Utilizing the Fediverse and AI-bots for Youth Engagement During COVID-19 in a Hybrid Preventative Intervention

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Abstract

Social media is a pervasive platform for delivering targeted interventions, albeit with cautionary ethical consequences. Recently AI robots or "bots" have been combined with social media platforms to enhance interaction, and enact behavior change through increased engagement and adherence to intervention protocols. This paper presents a customized social media platform for promoting engagement and adherence to a prevention intervention protocol. The protocol was originally developed in a group workshop format, and then online during COVID-19. A social media platform was utilized to connect group participants and deliver protocol activities. Bots encouraged participation via positive reinforcement mechanism for the entire group, and to remind a participant of protocol activities. While not a formal study, our exploratory results demonstrate that bots and a social media context support a group leader in increased engagement and adherence to the protocol. Our principal contribution in this paper is demonstrating that a personalized, adaptive instance of a Control Systems Engineering model may improve engagement-related outcomes in brief protocols.

Keywords: fediverse, chatbot, eHealth, preventative intervention, COVID-19.

1. Introduction

Social media platforms have tremendous potential for efficient delivery of micro interventions geared toward behavior change, particularly in youth. The pervasiveness of the technology and its popularity amongst youth creates a ready-made powerful delivery platform. Combined with the increased utilization of AI-based robots (*bots*), these technologies provide newer, sleeker mechanisms for delivering smaller (micro) interventions compared to prior generation robocalling or text messages. These technologies can be personalized and adaptive, responding to how users are engaging with the intervention activities, promoting improved engagement and higher rates of protocol adherence.

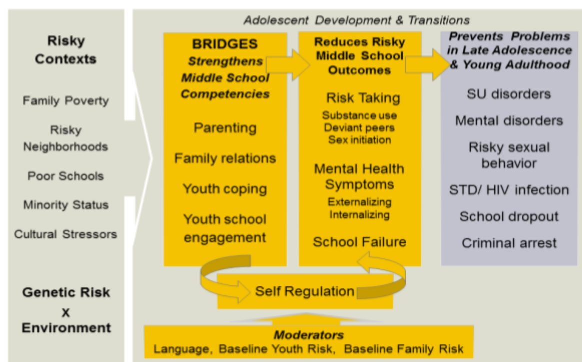

Figure 1. Family evidence-based intervention

COVID-19 served as an accelerator for developing online remote interventions. In the period just before COVID-19 our team was in the midst of designing and planning for digital health solutions to address brief protocol concerns. The onset of the pandemic pressed into a more flexible, responsive mode, where online adaptation became a necessary constraint. In this context, our contribution was in employing an open source social media *fediverse* platform, which maintains participant privacy through a distributed peer-to-peer architecture, and in utilizing AI-based *chatbots* to promote group protocol engagement and adherence to individual protocol-prescribed skill-building activities.

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2. A Family Evidence-Based Intervention

Bridges is a family-based program for middle school students at risk for longer-term negative outcomes (substance abuse, poor school performance/dropout, etc.). Bridges is a preventative evidence-based intervention protocol that includes multiple youth and parent group sessions (one per week) over a 9-week period facilitated by a group leader. The outcomes shown in Figure 1 have been validated through multiple Randomized Control Trials (RCTs) on Mexican-American populations (Gonzales et al. 2004, Gonzales et al. 2012, Jensen et al. 2014, Germán et al. 2017, Gonzales et al. 2018).

Despite the success of the program, it is costly to deliver. The length and the need to train reliable group leaders are impediments for a broad dissemination of the protocol. Focusing on re-engineering for efficiency of delivery, a brief version of the protocol was developed that spans 4 weeks (Thamrin et al. 2020, Thamrin et al. 2021a). Data[1] from the re-engineered 4-week protocol is showing substantial promise in the caregiver (parent) portion of the protocol (Thamrin et al. 2021b). However, youth outcomes show increases in awareness about vulnerabilities (e.g., coping ability), which might delay effects on the anticipated long-term youth outcomes. Our theory suggests that variability in outcomes between the standard evidence-based intervention and the re-engineered 4-week protocol is related to youth responsiveness (fewer opportunities for active participation during sessions, skill practice and application out-of-session) (Fisak et al. 2011, Stice et al. 2009, Crawley et al. 2013).

