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Why Do Episodic Volunteers Stay in FLOSS Communities?

Ann Barcomb*†§, Klaas-Jan Stol†‡, Dirk Riehle* and Brian Fitzgerald†§
*Open Source Research Group, Friedrich-Alexander-Universität Erlangen-Nürnberg
†Lero—the Irish Software Research Centre
‡School of Computer Science and Information Technology, University College Cork
§Dept. Computer Science and Information Systems, University of Limerick
ann@barcomb.org, klaas-jan.stol@lero.ie, dirk@riehle.org, bf@lero.ie

***Abstract*—Successful Free/Libre and Open Source Software (FLOSS) projects incorporate both habitual and infrequent, or episodic, contributors. Using the concept of episodic volunteering (EV) from the general volunteering literature, we derive a model consisting of five key constructs that we hypothesize affect episodic volunteers' retention in FLOSS communities. To evaluate the model we conducted a survey with over 100 FLOSS episodic volunteers. We observe that three of our model constructs (social norms, satisfaction and community commitment) are all positively associated with volunteers' intention to remain, while the two other constructs (psychological sense of community and contributor benefit motivations) are not. Furthermore, exploratory clustering on unobserved heterogeneity suggests that there are four distinct categories of volunteers: *satisfied*, *classic*, *social* and *obligated*. Based on our findings, we offer suggestions for projects to incorporate and manage episodic volunteers, so as to better leverage this type of contributors and potentially improve projects' sustainability.**

***Index Terms*—community management, episodic volunteering, open source software, volunteer management**

I. Introduction

An increasing trend in the volunteering sector, which has also been observed in Free/Libre Open Source Software (FLOSS) projects is that of the *episodic volunteer*. Episodic volunteers, in contrast to habitual volunteers, make contributions infrequently or irregularly, and for a short duration. The term encompasses one-off as well as returning contributors. It has been proposed that infrequent contributors have different motivations than frequent contributors [1], and recent research has shown differences in outlook between returning participants and those who make only one contribution [2], or who fail to have their contribution accepted [3]. Crowston [4] argued that highly skilled knowledge workers are extremely mobile, and cannot be retained through salary alone—rather, firms need competency in volunteer management. Understanding the factors that might affect retention of episodic volunteers can lead to a better understanding of voluntary participation. This in turn can lead to important insights for FLOSS communities as retaining contributors is essential to projects' sustainability.

While there have been a few studies of episodic volunteers in recent years, there has been scant research that seeks to understand what might make this specific type of volunteer stay in FLOSS communities. Interestingly, the general literature on volunteering (not specific to FLOSS) is in a more mature state. Hence, we draw on this general volunteering literature to investigate a set of common factors associated with episodic volunteers' retention. While some of these factors have been discussed in previous work, this study is the first to explore these factors in an integrated approach.

We do not suggest that the concepts we use cannot also be applied to habitual contributors, and indeed it is possible that the model might prove more broadly applicable. However, we have chosen to focus on episodic volunteers in order to produce less ambiguous results.

In this paper we make the following contributions:

- We develop a theoretical model of retention of episodic volunteers in FLOSS communities and assess it through a survey.
- We examine the moderating effects of age, gender, tenure, and contribution type on the retention of FLOSS episodic volunteers.
- We present the results of an exploratory cluster analysis of our data, which identified four distinct categories of volunteers.

The remainder of this paper is organized as follows. Sec. II presents related work from both the FLOSS and general volunteering literature, while Sec. III builds upon the literature to derive our hypotheses. Sec. IV describes our methodology. Sec. V explores the quality of the data and the measurement model, and Sec. VI tests the theory. Sec. VII discusses implications and limitations, and concludes the paper.

II. Related work

A. Contributor Retention

A key concern in any FLOSS project is its sustainability, and a major factor that affects this is the project's ability to retain contributors [5]. Previous studies found that a high level of developer turnover has negative impacts on the code quality and on a community's ability to retain knowledge [6], [7].

Some factors which affect retention cannot be controlled: the popularity of the project, and how early in the life-cycle a developer joins [8], [9]. However, there are also measures that communities can take to encourage retention. For example, modular code and early social interactions with peers are both associated with retention [8], [10]. But even *before* joining, people may face technical and social barriers. These barriers affect not only whether they will attempt or succeed at an initial contribution, but also whether they will attempt again [3], [11], [12]. The acceptance of a person's first contribution and their prior coding experience affects their eventual retention in the community [8], [13], [14]. Furthermore, a person's ability to overcome barriers can depend on the dissonance a person experiences between their motivations and experiences, and the type of barriers [15]–[17]. Steinmacher et al. [11] identified five categories of barriers affecting FLOSS newcomers: technical hurdles, documentation, social interaction, newcomers' previous knowledge, and finding a way to start. Diminishing barriers to entry has therefore become a focal point in the discussion of attracting and retaining contributors [18], [19].

Sustained participation depends not only on a person's experience with a community, but also on their own state of mind. People who are driven by a personal need are less likely to remain than those who enjoy the work [20]. However, people who identify with the community and see themselves as participants are more likely to remain [21], [22].

Despite considerable research, the FLOSS literature lacks an understanding that explains developer retention. In the general volunteering literature, Omoto and Snyder [23], [24] developed the Volunteer Process Model, which categorizes factors by level of analysis (agency, individual volunteer, and social system) and the stage of the volunteer process they pertain to (antecedents, experiences, and consequences). Based on the Volunteer Process Model, at least two models have been developed focusing on retention at the individual level of analysis: the Three-stage Model of Volunteers' Duration of Service [25], and the Episodic Volunteer Engagement and Retention (EVER) model [26]. The individual level of analysis is the logical place to focus, as it includes most of the factors identified in the FLOSS literature, such as demographics, prior experiences, motivations, and skills [23]. As we build our theoretical model (see Sec. III), we draw on these models, which also informed our recent exploratory study that focused on practices for managing EV in FLOSS communities [27].

