A Social-Ecological Approach to Modeling Sense of Virtual Community (SOVC) in Livestreaming Communities

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Participation in communities is essential to individual mental and physical health and can yield further benefits for members. With a growing amount of time spent participating in virtual communities, it's increasingly important that we understand how the community experience manifests in and varies across these online spaces. In this paper, we investigate Sense of Virtual Community (SOVC) in the context of live-streaming communities. Through a survey of 1,944 Twitch viewers, we identify that community experiences on Twitch vary along two primary dimensions: *belonging*, a feeling of membership and support within the group, and *cohesion*, a feeling that the group is a well-run collective with standards for behavior. Leveraging the Social-Ecological Model, we map behavioral trace data from usage logs to various levels of the social ecology surrounding an individual user's participation within a community, in order to identify which of these can be associated with lower or higher SOVC. We find that features describing activity at the individual and community levels, but not features describing the community member's dyadic relationships, aid in predicting the SOVC that community members feel within channels. We consider implications for the design of live-streaming communities and for fostering the well-being of their members, and we consider theoretical implications for the study of SOVC in modern, interactive online contexts, particularly those fostering large-scale or pseudonymized interactions. We also explore how the Social-Ecological Model can be leveraged in other contexts relevant to Computer-Supported Cooperative Work (CSCW), with implications for future work.

CCS Concepts: • **Human-centered computing → Empirical studies in collaborative and social computing**; **Social media**; • **Information systems → Chat**.

Additional Key Words and Phrases: Twitch; livestreaming; online communities; sense of community; SOC; sense of virtual community; SOVC; well-being; social-ecological model

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1 INTRODUCTION

Understanding the processes which support community engagement and attachment is important to supporting public health. Stronger levels of attachment to the communities in which one lives and/or participates has been associated with meaningful benefits to individual mental and physical

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health, including improved well-being and quality-of-life [39, 63, 76, 100] and buffers against sources of stress [29, 40, 119]. Increased feelings of connectedness among youth has been shown to reduce the risk of involvement in high-risk behaviors and increase resiliency [33, 36, 45, 56, 87]. Stronger connections to neighborhood and workplace communities can lead to higher levels of satisfaction and commitment [3, 24], and – when these communities face novel problems – can lead community members to work together more effectively to solve them [5].

In the community psychology literature, the relationship between individuals and their social groupings has been formalized as *sense of community* (abbreviated throughout as SOC) [49, 70, 89]. As framed by McMillan and Chavis [70], SOC represents "a feeling that members have of belonging, a feeling that members matter to one another and to the group, and a shared faith that members' needs will be met through their commitment to be together" (p.9). This framework has been validated and extended through a number of studies of different types of offline communities (e.g., [24, 26, 27, 29, 39, 40, 77–79, 84]). As social interaction shifts increasingly into online spaces, however, it has become essential to understand how SOC might manifest differently.

Many studies have also explored the extent to which McMillan and Chavis' definition and model captures community experience within online communities, where interaction among members takes place over the internet, with varying results (*sense of virtual community*, or SOVC, e.g. [1, 11, 13, 14, 41, 48, 55, 64, 76, 108, 116, 119]). From blogs to newsgroups to social networking sites (SNS) to multiplayer games, online communities vary broadly in terms of the affordances offered for communication and social experience. Our investigation here is motivated by the assumption that sociotechnical differences in the design of these online spaces may lead the community experience to manifest in substantially different ways.

In this paper, we explore SOVC in the specific context of live-streaming communities, through an exploration of community interactions on Twitch, where millions of people participate in a diverse collection of creator-led communities every day. Twitch communities offer a number of features common across modern online social spaces, including persistent screen names, synchronous chat, community moderation, and features supporting large-scale interaction, such as polls. We adopt a survey-based approach to collect viewer perceptions related to SOVC in a variety of live-streaming communities, guided by the following research questions (RQ):

- **RQ1.** How does SOVC manifest and vary across livestreaming communities on Twitch?
- **RQ2.** What markers of activity are associated with higher or lower SOVC in Twitch channels?

We answer these questions using data collected through an online survey of 1,944 Twitch viewers, who shared perceptions about the Twitch communities in which they regularly engaged. This survey evaluated individuals' perceptions of these communities using measures adapted from several prior studies of SOC/SOVC [1, 12, 15, 77–79, 83]. We answer the first research question using exploratory factor analysis, to identify meaningful dimensions which describe how the community experience varies across channels. In answering the second research question, we draw on the Social-Ecological Model [19–22], a theoretical framework which asserts that individual well-being and behavior can be understood as an interplay of factors at various levels of their social ecology. Specifically, we consider how behaviors at the individual, relationship, and community (channel, in this context) levels are associated with an individual's self-reported degree of attachment to the larger social collective within that channel. Drawing on trace data capturing viewer and channel behavior across these levels, we identify particular categories of activity associated with lower or higher SOVC.

This paper contributes to the literature on computer-mediated communication by identifying two primary dimensions which describe SOVC in the highly-interactive context of live-streaming communities. The first dimension, *belonging* (alternatively, membership), aligns closely with findings from prior studies of online and offline communities [1, 12–14, 64, 108]. The second, which we call *cohesion*, combines previously disparate notions into a single construct, which captures the effectiveness of a community and its leaders. Our analysis of behavior at multiple levels of the social ecology surrounding viewers in a channel identifies associations between SOVC and features describing individual and community-level activity. We find that individual engagement, both visibly through chat and anonymously through mass forms of participation (e.g., polls and predictions), are associated with stronger feelings of SOVC. SOVC is stronger in channels which adopt more community-specific symbols (i.e., subscriber emotes) and eschew those which are globally recognized (i.e., global emotes). SOVC also decreases reliably with channel size.

In our discussion, we address theoretical implications of these findings for supporting community development on Twitch and on related community-driven services. Our findings shed light on how 'community' manifests in online environments supporting mass or collective participation, as in fast-moving chat or in contexts like polls, where individual contributions give way to collective action. We also explore practical implications, both for encouraging stronger communities in livestreaming channels and for leveraging models for estimating SOVC across viewers and channels on Twitch. Finally, we consider opportunities for future research associated with the combination of perspectives from social computing and public health which guided our work.

2 RELATED WORK

This paper considers live-streaming communities on Twitch as a lens for understanding how psychological *sense of virtual community* (SOVC) can be measured and predicted from traces of online interaction. In this section, we start by describing the community experience within Twitch, which serves as the research context for this investigation. We then review relevant prior theoretical and empirical research on measuring community affiliation in offline (SOC) and online (SOVC) contexts. Finally, we discuss the Social-Ecological Model as a framework for studying individual behaviors and perceptions within a larger community context.

2.1 Community Experience on Twitch

Twitch[1] allows individuals (called *streamers* or *creators*) to broadcast activities live to others (*viewers*) anywhere around the world. As of June 2022, Twitch reported over 8 million unique individuals streaming each month to an average of over 30 million daily viewers [112]. Though Twitch has been associated historically with video gaming, streamers share a wide variety of content, including music, arts, sports, and a talk-focused category called `Just Chatting`. In addition to the live-stream video player, the website provides several mechanisms for viewers to interact with the streamer and each other. In the chat window, streamers and viewers with a Twitch account engage in real-time conversation using text and Twitch-specific emoji (*emotes*). *Global emotes* represent emotes available to all Twitch users, while *subscriber emotes* are created by specific streamers, and can be unlocked by subscribing to the channel or through other channel-specific activity. Users can also engage with channels outside of chat via a number of peripheral interaction features, such as *polls*, and through a loyalty program called *channel points* through which users earn points that they can redeem for rewards (e.g., streamer-specific emotes or recognition from the streamer).

Prior research has identified how integrating social interactivity, through features such as chat, can transform a passive, potentially isolating viewing experience into a form of spectatorship that is active and social [52, 57, 118]. Many viewers approach live-streaming services with social motivations in mind. Hilbert-Bruce et al. found that social motivations are more prevalent for consumers of live-streamed content than those of mass media [54]. Sjoblom & Hamari found that viewers' self-reported levels of social integrative motivations were predictive of differences in time

[1]https://twitch.tv

spent viewing [94]. Additionally, 'communication with others' has been identified as a notable part of the experience in Chinese live-streaming sites, indicating that these social motivations generalize beyond a western audience [67]. Live-streaming communities vary dramatically in terms of how the social experience is expressed. Early study of Twitch communities found that the distribution of viewership across stream channels was highly skewed, with a small number of massive streams and a large population of medium and small-sized streams [60]. Smaller channels appear to be more relationship-driven than larger channels [42, 93]. In large channels, conversations typically shift away from one-on-one interactions [52] to a more repetitive, fast-moving "crowdspeak" [46].

This paper draws on Twitch as a context for studying community processes and perceptions within a larger class of live-streaming communities and other online communities that offer similar platform affordances. These include leader-run, interest-based communities with affordances for text-based chat and other forms of communication and contribution. Our quantitative analysis tests and validates hypotheses about the relationship between community size and perceived SOC/SOVC which can be inferred from prior work (e.g. [42, 52, 93]). The value of studying these phenomena within Twitch is increased by this prior cross-platform research illustrating how our findings might generalize to other related services.

2.2 Sense of Community: Offline (SOC) and Online (SOVC)

This work is rooted in the community psychology concept of *sense of community* (SOC), characterizing the perceptions of the individual regarding a larger social grouping [49, 70, 89]. We draw specifically on the formalization of SOC by McMillan and Chavis, which proposes four elements of community involvement: *membership* (a feeling of belonging or relatedness to the group), *influence* (a feeling that the individual and group matter to each other), *integration and fulfillment of needs* (the feeling that the group will meet members' needs), and *shared emotional connection* (the feeling of shared history and experience). Survey instruments rooted in this underlying four-element framework have been evaluated in a variety of offline contexts, including neighborhood or geographically-based communities [26, 39, 84], workplace contexts [24, 26, 27, 29, 40], and communities-of-interest [77, 78].

More recently, researchers have sought to understand how and in which cases a notion equivalent to SOC in offline communities exists within online or virtual communities, as *sense of virtual community* (SOVC). SOVC has been studied within a variety of types of online communities, including listservs and newsgroups [13, 14], blogs [11, 41, 55], and discussion forums [1, 48, 64, 76, 95, 108, 116, 119]. Several of these prior studies have demonstrated that the concept of membership or belonging does translate into the experience of participating in online communities [1, 12–14, 64, 108]. However, several studies have indicated that other aspects of SOVC might align better along dimensions which differ from McMillan and Chavis' original four-element model, such as immersion [64], recognition [14], identification [12, 14, 108], and emotional feelings [12, 108].

Rather than viewing these findings as in conflict, a possible explanation is that differences in affordances for social interaction across online communities may lead to SOVC manifesting in different ways. In a qualitative study of SOVC within newsgroups, Blanchard and Markus highlighted the difference between community members who felt like "active participants" and those who viewed the community as one "in which other people were active", a distinction which may be more salient in computer-mediated spaces [14]. To date, studies of SOVC within modern interactive communities, such as those with synchronous chat, have been largely focused on gaming contexts (e.g. [80, 110]). In this study, we build on insights from this previous literature, providing the first investigation into how SOVC manifests within the fast-paced, interactive context of live-streaming communities.