Just before the onset of COVID-19, the research team was designing a digital health approach for the protocol to address some of the concerns surrounding the effectiveness of the 4-week protocol, such as:

- 40% of in-session time was used to review prior session work or other setup activity. Technology could improve review and setup efficiency, and offload other administrivia to make session time more productive.
- At-home between-session practice was done poorly due to a lack of guidance or procrastination (completing just before the next session). Technology could be used to make “homework” more productive and completed with greater guidance, focus, and scheduling.
- The existing gamification mechanism for encouraging home practice was analog and dated; technology provides more immediate feedback and modern aesthetic design (e.g. badging).
- The in-session protocol uses a workbook with multiple forms and surveys. In the digital age, youth are digital natives expecting these processes to be online.
- The group protocol has several group feedback and discussion activities that could be facilitated with online tools.

In the case of the protocol, a successful but analog protocol, there were these and many other opportunities to optimize the protocol for shorter and more scalable interventions using technology. The research team was in the midst of early design on digital solutions, including a companion website and mobile health (mHealth) app. We particularly envisioned employing new techniques seen in the literature for brief, small, personalized, and adaptive digital interventions, and had implemented on a separate prevention protocol in an mHealth app (Patwardhan et al. 2015, Stoll et al. 2017, Singal 2019) with some success in pilot studies.

Our psychology-computer science collaboration follows *agile science* (Hekler 2016), as the pace of technology is faster than the traditional RCT-based approaches to theory validation in clinical settings. This approach helped us adapt rapidly to the realities COVID-19 presented in terms of time and remote delivery. In a designed study we would have matched the 4-week brief protocol for direct comparison, but the 2-week remote sessions were immediately available so we use the opportunity to rapidly design and implement a social media based adaptive intervention. The multidisciplinary approach leveraged concepts from behavioral intervention technologies, behavior change theory, artificial intelligence, and micro-interventions. In particular we employed gamification - in-application mini-rewards and feedback to encourage engagement.

3. Theory of Digital Micro-Interventions

Substantial research (Forman et al. 2009, Langley et al. 2010, Wizemann 2017) has emerged to better affect public health impact by packaging evidence-based interventions into brief-interventions leveraging behavioral intervention technology (e.g., 3D immersive video games, mobile applications). A personalized and adaptive delivery of behavioral intervention technologies is a powerful tool for evidence-based intervention impact. Adaptiveness here is determining when and how to deliver a call-to-action for an intervention activity, which requires integrating personalized knowledge of what is effective for that youth at that time. Progressively, an intelligent delivery of intervention activities based on individual youth data

[1] Brief protocol RCT results for adolescents are not public and details only reported in the RCT study; what is stated herein comes from monitoring outcomes as part of quality assurance and DSMB/IRB requirements.

from the adaptive delivery would emerge during the evidence-based intervention, such that algorithms determining when and how to deliver calls-to-action that require some form of intelligence (reasoning) about the youth's individual situation. Intelligence can be taken beyond adaptiveness to consider how the youth is progressing toward positive evidence-based intervention related outcomes.

While this specific research project was opportunistic, our research approach in general is based on Control Systems Engineering (Pina et al. 2014).

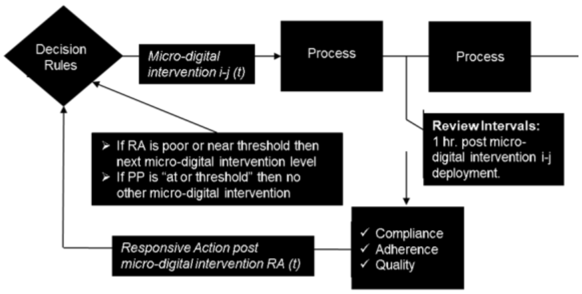

Figure 2. CSE model for micro-interventions

In this model (Figure 2), Program Progress (PP) is affected by Responsive Actions (RA) of the protocol participant. A feedback loop where underlying processes are monitored at brief discrete intervals (here shown as 1 hour, this could vary but remains short) and Ras prescribed to the participant by the protocol are adjusted based on personalized, adaptive decision rules.