B. *Episodic Volunteers in FLOSS Communities*

Episodic volunteering (EV) describes short-term, erratic, and conditional participation [28], including both one-off and returning contributors. In the general EV literature, retention does not describe the conversion of an *episodic* volunteer to a *habitual* volunteer (i.e., a non-episodic volunteer), but to an ongoing, low frequency relationship. A contributor is considered habitual when participation occurs at regular, predictable intervals, or when it persists for more than a few months continuously [28]–[30]. Episodic volunteers are part of the changing face of volunteerism, where more people contribute less time, less consistently [28], [31]. Understanding EV and informing organizations, including FLOSS communities, to make better use of the potential that episodic volunteers offer, is therefore extremely important for FLOSS projects' sustainability [32], [33].

It has long been established that a relatively small number of people, so-called *core* contributors, make the largest proportion of contributions [34], [35]. Yet other contributors, known as *peripheral contributors*, are still important for the well-being of the project. They disseminate information about the project to a wider audience, increase innovation, and engage in citizenship behaviors such as monitoring copyright infringement and enforcing community rules [1], [36]–[38]. Nonetheless, there are issues with peripheral contributors: their work is more likely to be rejected, and it is more likely to diverge from the project's vision [2], [3]. While there are similarities between core and peripheral contributors, for instance in the range of motivations that lead them to contribute [1], there are also differences that might affect retention. Peripheral contributors are more likely motivated to participate to gain a reputation, and may be more driven by a personal need [1], [20].

The challenges of episodic participation are not limited to FLOSS communities, but can also exist within firms. There are a number of parallels between knowledge workers and FLOSS participants, such as non-financial motivations and dynamic participation stemming from multi-teaming, which mean that managers may benefit from treating employees as volunteers [4], [39]. FLOSS development patterns are now also seen within firms, such as inner source, where voluntary inter-team collaboration are encouraged [40], [41]. Usually these contributions take the form of sharing expertise or adding features outside of an employee's assigned focus in order to facilitate their own work, and participation in a particular project is therefore typically episodic in nature. Episodic participation is thus widespread and should be of interest to both FLOSS projects and organizations which wish to grow flourishing communities.

So far, much of our discussion has focused on code contributions. Carillo et al. [42] pointed out that the omission of non-code contributions is a clear limitation of much existing FLOSS research. In any FLOSS project involving more than a few people, contributors engage in a wide range of non-code activities, from project planning to advocacy [21], [43]. Our current understanding of FLOSS contributors as either 'core' or 'periphery' comes from digital records such as code submissions and bug reports (e.g., [44]), and the literature on retention has a similar dependency. However, more than a quarter of FLOSS participants are primarily involved in non-code activities [45], making it difficult to generalize our understanding of FLOSS participation from code contributors alone. Thus, there are clear opportunities to address this gap in the FLOSS literature, and the current study seeks to contribute to this goal.

Surveys of FLOSS contributors have also inclined toward considering a small number of projects [42] or a group of large and mature projects [12]. The majority of FLOSS communities are, however, small [46], and even small projects can have episodic contributors [27]. Similarly, the general EV literature concerning retention has largely focused on single case studies (e.g., [26], [47]). One of our objectives was to consider a large number of projects of varying sizes.

III. Theory Development

We now turn our attention to developing a theoretical model to set the focus of our study. We ground our model in the general volunteering literature, which presents five key constructs that were identified as being particularly relevant to the retention of volunteers [23]–[26]. These constructs are: *contributor benefit motivations, social norms, psychological sense of community, satisfaction*, and *community commitment*. A previous study used this as a conceptual framework for a qualitative survey of episodic participation in FLOSS [27].

Consistent with Ajzen's Theory of Planned Behavior, a contributor's *intention* to remain is the single best predictor of their *actual behavior*, and is therefore widely used as a proxy for retention [25], [48]. We now discuss each construct and develop hypotheses pertaining to FLOSS episodic volunteers.

Contributor Benefit Motivations: Contributor motivations have been extensively studied and documented in the FLOSS literature; Von Krogh et al. provide an overview [49]. Despite the extensive attention this topic has received, there is still disagreement on whether FLOSS community members who have a personal need to use the software are *less likely* to remain [20] or *equally likely* to remain [21]. Generally it is accepted that among peripheral contributors, extrinsic motivations are not associated with retention [1], [12]. Motivation can also be classed as other-oriented (also known as altruistic), or self-oriented, when it concerns an individual contributor's personal benefit [26], [50]. Intrinsic motivations such as "to have fun" and extrinsic motivations such as "increased employment opportunities" are both examples of contributor benefit motivations. Disagreements exist in the general episodic volunteer literature as well; Hyde et al. found that general episodic volunteers are *less likely* to remain when they seek personal benefit [26], but Handy et al. found that motivation had no effect on retention [51]. Hyde et al. proposed that the *context* of EV determines the effect of contributor benefit motivations on retention [26]. We therefore are guided by the FLOSS literature in our hypothesis:

HYPOTHESIS 1 (H1). *Contributor benefit motivations are positively associated with intention to remain among FLOSS episodic volunteers.*

Social Norms: The term social norms refers to the pressure that participants experience as a result of how those in their environment view the volunteering activity [23]. In a FLOSS context, little research has been conducted on the effects of social norms on participation, although an exploratory study suggested that non-code contributors in particular are influenced by social norms [27]. The majority of work situating FLOSS contributors within their environment has looked at cultural factors [52] or organizational culture [53]. In the general volunteering literature, social norms are a significant contributing factor in recruitment [23]. Episodic volunteers are even more likely than habitual volunteers to be recruited out of a sense of civic responsibility [47], and social norms are an identified construct in EV retention [26]. We therefore propose:

HYPOTHESIS 2 (H2). *Social norms are positively associated with intention to remain among FLOSS episodic volunteers.*

