

When “Self-Harm” Means “Suicide”: Adolescent Online Help-Seeking for Self-Injurious
Thoughts and Behaviors

by

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DISSERTATION ABSTRACT

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Title: When “Self-Harm” Means “Suicide”: Adolescent Online Help-Seeking for Self-Injurious Thoughts and Behaviors

The sensitive period of adolescence facilitates key developmental tasks that equip young people to assume adult roles. Adolescence features important strengths, like the need to contribute, and some risks, like vulnerability to the onset of mental ill health. Adolescence increasingly occurs online, where existing in-person dynamics and new affordances of digital technology combine. Online help-seeking suits the needs and preferences of adolescents, and online peer support capitalizes on adolescent strengths. The success of online peer support communities for self-injurious thoughts and behaviors (SITB) may depend on the balance of social support and social contagion in these communities.

In this study, we investigated adolescent help-seeking and peer support for SITB online. We used topic modeling, machine learning classification, and multilevel modeling in pursuit of three aims. In the first aim, we discovered the topics that characterized help-seeking expressions of over 100,000 posters who chose to post in the “Self Harm” category of an online peer support platform. In the second aim, we measured the amount and type of social support provided in over a million comments in response to these posts. In the third aim, we tested whether the topics of help-seeking expressions predicted the presence and type of social support provided. The overarching goal of these aims was to help inform policy and guide the design of online spaces to support healthy adolescent development, especially amongst adolescents experiencing mental health challenges.

From the first aim, we learned that adolescents seek help online for serious problems and suffering. From the second aim, we learned that their peers provide social support most of the time, but this social support often lacks specificity and elaboration. From the third aim, we learned about the power of help-seeking expressions focused on “hopeless suicide,” “self-harm abstention,” and “hiding self-harm” to elicit social support. Across all three aims, we learned that platform design matters, and platform designers can do more to support healthy development. Adolescent online help-seekers need help that makes them feel connected. Academic researchers and corporations must work together to help young people help each other.

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Chapter 1: General Introduction

Adolescence is getting longer (Dahl et al., 2018). As secular trends push the onset of puberty earlier and the assumption of adult roles later, young people spend more time in the developmental stage between childhood and adulthood. Adolescence defies simplistic characterization, revealing different insights every time the viewing angle changes. An important change underway now is the integration of online spaces as key developmental settings. How does adolescence change (or stay the same) when it happens online? How can adults support healthy development online? How do adolescents use online opportunities to support their own development?

Why This Age?

The many facets of adolescence, including its purpose, plasticity, vulnerability, and strengths, make the study of people at this phase of life especially important as we grapple with society's move online. In this chapter, we will integrate these facets to build a case for the study of adolescents seeking help online from peers for self-injurious thoughts and behaviors.

The Purpose of Adolescence

The purpose of adolescence is three-fold: identity formation, social-emotional learning, and acquisition of skills to assume adult roles (Dahl et al., 2018). The task of identity formation has been conceptualized as having multiple stages. Erikson (1968) and Marcia (1966) established foundational ideas about the stages of identity formation. Erikson viewed adolescence as a “crisis” of “identity versus identity confusion,” while Marcia expanded on Erikson’s binary view of identity formation to include four stages: achievement, diffusion, moratorium, and foreclosure. The achievement of a well-defined identity in adolescence is associated with

positive outcomes, including more well-being and less depression and anxiety (Schwartz & Petrova, 2018).

Social learning occurs in the context of significant re-orientation of the adolescent's attention and motivation. As adolescents turn their attention toward peers, their motivation focuses on improving their social status and pursuing peer relationships, sexual and otherwise (Crockett & Crouter, 2014; Forbes & Dahl, 2010). Increasingly complex and fraught social environments make new demands on the adolescent brain, which shows substantial changes to support more sophisticated social thinking (Blakemore, 2012).

The acquisition of skills to assume adult roles develops from and contributes to both identity formation and social learning. For example, intentional self-regulation, which describes how people choose, plan, and execute their actions, is a key skill developed in middle adolescence (Gestsdottir et al., 2010). Stronger intentional self-regulation is associated with increased positive youth development and decreased problem behaviors. An increased ability to choose, plan, and execute actions might support identity formation and social learning by facilitating commitment and follow-through.

Adolescence as a Sensitive Period

Adolescence, defined approximately as ages 10-25 (Sawyer et al., 2018), is a sensitive period for physiological and socioemotional development. The term “sensitive period” refers to a period of development that is “experience-expectant,” i.e., the healthy development of the organism depends on timely exposure to certain experiences (Fuhrmann et al., 2015, p. 559). The sensitive period of adolescence is characterized by increased brain plasticity. Fuhrmann and colleagues (2015) review memory, social processing, and substance use as examples of increased plasticity. Memory exhibits a “reminiscence bump” between 10 and 30 years old, which suggests

increased malleability in brain functioning during this time (Rubin & Schulkind, 1997). Evidence for extra sensitivity to social stimuli comes in large part from studies of how social stress affects adolescents. Namely, adolescents appear to be prone to negative outcomes in response to social deprivation (Orben et al., 2020). Finally, there is strong evidence in rodent studies and some evidence in human studies that adolescents are particularly sensitive to harmful effects of substance use, especially cannabis (Lichenstein et al., 2022; Schneider & Koch, 2003).

While much of the research on adolescence as a sensitive period has focused on increased neural plasticity, brain development in adolescence occurs against a backdrop of significant hormonal shifts related to puberty. Many developmental scientists regard puberty as the beginning of the sensitive period of adolescence (Dahl et al., 2018). Pubertal changes that start in the brain cascade across the body and affect the way an adolescent interacts with the environment.

One can see the interplay of pubertal changes with the environment in the studies that suggest that pubertal timing affects outcomes in adolescence (Mendle, 2014). While *going through puberty* seems to confer plasticity, going through puberty *early* seems to confer risk. In particular, early pubertal timing increases the likelihood of internalizing and externalizing problems (Mendle et al., 2007; Mendle & Ferrero, 2012). It's possible that early pubertal timing has an entirely intra-individual mechanism of conferring risk. However, it seems more likely that the younger and less experienced a person is at the onset of puberty, the more challenging and riskier the task of navigating the social changes that come with puberty becomes.

Risk figures prominently in adolescence, both in terms of the vulnerabilities associated with increased plasticity and the tendency of adolescents to seek out risky experiences. To the adolescent, these risky experiences satisfy their growing interest in sensation-seeking (Forbes &

Dahl, 2010). To the worried adult, this interest in risky experiences represents a puzzle to be solved. One approach to the puzzle of adolescent impulsivity is the dual systems model, which highlights the mismatched developmental timing of reward sensitivity and cognitive control. Rapid increases in reward sensitivity push an adolescent toward exciting, novel experiences before their cognitive control capacity is strong enough to help them control these impulses (Shulman et al., 2016).

The dual systems model, though appealing in its parsimony and generative of much interesting research, has come under increasing scrutiny. Pfeifer and Allen (2012, 2016) led calls for precise specification and falsifiable tests of the dual systems perspective. Among others, Meisel and colleagues (2019) answered this call by using specific, precise measurement of the dual systems in question, plus longitudinal data analytic methods. Their findings did not support the dual systems model. Efforts to integrate neural, hormonal, behavioral, and social contributors to adolescent sensitivity and vulnerability continue (Pfeifer & Allen, 2021).

Onset of Mental Illness in Adolescence

Adolescence is a period of increased vulnerability to mental illness. A recent meta-analysis from Solmi and colleagues (2022) synthesized findings from 192 epidemiological studies from every continent. They found that the overall median age of onset for mental illness is 18 years old, with an initial peak of onset at 14.5 years old. While neurodevelopmental disorders, specific phobia, and separation anxiety disorder have their first peak in early childhood (at 5.5 years old), every other common mental illness sees its first peak during adolescence (between ages 10-25). Solmi and colleagues (2022) calculated the percentage of individuals with first onset of any mental illness by ages 14, 18, and 25. The onset of first mental disorder occurs by age 14 in about one-third of individuals, by age 18 in almost half (48.4%),

and by age 25 in almost two-thirds (62.5%). The mental health care system fails to meet this challenge in two important, related ways. First, the division of mental health training models between child/adolescent and adult specialties disrupts continuity of care for young people during a critical transition. Second, the cessation of pediatric services at age 18 creates a “transition cliff” where young people lose their familiar providers (Babajide et al., 2020).

Self-injurious thoughts and behaviors (SITB), including non-suicidal self-injury (NSSI) and suicidal thoughts and behaviors, are not well captured by epidemiological studies of mental disorders since SITB do not fit into a diagnostic category. However, there is evidence that SITB follow a similar pattern of first onset as common psychiatric diagnoses. Non-suicidal self-injury is the intentional infliction of injury to oneself without the explicit wish to die, and the most common form of NSSI is self-cutting (Liu, 2021). Non-suicidal self-injury has been shown to have a first peak of onset around ages 14-15, which aligns with the onset of other common mental disorders (Gandhi et al., 2018). Suicide is the second leading cause of death in adolescents (Shain et al., 2016). The most common method of suicide attempt in adolescence is self-poisoning, and the most common methods of completed suicide are suffocation and firearm discharge (Hawton et al., 2012; Shain et al., 2016). Hawton and colleagues (2012) review evidence that suggests that SITB emerge in adolescence and coincide with late or completed puberty.

Recent Upward Trends in Adolescent Mental Illness

The last 20 years have seen significant increases in mental illness and suicide among European and North American adolescents (Keyes et al., 2019; Potrebny et al., 2019; Wiens et al., 2020). After a promising decline in adolescent suicide during the 1990s, the adolescent suicide rate has increased by more than 50% since 2007 (Ruch et al., 2019). Depressive

symptoms and self-harm have seen similar increases from 2005 to 2015, as have parent-reported conduct problems, hyperactivity, peer problems, and emotional difficulties (Patalay & Gage, 2019). In contrast, several risky behaviors have seen a decline over the same time period, including substance use and sexual activity (Patalay & Gage, 2019).

The COVID-19 pandemic has exacerbated this upward trend in adolescent mental illness. In general, disasters and pandemics produce long-term increases in depression and anxiety, especially in children and adolescents (Newnham et al., 2022). Soon after the onset of the pandemic-related lockdowns, developmental scientists called attention to the particular threat social deprivation poses to healthy adolescent development (Orben et al., 2020). Over the next two years, many studies were published that documented the mental ill health experienced by adolescents during the pandemic (e.g., Zhou et al., 2020).

These abundant studies have since been synthesized via meta-analysis and systematic review (e.g., Samji et al., 2022), leading to an umbrella review of the 17 reviews of highest methodological quality (Hossain et al., 2022). In their umbrella review, Hossain and colleagues (2022) found that most studies reported significant increases in mental illness during the pandemic. However, they also found considerable heterogeneity and an alarming sparsity of data from the Global South. Hossain and colleagues (2022) also noted a lack of adequate baseline, i.e., pre-pandemic comparators. Clearly, the mental health impact of the pandemic on adolescents warrants further study.

There is a tremendous unmet need for effective intervention for adolescents. Even before the pandemic, about 40% of American, minor teens experienced a mental disorder within a given 12-month period, and less than half of them received *any* mental health care (Costello et al.,

2014; Kessler et al., 2012). In other words, some 10 million American teens are likely to endure mental illness this year without effective treatment.

The pandemic has had mixed effects on access to mental health care. COVID-19 increased demand for mental health care at the same time as it reduced access to outpatient mental health care and constrained inpatient psychiatric unit stays (Saunders et al., 2022; Witteveen et al., 2022). Furthermore, COVID-19 normalized the provision of mental health care via telehealth (Shore et al., 2020). While the shift to telehealth offers the promise of increased access for some (e.g., people living in rural settings or people with limited mobility), telehealth only benefits those on one side of the “digital divide,” i.e., those with stable internet access and technological knowledge (Cullen, 2001).

Special Strengths of Adolescents

Adolescence is a distinct developmental period that appears across species and eras. As puberty starts earlier and adult roles are assumed later, adolescence lengthens, exposing young people to an ever longer sensitive period (Crone & Dahl, 2012). This sensitive period confers opportunity and potential. The 20th century, Western characterization of adolescence by psychoanalysts and psychologists as a period of “storm and stress” underestimates the special strengths of adolescents (Arnett, 1999).

Adolescence is a time of increased flexibility, creativity, and contribution. Salient social and motivational contexts drive less automatic and more flexible cognitive engagement in adolescence (Crone & Dahl, 2012). This flexibility and the adolescent tendency toward exploration may underpin the increased creativity in the visuo-spatial domain seen in middle adolescence (Kleibeuker et al., 2013). The adolescent need to contribute to families, peers, schools, and communities supports the three-fold purpose of adolescence (Fulgini, 2019).

Susceptibility to peer influence, often maligned as “peer pressure,” can support learning, exploration, and prosocial development in adolescence (van Hoorn et al., 2016). While individuation and altruism appear at odds at first, evidence from neuroimaging studies suggests that learning to think about the self (e.g., identity formation) and learning to think about others (e.g., mentalizing) depend on each other and develop in the same parts of the social brain (Crone & Fuligni, 2020). Adolescent sensitivity to belonging and respect presents an avenue to increase motivation and improve wellbeing (Dahl et al., 2018; Yeager et al., 2018). These strengths present compelling targets for research and intervention as we face the challenge of supporting healthy development over a longer, adolescent sensitive period.

Why This Age Online

Adolescent Internet Use

Today’s adolescents in middle- and high-income countries are “digital natives” (Prensky, 2001). Nearly all American teens have access to a smartphone (95%), and almost half of American teens report being online “almost constantly” (Vogels et al., 2022). American teens told Pew Research Center that they *often* or *sometimes* use their smartphones to pass time (91%), connect with other people (84%), and learn new things (83%; Schaeffer, 2019). Internet activity and smartphone use figure prominently in teens’ self-reported friendship behaviors, with over half of teens having made a new friend online and spending time every day texting with friends (Lenhart, 2015). YouTube, TikTok, Instagram, and Snapchat dominate the social media landscape. About half of teens say they spend about the right amount of time on social media, and about a third say they spend too much time on social media (Vogels et al., 2022).

This largely subjective picture of self-reported adolescent smartphone use elides a critical problem in the study of this topic: self-report of internet use has only a moderate correlation with

objective measures (Parry et al., 2021). When the study is framed in terms of “problematic” internet use, the correlation of self-report and objective measures weakens further (Parry et al., 2021). Furthermore, the framing of self-report measures of internet use may have a priming effect on subsequent measures. Mieczkowski and colleagues (2020) compared self-report measures that focus on *intensity* of social media use versus *addiction* to social media. They found that completing addiction-focused scales produced self-report of worse depressive symptoms on subsequent wellbeing scales.

High-quality, objective measures of internet use from large, representative, adolescent samples are hard for academic researchers to come by. That is one of the reasons why 19 leading scholars wrote an open letter to Meta, the parent company of Facebook, Instagram, and Whatsapp (Przybylski et al., 2021). Following leaks and media reports of Meta’s in-house research on child and adolescent mental health, these scholars and over 250 signatories called on Meta to increase transparency and contribute to independent research. In their open letter, they note that large studies tracking cohorts of young people in many countries increasingly miss important facets of young people’s lives because tech companies like Meta do not share their data or collaborate with researchers. A year after this open letter was published, the debate over how to maximize the transparency and independence of research collaborations with corporations continues, including a call for multidisciplinary guidelines for best practices (Livingstone et al., 2022).

A final argument for studying adolescents *online* is that, in the context of vulnerability and risk, online life tends to recapitulate in-person life (Odgers & Jensen, 2020). In other words, online risk mirrors offline risk. This might be a scary realization given the increasing amount of time adolescents spend online and how difficult it can be to observe and intervene on online

behavior. Still, there is reason to view this mirroring with hope. Everything we have already learned about supporting healthy adolescent development can be brought to bear on the study of adolescents online. The internet is a brave new world... and it isn't.

Does Being Online Hurt Adolescents?

The lack of high-quality, objective measures of adolescent internet use has not stopped some researchers from making strong claims about harmful effects of “screen time” and social media use. Twenge and colleagues lead this argument, with highly cited publications touting positive associations between social media use and mental ill health in young people, especially girls (e.g., Twenge et al., 2018). Haidt (2020) defends this argument by pivoting its claims to dodge critiques. For example, Haidt responds to null findings in studies of screen time and mental health by claiming that the studies should focus on social media instead of screen time.

The argument advanced by Twenge and Haidt has been criticized by Orben and others for making causal claims from correlational data and using researcher degrees of freedom to produce larger effects (e.g., Orben et al., 2019). Orben and colleagues have conducted rigorous studies of large-scale, representative panel data typically favored by Twenge (Orben et al., 2019). Orben and colleagues satisfied Haidt's call for a focus on social media and avoided the shortcomings of Twenge's work by using a specification curve analysis framework, which minimizes the influence of researcher degrees of freedom by systematically accounting for different data analysis specifications. They found that associations between social media use and adolescent wellbeing defy simplistic characterization, fall short of clinically meaningful effect sizes, and depend on analytic method. Twenge and colleagues (2022) have responded to these findings by re-analyzing the same data using different specifications of the same technique, which produced findings that they interpret as support of their original claim. Their interpretation depends on

their re-specification of the analysis approach and their argument that an association at the very bottom of Cohen’s “small” effect size range merits our attention.

It seems unlikely that this debate will be settled via cross-sectional studies. As such, a growing body of research aims to improve on these large-scale, low-resolution, cross-sectional studies via two approaches. One approach maintains the scale and resolution of the Twenge-led studies and adds a longitudinal component. Orben and colleagues (2022) used a random intercept cross-lagged panel model to test whether adolescence is marked by different levels of sensitivity to social media. Their approach used longitudinal data from 17,409 participants aged 10 to 21 to reveal that adolescents appear to have windows of increased sensitivity to negative effects of social media. For girls, this window is open between ages 11 to 13; for boys, the window opens later, at ages 14 and 15.

Another approach scales down the number of participants and focuses on increasing the resolution for the within-person variables. Jensen and colleagues (2019) used ecological momentary assessment (EMA) to collect daily measures of digital technology use and wellbeing from 388 adolescents aged 12 to 15. With each adolescent serving as their own control, the analysis of the daily EMA data revealed that wellbeing was for the most part not related to digital technology use. The associations that did emerge were in the positive direction, e.g., heavier texters reported less depression than lighter texters.

These two studies seem to contradict each other. Orben and colleagues (2022) find an increased sensitivity to negative effects of social media in the same age range as Jensen and colleagues (2019) find mostly null associations between digital technology use and wellbeing. Both studies use self-report, albeit on different time scales. In this case and in general, research asking whether and how time spent online affects adolescent wellbeing may benefit from

naturalistic, objective, granular measures of digital technology use (George & Odgers, 2015).

The internet is vast and varied, and researchers would do well to map the territory before making claims.

Why This Age Online Help-Seeking

The Internet Suits Adolescent Help-Seeking Needs

Adolescents face special barriers regarding help-seeking for mental ill health. A systematic review of 53 quantitative and qualitative studies synthesized commonly reported barriers and facilitators to formal help-seeking in adolescence (Radez et al., 2021). Since barriers and facilitators often manifest as two sides of the same coin, Radez and colleagues opted to distill them into themes. The primary theme focused on barriers related to individual factors such as low mental health literacy, preference to deal with problems on one's own, preference for informal support, skepticism about formal treatment, reluctance to attend appointments, and symptoms of mental illness interfering with the ability to seek formal help.

Given these barriers, it is unsurprising that most adolescent help-seeking occurs via informal pathways and peer support (Rickwood & Braithwaite, 1994). Given the near universal access to connected devices and their near constant use for many teens (Vogels et al., 2022), the internet provides an ideal setting for informal, adolescent help-seeking. Accordingly, recent studies of adolescent, online help-seeking reveal frequent searching for health information online, but skepticism toward online mental health resources (Chan et al., 2016; Freeman et al., 2018).

A recent systematic narrative review has integrated findings from 28 studies of barriers and facilitators of young people's *online* help-seeking (Pretorius et al., 2019). They identified the following barriers to online help-seeking: lack of mental health literacy, concerns about privacy

and confidentiality, and uncertainty about the credibility of online resources. Key facilitators to online help-seeking included: anonymity and privacy, immediate access, ease of access, inclusivity, social connection, and more control over the help-seeking process.

Adolescents Want to Seek Help Online

Existing research from the fields of User Experience and Human-Computer Interaction provides intriguing insights about adolescent, online help-seeking through a variety of methods. Search log studies involve the collection and analysis of participants' search history and self-reported mental health. Search history is of particular interest since text-based query via search engine is the online help-seeking approach most commonly reported by adolescents (Pretorius et al., 2019). Search log studies have shown that search history data are associated with self-esteem and discrete mental disorders (Birnbaum et al., 2017; Zaman et al., 2019). Furthermore, in the three months prior to hospitalization, a majority of young people hospitalized for suicidal thoughts and behaviors (27/43, 63%) had conducted suicide-related searches and over three-quarters had made help-seeking queries (33/43, 77%; Moon et al., 2021).

Co-design studies involve the collection and analysis of qualitative data via focus groups' participation in activities that facilitate creative, collaborative problem-solving. Co-design studies of adolescent, online help-seeking have shown adolescents' strong interest in reliable, online mental health information, with particular preferences for design that facilitates connectedness, personalization, anonymity, and immediacy (Havas et al., 2011; Pretorius et al., 2020).

Platform studies involve the collection and analysis of posts and comments on social media platforms filtered by topic identifiers like hashtags. Platform studies have characterized the sharing of depression-related imagery on Instagram and the discussion of sexual health on a

youth peer support platform, allowing researchers to describe how young people seek and provide support online for behavioral health concerns (Andalibi et al., 2015; Razi et al., 2020). Studying image-based expressions of depressive symptoms on Instagram, Andalibi and colleagues (2017) found evidence of significant social support, a sense of community, and few antisocial behaviors like aggression or pro-illness statements.

Why This Age Online Help-Seeking from Peers

Peer support is a fitting option for adolescent help-seeking. In general, adolescence sees a shift in attention toward peers (Forbes & Dahl, 2010). This peer orientation and the adolescent need to contribute equip this age group to be enthusiastic supporters of each other (Fulgini, 2019). In terms of barriers to and facilitators of help-seeking, adolescents report needs that are well met by peer support. Adolescents prefer informal support, inclusivity, and social connection, all of which are satisfied by peer support in general (Radez et al., 2021). Adolescents also prefer immediacy, anonymity, and ease of access, all of which are satisfied by peer support online (Pretorius et al., 2019).

Given how well peer support suits young people's help-seeking needs and preferences, it is no surprise that young people are already increasingly using the internet to express distress to their peers (Marchant et al., 2017). In a study of older adolescents, i.e., college students, Cole and colleagues (2017) investigated whether online social support does more than just recapitulate social support already occurring in person. They found that: online relationships provide unique value for individuals with weaker in-person support; online social support is related to lower levels of depression; and online social support offsets some of the negative effects of peer victimization.

