (section 4.2);
(3) We carried out a survival analysis in order to study long-term project continuation (from 6 days to 5 months after the hackathon ending) and to identify aspects that can be associated with it, thus contributing to answering $\mathbf{RQ}_2$ (section 4.3).

We tested both models with all of the previously discussed parameters but only included variables that were statistically significant in either the logistic regression or survival analysis for our final models. We present the results of the analysis in the following.

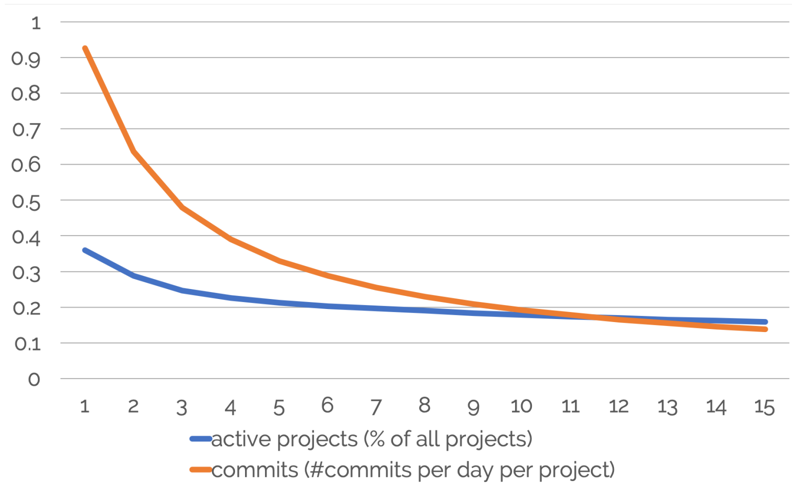

Fig. 3. Activity until 15 days after the hackathon.

4 RESULTS

4.1 Descriptive Analysis

On average, each hackathon hosted about 53 participants (SD = 57.14) and 21 projects (SD = 21.9). About one third of the events were (23 events, 29.49%) were non-collegiate events that had a specific theme and were connected to stakeholders outside of a university context while the remaining hackathons (55 events, 70.51%) were collegiate events. An overview of the descriptive statistics (mean, median and standard deviation as well as minimum and maximum) is provided in Table 2. For some projects GitHub repositories were created prior to the hackathon and teams started working on them thus showing technical preparation activity (number of commits prior to the hackathon in Table 2). Most of the teams (53.55%) voiced concrete continuation intentions (code 1a in Table 1) while 42.91% of teams did not mention if they intended to continue working on the project they started during the hackathon or not (code 1c). Only a small number (11.99%) of these groups aimed to finish their project as it was intended for the hackathon (code 2a). Most teams rather planned to add new features (73.19%, code 2b) or expand their user base (22.40%, code 2a).

Moreover, an analysis of potential correlations between the different variables revealed that teams either aimed to finish their prototype (code 2a) or add features (code 2b). Both intentions do not typically appear together as evident by a significant medium [15] negative correlation (r = -0.35, p < 0.001) between these two codes. Our analysis also revealed that teams who voiced intentions to add features to their prototype (code 2b) did not necessarily voice intentions to expand their user base (code 2c), acquire funding or create a startup and vice versa. This is evident by a small negative correlation (r = -0.29, p < 0.0001) between these codes.

Projects were carried out by teams of roughly 3 members (SD = 1.05) using an average of 5 different technologies (SD = 3.02). Teams were diverse in terms of their skills (mean skill diversity = 0.51, SD = 0.17) but their skill sets did not match the technical requirements of their project well. This is evident by the calculated skill matching (m = 0.25, SD = 0.21) and by the reported participant skills (Fig. 4 top) compared to the technologies they reported to be necessary for their projects (Fig. 4 bottom). This disparity may indicate that teams were not particularly qualified

Variable	Mean	Median	SD	Min	Max
Team size	3.28	3	1.05	2	8
Number of technologies used	4.82	3	3.02	1	18
Weighted win	0.21	0	0.32	0	0.9
Skill diversity	0.51	0.5	0.18	0	0.8
Skill matching	0.25	0.25	0.22	0	1
Common hackathon participation	0.08	0	0.3	0	3
Technical Preparation	0.25	0	0.43	0	1
Hackathon participation	1.73	1.33	1.31	0.5	17
Commit frequency	0.36	0	1.36	0.0	13.5
Average commit size	4.05	0	23.73	0.0	300
Average number of contributors	2.72	1	1.16	2	7