Psychological Sense of Community: The term psychological sense of community describes the motivation a person experiences upon encountering a simpatico group [23]. Psychological sense of community is believed to be associated with an increased intention to remain among FLOSS contributors [54], [55]. Even peripheral and one-time contributors can experience psychological sense of community [12], [56]. In EV it is unclear if psychological sense of community is associated with retention or not [26], [33]. One possible explanation for the difference is that Hyde et al. [26] considered only a local group, whereas psychological sense of community can encompass a geographically dispersed community of like-minded people [57], a point which is especially relevant in a FLOSS context. Previous FLOSS findings suggest:

HYPOTHESIS 3 (H3). *Psychological sense of community is positively associated with intention to remain among FLOSS episodic volunteers.*

Satisfaction: Satisfaction occurs when a person's expectations match their experiences [58]. Satisfaction has been identified as the single best predictor of FLOSS participants' intention to remain [59]. In EV, satisfaction has been found to be an extremely important factor in retention [26]. However, it has also been claimed that expectations of satisfaction decrease over time [25], [60] and that, consequently, satisfaction is not a distinguishing factor in EV retention [47]. Considering the mixed findings from the volunteering literature, but the clear message in the FLOSS literature, we propose:

HYPOTHESIS 4 (H4). *Satisfaction is positively associated with intention to remain among FLOSS episodic volunteers.*

Community Commitment: Community commitment describes how people identify as members of the community and agree with that community's goals [61], [62]. FLOSS contributors who identify with the values and objectives of FLOSS, or who see themselves as members of a community are more likely to remain [21]. This observation extends to peripheral contributors [38], [56]. In the general volunteering literature, community commitment and viewing oneself as a volunteer are predictors of intention to remain [25]. This is also true of episodic volunteers [26], [63], although the effect is less pronounced than among habitual volunteers [51]. The combined volunteering and FLOSS literature is in agreement on the relevance of community commitment, leading us to propose:

HYPOTHESIS 5 (H5). *Community commitment is positively associated with intention to remain among FLOSS episodic volunteers.*

IV. Research Design

We conducted an online survey among episodic volunteers in FLOSS projects. Surveys are suitable to gather a large number of responses, necessary to evaluate a theoretical model such as ours. We discuss the survey design, participant recruitment, data collection, and analysis procedures.

A. Survey Design

The survey consisted of eight sections: demographics, volunteering experience, and the six *constructs* in our theoretical model. Each of these six constructs is a so-called *latent variable*, representing abstract or complex phenomena. To measure latent variables, we can define each as a set of related indicators, which are called *measurement instruments*. For our model, we adopted instruments from the volunteer and organizational literature. All instruments had previously been applied to volunteering (e.g., [26]), and we tailored these to suit the FLOSS context. For each indicator, we used a five-point Likert scale (ranging from 1 representing strongly agree, to 5 representing strongly disagree). All constructs in our model are "reflective" (as opposed to "formative"); any change in a reflective construct is *reflected* by its indicators [64]. Our survey instrument is provided in an online appendix [65].

Below we provide details about the survey instrument:

- **Demographics.** Demographic information was optional. Participants self-reported their gender, year of birth, and education level.
- **Volunteering Experience.** Participants were asked about the number of projects they contributed to episodically and habitually, in the last year; when they first contributed; their estimated hours per month; and primary area of contributions, aligned with the language used in the FLOSS '13 survey [45].
- **Contributor Benefit Motivations.** We adapted an instrument developed by Won and Park [66]. Some questions could not be adapted to a FLOSS context and were dropped, leaving six questions.
- **Psychological Sense of Community.** We adapted an instrument developed by Costa et al. [67]. One question was not applicable to online participation and was removed, leaving three questions.
- **Social Norms.** We used an eight question instrument with three reverse-scored items developed by Callero [68].
- **Satisfaction.** Satisfaction was measured with six questions developed by Clary et al. [58].
- **Community Commitment.** We adapted an instrument developed by Mowday et al. [61]. Employment-specific questions were discarded, leaving 9 items, of which 4 were reverse-scored.
- **Intention to Remain.** We used an eight question instrument developed by Garner and Garner [69].

To ensure the language of the survey was appropriate, we conducted a small pilot study, during which we observed three experienced FLOSS contributors completing the survey, and interviewed them about their experience afterwards. Based on this, we improved our instructions on how to identify EV.

B. Participant Selection

We conducted an open survey which was advertised in a number of ways: at general FLOSS events such as FOSDEM and T-DOSE; at community-specific events such as Mozfest, the European Perl Conference, and DjangoCon; on community-specific forums and mailing lists such as Debian forums; and on social media such as Twitter, LinkedIn and Reddit. A complete list of the venues where the survey was promoted can be found in the appendix [65]. We decided on this approach over using a list of previously identified episodic volunteers obtained from GitHub because we wanted to ensure non-code contributors were adequately represented—as pointed out above, non-code contributors may not leave a digital trace.

TABLE I
VOLUNTEERING CHARACTERISTICS

	Mean	Med	Max	Min
No. projects participated in habitually	1.76	1	10	0
No. projects participated in episodically	4.43	3	79	1
Primary episodic project (years participated)	5.66	3	20	< 1

The survey only targeted episodic volunteers. The stated purpose was understanding volunteering habits, where volunteering was described as *"any type of unpaid activity, including: documentation, translation, bug reports, mentoring, programming, or any other activity you do for an open source project."* We only included participants who self-identified as engaging in EV in the previous 12 months. EV was described as not habitual, where habitual was defined as: *"10 or more substantial contributions"* or *"2 or more contributions of any size per month, for 6 consecutive months."* This description was the lead author's interpretation of the EV literature, based on her experience as a FLOSS contributor, and was provided in response to feedback from the pilot study. The EV literature provides only vague boundaries, such as *"someone who gives service on a regular basis for less than six months"* is episodic, while *"serving on a committee that meets once per month all year long"* is habitual engagement [28].

Our respondents participated in a wide range of projects, not only large projects such as Drupal and the Linux kernel, but also small projects like Butterfly Effect. In total, respondents represented 75 different communities. Projects with more than one mention included Blender, Debian, Perl, Joomla!, and ONOS. Table I presents the characteristics of our sample.