A study of transgender adolescents highlights the essential role that online social support can play in the lives of marginalized young people in particular (Selkie et al., 2020). Selkie and colleagues (2020) performed thematic analysis of 25 interviews of transgender, minor adolescents. Participants reported on how they use social media (YouTube, Instagram, Facebook, Twitter, and Tumblr) to connect with transgender people and seek peer support. Themes emerged related to emotional support, appraisal support, and informational support. Emotional support was described as connections that alleviated the pain of loneliness, prepared young people for major developmental tasks like coming out, and sustained hope for the future. Appraisal support was described as validation of one's experience and one's progress in transitioning. Informational support was described as advice about navigating medical transition and resources for educating family and friends.

Peer support, both in general and online, shows promise as a scalable, supportive mental health service for young people (Richard et al., 2022). A scoping review of 17 studies of peer support for young people found that peer support is associated with increases in happiness, self-esteem, and effective coping and decreases in depression, loneliness, and anxiety (Richard et al., 2022). However, the same scoping review highlighted concerns with the inconsistent operationalization of peer support in research and emphasized the potential importance of training the people providing peer support (Richard et al., 2022). A large study of minor adolescents active in online mental health forums suggested that online peer support is especially helpful when formal support is unavailable, e.g., at night (Banwell et al., 2022). A systematic review of the effectiveness of online peer support for young people found only six studies of varying quality with mixed results (Ali et al., 2015). All three papers called for additional research on peer support for young people.

Why This Age Online Help-Seeking from Peers for Self-Injurious Thoughts and Behaviors

The last 20 years have seen significant increases in self-injurious thoughts and behaviors in North American and European adolescents (Keyes et al., 2019; Potrebny et al., 2019; Wiens et al., 2020). Self-injurious thoughts and behaviors (SITB) include non-suicidal self-injury and suicidal behavior. Adolescent non-suicidal self-injury (NSSI) occurs at prevalence rates of approximately 15-20% in countries around the world (Muehlenkamp et al., 2012). Suicide is the second leading cause of death in adolescents (Shain et al., 2016).

Non-suicidal self-injury and suicidal behavior are lumped together under the SITB label because of: the shared component of deliberate self-harm; the shared function of relief from intolerable distress; and the evidence that NSSI and suicidal behavior influence each other (Jacobson & Gould, 2007; Joiner et al., 2012; Kiekens et al., 2018; Klonsky et al., 2018). NSSI increases the risk of transitioning from suicidal ideation to attempt, and NSSI is associated with suicidal thoughts and behavior above and beyond the effect of common mental disorders (Kiekens et al., 2018). It is thought that NSSI facilitates the development of suicidal behavior by increasing pain tolerance and therefore increasing capability for suicide (Joiner et al., 2012).

As adolescents increasingly share their distress with peers online, there has been a proliferation of online SITB peer support communities (Daine et al., 2013). The most common goals of young people seeking help online for SITB are emotional support and coping strategies (Daine et al., 2013). Young people seeking online peer support for self-harm are mostly already engaging in NSSI (Lavis & Winter, 2020). About one-third of young people with NSSI seek help online, and those online help-seekers have more severe NSSI and suicidal ideation than those who do not seek help online (Frost & Casey, 2016). Young people with more recent episodes of NSSI are more likely to go online to seek and give support (De Riggi et al., 2018).

These online SITB peer support communities carry potential risks and benefits. Risks include: content that triggers self-harm urges, reinforcement of self-harm, and experience of self-harm stigma (Lewis & Seko, 2016). Self-harm triggers and reinforcement of self-harm are related to social contagion, which is a well-documented phenomenon in suicide clusters (Phillips, 1974; Swedo et al., 2021). While NSSI is mostly maintained by reinforcement contingencies that develop over time, the initial onset of NSSI is especially vulnerable to social contagion (Jarvi et al., 2013). Benefits include: increased social connection and emotional self-disclosure, plus support for recovery and abstinence from self-harm (Lewis & Seko, 2016). Additional potential therapeutic affordances of online self-harm communities include: flexible use of these communities to suit individual needs, access to information and resources, and control over how to present oneself and how much to disclose (Coulson et al., 2017).

The interpersonal theory of suicide helps frame the analysis of risks and benefits. In this theory, perceived burdensomeness, thwarted belongingness, and hopelessness about these states drive suicidal desire, while acquired capability for suicide facilitates the transition from ideation to attempt (Van Orden et al., 2010). Acquired capability for suicide is thought to develop from repeated exposure to pain or fear. As such, suicidal desire emerges from a separate process than the capability to engage in suicidal behavior (Van Orden et al., 2010). Online SITB peer support communities have the potential to decrease perceived burdensomeness, thwarted belongingness, and hopelessness via social connection and support for recovery. These communities have the potential to increase acquired capability for suicide by propagating and reinforcing SITB via social contagion. These proposed mechanisms, i.e., social support and social contagion, are malleable and merit study.

Why This Study

The sensitive period of adolescence facilitates key developmental tasks that equip young people to assume adult roles. Adolescence features important strengths, like the need to contribute, and some risks, like vulnerability to the onset of mental ill health. Adolescence increasingly occurs online, where existing in-person dynamics and new affordances of digital technology combine. Online help-seeking suits the needs and preferences of adolescents, and online peer support capitalizes on adolescent strengths. The success of online peer support communities for SITB may depend on the balance of social support and social contagion.

This study focuses on adolescent, online help-seeking for SITB via analysis of posts and comments from a large, online, peer support platform. The first aim is to characterize expressions of help-seeking in posts. The second aim is to measure social support provided in comments. The third aim is to test whether the content of help-seeking expressions is related to the amount and type of social support provided. These aims will help reveal the components of adolescent help-seeking expressions that engender social support.

Chapter 2: Orientation to the Platform and Data Analysis Plan

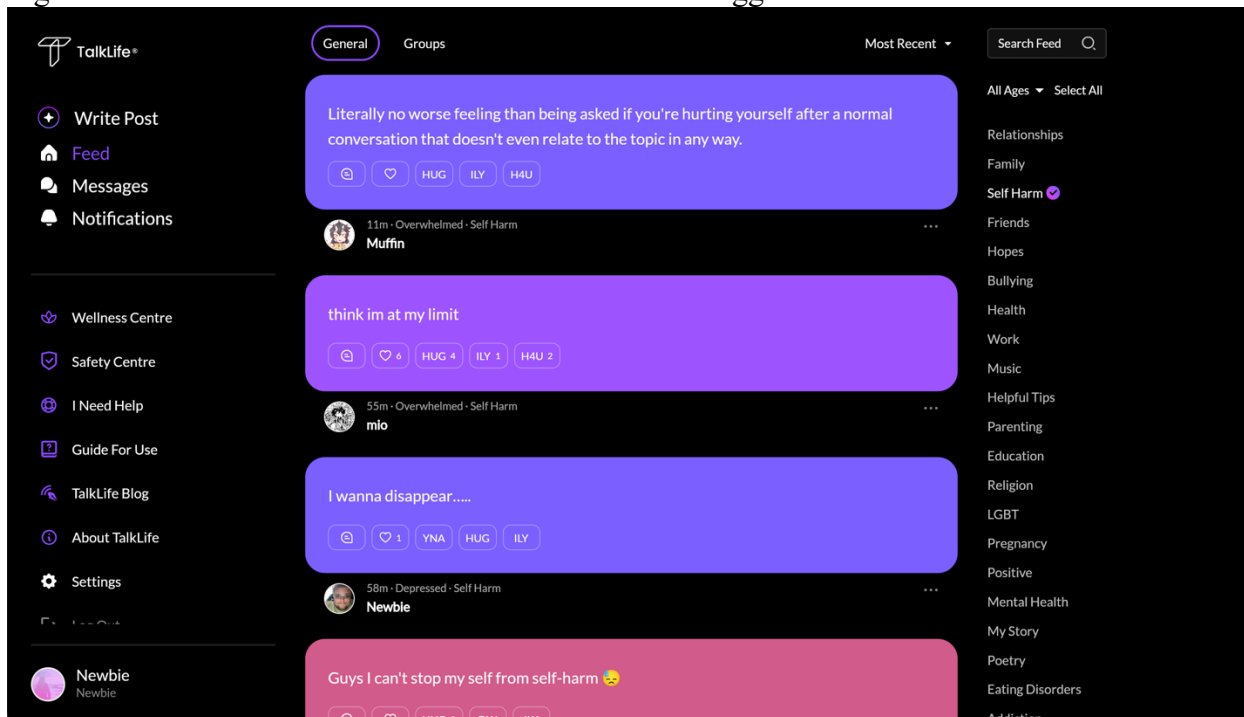
Adolescent, online help-seeking for self-injurious thoughts and behaviors occurs across many venues. Depending on the venue, online help-seekers and help-providers may interact differently. In this study, the design of the specific online venue and the structure of the available data is critical in shaping the research questions and the data analysis plan. In this chapter, we will provide an orientation to TalkLife, the online platform from which the data come, along with an overview of the data analysis plan for each aim.

Tour of the TalkLife Platform

Free to download on the Apple App Store and Google Play Store, TalkLife bills itself as a “mental health support community.” Launched in 2012, TalkLife reports having over 1.5 million users in over 125 countries (TalkLife Limited, 2018). TalkLife operates on mobile devices and in internet browsers, providing a venue for users to post about mental health-related topics. The home screen of TalkLife provides a central, scrollable feed of other users’ posts, plus sidebar menus that allow the user to navigate the site and adjust their view and preferences (see Figure 1 for the browser view).

The process of posting requires the user to first select a mood descriptor from a range of options then to select a category for their post. Categories vary widely and include “Relationships,” “Health,” “Bullying,” “Family,” and “Self Harm,” among others. “Self Harm” is the third most popular post category behind “Other” and “Relationships.” Selection by the user of the “Self Harm” category produces a screen that lists the “TalkLife Rules on Self Harm” (see Figure 2). If the user agrees to these rules, the user may proceed to write their post. Users may choose to post anonymously, i.e., hide their username, or label their post as “potentially triggering.” Users’ posts are the main content on TalkLife.

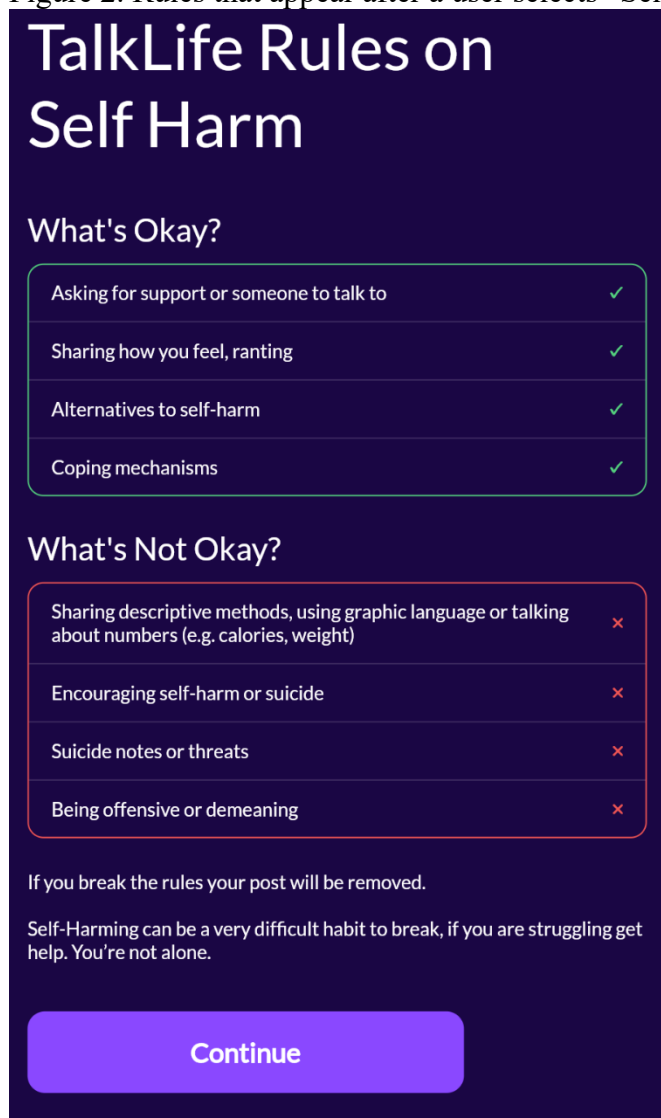
Figure 1. View of the TalkLife home screen for a user logged in via web browser



Users control which posts are displayed in their central, scrollable feed by selecting categories in the righthand sidebar. By default, a post is visible to all users viewing the post’s category (see Figure 3 for an example of the “Self Harm” category’s feed). Users have three options for responding to posts: write a comment, offer a “heart” emoji, or select a shorthand reaction (e.g., “ILY” for “I love you,” “H4U” for “Here for you”). The original poster (OP) receives notifications for all three response types.

Some automated moderation of user posts occurs. For example, a post including a profanity produces a prompt to consider whether the post is “appropriate” before finalizing it. Posts including the word “suicide” or related words produce a safety pop-up (see Figure 4). Human moderation depends on TalkLife volunteers who complete five hours of training and donate five to six hours of their time per week. TalkLife users can also flag posts for review.

Figure 2. Rules that appear after a user selects “Self Harm” as their post category



The TalkLife organization offers researchers access to platform data for a fee. Researchers attain Institutional Review Board approval from their home institution as per usual. The available data include myriad, time-stamped descriptors of platform behavior, including posts, categories, comments, reactions, flags, bans, and deletions, plus user-reported sex and date of birth. Users have unique identification numbers, which serve as the database key and allow researchers to reassemble TalkLife posts and comments into interactions.

Figure 3. A screenshot of the central feed with the “Self Harm” category selected

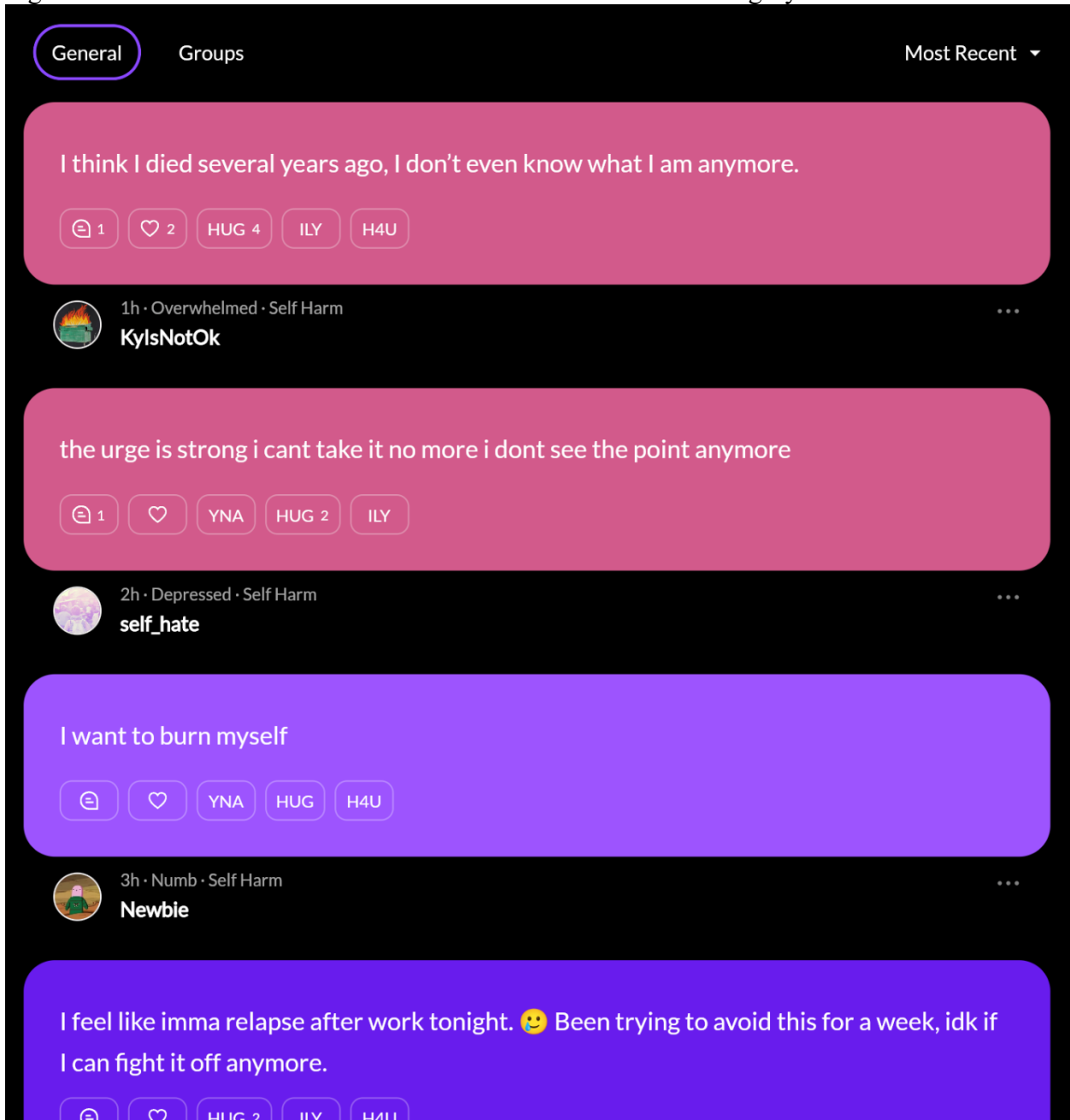
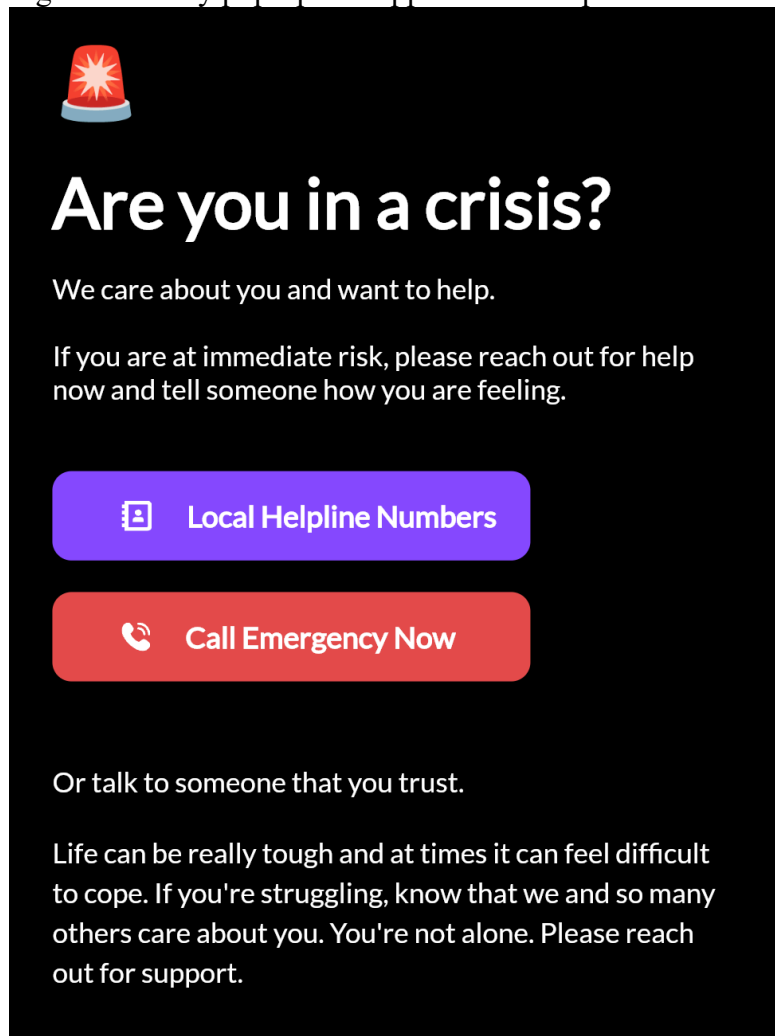


Figure 4. Safety pop-up that appears when a post includes “suicide” or related words



Orientation to Study Aims, Methods, and Data Analysis Plan

The data analysis plan for this study includes topic modeling, machine learning classification, and multilevel modeling. The first aim, to characterize expressions of help-seeking in posts, uses topic modeling to summarize the content of the full set of documents and define each post by its proportion of each topic. The second aim, to measure the amount of social support in the comments, uses machine learning classification to label comments for levels of emotional support and informational support. The third aim, to test whether the topics of posts

relate to the amount of social support provided in the comments, uses multilevel modeling to predict the presence of comments and the amount of support in the comments. Taken together, these approaches will help reveal the components of adolescent help-seeking expressions that engender social support.

Data Selection

Data for this study were selected based on specific inclusion and exclusion criteria. Inclusion criteria were: (1) posts that were placed in the “Self Harm” category by the poster (2) where the poster was between the ages of 13 and 24, plus (3) comments associated with those posts. Posts and comments were excluded if they were subsequently deleted by the user, as were posts and comments from accounts that were subsequently deleted. This data filtering resulted in a dataset of 575,261 posts and 1,041,410 associated comments.

Aim 1: Topic Modeling of Posts

The first aim of this study is to characterize expressions of help-seeking in the above-mentioned 575,261 posts. Topic modeling suits this aim because topic modeling turns a large corpus, or body of text, into digestible clusters of words. Described by one of its creators as “a tool for reading” (Bail, 2018), topic modeling takes as input a corpus of documents and produces as output a set of topics that characterizes the complete corpus. This output is broken down into two components: (1) gamma, the topics that categorize each document, and (2) beta, the terms that characterize each topic.

Topic modeling’s power and flexibility come from its core premise that documents include a mixture of topics and topics include a mixture of terms (Boyd-Graber et al., 2014). The definition of a document depends on the corpus being studied. Often, a document is one chunk of text, like a post, article, or speech. One term can belong to multiple topics, and one document can

include multiple topics. Whereas previous clustering approaches suffered from allocating terms exclusively, topic modeling mimics natural language by letting terms have multiple meanings. Topic modeling iterates across the corpus of documents, using the co-occurrence of terms in documents to define the topics.

Topic modeling is an unsupervised machine learning approach, meaning it operates without human-coded training data. However, the human data analyst determines k , the number of topics in the topic model. Sometimes there are theoretical or empirical reasons to set k at a certain value (Silge & Robinson, 2017). More often, the data analyst runs multiple topic models with varying values for k . In the most popular method of implementing topic modeling, the Python package “gensim” (Rehurek & Sojka, 2010), the data analyst sets a range and interval for k . The data analyst might choose to run a set of topic models with k ranging from eight to 26 by intervals of two. The analyst runs the ten models and chooses the best k based on their preferred performance metric.

Topic modeling performance metrics vary in their usefulness, with *perplexity* and *coherence* predominating in peer-reviewed research (Boyd-Graber et al., 2014). Perplexity measures how surprised a topic model is when it is applied to a held-out subset of data, i.e., how unlikely the held-out data is based on what the topic model learned from the training data. While this approach comports with best practices in machine learning, models with better perplexity scores have been shown to be *less* interpretable (Chang et al., 2009). After perplexity fell out of favor, coherence rose to prominence. Now coherence is the default performance metric used in the popular Python package “gensim.” Coherence measures the strength of the association between top terms in each topic based on those terms’ pairwise co-occurrence in an external, reference corpus. Researchers using topic modeling must choose from a variety of different

specifications of coherence (e.g., UMASS, UCI, c_v , etc.; Rosner et al., 2013). Still, human ratings of topic interpretability serve as the gold standard against which these coherence metrics are judged (Rosner et al., 2013).