2.3 Benefits and Antecedents of SOC/SOVC

2.3.1 Real-world benefits. In face-to-face communities, those which cultivate a stronger SOC have been found to generate tangible benefits for members and the organization. In geographically-based communities, stronger SOC has been associated with more commitment, satisfaction, and loyalty to the neighborhood [3], as well as with more problem-focused coping behavior to solve problems faced by the community [5]. Stronger feelings of SOC within the workplace have been associated with higher levels of job satisfaction and commitment to the organization [24].

Stronger SOC has also been associated with concrete benefits for individual physical and mental health. For example, a study of Winnipeg, Canada residents identified that stronger SOC among neighbors increased residents' well-being in the face of neighborhood instability [39]. In caregiving scenarios, stronger SOC has been shown to predict lower levels of stress for firefighters [29] and workers in an eldercare facility [40].In the healthcare context, a sense of community among palliative care patients has been linked to increased quality of life [63].

Similar health benefits are accessible through participation in online communities. For example, stronger SOVC has been associated with increased personal well-being for older adults who participate in online communities [100], and among participants of an online support site for people with physical disabilities [76]. A study of participants in online infertility groups by Welbourne et al. demonstrated that SOVC can serve as a 'buffer' between stress and physical health symptoms [119].

Stronger feelings of attachment to a community can translate into increased feelings of connectedness, defined as the degree to which individuals are socially close, interrelated, or share resources with others [45, 96]. Youth embedded in environments which provide access to caring adults who can model prosocial behaviors have been found to reduce their risk for involvement in violence, crime, substance use and misuse, and high-risk sexual behaviors [33, 36, 56, 87]. Stronger community attachment could also provide access to more social capital, defined as the sense of trust, social integration, availability, and participation in one's social organizations [10, 75]. Together, connectedness and social capital have been found to protect against suicide-related behaviors and other forms of violence, by providing better access to social supports and resources, decreasing isolation, encouraging adaptive coping behaviors, and helping build resiliency [45].

These observations about the relationship between community attachment and tangible individual and social health benefits motivate substantially our investigation into how SOVC is expressed in online contexts, how it can be measured, and how it can be more effectively supported.

2.3.2 Antecedents of SOC/SOVC. The present study is concerned not only with characterizing SOVC within live-streaming communities, but also identifying measurable traces of activity associated with viewers and communities in which feelings of SOVC are higher or lower. Several prior studies of offline communities have identified links between SOC and the exchange of support [24, 27, 76, 84, 90, 123]. Similarly, research on virtual communities has identified positive relationships between SOVC and the exchange of support [12, 14, 64]. For instance, Sutanto et al. used longitudinal panel data to illustrate that mutual fulfillment of needs within a knowledge community was an antecedent to future levels of SOVC [102].

In contexts where participation can be measured, a strong relationship has been drawn between levels of interaction and SOVC. Du et al. observed that the use of interactive public displays to comment on videos led students to feel a stronger SOVC in a university context [35]. In an online support group for individuals with hearing loss, Cummings et al. demonstrated that active participation in the form of reading and posting messages was associated with stronger feelings of belonging [31]. For students participating in an online course, Wu et al. found that SOVC was positively associated with both the number of messages shared in chat and the use of asynchronous

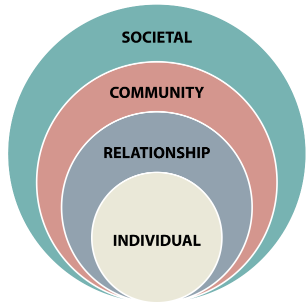

Fig. 1. The Social-Ecological Model summarizes the social environment that governs individual behaviors and perceptions using four levels: the individual, their immediate relationships, activity in the community in which they live, and societal-level factors.

communication tools [122]. Finally, in the online card game Hearthstone[2], Turkay & Adinoff illustrated that spectating, scorekeeping, sending gifts, and the use of synchronous chat could be associated with stronger feelings of SOVC [110].

Prior work has identified certain classes of activity that are associated with higher levels of SOVC within online communities. In this work, we explore for the first time which behaviors within live-streaming communities can be associated with SOVC, considering a broad class of features describing various levels of the social ecology surrounding viewers.

2.4 Social-Ecological Model

This study seeks to increase our understanding about the various factors influencing the relationships between individuals and the communities in which they participate, requiring knowledge of the complex, multi-layered context in which the individual is situated. Beginning in the 1970's, conceptualization and articulation of this concept began with what is now known as the Social-Ecological Model [19–22]. Widely used in the domains of public health, psychology, and medicine, the Social-Ecological Model is a theoretical framework that asserts that individuals' well-being and behaviors are the result of an active, dynamic and progressive interplay of factors at different levels of their social ecology. The Social-Ecological Model articulates the various nested "levels" in which an individual is situated and affected, as illustrated in Figure 1. We introduce these levels as follows:

- **Individual.** At the center of the model is the individual. Factors influencing persons at this level include personal characteristics such as age, gender, education, income, and personal health history as well as beliefs, attitudes, and behaviors [43]. Individual-level factors are some of the most widely-studied aspects in health-related research. However, prevention activities solely focused on individuals typically have a lesser impact on overall population health and well-being [47]. Individual-level interventions can also be particularly costly and intensive to tailor and scale to larger populations.
- **Relationship.** The next level of the model refers to the close relationships which influence an individual, such as family and friends. Programs and prevention strategies at this level focus on teaching or facilitating healthy interpersonal relationships and have classically utilized educational efforts teaching effective communication and problem solving skills or establishing new, healthy interpersonal relationships such as through mentorship programs [43].
- **Community.** This third level represents the immediate social settings that influence individuals, such as places of work, education, recreation, and worship, among other activities.

[2]https://playhearthstone.com/

Traditionally, the community level of the framework is focused on the direct neighborhood context in which an individual exists. Prevention strategies focused at the community level seek to mitigate broader factors influencing the community, such as poverty or violence [43].

- **Societal.** The outermost layer of the Social-Ecological Model encompasses the broadest set of factors that influence individuals and their communities. These factors include things such as governmental or institutional policies as well as cultural norms. Prevention strategies exerted at this level of the social ecology can have broad downstream benefits on human health, educational attainment, economic well-being, and other elements of individual and community flourishing [43].

The Social-Ecological Model has been used widely not only to comprehensively study the risk and protective factors that may influence an individual, but also to plan interventions, programs, and policy to affect human health and well-being. An appreciation of what is happening at each level helps to avoid oversight of key factors influencing an individual or an erroneously narrow perspective when identifying risk factors or proposing strategies or programs.

2.4.1 Online communities and the social ecology. The Social-Ecological Model as an organizing framework for studying individuals within their community context has been widely used in health and psychology related research including mental health [121], violence and bullying [38], obesity and physical activity [81], maternal and infant health [50], HIV and other infectious diseases [8], and a wide spectrum of other conditions. Increasingly, online communities are being recognized as an important component of the social ecology with tangible effects on individual's health and well-being (e.g., [107, 109]).

The need to understand how online communities impact health behaviors has been accelerated due to the COVID-19 pandemic. The Pew Research Center estimates that more than half of U.S. adults considered the internet essential during the pandemic [114]. This is consistent with reports of 20-40% increases in broadband internet traffic during that time [18]. Video streaming has potentially seen even larger growth during this period. Between July 2020 and July 2021, coinciding with a time when physical distancing was being commonly practices as a way to mitigate and reduce the spread of the virus that causes COVID-19 [44], viewership on Twitch grew from 17.5 million daily visitors [113] to over 30 million [111].

Considering how digital technologies and online environments have greatly affected the way we connect and relate to others, expanding our understanding of the digital sphere is "necessary to enhance social ecology research, both as an addition to the theoretical framework and as a subject of study to tackle today's urgent and complex global issues" [109]. Some of the earliest works in exploring online social experiences are rooted in video gaming research. Rich in potential for interaction and interactivity, online gaming environments have been referred to as "a civic space, political domain, media sphere, and site of critical work, while simultaneously being a place of leisure, even rest and respite (p. 13)" [107].

2.5 Applying the Social-Ecological Model to Online Communities

Virtual environments are diverse, multidimensional, and heterogeneous [16], making it imperative to be specific in defining these whenever they are the unit of research. Their multilayered complexity allows for individuals to interact at different levels of their virtual environments. Beyond considering how these are part of an individual's holistic social-ecology, it is also valuable to explore the applicability of the Social-Ecological Model within virtual communities. What types of interactions do individuals have across different levels of the virtual social ecology? Would a social-ecological lens help better understand the complexity of online communities' interactions?

2.5.1 Individual level of the virtual social ecology. The same individual-level factors (e.g., age, gender, education) that influence individuals in their traditional community context likely also influence individuals and their behaviors in online communities, although with some important nuances [53, 98]. The existence of an online disinhibition effect [97] — that is, how people say or do things online that they otherwise wouldn't face-to-face — has been noted; virtual environments grant people vastly diverse opportunities to choose how to present themselves to others. That is why understanding the relationship between an individual's identity online and offline has become a key dimension in the field of cyberpsychology [98].

An individual's online identity cannot be strictly separated from who the person is offline. For instance, research suggests that male and female users behave differently in online communities – one study suggests that females' online community activity is more susceptible to emotions [101]. Furthermore, some females may opt to present themselves as male or gender-neutral online to avoid gender-based stereotypes or harassment [62]. Additionally, virtual community engagement can impact differently persons of different age, gender, and race/ethnicity. For example, moderate use of digital technology can result in enhanced well-being among youth [2, 34].

2.5.2 Relationship level of the virtual social ecology. At the relationship level, online communities can be an everyday source of connectedness and social capital for users (e.g., [37, 51]). In fact, online community engagement has been associated more with connecting with others and entertainment than with information-seeking behaviors (e.g., [86]). Suler has suggested that if the relationship is what heals in psychotherapy, then online communities could provide different types of therapeutic relationships, depending on the type of communication it offers [99]. Furthermore, significant long-term friendships and intimate partnerships have originated and developed via online communities. Even if members never meet in person, or even if social interaction is not personal (e.g., streamers, influencers), some online relationships can be as important and influential as offline ones.

As with other types of communities, virtual environments that allow for human interaction can place members at risk for exposure to adverse online experiences, now increasingly referred to by the video gaming industry as "disruptive behavior". Beyond the commonly referred to toxicity that can at times be encountered in some environments, "disruptive behaviors" also includes a subset of "harmful conducts" that can cause significant physical, mental or emotional harm [4], such as cyberbullying [88], sexual harassment [71], and underage sexting [28]. Online communities can also be used by some as a tool to facilitate offline violence, such as gang violence [65, 85].