This model allows for some flexibility in implementation, which we have experimented with in different context (the agile science approach). In this project, our micro-interventions are represented by the bots, which constitute both groupwide (general bot) and personalized adaptive (individual bot) micro-interventions. These micro-interventions are meant to improve compliance, adherence, and quality of skills practice, in the hope (but not assurance) that satisfying RAs will lead to improve program progress (PP).

At the onset of COVID-19, we were at a point in our research where we sought to employ personalized adaptive digital behavioral intervention technologies to promote engagement and adherence for out-of-session skill practice in youth. The behavioral intervention technologies approach we were intent on pursuing was based on *micro-interventions* (Kalsnja et al. 2015, Nahum-Shani et al. 2015), a behavior change element "in the small" targeting a specific action the evidence-based intervention indicates the youth should do at a time or setting (e.g., use positive self-talk to alleviate worries about failing a test). Micro-interventions require targeted, repeated, and sustained application over time to achieve a cumulative behavior change effect. In more direct terms, an individual micro-intervention may have little or no behavior change effect on the user, but efficient repeated micro-interventions may have the desired impact of promoting increased engagement in the protocol and adherence to specific activities (skill practice) required by the protocol. In the context of Figure 2, this suggests an individual feedback loop may be of little consequence, but repeated iterations achieve the desired impact on participant behavior.

The sudden onset of COVID-19 presented an opportunity to immediately develop a digital behavioral intervention technology for rapid deployment to augment a remote (video conference) "summer camp" format of the brief protocol. The summer camps engaged multiple groups over two-week periods in remote sessions, augmented by our digital behavioral intervention technologies solution. Due to the relatively short design and development time, we employed an open-source social media platform known as *Mastodon.* We customized the platform to support groups and group participants in a de-identified mode, and isolated our servers so only authenticated group members could participate. We implemented an activity from the protocol within the platform, trained users on how to perform related protocol activities using social media features, and deployed two bots; one to promote general engagement (keep energy "up" on the platform) and a second bot to target individual users with notifications (in-platform messages from the bot) to encourage and direct them to complete protocol activities (adherence). The next section presents the design and implementation of the modified open source platform and the two bots.

4. Design and Implementation

This section describes the design and implementation of the modified short program within the Mastodon platform. We start with a description of the technology and its capabilities, followed by how protocol activities were embedded in the platform, and conclude with the implementation of the bots.

4.1. The Fediverse Platform

Mastodon is an open-source fediverse platform for social media, utilizing activity feeds in a user interface (UI) resembling popular platforms such as Twitter and Facebook (example below). A *fediverse* architecture is one where social media servers are federated and coordinate sharing information through a standard protocol (in Mastodon's case ActivityPub). The federated architecture ensures no one centralized (or commercial) entity is managing sensitive personal information and posts (Raman et al. 2019). For our purposes, we isolated our server by blocking the fediverse component services so that no external remote servers could access the information on our server.

Mastodon is what is called a *microblogging* platform. Like other social media platforms, users make *Posts* that include a restricted amount of text and possibly media (images or short video clips). Other users may *reply, reblog, mark as favorite,* or *boost*[2] a post. Posts may be scoped as private, public, or as direct messages to other users. Users are shown posts by others or reactions to their own posts in the central UI activity feed component. Users can exert control over their feeds, blocking certain posts, hashtags, or users if they wish. Microblogging platforms like this have the advantage of being instantly familiar to social media users of other sites such as Twitter or Facebook. Due to its architecture and the open source license, Mastodon afford the opportunity to customize a familiar user experience while maintaining participant privacy and our local management of participant data.

Mastodon supports modern best practices for distributed platforms, most importantly a full-featured application programmer interface (API), and a secure mechanism for adding custom extensions (mini-applications, or "apps"). These mechanisms allowed us to create AI-bots and collect data for our study relatively quickly and easily. Furthermore, the maturity of the platform made it fairly straightforward to introduce code modifications allowing us to embed protocol activities in the platform. Finally, we modified user management features to create a provisioning process supporting de-identified users, group leaders, and master moderators.