Table 2. Descriptive statistics for the dataset on various aspects of hackathon projects.

to carry out the projects they attempted. It may also point towards the desire of participants to work with technologies they were not familiar with. Most teams had members that had been to a hackathon at least one prior time (mean hackathon participation = 1.73, SD = 1.31). However, it was rare for team members to participate in multiple hackathons together (mean common hackathon participation = 0.08, SD = 0.3). Roughly one out of 5 projects won a prize at a hackathon (m = 0.21) but the relatively large standard deviation (SD = 0.43) points towards a disparity between different hackathons in terms of how many prizes were offered compared to the number of teams present.

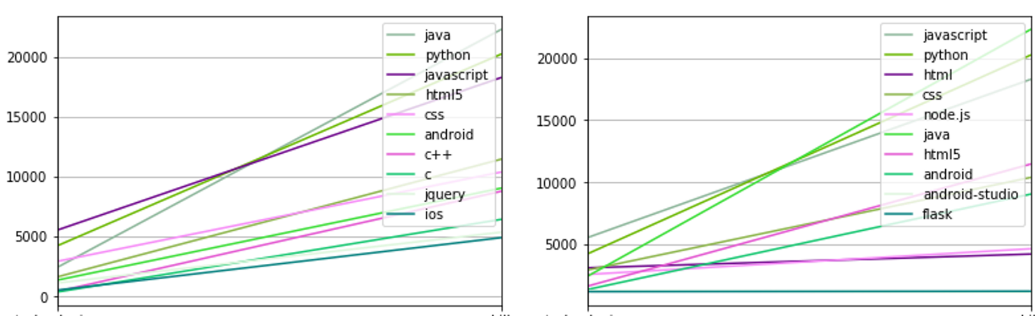

Fig. 4. 10 most frequently reported participant skills (left) and 10 most frequently used technologies to create the different hackathon projects (right).

4.2 Regression analysis

We fitted a mixed-effects logistic regression model to our data in order to investigate the relationship between the likelihood that a hackathon project will be continued short-term – that is within the first 6 days after the end of a hackathon (*project continuation*) – and the previously discussed aspects that might be associated with continuation, namely *number of technologies used in a project, winning, technical preparation, skill diversity, skill matching* and different aspects related to *continuation intentions*. We used logistic regression since the dependent variable is dichotomous and we ensured that the number of projects that show short-term continuation (rare outcome) is sufficient. To further address skewed variables, we also explored log transformation of our data which did not have a significant impact on the analysis. In order to account for projects not being independent but potentially taking place at the same hackathon, we modeled the hackathon (in terms of *hackathon.id*) for each project as a random effect. We further explored other potentially confounding variables, such as the *hackathon type* (in terms of its focus on e.g. providing learning opportunities to students, fostering entrepreneurship or building a community) and the *hackathon size* (in terms of the number of participants) and compared the resulting models and their regression coefficients using ANOVA . The results suggested that these variables are neither confounding nor having a statistically significant impact on the regression model. The results of the logistic regression are presented in Table 3. We only included those variables in the model that were either associated with short- or long-term continuation.

According to the model, technical continuation of a hackathon project after the end of a hackathon is positively associated with the number of technologies used in a project ($p < 0.001$) thus providing support for hypothesis $\mathbf{H}_8$. Our data also provides support for hypothesis $\mathbf{H}_9$ by indicating that a project winning one among the few prizes during a hackathon ($p < 0.001$) is positively associated with technical project continuation after a hackathon has ended. We also found support for hypothesis $\mathbf{H}_6$ in that technical preparation activities prior to the event ($p < 0.005$) were positively associated with continuation activity. In particular, for hypothesis 8 – which relates to the *number of technologies* of a project – the regression model suggests that the odds-ratio of a project being continued in the short-term by adding one more technology than originally planned is 1.29 (that is, $e^{0.26}$, regression coefficient in Table 3). Thus, holding all the other variables fixed, by increasing the number of technologies used by one unit we expect to see the odds of the project being continued in the short-term increase by 29%. Similarly, for hypothesis $\mathbf{H}_9$ – which relates to the continuous variable *weighted win* – the regression model suggests that the odds-ratio for a project being continued in the short-term with one-unit increase regarded the weighted win is 6.43 (or else, $e^{1.86}$) if all other variables are fixed. For hypothesis $\mathbf{H}_6$ as indicated by the binary variable *technical preparation* (1 indicates that the team technically prepared for the project before the hackathon and 0 indicates that the team did not prepare beforehand), the regression model suggests that the odds-ratio of a project that has been technically prepared being continued in the short-term over a project that has not been technically prepared is 2.12 (or else, $e^{0.75}$), thus the odds are 2.12 times higher. The marginal effects plots referring to the logistic regression model are presented in Figure 5.

