Appendix C: Robustness Checks

Attention Intensity Levels. In constructing our dataset, we record an attention allocation event whenever a developer chooses to allocate attention on – and thus visibly "touch" – a bug report without distinguishing between the varying levels of effort required. All actions leave visible cues potentially catching the attention of other participants; thus, our modelling approach reflects the fact that the intensity of the effort behind each specific act of attention allocation does not directly affect the theoretical arguments that underlie our hypothesized mechanisms. However, could it be that attention allocation patterns do vary significantly depending on the level of effort put into the acts visible to participants? To answer this question, we estimated new models including interaction effects between the four variables capturing the attention mechanisms we hypothesized and a new variable called *High attention effort.* In our empirical setting, the intensity of attention acts can be inferred by considering the nature of the bug report modification that each act represents. We consider acts that involve the direct production or review of software code – intended as a patch for the focal bug – as a proxy for "high attention effort". Conversely, "low attention effort" acts are those addressed at more mundane tasks contributing to the description, general classification, and maintenance of software bugs (Lakhani & von Hippel, 2003). The results of these additional tests show that all four main effects are still significant and consistent with our hypotheses (see Table C.1). *Attention focusing* and *Attention mixing* show significant interactions going in the same direction of their respective main effect, thus representing a reinforced effect for high attention effort events. Our additional findings suggest that the dynamics that underlie the self-organizing properties of the attention structures that we investigate are substantively similar for high and low attention efforts.

Crowding. In our modelling approach the idea that attention is limited is just assumed – in line with our theoretical framework– and thus not directly tested. However, within that assumption, to which problem a participant allocates attention could depend on the amount of choice opportunities available, a concept referred to as "crowding" in related literature (e.g., Piezunka and Dahlander, 2015). According to this view, attention could become more limited as there are more choice opportunities available, and individuals could become more selective in allocating their limited attention to competing issues. Do crowding levels have a significant effect of the mechanisms of attention allocation we hypothesize? To answer this question, we coded a new variable *Crowding* – similarly to what done by Piezunka and Dahlander (2015) – by counting, for each attention allocation event recorded, all problems "at risk" of attracting attention acts. We also applied an exponential decay function to the count, with 60 days half-life, thus giving more emphasis to newer problems (we tested alternative specifications of 30 and 90 days with similar results). We then interacted *Crowding* with the four variables capturing the attention mechanisms we hypothesize. The results in Table C.2 show that all four main effects are still significant and consistent with our hypotheses. While all new interaction effects are statistically significant, our main effects maintain the same direction and significance once the moderator is included in the model, with crowding only affecting the relative magnitude of the effects. These results suggest that the mechanisms underlying our hypotheses are robust to this "ecological" conceptualization of limited attention.

Returning Problems. In our modelling approach, problems that are considered solved remain in the risk set as they could be re-opened at a later stage and still attract the attention of participants. It is however reasonable to expect a reduced attractiveness of problems marked as resolved and our control variable Problem resolved confirms this intuition consistently in our models. However, distinct attention mechanisms pertaining to problems resolved and re-opened could exist and potentially confound our results. To address the point, we re-estimated our models excluding problems from the risk set after they were marked as resolved once. The number of bugs excluded from the analysis is not high (approximately 200) and the estimates are stable and fully consistent with our previous results (see Table C.3).

Extreme Outliers. In our empirical setting the number of recorded attention allocation acts vary significantly across participants and is not normally distributed. Indeed, we expect the mechanisms underlying our hypotheses to produce an uneven concentration in attention allocation and our modelling approach is suited to handle this skew. Nonetheless, could it be that the results we find are only driven by the actions of the most active participants? To answer this question, we re-estimated our models excluding the more severe outliers amongst the participants. We computed the 90% quantile of cumulative attention over all events and removed all observations above that threshold from the dataset. The results in Table C.4 show that the new estimates are stable and consistent with our previous results.