A common challenge in sample studies such as ours is to achieve a sufficiently large number of respondents. Given the time commitment that was required of respondents, we used the incentive of a prize draw (with gift certificates of $100, $50, $25, $25) in order to increase the number of responses. Prize draws have been shown to improve completion rates for web-based surveys, and are in fact often expected [70], [71].

C. Data Collection and Analysis

The data were collected between 2016 and 2017. In total, 118 people started the survey and identified themselves as episodic volunteers. Of these, 101 completed the survey, for a completion rate of 86%.

We used Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the data, because it focuses on explaining variances of dependent variables. PLS-SEM is suitable because the instruments were not previously applied to a FLOSS context—therefore, we could not be certain of the fitness of all item measures [72]. A second consideration for PLS-SEM was its capability of achieving a solution with smaller numbers of respondents than what would be required for covariance-based structural equation modeling (CB-SEM), although adequate sample sizes of at least 90 are still required to recognize medium effects and avoid falsely identifying significant paths [73]. We conducted our analyses using the PLSPM package in R [74] and SmartPLS version 3 [75].

V. Data Quality and Measurement Model

In this section we first evaluate the quality of the collected data, followed by an evaluation of the measurement model. These analyses are necessary to be able to trust the evaluation of the theoretical model. Sec. VI presents that evaluation.

A. Data Quality

We conducted a number of tests to evaluate the quality of the data, including sampling adequacy, common method bias, and representativeness.

1) Sampling Adequacy: To ensure that our data were suitable for factor analysis, we conducted two tests. We first conducted Bartlett's test of sphericity on all constructs. P values less than .05 indicate that factor analysis may be useful; we found a p value $=$ .0000. Second, we calculated the Kaiser-Meyer-Olkin measure of sampling adequacy. Our result (.78) was well above the recommended threshold of .6.

2) Common Method Bias: All data were collected through a single instrument (the survey), and methodological researchers have suggested this may lead to a systematic measurement error known as Common Method Bias (CMB) (or Common Method Variance). We tested for the presence of CMB using Harman's single factor test [76] on the six latent variables in our model. Results showed that no factor explained more than 22% of the variance. An exploratory factor analysis (EFA) without rotation was run with a forced single factor solution, which accounted for 28% of variance. This is well below the maximum cut-off value of 50%. These results indicate that common method bias was not a concern in this study.

3) Representativeness: Our survey was targeted at episodic volunteers in FLOSS projects. We compared our sample to a recent large-scale survey of FLOSS participants (which we refer to as "FLOSS '13" [45]) in order to assess the extent to which our sample is representative of the more general FLOSS volunteer population. Table II presents a summary of the descriptive statistics, which we discuss below. We also compared our sample to "OS '17" [77], another large survey, but in a more limited fashion because contribution types could not be directly compared.

TABLE II
Descriptive statistics of this study, FLOSS '13 [45], OS '17 [77], EV '14 [26],

	This study	FLOSS '13	OS '17	EV '14
Age (n)	96	1818	3578	340
Mean birth year	1977	1979	1987	1971
Gender (n)	90	2032	3551	337
Female	13.33%	11.12%	3.52%	89.61%
Male	84.44%	87.40%	95.38%	10.39%
Other	2.22%	1.48%	1.10%	n/a
Education (n)	98	2017	3697	338
University	78.57%	77.69%	65.70%	39.64%
Trade school	8.16%	3.27%	3.44%	28.11%
High school	11.22%	17.85%	27.45%	0.47%
Primary school	2.04%	1.19%	3.41%	1.78%
Contribution (n)	101	2155	n/a	n/a
Primarily code	33.66%	48.63%	n/a	n/a
Primarily other	28.71%	26.77%	n/a	n/a
Both equally	37.62%	24.59%	n/a	n/a

The FLOSS '13 data has two variables from which birth year is derived (the year participation began and the age of the contributor at that time) which contain unbounded intervals. They were adapted as follows: "before 1960" was set to 1960, "between 1970 and 1980" was given a distribution from $\{1970, ..., 1980\}$, "10 or younger" was given a distribution from $\{8, 9, 10\}$, and "55 or older" was given a distribution from $\{55, ..., 65\}$ [78]. OS '17 used ranges for age and we also replaced these with distributions. Using a Welch two-sample t-test for age, and a χ^2 test for gender, we found no statistically significant difference between our sample and the FLOSS '13 survey sample. However, OS '17 significantly differed from our sample on both gender and age.

When comparing contribution types, respondents of our survey were more evenly distributed over the three categories of code, other (non-code), and both code and other contributions. We found that both contribution type and education differ significantly between our sample and the FLOSS '13 sample ($p < .05$). OS '17 also differs significantly from our sample on education. However, in an analysis of FLOSS '13 and our sample combined, we determined that education and contribution type are strongly correlated ($p < .01$). Therefore, we attribute differences in education to our participant selection approach, which involved deliberately seeking to include non-code contributors. Contribution type is not correlated with age, hours contributed, number of episodic projects participated in, number of habitual projects, or gender ($p < .05$).

4) Comparison to General Episodic Volunteers: We also compared our sample of episodic volunteers in FLOSS to a general study of (non-FLOSS) episodic volunteers conducted in 2014 (referred to as "EV '14") by Hyde et al. [26]. Compared to volunteers in general, volunteer FLOSS contributors are younger, more likely to be educated, and more likely to be male [79]. In a study of retention among episodic volunteers, Hyde et al. reported a sample which was almost 90% female, almost 40% university educated, and older on average than our respondents with 1971 as mean birth year [26]. Compared to our sample, these are very significant differences; hence, conclusions from general studies of episodic volunteers do not automatically translate to FLOSS episodic volunteers. This further strengthens our motivation to investigate factors associated with retention of FLOSS episodic volunteers.