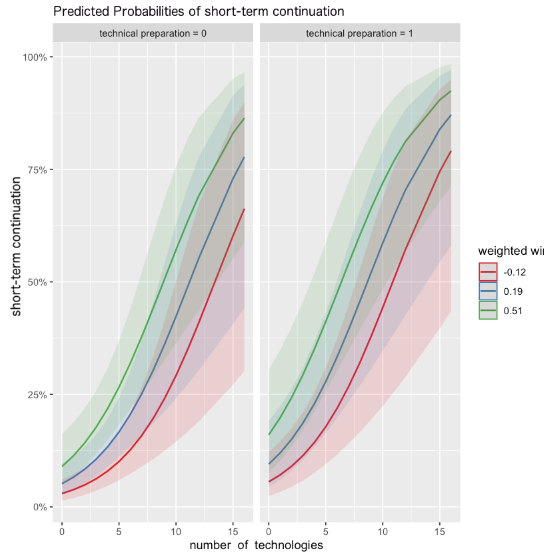

Fig. 5. The marginal effect plots for the logistic regression model and the statistically significant independent variables

Overall, projects that involve many technologies, projects for which teams worked on their respective code base prior to the hackathon and projects that won a prize at a hackathon where only few prizes were awarded compared to the number of competing teams had an increased probability to be continued in the short-term after the end of the hackathon compared to other projects. The remaining hypotheses $\mathbf{H}_1$ to $\mathbf{H}_5$ and $\mathbf{H}_7$ did not receive any support from our data analysis in the case of short-term project continuation and thus had to be rejected.

With respect to the goodness of fit, the marginal R^2 for the mixed-model was 0.27 and the conditional R^2 was 0.5 [49]. To explore the predictive accuracy of our model, we split the dataset following the Pareto principle [38]. We randomly selected 80% of projects in the original dataset for training our model and for testing we used the remaining 20%. Following this procedure, the predictive accuracy of the model was 0.76. That is, the model predicted correctly in 76% of the cases, whether a hackathon project would be continued short-term after the hackathon. Overall, the model classified 5 cases as true positives (TP) and 71 cases as true negatives (TN) while 3 cases were classified as false positives (FP) and 20 as false negatives (FN).

4.3 Survival analysis

The initial analysis of project activity after a hackathon revealed that more than 50% of the projects that initially showed continuation activity had stopped showing changes to their GitHub repository by day 6 after the end of the hackathon (Fig. 3). In order to explore project continuation beyond this point, we conducted a survival analysis focusing on projects that showed commit activity 6 months after the hackathon. This means that we consider a project to be active if it had at least one commit beyond 5 months after the hackathon had ended.

We used survival analysis as a modeling technique because it specializes in time to event data and is suitable for right-censored data [47], like in our case. Here – as in the regression analysis presented earlier – we confirmed that skewed distribution of data does not pose a problem. Following, we employed a Cox proportional-hazards regression model using eighteen covariates: the fifteen

	Short-term (GLM)			Long-term (Cox)		
	Coeffs (Err.)		LR Chisq	Coeffs (Err.)		LR Chisq
(Intercept)	-3.32	$(0.91)^{***}$				
Number of technologies	0.26	$(0.06)^{***}$	15.11	0.01	(0.03)	
Weighted win	1.86	$(0.40)^{***}$	18.93	0.28	(0.22)	
Technical preparation	0.75	$(0.34)^{*}$	3.79	0.29	(0.16)	
Skill diversity	-0.32	(0.89)		-1.25	$(0.61)^{*}$	3.93
Skill matching	-0.35	(0.62)		-0.75	$(0.34)^{*}$	5.02
Expanding reach	0.09	(0.49)	3.18	-0.55	$(0.23)^{*}$	6.07
Commits frequency (per day, until day 6)				0.11	$(0.03)^{**}$	7.94
Average commit size (until day 6)				-0.01	$(0.003)^{***}$	22.11