Table C.1: Cox Regression Model: High vs. low attention effort

	Model 1	**Model 2**
Cumulative attention	0.9125 (0.0147) ***	0.8098 (0.0142) ***
Experienced participant	1.4348 (0.0554) ***	1.2900 (0.0556) ***
Institutional participant	1.1685 (0.0373) ***	1.1428 (0.0377) ***
Problem priority	-0.0250 (0.0270)	-0.0223 (0.0275)
Problem severity	0.1710 (0.0347) ***	0.1498 (0.0350) ***
Problem latency	-0.0020 (0.0000) ***	-0.0018 (0.0000) ***
Problem resolved	-1.9565 (0.0412) ***	-1.8208 (0.0411) ***
Problem recognition	0.3474 (0.0153) ***	0.3340 (0.0151) ***
Time inactive	-0.0170 (0.0003) ***	-0.0155 (0.0003) ***
Attention focusing (H1)	0.2357 (0.0067) ***	0.2096 (0.0066) ***
Attention reinforcing (H2)	0.1608 (0.0119) ***	0.1448 (0.0120) ***
Attention mixing (H3)	-0.0342 (0.0028) ***	-0.0322 (0.0027) ***
Attention clustering (H4)	0.0449 (0.0070) ***	0.0444 (0.0070) ***
Module 1	-0.1431 (0.0609) *	-0.1132 (0.0616)
Module 2	-0.1652 (0.0640) **	-0.1386 (0.0645) *
Module 3	0.1328 (0.0709)	0.1175 (0.0719)
Module 4	-0.5976 (0.0542) ***	-0.5334 (0.0547) ***
Preferential modularity	0.4003 (0.0232) ***	0.3830 (0.0234) ***
Attention clustering w/in modules	-0.0055 (0.0069)	-0.0045 (0.0069)
High attention effort		-3.0232 (0.0849) ***
Attention focusing * High attention effort		0.1266 (0.0208) ***
Cumulative attention * High attention effort		-0.4138 (0.0990) ***
Attention reinforcing * High attention effort		-0.0442 (0.0402)
Attention clustering * High attention effort		-0.0287 (0.0289)
Attention mixing * High attention effort		-0.2865 (0.0931) **
AIC	29,255.1392	24,287.3073
Num. events	11,599	11,599
Num. obs.	2,330,137	2,330,137

*** p < 0.001, **p < 0.01, *p < 0.05

Table C.2: Cox Regression Model: Interacting attention crowding with effects of interest

	Model 1	**Model 2**
Cumulative attention	0.7706 (0.0139) ***	1.0765 (0.0240) ***
Experienced participant	1.2818 (0.0560) ***	1.2079 (0.0589) ***
Institutional participant	1.1832 (0.0377) ***	1.2699 (0.0389) ***
Problem priority	-0.0526 (0.0276)	-0.0446 (0.0287)
Problem severity	0.1494 (0.0349) ***	0.1579 (0.0357) ***
Problem latency	-0.0017 (0.0000) ***	-0.0018 (0.0001) ***
Problem resolved	-1.7850 (0.0407) ***	-1.7857 (0.0424) ***
Problem recognition	0.3223 (0.0154) ***	0.2941 (0.0154) ***
Time inactive	-0.0150 (0.0003) ***	-0.0139 (0.0003) ***
Attention focusing (H1)	0.2112 (0.0066) ***	0.2513 (0.0077) ***
Attention reinforcing (H2)	0.1298 (0.0117) ***	0.1815 (0.0126) ***
Attention mixing (H3)	-0.0285 (0.0027) ***	-0.1173 (0.0067) ***
Attention clustering (H4)	0.0509 (0.0067) ***	0.0416 (0.0081) ***
Module 1	-0.1247 (0.0614) *	-0.1120 (0.0631)
Module 2	-0.1498 (0.0641) *	-0.1098 (0.0653)
Module 3	0.1419 (0.0713) *	0.1515 (0.0730) *
Module 4	-0.5139 (0.0543) ***	-0.4888 (0.0554) ***
Preferential modularity	0.3780 (0.0234) ***	0.3843 (0.0239) ***
Attention clustering w/in modules	-0.0052 (0.0067)	-0.0040 (0.0070)
Attention focusing * Crowding		0.0636 (0.0063) ***
Cumulative attention * Crowding		-0.4220 (0.0244) ***
Attention reinforcing * Crowding		-0.0531 (0.0121) ***
Attention clustering * Crowding		0.0273 (0.0077) ***
Attention mixing * Crowding		0.0857 (0.0062) ***
AIC	23,256.4512	22,405.9749
Num. events	11,599	11,599
Num. obs.	1,170,870	1,170,870