2.5.3 Community level of the virtual social ecology. How much members contribute and relate to others in the online community is associated with their motivations for being part of that community, mediated by how conducive the community is for such active contributions [115]. This suggests that online communities' policies, automated moderation systems, hosts (e.g., streamers, administrators, influencers), human moderators and users play a key role in establishing the context of communication and trust that is essential for members to feel they belong to the group [62, 106]. For example, Jodén and Strandell found that streamer authenticity, recognition and use of collective pronouns are key inclusion techniques to help members feel they belong to their virtual community [59]. While virtual communities can be forged through narrative, speech, and social action, sense of community goes beyond to require interaction, social motivation, and shared goals [59, 73]. Furthermore, community level interactions within virtual environments can have offline impact. For example, online community developers, streamers and moderators can contribute to patterns of dominance in society offline [69].

2.5.4 Societal level of the virtual social ecology. As in offline communities, virtual communities have developed formal and informal governance mechanisms which guide behavior [23]. While most emphasis has been on the legally sanctioned terms of service (e.g., regulating data use, copyright infringement), many virtual communities also create behavioral policies to guide the type of shared content and interactions expected within the community (e.g., community norms) that can be service-wide and/or community-specific (e.g., channel-level), and which are affected by its specific characteristics/context. Services can vary widely with respect to which behaviors they choose to capture in their policies [58] and how specific behaviors are characterized or addressed [82]. Within a given service, the set of 'societal' rules can change over time to adapt to new challenges [61]. Both the formulation and presentation of rules impacts the social ecology; a large-scale field experiment on community rules and online harassment, for instance, found that announcing rules up front increases both compliance and newcomer participation increases [68].

Our review of the prior literature has demonstrated the importance of each level of the social ecology and potential impacts on individual perceptions, behaviors, and health outcomes. In this study, we adapt the Social-Ecological Model towards a novel application, looking specifically at aspects of this social ecology as it manifests online, within a virtual community. We observe a clear mapping of the individual, relationship, and community levels to the online context. In this context, the 'societal' level could be most closely understood as the impact of service-level or internet-level governance, policies, and norms on community development. As the present study consisted of a single round of data collection within a single service, we are unable to evaluate how changes in societal-level factors influence SOVC. As a result, in the study below, we focus specifically on the individual, relationship, and community-level factors which influence the community experience.

3 METHODS

We designed a survey to capture viewers' sense of virtual community (SOVC), with respect to the Twitch channels in which they regularly participated. This survey was distributed via email in April 2020 to Twitch viewers aged 18 and over in the United States and completed by 1,944 Twitch viewers (response rate: 13.1%). In this section, we first describe the study design, including the survey instrument and participant selection. We then discuss the data collected, both through the survey and logged data capturing on-service behavior (i.e., behavioral trace data). Finally, we outline the statistical methods used to analyze these data and develop our models of SOVC.

In this work, we invoke the Social-Ecological Model as an organizing framework for thinking about SOVC in the context of live-streaming communities, from the individual, relationship, and community perspectives within a channel. The value of applying the Social-Ecological Model to this problem in the context of live-streaming communities extends beyond our study of SOVC; it is increased by prior cross-platform research indicating that applications of this model may be beneficial across a number of areas relevant to CSCW.

3.1 Survey Design

The survey started with demographic and screening questions, and then asked respondents to identify a specific Twitch channel in which they regularly engaged. Subsequently, they were asked to respond to a set of survey measures regarding their identified channel, including a set of 37 items designed to capture SOVC. We discuss the design of our survey instrument below, with particular attention to measures of SOVC. We then explain our participant sampling and recruitment strategy.

3.1.1 Survey instrument. The full online questionnaire consisted of four sections. Two of these sections, covering demographic information and measures of SOVC, are relevant to the present study and represent the subject of our analysis (these measures are provided in full in the Appendix). The remaining two sections contained six questions, probing other aspects of the social experience within channels unrelated to the present study; we have not included a discussion of these measures.

Demographic information (e.g., age, gender) was collected in the first section; any respondent self-reporting that they were under 18 years of age was immediately skipped to the end and excluded from participation. The demographic characteristic section ended with the following screening question, *"How important is it to you to feel a 'sense of community', in general, when you watch or participate on Twitch?"*, with five response options ranging from *Not important at all* to *Very important*. This question was intended to focus our respondent population to those with at least some social or community-based motivation for using Twitch. 35 respondents (2%) who selected *Not important at all* were excluded from the section with measures covering SOVC, and thus not considered in the data analyzed for this study.

The SOVC section included 37 measures capturing SOVC (discussed in greater detail below). First, respondents were asked to name the Twitch channel in which they had "spent the most time over the past month." When answering subsequent questions about this channel, they were directed to "think about the community associated with this channel, as you experience it on chat, on other channels or other platforms (e.g., Discord, Twitter) or through offline events." Two additional prompts asked participants to describe using open-ended text what aspects of that channel made it a particularly "fun and rewarding" place to meet and engage with others, and what aspects made it "difficult or less rewarding."

3.1.2 Sense of virtual community measures. All SOVC measures were adapted from prior published work, selected to cover a broad range of concepts which may or may not be relevant to the experience within live-streaming communities. The primary sources for 29 of the 37 items in the survey included the following:

- The original 12-item Sense of Community Index (SCI) (Perkins et al. [83]).
- A revision of the SCI validated in a sci-fi fandom community (Obst et al. [77, 78]).
- A second revision of the SCI validated within university interest groups (Obst et al. [79]).
- A 22-item scale for evaluating SOVC in online newsgroups (Blanchard [12]).
- A 15-item variation on the SCI2 [25], developed and tested in a German online community (Abfalter et al. [1]).

An additional eight items were adapted from a study by Blanchard [15], which captured development and adherence to norms in virtual communities. We provide the full set of 37 items in Table 1 below, along with a mapping to the studies listed above describing where these items (or similarly-phrased items) had been previously tested. Participants responded to each item using a 5-point Likert-type scale (1 = 'Strongly Disagree' to 5 = 'Strongly Agree').

3.2 Data Collection

The online survey was distributed in April 2020 and completed by 1,944 Twitch viewers aged 18 years or older, located in the United States. Participants were contacted using an email invitation and compensated a $10 gift card for completing the survey. All participants were recruited based on their prior Twitch viewing history (as described below), to purposefully include viewers engaging in a broad variety of channels. However, participants could respond to the survey in relation to a Twitch channel of their choosing, as described above.

Survey respondents were informed that all data is governed by Twitch's Privacy Policy, which allows for combining data with other sources in accordance with the privacy terms set forth. For responses that could be matched to an active Twitch channel in which the viewer had participated, we collected aggregated behavioral trace data to supplement our analysis. We describe the data used in our analysis in greater detail below.

Item	Perkins 1990 [83]	Obst 2002 [77, 78]	Obst 2004 [79]	Blanchard 2007 [12]	Abfalter 2012 [1]	Blanchard 2011 [15]
I expect to be a part of this community for a long time.	X	X		X	X	
I think this community is a good thing for me to be a part of.	X	X	X	X		
It is important to me to be a part of this community.	X	X	X	X	X	
I feel at home in this community.	X	X	X	X		
I recognize the screen names of most participants in this community.	X	X		X	X	
If there is a problem in this community, members can get it solved.	X	X	X	X	X	
Members of this community can be counted on to help others.	X		X			
I want the same things from this community as other members.	X	X	X	X		
Members of this community share the same values.	X	X	X	X		
I have friends in this community that I can depend on.	X			X		
If I have a personal problem, I can turn to members of this community.	X				X	
I care about what other community members think of me.	X	X	X	X		
Most members of this community know me.	X	X	X		X	
I feel like I have influence over what this community is like.	X	X	X		X	
I get important needs of mine met because I am part of this community.					X	
People in this community have similar needs, priorities, and goals.					X	
I can trust other members within this community.					X	
Fitting into this community is important to me.					X	
This community is influential in other parts of Twitch or the internet.					X	
This community has good leaders.					X	
I feel hopeful about the future of this community.					X	
Members of this community care about each other.					X	
This community has shared symbols and expressions of membership (such as emotes and logos) that people can recognize.					X	
Members of this community have shared important events together, online or offline.					X	
I can anticipate how some members will respond to certain questions or topics in chat.				X		
I've had questions that have been answered by this group.				X		
Some members of this group have friendships with each other.				X		
I've gotten support from this group in the past.				X		
I feel obligated to help others in this group.				X		
This community has clear norms about what types of language and behavior are appropriate.						X
I understand what language and behavior is appropriate in this community.						X
People generally behave appropriately in this community.						X
I approve of how most people behave in this community.						X
I believe that most people approve of how I behave in this community.						X
If someone does something inappropriate in this community, other community members will respond.						X
If someone does something inappropriate in this community, the moderators or streamer will take appropriate action.						X
If someone new were to join this community, the rules and norms for how to behave would be clear.						X

Table 1. This table summarizes the full set of 37 measures related to SOVC evaluated in this study, along with their evaluation in prior research. These prior studies evaluated SOVC in a variety of online contexts, including fandom communities [77, 78], interest groups [79], newsgroups [12], and online communities [1, 15].

3.2.1 Participant sampling and recruitment. Our participant pool started with Twitch viewers who had an email-verified account, were located in the United States with their language set as English, and had viewed content on Twitch from any device (e.g., PC, mobile, smart TV) within the prior 28 days. We designed our sampling strategy to enable us to capture multiple responses per channel, across a broad range of channels. From this pool, potential participants were chosen based on recent activity in a set of 200 seed channels, selected to cover channels ranging widely in size (from 50 - 25,000 average concurrent viewers[3] or *CCU*) and genre (covering gaming, creative, talk, and other non-gaming content). A breakdown of these seed channels by size and genre is shown in Table 2. For each seed channel, we distributed survey invitations to approximately 80-150 individuals who had spent most of their viewing time over the preceding 28 days within that channel.

[3] Average concurrent viewer count (CCU) is defined as the average number of logged-in or anonymous viewers present during a typical minute that a channel is streaming. This number is visible next to the stream title when a streamer is broadcasting

	Seed Channels				Respondent-Provided Channels			
CCU:	50-100	100-200	200-4000	4000+	0-100	100-200	200-4000	4000+
Gaming	18.0%	18.0%	18.0%	5.5%	19.0%	10.7%	27.3%	9.3%
Talk	7.5%	7.5%	7.5%	4.0%	5.9%	5.5%	6.2%	3.5%
Creative	3.0%	3.0%	3.0%	0.5%	3.1%	2.1%	2.4%	0.3%
Other	1.5%	1.5%	1.5%	0.0%	1.4%	1.4%	1.0%	0.0%

Table 2. These tables summarize the distributions of the initial seed channels and the channels self-selected by survey respondents with respect to audience size and genre. We note that respondent-provided channels are biased slightly towards larger, gaming channels. (CCU: Avg. Concurrent Users, as defined above)

The survey was distributed via a Twitch-branded email to 18,821 Twitch viewers and was kept open with the aim of receiving 2,000 completed responses. The email invitation (full text in the Appendix) indicated that the topic of the survey concerned participants' "experiences with social and community interaction on Twitch," intentionally biasing responses towards those interested in engaging socially on Twitch. This invitation also clearly indicated the requirement that participants be 18 years of age or older. This survey was published and distributed using Qualtrics.