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Table 3. Regression models for short-term continuation and long-term survival. We define as "short-term" the timeframe between the first and the sixth day after the end of the hackathon and as "long-term" the time frame between the seventh day after the hackathon until the last day of observations. Short-term continuation is reported related to the probability of a project to get continued (positive) while long-term survival is reported related to the probability of a project to be discontinued (negative). The Likelihood Ratio (LR) test is reported only for the statistically significant aspects.

aspects that were based on the hypotheses discussed in section 2 and that were also used for the regression analysis and three additional metrics to describe the activity in a project's GitHub repository from day 1 after the hackathon until day 6 (commits frequency, average commit size and the number of contributors). As in the previous section, we modeled the hackathon during which a project was conducted as a random effect. For the survival analysis, we only used projects that showed commit activity beyond the first six days after the end of the hackathon. The test for the proportional hazard assumption in the Cox regression model (6 in appendix A.3) and the Kaplan-Meier plots (7 in appendix A.4) indicate that the proportionality assumption for the Cox regression model is not violated.

The results of the survival analysis are presented in Table 3. The results suggest that a team's skill match and diversity are significantly associated with long-term project continuation thus providing support for hypotheses $\mathbf{H}_4$ and $\mathbf{H}_5$ respectively. Our findings also provide support hypothesis $\mathbf{H}_7$ in that they indicate that a teams' intention to expand the reach of their project is significantly associated with long-term project continuation. One unit increase in a team's skill diversity is associated with 71% decrease in the hazards ratio. This suggests that projects of skill diverse teams are 71% less likely to be discontinued. Similarly, projects carried out by teams with matching skills are 53% less likely to be discontinued. Hypotheses $\mathbf{H}_1$ to $\mathbf{H}_3$, $\mathbf{H}_6$ and $\mathbf{H}_8$ to $\mathbf{H}_9$ did not received any support from our analysis related to long-term project continuation and thus will be rejected.

In addition, we also found that a project's activity during the first six days after a hackathon regarding commits to the respective GitHub repository to be significant. Our findings suggest that projects with intense activity during the first week after a hackathon (in terms of commits frequency) have an increased risk of being discontinued ($p < 0.01$). The unit increase in commit frequency is associated with 12% increase in the hazards ratio. This indicates that projects with high commit frequencies are 12% more likely to be discontinued. At the same time, we found larger commits to indicate continuation activity, however the hazard ratio is close to 1 (0.9, $p < 0.001$). This suggests that projects with large commits are only 1% less likely to be discontinued. Our findings are also depicted in the forest plot for the Cox proportional-hazards regression model (Fig. 6 in appendix A.2). The forest plot shows the hazard ratios (HR) for all covariates that we employed in the Cox regression. A HR > 1 indicates an increased risk of project discontinuation while a HR < 1 indicates a decreased risk for a project to be discontinued.

5 DISCUSSION

Our aim was to study if hackathon projects get continued after a hackathon has ended (**RQ**$_1$) and to identify how specific team and project related aspects can be associated with continuation (**RQ**$_2$, **H**$_1$ to **H**$_9$). Table 4 provides an overview of our findings which extend the theory of theory of collaboration by open superposition (COSP) [35] and test it in a new context, giving potentially broader reach, including team-based work, not just individual work.

	Continuation behavior		
	Short-term	Long-term	Neither
Task completion			
Small teams, lower coordination cost (**H**$_1$)			X
Team familiarity, more efficient (**H**$_2$)			X
Prior hackathon participation, realistic expectations (**H**$_3$)			X
Skill fit helps to cope with technical challenges (**H**$_4$)		X	
Skill diversity supports creativity, helps with progress on challenging tasks (**H**$_5$)		X	
Preparation activities prior to hackathon make follow-up easier (**H**$_6$)	X		
Motivation			
Continuation intentions are an indicator of motivation to continue (**H**$_7$)		X	
Technical complexity sparks interest (**H**$_8$)	X		
Prizes create motivation (**H**$_9$)	X		
Short-term activity lowers probability of long-term continuation			

Table 4. Overview of aspects related to different continuation behavior patterns.

5.1 Do hackathon projects get continued after the event has ended? (RQ$_1$)

One contribution of this work is the systematic analysis of a relatively large number of hackathon teams participating in various hackathons in different domains while prior work has mainly focused on continuation activity of a small number of teams after individual events in a specific context [13, 33, 53]. Our work extends the current focus of research on hackathon sustainability by providing a large-scale overview of technical project continuation after a hackathon's end including aspects that can be associated with continuation activity.