4.2. Protocol Activities in Mastodon

The brief protocol was adapted to a "summer camp" format comprising of 6 sessions delivered over a 2-week period. The reduction from a 4-week brief protocol to a 2-week protocol was accomplished by cutting some activities that were not possible to conduct over video conferencing, reducing the time between sessions, and relying on out-of-session practice through the technology platform. Groups were provisioned on the platform through a modification to Mastodon's invitation service, ensuring only participants in the same group could receive that group's activity feed. A Group Leader, under the oversight of the Group Master Moderator, oversaw activity delivery and training for both the video conference component and the social media component. The research team provided modified program manuals to the Group Leaders to include training on using Mastodon and the custom features.

Participants were given pre-configured user accounts with anonymized identities, though they were free to reveal their identity within their group if they chose to do so. De-identification (the group moderator had an externalized list of usernames to participant identities) ensured even if externally hacked no sensitive personal information was available to malicious hackers. Employing a social media platform like this could raise concerns about online bullying or other abusive behavior; two defenses were implemented:

1. A *netiquette* section was added to the Group Leader training manual with a short activity to perform with the group at the start of camp to ensure a positive environment.
2. A user can perform user level moderation specific to their account in relation to other accounts/statuses.
   - Mute: Mute all status from a particular user
   - Block: Block all contact by a particular user
   - Report - Report a user to moderators/admin

Also, as part of IRB approval a safety valve was added where if researchers saw concerning language from a participant, an appropriate intervention including notifying the youth's parents would take place.

The Bridges brief protocol involves 5 major activities: *Future Self, SMART, IfThen, BOLD,* and *Coping*. A full description of the protocol and theoretical underpinnings of these activities is beyond the scope of this paper and may instead be found in (*Reference blinded*). For this online implementation, a version of Future Self was implemented, with additional built-in and custom UI features of the social media platform utilized for the remaining activities as described next.

Future Self is an activity where an individual uses media (images) to identify with a positive future version of oneself. In the regular protocol, this is done by cutting images out of magazines, newspapers, or a pre-identified collection. For our online implementation, we utilized Mastodon's media capabilities to allow participants to copy-paste images from the Internet, upload from their own device, or copy from a collection of images we provided on our server. This media was then used in a custom typed post for Future Self, as shown in Figure 3.

[2] *Boosting* is a social media concept where one may increase the influence of a post to recommendation algorithms. Boost may cost a fee on commercial social media, and can be for oneself or for others.

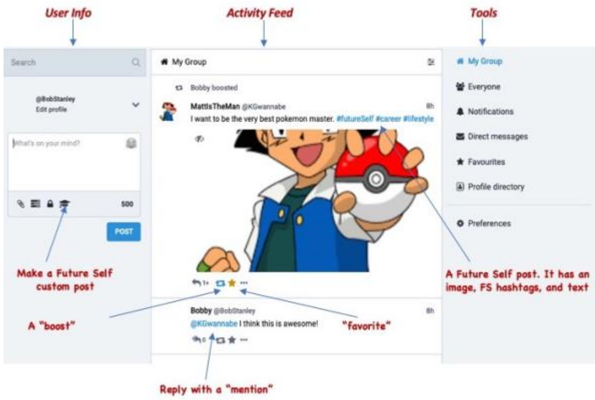

Figure 3. Example Mastodon Future Self Post

A Future Self custom typed post requires an image, a special hashtag (#) for easy searching, and some descriptive text. Peer participants are encouraged to react to the post with positive encouragement, through replies, mentions, boosting, or marking as a favorite. The user that made the Future Self post may also set specific Goals (as defined in the protocol) as stepstones to achieving their vision for themselves by clicking on a Flag icon under the submenu (the 3 dots next to the Favorite star).

The hashtag feature was customized to allow posts for the other activities to be typed and tracked (*#SMART*, *#IfThen*, *#BOLD*, *#Coping*). These hashtags provided several capabilities in the platform; it was easy for Group Leaders to determine if in- or out-of-session practice was being completed (adherence), it was easy for participants to complete their skill practice and react to their peers, and importantly these hashtags were used as input to the algorithms for the AI-bots adaptive content delivery.