The implementation of topic modeling in this study requires consideration of the length of the individual documents that comprise the corpus. Best practices suggest that documents should be at least 50 terms long to produce stable, meaningful topics using the most popular topic modeling methods (e.g., Latent Dirichlet Allocation; Vayansky & Kumar, 2020). In this corpus, individual posts have a mean length of 26.46 terms ($SD = 51.31$; median = 15), which is well below the 50-term threshold. A similar problem arises in topic modeling studies of Twitter data, and an aggregation approach has been developed to address it (Hong & Davison, 2010; Steinskog et al., 2017). This aggregation approach takes a corpus with document labels, e.g., author, keyword, or hashtag, and aggregates across the chosen label to create longer documents. The data for this study include the unique user identification number, i.e., author label for all posts. After aggregating posts by author, such that each document is an aggregation of all posts by a given author, the mean length increases to 132.48 terms per document ($SD = 587.28$; median = 37). These longer documents will be analyzed via topic modeling with varying numbers of topics and assessed for interpretability via integration of human ratings and coherence metrics.

Aim 2: Social Support Classification of Comments

The second aim of this study is to measure the amount of social support provided in the 1,041,410 comments. Machine learning classification suits this aim because machine learning classification labels a huge corpus of documents based on a modest amount of human-coded, training documents. In contrast to the unsupervised approach of topic modeling, machine

learning classification is a supervised approach that takes as its input a training set of human-coded data and produces as its output an algorithm for automatically labelling similar data.

Popular machine learning classification algorithms include logistic regression, support vector machine, random forests, k-nearest neighbors, naïve Bayes, and boosted trees (Kuhn & Johnson, 2013). Each of these classification algorithms is explained in depth in the authoritative book by Kuhn and Johnson (2013); a summary of each follows. Logistic regression classification works by using the logistic function with a decision boundary or threshold value to determine the class of an observation. Support vector machine classification works by mapping the training data in space and then creating a boundary that delineates the classes. Random forests classification works by fitting multiple decision trees to the training data then returning the class agreed upon by the majority of the decision trees. K-nearest neighbors classification works by determining the class of an observation based on the class of a set number of other observations closest to the observation in question. Naïve Bayes classification works by applying Bayes' theorem with strong assumptions of independence. Boosted trees classification works by building off of consecutive decision trees to optimize classifier performance.

Training a machine learning classifier sometimes includes a process called “tuning,” in which various parameters are adjusted to improve the performance of the classifier. Each algorithm has its own parameters based on how it works. Some classification algorithms depend on tuning to perform well, e.g., k-nearest neighbors and boosted trees, while others are more likely to work well “right out of the box,” e.g., logistic regression and random forests. Tuning a machine learning algorithm is widely regarded as “black magic,” and experts in the field discourage tuning unless classifiers perform inadequately (M. De Choudhury, personal communication, April 29, 2022).

Classifier performance is measured via five common metrics: accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve (AUC ROC; Sharma & De Choudhury, 2018). Accuracy is the overall proportion of correct classifications. Precision is the proportion of correct positive classifications out of all positive classifications. Recall is the proportion of actual positives that were classified as positive. Since precision and recall are in tension with each other, the F1 score seeks to balance them by taking their harmonic mean. Finally, AUC ROC summarizes the relationship between the true positive rate and the false positive rate of a classifier at varying thresholds to determine the overall performance of a classifier. The relative importance of these five metrics depends on the classification task. In this study, AUC ROC provides the best assessment of classifier performance because it balances the “cost” of tolerating false positives with maximizing true positives.

In this aim, the six popular machine learning classifiers described above will be trained on a set of about 5,000 human-labeled comments, which is a training set over ten times the size of many published studies (e.g., Sharma & De Choudhury, 2018). The above performance metrics will be assessed for each classifier, with an emphasis on AUC ROC. The “winning” classifier will label the million outstanding comments.

Aim 3: Do Topics of Posts Relate to Social Support Provided?

The third aim of this study is to examine the association between topics of posts and social support in the comments. Multilevel modeling suits this aim because the dataset is nested across several levels. These levels include multiple posts by individual posters, multiple comments by individual commenters, and multiple comments on a given post.

A particular challenge of this dataset is that many posts received zero comments. As such, it is not possible to treat level of support in a comment as the dependent variable for the

entire dataset. To address this issue, this study uses a hurdle model to break the research question down into two components (Cragg, 1971). The first part of the hurdle model uses the entire dataset to test whether the topics of a post relate to whether the post does or does not receive any comment. The second part of the hurdle model uses only the posts that received comments to test whether the topics of a post relate to the presence or absence of social support in the comments. In other words, the first part of the hurdle model tests which topics were more likely to receive any comment, and the second part of the hurdle model tests which topics were more likely to receive a supportive comment.

Summary

This study leverages the rich, behavioral data offered by TalkLife to examine social support for adolescent posts related to self-harm on an online mental health peer support platform. To our knowledge, this study is the first application of these methods, i.e., topic modeling, machine learning classification, and multilevel modeling, to data from the TalkLife platform.

The over-arching goal of this study was developed during an interdisciplinary workshop of social scientists at Georgia Tech University in December, 2019. The specific aims were developed by this doctoral candidate (MNL) in collaboration with her advisor (NBA). The next three chapters address each aim in turn and take the format of stand-alone empirical papers. The empirical chapters do not utilize formal hypotheses but rather are guided by a series of clear research questions. This is because of the formative nature of the research as well as concerns regarding the influence of generative discussions and pilot analyses during the interdisciplinary workshop. We decided to err on the side of avoiding any appearance of hypothesizing after

results are known (HARKing). The final chapter provides a grand discussion of the results of all three aims.

Chapter 3: Topic Modeling of Help-Seeking Expressions

Non-suicidal self-injury (NSSI) in adolescence is common and risky. Around the world, adolescent NSSI occurs at prevalence rates of 15-20% (Muehlenkamp et al., 2012). This behavior is a compelling target of basic psychological science because of its seeming rejection of core survival instincts (Hooley & Franklin, 2018). That said, much of the research and clinical interest in NSSI concerns its relationship to suicide, the second leading cause of death in American teens (Shain et al., 2016). Non-suicidal self-injury is associated with suicidal thoughts and behaviors over and above the effect of common mental disorders, and NSSI increases the risk of transitioning from suicidal ideation to suicide attempt (Kiekens et al., 2018). Reducing NSSI could reduce suicide.

Numerous barriers have impeded the progress of programs that aim to reduce NSSI. Clinician-delivered, evidence-based treatments for NSSI show minimal or mixed effectiveness (for excellent summaries, see: Dobias et al., 2021; Preston & West, 2022). Stigma can also prevent people with NSSI from seeking professional help and in-person peer support (Lavis & Winter, 2020). Service gaps, such as long waiting lists that occur both in-person and online, can thwart even those who do seek help (Lavis & Winter, 2020).

People with NSSI often seek peer support online, as seen in the online NSSI support communities that have many thousands of users (e.g., /r/selfharm subreddit on Reddit.com). These online help-seekers comprise about one-third of all people with NSSI (Frost & Casey, 2016). Online help-seekers tend to have more severe and more recent NSSI than those who do not seek help online (De Riggi et al., 2018; Frost & Casey, 2016). Of online help-seekers, two-thirds report that they are actively trying to stop engaging in NSSI (Corcoran & Andover, 2020).

When people seek help online for NSSI, they typically seek social support in the form of emotional support and coping strategies (Daine et al., 2013). Online NSSI help-seekers tend to discuss more than just the specifics of NSSI; rather, they typically discuss the socioemotional contexts in which NSSI occurs (Preston et al., 2023). The animating moral concern of online NSSI communities is care, both seeking and providing (Preston et al., 2023). Young-adult online help-seekers retrospectively report seeking out a sense of belonging and identity (Stänicke, 2023). Clearly, prosocial goals figure prominently in the online help-seeking pursuits of people with NSSI.

Online NSSI support communities carry significant risks alongside prosocial opportunities. While social media use in general has not been shown to be associated with NSSI (Nesi et al., 2021), there is some evidence that the onset of NSSI is particularly vulnerable to social contagion, i.e., the spread of a behavior within a group, which can occur online (Jarvi et al., 2013). Young-adult users of online NSSI support communities describe an environment that facilitates risk-taking and lacks structure and accountability, i.e., there is “no one in charge” (Stänicke, 2023, p. 160). A recent systematic review on the impact of viewing and sharing self-harm-related imagery and videos found a wide range of potential effects, including concerns about imitation, reinforcement, and normalization of NSSI (Marchant et al., 2021).

It is often unclear who is responsible for the risky aspects of online NSSI communities. In qualitative studies, users of these communities describe the burden associated with being exposed to the intense suffering of others and the desire for someone knowledgeable to intervene when suicide risk appears (Lavis & Winter, 2020; Stänicke, 2023). Qualitative studies further reveal that while risk and protective factors for safe use of these communities tend to focus on individual factors, platform policies and procedures can also support safety (Thorn et al., 2023).

There is debate over appropriate measures platforms should take to protect users with NSSI. For example, in February of 2019, Facebook and Instagram banned graphic images of self-harm following the suicides of multiple young users of the platforms (Smith & Cipolli, 2022).

Discussion of self-harm images on those platforms was studied via natural language processing to detect changes in user discourse following the ban, revealing grief that users expressed over the loss of these platforms as communities for social support and celebration of recovery (Smith & Cipolli, 2022).

Researchers of online NSSI communities agree that a social contagion view misses crucial aspects of the picture, and they argue for policies and platform design that promote social support and harm reduction (Alhassan et al., 2021; Lavis & Winter, 2020; Preston & West, 2022; Smith & Cipolli, 2022; Thorn et al., 2023). Thorn and colleagues (2023) oppose blanket bans on NSSI content and encourage case-by-case assessment by moderators to avoid removal of effective social support. Preston and West (2022) promote online NSSI communities as the best setting to study the benefits of NSSI harm reduction practices since harm reduction practices like wound care are already promoted by users of online NSSI communities. Finally, scholars agree that further research is needed to guide policy and design (Lavis & Winter, 2020; Preston & West, 2022; Smith & Cipolli, 2022; Thorn et al., 2023).

TalkLife stands out among online NSSI support communities because it combines a large userbase (over 1 million users) with the specific goal of providing mental health support. In the studies reviewed above, the online NSSI support communities tend to be subgroups that operate on general use platforms like Reddit, Twitter, or Instagram. They congregate via user-created and user-moderated message boards on Reddit or via hashtag on Twitter or Instagram. In contrast, TalkLife bills itself as a “mental health support community.” TalkLife further differs

from previously studied NSSI support communities because TalkLife requires users to label their posts from a TalkLife-provided set of options. Finally, to our knowledge, TalkLife is the only large-scale platform hosting an NSSI support community that does not allow users to upload images.

These aspects of TalkLife make it a valuable platform to study for the promotion of safety in online NSSI communities. As a platform purpose-built for mental health support, its design can be examined for how well it serves only that purpose, in contrast to other general use platforms. TalkLife's requires users to label their posts from a list of TalkLife-provided options, including a "Self Harm" label. This creates a means by which to filter only for "Self Harm"-related content. This labeling requirement also may narrow the topics of discussion under that label, since users can only pick one label and there are other labels for "Family," "Work," "Friends," "Education," and other important socioemotional contexts. Finally, disallowing images yields user content that is entirely text and ideal for study with validated natural language processing approaches.

A popular natural language processing approach, topic modeling has been applied to online behavior and communities relevant to online help-seeking for NSSI. Scholars have incorporated topic modeling into studies of how users reacted to platforms banning graphic self-harm imagery (Facebook and Instagram; Smith & Cipolli, 2022), how lay users and organized advocacy groups discuss self-harm (Twitter; Alhassan et al., 2021), how users of support communities for NSSI and suicide discuss moral concerns (Reddit; Preston et al., 2023), how users tend to respond via comments to others' NSSI-related posts (Reddit; Preston & West, 2023), what topics users focus on when they post self-harm-related queries (Naver Q&A, leading Korean search engine; Kim & Yu, 2022), how topics discussed on a suicidal ideation support

community changed during the onset of the COVID-19 pandemic (Reddit; Feldhege et al., 2023), and whether topic modeling could match human detection of suicide content in posts (TeenHelp.org; Franz et al., 2020).

In this study, we will use topic modeling to explore the content of help-seeking posts under the “Self Harm” category on the TalkLife platform. Results will be examined through three lenses: (1) in context of previous findings about the goals of online help-seekers with NSSI, (2) in comparison to other topic model-based studies of related online communities, and (3) in consideration of TalkLife’s purpose and design. This approach will contribute to the important tasks of describing online help-seeking behavior and guiding policy and platform design.

Methods

Data Selection

Data were licensed from TalkLife according to the terms of their TalkLife Data Sharing Agreement (see Appendix A). The Institutional Review Board at the University of Central Florida reviewed this project and made a determination of Not Human Research (IRB ID: SBE-18-14660; Research ID: 1066191). Data were obtained via SQL query from the TalkLife database in June of 2021. Data were filtered to include posts that users labeled with the “Self Harm” category from users that were aged 13 to 24 at the time of posting, which was calculated from post timestamp and user-reported date of birth. Data were excluded that had been subsequently deleted by the user or that were produced by users who subsequently deleted their account. These criteria yielded a dataset of 575,261 posts.

Participants

There were 114,937 unique users identified in the set of all posts. Aligning with previous research on who seeks help online for self-injury (Frost & Casey, 2016), the majority of users

self-reported “female” gender (N = 69,668; 60.61%). The remaining 45,269 users are approximately evenly split between “male” (N = 18,549; 16.14%) and “other” (N = 26,720, 23.25%) gender identifiers. Poster age range was calculated at time of first post in the “Self Harm” category. Poster age range hews to the inclusion criteria (13-24), with a mean age of 17.5 years old (SD = 2.58 years).

Data Pre-Processing

Following the data pre-processing steps for topic modeling reported by Franz and colleagues (2020), we removed excess whitespace, punctuation, numbers, and stop words. Stop words are common terms with little unique semantic meaning, e.g., “and” or “the.” To further pare down meaningless terms in the data, we filtered out words that appeared only once (e.g., misspellings, nonsense terms, dozens of permutations of “Ahhhhhhh”). To improve stability and interpretability of topic model results, we followed the aggregation method developed for shorter texts and aggregated the posts by author (Hong & Davison, 2010; Steinskog et al., 2017).

Model Selection Plan

Three topic models were run with varying levels of k , i.e., researcher-specified numbers of topics. Based on previous literature on similar datasets showing interpretable topic model fits around 10 topics and due to computational limitations of this researcher’s laptop, topic models were run with eight, 10, and 12 topics respectively. This researcher assessed each topic model based on two criteria: coherence score and human interpretability. Human interpretability was assessed based on the top 10 terms of each topic. For the three models (of eight, 10, and 12 topics each), clinical expertise and holistic judgment were used to label each topic with a theme. Models were judged based on how many of the topics were interpretable, how many topics were

not interpretable, and whether the added topics captured meaning that was not already covered by other topics.

R Packages

Data were analyzed using *R* version 4.3.0 and *R* packages *rio* (version 0.5.29), *here* (version 1.0.1), *tidyverse* (version 2.0.0), *tidytext* (version 0.4.1), *tm* (version 0.7-11), *topicmodels* (version 0.2-14), *topicdoc* (version 0.1.1), and *beepr* (version 1.3). Execution of these methods in *R* was guided by the invaluable book, Text Mining with R by Julia Silge and David Robinson (<https://www.tidytextmining.com>).

Results

Descriptive Results

The complete set of posts included 575,261 posts from 114,937 users. Posts had a mean length of 26.46 terms and a median length of 15 terms. After aggregating posts by author, the author-aggregated documents (N = 112,626) had a mean length of 132.48 terms and a median length of 37 terms. Number of posts per poster ranged from one to 3,086 (mean = 5.02, SD = 21.48; median = 1).

After data pre-processing steps including removing stop words, the data retained 113,506 total discrete terms. We determined the top 20 terms (see Table 1).

Table 1. Top 20 terms by number of times used

Term	Frequency
feel	96,323
cut	86,894
life	55,088
people	46,986
die	42,549
anymore	41,854
time	38,439
hate	36,602

talk	32,248
cutting	32,219
wanna	30,658
stop	30,631
kill	29,159
day	29,007
bad	28,688
clean	26,384
love	25,092
pain	24,292
fucking	23,991
feeling	23,682

Topic Model Results

Topic modeling yielded three models of eight, 10, and 12 topics each. Coherence scores were calculated (see Table 2). Scores closer to zero denote better performance. Topic coherence scores were similar across the three models, both in terms of range and mean.

Table 2. Coherence scores for three topic models

Topic	Model 1 ($k = 8$)	Model 2 ($k = 10$)	Model 3 ($k = 12$)
1	-104.37	-112.21	-96.80
2	-100.02	-103.50	-103.50
3	-97.60	-98.22	-101.95
4	-105.17	-91.71	-92.12
5	-117.77	-118.26	-112.98
6	-85.84	-99.13	-103.79
7	-93.32	-101.30	-97.96
8	-85.51	-90.84	-88.58
9		-103.11	-97.95
10		-94.43	-104.30
11			-123.10
12			-106.37

The top-20 terms for each topic were identified for the three models, and themes were inferred based on clinical expertise and holistic judgment (see Tables 3, 4, 5). Topics from which themes do not emerge are labeled by that topic’s top-three terms. The author-aggregation

approach employed here limits the ability to share exemplary posts since documents are aggregated across multiple posts.

Table 3. Top-20 terms per topic of model 1 ($k = 8$)

Topic	Terms	Theme
1	hurt, skin, pain, blood, harm, feel, people, time, body, red, write, start, trigger, watch, hand, cut, mind, thinking, feeling, scars	Self-harm body
2	people, love, guys, day, stay, hope, beautiful, strong, friends, person, stop, feel, god, talk, post, life, happy, hey, selfharm, app	Stay strong
3	hate, wanna, die, talk, fucking, kill, shit, fuck, kik, gonna, sleep, depressed, fat, bad, idk, feel, hurt, ugly, cry, stupid	Explicit self-loathing
4	time, mom, told, school, day, heart, left, girl, dad, home, friend, night, crying, eyes, smile, friends, head, inside, broken, cry	<i>Time, mom, told</i>
5	feel, feeling, depression, people, family, afraid, sad, mind, anxiety, mental, pain, understand, makes, worse, hard, depressed, life, suicidal, person, day	Mental ill health
6	life, anymore, suicide, tired, die, care, live, people, feel, happy, world, cares, living, dead, alive, kill, friends, goodbye, worthless, suicidal	Hopeless suicide
7	clean, harm, scars, months, days, cuts, weeks, cut, school, week, time, started, relapsed, bad, relapse, ago, day, night, urge, told	Self-harm abstention
8	cut, feel, cutting, stop, bad, time, pain, days, hard, blade, feeling, tonight, fuck, hurts, scared, numb, hurt, deep, razor, boyfriend	Self-harm struggle

Table 4. Top-20 terms per topic of model 2 ($k = 10$)

Topic	Terms	Theme
1	hurt, harm, people, skin, feel, time, write, body, start, attention, trigger, watch, pain, red, play, burn, remember, thinking, music, water	Distraction from self-harm
2	love, talk, people, kik, guys, stay, strong, day, hope, beautiful, stop, person, message, post, friends, hey, selfharm, app, amazing, happy	Stay strong
3	hate, die, wanna, fucking, kill, fuck, gonna, shit, talk, fat, ugly, idk, cry, stupid, crying, sleep, bad, rn, scared, hurt	Explicit self-loathing

4	feel, feeling, people, tired, time, sad, happy, hard, talk, hurt, makes, wrong, sleep, friends, understand, feels, lonely, bad, depressed, sick	Expressing feelings
5	depression, suicidal, anxiety, afraid, mental, family, depressed, feeling, worse, hospital, feel, bad, pain, taking, times, thinking, eating, day, stop, suicide	Mental ill health
6	life, anymore, suicide, live, die, care, living, world, cares, dead, alive, worthless, goodbye, people, kill, killing, ready, tired, leave, death	Hopeless suicide
7	clean, harm, scars, months, cuts, days, weeks, relapsed, relapse, week, urge, time, harming, ago, night, arm, month, day, bad, urges	Self-harm abstention
8	cut, cutting, stop, bad, days, feel, blade, tonight, time, deep, clean, pain, wrist, razor, friend, scared, boyfriend, cuts, blades, badly	Self-harm struggle
9	pain, heart, head, inside, love, smile, day, eyes, broken, cry, tears, time, mind, night, world, blood, girl, left, body, fall	<i>Pain, heart, head</i>
10	school, mom, told, friends, friend, dad, home, parents, time, started, people, called, girl, day, sister, family, house, brother, guy, mother	Family and friends

Table 5. Top-20 terms per topic of model 3 ($k = 12$)

Topic	Terms	Theme
1	clean, cut, days, harm, months, weeks, relapsed, urge, relapse, bad, week, day, month, tonight, stop, hard, harming, urges, blades, cutting	Self-harm abstention
2	love, people, kik, talk, guys, stay, strong, day, hope, beautiful, stop, message, selfharm, hey, post, person, amazing, friends, app, abused	Stay strong
3	die, hate, kill, fucking, wanna, shit, fuck, gonna, fat, ugly, stupid, sick, ugh, talk, bad, deserve, god, hates, depressed, tonight	Explicit self-loathing
4	feel, people, talk, happy, time, tired, friends, depression, sad, feeling, wrong, understand, hard, lonely, friend, honestly, makes, lot, person, feels	Expressing feelings
5	feeling, feel, depressed, suicidal, family, hurt, afraid, worse, mental, reason, sad, anxiety, bad, thinking, makes, depression, stop, parents, recently, hurting	Mental ill health
6	life, anymore, suicide, live, care, tired, living, cares, dead, alive, world, worthless, goodbye, die, killing, ready, suicidal, bye, worth, commit	Hopeless suicide
7	scars, cuts, arm, school, started, deep, scared, time, cut, arms, wrist, hide, cutting, told, blood, blade, found, coward, wear, bad	Hiding self-harm

8	cut, feel, cutting, stop, bad, wanna, idk, pain, fuck, time, scared, hurt, hurts, rn, numb, friend, broke, boyfriend, kinda, thinking	Self-harm struggle
9	night, cry, sleep, crying, day, time, head, smile, girl, left, eyes, wake, tears, love, bed, stay, blood, blade, fault, gonna	Crying
10	mom, told, school, dad, home, friend, parents, friends, called, sister, started, time, house, mother, guy, brother, family, people, girl, day	Family and friends
11	skin, people, write, hurt, feel, harm, watch, time, red, play, water, start, music, safe, cut, friend, remember, burn, read, listen	Distraction from self-harm
12	pain, feel, mind, inside, life, heart, world, lost, broken, death, body, god, real, time, love, head, control, hope, fight, change	Philosophical thoughts

Model three was selected because its topics were the most distinct from each other and the additional topics introduced new themes. Many themes recur across the three models, and the 12-topic model includes the strongest themes from the 8- and 10-topic models (e.g., self-harm abstention and stay strong) while adding strong new themes (e.g., crying and hiding self-harm).