Our analysis suggested that most projects in our sample (about 65%) get discontinued after a hackathon, at least in terms of commits to their connected GitHub repositories. This finding is in line with prior work on civic hackathons [7] and on events that aim to attract newcomers to online production communities such as Wikipedia where scholars found that newcomers that individuals who attend such events rarely continue to contribute to a community afterwards [21].

From the remaining projects in our dataset, almost half of them show activity in their connected GitHub repositories during the first week after the hackathon. After this point only 17% of the projects carry on their work. This may indicate that teams exhibit different continuation behaviors. Some might polish their prototype within a week after a hackathon while others may disengage from continuation for a short period of time and continue working on their project afterwards. Differences related to continuation behavior have not been extensively studied in related work on hackathon project continuation yet [7, 53]. Our analysis also revealed a connection between winning one of the few prizes at a large hackathon and short-term technical project continuation. We did not find the same connection between winning a prize during a hackathon in general and short-term continuation which provides indication that competition as such might only serve as motivation to continue working on a project when winning it can reasonably be perceived as a major achievement. This finding is in line with the theory of superposition in that winning can serve as motivation for individuals to continue working on their projects [35]. Extrinsic rewards such as prizes have been controversially discussed e.g. in the context of education. Some researchers argue that they can negatively affect intrinsic motivation [20] while others suggest the opposite [17]. Our work contributes to our understanding of the potential positive effect of extrinsic rewards which are perceived to be significant in short-term collaborative settings such as project-based learning [66]. One could however also reasonably interpret this finding as an indicator that great projects – as evident by them winning one of the few prizes at a large event – by themselves provide motivation for teams to continue working on them with the prize only being an indicator for the quality of a project.

5.2 Which aspects may be associated with technical project continuation? ($\mathbf{RQ}_2$)

Our findings provide insights into antecedents of technical continuation after a hackathon has ended indicating how different aspects related to task completion and motivation are associated with post-hackathon activity (Table 4 provides an overview) thus extending the theory of collaboration by open superposition (COSP) [35]. Moreover, our findings contribute to our understanding of how different team and project related aspects can relate to continuation behavior after a hackathon and may extend to continuation behavior after time-based social computing events in general. Our findings suggest that various team and project related aspects – such as winning a prize ($\mathbf{H}_9$), skill diversity ($\mathbf{H}_5$) and others – that are associated with project continuation are different regarding **short- and long-term** continuation activity. To the best of our knowledge, this distinction has not been extensively studied in literature on hackathon continuation or other work on time-based social computing settings such as civic data related events [34] or events that aim to attract newcomers to online production communities [21]. Moreover, it is important to note that while there are certain task completion and motivation aspects associated with both short- and long-term continuation, there is no single aspect that is associated with both. This, along with the finding that intensive short-term continuation activity is associated with a lower probability of long-term continuation suggests that these two types of continuation are very different phenomena as we will discuss in detail in the following.

In addition to the previously discussed relation between winning one of the few prizes at a large hackathon and short-term technical project continuation activity ($\mathbf{H}_9$) our analysis revealed a similar connection between the number of technologies that were used for a project on short-term technical project continuation activities ($\mathbf{H}_8$). This finding can indicate that teams who attempted to complete complex projects using many different technologies might have not reached the state of completion they envisioned during the short duration of a hackathon. They thus might have needed to continue working on their projects after the event to get it in a state of completion that is acceptable to them. Finally, the effect of preparation activities as represented by commits to a GitHub repository prior to a hackathon (**H_6**) also points towards a teams' focus on technical project aspects – such as setting up a working space for a project – which may suggest a strong focus on the competitive aspect of a hackathon rather than the intent for long-term continuation. It can also point to teams potentially perceiving a hackathon as a means to create technically impressive prototypes that can be added to their open source portfolio to showcase their skills for potential future employers [45]. Other activities such as pre-hackathon discussions that were found to foster project continuation in a civic [33] or corporate [53] setting have not been studied here.