4.3. Bots for Engagement and Adherence

An AI robot, or *bot*, is an automatically running program that performs some activity on a platform. Multiple recent literature reviews (Abd-Alrazaq et al. 2019, Vaidyam et al. 2019) discuss the potential of such bots for digital mental health applications, but without general conclusions and suggesting further study is necessary. In reality, the technology is evolving faster than rigorous study can keep pace, raising ethical concerns about their utility in sensitive domains such as mental health. In our platform, the implementation is rudimentary and not "leading", instead acting as a semi-intelligent reminder mechanism instead of providing medical advice.

On the Mastodon platform, we implemented the following two "bots":

- A general bot that periodically posts encouraging and/or whimsical messages. Most of the messages were taken directly from the protocol manual. These are seen by all users in the Everyone feed.
- An "adaptive and intelligent" bot that (based on an algorithm) Direct Messages (DMs) users who need more engagement or homework practice. These DMs will result in per-user Notifications with personalized (but not repeated) messages encouraging the specific skill practice activity be completed on the desired schedule.

The bots were created as self-contained client applications (apps) written in Javascript. Mastodon features a secure process for authenticating 3rd party applications and enabling leased access to the API. The apps are given permissions to read activity feeds from end users, and also make posts to different realms. In the general case, this is to the group level and universal feed, and in the personalized AI-bot DMs and group feed posts may be made. These apps were run nightly using NodeJS via a Unix cron process. The messages each bot delivered were drawn directly from the original protocol's manual.

The general bot is not intelligent in any sense. It used a randomized algorithm with an interval schedule to post motivational messages on the universal feed to promote continued "chatter" and to make context-free reminders of the importance of participating in the group protocol.

The AI-bot is partially intelligent; it uses a rule-based mechanism to send DMs based on whether certain conditions of inactivity are reached, such as not completing a skill practice at an expected interval, or not engaging with group members in conversations. An overall engagement score was calculated for each user by the bot based on frequency and richness (length, media) of posts, use of protocol-specific hashtags, and use of various features (user shows a lack of mentions, replies, likes, etc.). The individual bot varied message reminders so as to not seem repetitive, and would also monitor whether prior messages increased activity and if not would send messages that were more aggressive (more pointed in their direction to complete an activity but still positive in tone). These conditions are fully parameterized, so the intervals and aggressiveness of message reminders may vary. Note the AI-bot was not based on machine learning as modern large-scale chatbots (e.g. ChatGPT) are due to the time constraints in rapidly setting up a technology solution around the clinical protocol in such a short period of time. The chatbot was also a "one-way" bot; meaning it posted messages to the various feeds but did not accept or respond to user input.

Both bots appeared as first-class users on Mastodon, with usernames, profiles, and avatars. The fact they were bots was not concealed to users, as the avatar was taken from the group manual and usernames ended with "bot". Users were trained by group moderators regarding the existence of the bots and why they might see messages in their feeds or as DMs at the outset of the camp.

5. Pilot Study: Summer Camps

Four summer camps were conducted online in the summer of 2020 via Zoom for in-person sessions and using our customized Mastodon for some in-session activities and for between-session skill practice activities as described above. A staff member facilitated the camps, hiring and training PhD students as camp group leaders. Each camp was for 2 weeks, with camps 2 and 3 happening concurrently (camps were limiting to a max enrollment of 20).

Camp participants were recruited through Arizona State University's summer camp marketing, and ad hoc marketing and communication within the Psychology department, which runs a care facility on campus. Participants were late middle/junior high school age with no qualifiers on participation. The camps and the use of the technology were approved by the university's Institutional Review Board (IRB) process.

Groups met in-person every other day (6 total meetings), and were "assigned" skill practice activities between sessions on the Mastodon platform. As indicated above, the Future Self activity was implemented directly within the platform, including goal setting as part of the activity post. Other activities were completed offline but results and discussion were meant to be shared using the custom hashtags in a user's activity feed posts *(#SMART, #IfThen, #BOLD, #Coping*). This use of hashtagging was intended to reduce the time and awkwardness of group discussions in-person over Zoom.