TABLE III
CRONBACH ALPHA, COMPOSITE RELIABILITY (CR), EIGENVALUES (EV), AND AVERAGE VARIANCE EXTRACTED (AVE)

Construct	Cronb. α	CR	1st EV	2nd EV	AVE
Social Norms	0.779	0.858	2.410	0.653	0.602
Satisfaction	0.864	0.908	2.847	0.508	0.711
Comm. Commitm.	0.862	0.898	3.569	0.755	0.593
Intention to Remain	0.885	0.913	3.815	0.647	0.635

B. Evaluation of the Measurement Model

The measurement model represents the operationalization of the research model. We adapted existing measurement instruments for each of the constructs (see Sec. IV). In this section, we evaluate the measurement model. Given that all constructs are reflective, we evaluate their convergent validity, internal consistency reliability, multi-collinearity, and discriminant validity [64].

1) Convergent Validity: Convergent validity refers to how well indicators of a given construct correlate. All constructs in our model are reflective (not formative), which means that indicators are considered to be different ways to measure the same construct—they should share a considerable proportion of variance, or *converge*. To assess convergent validity, two metrics are important: the outer loadings of a construct's indicators and the Average Variance Extracted (AVE).

A common rule of thumb suggests that a construct should explain at least 50% of variation in its indicators [64]. This variance is indicated by the squared value of an indicator's outer loading; hence, loadings should be at least the square root of 0.5, which is 0.708. In practice, a loading of 0.7 is widely considered sufficient.

Indicators with loadings below 0.4 are considered too weak to retain [80]. This led us to drop three indicators. Indicators with outer loadings between 0.4 and 0.7 should be considered for removal when the internal consistency reliability (discussed below) is improved by doing so [64]. We removed indicators with loadings below 0.7 in an iterative fashion, at any time removing the indicator with the lowest loading. As we progressed, we evaluated the AVE and metrics for internal consistency reliability and unidimensionality (discussed below). After an indicator was removed, recalculating the remaining loadings could result in additional loadings less than 0.7. Ultimately, all indicators with loadings greater than 0.7 were retained, and none of them had loadings less than 0.7.

The AVE is equivalent to a construct's *communality* [64], which is the proportion of variance that is shared across indicators. A reflective construct is supposed to *reflect* (or "cause") any change in its indicators. As we are looking for convergence of the indicators, this shared variance must be considerable, and a rule of thumb is that this value be at least 0.5 (so that at least half of the variance is shared across indicators). As Table III shows, AVE values for all multi-item constructs are well above that threshold.

2) Internal Consistency Reliability and Unidimensionality: Internal consistency reliability refers to the extent to which the indicators (*manifest variables*, or *items*) are consistent with one another. A high degree of consistency means that the indicators refer to the same construct. A common measure of this is Cronbach's α, which varies between 0 and 1—higher values suggest a higher level of reliability. Cronbach's α has a number of limitations, in that it is sensitive to the number of items of a construct and it tends to *underestimate* the internal consistency reliability. In practice, researchers use Cronbach's α as a conservative measure of internal consistency. An alternative measure is Composite Reliability (CR), which has the same scale as Cronbach's α, and can generally be interpreted in the same way [64]. However, the CR tends to *overestimate* internal consistency reliability. Hence, we report both. For exploratory research, values of 0.6–0.7 are acceptable, while for research in a more advanced stage values between 0.7 and 0.9 are recommended [80]. Values below 0.6 suggest a lack of internal consistency reliability, whereas values over 0.95 suggest that indicators are too similar and therefore not desirable. Table III shows that the Cronbach α and CR values for our latent variables all score well above 0.7, with three out of four scoring between 0.8 and 0.9, and none over 0.95.

Another way to assess multi-item constructs is to look at the first and second Eigenvalues. The first Eigenvalue should be well over 1.0, whereas the second Eigenvalue should be less than 1.0. As Table III shows, this is the case for all constructs.

3) Discriminant validity: Discriminant validity refers to the extent to which the different constructs in a model are unique—that is, they capture distinct phenomena. There are several ways to evaluate this. The first is to investigate cross-loadings of indicators. The outer loadings of a construct's indicators should be greater than those indicators' loadings on other constructs. That is, an indicator of construct A should not load higher onto a different construct B than on A, because that implies it is a better indicator of construct B. Table IV shows the cross-loadings. Loading values should be inspected row by row (not by column). The results in the table suggest there is no issue with discriminant validity.

A measure for identifying discriminant validity is Henseler's Heterotrait-monotrait ratio (HTMT). HTMT replaces the Fornell-Larcker criterion, which was previously a common method of assessing discriminate validity, but has recently been demonstrated to be unreliable [81], [82]. First, pairwise correlations are calculated between all indicators. Correlations with indicators from the *same* construct are *within-trait* correlations, while correlations with *other* indicators are *between-trait* correlations. For each construct, each mean between-trait correlation is compared to the mean within-trait correlation. The cut-off value is 0.9, beyond which discriminant validity is considered problematic [81], though some researchers consider a more conservative cut-off of 0.85 [64]. Besides this, the HTMT ratio should be significantly different from 1.0, which can be established through a bootstrapping procedure. Table V lists these HTMT ratios—as can be seen, none of the HTMT ratios are problematic, with all but one value under the conservative cut-off; the remaining value is still below the cut-off of 0.9. After bootstrapping, we found that all HTMT

TABLE IV
CONVERGENT VALIDITY OF RETAINED INDICATORS (CROSS-LOADING). ITEMS MARKED WITH (R) ARE REVERSE-CODED.