Another intriguing finding – that contrasts with existing work on hackathon continuation in corporate [53] and civic [33] events – is that while winning can potentially provide a short-term boost to follow-up activities, **intensive activity following a hackathon** can be detrimental to long-term continuation. Intensive short-term continuation activity may indicate prototype polishing, rather than the search for an appropriate continuation setting, which has been found to lead to continuation in corporate and civic settings [34, 53]. This interpretation also appears to be supported by our finding that **larger commits** during the first few days after a hackathon may point towards longer-term continuation activity since larger commits might indicate larger changes as compared to smaller polishing activities. The aforementioned aspects expand our current understanding of the potential long-term effects of short-term continuation activity. The observed detrimental effect of intensive short-term continuation activity should however not be interpreted as a suggestion to discourage continuation activity directly after a hackathon. It rather provides additional indication that technical continuation activity might take different forms including short-term polishing activities and longer-term developments of larger changes.

Related work in the context of organizational [36] and software development teams [26] and learning groups [44] suggests that **skill diversity** (**H_5**) within a team can positively affect team performance in particular when working on creative or innovative tasks. As with skill alignment, better team performance could result in a product more worthy of follow-up work. Skill alignment has also been discussed in prior work on project continuation in a corporate context [53]. Our analysis provides indication that skill diversity can indeed be beneficial for teams not only related to their performance during a specific task but also related to technical continuation behavior. Our work thus contributes to extending the findings of related research and indicates that skill alignment might benefit long- rather than short-term project continuation, presumably by allowing teams to make technical progress easier [35]. Moreover, our findings also reveal a positive influence of a teams' capability to cope with the technical requirements of a project (**skill matching**, **H_4**) and long-term project continuation thus suggesting that attempting to learn new skills during a hackathon can make it harder for teams to continue working on their project [35] and also inhibit a teams' ability to develop a technical artifact they perceive to be worthy for continuation as previously reported in the context of corporate hackathons [53].

Our data did not reveal a strong connection between **continuation intentions** in general and actual continuation behavior in the form of continued GitHub activity after a hackathon (**H_7**). We did however find the intention of teams to **expand their user base, acquire funding or create a startup** (code 2c) to be positively associated to longer-term continuation activity while technical continuation intentions such as **finishing the technical development of a team's project as it was intended during the hackathon** or **adding new features** was not connected to continuation activity. Our analysis thus expands the findings of Carruthers [7] who found that most projects did not get continued despite participants voicing continuation intentions by indicating that specific continuation intentions are associated with longer-term continuation activity while continuation intentions in general are not necessarily related to longer-term continuation activity. This distinction has not been extensively discussed in prior work on hackathons or similar time-based social computing settings e.g. in the context of online communities [21].

Our findings also did not reveal a strong connection between the **type of a hackathon** and project continuation activities after an event has ended. The type of a hackathon in our study reflects its goals in terms of e.g. providing learning opportunities, fostering entrepreneurship or building a community. This finding can thus indicate that most events we studied might not have focused on supporting project continuation. It can however also indicate that hackathon teams might require additional support from hackathon organizers and potential stakeholders to foster project continuation. Stakeholder involvement has been discussed the context of civic [3, 11] and entrepreneurial hackathons [13]. This support can e.g. include them suggesting challenges as reported by Ciaghi et al. [11] or provide data and serve as participants as reported by Baccarne et al. [3]. Both studies took place in a civic context.

Finally, we did not find a strong connection between **team size** ($\mathbf{H}_1$) and prior **individual or common hackathon participation** ($\mathbf{H}_2$ and $\mathbf{H}_3$) on continuation activities neither short- nor long-term. There was however little variance in team sizes since teams in general had between three and four members (Table 2). It is surprising though that previous individual and joint hackathon participation does not appear to influence technical continuation behavior since team familiarity has been found to improve team coordination and efficiency [27] which has been linked to project continuation in the context of corporate hackathons [53]. This finding can also point to other common activities we did not observe in this study such as common classes or common projects outside of the context of hackathons being more important than common hackathon participation.

5.3 Limitations

This work is based on an archival analysis of a hackathon database and as such, it has certain limitations.

We only had access to events and activities that were logged in the Devpost hackathon database. While being a rich dataset, Devpost does not cover potentially relevant information about aspects that can affect team practice, such as a team's motivations for participating in a hackathon, their preparation activities before the actual hackathon beyond collaborating on a common code base, the relationships between participants beyond attending hackathons together including their potential affiliation to hackathon organizers, informal communication while working on their project and the way they share information and resources. The nature of the dataset also limits our ability to provide evidence for causal relationships. The dataset implies that project and team characteristics were manifest prior to the observed continuation activities, which argues against reverse causality, i.e., those activities could not bring out the project characteristics. There could, however, be aspects that are associated with both project characteristics and continuation. Our study design cannot rule this out. Our findings might also be confounded by factors that we either were not aware of despite a thorough investigation of prior work or that we could not study does to the nature of our dataset.