3.2.2 Survey respondents. We received a total of 2,474 attempted responses (13.1% response rate), of which 530 (21.4%) were either screened out immediately because they self-reported their age as under 18 or disqualified because they didn't complete all required survey measures, providing a total of 1,944 completed responses. An additional 295 responses were excluded based on the following criteria: (1) did not provide the name of a valid Twitch channel, (2) indicated that a 'sense of community' on Twitch was 'not important' to them personally, or (3) 'straight-lined' responses to our SOVC measures. After these data cleaning steps, we were left with 1,649 completed responses to our SOVC measures, which represent the dataset used in our exploratory factor analysis. Respondents were compensated with a $10 Amazon gift card, regardless of whether they were screened out at this second stage. The average completion time for respondents who completed the entire survey was 845 seconds, with 77% completing the survey within 15 minutes, leading to an average compensation rate of $42.60 per hour.

The overall demographics of the survey population skewed younger and predominantly male. The mean self-reported age of respondents was 29.6 (σ_{age} = 11.1), with 42% reporting that they were under 25 and 72% under 35. 73% of respondents self-reported their gender as 'Male', 24% as 'Female', and 4% as 'Non-binary', 'third gender' or chose to self-describe. We note that this population resembles statistics from recent, comparable, survey-based research on Twitch (e.g., [93]).

3.2.3 Behavioral traces. We hypothesized that SOVC experienced by viewers in their self-identified frequently viewed channels would vary with both viewer-level and channel-level features that could be derived from behavioral data. As described above, respondents provided channel names as user-generated strings. We manually modified a small number of these strings, only in cases that were unambiguous (e.g., changing "http://www.twitch.tv/teamsp00ky" to "teamsp00ky"); all other responses were left as provided. Using case-insensitive matching, 1,412 responses could be matched to an active Twitch channel that the respondent had viewed within the preceding 28 days. These 1,412 responses referenced 295 unique channels; 168 channels were mentioned by multiple respondents, and the most-frequently mentioned channel appeared in 17 responses. The breakdown of these respondent-provided channels, summarized on the right side of Table 2, largely matched the seed set, with a slight bias towards larger, gaming channels.

For each respondent and channel mentioned, we developed the following sets of features corresponding to the four levels of the Social-Ecological Model, as summarized below in Table 3. Unless otherwise specified, all features captured activity over the 28-day period preceding survey deployment. Some variables were log_2-scaled (as indicated in the table). Data was matched to survey responses and then separated from any personally identifying account information. All data was captured as aggregate counts such that no individually identifying information, such as specific chat messages, were viewed and analyzed as part of this analysis.

Individual-level features. We included three categories of features capturing characteristics of the individual viewer. The first category included features capturing sitewide engagement, including *tenure* (days since account creation), *visit days* (frequency of visits to Twitch), and *chat days* (frequency of chat activity on Twitch). The second captured individual engagement with the channel, including *chat volume* (number of messages sent), *chat visibility* (fraction of time that chat was visible to the user), and *peripheral participation* (use of non-chat affordances for interaction, such as polls or channel points).

Relationship-level features. We included features capturing two types of relationships. Viewer-viewer relationships was captured through *mentions sent* and *mentions received* by the viewer, and whether the viewer *has gifted subscriptions* to other viewers in the channel. Viewer-creator relationship was captured through other spending activity, such as whether the viewer *has cheered* using bits to reward the creator, whether the viewer *has a paid subscription* or whether the viewer *has a prime subscription*, subscribing to the channel using the free subscription afforded by an Amazon Prime membership.

Community-level features. We included four categories of features describing the community experience within a channel, summarizing behavior across all Twitch viewers (logged-in or anonymous) who engaged with the channel, as daily averages over all broadcast days with 15 or more minutes. The first category captured community composition, including the *fraction logged-in* (fraction of all viewers who are logged-in), *fraction regulars* (fraction of logged-in viewers with an account) and *average tenure* (average days since first visit for logged-in viewers). The second category captured collective interaction. This included the *fraction chatters* (fraction of logged-in viewers who chat), *chat intensity* (number of chat messages per chatter), and whether the channel *has mentions*. We also considered the *fraction of chatters using global emotes* and *fraction of chatters using sub emotes* to capture the balance of Twitch-wide and channel-specific language. Finally, this category included whether viewers in the channel engaged in *peripheral participation*. The third category captured community creator interaction, based on spending in the channel through *prime subscriptions*, *paid subscriptions*, *gift subscriptions*, and *cheers* (also referred to on Twitch as 'Bits'). The fourth category captured high-level overall channel features, outside of the immediate social experience, including *channel age*, *live CCU*, and *days broadcast*.

3.3 Data Analysis

Our data analysis took place in two primary stages. In the first, we used exploratory factor analysis over the 37 items capturing SOVC, in order to identify a smaller number of dimensions which described the community experience within Twitch channels. We then developed a multi-level model to determine how well these dimensions could be predicted based on behavioral traces.

3.3.1 Exploratory factor analysis. We conducted exploratory factor analysis (EFA) of the 1,649 responses to the 37 items capturing SOVC. We used an iterative approach which alternated between identifying factors and removing poorly-fitting items until a satisfactory solution was achieved, following procedures used in previous CHI/CSCW research (cf. [9, 72]).

Social-Ecological Model Levels		Independent Variables : Behavioral Traces		
Level	Description	Construct	Measure	Description
Individual	Features describing the individual viewer's engagement.	Individual Sitewide Activity	Sitewide Tenure	Total days since initial account creation [log-scaled]
			Sitewide Visit Days	Unique days with visits on Twitch (any channel)
			Sitewide Chat Days	Unique days with chat activity on Twitch (any channel)
		Individual Channel Engagement	Channel Tenure	Total days since first visit to channel [log-scaled]
			Channel Visit Frequency	Fraction of sitewide visit days with channel visit
			Channel Visit Duration	Average session length per channel-day visited [log-scaled]
		Individual Channel Participation	Chat Volume	Total number of chat messages sent in channel [log-scaled]
			Chat Visibility	Total fraction of time in channel with chat visible
			Peripheral Participation	True, if viewer has participated using affordances outside of chat, such as polls or channel points; False, otherwise
Relationship	Features describing the viewer's dyadic interactions with others in the community.	Viewer-Viewer Relationship	Has Sent Mention	True, if viewer has mentioned in chat at least one other community member; False, otherwise
			Has Received Mention	True, if viewer has been mentioned in chat by at least one other community member; False, otherwise
		Viewer-Creator Relationship	Has Cheered	True, if viewer has "tipped" or "cheered" at least once using bits; False, otherwise
			Has Paid Subscription	True, if viewer had an active paid subscription to the channel at any point during the data collection period; False, otherwise
			Has Prime Subscription	True, if viewer had a Prime subscription to the channel at any point during the data collection period; False, otherwise
Community	Features describing the broader social environment within the channel.	Community Composition	Fraction Logged-In	Average daily fraction of viewers who are logged in to an account (log-scaled)
			Fraction Regulars	Average daily fraction of logged-in viewers who have viewed the channel at least once before, within the prior 28 days (log-scaled)
			Average Tenure	Average number of days since the first visit to the channel among logged-in viewers (log-scaled)
		Community Collective Interaction	Fraction Chatters	Average daily fraction of logged-in viewers who sent at least one chat message
			Chat Intensity	Average number of daily chat messages sent per chatter (log-scaled)
			Has Mentions	True, if 1 or more mentions were sent in chat during the data collection period; False, otherwise
			Fraction Global Emote Users	Average daily fraction of chatters who used at least one global emote
			Fraction Sub Emote Users	Average daily fraction of chat users who used at least one subscription emote
			Peripheral Participation	True, if channel has any viewers who participated using affordances outside of chat, such as polls or channel points; False, otherwise
		Community Creator Interaction	Paid Subscription Rate	Average daily fraction of logged-in viewers with a paid subscription
			Prime Subscription Rate	Average daily fraction of logged-in viewers with a Prime subscription
			Gift Subscription Rate	Average daily fraction of viewers who have gifted 1+ subscription to another viewer in the channel.
			Cheer Rate	Average daily fraction of viewers who have "cheered" or "tipped" the creator using bits.
		Overall Channel	Channel Age	Months since the first broadcast on the channel
			Live CCU	Average live concurrent viewers, as computed over the data collection period (log-scaled)
			Broadcast Frequency	Fraction of days during data collection period where channel broadcast live for 5 or more minutes

Table 3. Features capturing levels of individual, relationship, and community–level activity within Twitch channels. Unless otherwise specified, features capture aggregated activity over the 28-day period preceding survey deployment. A 'visit' is defined as five or more minutes spent in the channel during a given session, and a 'viewer' is defined as an individual with one or more visits. Variables marked as 'log-scaled' were transformed as $log_2(x)$.

$$\overbrace{\hat{y}_{ij}}^{\text{Individual Viewer SOVC Score}} = \overbrace{\alpha_i}^{\text{Channel-Level Intercept}} + \overbrace{(\beta_1 x_{ij1} + \beta_2 x_{ij2} + \cdots + \beta_n x_{ijn})}^{\text{Viewer-Level Fixed Effects (Individual + Relationship)}}$$

$$\hat{\alpha}_i = \underbrace{\gamma_1 x_{i1} + \gamma_1 x_{i1} + \cdots + \gamma_m x_{im}}_{\text{Community-Level Fixed Effects}}$$

Fig. 2. Equations describing the two levels of our hierarchical model. In the first level of the model, we estimate the SOVC score (cohesion or belonging) for an individual viewer j in a channel i using a mixed-effects model with viewer-level fixed effects (individual-level and relationship-level features) and random intercepts for each channel i. In the second level of the model, we estimate these random intercepts for each channel i using only fixed effects capturing community-level features describing that channel.

As our data comprised ordinal scales, we utilized polychoric rather than Pearson correlations, as these have been shown to provide a less biased estimate of the underlying relationships, as illustrated through a literature review and simulation study by Baglin [7]. In each round, we tested the data for factorability, using the Kaiser-Meyer-Olkin test of sampling adequacy and Bartlett's test of sphericity to evaluate the suitability of the remaining data for factor analysis; in each round, the KMO value exceeded 0.95 and the Bartlett test returned a p-value less than 0.0001. The number of factors in each round was chosen such that all factors had eigenvalues exceeding 1. We then removed all items that loaded on multiple factors or failed to load above 0.40 on any factor. This procedure was iterated three times until a stable factor solution emerged, which is the solution discussed in our results. Our aim was to develop a SOVC scale that was as concise as possible, while maintaining internal consistency and meaningful factor structure. Through this process, we reduced the set of SOVC items from 37 to 19, and the number of factors from five to two. To compute a single score for each dimension for each viewer, we averaged the scores (mapped from 'Strongly Disagree' = 1 to 'Strongly Agree' = 5) across the items associated with that dimension.