Topic modeling defines each document by how strongly present each topic is in that document. In other words, each document is defined as a mix of all the topics, with *gamma* denoting the strength of a topic's presence in the document. This *gamma* output is a proportion, such that each document is assigned k weights, summing to one. *Gamma* allows us to summarize each document by top topic, i.e., which topic has the largest *gamma* for that document.

Accordingly, the top topic was calculated for all documents, which has been summarized to show which topics predominate in the corpus; given that the most common topic focuses on suicidal content, all topics have also been assessed and labeled for NSSI content and morbid/suicidal content (see Table 6).

Table 6. Top topics of author-aggregated posts (N = 112,626), plus whether NSSI or morbid/suicidal content appeared in the top-20 terms

Rank	Topic	Frequency	Theme	NSSI content	Morbid/suicidal content
1	6	14,185	Hopeless suicide		Yes
2	4	12,164	Expressing feelings		
3	3	11,907	Explicit self-loathing		Yes
4	1	11,487	Self-harm abstention	Yes	
5	8	10,175	Self-harm struggle	Yes	
6	12	9,374	Philosophical thoughts		Yes
7	5	8,956	Mental ill health		Yes
8	7	8,397	Hiding self-harm	Yes	
9	10	8,235	Family and friends		
10	9	7,562	Crying	Yes	
11	2	6,834	Stay strong	Yes	
12	11	3,350	Distraction from self-harm	Yes	

Of the total set of 112,626 documents, 47,805 had a NSSI-related top topic (42.45%) while 44,422 had a morbid or suicidal top topic (39.44%).

Discussion

In this study, we set out to use topic modeling to explore the content of help-seeking posts under the “Self Harm” category on the TalkLife platform. Our goal was to contribute to the important tasks of describing online help-seeking behavior and guiding policy and platform design. Our approach produced a 12-topic model with interpretable themes. The themes ranged from discussion of NSSI urges, abstention, and relapse (topic 1, “self-harm abstention”) to angry or hopeless suicidality (topics 3 and 6, “explicit self-loathing” and “hopeless suicidality”) to encouragement and offers of connection (topic 2, “stay strong”). We found that the top topics of the documents were approximately evenly split between NSSI-related topics and morbid or suicidal topics. The topic model separated NSSI-related terms and suicide-related terms into different topics.

Our findings show some agreement with previous findings on the goals of online help-seekers with NSSI. The presence of topics related to abstaining from NSSI, feeling conflicted about engaging in NSSI, hiding NSSI, and distracting oneself from urges to self-injure supports the finding that most help-seekers are actively trying to stop engaging in NSSI (Corcoran & Andover, 2020). The prevalence of terms related to suffering, struggle, and hopelessness supports the finding that online help-seekers want emotional support (Daine et al., 2013). The prevalence of these terms may also support models of NSSI that incorporate NSSI's ability to improve affect via relief of negative affect (Hooley & Franklin, 2018).

On the other hand, the narrow range of topics, limited mostly to NSSI and suicide, may not align with findings that online NSSI help-seekers favor discussions of the varied events, relationships, and contexts related to NSSI (Preston et al., 2023). Finally, the severe suffering and suicidality captured by the topic model align with concerns expressed by qualitative study participants regarding the burden associated with being exposed to the intense suffering of others and the desire for someone knowledgeable to intervene when suicide risk appears (Lavis & Winter, 2020; Stänicke, 2023).

Our findings share numerous themes with topic modeling studies of online behavior and communities relevant to online help-seeking for NSSI. While our study lacks the longitudinal component used by Feldhege and colleagues (2023), we found similar themes of suicidality, hopelessness, offering connection, and social support. While we focused on unigrams, i.e., single terms, in contrast to Alhassan and colleagues' focus on trigrams (2021), we found similar themes of self-harm struggle or infliction and self-harm abstention or recovery. While we selected a model with 12 topics versus the 26-topic model selected by Preston and colleagues (2023), we found that there were eight similar topics that appeared in both models (hopeless suicide, explicit

self-loathing, self-harm struggle, philosophical thoughts, mental ill health, hiding self-harm, family and friends, and distraction from self-harm). While Kim and Yu focused on NSSI-related search queries (2022), shared themes emerged including anger and struggle, hiding self-harm scars, and mental ill health or depression. A key difference between our findings and others is that we did not find topics that expressed pro-self-harm sentiment, nor did we find topics focused on NSSI or suicide methods, at least one of which appeared in all of the above-mentioned studies.

Regarding the purpose and design of TalkLife, our findings highlight the importance of major platform characteristics. First, TalkLife’s rules for the “Self Harm” category forbid pro-self-harm content and graphic descriptions of NSSI. The absence of this content from our topic model, while it appears in the topic models of other studies of online NSSI support communities, suggests that TalkLife’s rules are helping reduce this content. For example, Kim and Yu (2022) identified a topic that included queries about how to self-injure without pain, and Preston and colleagues (2023) identified a topic that included specific descriptions of suicide attempts. Second, TalkLife requires that users select a single label for each post from 33 pre-defined options (e.g., “Self Harm,” “Family,” “Bullying,” “LGBT,” “Depression”). The narrow focus of our topic model on NSSI and suicide, which contrasts with the varied content found by Preston and colleagues (2023), may indicate that the post-labeling system creates exclusive silos that curtail the inclusion of broader socioemotional context.

We discovered perhaps the most important platform characteristic when we grappled with our surprise at the prevalence of suicide-related topics in our topic model. Previous topic modeling studies that focused on a body of text collected around the term “self-harm” had found topics more specifically focused on NSSI (Alhassan et al., 2021; M.-S. Kim & Yu, 2022; Preston

& West, 2023). Why then did morbid or suicidal content match the prevalence of NSSI-related content in our results? While TalkLife provides a wide range of category labels for posts, they do not offer a “Suicide” label. This omission appears to cause those expressing suicidal thoughts and feelings to use the “Self Harm” label to identify their posts.

A mental health organization might avoid providing a space for suicidal young people to gather for many reasons, including possible concern about liability for completed suicide or a suicide cluster. There is evidence in our findings for a likely consequence of this design choice: a person looking for help in a suicidal crisis will not find a “Suicide” label for their post and will choose the next best fit, “Self Harm.”

The conflation of NSSI and suicide poses risks to all parties. For a suicidal young person naïve to NSSI, exposure to discussions of NSSI urges and experiences might cause the onset of NSSI. Initiation of NSSI is thought to be more vulnerable to social contagion than recurrence of NSSI (Jarvi et al., 2013), and the use of NSSI as an anti-suicide measure is commonly reported (Czyz et al., 2021). For a young person with NSSI who is not experiencing suicidal ideation, concerns loom about suicide clustering and the burden of supporting people with intense suffering while trying to manage one’s own challenges (Lavis & Winter, 2020; Swedo et al., 2021).

Strengths and Limitations

Strengths of this study include a large dataset representing help-seeking behavior of over 100,000 adolescent users, a natural language processing approach that is underused in clinical science, the use of clinical expertise to interpret topic model findings, and platform design considerations that may inform future policy and design.

Limitations of this study include subjectivity in the implementation and interpretation of topic models, lack of computational power to run topic models with higher k 's, brevity of user posts that necessitated author-aggregation, and the speculation inherent in our guess about what is causing so much suicidal content to appear in the “Self Harm” community. A fuller treatment of strengths and limitations will be undertaken in chapter six.

Implications and Future Directions

This study reveals the immense suffering experienced and expressed by the adolescent users seeking help for self-harm on TalkLife. The themes revealed in our topic model mostly align with previous findings about the goals of online NSSI help-seekers and the discourse in online NSSI communities. The differences that emerged may point to important design considerations for online mental health support communities: rules probably help, categories may create silos, and not offering a “Suicide” label may increase risk.

Future directions grow out of limitations and implications. The value gleaned from comparing and synthesizing topic model findings would be increased by similar pre-processing and transparent reporting (Hagg et al., 2022). This dataset merits additional study with more robust computational resources to power topic models with higher k 's. Further investigation of whether platforms that limit suicidal expressions might see suicidality bubble up in unintended places would help test our speculation. Implications regarding platform design should support three practical next steps: encourage the implementation of safety-focused rules, bring attention to unintended outcomes of requiring categorization of content, and require online mental health support platforms to grapple with their responsibility to people seeking help for self-injurious and suicidal thoughts and behaviors.

Conclusion

In this study, we used topic modeling to explore the content of adolescent help-seeking expressions under the “Self Harm” category on the TalkLife platform. Our results mostly aligned with previous studies. Important exceptions included relatively less specific situational narrative, absence of pro-self-harm sentiment and specific descriptions of self-harm methods, and the high prevalence of morbid/suicidal content. Each of these exceptions point to a design feature of the TalkLife platform that may explain the findings. TalkLife’s category labels may silo content more than other platforms; TalkLife’s rules may reduce content that can contribute to social contagion; and TalkLife’s omission of a “Suicide” category may funnel suicidal users into the “Self Harm” category. We hope that future research will investigate the effects of these features, and we encourage TalkLife and similar online mental health platforms to work with researchers in pursuit of this goal.

Chapter 4: Machine Learning Classification of Social Support

People who seek help online for self-injurious thoughts and behaviors (SITB) are vulnerable. Online help-seekers with non-suicidal self-injury (NSSI) tend to have more recent and more severe NSSI than those who do not seek help online (De Riggi et al., 2018; Frost & Casey, 2016). Online help-seekers with suicidality tend to have more severe suicidality, substantial social anxiety, and lower perceived in-person social support (Harris et al., 2009; Mok et al., 2016).

Online SITB help-seekers want social support, connection, and to stop self-injuring or avoid suicide; however, they also sometimes seek and share methods for SITB (Corcoran & Andover, 2020; Daine et al., 2013; Harris et al., 2009; Mok et al., 2016; Stänicke, 2023). They report struggling with their exposure to the suffering of other help-seekers and the burden of providing “enough” support to their peers (Lavis & Winter, 2020; Stänicke, 2023). The severity of suffering experienced by online SITB help-seekers combined with the goals of social support, connection, and abstention from SITB create high stakes for the response that these help-seekers find when they post online.

Social support is generally important to mental health (Walen & Lachman, 2000). This finding and its mechanisms have been under study for at least as long as this doctoral candidate has roamed the Earth (Cohen & Wills, 1985). In fact, Goffman wrote in the birthyear of this doctoral candidate’s advisor that people with stigmatized maladies may benefit more when social support comes from people who share the same affliction (Goffman, 1963). These findings undergird the 21st-century investigation of social support in online mental health communities.

The “Social Support Behavioral Code” is a framework for assessing types and levels of social support, which includes five categories of social support (Cutrona & Suhr, 1994). Since

foundational work adapting this coding scheme for online social support communities (Bambina, 2007), studies of online social support have focused on two categories of social support in this framework: emotional support and informational support (E. Sharma & De Choudhury, 2018). Emotional support provides understanding, encouragement, affirmation, sympathy, or caring; informational support provides advice, referrals, or knowledge (Wang et al., 2012).

Online help-seekers receive varying levels and types of social support. Most studies find that emotional support far outstrips informational support in terms of frequency (De Choudhury & De, 2014; M. Kim et al., 2023; Kruzan et al., 2021). Interestingly, Sharma and De Choudhury (2018) found that the ratio of emotional support to informational support varied across 55 mental health communities on Reddit depending on the focus of the community. They found that emotional support was more prominent in all communities except for those focused on compulsive disorders, wherein informational support predominated (E. Sharma & De Choudhury, 2018). Users of communities focused on compulsive disorders were encouraged to seek advice and assistance with resisting urges, which may explain the predominance of informational support (E. Sharma & De Choudhury, 2018).

In online mental health communities, the provision and receipt of social support predict future platform behavior and may affect wellbeing. Saha and Sharma (2020) used a case-control design to reveal that users' affective, cognitive, and behavioral outcomes on the platform improved when users received comments that were longer, reflected the original post, used varied language, and contained emotional support. Sharma and colleagues (2020) found that repeated back-and-forth interactions between the original poster and a commenter predicted platform retention of both poster and commenter. Chen and Xu (2021) found that on a user's first post, more comments and more empathy in the comments predicted more activity and more

empathy in the user's later platform behavior. In a study of frequent platform users (requiring >10 posts), Kushner and Sharma (2020) found that a user providing complex emotional support to others predicted that user's cognitive and emotional improvement.

Recent large-scale studies of online peer support communities have used machine learning to characterize their data. Some studies used topic modeling, an unsupervised machine learning approach, to discover social support themes (De Choudhury & De, 2014; Preston & West, 2023). Other studies used hand-labeled data to train classifiers to identify levels of social support using various algorithms, e.g., multinomial regression or support vector machine (M. Kim et al., 2023; Saha & Sharma, 2020; E. Sharma & De Choudhury, 2018; Wang et al., 2012). The latter set of studies used hand-labeled datasets of 400 and 1,000 observations respectively, which were coded without the supervision of a clinical scientist.

This study will build on the existing literature in two ways. First, it will seek to improve on machine learning classification methods used in previous studies by applying clinical expertise and more person-hours to the labeling of a larger training dataset. Second, building on the finding that the ratio of emotional support to informational support may depend on the focus of the online mental health community (E. Sharma & De Choudhury, 2018), this study will assess the ratio of emotional support to informational support within the "Self Harm" category of TalkLife to understand the social support dynamics within that context.

In this study, we will use machine learning classification to measure the social support present in the comments of TalkLife's "Self Harm" category. We will train two classifiers, one for emotional support and one for informational support, based on a training dataset of over 5,000 hand-labeled comments. We will assess our findings through three lenses: (1) in context of previous findings about the ratio of emotional support to informational support, (2) in

comparison to classifier performance in similar studies, and (3) in consideration of TalkLife’s purpose and design.

Methods

Data Selection

Data were licensed from TalkLife according to the terms of their TalkLife Data Sharing Agreement (see Appendix A). The Institutional Review Board at the University of Central Florida reviewed this project and made a determination of Not Human Research (IRB ID: SBE-18-14660; Research ID: 1066191). Data were obtained via SQL query from the TalkLife database in June of 2021. Data were filtered to include comments associated with posts that users labeled with the “Self Harm” category from users that were aged 13 to 24 at the time of posting, which was calculated from post timestamp and user-reported date of birth. Comments were excluded that (1) had been deleted by the user, (2) were produced by users who subsequently deleted their account, or (3) were replies by the original poster. These criteria yielded a dataset of 1,048,655 comments.

Participants

There were 155,282 unique users identified in the set of all comments. The majority of users self-reported “female” gender (N = 85,110; 54.81%). The remaining 70,176 users are approximately evenly split between “male” (N = 39,024; 25.13%) and “other” (N = 31,152, 20.06%) gender identifiers. Commenter age was not possible to calculate due to errors in the TalkLife database (e.g., thousands of users reported to have been born before World War I!)

Classifier Training

Hand-Labeling of Training Dataset

A total of 5,119 comments were randomly selected from the complete set. We requested 5,000 comments and received 119 extra, which we chose to include. The 5,119 comments were hand-labeled for emotional support and informational support by two research assistants, who were supervised by the doctoral candidate (MNL). The process followed these steps:

1. Doctoral candidate drafted a coding scheme for emotional support and informational support based on methods from previous studies (E. Sharma & De Choudhury, 2018; Wang et al., 2012). This scheme included three levels of the two types of support: 0 = absent, 1 = present, 2 = strongly present.
2. Doctoral candidate explored random subset of 100 comments to refine coding scheme.
3. Doctoral candidate trained two research assistants in coding scheme (see Appendix B, “TalkLife Comment Coding Manual”).
4. Doctoral candidate performed “expert labeling” of 150 comments, which was then used to test performance of research assistants (minimum acceptable inter-rater reliability of $K > 0.6$).
5. Research assistants coded eight batches of about 720 comments, with 20% of each batch overlapping.
6. Research assistants met with doctoral candidate between each batch to review mismatches in overlapping comments, maintain fidelity to coding scheme, and refine coding scheme. Doctoral candidate checked inter-rater reliability between each batch to ensure satisfactory performance ($K > 0.6$).

7. Upon completion of hand-labeling, doctoral candidate measured inter-rater reliability of about 1,000 double-coded comments.
8. Research assistants consensus coded discrepant double-coded comments.
9. Complete training set of 5,119 comments coded for emotional support and informational support was assembled.

Feature Selection

The training set of hand-labeled comments was broken down into classification features using LIWC-22 (Tausczik & Pennebaker, 2010). Forty-five LIWC-22 categories were selected based on previous psycholinguistic classification work (Kumar et al., 2015; Saha & De Choudhury, 2017). None of these features had zero variance, so all were retained.

Classifier Selection Plan

The following steps were taken twice, once for emotional support and once for informational support. First, the training set was split into a training set (N = 4,064; 80%) and a test set (N = 1,017; 20%). The training set was then divided into 10 sections or “folds,” which were then used for 10-fold cross validation of all the subsequent classifiers. Six popular machine learning classifiers were trained and assessed on the training set. The classifier with the best overall performance, emphasizing area under the receiver operating characteristic curve (AUC ROC), was selected. The selected classifier was tested on the held-out test set for adequate performance. The classifier was then applied to the approximately 1,000,000 unlabeled comments.

R Packages

Data were analyzed using *R* version 4.3.0 and *R* packages *rio* (version 0.5.29), *here* (version 1.0.1), *tidymodels* (version 1.1.0), *discrim* (version 1.0.1), *caret* (version 6.0-94), *ranger*

(0.15.1), and *readr* (version 2.1.4). Execution of these methods in *R* was guided by the invaluable book, Tidy Modeling with R by Max Kuhn and Julia Silge (<https://www.tnwr.org>).

Results

Descriptive Results

The complete set of comments included 1,048,655 comments from 155,282 users. Comments had a mean length of 16.21 terms (SD = 27.38) and a median length of 9 terms. Number of comments per commenter ranged from one to 1,561 (mean = 6.71, SD = 23.88, median = 2).

Classifier Selection Results

Inter-rater reliability of hand-labeled training was adequate ($K > 0.7$ for both emotional and informational support). Six popular machine learning classifiers were trained and tested for both emotional support and information support (see Tables 7 and 8).

Table 7. Performance of six classifiers for emotional support

Classifier	Accuracy	F1	Precision	Recall	AUC ROC
Random forests	0.748	0.55	0.811	0.538	0.87
Boosted trees	0.738	0.595	0.697	0.572	0.857
Logistic regression	0.692	0.588	0.631	0.569	0.842
Support vector machine	0.696	0.548	0.662	0.528	0.833
Naïve Bayes	0.471	0.35	0.504	0.563	0.813
K-nearest neighbors	0.668	0.555	0.549	0.569	0.777

Table 8. Performance of six classifiers for informational support

Classifier	Accuracy	F1	Precision	Recall	AUC ROC
Random forests	0.797	0.688	0.726	0.662	0.877

Boosted trees	0.797	0.691	0.709	0.677	0.877
Logistic regression	0.795	0.698	0.717	0.686	0.873
Support vector machine	0.795	0.695	0.707	0.689	0.871
Naïve Bayes	0.618	0.548	0.539	0.673	0.852
K-nearest neighbors	0.719	0.568	0.568	0.575	0.797

Random forests for emotional support surpassed the other classifiers on Accuracy, Precision, and AUC ROC and performed comparably on F1 and Recall. Random forests for informational support equaled or surpassed the other classifiers on Accuracy, Precision, and AUC ROC and performed comparably on F1 and Recall. As discussed in chapter two, AUC ROC provides the best assessment of classifier performance in this case because it balances the “cost” of tolerating false positives with maximizing true positives. Taking a holistic view and favoring AUC ROC, the random forests classifier was selected for both emotional support and informational support. The selected classifiers were tested on the held-out test set and performed slightly less well but still adequately (e.g., AUC ROC > 0.80), as is expected when a classifier is applied to novel data.

Social Support Classification Results

The selected classifiers for emotional support and informational support were used to label the remaining 1,043,603 comments (see Tables 9 and 10).

Table 9. Rates of emotional support and informational support in the complete set of comments

Level of Support	Emotional Support	Informational Support
0 (absent)	431,659	783,748
1 (present)	614,714	213,623
2 (strongly present)	2,309	51,311

Table 10. Rates of each combination of emotional support and informational support in the complete set of comments

		Emotional Support		
		0	1	2
Informational Support	0	321,552	461,898	296
	1	98,519	114,578	526
	2	11,587	38,237	1,487

Emotional support was present or strongly present in 59.12% of comments. Informational support was present or strongly present in 25.39% of comments. Emotional support and informational support co-occurred in 14.84% of comments (N = 154,828; see Table 11 for exemplary comments). Comments without either form of support comprised 30.81% of the dataset (N = 321,552).

Table 11. Exemplary comments of each combination of emotional support (ES) and informational support (IS); comments are separated by slashes; personally identifiable information is replaced by hashmarks

ES	IS	Comment
0	0	“Kik me #####” // “What’s the disease?” // “Now I kno”
1	0	“That’s exactly how I feel” // “No struggling makes you stronger” // “I’m so sorry. How old are you?” // “Don’t do it honey! :(“ // “It really is” // “That’s good” // “Me too” // “Same <3” // “It gets better” // “Store of my life!” // “My kik is ##### if you need to talk <3”
2	0	“One slip up does not mean you’re a failure, it just means you were able to go that many days without hurting yourself. Whether its one or a hundred, any amount of time is an accomplishment.” // “It’s hard but you seem like a strong girl and I believe in you. You are so strong anyone who cuts them self are the strongest people yet just know in the future everything will be better stay strong ❤️” // “This is great! Keep up the good work #####”
0	1	“distraction distraction 😊” // “Babe, you have to eat. There are a millions ways to be skinny.” // “I can’t answer that. Do you honestly love it? You might want to try focusing your energy someplace else.”
0	2	“When you have the urge distract yourself. Watch a movie, work out, talk to friends. To get your mind off of it.” // “Take a red marker and draw on your arm where you would cut. It obviously will not have the EXACT same effect as cutting, the actions will be the same enough that your urge to cut will hopefully be satisfied.” // “Try and find a psychologist for free or most universities have student counsellors or pyschologist to help those who are going through a rough time so maybe find out about the student support services”

1	1	“They are not your friends. You are worth so much more than that try and find opportunities to meet genuine people who will become real friend good luck dear.x” // “Stay strong, don't do it!!! ❤️❤️ distract yourself!! Kik me if you want, #####” // “It's okay. A lot of people do sick things but just focus on something else.”
2	1	“You're not weak. We all relapse. Me? I just relapsed after a year. It feels like a failure. It's just a bump in the road. Just take it one day at a time. Xx” // “please stay strong, don't cut yourself. you are too beautiful and important to be hurting yourself. tell a parent or someone you can trust about how you're feeling. I love you xx” // “Awe im srry im glad u didnt cut ik how hard it is not to i do it everyday i hate my scars but it shows my past was hard and painful u should put ice on your knuckles to numb the pain plz keep your head up im here if u need someone”
1	2	“Hang in there! Hold a cloth on the cuts and put pressure on them to stop the bleeding! Tell your parents or call the ambulance please tell somebody!! If you need to talk I'm here but please tell an adult!” // “I can tell you that some days it will be easier to control those urges, and you'll feel great! Other days it will be harder, and when it gets hard, you'll question if you're going backwards. You're not. This is just a rough day on the road to happiness. I promise, it gets better.“
2	2	“I've been here. I've said these exact words. I've even acted on it. I want you to think about everyone that has had an impact on your life. Anyone that you have impacted. You probably don't know half of the people that you have touched. Be strong. Even if you feel that you're at rock bottom, you can only go up. Find someone to vent to, even if it's a complete stranger. You are loved and you only have one life, your future holds so much. Think, imagine, believe that you will have better days. Because you will. I promise.”