A second limitation is that we defined technical project continuation in terms of activities in a project's linked GitHub repository. This is a conservative measure, since a team may choose to transfer their work to another repository or move their work to another workspace. Alternatively, a team may use their hackathon project as inspiration for other projects, thus continuing a project in another form or with a different objective. Additionally, continuation is not the objective for every project. In some cases, participants try out new technologies or simply attend hackathons for the experience. The fact that specific continuation intentions were associated with long-term continuation suggests that the plans and goals of participants can be important, and merit further attention on continuation though. Participants also might engage in other types of continuation activities that are not related to the technical development of their hackathon project. Moreover, our study focuses on two specific points in time after a hackathon event has ended which poses a limitation towards the generalizability of our findings. We attempted to mitigate this threat by making an empirically founded decision based on our available dataset and our analysis of continuation activity which pointed towards day 6 as a major turning point for continuation activity.

Finally, we only used a small part of the data that was recorded in Devpost which itself allows the post-editing of hackathon-related information without providing access to revision history. This means, that a participant, desiring to keep their information up to date, may add or remove skills from her/his profile after the end of a hackathon, thus resulting in a different reported skill set than the one s/he had while s/he participated in a particular project. In order to limit the effect of such inaccuracies, we focused our analysis on hackathons that took place during the last month before we collected the dataset. Nonetheless, this does not ensure that all data collected was exactly the same as the day the hackathons took place.

6 IMPLICATIONS AND OPEN RESEARCH QUESTIONS

The findings presented in this paper have a number of implications for research and practice. Our findings can serve as valuable guidance for organizers and participants of time-based social computing settings that are interested in project continuation. Organizers could use these insights to rethink their strategy of providing prizes or suggest forming diverse teams whose skills fit the technical requirements of a project. Participants that aim to continue a project after an event could also use the same insights and search for individuals with diverse skills that fit the requirements of their project to join their team. Moreover, our findings shed light onto differences between aspects associated with short- and long-term continuation activity. Insights into short-term activity e.g. through automated monitoring of GitHub repositories directly after an event might provide valuable insights into technical progress and serve as a basis for targeted suggestions.

Moreover, hackathons and similar time-based social computing events can be perceived as impromptu learning opportunities and, as such, participants might attend them simply to gain or practice certain skills. On the one hand, this can be suggested by the discrepancy between technologies required by a project and a team's skillset (Fig. 4): participants choose to join a project even though, at the outset, they do not have the necessary skills for carrying it out. On the other hand, this could also be indicated by the skill diversity of teams working on the same project: participants from different backgrounds with diverse skillsets, get together to work on a common task from a different individual viewpoint. One could argue that such discrepancies or skill diversity could potentially be harmful for the successful completion of the project. However, this could also serve as a learning opportunity if the activity itself is appropriately structured and the participants receive appropriate scaffolding. As discussed previously, skill diversity along with skill matching appear to be positively associated with long-term continuation. This could suggest that through long-term, consistent collaboration, teams build collaborative knowledge: they contribute complementing expertise, but they also learn from each other in a social context [61]. In this sense, one could envision these events as a project-based learning paradigm with continuation here does not only refer to the actual "life" of the project after the end of the event. Instead, it extends to the knowledge that has been built and shared and how participants transfer this new knowledge and apply it in their own contexts: people working together to carry out a common project and learn together through practice [10]. Therefore, it would be interesting to explore whether and how time-based social computing setting such as hackathons can impact participants' skillsets and future endeavors.

Further studies incorporating experiments could more definitively provide evidence about the causal relationship between event, project and team characteristics and continuation activity. The following questions could guide researchers in this direction. Which other aspects beyond the ones discussed here can be associated with project continuation? How are short- and long-term project continuation different from one another? How is skill diversity associated with other aspects of such events beyond long-term project continuation? How is external motivation such as handing out prizes after an event associated with intrinsic continuation intentions? How can analytics to monitor technical progress of teams after an event be used to make targeted suggestions to foster longer-term continuation activity?