3.3.2 Hierarchical linear model. To identify patterns of on-Twitch activity associated with stronger or weaker perceptions of SOVC we developed a predictive model, summarized above in Figure 2, using our SOVC scores as dependent variables, and the behavioral traces discussed above as independent variables. This model combined two separate linear models, a viewer-level model characterizing how individual viewers' scores differ within a single channel, and a channel-level model which characterizing how typical scores vary from channel to channel. These models include only features measurable using data from on-service activity and exclude offline characteristics, such as user demographics. Combining the output of these two models, we can generate predictions for Twitch viewers in arbitrary channels, even those outside of the set captured in our survey.

Individual/relationship-level model. To identify viewer-level features associated with perceptions of SOVC, we utilized a linear mixed-effects model, using our SOVC scores as the outcomes, individual-level and relationship-level features describing the viewer as fixed effects, and `channel` as a random intercept. This formulation assumes that each channel has a different underlying distribution for SOVC scores, which describes differences in how a "typical" set of viewers might score that channel. Within that distribution, we assume that individual viewers may generate scores lower or higher than the mean, based on their individual-level and relationship-level activity.

For each dimension of SOVC, features were selected using an abbreviated forward stepwise selection process. A model including random intercepts for channels and a single fixed effect to be evaluated was compared against a null model, which included only the random intercepts, using a likelihood ratio test. Any feature which provided a significant improvement to the model

Scale / Item	Factor 1	Factor 2
Cohesion (α = 0.893)		
If someone does something inappropriate in this community, the moderators or streamer will take appropriate action.	**0.80**	0.18
People in this community generally behave appropriately.	**0.76**	0.18
I approve of how most people behave in this community.	**0.74**	0.23
This community has good leaders.	**0.73**	0.34
I'm hopeful for the future of this community.	**0.71**	0.35
If a new member joined, the rules of this community would be clear.	**0.71**	0.24
If someone does something inappropriate, members of this community will respond.	**0.71**	0.21
This community has clear norms about what behavior is important.	**0.70**	0.24
Members of this community share the same values.	**0.60**	0.39
Most people in this community approve of me.	**0.50**	0.39
Belonging (α = 0.896)		
Most members of this community know me.	0.08	**0.82**
I have friends in this community that I can depend on.	0.20	**0.77**
I have influence over what happens in this community.	0.17	**0.71**
Fitting into this community is important to me.	0.33	**0.70**
I've gotten support from this community in the past.	0.33	**0.70**
I feel obligated to help others in this community.	0.31	**0.66**
If I have a personal problem, there are people in this community I can turn to.	0.34	**0.65**
I care what other people in this community think of me.	0.27	**0.63**
I can recognize the names of most participants.	0.33	**0.61**

Table 4. Dimensions of SOVC for Twitch communities identified through Exploratory Factor Analysis, with factor loadings for items and Cronbach's alphas (α) for factors. All items were tested using a 5-point Likert scale ranging from "1: Strongly Disagree" to "5: Strongly Agree".

fit, compared to the null model, was included in the full model, for each SOVC dimension. This combined model is the model discussed below in our results. In addition to coefficients for viewer-level features which have a meaningful relationship with perceptions of SOVC, this model also produced channel-level intercepts for each of the 295 channels captured in our survey.

Community/channel-level model. The second level used simple linear regression to predict the channel-level intercepts inferred from the first level of the model. These represent channel-specific baselines for SOVC scores, after controlling for differences in individual behavior. The independent variables in this model are the community-level features describing the channel. This model assumes that systematic differences in viewers' perceptions of SOVC within a channel can be predicted based on community-level and societal-level differences. Due to the large number of variables considered, we further abbreviated the process of selecting variables. We first created a set of four smaller models, corresponding to each sub-group of behavioral features discussed above (e.g., community composition, community creator interaction), in which all relevant features were added. For each dimension of SOVC, any features identified as having a significant relationship with the outcome were added to the full models presented below in our results.

4 DESCRIBING SOVC WITHIN LIVESTREAMING COMMUNITIES

Through the iterative EFA procedure described above, we identified two primary dimensions describing how perceptions about communities vary on Twitch. We have manually assigned to these dimensions the names **Cohesion** and **Belonging**, based on consideration of the items loading on each factor. We describe each dimension and the distribution of scores across survey respondents in detail below. We also provide a high-level validation of these scores by demonstrating how they can be used to help predict long-term retention for individual viewers within channels.

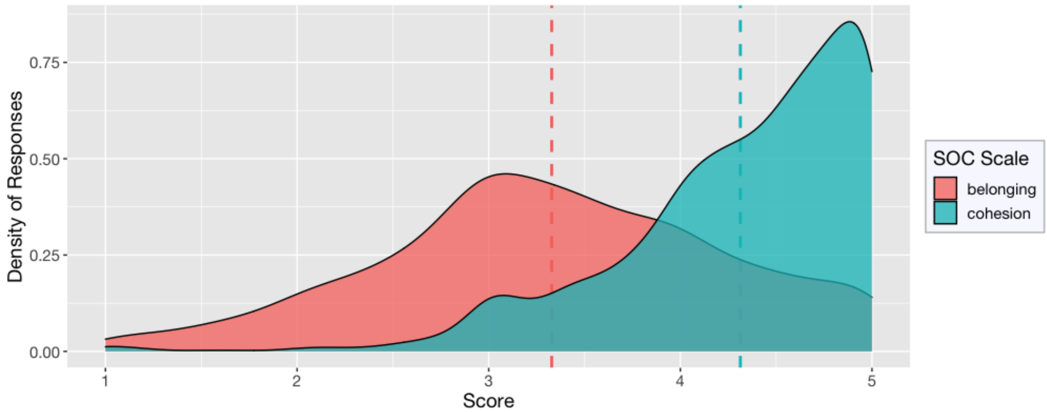

Fig. 3. Distribution among survey respondents of scores computed for cohesion and belonging, on a scale from 1 (low) to 5 (high). Scores for cohesion were noticeably left-skewed ($\mu = 4.3, SD = 0.6$), while scores for belonging were more evenly distributed along the range of possible scores ($\mu = 3.3, SD = 0.9$).

4.1 Cohesion

Cohesion captures the extent to which viewers feel that a channel functions well as a community, from the quality of its leadership to its ability to establish and enforce standards of behavior. We can measure viewers' scores on this dimension with respect to a channel using the first list of survey items provided in Table 4. High levels of agreement with measures on this scale indicate a stronger perception that the community is well-managed. Items loading on this factor have been categorized in prior work as a variety of constructs related to SOVC, including 'cooperation/values' [77, 78], 'integration/needs fulfillment' [1, 79], and 'shared emotional connection' [1, 79]. This factor also included several of the items which we added to capture aspects of norm development and adherence. While prior work (e.g., Blanchard et al. [15]) has conceptualized perceptions about community norms as distinct from SOVC, our findings with respect to Twitch indicate that these can be viewed as part of a larger construct characterizing the collective efficacy of a community.

4.2 Belonging

Belonging captures the extent to which an individual viewer feels personally integrated into a channel and supported by other community members. We can measure viewers' scores on this dimension with respect to a channel using the second list of survey items provided in Table 4. High levels of agreement with measures on this scale indicate a stronger perception that the viewer 'fits into' or 'meshes with' the social fabric of the channel. Items loading on this factor have been categorized in prior work across several related concepts, including 'belonging' [77, 78], 'membership' [1, 79], 'integration/needs fulfillment' [1, 79] and 'influence' [1, 79]. This dimension aligns more closely with traditional notions of membership and integration, grouping them together into a holistic construct in the context of communities on Twitch.

4.3 Computing and Validating SOVC Scores.

As shown in Table 4, the inter-item reliability for these scales was high ($\alpha_{cohesion} = 0.893$; $\alpha_{belonging} = 0.896$), indicating that items on each scale are highly-related, but below the maximum recommended threshold of 0.90 or 0.95, indicating also that items are not redundant [105]. By mapping responses from 1 (Strongly Disagree) to 5 (Strongly Agree) and averaging scores across items in a scale, we can compute individuals scores for cohesion and belonging for each respondent; these scores represent

Variable	**Cohesion**		**Belonging**	
	β	p	β	p
(Intercept)	4.02	***	3.46	***
Individual-Level				
Individual Sitewide Activity				
Sitewide Tenure (log_2)	—	—	-0.06	—
Sitewide Visit Days	—	—	0.01	—
Sitewide Chat Days	-0.06	—	0.28	—
Individual Channel Engagement and Participation				
Channel Tenure (log_2)	—	—	0.03	**
Average MW (log_2)	0.02	—	-0.03	—
Chat Volume (log_2)	0.04	***	0.07	***
Chat Visibility Low (T/F)	—	—	-0.06	—
Peripheral Participation (T/F)	0.07	—	0.155	*
Relationship-Level				
Viewer-Viewer Relationship				
Sent Mention (T/F)	—	—	-0.09	—
Received Mention (T/F)	—	—	0.13	—
Gifted Subscription (T/F)	0.06	—	0.09	—
Viewer-Creator Relationship				
Has Cheered (T/F)	0.04	—	0.17	—
Has Paid Subscription (T/F)	0.05	—	0.08	—

Table 5. β coefficients for the two linear mixed-effects models evaluating which individual-level and relationship-level activity are associated with feelings of belonging and cohesion. Features were included in each model only if they were significantly associated, on their own, with the outcome variable. Variables not tested in the full models have β coefficients marked as —. Indicators for p-values are as follows: $^{*}: p < 0.01$, $^{**}: p < 0.005$, $^{***}: p < 0.001$.

the dependent variable in our viewer-level SOVC model below. We summarize the distributions for each of these scores in Figure 3 above.

We note that scores for cohesion are left-skewed, clustered towards the high end of the scale ($\mu_{cohesion} = 4.3$, $\sigma_{cohesion} = 0.6$), while scores for belonging are more evenly distributed across the range of possible scores ($\mu_{belonging} = 3.3$, $\sigma_{belonging} = 0.9$). These distributions represent the population surveyed, where respondents specifically selected channels in which they spent a lot of time, and are likely not representative across viewer-channel relationships on Twitch. We note that many respondents scored high on cohesion and low on belonging, but few scored high on belonging and low on cohesion. Our hypothesis is that cohesion may be more of a necessary condition for regular channel engagement than belonging, at least among users who value community engagement on Twitch, such as those in our survey participant pool. In other words, participants may be less willing to remain in communities with less cohesion, and thus may have been less likely to provide these channels in response to the survey.