Item	Item description	Cont. Benefit Motiv.	Social Norms	Psych. Sense Comm.	Satis-faction	Community Commitm.	Intention to Remain
cbm6	I volunteer to learn and develop new skills.	**1.000**	0.077	0.180	0.173	0.123	0.241
sn2	Other people think that volunteering is important to me.	0.167	**0.755**	0.221	0.254	0.408	0.474
sn3	It is important to my friends and relatives that I continue volunteering.	0.101	**0.791**	0.263	0.363	0.463	0.520
sn6	Many of the people that I know expect me to continue as a volunteer.	−0.014	**0.828**	0.270	0.355	0.521	0.502
sn7	No one would really be surprised if I just stopped volunteering. (R)	−0.016	**0.726**	0.489	0.388	0.513	0.466
psc3	If there was a serious problem in the community, the people could get together to solve it.	0.180	0.391	**1.000**	0.447	0.445	0.493
s1	I enjoy my volunteer experience.	0.187	0.416	0.341	**0.830**	0.407	0.608
s2	My volunteer experience is personally fulfilling.	0.109	0.388	0.442	**0.900**	0.538	0.648
s3	My volunteer experience is worthwhile.	0.128	0.286	0.345	**0.833**	0.443	0.559
s6	I am likely to continue to volunteer for this project.	0.159	0.380	0.374	**0.806**	0.591	0.670
cc2	I feel very little loyalty to this community. (R)	0.155	0.391	0.296	0.450	**0.701**	0.545
cc4	I am proud to tell others that I am a part of this community.	0.123	0.521	0.351	0.510	**0.753**	0.683
cc6	It would take very little change in my present circumstances to cause me to leave the community. (R)	0.510	0.417	0.297	0.473	**0.756**	0.477
cc7	There's not too much to be gained by sticking with this community indefinitely. (R)	0.104	0.439	0.423	0.456	**0.821**	0.602
cc8	I really care about the fate of this community.	0.027	0.514	0.386	0.485	**0.850**	0.714
cc9	For me this is the best of all possible communities to participate in.	0.118	0.530	0.285	0.355	**0.730**	0.575
ir1	I plan to volunteer for this community in the future.	0.197	0.445	0.425	0.705	0.682	**0.826**
ir2	I will recommend that others volunteer for this community.	0.188	0.643	0.469	0.636	0.680	**0.821**
ir3	I will tell others about the positive experiences that I had volunteering for this community.	0.142	0.468	0.305	0.511	0.491	**0.743**
ir4	I hope that volunteering is a part of my life for years to come.	0.265	0.476	0.324	0.578	0.524	**0.769**
ir7	I am more motivated to volunteer because of my recent volunteer experience with this community.	0.236	0.464	0.358	0.556	0.556	**0.773**
ir8	I care about the community for which I volunteer.	0.133	0.513	0.449	0.542	0.802	**0.845**

ratios are significantly different from 1.0. This suggests that the constructs in our model capture different phenomena.

To summarize, we have established that the construct measures are reliable and valid, allowing us to assess the results of the structural model and our hypotheses.

VI. THEORY TESTING AND EXPLORATION

This section presents the results of the evaluation of the structural model. In addition we also discuss moderating effects of several factors including age, tenure, gender, and contribution type. Finally, we conducted a cluster analysis to explore unobserved heterogeneity.

A. Structural Model Evaluation

1) Assessing Collinearity: Our theoretical model consists of five constructs that—we hypothesized—together predict episodic volunteers' intention to remain active in a FLOSS community. To ensure that the five exogenous constructs are independent, we evaluate their collinearity by means of Variance Inflation Factors (VIF). In our model, all VIF values are between 1.04 and 2.08, well below the accepted cut-off value of 5 [80].

TABLE V
DISCRIMINANT VALIDITY: HETEROTRAIT MONOTRAIT RATIO (HTMT)

	Social Norms	Satisfaction	Community Commitment
Satisfaction	0.532		
Community Commitment	0.744	0.679	
Intention to Remain	0.758	0.840	0.882

2) Path Coefficients and Significance: PLS does not make any assumptions about the distribution underpinning the data, and hence it cannot use any parametric tests of significance. In order to determine whether path coefficients are statistically significant, PLS packages implement a bootstrapping procedure. This involves drawing a large number (typically 5,000) of random "subsamples" with replacement. All subsamples contain the same number of observations as the original data set. For each subsample, the PLS path model is estimated—together, these sets of coefficients form a bootstrap distribution, which can be considered as an approximation of the sampling distribution. From this, a standard error and standard deviation can be determined [64]. Table VI shows the results for our five hypotheses. The mean path coefficient determined by bootstrapping can differ slightly from the path coefficient calculated directly from the sample; this variability is captured in the standard error of the sampling distribution of the mean.

Based on the bootstrap results, three hypotheses were supported (H2, H4, H5) all with $p < .05$. While H3 was not supported ($p = .4386$), based on the bootstrap results we found moderate support for H1 ($p = .0611$).

TABLE VI
RESULTS OF THE BOOTSTRAP PROCEDURE: MEAN PATH COEFFICIENTS, STANDARD ERROR ESTIMATES, AND CONFIDENCE INTERVALS

Hypothesis	Mean	se*	95% CI
H1: Cont. Benef. Mot. $\rightarrow$ Int. rem.	0.100	0.054	$(-0.007, 0.205)$
H2: Soc. Norms $\rightarrow$ Int. rem.	0.182	0.057	(0.070, 0.294)
H3: Psy. Sense Comm. $\rightarrow$ Int. rem.	0.054	0.063	$(-0.067, 0.186)$
H4: Satisfaction $\rightarrow$ Int. rem.	0.364	0.064	(0.243, 0.492)
H5: Com. Commitm. $\rightarrow$ Int. rem.	0.425	0.300	(0.554, 0.537)

3) Coefficient of Determination and Effect Sizes: Finally, the coefficient of determination (R^2) is a measure of the model's predictive power. It represents the amount of variance in the endogenous construct (i.e., intention to remain) explained by the exogenous constructs (the remaining five constructs). The R^2 value of our model is .774, which can be considered as substantial [64]. Table VII shows the effect sizes of the exogenous constructs on the endogenous construct. The effect sizes of contributor benefit motivations and social norms are what Cohen labeled as 'small' (values between .02 and .15) [83], and neither is statistically significant. The effect size of psychological sense of community is well below the minimum threshold of .02 to suggest any effect. The effect size of satisfaction and community commitment can be classified as large ($> .35$), and both are statistically significant ($p < .05$).