Between camps the technology team met with the staff member to get debriefed on the efficacy of the technology. The technology team also had access to the full logs and database of the system, and between these 2 sources of data refinements were implemented such as tweaking frequency intervals (to follow up during specific periods where we anticipated youth would immediately respond, such as after dinner but before video gaming with friends started) and refining message language (be more engaging and sms-message like, massaging the manual language). Therefore there were multiple parameterizations used across the four camps.

Table 1 gives the respective enrollments of each camp together with some descriptive data on social media activity. The *number posting* column indicates how many of the participants made a post, while the rightmost column provides the raw engagement score computed by the bots when determining a user's level of engagement. Factors that went into engagement score included the number of posts, the number of logins to the system, and the use of reactions (mentions, likes, replies, etc.). Note the engagement score is based on the raw number of system-reported events for each participant and not normalized to any range. After camp 1 the technology team re-weighted how the score was calculated based on feedback from the group leaders and the logs of the system. This admittedly makes the raw data difficult to interpret, but the bimodal shapes of the distributions show that roughly half of camp participants actively engaged on the platform while the other half engaged minimally using reactions, or not at all. This may be due to apathy or due to shyness about posting their own personal progress online. Anecdotally this roughly follows historical in-person behavior (some users too shy to share or simply did not do the homework), and a seasoned group leader will notice and encourage participation. For these online camps, we noted some group leaders were more experienced and engaged than others. The varying nature of user participation reinforces the need for technology-driven solutions like the individual bot.

Table 1. Camp participants and participation

Camp	Users	Number posting	Group Leader posts	Engagement score avg/range
1	16	7	7	814 / 5756
2	15	8	6	23 / 67
3	15	8	25	56 / 259
4	4	2	26	64 / 167

Perhaps the most useful direct comparison in Table 1 is between camps 2 and 3, as these ran concurrently with the same number of participants and configuration of the Mastodon platform and the bots. While the number of posting participants is the same (8 of 15), the engagement score is significantly different. The primary difference in Table 1 is in the Group Leader posts column; camp 3's group leader made significantly more efforts to engage the group through the platform.

The technology team also implemented engagement and adherence reporting directly within the Mastodon platform as an open source plugin. This enabled the staff member, researchers, and group leaders to review in real time how a group was performing without having to manually export data. Graphs for engagement and adherence data from this tool are given for camps 2 (nicknamed BOLD) and 3 (nicknamed SMART) in Figures 4 and 5 respectively.

The top part of the figures shows the engagement and adherence of the group during the camp period, while the bottom part shows the same for just the group Leader. The green curve depicts posts (Active Events) while the orange curve depicts reactions of some kind (Passive Events). The purple curve indicates those active or passive events that are specific to the protocol. Unfortunately, these charts did not report bot activity (despite the chart legend) due to a lack of time.