4.3.1 Evaluating predictive validity. To validate these measures, we explored the relationship between the participants self-reported SOVC and their long-term retention in those channels, operationalized as whether they had returned to view content in that channel during a 28-day period in April 2021, exactly one year after providing their survey responses. In total, we found that 44.9% of participants surveyed had returned to the channel during this period. We used a logistic regression model, including as predictors for each viewer their two computed scores for cohesion and belonging, with no additional control variables. This model identifies a significant relationship between users' perceptions of belonging and their long-term retention ($\beta = 0.24$, $p < 0.005$), but

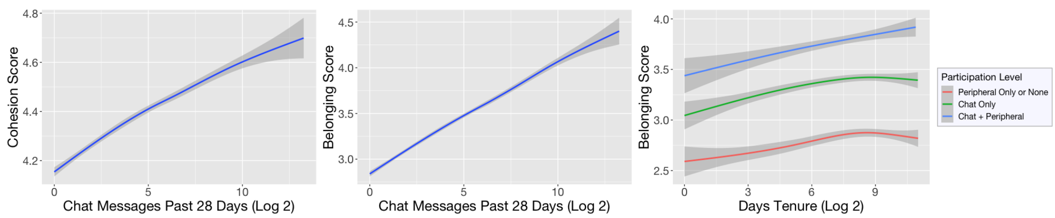

Fig. 4. Relationships between individual-level features and SOVC. (Left) Predicted cohesion scores as a function of the number of chat messages sent by the viewer in the channel (log_2-scaled). (Middle) Predicted belonging scores as a function of the number of chat messages (log_2-scaled). (Right). Predicted belonging scores as a function of tenure (days since first visit) in the channel (log_2-scaled), split by viewers who don't participate or participate only peripherally (red), viewers who engage only in chat (green), and viewers who engage in both chat and peripheral forms of participation, such as polls and community points (blue).

no such relationship for cohesion. Specifically, for users scoring a 1 (Low Belonging), the model predicts a 32.4% chance of retention in the channel one year later; for those scoring a 5 (High Belonging), the model predicts a 53.9% chance of retention. These results demonstrate that SOVC scores have predictive validity with respect to viewers' long-term attachment to communities.

5 BEHAVIORAL INDICATORS FOR SOVC ON TWITCH

Our second research question focused on whether and which individual-level, relationship-level, community-level, and channel-level activity features are associated with stronger or weaker SOVC perceptions. We used the two-level linear model described above to evaluate features at each level using behavioral traces describing activity on Twitch. In the first level, we use individual viewer activity to evaluate individual- and relationship-level indicators. In the second level, we use aggregate channel activity to evaluate community- and channel-level indicators. We describe the results of these models below.

5.1 Individual-Level and Relationship-Level Indicators of SOVC

In our viewer-level model, we evaluated relationships between each SOVC dimension and the individual- and relationship-level features detailed in Section 3.2.3 using a generalized linear mixed model. We summarize the results of these models in Table 5, with β-coefficients provided for all features tested in each model. In each case, a likelihood-ratio test, which compared this full model (with fixed effects and channel-specific random intercepts) to a null model (with only channel-specific random intercepts) demonstrated that the fixed effects contribute statistically significant explanatory power for both cohesion ($\chi^2(5) = 68.125$, $p < 0.001$) and belonging ($\chi^2(13) = 257.52$, $p < 0.001$). In our full viewer-level model for cohesion, 5.3% of the variance is explained by the fixed effects and 14.6% by the random effects (Conditional $R^2 = 0.199$). In our full viewer-level model for belonging, 19.3% of the variance is explained by the fixed effects and 11.9% by the random effects (Conditional $R^2 = 0.311$).

Findings suggest that the volume of chat messages contributed by an individual is the only feature that has a significant relationship with both cohesion and belonging. For two otherwise-identical viewers in the same channel, we would expect the one with twice as many chat messages to score 0.04 points higher on cohesion (stats) and 0.07 points higher on belonging (stats), on a scale from 1 to 5. This relationship is shown in Figure 4 (left and middle), which plot predicted scores against total chat volume (log-scaled). We also find that longer channel tenure (stats) and peripheral participation (stats) are both predictive of stronger scores for belonging. For two otherwise identical

Variable	Cohesion		Belonging	
	β	p	β	p
(Intercept)	-0.05	—	0.27	***
Community-Level				
Community Composition				
Fraction Logged-In (log_2)	0.29	**	—	—
Fraction Regulars (log_2)	-0.10	—	-0.11	—
Community Collective Interaction				
Fraction Chatters	-0.03	—	0.03	—
Fraction Global Emote Users	-0.23	—	-0.30	*
Fraction Sub Emote Users	0.19	*	0.25	—
Community Creator Interaction				
Prime Subscription Rate	5.38	***	—	—
Gift Subscription Rate	—	—	2.68	—
Overall Channel Features				
CCU (log_2)	-0.01	**	-0.02	***
Broadcast Frequency	-0.07	—	0.02	—

Table 6. β coefficients for the two models evaluating which community-level and channel-level activity are associated with feelings of belonging and cohesion. Features were included in each model only if they were identified as significantly associated with the outcome in a smaller model testing groups of variables outlined in Section 3.2.3. Variables not tested in the full models have β coefficients marked as —. Indicators for p-values are as follows: * : $p < 0.01$, ** : $p < 0.005$, *** : $p < 0.001$.

viewers in the same channel, we would expect the one with a tenure twice as long would score 0.03 points higher on belonging, and the one who participates peripherally to score 0.15 points higher. In Figure 4 (right), we can see interesting temporal trends stratified by feature use. For viewers who participate using peripheral features, feelings of belonging continue to increase with tenure while for those who don't participate peripherally, feelings of belonging appear to start declining after around half a year ($2^7 = 128$ days).

5.2 Community-Level Indicators of SOVC

In our channel-level model, we evaluated the relationships between the channel-level intercepts identified for each SOVC dimension in the first model and the community-level features detailed in Section 3.2.3. We summarize the results of these model in Table 6 below, with β-coefficients provided for all features tested in each model. We found that the community-level features explained a significant proportion of variance in the estimated channel-level intercepts for cohesion ($R^2 = 0.1937$, $F(8, 284) = 9.77$, $p < 0.001$) and for belonging ($R^2 = 0.1832$, $F(8, 284) = 9.187$, $p < 0.001$).

Channels with stronger cohesion scores typically have more logged-in viewers ($\beta = 0.29$, $p < 0.005$). Channels with stronger cohesion scores also have more chatters who use subscriber (channel-specific) emotes ($\beta = 0.19$, $p < 0.01$), though we observed no relationship with the use of global (Twitch-wide) emotes. Channels with stronger cohesion scores had more users who subscribed using their Amazon Prime benefit ($\beta = 5.38$, $p < 0.001$), but we observed no clear relationship with paid subscriptions. Channels with stronger belonging scores typically had fewer chatters who used global emotes ($\beta = -0.30$, $p < 0.01$), with no clear relationship for subscriber emote use. In Figure 5, we illustrate the relationships between subscriber/global emote use and predicted channel-level SOVC intercepts (relative to the average channel scored in the survey). A clear pattern is evident for cohesion, in which the use of more subscriber emotes and fewer global emotes predicts higher scores. The relationship between emote usage and belonging appears to be more complicated, potentially due to some interaction effect not explored in our model.

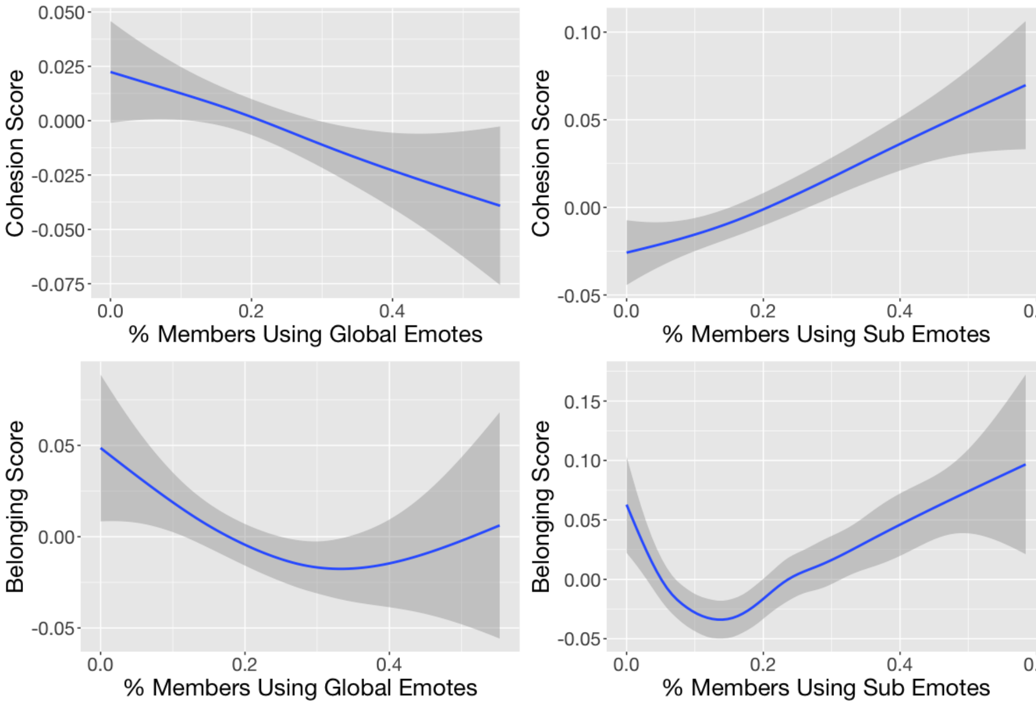

Fig. 5. Relationships between community-level features and SOVC. The top two figures show predicted *cohesion* scores as a function of the fraction of chatters who use global or sub emotes. We note a clear linear trend, with stronger cohesion scores associated with the use of more sub emotes and fewer global emotes, though only the relationship with global emotes was significant ($\beta = 0.19$, $p < 0.01$). The bottom two figures show predicted *belonging* scores as a function of global/sub emote usage. Though the model identifies a negative linear relationship between global emote use and belonging ($\beta = -0.30$, $p < 0.01$), we note that the association appears to be more complex. Note that the Y-axes capture the predicted channel-level intercept for a score, relative to the set of channels captured in our survey responses, rather than absolute scores.

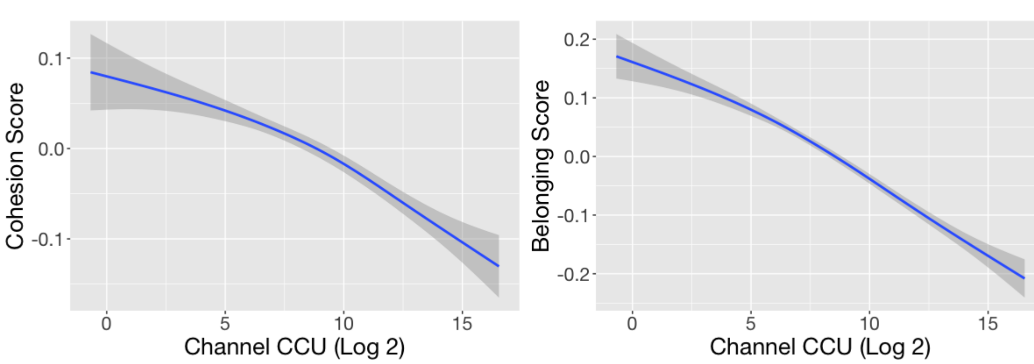

Fig. 6. Relationships between channel size (CCU, log_2-scaled) and SOVC. On the left, we see a clear negative relationship between CCU and scores for cohesion ($beta = -0.01$, $p < 0.005$). On the right, we observe a slightly stronger relationship between CCU and scores for belonging ($beta = -0.02$, $p < 0.001$). Again, the Y-axes capture the predicted channel-level intercept relative to a typical channel, rather than the raw score.