7 CONCLUSION

This paper contributes to our understanding of short- and long-term technical continuation behavior after a time-based social computing event by reporting on findings from a large-scale study of the hackathon database Devpost. Studying project continuation related to a theoretically founded selection of potential antecedents of continuation behavior we established that short- and long-term project continuation behavior are different phenomena. We found short-term continuation behavior to be associated with technical preparation activities prior to a hackathon, the number of technologies a team uses to create a project and winning one of the few prizes at a large event, while long-term continuation was conversely related to skill diversity and skill matching among team members and their intention to expand their project's reach. Moreover, we also found that intensive short-term activity can be detrimental to long-term continuation. These insights provide hints for organizers and participants of time-based social computing events on how to prepare, conduct and follow up on an event to be positively associated with project continuation after it has ended. In the future we are planning to conduct additional qualitative studies to assess the potential impact of participant and organizers motivations and expectations on continuation behavior and to explore continuation activities beyond technical contributions to the same repository that teams used during an event.

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A APPENDIX

A.1 Inter coder agreement scores

Code	1a	1b	1c	2a	2b	2c
Percentage agreement	96.79	100.00	98.48	95.95	99.16	92.91
Cohen's kappa [14]	0.94	1.00	0.97	0.74	0.83	0.76

Table 5. Percentage agreement and inter-rater agreement for coded continuation intentions.

A.2 Forest plot

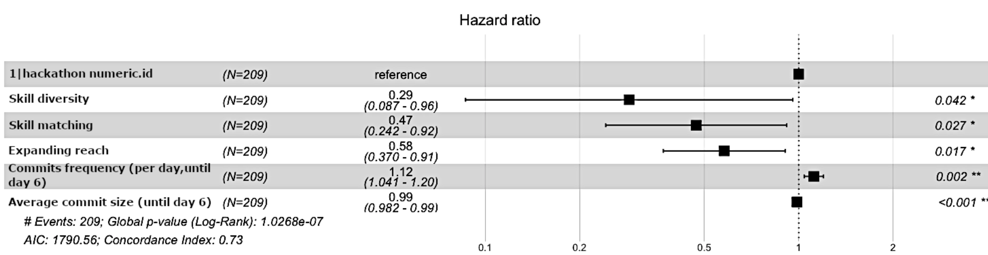

Fig. 6. Forest plot for the Cox proportional-hazards regression model.

A.3 Testing the proportional hazards assumption

(Variable)	chisq	df	p
Number of technologies	0.8995	1	0.343
Weighted win	0.2959	1	0.586
Technical preparation	0.0480	1	0.827
Skill diversity	1.5773	1	0.209
Skill matching	1.1858	1	0.276
Expanding reach	0.4485	1	0.503
Commits frequency (per day, until day 6)	2.8648	1	0.091
Average commit size (until day 6)	2.9632	1	0.085
GLOBAL	25.3505	19	0.149

Table 6. Test for the proportional hazard assumption in the Cox regression model using the function cox.zph(). The test is not statistically significant for any of the covariates, and the global test is also not statistically significant. Therefore, we can assume the proportional hazards.

A.4 Kaplan-Meier plots

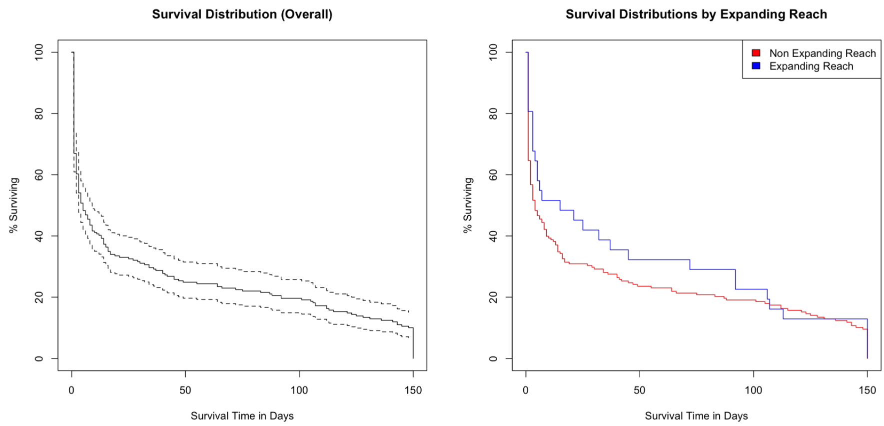

Fig. 7. Kaplan-Meier plots for the null Cox proportional-hazards model and for the model including the categorical variable *Expanding Reach*

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