B. Moderating Factors

We examined our data in order to determine if our participants varied according to characteristics previously reported as affecting EV. Specifically, we looked at age, gender, and tenure. For all variables we examined if there were any correlations with (other) demographic and volunteer experience variables. We then treated each variable as a moderating effect in the model. Only results which were significant at .05 are reported, with confidence intervals calculated through bootstrapping.

1) Age: Age has been reported to affect the number of hours contributed [51], but not to affect retention [26]. We did not find any significant correlations between age and demographic or volunteer experience variables. Age did not have a significant moderating effect on our model.

2) Gender: Handy et al. [51] found women were more likely to be habitual volunteers, and men were more likely to be episodic volunteers. We cannot examine this claim, due to our data only containing episodic volunteers. We did not find any significant correlations between gender and demographic or volunteer experience variables. Gender as a moderating effect in our model showed large differences between women and men. Women had higher path coefficients for contributor benefit motives, social norms, psychological sense of community and community commitment and a lower path coefficient for satisfaction. However, due to the extremely small number of women and non-binary participants in our sample, we were unable to bootstrap to determine if the results were significant. We strongly caution against overestimating the significance of these findings, which at most recommend further research into gender differences in retention.

TABLE VII
EFFECT SIZES

Exogenous Construct	Effect size	p
Contributor Benefit Motivations	0.043	0.4367
Social Norms	0.087	0.1500
Psychological Sense of Community	0.008	0.7812
Satisfaction	0.360	0.0214
Community Commitment	0.391	0.0177

3) Tenure: It has been proposed that a volunteer's tenure affects which constructs are more strongly associated with retention [25], [26]. Tenure was calculated as the number of years between when the person first contributed and the year the data was collected. We found no significant differences in any demographic or volunteer experience variables based on tenure. When tenure was treated as a moderating effect in our model, we were unable to find a significant moderating effect.

4) Other Moderating Effects: We considered contribution type as a moderating variable because it has been suggested that failure to take non-code contributors into consideration may affect the generalizability of studies on FLOSS contributors [42]. Contribution type did not have a significant effect.

C. Cluster Analysis of Contributor Categories

SEM techniques including PLS-SEM traditionally assume that all observations are homogeneous and can be represented by a single model [84]. However, it is reasonable that this assumption does not always hold, and to expect that a number of classes of observations exist, each of which exhibit certain characteristics and behaviors. When a single model is applied to all individuals, who may or may not be similar, there is a risk of the explanatory power of the model being diminished. In Sec. VI-B we investigated *known* categories, such as gender, tenure, and type of contribution as moderating factors.

To examine unobserved heterogeneity, or *unknown* factors, we utilized response-based unit segmentation (REBUS). REBUS seeks to improve the predictive capacity of a model by assigning observations to groups based on their distance from the global and local models, taking into consideration both the inner and outer model [84], [85]. A naïve hierarchical clustering analysis based on the outer model recommended a four cluster solution; because this recommendation is an estimate, we explored three, four, and five cluster solutions with REBUS. The four cluster solution was optimal, in terms of the Group Quality Index (GQI, a measure comparable to Goodness of Fit Index, or GoF) and differentiation between groups. The GQI was 0.795, higher than our original GoF of 0.699. The four clusters contained 31, 20, 19 and 31 observations, respectively. Differences between the categories were significant at .05.

We examined the inner path coefficients for insight on the differences between the groups (Table VIII) and named them according to the perceived key distinguishing characteristics. The first group is described as *satisfied* because satisfaction is the only independent variable which significantly correlates with intention to remain. The effect of satisfaction

TABLE VIII
GROUP PATHS COEFFICIENTS AND MODEL QUALITY

Group	Cont. Benef. Motiv.	Social Norms	Psych. Sense comm.	Satis-faction	Community Commitm.	GoF
Satisfied	-0.011	-0.102	-0.085	**1.054**	0.077	0.871
Classic	**0.169**	**0.450**	**0.170**	**0.187**	**0.236**	0.883
Social	0.075	**0.417**	-0.134	**0.354**	**0.424**	0.858
Obligated	-0.105	-0.091	-0.059	0.013	**1.031**	0.807

is extremely strong. The second cluster, *classic*, consists of people who most closely fit the model we originally predicted. All path coefficients are positive. *Social* contributors are most strongly motivated by social norms and community commitment, although satisfaction also plays a strong role. Finally, *obligated* volunteers are extremely community-minded and derive their intention to remain not from their *perception* of the community (psychological sense of community), but from their *identification* with it (community commitment). We discuss these findings in more detail in Sec. VII.

VII. Discussion and Conclusion

A. Contributions and Implications for Practice and Research

This research has significance for both FLOSS projects as well as organizations which incorporate knowledge workers in episodic work. Novel aspects of our research are that it incorporated a large number of non-programmers, and also covered a large number of projects, including small projects. Table IX summarizes our findings.

Social norms, satisfaction, and community commitment are all positively associated with an intention to remain among episodic volunteers. By contrast, contributor benefit motivations and psychological sense of community cannot be demonstrated to have a relationship with intention to remain.

Although the path coefficient of social norms is small, it demonstrates that this largely neglected influence of environment is a factor among FLOSS episodic volunteers. Satisfaction and community commitment are both strongly linked with retention, in agreement with previous findings [38], [56], [59], [86]. There is a widespread belief in FLOSS communities that episodic volunteers are not emotionally attached [27] which should be reconsidered in light of our findings, which shows that community commitment is the construct most strongly associated with retention.

Comparing non-code contributors to code contributors showed they were similar in terms of the factors correlated with retention. Studies which generalize about all FLOSS contributors based on examining only code contributors may be accurate when it comes to retention.

Gender seems to have a strong effect on the constructs associated with retention, although our sample contains too few women and non-binary participants to draw clear conclusions. This corresponds to recent findings that newcomer barriers are gender-biased [17]. It is not inconceivable that retention mechanisms may also be tuned toward some constructs over others, to the detriment of retaining women. However, further research is clearly needed on this issue.