In terms of overall channel indicators, we find that channel size is strongly negatively associated with perceptions of both cohesion ($\beta = -0.01$, $p < 0.005$) and belonging ($\beta = -0.02$, $p < 0.001$). For two otherwise-identical channels which vary only in channel size, we would expect a 10K-CCU channel to score, on average, 0.1 points lower on cohesion and 0.2 points lower on belonging than a 10-CCU channel, indicating that while this is a consistent effect, it is relatively small. In Figure 6 above, we illustrate the relationships between channel size and predicted channel-level intercepts for SOVC, again relative to the average channel scored in the survey.

6 DISCUSSION

This work was motivated by a desire to understand how *sense of virtual community* (SOVC) varies across channels on Twitch, and to identify aspects of the social experience within channels that are associated with stronger or weaker communities. In the sections below, we start by presenting a brief summary of our results and their contribution to the literature. We then discuss some of the design implications for livestreaming and other types of online communities. Finally, we consider some of the theoretical implications raised by this work, both within CSCW and beyond.

6.1 Summary of Results

Using data collected through a survey of 1,944 Twitch viewers, who were participants in communities which ranged widely in size and content, we evaluated a large set of SOVC measures developed and evaluated in prior study of offline and online communities [1, 12, 13, 15, 77, 78, 83], to identify which characterize meaningful differences across community experiences in livestreaming communities on Twitch. Drawing on the Social-Ecological Model as a theoretical framework, we articulate the various nested levels describing how an individual participant is situated within an online community, specifically capturing three levels of factors: 1) those describing the individual, 2) those describing one-to-one relationships within the community, 3) those describing distributed interactions and the community as a whole.

6.1.1 How SOVC varies across livestreaming communities on Twitch. Our analysis found that SOVC is best captured using two distinct dimensions: cohesion and belonging. Cohesion primarily represents how the community functions, but not the individual viewer's relationship to that community. Belonging captures how individuals relate to the larger group structure, but not their thoughts on how effectively it functions. While belonging aligns closely with constructs from prior research (e.g., [1, 12–14, 64, 108]), cohesion represents a novel combination of community perceptions which previous studies have identified as separate, including cooperation and shared values [77, 78], integration and needs fulfillment [1, 79], shared emotional connection [1, 79], and adherence to norms [15].

We found that many respondents scored their preferred communities as high on cohesion and low on belonging, but few scored communities as high on belonging and low on cohesion. This seems to indicate that respondents were unlikely to spend time in or call to mind communities that were poorly-run or did not have clear guidance for behavior. When examining SOVC scores by predicting one-year retention in the channel, we identified a strong relationship between scores of belonging and retention ($\beta = 0.24$, $p < 0.005$), but found no evidence for such a relationship between cohesion scores and retention. It may thus be the case that cohesion is a necessary precursor to engagement, while belonging is strongly associated with retention. It is also possible, however, that we were unable to detect a relationship between cohesion and retention due to the lower variation observed in cohesion scores across the dataset.

In the offline (e.g., geographically-based communities, workplaces, communities of interest) and online (e.g., blogs, newsgroups, and discussion forums) contexts in which SOC and SOVC have previously been studied, participation typically occurs in the form of individual, discrete contributions. When one attends a meeting, contributes to a project, comments on a blog post, or answers a question in a discussion thread, one does so as an individually-identifiable participant. In contrast, Twitch supports several forms of mass participation, where individual contributions may only be visible in terms of their collective effect. This is particularly clear in some forms of peripheral participation, such as polls, where only an aggregated outcome of activity is publicly visible, or in extremely fast-moving chat, where individual contributions give way to shorter messages [42] or repetitive forms of 'crowdspeak' [46]. This may explain why the community experience manifests differently on Twitch, and why it may still be appealing to participate in a community with strong cohesion, even if one does not feel that they personally belong or are integrated into the community.

6.1.2 Behavioral predictors of SOVC. Findings from our hierarchical model identified how scores for belonging and cohesion varied with factors at a number of levels describing how individuals were situated within a larger social context when participating in communities on Twitch. We walk through these levels in detail below, along with some immediate considerations:

Individual-level factors. Our analysis of individual-level features found first that sitewide activity was not associated with an individual's SOVC scores within their chosen channel. This finding echoes insights from prior work indicating that sitewide activity is not a strong predictor of a viewer's likelihood of forming interpersonal bonds within a channel [93]. However, it should be noted that in both of these studies, survey respondents were selected because they had participated on Twitch beyond some minimum level; it is possible that viewers who participate less frequently might have lower levels of SOVC. In terms of individual channel engagement, we identified that chat volume was a significant predictor of both cohesion and belonging. Furthermore, we found that both channel tenure and peripheral participation were predictive of an individual's scores of belonging. Post hoc analysis identified an interesting potential interaction, such that scores for belonging showed a strong linear relationship with channel tenure for viewers who participated, either peripherally or through chat, but peaked at around 2 months and then declined for viewers who 'lurked' without participating.

Relationship-level factors. Interestingly, none of the relationship-level factors that we tested were significant predictors of either cohesion or belonging. It is important to note that the relationship-level factors capturing viewer-viewer relationships which were included in our model were features that indicated a more explicit one-to-one interpersonal interaction with other viewers. Thus, our findings point to the notion that 'interpersonal' interaction, in the form of one-to-one relationships, may be less important within livestreaming communities in terms of shaping participants' sense of cohesion and belonging. However, we also provide the caveat that our study design of targeting multiple viewers within the same communities required targeting larger communities as a rule; prior research has shown that the probability of having strong relationships within a channel on Twitch diminishes quickly with channel size [93]. Future research could use a different study design to evaluate the connection between interpersonal relationships and SOVC within smaller communities, where such a connection may be more likely.

None of our viewer-creator relationship indicators were significant predictors of either SOVC score. We note that coefficients for these variables did trend in the expected direction of a positive relationship to belonging and cohesion. Thus, it may be that our study was underpowered to detect these weaker but still important relationships, or that in a multivariable model most of the strength of the association of interpersonal interactions with sense of belonging and cohesion was captured in general chat volume and participation related variables. Future work could explore in greater detail associations between viewer-creator relationships and SOVC in creator-led communities.

Community-level factors. Regarding the community-level variables considered, the most interesting findings concerned the usage of emotes. Subscriber emotes are unique emoticons that channels can create and utilize, and increased community-wide use of subscriber emotes is associated with stronger assessments of community cohesion. Global emotes, in turn, are available to all users across the service; increased community-wide use of global emotes was actually associated with lower levels of belonging. This finding points to the impact of developing unique symbolic and linguistic forms of communications within a community, aligning with findings that are well-established in the larger sociological and anthropological literature [66]. In terms of the connection between shared symbols and SOC/SOVC, McMillan and Chavis highlighted a 'common symbol system' as one of the components in their model of membership [70], focusing on the fact that understanding of common symbols is required to participate. On Twitch, the set of global emotes is available to all participants; our findings illustrate that developing a unique and distinct symbolic language may play a specific role in defining boundaries around the group that foster a sense that the community is a cohesive unit.

We found a strong negative relationship between channel size and scores for both cohesion and belonging. Thus, it appears that while SOC on Twitch may not be primarily driven by strong one-to-one interpersonal relationships, sense of community may be adversely affected when communities become too large. Again, this finding aligns with prior work indicating that larger channels may be less amenable to the formation of interpersonal bonds [93]. Future work might explore the optimal community size to foster users' relationships with the larger social grouping in a channel, and compare these with optimal sizes for fostering strong interpersonal bonds.

Factors not considered. Although our study considered factors at multiple levels of the Social Ecological Model, we were unable to examine many factors which may have been predictive of viewer's sense of cohesion or belonging. For example, at the relationship-level, we did not assess the effects of negative interactions (e.g., hate speech, bullying, harassment) and at the community-level, we were unable to study the effects of channel-specific policies or community rules.

In general, we were unable to explore the outermost layer of the Social-Ecological Model (the societal layer), which would include elements such as internet-level or service-level policies or broad community norms that may influence SOVC. Services differ broadly in which behaviors a service chooses to govern through policy [58] and how individual categories of behaviors are defined and regulated [82]; a cross-service investigation, for instance, could potentially explore how these differences in policy influence SOVC in the communities that each service supports. Similarly, in services like Wikipedia, where policy choices are documented over time [61], longitudinal research could explore how changes in policy impact the social ecology. Finally, cross-platform studies could also compare differences in emergent community norms, such as differences in how emotional expression is received [117].

Learning which policy choices or community norms have broad positive impacts on feelings of belonging and community cohesion could provide a valuable area of future research. Because we have omitted societal-level features from our quantitative models for estimating SOVC scores, future research could use these models to study associations between SOVC and these items (i.e., the association of community cohesion on preventing hate speech) or the independent effects of policy strategies (i.e., policies for community safety) on viewer or channel level outcomes that are independent of community cohesion or feelings of belonging.

In addition, prior work has illustrated that social processes on Twitch often extend into other online services, or even online meetups [93]; a full picture of activity related to the community experience within a channel would require capturing interactions which occur outside of Twitch. Finally, this study focuses specifically on the SOVC experienced by viewers within a community; future work could explore SOVC within Twitch channels from the perspectives of creators or moderators, who are likely to experience the community and assign value to interactions differently. All of these represent opportunities for future work exploring how differences in individual and community activity relate to differences in perceptions about the community.

6.2 Design Implications

In this paper, we have not only identified dimensions along which SOVC varies within livestreaming communities, we have also developed a model which allow us to identify channels that foster stronger community perceptions and viewers within those channels who have higher SOVC. This provides a number of opportunities for design, for Twitch and for related kinds of virtual communities, which could be developed and evaluated in future work.

6.2.1 Designing to foster stronger virtual communities. A primary motivation for employing the Social-Ecological Model was to encourage reasoning about the design of interventions at each level addressed. Though the present study can't identify causal relationships between behavioral features and SOVC scores, the associations inform hypotheses about causal relationships which could be studied in future research across a variety of virtual community contexts. At the individual level, we recognize that a community member's level of participation, through chat or other means, is predictive of higher SOVC scores, corroborating findings from studies of a variety of virtual community contexts (e.g., [31, 35, 110, 122]), and providing confidence that this finding would generalize to a variety of types of online communities, including social networks, forums, and gaming contexts. Prior work spanning multiple kinds of online communities has explored the role that community moderators can play in socializing newcomers and encouraging participation [30, 91, 92, 120]. Similarly, recent work has identified relationships between the use of bots for community governance and SOVC [95]. On services that encourage community moderation, future work could explore the role that both human and algorithmic moderation play specifically with respect to fostering a sense of community within channels.