Discussion

In this study, we set out to use machine learning classification to measure the presence of emotional support and informational support in the comments received by adolescent help-seekers in the “Self Harm” category on TalkLife. Our goal was to optimize the performance of the classifier, assess the ratio of emotional support to informational support in the comments, and consider how the findings reflect TalkLife’s purpose and design. Our approach produced two random forests classifiers, one for emotional support and one for informational support, with excellent performance metrics. We found that emotional support exceeded informational support in general; however, there were over 20 times as many comments with high levels of

informational support, i.e., “strongly present,” than there were comments with high levels of emotional support.

Our findings show some agreement with previous findings on the prevalence of emotional support and informational support in online mental health communities. We find that emotional support is present in 59% of comments, and informational support is present in 25% of comments. The finding that emotional support exceeds informational support aligns with most existing research (De Choudhury & De, 2014; M. Kim et al., 2023; Kruzan et al., 2021; Saha & Sharma, 2020; E. Sharma & De Choudhury, 2018).

Some prior studies have found lower overall prevalence of both emotional support and informational support than was observed here, around 30% and 10% respectively (De Choudhury & De, 2014; Kruzan et al., 2021). There are two methods differences that may explain the discrepancy. First, the discrepant studies use different methods to detect social support, i.e., topic modeling and hand-labeling. Second, the discrepant studies include numerous other codes in their coding scheme, which may divert some comments into other categories that would be classified as social support in our two-way coding scheme. Studies with similar methods and coding schemes find levels of social support comparable to ours (M. Kim et al., 2023; E. Sharma & De Choudhury, 2018).

Our finding that there were over 20 times as many comments with high levels of informational support than there were comments with high levels of emotional support does not align with previous studies (M. Kim et al., 2023; E. Sharma & De Choudhury, 2018). These studies found that emotional support was more common than informational support at both moderate and high levels, except in online communities dedicated to compulsive disorders (M. Kim et al., 2023; E. Sharma & De Choudhury, 2018). Even in the case of compulsive disorders,

comments with high informational support were not even twice as common as comments with high emotional support, let alone 20 times more common (E. Sharma & De Choudhury, 2018). Commenters with long tenure or frequent commenting tend to provide the majority of content in online social support communities, especially comments with diverse informational support (M. Kim et al., 2023; Yao et al., 2021). It is possible that such “super users” drove the prevalence of high informational support in the TalkLife “Self Harm” category. It is also possible that this finding reflects an idiosyncrasy of the machine learning classifiers, since the informational support classifier had better Recall than the emotional support classifier, which might explain why more high-level informational support was detected.

Our classifiers outperformed machine learning classifiers from previous studies on Accuracy, Precision, and AUC ROC (M. Kim et al., 2023; Saha & Sharma, 2020; E. Sharma & De Choudhury, 2018). Given that these previous classifiers were trained on a set of only 400 hand-labeled comments, it is likely that our set of about 5,000 hand-labeled comments contributed to better classifier performance. We found similar levels of social support as these three studies, which raises the question of how the improved performance of our classifiers changed the outcome of the classification. The one metric on which previous classifiers outperformed ours was Recall, the proportion of actual positives that were classified as positive. This may suggest that our classifier under-reported the presence of social support.

Overall, we find that comments in the “Self Harm” category of TalkLife tend to contain social support. Over two-thirds of comments in our dataset contained either emotional support or informational support. This aligns with TalkLife’s purpose of facilitating peer support for mental health. The majority of these supportive comments were at the middle level in our coding scheme, suggesting that the support was generic or brief. Given that better outcomes on TalkLife

are associated with receiving more verbose comments with more varied language (Saha & Sharma, 2020), the predominant level of support in our findings suggests limited benefit to recipients. In sum, we find mixed evidence regarding whether the comments in the “Self Harm” category support TalkLife’s purpose.

Strengths and Limitations

Strengths of this study include a large dataset representing peer support behavior of over 150,000 users, a rigorous process by which a large machine learning training set was created, the application of clinical expertise to this machine learning training process, excellent performance of the machine learning classifier, and important insights into the prevalence and quality of social support provided in TalkLife’s “Self Harm” category.

Limitations of this study include relatively weak Recall performance of our machine learning classifier, lack of tuning of our machine learning classifier, narrow classification of only two types of social support, missing out on conversational context by focusing on single comments in isolation, and lack of user outcome measures, which constrains clinical or causal claims. A fuller treatment of strengths and limitations will be undertaken in chapter six.

Implications and Future Directions

This study describes the level and type of social support provided to adolescent users seeking help for self-harm on TalkLife. Our rigorous approach to machine learning classification produced superior performance on most metrics. The ratio of emotional support to informational support aligns with most previous findings, as does the overall amount of social support. The relatively high level of informational support in our dataset raises questions about whether user behavior or classifier idiosyncrasy is driving this discrepancy. Regarding TalkLife’s functioning as a mental health support community, we do find that over two-thirds of comments include

some social support. However, the brevity and generality of most of the social support detected by our classifier may limit the support's helpfulness.

Future directions grow out of limitations and implications. Our machine learning classifier's Recall could be improved by attempting the “black magic” of hyperparameter tuning. We could investigate the characteristics of the users more likely to provide high levels of informational support. We could expand our narrow focus—limited to two types of social support within individual comments without outcome measures—by assessing more facets of each comment, embedding the comments within conversations, and tying these characteristics to meaningful outcomes. One option for operationalizing a meaningful outcome is to select conversations where the original poster replies in the thread and use sentiment analysis to assess the valence of the original poster's ultimate mood. Assessing social support *in context* may yield important insights.

Conclusion

In this study, we used machine learning classification to measure the social support offered in the comments on posts by adolescents in TalkLife's “Self Harm” category. Our results mostly align with previous findings on the prevalence of emotional support and informational support in online mental health communities. One exception is our finding of relatively more comments with high-level informational support, which may result from the behavior of “power users” or from an idiosyncrasy of our classifiers. Our classifiers out-performed classifiers in previous studies, which was probably due to our much larger training set. Our most important finding was that social support offered to adolescent help-seekers was usually of a moderate level, i.e., generic or brief. This finding represents a compelling target for intervention by researchers and platform designers alike.

Chapter 5: Modeling the Relationship between Post Topics and Social Support

Young people seek out online communities for self-injurious thoughts and behaviors (SITB) with the goal of receiving and providing support and care (Lavis & Winter, 2020; Preston et al., 2023). Qualitative evidence suggests that users of online SITB communities value the nonjudgmental stance they find there; furthermore, users note that this nonjudgmental stance contrasts starkly with the judgment and stigma present in in-person SITB-related interactions (Lavis & Winter, 2020). Quantitative evidence suggests that online help-seekers benefit from persistent posting during bursts of activity (Kushner & Sharma, 2020), perhaps because persistent posting elicits more supportive comments (M. Kim et al., 2023).

Meanwhile, social isolation harms vulnerable young people (Orben et al., 2020). This impacts online SITB help-seekers in two ways. First, online social support grows in importance because of the potential isolation caused by in-person stigma (Lavis & Winter, 2020). Thankfully, online social support can provide unique benefits for young people with low in-person social support (Cole et al., 2017). Second, the danger of social isolation threatens online SITB help-seekers who do not find the social support they are looking for in online SITB communities. Persistent activity and interaction with other users may cause increased receipt of social support, perseverance in the help-seeking community, and cognitive and emotional changes (M. Kim et al., 2023; Kushner & Sharma, 2020; A. Sharma et al., 2020). As such, it's important to discover what factors determine whether a help-seeker receives social support.

Several known factors contribute to the receipt of social support in online mental health communities. Longer posts elicit more support, as does self-disclosure in the form of personal narratives (Andalibi et al., 2017b). Length of a user's tenure in the community is related to their adoption of community linguistic norms (Nguyen & Rosé, 2011), and this adoption is associated

with receiving more social support (E. Sharma & De Choudhury, 2018). More disinhibited posts, e.g., posts with more negative sentiment or more caustic tone, tend to receive more social support (De Choudhury & De, 2014). Finally, repeated posting of similar content yields more attention and support (M. Kim et al., 2023).

Less is known about determinants of social support in online SITB-specific communities. Messages with specific situational details receive more “likes” than do expressions of generic sadness, as do messages that include concerns related to care, fairness, loyalty, and purity (Preston et al., 2023). Emotional support is doled out often and indiscriminately, while informational support appears mostly in response to specific information-seeking queries (Kruzan et al., 2021).

Three factors that determine social support relate to the *form* of the help-seeking expressions as opposed to the *content*. Form-focused factors include post length, degree of linguistic accommodation, and repeated posting (Andalibi et al., 2017b; M. Kim et al., 2023; E. Sharma & De Choudhury, 2018). Four factors relate to the *content* of the help-seeking expression: self-disclosure, situational specificity, information-seeking queries, and disinhibition (Andalibi et al., 2017b; De Choudhury & De, 2014; Kruzan et al., 2021; Preston et al., 2023). Most of these seven factors were discovered in studies of multi-purpose online mental health communities. Only two, situational specificity and information-seeking queries, were discovered in SITB-specific communities. Notably, neither situational specificity nor information-seeking queries are specific to SITB content.

In the foregoing chapters, we have shown that adolescent help-seekers in the “Self Harm” category on TalkLife express intense SITB-focused suffering, and the responses they receive are likely to include some social support. In this study, we will use topic modeling, machine learning

classification, and multilevel modeling to discover which help-seeking expressions engender social support. Results will be examined through three lenses: (1) in context of other known factors that influence the receipt of online social support, (2) with attention to novel findings produced by this study, and (3) in consideration of TalkLife’s purpose and design. This approach will contribute to the important task of supporting healthy adolescent development online.

Methods

Data Selection

Data were licensed from TalkLife according to the terms of their TalkLife Data Sharing Agreement (see Appendix A). The Institutional Review Board at the University of Central Florida reviewed this project and made a determination of Not Human Research (IRB ID: SBE-18-14660; Research ID: 1066191). Data were obtained via SQL query from the TalkLife database in June of 2021. Data were filtered to include posts that users labeled with the “Self Harm” category from users that were aged 13 to 24 at the time of posting, plus comments associated with those posts. Posts were excluded that had been deleted by the user or that were produced by users who subsequently deleted their account. These criteria yielded a dataset of 575,261 posts. Comments were excluded that (1) had been deleted by the user, (2) were produced by users who subsequently deleted their account, or (3) were replies by the original poster. These criteria yielded a dataset of 1,048,655 comments.

As described in chapters three and four, these posts and their associated comments were analyzed via author-aggregated topic modeling and machine learning classification. The pre-processing steps of both approaches removed some posts and comments that were empty or contained only numbers and punctuation, leaving a final dataset of 571,612 posts and 1,041,410 comments. After topic modeling, each author-aggregated document is characterized by 12

variables denoting the strength of that document's belonging to each of the 12 topics. After machine learning classification, each comment is characterized by its levels of emotional support and informational support. This creates a multilevel dataset where comment social support is the lowest level and the identity of the original poster is the highest level.

Participants

There were 219,024 unique users identified in the complete dataset. Aligning with previous research on who seeks help online for self-injury (Frost & Casey, 2016), the majority of users self-reported "female" gender (N = 120,590; 55.06%). The remaining 98,434 users are approximately evenly split between "male" (N = 48,465; 22.13%) and "other" (N = 49,969, 22.81%) gender identifiers. Poster age was calculated at time of first post in the "Self Harm" category. Poster age range hews to the inclusion criteria (13-24), with a mean age of 17.5 years old (SD = 2.58 years). An accurate summary of the age of those who only commented (N = 104,087; 47.52%) was not possible to calculate due to errors in the TalkLife database (e.g., thousands of commenters reported to have been born before World War 1).

Data Analysis Plan

The data analysis plan is designed to suit the structure and characteristics of the dataset. Two main factors guide our approach. First, the outcome of level of social support in a comment is on a different level than the predictors of topic strength per document. The author-aggregation step of our topic modeling approach makes this a two-level discrepancy because the posts are taken to the author level by aggregation. Second, a significant minority of posts (N = 173,055; 30.27%) did not receive any comments. This works out to 17,402 users (15.14%) who posted on the platform and never received a comment. For these comment-less posts and posters, it is not possible to use level of social support as the dependent variable.

To address these issues, we will use a hurdle model similar to the approach used by Chen and Xu (2021). Part one of the hurdle model uses multilevel logistic regression to test whether the topics explain which posts received no comments versus any comments. Part two of the hurdle model takes the posts that did receive comments and uses multilevel modeling to test whether the topics explain whether support is present in the comments. There are two levels in our multilevel models: level one includes post-level variables (e.g., presence or absence of comment, word count), and level two includes and poster-level variables (e.g., topic model *gamma*). In other words, posts are nested within posters. Because we ultimately used only one comment per post, comments are *not* nested within posts.

R Packages

Data were analyzed using *R* version 4.3.0 and *R* packages *tidyverse* (version 2.0.0), *lme4* (version 1.1-33), *multilevelTools* (version 0.1.1), *performance* (version 0.10.4), *lmerTest* (version 3.1-3), and *beepr* (version 1.3). Execution of these methods in *R* was guided by stats mavens John Flournoy and Ryann Crowley, plus the invaluable book, [Introduction to Multilevel Modeling](https://www.learn-mlms.com/index.html) by Mairead Shaw and Jessica Kay Flake (<https://www.learn-mlms.com/index.html>).

Results

Descriptive Results

The complete dataset includes 219,024 users who made 571,612 posts and 1,041,410 comments. Number of comments per post ranged from 0 to 1,790 (mean = 1.82, SD = 3.61; median = 1). About 30% of posts received no comments (N = 173,055), and about 15% of posters received no comments (N = 17,402). Posters who received no comments usually posted only once (range: 1-9; mean = 1.16, SD = 0.50; median = 1).

For posts that received comments, the total amount of social support per post was calculated by summing the emotional support and informational support scores attributed to the comments on each post (see Table 12).

Table 12. Emotional support, informational support, and total combined social support per post

	Range	Mean (SD)	Median
Emotional support	0-318	1.55 (1.91)	1
Informational support	0-95	0.79 (1.46)	0
Total social support	0-368	2.34 (2.96)	2

For posters that received comments, the total amount of social support per poster was calculated by summing the emotional support and informational support scores attributed to the comments on each post (see Table 13).

Table 13. Emotional support, informational support, and total combined social support per poster

	Range	Mean (SD)	Median
Emotional support	0-2,241	6.47 (22.97)	2
Informational support	0-813	3.31 (10.93)	1
Total social support	0-2,826	9.78 (33.41)	3

The mean amount of social support per post per top topic was calculated by taking the mean amount of social support per poster then summarizing that support by the top topic that characterized that poster's posts (see Tables 14-16 and Figures 5-7).

Table 14. Mean emotional support (ES) per post per top topic

Rank	Topic	Theme	Mean ES per post
1	6	Hopeless suicide	1.50
2	3	Explicit self-loathing	1.50
3	1	Self-harm abstention	1.36
4	8	Self-harm struggle	1.36
5	4	Expressing feelings	1.35
6	10	Family and friends	1.34

7	5	Mental ill health	1.33
8	2	Stay strong	1.20
9	9	Crying	1.17
10	7	Hiding self-harm	1.17
11	12	Philosophical thoughts	1.14
12	11	Distraction from self-harm	1.12

Figure 5. Mean emotional support per post per top topic with standard error bars

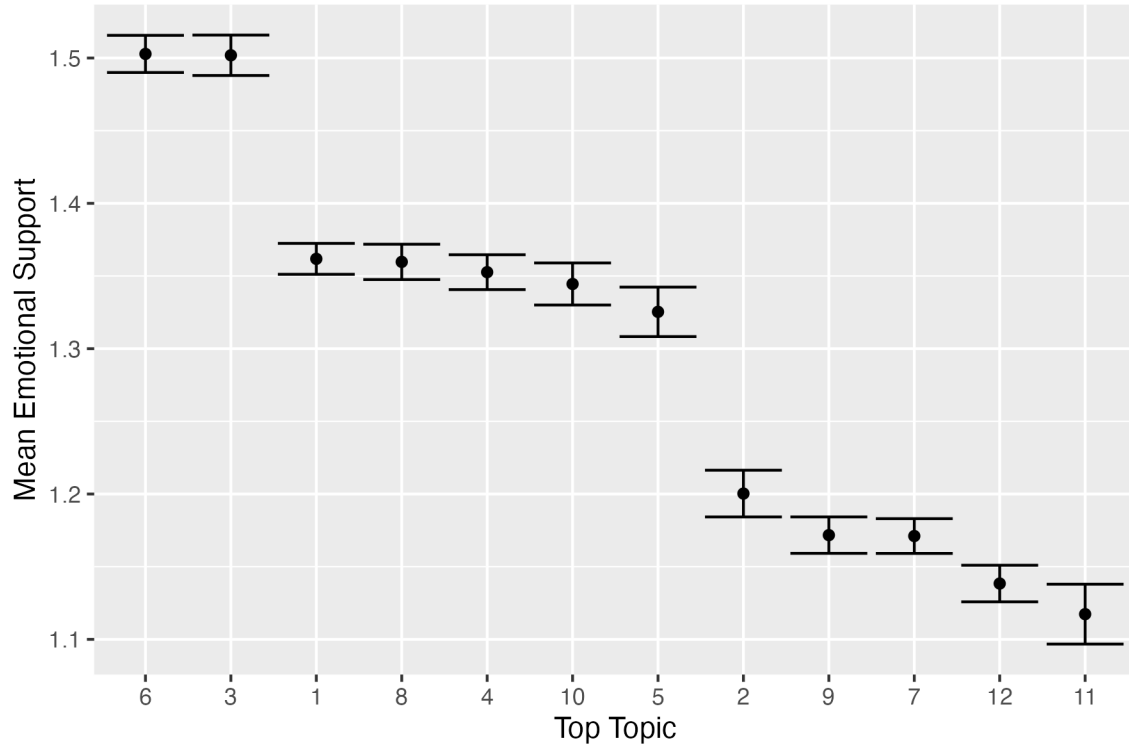


Table 15. Mean informational support (IS) per post per top topic

Rank	Topic	Theme	Mean IS per post
1	10	Family and friends	0.98
2	5	Mental ill health	0.85
3	7	Hiding self-harm	0.84
4	6	Hopeless suicide	0.80
5	8	Self-harm struggle	0.78
6	1	Self-harm abstention	0.72
7	3	Explicit self-loathing	0.70
8	12	Philosophical thoughts	0.68
9	11	Distraction from self-harm	0.67
10	4	Expressing feelings	0.66
11	9	Crying	0.60

12	2	Stay strong	0.54
----	---	-------------	------

Figure 6. Mean informational support per post per top topic with standard error bars

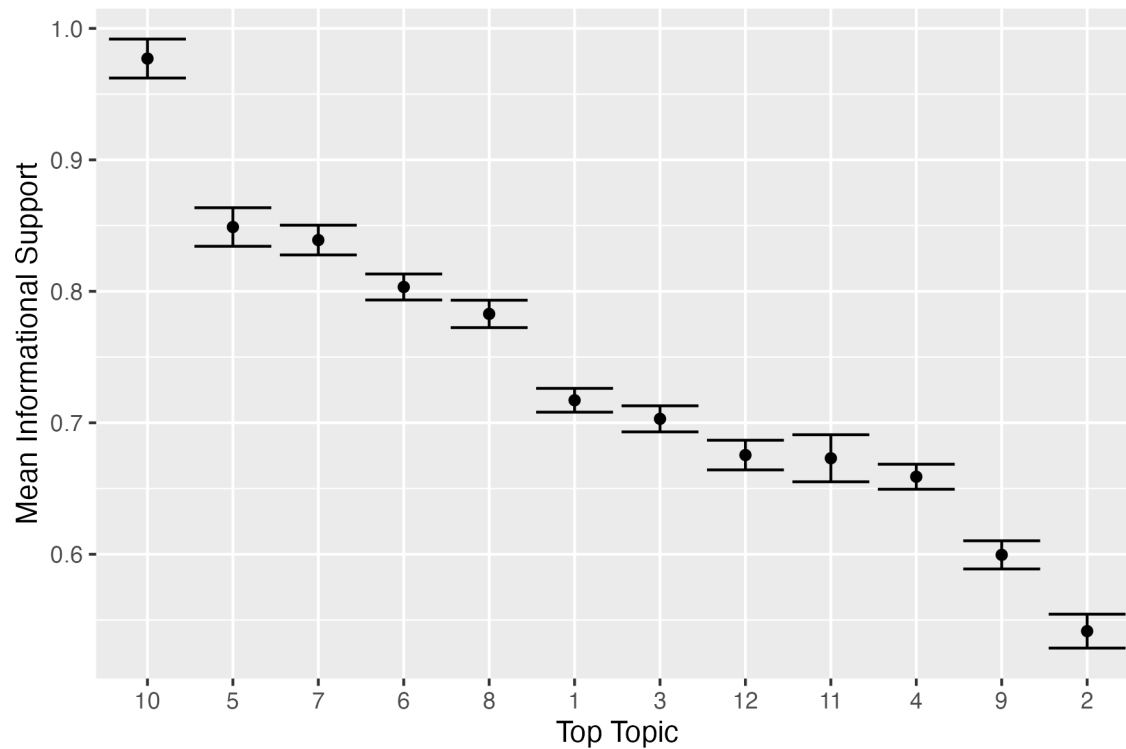
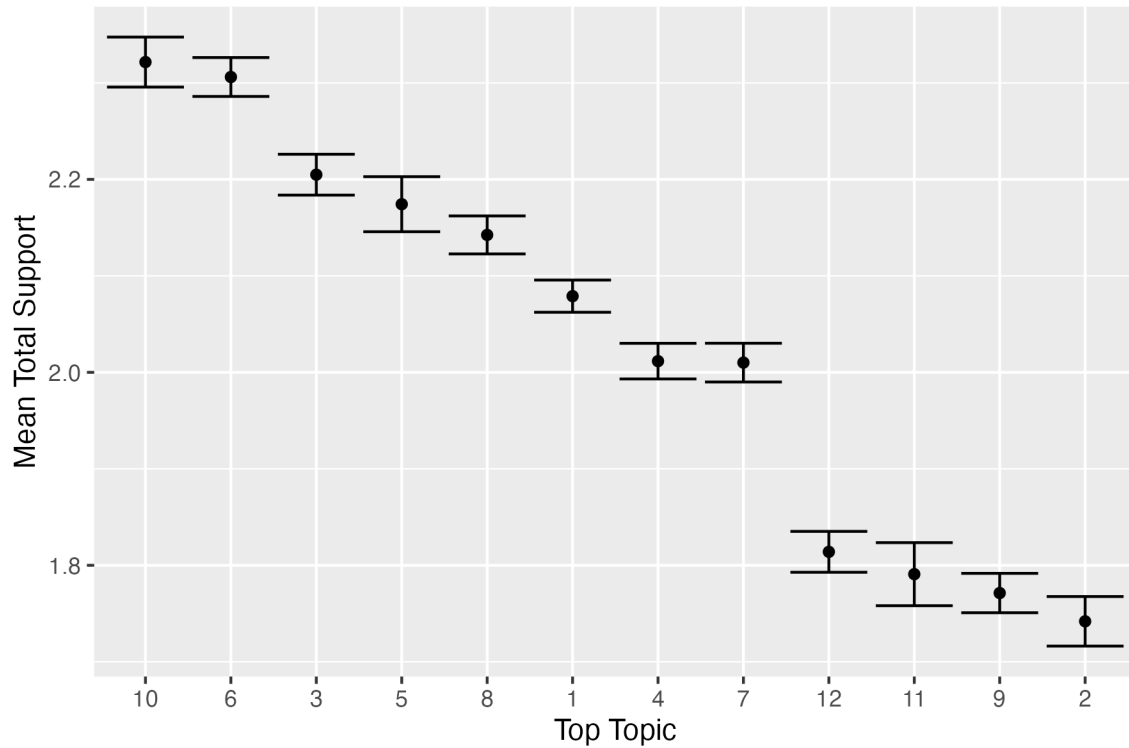


Table 16. Mean total social support (TSS) per post per top topic

Rank	Topic	Theme	Mean TSS per post
1	10	Family and friends	2.32
2	6	Hopeless suicide	2.31
3	3	Explicit self-loathing	2.20
4	5	Mental ill health	2.17
5	8	Self-harm struggle	2.14
6	1	Self-harm abstention	2.08
7	4	Expressing feelings	2.01
8	7	Hiding self-harm	2.01
9	12	Philosophical thoughts	1.81
10	11	Distraction from self-harm	1.79
11	9	Crying	1.77
12	2	Stay strong	1.74

Figure 7. Mean total support per post per top topic with standard error bars



Multilevel Modeling Results

We ran a hurdle model to test whether the topics in a document predicted social support in the comments. Part one tested whether the topics predicted a post receiving any comment. Part two tested whether the topics predicted the presence of emotional support or informational support in the comments. While part one of the hurdle model proceeded as planned, part two required multiple adjustments to account for insufficient variance.