Tenure does not appear to affect the constructs associated with retention among FLOSS volunteers, which contradicts existing models on volunteerism [25], [26]. More research, especially incorporating volunteers from many types of organizations, is needed to determine if FLOSS is unusual in this regard, or if the effects of tenure vary by charitable focus.

Age does not have a significant moderating effect on our model, either. As with tenure, this suggests that studies generalizing about EV should include a wide range of communities.

Although our conceptual model only retains three independent variables and does not fully explain intention to remain, it provides a basis for further attempts to model retention in FLOSS. The addition of further constructs, such as altruistic motivations, may lead to a more complete model.

Our most unexpected and interesting finding is that considering unobserved heterogeneity, four distinct groups of episodic volunteers can be identified. The higher GoF of the clustered model over the original model may explain why it has been difficult to generalize factors associated with retention. Rather than dividing participants into two groups, those who remain and those who do not [20], we can further divide those who remain into different types. We can see evidence of the groups in prior literature. The *satisfied* group is, of course, well-represented in Wu et. al's study [59]. The *classic* group corresponds closely with the type of episodic volunteers described in the general volunteering literature [26]. *Social* contributors are perhaps the pro-social people who are are motivated to engage in governance activities [38], [50] and "hobbyists" who enjoy the activity and interacting with the community [20]. Of particular curiosity is the *obligated* group, which is affected by none of the usual sources of retention, most notably satisfaction, but is instead associated with commitment to the community. These could be people who have formed a psychological contract with either the project or the global FLOSS movement and believe in the social value of FLOSS [87]. Subdividing returning participants offers an interesting opportunity for further research, and tantalizing possibilities for communities to refine their retention techniques.

B. Limitations

Measurement error, sampling error, and internal validity error are common concerns with survey research [88]. To address these, we conducted a pilot test, a comparison to three previous data sets, and employed previously validated instruments.

Our research relied on a self-selecting sample. Given that this was an online survey, we cannot report a response rate. It is unclear what the response rate was as we do not know how many people were aware of the study.

Self-reporting bias may pose a threat to validity. However, the survey was anonymous, which may reduce respondents' inclination to give socially desirable answers. When we examined statements which might be most affected by negative bias, specifically contributor benefit motives excluding skill

TABLE IX
SUMMARY OF RESULTS OF HYPOTHESES, MODERATING EFFECTS, AND CLUSTER ANALYSIS

Findings	Implications
	Hypotheses
Contributor benefit motivations are not significantly positively associated with intention to remain among FLOSS episodic volunteers.	• FLOSS communities should consider retention techniques based on satisfaction and community commitment, which together explain 80% of the variability in our model. • Community commitment explains more differences in intention to remain than any other construct we explored. Communities should not assume episodic volunteers do not experience community commitment. • Future research should investigate the effects of social environment *outside* of FLOSS communities on FLOSS participation. • Future research could consider other factors to explain additional variation in intention to remain. • Future research could develop FLOSS-specific measurement instruments for the constructs which did not perform well.
Social norms are positively associated with intention to remain among FLOSS episodic volunteers.	
Psychological sense of community is not significantly positively associated with intention to remain among FLOSS episodic volunteers.	
Satisfaction is positively associated with intention to remain among FLOSS episodic volunteers.	
Community commitment is positively associated with intention to remain among FLOSS episodic volunteers.	
	Moderating effects
Tenure does not have a moderating effect in our model.	• The effects of tenure and age on intention to remain may be community-specific. A general model of EV retention should incorporate multiple communities to improve generalizability.
Age does not have a moderating effect on our model.	
Type of contribution does not have a moderating effect in our model.	• Type of work performed does not appear to affect intention to remain among FLOSS contributors.
Gender had strong effects on the model. Our sample did not include enough women and non-binary participants to verify the finding.	• More research is needed on the effect of gender on intention to remain. • Studies on FLOSS participation should probably incorporate gender as a potential moderating effect.
	Contributor categories
When participants were divided into four distinct clusters—*satisfied*, *classic*, *social*, and *obligated*—our model was able to explain approximately 80% of the variability in intention to remain.	• Considering different categories may help explain some differences in previous studies on the effects of various factors on intention to remain. • More research is recommended to explore the four distinct types of episodic volunteers. • Different categories of contributors may need different retention techniques.

development, we found that at least 50% of people agreed or strongly agreed with each motive.

Two of the measurement instruments did not perform well (contributor benefit motivations, psychological sense of community), and after removing indicators, these became single-item constructs. Although we conducted a pilot study to determine that the instruments had been tailored to a FLOSS context, future research could explore these two constructs by developing new instruments based on previous FLOSS research. Also, as these constructs did not seem to loom large in the model, further research could identify alternative constructs.

The most common method for controlling for non-response bias is to compare early responses against later responses to see if there is a significant difference between responses. However, our approach of using a series of one-off pushes through different mediums means that it is not possible to perform this comparison. Because our target population is largely unknown to us, we are unable to pursue follow-up pushes. We tried to control for this through external validity.

C. Conclusion and Future Work

In this research, we proposed a model of constructs pertaining to the retention of episodic volunteers in FLOSS. Social norms, satisfaction and community commitment were all found to be positively associated with intention to remain, while psychological sense of community and contributor benefit motives were not. Together, satisfaction and community commitment explained the majority of difference in the model.

This study also uncovered several differences between participants based on gender, suggesting opportunities for further research. Tenure and age did not affect the outcome.

An exploratory clustering approach suggested that our respondents can be divided into four categories with seemingly different factors influencing retention. For example, *social* episodic volunteers and *obligated* episodic volunteers seem to represent two distinct classes of contributors. We call for further research to explore these different categories of episodic volunteers, which could advance our understanding episodic volunteers, or any context where knowledge workers have autonomy to self-direct at least a part of their time.

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