With respect to community-specific factors, we identified relationships between SOVC and the use of global and subscriber emotes. While this specific finding is novel, it is corroborated by prior work identifying that divergence from community-specific language can predict a viewer's propensity to churn from that community [32], indicating that relationships between community-specific language and SOVC may generalize across various kinds of communities. Many services related to Twitch, such a YouTube, Reddit, and Discord, offer communities the ability to create custom symbols, such as badges, emotes, or flair; design interventions which draw on our findings regarding emotes might seek to help community members learn and contribute to the unique language and symbols of the community. These could start as simple as automated or manually-created guides to community symbols, language, and shared history, or could explore more complicated strategies for fostering community co-production of new cultural content.

6.2.2 Leveraging SOVC as a signal in other applications. The proposed hierarchical model enables us to predict which channels foster stronger or weaker communities and which viewers within those channels have stronger or weaker attachment to the community, for all viewers and channels across the service. These signals could be leveraged in a number of ways. While it's well-established that many viewers participate on livestreaming services because of social and community motivations (e.g., [54, 67, 94]), it's typically quite difficult to search for new channels based on the community experience they offer; SOVC scores could be integrated into recommendation algorithms to help community-oriented viewers find new channels in which to engage. Prior work has identified that community moderators on Twitch are often drawn from regular viewers with a desire to support the channel [92, 120]; identifying viewers within a channel with higher SOVC scores could provide opportunities for identifying and recommending potential moderators to streamer.

6.3 Theoretical Implications

In this paper, we have approached the study of online communities through the joint perspectives of social computing and public health. Our findings motivate implications and opportunities for future research which builds on this interdisciplinary connection.

6.3.1 Online communities and public health. Our findings suggest interesting future directions for studying online communities as they pertain to public health. SOVC served as the outcome variable in our analyses; in future work, measures of SOVC could be leveraged as a predictor for important on-platform outcomes, such as the prevalence or prevention of harmful online behaviors (e.g., hate speech, bullying, or promotion of misinformation) against which healthy communities may be more resilient. There is a need to further identify the communities most effective at promoting well-being and mitigating harms and characterizing the strategies that successful community use to develop healthy community practices. In addition, our review of prior work has illustrated how SOC/SOVC within offline and online communities is associated with meaningful, real-world outcomes pertaining to individual and social health. In conjunction with a model for estimating differences in SOVC across viewers, longitudinal panel studies could identify causal relationships between SOVC fostered in online communities and offline indicators of health.

6.3.2 The social-ecological model in CSCW contexts. A small number of prior studies across HCI/CSCW have leveraged the Social-Ecological model as a means for studying technology use (e.g., [6, 17, 74, 103, 104]). However, in all of these cases, the Social-Ecological Model was used to study how offline social determinants influenced the adoption and use of technologies. We believe this is the first study in the CSCW literature to apply the Social-Ecological Model entirely within an online context. Here, the application of the model provided a structured way of examining features, providing insights about which layers of social embedding impacted a phenomenon of interest. We believe that there are opportunities to apply this model to other situations in which multiple layers of social relationships impact an individual's perceptions or behaviors, such as pro-social and anti-social behavior within online communities, patterns of conversation and connection in online social networks, dynamics of collaboration and cooperation in co-production sites such as Wikipedia, and applications to CSCW practices in healthcare and education.

6.4 Limitations and Future Work

Before concluding, we first discuss some limitations of our findings and opportunities for addressing these and other questions in future work. Respondents self-selected into our survey, which had a 13.1% response rate overall. Our respondent sample did match, at least with respect to gender and age, demographic distributions observed in similar large survey studies of Twitch (e.g., [93]), providing some assurance that our findings are representative of the intended population. However, subgroups based on these demographics may exhibit differences not explored in the current study, as well as those based on other important dimensions of identity, such as sexual orientation and race/ethnicity, which influence both the community experience within Twitch channels and the likelihood to respond to a survey such as the one described here. As demographic data was not available for non-respondents, it's impossible to assess how completely our findings would generalize across the full population of Twitch viewers and communities. In addition, we note that the survey was conducted with English-speaking viewers in the United States; as such, these findings can only be interpreted as representing that audience. Given the potential for cultural differences in attitudes regarding community perceptions, it would be exciting in future research to explore the extent to which the findings outlined here generalize to the global population participating on Twitch and other live-streaming services.

We expected some degree of selection bias; our recruitment strategy was specifically designed to collect responses from individuals who are motivated to participate socially and who perceive community engagement on Twitch as important. Individuals for whom community engagement is unimportant are unlikely to provide meaningful evaluations of the community experience within a channel. Combined with the expectation that respondents would discuss channels in which they participated frequently, this contributed to high overall assessments of the community experience within channels. Further evaluation of users more peripherally interested in community features and dynamics, or the experience of viewers who participate in communities that they perceive as low in cohesion, are important future directions. In addition, we targeted viewers using a set of seed channels with a minimum of 50 average CCU, meaning that our findings largely capture the experiences of viewers participating in medium-sized and larger channels. As identified above, this may have limited the role that relationship-level factors play in our models; future work should explore these features in the context of smaller channels.

This study draws on survey and behavioral trace data belonging to and provided by Twitch. Privileged access to this data was made available through a relationship with Twitch, leading to questions about the objectivity of the research and findings. Were the analysis at hand biased, a primary concern would be inflated estimates of the prevalence of strong communities across the service. For this reason, we have not focused in this paper on estimating community strength or the prevalence of strong communities across Twitch channels, as a whole. Instead we have started with a well-documented observation that the nature of the social and community experience can vary dramatically across Twitch channels (e.g., [42, 46, 52, 93]) and focused our attention on identifying the specific features of communities and their members associated with these variations.

The privacy of participants was addressed in several ways. First, survey respondents were informed that all data collected through the survey would be handled in accordance with Twitch's Privacy Policy[4], meaning that all data collected was subject to the storage, handling, and retention procedures outlined there. All survey and behavioral data was stored and analyzed using hashed user identifiers, so that respondents' screen names were not visible in the data. All analysis was completed using aggregated usage data, which could not be used to personally identify an individual.

Finally, our research investigation was motivated by the notion that SOVC may manifest differently in online communities with different properties or affordances. It is unclear to what extent our findings will generalize to livestreaming communities with substantially different features or other types of online communities. Nonetheless, our findings have practical implications for addressing the community experience for the substantial Twitch user base, and provide a point of comparison for similar types of communities, such as those which support large-scale synchronous chat or creator-focused communities. Lastly, it remains largely unexplored how SOVC influences many viewer and community outcomes, such as wellbeing and mental health, promotion of healthy norms, and community longevity. Future research, particularly longitudinal studies, could explore the causal effects of participating in virtual communities, such as those on Twitch, on individual and social health.

7 CONCLUSION

This study presented a detailed examination of SOVC and its predictors in the context of one of the largest services hosting online communities available today. To the authors' knowledge, this is the first published study on SOVC and associated behaviors within live-streaming communities. Our findings identified and characterized two dimensions of SOVC within livestreaming communities, including one construct – community cohesion – which has not previously been identified in the

[4]https://www.twitch.tv/p/en/legal/privacy-notice/

literature. As livestreaming grows in popularity, and an increasing number of online communities grow to support large-scale, synchronous communication, it's likely that cohesion will represent an important construct in contexts beyond Twitch.

Through hierarchical linear modeling we explore the predictors of SOC, as expressed through cohesion and belonging, examining the findings in light of the well-established Social Ecological Model for describing individuals within the context of their communities. We were surprised by the extent to which these SOVC scores could predict long-term outcomes within channels, such as retention. The findings from this work provide insight into the various ways that online communities can shape and foster strong community experiences, with the hopeful outcome of improving both individual and community health.

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9 DISCLAIMER

The findings and conclusions in this report are those of the authors and do not necessarily represent the official position of the Centers for Disease Control and Prevention.

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A SURVEY MATERIALS

A.1 Email Invitation

Survey participants were recruited through a Twitch-branded email with the following body text:

> Hey <twitchID>,
>
> Thank you for being a part of the Twitch community!
>
> You've been randomly selected to take part in a survey about your experiences with social and community interaction on Twitch. This survey should take no more than 10 minutes to complete. If you are eligible and complete the survey, we'd like to offer you a $5 Amazon gift card for your time and interest.
>
> Take Survey [CTA Button]
>
> Your ideas and feedback help us make Twitch better for everyone. Thank you for sharing your time and your experiences with us.
>
> Love,
> Twitch Science

A.2 Survey Instrument

The following measures were included as part of the survey:

A.2.1 Demographics and screening questions.

- What is your current age? [free numerical response]
- Please indicate your gender:
  - Female
  - Male
  - Non-binary / third gender
  - Prefer to self describe [free text response]
  - Prefer not to answer
- Which of the following **best** describes you?
  - Non-Gamer: I am not interested in playing video games
  - Casual Gamer: I dabble in video games, but in short sessions or infrequently
  - Core/Mid-Core Gamer: I regularly play video games, but I am not super-serious or competitive.
  - Hardcore Gamer: I play video games frequently, and I play seriously or competitively.
- How interested are you in feeling a "sense of community", in general, when you watch or participate on Twitch?
  - Not important at all
  - Not very important
  - Somewhat important
  - Important
  - Very important

A.2.2 Primary measures (SOVC).

- In which Twitch channel did you spend the most time over the past month? Please provide the exact name of the channel below. *Please provide only one channel – it may be helpful to copy and paste the name from the channel page:* [free text response]
- Throughout the rest of these questions, please think about the overall **community** associated with this channel (<channel name>), as you experience it on this channel itself, on other channels or platforms (e.g. Discord, Twitter), or through offline events.

- How much do you agree or disagree with each of the following statements regarding the **community** around <channel name>'s channel? Please choose the option that best describes how you feel:
  - **Answer choices:**
    - Strongly disagree (1)
    - Disagree (2)
    - Neither agree nor disagree (3)
    - Agree (4)
    - Strongly agree (5)
  - **Items (displayed in randomized order):**
    - I expect to be a part of this community for a long time.
    - I think this community is a good thing for me to be a part of.
    - It is important to me to be a part of this community.
    - I feel at home in this community.
    - I recognize the screen names of most participants in this community.
    - If there is a problem in this community, members can get it solved.
    - Members of this community can be counted on to help others.
    - I want the same things from this community as other members.
    - Members of this community share the same values.
    - I have friends in this community that I can depend on.
    - If I have a personal problem, I can turn to members of this community.
    - I care about what other community members think of me.
    - Most members of this community know me.
    - I feel like I have influence over what this community is like.
    - I get important needs of mine met because I am part of this community.
    - People in this community have similar needs, priorities, and goals.
    - I can trust other members within this community.
    - Fitting into this community is important to me.
    - This community is influential in other parts of Twitch or the internet.
    - This community has good leaders.
    - I feel hopeful about the future of this community.
    - Members of this community care about each other.
    - This community has shared symbols and expressions of membership (such as emotes and logos) that people can recognize.
    - Members of this community have shared important events together, online or offline.
    - I can anticipate how some members will respond to certain questions or topics in chat.
    - I've had questions that have been answered by this group.
    - Some members of this group have friendships with each other.
    - I've gotten support from this group in the past.
    - I feel obligated to help others in this group.

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