It is important to keep in mind that the topics as predictors in the following analyses are aggregated at the author level. For example, for a poster with three posts, the topic model aggregated those three posts into one document and characterized the topics within that one document. That means that, in the results that follow, when we report that the topics predicted the social support a post received, what we are really saying is that the topics that characterized

all of that poster's posts predicted the social support that each post received. In sum, social support is measured at the post level, and topics are measured at the poster level.

Part One of Hurdle Model

We ran three nested multilevel logistic models with the presence or absence of a comment as the dependent variable. The null model (Model 1.1) included random intercepts only with poster identity as the grouping variable. The second model (Model 1.2) added two scaled and centered fixed effects representing word count per post and mean word count per poster. The third model (Model 1.3) added as predictors 11 of the 12 topics from the selected topic model.

One topic was dropped because *gamma*, the parameter that represents the topics, is a proportion, which means the 12 gammas that define each document sum to one. This creates singularity when we use the topics as predictors because the topics predict each other perfectly. To fix the singularity, we dropped one topic from the model. We chose to drop topic 11 (“Distraction from self-harm”) because it had the lowest coherence score and it was the least common top topic.

The syntax of the three models follows:

Model 1.1:

```
glmer(has_comment ~ 1 + (1 | poster_id), data = df_comment, family = binomial)
```

Model 1.2:

```
glmer(has_comment ~ 1 + post_wc + mean_wc + (1 | poster_id), data = df_comment, family = binomial)
```

Model 1.3

```
glmer(has_comment ~ 1 + post_wc + mean_wc + topic_1 + topic_2 + topic_3 + topic_4 + topic_5 + topic_6 + topic_7 + topic_8 + topic_9 + topic_10 + topic_12 + (1 | poster_id), data = df_comment, family = binomial)
```

A comparison of the three nested models revealed that the model fit improved with each iteration, and the addition of the topics as fixed effects in Model 1.3 accounted for 4% of the variance (see Table 17).

Table 17. Odds ratios and Wald 95% confidence intervals for Models 1.1, 1.2, and 1.3, plus conditional and marginal R² denoting variance explained by added fixed effects and Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and chi-square denoting model goodness of fit

	Model 1.1	Model 1.2	Model 1.3
Intercept	2.68 (2.65-2.70)***	2.69 (2.66-2.71)***	3.33 (2.79-3.97)***
Post word count		0.96 (0.95-0.97)***	0.96 (0.95-0.97)***
Poster word count		0.98 (0.97-0.99)***	1.00 (1.00-1.01)
Topic 1			0.96 (0.77-1.21)
Topic 2			0.28 (0.22-0.35)***
Topic 3			1.71 (1.34-2.16)***
Topic 4			0.79 (0.62-1.01)
Topic 5			1.31 (1.02-1.69)*
Topic 6			3.45 (2.71-4.40)***
Topic 7			0.79 (0.62-1.00)
Topic 8			1.17 (0.92-1.49)
Topic 9			0.20 (0.16-0.25)***
Topic 10			1.30 (1.03-1.65)*
Topic 12			0.18 (0.14-0.23)***
Conditional R ²	0.26	0.26	0.27
Marginal R ²	0	0	0.04
AIC	686,437	686,135	684,405
BIC	686,460	686,180	684,574
Chi-square (df)		306.17 (2)***	1,751.98 (11)***

Seven of 11 topics predicted the presence or absence of any comment on a post at a statistically significant level. The increased presence of three topics decreased the odds that a post would receive a comment: topic two (“stay strong”), topic nine (“crying”), and topic 12 (“philosophical thoughts”). In contrast, the increased presence of four topics increased the odds that a post would receive a comment: topic three (“explicit self-loathing”), topic five (“mental ill health”), topic six (“hopeless suicide”), and topic 10 (“family and friends”).

To interpret the odds ratios, we must consider the meaning of a one-unit change of the predictors. Topic scores sum to one, meaning that they show the proportion of a document that belongs to each topic. Therefore, a score of one on a given topic would denote that the document belonged entirely to that topic. As such, the odds ratio shows the change in the odds of a post receiving a comment if it belongs entirely to the topic.

A post belonging fully to topic two (“stay strong”) is associated with a 72% reduction in the odds that the post will receive a comment (OR = 0.28, CI: 0.22-0.35). A post belonging fully to topic nine (“crying”) is associated with an 80% reduction in the odds that the post will receive a comment (OR = 0.20, CI: 0.16-0.25). A post belonging fully to topic 12 (“philosophical thoughts”) is associated with an 82% reduction in the odds that the post will receive a comment (OR = 0.18, CI: 0.14-0.23).

A post belonging fully to topic three (“explicit self-loathing”) is associated with a 71% increase in the odds that the post will receive a comment (OR = 1.71, CI: 1.34-2.16). A post belonging fully to topic five (“mental ill health”) is associated with a 31% increase in the odds that the post will receive a comment (OR = 1.31, CI: 1.02-1.69). A post belonging fully to topic six (“hopeless suicide”) is associated with a 245% increase in the odds that the post will receive a comment (OR = 3.45, CI: 2.71-4.40). A post belonging fully to topic 10 (“family and friends”) is associated with a 30% increase in the odds that the post will receive a comment (OR = 1.30, CI: 1.03-1.65). Of these four topics that result in increased odds of receiving comments, three contain morbid or suicidal content.

Part Two of Hurdle Model

The aim of part two of the hurdle model was to test whether the topics predicted the presence of emotional support or informational support in the comments. The original plan was

to use the amount of social support (0, 1, or 2) as the outcome in a multilevel model with topics as the predictors of interest and random effects to account for grouping by post, poster, and commenter. Syntax for the original full model for emotional support follows:

```
lmer(emotional_support ~ 1 + post_wc + mean_wc + topic_1 + topic_2 + topic_3 + topic_4 +  
topic_5 + topic_6 + topic_7 + topic_8 + topic_9 + topic_10 + topic_12 + (1 | poster_id:post_id)  
+ (1 | poster_id) + (1 | commenter_id), data = df_support)
```

Unfortunately, this model failed to run due to insufficient variance in multiple components. First, there were relatively few comments that received the highest rating for emotional support (0.22%) or informational support (4.89%). We addressed this issue by converting emotional support and informational support to binary outcomes, i.e., denoting that support is either absent or present in the comment. Second, almost two-thirds of posts received only one or two comments (64.61%). We addressed this issue by retaining only the first comment each post received (N = 398,589). Third, well over a third of commenters only posted one comment (43.01%). We addressed this issue by dropping the random-intercept term for commenters.

Similar to the nested models in part one of the hurdle model, we used two sets of nested models to test whether topics predicted the presence of social support in the first comment each post received. The syntax for the emotional support models follows:

Model 2.1

```
glmer(es_binary ~ 1 + (1 | poster_id), data = df_first_comment, family = binomial)
```

Model 2.2

```
glmer(es_binary ~ 1 + post_wc + mean_wc + (1 | poster_id), data = df_first_comment, family =  
binomial)
```


Model 2.3

```
glmer(es_binary ~ 1 + post_wc + mean_wc + topic_1 + topic_2 + topic_3 + topic_4 + topic_5 +
topic_6 + topic_7 + topic_8 + topic_9 + topic_10 + topic_12 + (1 | poster_id), data =
df_first_comment, family = binomial)
```

The syntax for the informational support models mirrors the emotional support models:

Model 2.4

```
glmer(is_binary ~ 1 + (1 | poster_id), data = df_first_comment, family = binomial)
```

Model 2.5

```
glmer(is_binary ~ 1 + post_wc + mean_wc + (1 | poster_id), data = df_first_comment, family =
binomial)
```

Model 2.6

```
glmer(is_binary ~ 1 + post_wc + mean_wc + topic_1 + topic_2 + topic_3 + topic_4 + topic_5 +
topic_6 + topic_7 + topic_8 + topic_9 + topic_10 + topic_12 + (1 | poster_id), data =
df_first_comment, family = binomial)
```

Nested Emotional Support Models Results. A comparison of the nested emotional support models revealed that the model fit improved with each iteration, and the addition of the topics as fixed effects in Model 2.3 accounted for 4% of the variance (see Table 18).

Table 18. Odds ratios and Wald 95% confidence intervals for Models 2.1, 2.2, and 2.3, plus conditional and marginal R² denoting variance explained by added fixed effects and Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and chi-square denoting model goodness of fit

	Model 2.1	Model 2.2	Model 2.3
Intercept	1.47 (1.46-1.48)***	1.47 (1.46-1.48)***	0.38 (0.32-0.44)***
Post word count		1.15 (1.14-1.16)***	1.15 (1.14-1.16)***
Poster word count		1.02 (1.01-1.03)***	1.10 (1.09-1.11)***
Topic 1			19.93 (16.21-24.51)***
Topic 2			1.74 (1.42-2.13)***
Topic 3			5.64 (4.58-6.95)***
Topic 4			4.79 (3.86-5.93)***
Topic 5			1.80 (1.42-2.28)***
Topic 6			14.13 (11.45-17.43)***
Topic 7			2.18 (1.75-2.70)***

Topic 8			7.14 (5.76-8.86)***
Topic 9			4.98 (4.02-6.17)***
Topic 10			1.41 (1.14-1.74)**
Topic 12			1.94 (1.55-2.44)***
Conditional R ²	0.09	0.11	0.12
Marginal R ²	0	0.02	0.06
AIC	537,317	536,175	533,459
BIC	537,339	536,219	533,622
Chi-square (df)		1,146.1 (2)***	2,738.6 (11)***

All 11 topics predicted the presence of emotional support in a post’s first comment at a statistically significant level. In all cases, increased belonging to a topic was found to increase the odds of emotional support in a post’s first comment. The findings can be broken down into three tiers: low (OR: 1-3), medium (OR: 3-10), and high (OR > 10).

Five topics fall into the low category. A post belonging fully to topic two (“stay strong”) is associated with a 72% increase in the odds that the post’s first comment will contain emotional support (OR = 1.72, CI: 1.42-2.13). A post belonging fully to topic five (“mental ill health”) is associated with a 80% increase in the odds that the post’s first comment will contain emotional support (OR = 1.80, CI: 1.42-2.28). A post belonging fully to topic seven (“hiding self-harm”) is associated with a 118% increase in the odds that the post’s first comment will contain emotional support (OR = 2.18, CI: 1.75-2.70). A post belonging fully to topic 10 (“family and friends”) is associated with a 41% increase in the odds that the post’s first comment will contain emotional support (OR = 1.41, CI: 1.14-1.74). A post belonging fully to topic 12 (“philosophical thoughts”) is associated with a 94% increase in the odds that the post’s first comment will contain emotional support (OR = 1.94, CI: 1.55-2.44).

Four topics fall into the medium category. A post belonging fully to topic three (“explicit self-loathing”) is associated with a 464% increase in the odds that the post’s first comment will contain emotional support (OR = 5.64, CI: 4.58-6.95). A post belonging fully to topic four

(“expressing feelings”) is associated with a 379% increase in the odds that the post’s first comment will contain emotional support (OR = 4.79, CI: 3.86-5.93). A post belonging fully to topic eight (“self-harm struggle”) is associated with a 614% increase in the odds that the post’s first comment will contain emotional support (OR = 7.14, CI: 5.76-8.86). A post belonging fully to topic nine (“crying”) is associated with a 398% increase in the odds that the post’s first comment will contain emotional support (OR = 4.98, CI: 4.02-6.17).

Two topics fall into the high category. A post belonging fully to topic one (“self-harm abstinence”) is associated with a 1,893% increase in the odds that the post’s first comment will contain emotional support (OR = 19.93, CI: 16.21-24.51). A post belonging fully to topic six (“hopeless suicide”) is associated with a 1,313% increase in the odds that the post’s first comment will contain emotional support (OR = 14.13, CI: 11.45-17.43).

Nested Informational Support Models Results. A comparison of the nested informational support models revealed that the model fit improved with each iteration, and the addition of the topics as fixed effects in Model 2.6 accounted for 4% of the variance (see Table 19).

Table 19. Odds ratios and Wald 95% confidence intervals for Models 2.4, 2.5, and 2.6, plus conditional and marginal R² denoting variance explained by added fixed effects and Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and chi-square denoting model goodness of fit

	Model 2.4	Model 2.5	Model 2.6
Intercept	0.28 (0.28-0.29)***	0.28 (0.28-0.28)***	0.11 (0.09-0.13)***
Post word count		1.23 (1.22-1.25)***	1.23 (1.21-1.24)***
Poster word count		1.10 (1.09-1.11)***	1.11 (1.10-1.13)***
Topic 1			3.80 (3.01-4.79)***
Topic 2			0.49 (0.38-0.62)***
Topic 3			1.42 (1.12-1.81)**
Topic 4			3.28 (2.57-4.17)***
Topic 5			5.75 (4.41-7.51)***
Topic 6			3.70 (2.90-4.71)***

Topic 7			11.56 (9.05-14.76)***
Topic 8			6.16 (4.83-7.86)***
Topic 9			0.95 (0.74-1.22)
Topic 10			3.94 (3.10-5.00)***
Topic 12			1.83 (1.41-2.37)***
Conditional R ²	0.14	0.17	0.17
Marginal R ²	0	0.06	0.10
AIC	418,517	414,795	412,702
BIC	418,539	414,838	412,866
Chi-square (df)		3,726.6 (2)***	2,114.3 (11)***

Ten out of 11 topics predicted the presence of informational support in a post’s first comment at a statistically significant level. Topic nine (“crying”) did not. Only one topic predicted a reduction in the odds of informational support in a post’s first comment. A post belonging fully to topic two (“stay strong”) is associated with a 51% reduction in the odds that the post’s first comment will contain informational support (OR = 0.49, CI: 0.38-0.62). The other nine topics that reached statistical significance can be broken down into three tiers: low (OR: 1-3), medium (OR: 3-10), and high (OR > 10).

Two topics fall into the low category. A post belonging fully to topic three (“explicit self-loathing”) is associated with a 42% increase in the odds that the post’s first comment will contain informational support (OR = 1.42, CI: 1.12-1.81). A post belonging fully to topic 12 (“philosophical thoughts”) is associated with an 83% increase in the odds that the post’s first comment will contain informational support (OR = 1.83, CI: 1.41-2.37).

Six topics fall into the medium category. A post belonging fully to topic one (“self-harm abstention”) is associated with a 280% increase in the odds that the post’s first comment will contain informational support (OR = 3.80, CI: 3.01-4.79). A post belonging fully to topic four (“expressing feelings”) is associated with a 228% increase in the odds that the post’s first comment will contain informational support (OR = 3.28, CI: 2.57-4.17). A post belonging fully

to topic five (“mental ill health”) is associated with a 475% increase in the odds that the post’s first comment will contain informational support (OR = 5.75, CI: 4.41-7.51). A post belonging fully to topic six (“hopeless suicide”) is associated with a 270% increase in the odds that the post’s first comment will contain informational support (OR = 3.70, CI: 2.90-4.71). A post belonging fully to topic eight (“self-harm struggle”) is associated with a 516% increase in the odds that the post’s first comment will contain informational support (OR = 6.16, CI: 4.83-7.86). A post belonging fully to topic 10 (“family and friends”) is associated with a 294% increase in the odds that the post’s first comment will contain informational support (OR = 3.94, CI: 3.10-5.00).

One topic falls into the high category. A post belonging fully to topic seven (“hiding self-harm”) is associated with a 1,056% increase in the odds that the post’s first comment will contain informational support (OR = 11.56, CI: 9.05-14.76).

Integrated Results

Across the three sets of models, only three topics were associated with decreased odds of receiving social support: topic two (“stay strong”), topic nine (“crying”), and topic 12 (“philosophical thoughts”). All three were associated with decreased odds of a post receiving any comment, and topic two (“stay strong”) was associated with decreased odds of receiving informational support in a post’s first comment.

In contrast, all 11 topics were associated with increased odds of receiving social support. Four topics were associated with increased odds of receiving any comment: topic three (“explicit self-loathing”), topic five (“mental ill health”), topic six (“hopeless suicide”), and topic 10 (“family and friends”). Three of these four topics contain morbid or suicidal content. All 11 topics were associated with increased odds of emotional support in a post’s first comment, and

all topics except for topic two (“stay strong”) were associated with increased odds of informational support in a post’s first comment.

In each set of models, select topics stand out for their strong odds ratios. In the test of which topics are related to increased odds of receiving any comment, topic six (“hopeless suicide”) had the highest odds ratio. In the test of which topics are related to increased odds of receiving emotional support, topic one (“self-harm abstention”) and topic six (“hopeless suicide”) had the highest odds ratios. In the test of which topics are related to increased odds of receiving informational support, topic seven (“hiding self-harm”) had the highest odds ratio.

Nine topics at least doubled the odds of receiving emotional support or informational support. Of these nine, four at least doubled the odds of receiving both emotional support and informational support models: topic one (“self-harm abstention”), topic four (“expressing feelings”), topic six (“hopeless suicide”), and topic eight (“self-harm struggle”). Two topics at least doubled the odds of emotional support only. Topic three (“explicit self-loathing”) and topic nine (“crying”) at least doubled the odds of a post receiving emotional support in its first comment. Three topics at least doubled the odds of informational support only. Topic five (“mental ill health”), topic seven (“hiding self-harm”), and topic 10 (“family and friends”) at least doubled the odds of a post receiving informational support in its first comment.

Discussion

In this study, we set out to use topic modeling, machine learning classification, and multilevel modeling to discover which adolescent help-seeking expressions elicit different types of social support. Our goal was to expand on previous research by focusing on SITB-related content in a dedicated mental health support community. Our approach produced three sets of

nested multilevel models, which revealed the topics in help-seeking expressions that were associated with increased or decreased odds of receiving social support.

Our findings show some agreement with previous findings on *form*-related factors of help-seeking expressions that engender social support in online mental health communities. Whereas Andalibi and colleagues (2017) found that longer posts received more social support, we found mixed evidence regarding how the length of a post relates to receipt of social support. Longer posts had slightly decreased odds of receiving any comment; however, comments that longer posts did receive were more likely to contain emotional support and informational support. Repeated posting has also been found to engender more social support (M. Kim et al., 2023). Similarly, we found that the majority of posters who never received a comment only ever posted once.

Our findings show some agreement with previous findings on *content*-related factors of help-seeking expressions that engender social support in online mental health communities. Our results align with Kruzan and colleagues' (2021) finding that emotional support is doled out often and indiscriminately, given that all topics predicted increased odds of receiving emotional support. We also found some support for Kruzan and colleagues' (2021) finding that information-seeking queries most often engendered informational support. Two of the three topics that most increased the odds of receiving informational support (“mental ill health” and “hiding self-harm”) can be interpreted as seeking specific advice. Preston and West (2023) found that comments in an online SITB community contained a lot of social support encouraging recovery or abstention from self-harm, which was echoed in our finding that “self-harm abstention” was associated with the largest increase in the odds of emotional support in a post's first comment. Preston and colleagues (2023) found that specific situational narratives were

associated with more “likes,” which may align with our finding that “family and friends” was associated with increased odds of receiving any comment and receiving informational support. Finally, we found some support for De Choudhury and De’s (2014) finding that disinhibition engenders more social support. Negative sentiment and caustic tone, key aspects of disinhibition in this context, are prominent in the “explicit self-loathing” topic, which increased the odds of a post receiving any comment and a post’s first comment including social support, especially emotional support.

To our knowledge, this is the first study to test how the topics of adolescent online SITB help-seeking posts relate to receipt of emotional and informational support in comments. As such, several novel findings emerge. Whereas most if not all other studies focus on factors that increase social support, we found that three topics, “stay strong,” “crying,” and “philosophical thoughts,” reduced the odds that a post will receive a comment. We speculate that the “stay strong” topic reduced the odds of receiving a comment because these posts already provide social support, so they do not elicit supportive comments. The “crying” topic’s reduction in the odds of receiving a comment is interesting because the same topic also increased the odds that a post’s first comment would include emotional support. This mixed response to “crying” aligns with the finding that people both intend to provide more emotional support to a crying person and feel more negative sentiment and judgment toward the crying person (Hendriks et al., 2008). The “philosophical thoughts” topic paints a similarly mixed picture— reducing the odds of receiving any comment while increasing the odds, albeit much more weakly, of receiving emotional support. This mixed finding may align with Preston and colleagues’ (2023) observation that messages with the theme, “Society/Philosophy,” received little attention in the form of “likes.”

In chapter three, we showed that help-seeking expressions in the “Self Harm” category are about evenly split between suicidal/morbid content and non-suicidal self-injury (NSSI) content. When we examined the topics with the highest odds ratios across our three sets of models, we found that these were evenly split as well. “Hopeless suicide” appeared twice; it was associated with the most increased odds of receiving any comment and the second-most increased odds of receiving emotional support. Meanwhile, “self-harm abstention” was associated with the most increased odds of emotional support, and “hiding self-harm” was associated with the most increased odds of informational support. This suggests that neither morbid/suicidal content nor NSSI content draw so much social support that the other category suffers.