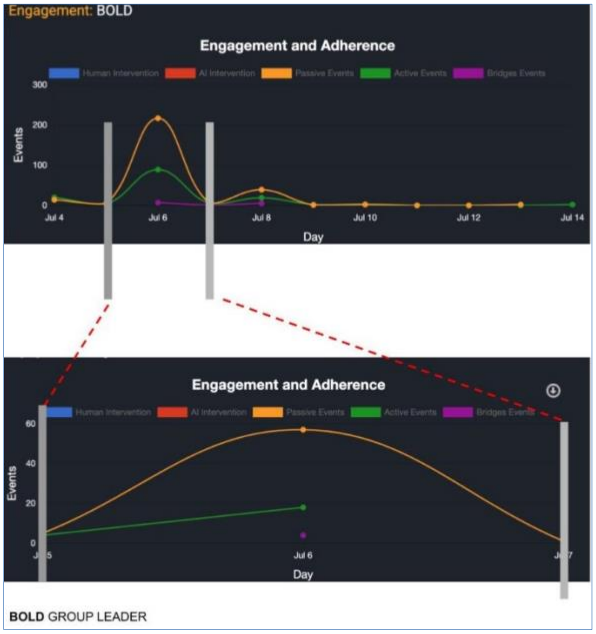

Figure 4. Camp 2 (BOLD) Engagement/Adherence

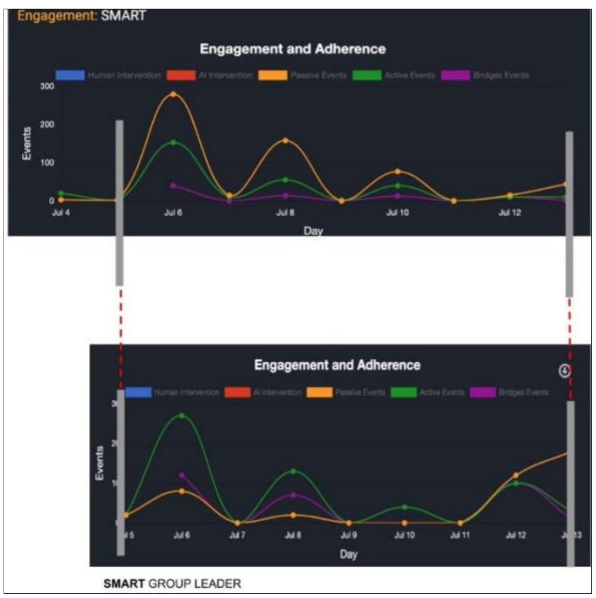

Figure 5. Camp 3 (SMART) Engagement/Adherence

These graphs show distinct behaviors between the group leaders, and corresponding responses by the participants. In camp 2 the group leader only posted on the first homework day, and also only reacted to participant activity on that day. Participant activity started strong but quickly faded after the second between-session day. Conversely, the group leader for camp 3 actively posted throughout the camp, and we see corresponding active and passive events are sustained throughout the between-session days for the participants in the group. This group leader might have taken more time to review and react to participant posts (low orange curve) to provide more positive encouragement, but it is clear the increased visibility had an effect on the group.

Keep in mind adherence differs from engagement, and we see these activities (purple curve) below the overall engagement which makes sense as not all interactions on the platform used the hashtags. Non-protocol interactions were encouraged to form community, further many participants simply failed to properly apply the hashtags to their posts or reactions. Given the relatively low adherence to engagement ration, it may also be the case that the social media platform acted as a distractor from protocol activities (Gary et al. 2017). It may also simply be the case that participants do not want to do outside practice (Hughes & Kendall 2007), and without an extrinsic motivator like grades, motivation may be too low to complete outside work for a “summer camp”.

The research team did review the log data for bot activity and responses for each camp. The general bot posts the same number of times as it is not specific to an individual’s activity. For camps 2 and 3 detailed above, the number of DMs sent by the AI-bot were lower in camp 2 than in camp 3, in accordance with the lower overall activity. The bots will not send repeated messages if prior messages are ignored (to avoid *app fatigue* – the digital platform equivalent of alarm fatigue in a hospital or similar environment), or the user does not log in. One might expect AI-bot activity to be inversely correlated with user activity, but this is not that straightforward. User engagement varies over time, and the AI-bot considers adherence as much as engagement, and as noted above these values may not be as accurate.

At the conclusion of each camp we also conducted a survey of the camp experience. Survey responses are anonymized. The same survey has been used each year, but for the given year, a question was added based on the technology. A 14-part question was asked on a 5-point Likert scale using Qualtrics. The first 9 parts were derived from the System Usability Scale (SUS, Brooke 1996) while the remaining 5 were custom questions based on the implementation of the protocol activity within the social media platform. Results are given in Figure 6.

Q14 - The following items are about the social media website.