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table C.3: Cox Regression Model: Exclusion of problems attracting attention of developers after resolution

	Model 1	**Model 2 (excluding resolved problems)**
Cumulative attention	0.8171 (0.0144) ***	0.7604 (0.0137) ***
Experienced participant	1.2219 (0.0558) ***	1.2506 (0.0559) ***
Institutional participant	1.1508 (0.0379) ***	1.1406 (0.0380) ***
Problem priority	-0.0447 (0.0274)	-0.0133 (0.0284)
Problem severity	0.1379 (0.0351) ***	0.1734 (0.0351) ***
Problem latency	-0.0018 (0.0000) ***	-0.0018 (0.0001) ***
Problem resolved	-1.8088 (0.0412) ***	-1.8164 (0.0416) ***
Problem recognition	0.3507 (0.0153) ***	0.3192 (0.0156) ***
Time inactive	-0.0148 (0.0003) ***	-0.0153 (0.0003) ***
Attention focusing (H1)	0.2054 (0.0065) ***	0.2090 (0.0067) ***
Attention reinforcing (H2)	0.1255 (0.0117) ***	0.1424 (0.0123) ***
Attention mixing (H3)	-0.0310 (0.0027) ***	-0.0284 (0.0029) ***
Attention clustering (H4)	0.0465 (0.0069) ***	0.0527 (0.0067) ***
Module 1	-0.1408 (0.0622) *	-0.0717 (0.0624)
Module 2	-0.1968 (0.0650) **	-0.1304 (0.0646) *
Module 3	0.1266 (0.0719)	0.1274 (0.0723)
Module 4	-0.5065 (0.0550) ***	-0.4660 (0.0548) ***
Preferential modularity	0.3562 (0.0237) ***	0.3556 (0.0236) ***
Attention clustering w/in modules	-0.0040 (0.0069)	-0.0059 (0.0066)
AIC	23,022.6114	22,901.9335
Num. events	11,599	11,369
Num. obs.	1,170,871	1,147,640

*** $p < 0.001$, **$p < 0.01$, *$p < 0.05$

Table C.4: Cox Regression Model: Observations above the 90% quantile of *Cumulative attention* removed

	Model 1	**Model 2 (excluding observation > 90% quantile of *Cumulative attention*)**
Cumulative attention	0.8171 (0.0144) ***	1.2232 (0.0204) ***
Experienced participant	1.2219 (0.0558) ***	1.0198 (0.0584) ***
Institutional participant	1.1508 (0.0379) ***	1.1627 (0.0407) ***
Problem priority	-0.0447 (0.0274)	-0.0536 (0.0291)
Problem severity	0.1379 (0.0351) ***	0.1519 (0.0378) ***
Problem latency	-0.0018 (0.0000) ***	-0.0018 (0.0001) ***
Problem resolved	-1.8088 (0.0412) ***	-2.0719 (0.0465) ***
Problem recognition	0.3507 (0.0153) ***	0.3597 (0.0163) ***
Time inactive	-0.0148 (0.0003) ***	-0.0129 (0.0003) ***
Attention focusing (H1)	0.2054 (0.0065) ***	0.2272 (0.0071) ***
Attention reinforcing (H2)	0.1255 (0.0117) ***	0.1746 (0.0121) ***
Attention mixing (H3)	-0.0310 (0.0027) ***	-0.1164 (0.0062) ***
Attention clustering (H4)	0.0465 (0.0069) ***	0.0442 (0.0082) ***
Module 1	-0.1408 (0.0622) *	-0.1033 (0.0670)
Module 2	-0.1968 (0.0650) **	-0.1749 (0.0699) *
Module 3	0.1266 (0.0719)	0.1733 (0.0771) *
Module 4	-0.5065 (0.0550) ***	-0.4707 (0.0595) ***
Preferential modularity	0.3562 (0.0237) ***	0.3598 (0.0253) ***
Attention clustering w/in modules	-0.0040 (0.0069)	-0.0087 (0.0082)
AIC	23,022.6114	20,078.9980
Num. events	11,599	10,439
Num. obs.	1,170,871	1,169,235

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

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