It is also interesting to consider why “hopeless suicide” was associated with more than double the increased odds of receiving any comment and receiving emotional support than all other morbid/suicidal topics. The “hopeless suicide” topic has multiple terms that convey a sense of imminence (e.g., “bye,” “goodbye,” “ready”), which distinguish it from two other morbid/suicidal topics, “mental ill health” and “philosophical thoughts.” This sense of imminence in the “hopeless suicide” topic may prompt more intervention and support from commenters. However, the “explicit self-loathing” topic also contains terms that convey a sense of imminence (e.g., “wanna,” “gonna,” and “tonight”) in its top-20 terms. How, then, do we explain the difference? In a study of 42 diverse warning signs in adolescents, hopelessness and pain most commonly preceded serious suicide attempts (Klonsky et al., 2018). It is possible that the “hopeless suicide” topic has the most increased odds of eliciting any comment and emotional support because commenters intuit the serious risk associated with the sentiment. Finally, given

that we know TalkLife monitors profanity use in posts (see chapter two), it is also possible that the profanity in “explicit self-loathing” affects how the platform presents it to other users.

Consideration of the topics that distinguish emotional support from informational support suggests that strong emotional expression may encourage emotional support more than informational support. The two topics that at least doubled the odds of emotional support only, “explicit self-loathing” and “crying,” share only one top-20 term in common: “gonna.” Still these topics stand out in their strong, disinhibited, emotional content. “Explicit self-loathing” includes profanity, derisive language, and the only instance of “hate” in any topic’s top-20 terms. “Crying” includes four terms related to crying and evokes an image of crying oneself to sleep. The strong emotional expressions evident in “explicit self-loathing” and “crying” can be synthesized as *disinhibition*, which has previously been shown to increase emotionally supportive comments (De Choudhury & De, 2014).

The three topics that at least doubled the odds of receiving informational support only (“mental ill health,” “hiding self-harm,” and “family and friends”) do not cohere as easily. “Mental ill health” contains the most clinical language in its top-20 terms of any topic, including more formal terms like “depression,” “anxiety,” and “suicidal.” This suggests that a post that articulates the poster’s suffering in more formal terms may elicit more referrals, knowledge, or advice. “Hiding self-harm” contains terms that imply the poster’s effort to “hide” signs of NSSI to avoid being “found.” This suggests that the practical concern of hiding NSSI is more likely to be met with advice than commiseration. “Family and friends” mostly contains terms for people and places in the poster’s life along with two terms that imply communication, “told” and “called.” This suggests that focusing on the social context of a poster’s symptoms and suffering may encourage more informational support than emotional support. These three topics may each

suggest separate conclusions; however, it is also possible that all three of these topics are more likely to be present in direct, information-seeking queries, which have been shown to elicit more informational support (Kruzan et al., 2021).

Regarding TalkLife’s purpose and design, we found that TalkLife facilitated social support for many of its posters. We found that few topics deterred social support, and neither morbid/suicidal content nor NSSI content drew so much social support that the other category suffered. Our concerns focus on the 30% of posts and 15% of posters that did not receive any comments. Around the time of data acquisition (June 2021), TalkLife advertised itself as, “Your community to get instant support for your mental health.” TalkLife should consider its obligation to the users who join the platform to escape in-person stigma and isolation and find timely social support.

Strengths and Limitations

Strengths of this study include a large dataset representing help-seeking behavior and social support of over 100,000 adolescent users, a natural language processing approach that is underused in clinical science, machine learning classifiers with excellent performance, and a novel examination of how the content of help-seeking expressions relates to receiving social support.

Limitations of this study include the small amount of social support variance (4%) explained by the topics in each set of models, the author-aggregation approach necessitated by the length of the posts, the unknown influence of TalkLife’s algorithm on how posts were presented, and the subjectivity of inferring themes from topics and groups of topics. A fuller treatment of strengths and limitations will be undertaken in chapter six.

Implications and Future Directions

This study reveals the social support that awaits adolescent SITB help-seekers online depending on what they post. Our findings showed that adolescent help-seeking posts in the “Self Harm” category of TalkLife have the most increased odds of receiving social support when they feature prominent themes of “hopeless suicide,” “self-harm abstention,” and “hiding self-harm.” Posts have decreased odds of receiving any comment when they have prominent themes of “stay strong,” “crying,” and “philosophical thoughts.” Of the four topics with morbid/suicidal content, “hopeless suicide” increased the odds of receiving a comment and emotional support much more than the other three. We found that highly emotional help-seeking expressions may engender emotional support more than informational support, while help-seeking expressions focused on mental ill health, hiding self-harm, or social context may engender informational support more than emotional support.

Future directions grow out of limitations and implications. Two valuable, follow-up research questions could be addressed within these data. First, it is possible that topic modeling at the post level, as opposed to our author-aggregated approach, would increase the amount of social support variance explained. One approach would be to take a subset of longer posts, i.e., posts over 50 terms long, and re-run these analyses without author aggregation. Second, the finding that all topics were associated with increased odds of receiving emotional support raises the question of whether a post’s coherence or clarity is a primary driver of receiving emotional support. One option for testing this would be to select the highest *gamma* of each post as a proxy for how focused a post’s content is and test whether each post’s highest *gamma* predicts social support.

Given that our findings mostly align with and extend previous findings, we hope that future research will return the favor of re-testing and contextualizing our findings. For example, it would be interesting to conduct similar analyses within different categories of TalkLife. We have interpreted our findings to suggest that suicidal users find their way to the “Self Harm” category because there is no “Suicide” category. However, it is possible that morbid/suicidal content would appear in other TalkLife categories as well. A recapitulation of this study via qualitative methods could provide convergent validity to our findings while extending them by integrating more context. For example, a qualitative study could incorporate comments by the original poster as a window into whether the social support in the comments was helpful to the original poster. Ultimately, close collaboration with TalkLife would allow for ideal research conditions under which user outcomes could be measured over time and interventions via innovative design features could be tested.

Conclusion

In this study, we used topic modeling, machine learning classification, and multilevel modeling to discover which adolescent help-seeking expressions elicited social support. Our results painted a complex picture, with implications for researchers and online social support platform designers. We learned about the power of help-seeking expressions focused on “hopeless suicide,” “self-harm abstention,” and “hiding self-harm” to elicit social support. On the other hand, we learned that some topics may actually decrease the odds of receiving social support, and many help-seekers never receive any responses. We hope that these findings will prompt further investigation by researchers and innovation by platform designers.

Chapter 6: General Discussion

In this study, we investigated adolescent help-seeking and peer support for self-injurious thoughts and behaviors (SITB) online. We used topic modeling, machine learning classification, and multilevel modeling in pursuit of three aims. In the first aim, we discovered the topics that characterized help-seeking expressions of over 100,000 posters who chose to post in the “Self Harm” category. In the second aim, we measured the amount and type of social support provided in over a million comments in response to these posts. In the third aim, we tested whether the topics of help-seeking expressions predicted the presence and type of social support provided. The over-arching goal of these aims was to help inform policy and guide the design of online spaces to support healthy adolescent development, especially amongst adolescents experiencing mental health challenges.

Our findings paint a picture of an online mental health community that co-mingles help-seekers’ morbid/suicidal content and non-suicidal self-injury (NSSI) content. Brief or generic social support predominates in the responses to these SITB-focused expressions, with relatively few offers of multifaceted social support, such as responses that elaborate on the specifics of a post or provide multiple types of support (e.g., encouragement and validation or advice and a referral). Almost one-third of help-seeking expressions receive no comments. When help-seekers post about self-harm abstention, hopeless suicidality, and hiding self-harm, their odds of receiving social support increase the most. The two types of social support that we examined, emotional and informational, show different patterns. Highly emotional, disinhibited help-seeking expressions seemed to elicit more emotional support than informational support. Help-seeking expressions focused on practical concerns —like mental health disorders, hiding NSSI,

and communicating with friends and family— may elicit more informational support than emotional support.

In the first aim, the themes we discovered via topic modeling aligned with previous topic modeling studies of online NSSI or SITB communities. We found that the top three themes were “hopeless suicide,” “expressing feelings,” and “explicit self-loathing.” Morbid/suicidal content and NSSI content predominated and had about equal prevalence. Eleven of the 12 themes that we inferred from our topic model were mirrored in previous studies (Alhassan et al., 2021; Feldhege et al., 2023; M.-S. Kim & Yu, 2022; Preston et al., 2023). Only the “crying” topic did not have a parallel in a previous study. Another difference between our topic model and previous findings is that we did not find topics that reflected pro-self-harm sentiment or focused on NSSI or suicide methods.

In the second aim, the types and amounts of social support we measured via machine learning classification aligned with previous studies of social support in online mental health communities. While all studies, including ours, agree that the frequency of emotional support tends to exceed informational in online mental health communities (De Choudhury & De, 2014; M. Kim et al., 2023; Kruzan et al., 2021; Saha & Sharma, 2020; E. Sharma & De Choudhury, 2018), the exact prevalence of these types of social support varies. Our finding of emotional support in 59% of comments and informational support in 25% of comments most closely aligns with studies that used similar coding schemes and machine learning classifiers (M. Kim et al., 2023; E. Sharma & De Choudhury, 2018).

In the third aim, we used multilevel modeling to test whether the topics of help-seeking expressions were associated with the social support provided in the comments. The research question and analytical methods of aim three are novel, so there are few similar studies with

which to compare the findings. If we consider the three studies with some methods in common that focus on online SITB communities only, we see that our findings generally align with their findings. All topics were associated with increased odds of receiving emotional support in the first comment, which aligns with the previous finding that emotional support is doled out often and indiscriminately in online SITB communities (Kruzan et al., 2021). Two of the topics most strongly associated with increased odds of receiving informational support can be interpreted as information-seeking queries, which aligns with previous findings that information-seeking queries most often elicited informational support (Kruzan et al., 2021). In addition, “self-harm abstinence” was associated with the greatest increase in the odds of receiving emotional support, which aligns with previous findings that comments in online SITB communities contain frequent encouragement of recovery and abstinence (Preston & West, 2023). Finally, the “family and friends” topic was associated with increased odds of receiving any comment and receiving informational support, which may align with the finding that specific situational narratives were associated with more “likes” (Preston et al., 2023). It is possible that the “family and friends” topic denotes narration of the events and social context around SITB concerns, which would parallel Preston and colleagues’ (2023) finding.

Novel findings emerged from all three aims. Aim one yielded two novel findings. First, in contrast to all other prior topic modeling studies of online SITB communities (Alhassan et al., 2021; Feldhege et al., 2023; M.-S. Kim & Yu, 2022; Preston et al., 2023), we did *not* identify a topic with pro-self-harm sentiment or information about self-harm methods. Second, whereas all other topic modeling studies focused on a body of text collected around the term “self-harm” had found topics focused on NSSI (Alhassan et al., 2021; M.-S. Kim & Yu, 2022; Preston & West, 2023), we found as much morbid/suicidal content as NSSI content. Aim two yielded one notable

novel finding: the vast majority of the social support provided in the comments was of a moderate level, i.e., generic or brief, which casts some doubt on the social support's benefit to help-seekers.

Given its innovative approach, aim three produced a complex picture of help-seeking and social support with several novel findings. To our knowledge, this is the first study to investigate which topics of help-seeking expressions reduce the odds of receiving social support. We found that “stay strong,” “crying,” and “philosophical thoughts” reduced the odds of receiving any comment. Building on the novel finding of aim one, we found that morbid/suicidal content and NSSI content in help-seeking expressions yielded comparable increases in the odds of receiving social support. Finally, we found that one of the four topics with morbid/suicidal content stood out. “Hopeless suicide” was associated with more than double the increased odds of receiving any comment and receiving emotional support than the other morbid/suicidal topics. Recent findings in the field of ideation-to-action suicide research suggest that of 42 diverse warning signs, hopelessness and pain most commonly precede serious suicide attempts in adolescents (Klonsky et al., 2018). Perhaps the “hopeless suicide” topic has increased odds of eliciting social support because commenters intuit the serious risk associated with the sentiment.

Revisiting the themes and theories explored in the first chapter, we consider how our findings fit in. True to the adolescent vulnerability to the onset of mental ill health and the recent upward trend in adolescent suicide (Ruch et al., 2019; Solmi et al., 2021), we found extensive suffering and struggle expressed by adolescent help-seekers. At the same time, we found over 700,000 comments with social support, confirming that adolescents possess a strong urge to affiliate with peers and contribute to their community's wellbeing (Forbes & Dahl, 2010; Fuligni, 2019). We cannot speak directly to the hot topic of whether time spent online hurts

adolescents; rather, we can translate our findings into recommendations for online mental health communities that serve adolescents, which we undertake in the next section.

Revisiting the barriers to and facilitators of online help-seeking in young people (Pretorius et al., 2019), we found evidence that young people’s concerns about privacy and confidentiality are well-founded. In our hand-labeling of social support in the comments, we encountered frequent personal identifiable information (PII). The most common form of PII was usernames for a messaging app, Kik. In rarer cases, we found full names, email addresses, and phone numbers. We replaced all PII that we found in our training set with hashmarks so that the PII would not inform the classifier. More broadly speaking, however, the PII present in these data reinforce the idea that close collaboration between academic researchers and corporations could improve corporate research ethics (Livingstone et al., 2022).

Revisiting the popularity and potential power of peer support for adolescents (Marchant et al., 2017; Richard et al., 2022), we found evidence that adolescents do indeed seek help online for serious mental health concerns. Furthermore, we found evidence that concerns regarding the quality of peer support and the burden of supporting peers with intense suffering are well-founded (Lavis & Winter, 2020; Richard et al., 2022). Commenters provided frequent support of only moderate quality in response to abundant expressions of suffering and struggle. We should listen to calls for training of young people to provide effective peer support and integration of professional intervention in online mental health communities (Richard et al., 2022; Stänicke, 2023).

Revisiting the interpersonal theory of suicide and related ideation-to-action theories (Klonsky et al., 2018; Van Orden et al., 2010), we found an uncertain balance between risk and protective factors of suicide in the “Self Harm” category on TalkLife. The mix of

morbid/suicidal and NSSI content, the intensity of expressed suffering, the lack of comments on 30% of posts, and the generic or brief quality of most of the social support align with risk factors like pain, hopelessness, perceived burdensomeness, thwarted belonging, and acquired capacity for suicide (Klonsky et al., 2018). On the other hand, celebration of self-harm abstention, absence of pro-self-harm sentiment and discussion of self-harm methods, commenters responding at least once to 85% of posters, the presence of social support in 70% of first comments, the over 50,000 comments with high informational support, and the increased odds of receiving support for topics like “hopeless suicide” align with protective factors like connectedness and preventative intervention like means safety (Anestis et al., 2017). Perhaps we should have expected this tension since online life tends to recapitulate in-person life (Odgers & Jensen, 2020). Thankfully, the built, online environment can be designed to tip the balance.

TalkLife’s Purpose and Design

An over-arching goal of this work was to examine all of the findings in consideration of TalkLife’s purpose and design. TalkLife bills itself as a “mental health peer support community” that is “safe and encouraging,” and provides assurance that, “You are not alone!” In light of this stated purpose, our findings reveal successes and areas for growth of the TalkLife platform. Aim one showed that the “Self Harm” category contains far more morbid/suicidal content than expected. This may suggest that the lack of a “Suicide” category on the platform funnels suicidal help-seekers to the “Self Harm” category. Aim one also showed that the “Self Harm” category contains less pro-self-harm sentiment and less discussion of self-harm methods than expected. This may suggest that TalkLife’s rules prohibiting this content are effective.

Aim two showed that most of the social support offered to adolescent help-seekers in the “Self Harm” category is of a moderate level, meaning that the support tends to be generic or

brief. This may suggest that commenters do not have the knowledge or skill to provide the verbose and varied social support that is more likely to help posters. Aim three showed that most adolescent help-seekers in the “Self Harm” category received some support in the comments, with all topics associated with increased odds of receiving emotional support and most topics associated with increased odds of receiving informational support. Aim three also showed that 30% of posts and 15% of posters never received any comment, and three topics (“stay strong,” “crying,” and “philosophical thoughts”) were associated with decreased odds of receiving any comment.

TalkLife succeeds in facilitating peer support for many of its users. This aligns with its stated purpose and the content it endorses in the “Self Harm” category: “asking for support or someone to talk to; sharing how you feel, ranting; alternatives to self-harm; coping mechanisms.” TalkLife succeeds in limiting the prevalence of pro-self-harm sentiment and discussion of self-harm methods. This aligns with the content it prohibits in the “Self Harm” category: “sharing descriptive methods, using graphic language; encouraging self-harm or suicide; suicide notes or threats; being offensive or demeaning.” It is possible that the rules of the “Self Harm” category are differentially enforced since their prohibition against posting about “descriptive methods” and “encouraging self-harm or suicide” mostly succeeds while the “hopeless suicide” and “explicit self-loathing” topics suggest that the prohibition against “suicide notes and threats” at least partly fails. One can imagine the challenges that would arise when asking volunteer moderators with five hours of training to determine which expressions of suicidal ideation count as “suicide notes and threats.”

TalkLife also falls short of its purpose in important ways. About 30% of posts and 15% of posters never received any comment. This lack of comments is concerning given TalkLife’s

assurance that, “You are not alone!” Online peer support is seen by adolescent help-seekers as especially important when in-person help is not available, whether due to stigma, service gaps, or timing (e.g., night-time crisis; Banwell et al., 2022; Lavis & Winter, 2020). The social support adolescent SITB help-seekers on TalkLife do receive in the comments is usually of a moderate level, meaning that it tends to be generic or brief. This generic or brief social support is less likely to benefit both the receiver and the giver (Kushner & Sharma, 2020; Saha & Sharma, 2020). Finally, the “Self Harm” category contains far more morbid/suicidal content than expected. The co-mingling of expected NSSI content with unexpected morbid/suicidal content poses significant risks to users. A suicidal help-seeker exposed to NSSI content might try NSSI for its “anti-suicide” potential (Czyz et al., 2021), while a self-injuring help-seeker might feel pulled into a suicide cluster or struggle under the burden of exposure to suicidal suffering (Lavis & Winter, 2020; Swedo et al., 2021).

Recommendations grow out of TalkLife’s successes and shortcomings. The popularity of the platform and the prevalence of social support in the comments highlight the potential of online peer support as a pillar of healthy adolescent development. The prevalence of social support and the absence of pro-self-harm content highlight the power of platform rules to promote healthy interactions. The help-seekers who never receive any comment highlight an opportunity for innovative design. Where many social media platforms promote posts based on the attention the post has already attracted, a peer support platform could promote posts that have not yet received any attention. The prevalence of generic or brief social support highlights an opportunity to promote more effective peer support via platform guidelines, resources, prompts, and training. TalkLife could promote specific and elaborate social support to commenters the same way that TalkLife displays the rules of the “Self Harm” category to posters. Finally, the

prevalence of morbid/suicidal content in the “Self Harm” category highlights the obligation of online mental health communities to design for the inevitable presence of suicidal ideation in community members. Regardless of whether the omission of a “Suicide” category was intentional, the potential consequence of co-mingling suicidal and self-injuring help-seekers poses serious risks. TalkLife could provide a “Suicide” category that provides a forum for moderated peer support and multiple avenues for escalated intervention inside and outside of TalkLife’s platform.

Strengths and Limitations

Numerous aspects of this study strengthen its findings. This study examines the help-seeking behavior of over 100,000 adolescents, surpassing the scale of qualitative studies and the specificity of studies that lack demographic information, e.g., Reddit-based studies (M. Kim et al., 2023; Stänicke, 2023). The naturalistic, observational quality of this study’s data provides important convergent evidence to integrate with previous interview- or questionnaire-based studies of online help-seeking and social support. Topic modeling and machine learning classification are powerful data-driven approaches that are underused in clinical science. These approaches are more common in computer science, and it is a particular strength of this study that the development and interpretation of the topic model and classifier benefit from clinical expertise. This clinical expertise was part of the rigorous process by which we trained the machine learning classifier, which outperformed classifiers from other similar studies on most metrics. Finally, our novel examination of how the content of help-seeking expressions relates to receiving social support was strengthened by our multilevel modeling approach, which accounted for the structure of the dataset and poster characteristics in particular. We did not find

any other study in this subfield that reported modeling the nested structure of data from online mental health communities.

Numerous aspects of this study limit its findings. As many scholars have pointed out (e.g., Hagg et al., 2022), topic modeling is rife with subjectivity and researcher-determined degrees of freedom. For example, the pre-processing of a corpus of text for topic modeling requires multiple decisions about inclusion and exclusion of terms and documents (e.g., choice of stopword list) that can be idiosyncratic. Furthermore, the interpretation of topic models calls on close reading skills from AP English class alongside more evidence-based clinical skills. In our case, we must add the lack of computational power to run topic models with higher k 's and the brevity of user posts that necessitated author-aggregation to the cold shower that tempers the claims we make. The author-aggregation in particular complicated the interpretation of the multilevel models and may have weakened the associations we were able to detect between topics and social support provided. Our classification of social support was focused on only two types of social support, and we did not attempt any tuning of classifier hyperparameters. It is possible that these choices contributed to the relatively weak Recall performance of our classifier. Relatively weak Recall may suggest that our classifier missed a significant amount of social support in the comments.

Several other important factors were missing or unknown in our study. Because we pared down to just the first comment on each post, we missed out on conversational context and the possible provision of social support in later comments on a post. Another aspect of conversations we missed was the number of “reactions” posts received; it is possible that posts that did not receive comments did still receive some feedback. We also lacked user wellbeing outcome measures, which curtails our ability to make claims about the benefit of social support. We know

little about how TalkLife’s algorithm influences which posts are seen by which users when, which could have a significant impact on how much social support posts receive. We also know nothing about why TalkLife does not have a “Suicide” category, nor have we explored whether morbid/suicidal content emerges in other categories like it does in the “Self Harm” category. Finally, we are missing a specific explanation for 96% of the variance in each of our sets of multilevel models. While we would hope that shoring up the limitations described above would increase the amount of social support variance explained by the content of the help-seeking expressions, it is possible that the reverse would occur.

Future Directions

Future directions break down into three categories. The first, recommendations for online mental health community design, has been covered in a previous section. The second category of future directions includes improvements or adjustments to the methods of this study that would strengthen and contextualize our findings. Our topic model methods would be improved by using more robust computational resources to investigate topic models with higher k 's. It would also be interesting to conduct topic modeling of the same data in Python using the popular package, “gensim,” in order to better understand the impact of different analysis packages on the reliability of the results obtained. Finally, we could investigate whether similar topics emerge using only posts that exceed 50 terms so that we could avoid having to aggregate by author. These steps would allow us to determine the stability of our topic model results. Our machine learning classifier methods could be improved by using hyperparameter tuning to optimize the algorithm. It is possible that we could improve the Recall performance via this tuning.

The third category of future directions concerns subsequent studies to retest, contextualize, and extend our findings. The simplest next study would be to use topic modeling

to investigate whether morbid/suicidal content emerges in other categories on TalkLife, e.g., “Family,” “Depression,” “Academics,” like it does in the “Self Harm” category. This insight would be important to the process of designing for suicidal users of TalkLife. Another valuable follow-up study would be to consider the original poster’s own replies in the thread as a measure of the effect of the social support provided by commenters. This could be achieved via qualitative analysis of a subset of conversations or quantitative sentiment analysis of original poster replies. Across other online mental health communities, it would be interesting to measure the amount of morbid/suicidal content depending on the stated category/focus of the community. Finally, an investigation of the user experience of help-seekers expressing SITB-related content on various platforms, both in terms of how community members and the platform itself respond, would fill a significant gap in the literature and inform further design and policy recommendations.