#	Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
1	It is easy to use.	2.00	4.00	3.42	0.70	0.49	24
2	It is easy to understand.	1.00	4.00	3.46	0.91	0.83	24
3	I can use it without written instructions.	0.00	4.00	3.00	1.19	1.42	24
4	I can use it well every time.	1.00	4.00	3.13	1.12	1.24	23
5	It is easy to learn to use it.	0.00	4.00	3.46	1.04	1.08	24
6	I learned to use it quickly.	0.00	4.00	3.29	1.17	1.37	24
7	I am happy with this activity.	1.00	4.00	3.46	0.76	0.58	24
8	This activity is fun to use.	1.00	4.00	3.33	0.90	0.81	24
9	This activity works the way I would want it to work.	1.00	4.00	3.50	0.76	0.58	24
10	Posting my home practice was helpful.	0.00	4.00	2.74	1.15	1.32	23
11	Reading other people's posts was helpful.	1.00	4.00	2.79	1.15	1.33	24
12	I liked receiving comments on my posts.	0.00	4.00	2.79	1.26	1.58	24
13	I liked commenting on other people's posts.	0.00	4.00	2.83	1.21	1.47	24
14	Using the social media website improved my camp experience.	0.00	4.00	3.04	1.17	1.37	24

Figure 6. Usability question survey results

User responses to the 9 SUS questions are very positive. The first 4 questions are from the System Ease of Use component of SUS, the next 2 from System Ease of Learning, and the last 3 from the System Satisfaction component. The mean for all 9 SUS questions is above 3 (or 4/5). The next 4 custom questions specific to protocol activities do not perform as well. It could be that these questions are not independently validated, or it could be that there is some apprehension using the platform for sensitive personal activities – putting oneself out there online before having an opportunity to create community and friendships. This differentiates this experience from typical usage of social media amongst teens, where communities are formed through trusting relationships (friendships or friends of friends). The protocol does try to address these concerns in the in-person classic implementation, and this brief online version did not benefit from such face-to-face interaction. We also note a high standard deviation in these responses so it may be the case that these feelings are only held by a subset of the participants. Finally, we note that overall participants believed the social media platform enhanced the camp experience (last question).

6. Conclusions and Future Work

This paper presented our experience running remote online summer camps for a proven preventative intervention protocol for youth. An open source fediverse social media platform was customized and two bots created to promote engagement during the camp and adherence to the practice activities required by the protocol. Logs of participant activity were analyzed for engagement and adherence, with our primary finding that participation was driven mostly by group leaders, which is consistent with findings from the classic version of the protocol. The bots seemed to act as a strengthening moderator of the group leader's activity, but did not appear to fundamentally change adherence to the protocol on their own. Future work should involve making the bots interactive and the timing of their DMs optimized to when participants are likely to complete the work. We also envision a mobile app client to the platform that will enable notification messages to be seen, instead of the web-based messages in the platform (meaning the user had to proactively login to the platform to even see the DMs in the first place).

Our principal contribution in this paper is demonstrating that a personalized, adaptive instance of a Control Systems Engineering model may improve engagement-related outcomes in brief protocols. Specifically, in hybrid in-person (or synchronous remote) protocols with digital components, personalized and adaptive messages and calls-to-action may motivate participants to "follow through" on the skills practice originally practiced in-session. Through increased compliance, adherence, and alone skills practice (with quality), the expectation is that program outcomes are not only achievable but done so in a more timely and cost-effective fashion. Future work should continue through to ensure that program outcomes are fully achieved, or at least close enough to merit implementation.

There are many limitations to this work, as it was originally undertaken in an opportunistic manner as opposed to a designed research study. For this reason there is no control group, structured recruitment of participants, or *a priori* research questions. At the time (early summer 2020) the research team was engaged in design activities but COVID-19 necessitated an immediate solution. Practically, the open source Mastodon platform provided a ready "buy" over "build" solution in the short term, and the bots features are somewhat rudimentary compared to the power shown by recent advances in large-language learning models for advanced technologies like ChatGPT. Further, we do not have data on whether program outcomes were (partially) achieved in this format, which would be very useful, nor do we have data comparing the satisfaction with the hybrid brief protocol versus the original or brief versions of the in-person protocol. However, this small study does demonstrate feasibility in the approach from a process perspective. Social media platforms are a familiar and modern delivery channel for interventions, and the fediverse may provide a path that is both customizable and avoids concerns over privacy from large social media companies. Intelligent bots can be used to further engagement and protocol adherence, though study remains as to how such technologies may overcome limitations of group leaders.

7. References

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