Conclusion

We began chapter one with three questions. How does adolescence change (or stay the same) when it happens online? How can adults support healthy development online? How do adolescents use online opportunities to support their own development? In this study, we learned that adolescents seek help online for serious problems and suffering. We learned that their peers provide social support most of the time, but this social support often lacks specificity and elaboration. We also learned that platform design matters, and platform designers can do more to support healthy development. Adolescent online help-seekers need help that makes them feel connected. Academic researchers and corporations must work together to help young people help each other.

APPENDIX A
TALKLIFE DATA SHARING AGREEMENT



TalkLife Data Sharing Agreement

Parties	TALKLIFE LTD incorporated and registered in England and Wales with company number 09104043 whose registered office is at 40 Huller and Cheese, Redcliff Backs, Bristol, BS1 6WJ (TalkLife)	
	The University of Central Florida Board of Trustees 12201 Research Parkway, Suite 501, Orlando, FL 32826	
Terms	This agreement incorporates TalkLife's Terms and Conditions as appended to this Order Form.	
Description of Data	TalkLife Complete De-Identified Dataset	
Project	For this project, I would like to explore the intersection of adolescent online safety, mental health, social support, and coping for teens (ages 13-17). I plan to use primarily qualitative methods, which may take up to 5 years to fully analyze and publish my results. Since grounded approaches will be used, the scope of the reach may change based on the preliminary analysis of the data.	
Licence Fee	\$5,000	
Address for Notices	TalkLife: 40 Huller and Cheese, Redcliff Backs, Bristol, BS1 6WJ data@talklife.co	Customer: The University of Central Florida Board of Trustees 12201 Research Parkway, Suite 501, Orlando, FL 32826 Amber.Thorne@ucf.edu
Other as applicable	N/A	
THIS AGREEMENT has been executed by or on behalf of the parties on the date below.		
Signed by a duly authorized signatory of TalkLife Ltd	 Signature Date Wednesday, June 13th, 2018 Name Jamie Druitt / CEO TalkLife Status: _____	

Signed by a duly authorized signatory of the Customer:	<i>Mindy Solivan</i>
	Signed: Tuesday, June 12, 2018
	_____ Date
	Name: Mindy Solivan Status: <u>Assistant Director</u>

1 INTERPRETATION

- 1.1 The definitions and rules of interpretation in this clause apply in this Agreement.

Agreement: the Order Form together with these terms and conditions.

Confidential Information: all confidential information (however recorded or preserved) disclosed by a party or its employees, officers, representatives, advisers or sub-contractors involved in the provision or receipt of the Data who need to know the confidential information in question (**Representatives**) to the other party and that party's Representatives in connection with this Agreement, shall be clearly labelled as confidential. If confidential information is disclosed orally or in any other form, it shall be identified as confidential by the disclosing party at the time of disclosure, summarized in a writing clearly marked as confidential, and delivered to the receiving party within thirty (30) days of initial disclosure by disclosing party.

Customer: the customer identified on the Order Form.

Customer System: any information technology system or systems owned or operated by the Customer from which Data is received in accordance with this Agreement.

Customer User: any employee, worker, student or sub-contractor of the Customer authorised by the Customer to work on the Project,

Customer User Restrictions: the obligations on the Customer set out in clause 6.

Data: the data licensed by TalkLife to the Customer, as described in the Order Form.

Effective Date: the date the Order Form is signed by both parties.

Intellectual Property Rights: all patents, rights to inventions, utility models, copyright and related rights, trade marks, service marks, trade, business and domain names, rights in trade dress or get-up, rights in goodwill or to sue for passing off, unfair competition rights, rights in designs, rights in computer software, database rights, semi-conductor topography rights, moral rights, rights in confidential information (including know-how) and any other intellectual property rights, in each case whether registered or unregistered and including all applications for and renewals or extensions of such rights, and all similar or equivalent rights or forms of protection in any part of the world.

License Fee: the license fee payable by the Customer set out in the Order Form and in accordance with clause 4.

- 1.2 Clause and paragraph headings shall not affect the interpretation of this Agreement.

- 1.3 A **person** includes a natural person, corporate or unincorporated body (whether or not having separate legal personality).

- 1.4 The Order Form forms part of this Agreement and shall have effect as if set out in full in the body of this Agreement. Any reference to this Agreement includes the Order Form.

- 1.5 A reference to a **company** shall include any company, corporation or other body corporate, wherever and however incorporated or established.

- 1.6 Unless the context otherwise requires, words in the singular shall include the plural and in the plural shall include the singular.

- 1.7 Unless the context otherwise requires, a reference to one gender shall include a reference to the other genders.

- 1.8 A reference to a statute or statutory provision is a reference to it as amended, extended or re-enacted from time to time.

- 1.9 A reference to a statute or statutory provision shall include all subordinate legislation made from time to time under that statute or statutory provision.

- 1.10 Unless otherwise expressly stated in this Agreement, a reference to **writing** or **written** includes email.

- 1.11 References to clauses are to the clauses of this Agreement.

- 1.12 Any words following the terms **including**, **include**, **in particular** or **for example** or any similar phrase shall be construed as illustrative and shall not limit the generality of the related general words.

- 1.13 The terms of this Agreement shall prevail over and to the exclusion of any other terms that the Customer seeks to impose or incorporate, or which are implied by trade, custom, practice or course of dealing.

2 LICENSE

In consideration of the License Fee, TalkLife hereby grants to the Customer a non-exclusive, non-transferable, revocable, worldwide license for the duration of the Project to use, modify and adapt the Data for the Project only and subject to the Customer User Restrictions.

3 DELIVERY

- 3.1 TalkLife shall provide the Customer on the agreed form of recordable media, or make available for download, one copy of the Data within a

	reasonable period following the receipt of the License Fee by TalkLife from the Customer. Risk in any tangible media on which the Data is delivered shall pass on delivery.	Customer's premises or on the Customer System; and
3.2	TalkLife may change at any time, with as much prior notice to the Customer as is reasonably practicable:	522 inspect all Records and Customer Systems relating to the use, modification, adaptation, permissions and control of the Data,
	321 the content, format or nature of Data; and	
	322 the means of access to the Data.	
3.3	Any dates quoted for delivery of the Data are approximate only, and the time of delivery is not of the essence. TalkLife shall not be liable for any delay in delivery of the Data that is caused by an event within the scope of clause 16 or the Customer's failure to provide TalkLife with adequate delivery instructions or any other instructions that are relevant to the supply of the Data.	for the purpose of auditing the Customer's compliance with its obligations under this Agreement including the Customer User Restrictions and clauses 2, 8, 9 and 10. Such audit rights shall continue for three years after termination of this Agreement. The Customer shall give all necessary assistance to the conduct of such audits during the term of this Agreement and for a period of three years after termination of this Agreement.
		6 CUSTOMER USER RESTRICTIONS
4	LICENCE FEE	6.1 The Customer shall:
4.1	In consideration of the Data, the Customer shall pay to TalkLife the Licence Fee.	611 ensure that only Customer Users have access to and use the Data;
4.2	TalkLife shall invoice the Customer on or after the Effective Date for the Licence Fee due for the Data and the Customer shall pay each invoice within 30 days after the date of receipt of such invoice.	612 procure that Customer Users comply with the terms of this Agreement and at all times be responsible for such Customer Users' compliance with the terms of this Agreement;
4.3	Time shall be of the essence regarding the Customer's obligations to make payments in accordance with this clause 4 and breach of such obligations shall be deemed to be a material breach for the purpose of clause 14.2.2.	613 not redistribute, re-disseminate, sublicense or transfer the Data;
5	AUDIT	614 unless otherwise expressly agreed by the parties in writing, complete the process set by, and ensure any use, modification or adaptation of Data receives approval from, the relevant Institutional Review Board for human subjects research and/or any other applicable ethics approval;
5.1	The Customer shall keep, in paper and electronic form, at its normal place of business detailed, accurate and up-to-date records (Records) showing the steps taken by the Customer to comply with the Customer User Restrictions. The Customer shall ensure that the Records are sufficient to enable TalkLife to verify the Customer's compliance with its obligations under this clause 5.	615 carry out the Project in accordance with good academic practice and/or good industry practice (as applicable);
5.2	The Customer shall permit TalkLife and its third party representatives, on reasonable notice during normal business hours, but without notice in the case of any reasonably suspected breach of clauses 2, 6, 7 or 10, to:	616 not use the Data for any purpose contrary to any law or regulation or any regulatory code, guidance or request;
	521 gain (physical and remote electronic) access to, and take copies of, the Records and any other information held at the	617 not extract, reutilize, use, exploit, redistribute, re-disseminate, copy or store the Data for any purpose not expressly permitted by this Agreement; and
		618 not do anything which may damage

the reputation of TalkLife, the Data or the Data, including by way of using the Data (wholly or in part) in any manner which is pornographic, racist or that incites religious hatred or violence.

who, to the receiving party's knowledge, is not bound by a confidentiality agreement with the disclosing party or otherwise prohibited from disclosing the information to the receiving party;

7 UNAUTHORISED USE

7.1 If any unauthorized use is made of the Data and such use is attributable to the act or default of, or through, the Customer (including breach of any Customer User Restrictions or the scope of the license at clause 2) then, without prejudice to TalkLife's other rights and remedies:

7.1.1 the Customer shall immediately be liable to pay TalkLife an amount equal to the License Fee that TalkLife would have charged, had TalkLife or the Customer (as the case may be) authorized the unauthorized user at the beginning of the period of that unauthorized. These costs shall not exceed 4 (four) times the Purchase Price or \$20,000.00 USD. ; and

7.1.2 TalkLife may terminate this Agreement with immediate effect on written notice to the Customer.

8 PUBLICATION

Notwithstanding the provisions of clause 9, TalkLife recognises that the Customer may wish to publish information derived from the Data in the academic press and/or to divulge such information at academic meetings or symposia which information may include the Data. Any such publication or disclosure during the term of the Agreement may only be made after notifying TalkLife of such publication or disclosure.

9 CONFIDENTIALITY

9.1 The term Confidential Information does not include any information that:

9.1.1 is or becomes generally available to the public (other than as a result of its disclosure by the receiving party or its Representatives in breach of this clause 9);

9.1.2 was available to the receiving party on a non-confidential basis before disclosure by the disclosing party;

9.1.3 was, is, or becomes, available to the receiving party on a non-confidential basis from a person

9.1.4 was known to the receiving party before the information was disclosed to it by the disclosing party;

9.1.5 the parties agree in writing is not confidential or may be disclosed; or

9.1.6 was developed independently of or without reference to the disclosing party's confidential information

9.2 Each party shall keep the other party's Confidential Information confidential and shall not:

9.2.1 use any Confidential Information except for the purpose of exercising or performing its rights and obligations under this Agreement for the Project; or

9.2.2 disclose any Confidential Information in whole or in part to any third party, except as expressly permitted by this clause.

9.3 A party may disclose the other party's Confidential Information to those of its Representatives who need to know that Confidential Information for the Project, provided that:

9.3.1 it informs those Representatives of the confidential nature of the Confidential Information before disclosure; and at all times, it is responsible for the Representatives' compliance with the confidentiality obligations set out in this clause 9.

9.4 The Customer acknowledges that TalkLife's Confidential Information includes the Data.

9.5 A party may disclose Confidential Information to the extent required by law, by any governmental or other regulatory authority, or by a court or other authority of competent jurisdiction provided that, to the extent it is legally permitted to do so, it gives the other party as much notice of the disclosure as possible.

9.6 Each party reserves all rights in its Confidential Information. No rights or obligations in respect of a party's Confidential Information, other than

- those expressly stated in this Agreement, are granted to the other party, or are to be implied from this Agreement.
- 9.7 The provisions of this clause 9 shall continue to apply after termination of this Agreement for a period of five (5) years from the Effective Date.
- 10 SECURITY AND PASSWORDS**
- 10.1 The Customer shall ensure that the Data and TalkLife's Confidential Information is kept secure and in an encrypted form, and shall use the best available security practices and systems applicable to the use of the Data and TalkLife's Confidential Information to prevent, and take prompt and proper remedial action against, unauthorized access, copying, modification, storage, reproduction, display or distribution of the Data and TalkLife's Confidential Information.
- 10.2 If the Customer becomes aware of any misuse of any Data and/or TalkLife's Confidential Information, or any security breach in connection with this Agreement that compromises the security or integrity of the Data and/or TalkLife's Confidential Information or otherwise adversely affect TalkLife, the Customer shall, at the Customer's expense, promptly notify TalkLife and fully co-operate with TalkLife to remedy the issue as soon as reasonably practicable.
- 10.3 The Customer agrees to co-operate with TalkLife's reasonable security investigations; provided that TalkLife gives Customer written notice at least twenty-four (24) hours prior to commencement of any security investigations.
- 11 INTELLECTUAL PROPERTY RIGHTS**
- 11.1 The Customer acknowledges that:
- 11.11 all Intellectual Property Rights in the Data are the property of TalkLife or its licensors, as the case may be;
- 11.12 it shall have no rights in or to the Data other than the right to use them in accordance with the express terms of this Agreement; and
- 11.13 TalkLife or its licensors has or have made and will continue to make substantial investment in the obtaining, verification, selection, coordination, development, presentation and supply of the Data.
- 11.2 The Customer shall, and shall use all reasonable endeavours to procure that any necessary third party shall, at TalkLife's cost, promptly execute such documents and perform such acts as may reasonably be required for the purpose of giving full effect to this Agreement.
- 11.3 Any use of the Data by the Customer shall credit, wherever technically and commercially feasible, TalkLife, any licensor of TalkLife or any other source of the Data specified by TalkLife as the source of the Data.
- 11.4 Subject to clause 13.4, TalkLife undertakes to defend the Customer from and against any claim or action that the provision, receipt or use of the Data (wholly or in part) infringes any Intellectual Property Right of a third party (**IPR Claim**) and shall be responsible for any losses, damages, costs (including all legal fees) and expenses incurred by or awarded against the Customer as a result of, or in connection with, any such IPR Claim, provided that, if any third party makes an IPR Claim, or notifies an intention to make an IPR Claim against the Customer, the Customer shall:
- 11.41 give written notice of the IPR Claim to TalkLife as soon as reasonably practicable;
- 11.42 not make any admission of liability in relation to the IPR Claim without the prior written consent of TalkLife;
- 11.43 at TalkLife's request and expense, allow TalkLife to conduct the defense of the IPR Claim including settlement; and
- 11.44 at TalkLife's expense, co-operate and assist to a reasonable extent with TalkLife's defense of the IPR Claim.
- 11.5 If any IPR Claim is made, or in TalkLife's reasonable opinion is likely to be made, against the Customer, TalkLife may at its sole option and expense:
- 11.51 procure for the Customer the right to continue using, developing, modifying or retaining the Data (wholly or in part) in accordance with this Agreement;
- 11.52 modify the Data (wholly or in part) so that they cease to be infringing;
- 11.53 replace the Data (wholly or in part) with non-infringing items; or
- 11.54 terminate this Agreement

	immediately by notice in writing to the Customer and refund any License Fee paid by the Customer as at the date of termination (less a reasonable sum in respect of the Customer's use of the Data to the date of termination) on return of the Data and all copies of each of them.		misrepresentation (whether innocent or negligent), restitution or otherwise, for:
11.6	Clause 11.4 constitutes the Customer's sole and exclusive remedy and TalkLife's only liability in respect of IPR Claims.		1321 any loss (whether direct or indirect) of profits, business, business opportunities, revenue, turnover, reputation or goodwill;
12	WARRANTIES		1322 any loss or corruption (whether direct or indirect) of data or information;
12.1	TalkLife warrants that it has the right to license the Data as specified in this Agreement.		1323 loss (whether direct or indirect) of anticipated savings or wasted expenditure (including management time); or
12.2	Except as expressly stated in this Agreement, all warranties, conditions and terms, whether express or implied by statute, common law or otherwise are hereby excluded to the extent permitted by law.		1324 any loss or liability (whether direct or indirect) under or in relation to any other contract.
12.3	Without limiting the effect of clause 12.2, TalkLife does not warrant that:	13.3	Clause 13.2 shall not prevent claims, which fall within the scope of clause 13.4, for:
	1231 the Data will run on the Customer System;		1331 direct financial loss that are not excluded under any of the categories set out in clause 13.2.1 to clause 13.2.4; or
	1232 the Data is accurate, complete, reliable, secure, useful, fit for purpose or timely; or		1332 tangible property or physical damage.
	1233 the Data has been tested for use by the Customer or any third party or that the Data will be suitable for or be capable of being used by the Customer or any third party.	14	Subject to clauses 13.1 and 13.2, TalkLife's total aggregate liability in contract, tort (including negligence and breach of statutory duty howsoever arising), misrepresentation (whether innocent or negligent), restitution or otherwise, arising in connection with the performance or contemplated performance of this Agreement shall in all circumstances be limited to a sum equal to the License Fee paid by the Customer to TalkLife.
13	LIMITATION OF LIABILITY	15	TERM AND TERMINATION
13.1	In no event will either party be responsible for any indirect, incidental damages, consequential damages, exemplary damages of any kind, lost goodwill, lost profits, lost business and/or any indirect economic damages whatsoever regardless of whether such damages arise from claims based upon contract, negligence, tort (including strict liability or other legal theory), a breach of any warranty or term of this Agreement, and regardless of whether a Party was advised or had reason to know of the possibility of incurring such damages in advance. :	15.1	This Agreement shall commence on the Effective Date. Unless terminated earlier in accordance with clauses 7, 14.2, or 16, this Agreement shall continue until the earliest of the following occurs: (1) completion of the Project; or (2) five (5) years from the Effective Date.
13.2	Subject to clause 13.1, TalkLife shall not in any circumstances be liable whether in contract, tort (including for negligence and breach of statutory duty howsoever arising),	15.2	Without prejudice to any rights that have accrued under this Agreement or any of its rights or remedies, either party may terminate this Agreement by giving thirty (30) days written notice to the other party if:
			1521 the other party fails to pay any amount due under this Agreement on the due date for payment and remains in default not less than 14 days after being notified in writing to make that payment;
			1522 the other party commits a material breach of any material term of this

	Agreement (other than failure to pay any amounts due under this Agreement) and (if that breach is remediable) fails to remedy that breach within a period of 30 days after being notified in writing (including email) to do so;		to appoint or has appointed an administrative receiver;
1523	the other party:	1528	a person becomes entitled to appoint a receiver over the assets of the other party or a receiver is appointed over the assets of the other party;
	15.2.3.1 suspends, or threatens to suspend, payment of its debts;	1529	a creditor or encumbrancer of the other party attaches or takes possession of, or a distress, execution, sequestration or other similar process is levied or enforced on or sued against, the whole or any part of the other party's assets and that attachment or process is not discharged within 14 days;
	15.2.3.2 is unable to pay its debts as they fall due or admits inability to pay its debts; or	15210	any event occurs or proceeding is taken with respect to the other party in any jurisdiction to which it is subject that has an effect equivalent or similar to any of the events mentioned in clause 14.2.3 to clause 14.2.9 (inclusive); or
	15.2.3.3 (being a company) is deemed unable to pay its debts within the meaning of section 123 of the Insolvency Act 1986;	15211	the other party suspends or ceases, or threatens to suspend or cease, carrying on all or a substantial part of its business.
1524	the other party commences negotiations with all or any class of its creditors with a view to rescheduling any of its debts, or makes a proposal for or enters into any compromise or arrangement with its creditors other than for the sole purpose of a scheme for a solvent amalgamation of that other party with one or more other companies or the solvent reconstruction of that other party;	16	CONSEQUENCES OF TERMINATION
		16.1	Any provision of this Agreement that expressly is intended to come into or continue in force on or after termination of this Agreement shall remain in full force and effect.
1525	a petition is filed, a notice is given, a resolution is passed, or an order is made, for or in connection with the winding up of that other party other than for the sole purpose of a scheme for a solvent amalgamation of that other party with one or more other companies or the solvent reconstruction of that other party;	16.2	Termination or expiry of this Agreement shall not affect any rights, remedies, obligations or liabilities of the parties that have accrued up to the date of termination or expiry, including the right to claim damages in respect of any breach of the Agreement which existed at or before the date of termination or expiry.
		16.3	On expiry or termination of this Agreement for any reason, the Customer shall immediately pay any outstanding amounts owed to TalkLife under this Agreement.
1526	an application is made to court, or an order is made, for the appointment of an administrator, or if a notice of intention to appoint an administrator is given or if an administrator is appointed, over the other party;	16.4	On termination of this Agreement in accordance with clause 7, the licence granted to the Customer at clause 2 shall immediately terminate and the Customer must return or destroy (at TalkLife's option) all Data, information, software, and other materials provided to it by the other party in connection with this Agreement including Confidential Information.
1527	the holder of a qualifying floating charge over the assets of that other party has become entitled	16.5	On completion of the Project, the Customer party shall as soon as reasonably practicable return or

<p>destroy (as directed in writing by TalkLife) all Data, information, software, and other materials provided to it by TalkLife in connection with this Agreement including TalkLife's Confidential Information and the Customer shall ensure that all Data and Confidential Information is deleted (as far as reasonably technically possible) from the Customer System. For the avoidance of doubt, TalkLife acknowledges that such return or destruction shall not include the Customer's findings or research results which has been derived from the Data and that this shall not apply to any information contained, reflected or referred to in (i) any board minutes or other documents which either party, its consultants or financiers or professional advisers are required to retain under any applicable law or regulation or to comply with the rules of any regulatory body or authority, or (ii) any electronic back-up copies made automatically in the ordinary course of safe-guarding electronic records).</p> <p>16.6 The Customer shall, on TalkLife's request, provide written confirmation (in the form of a letter signed by an authorized signatory) of compliance with clause 15 no later than 14 days after TalkLife's request.</p> <p>17</p>	<p>FORCE MAJEURE</p> <p>Neither party shall be in breach of this Agreement nor liable for delay in performing, or failure to perform, any of its obligations under this Agreement if such delay or failure result from events, circumstances or causes beyond its reasonable control. In such circumstances the affected party shall be entitled to a reasonable extension of the time for performing such obligations. If the period of delay or non-performance continues for [4] [weeks], the party not affected may terminate this Agreement by giving [30] [days'] written notice to the affected party.</p> <p>18</p>	<p>ASSIGNMENT</p> <p>18.1 This Agreement is personal to the Customer and it shall not assign, transfer, mortgage, charge, subcontract, declare a trust of or deal in any other manner with any of its rights and obligations under this Agreement without the prior written consent of TalkLife (which is not to be unreasonably withheld or delayed).</p> <p>18.2 The Customer confirms it is acting on its own behalf and not for the benefit of any other person.</p> <p>18.3 TalkLife may at any time assign, transfer, mortgage, charge, subcontract, declare a trust of or deal in any other manner with any of its rights and obligations under this Agreement without the consent of the Customer.</p> <p>19</p>	<p>WAIVER</p>	<p>No failure or delay by a party to exercise any right or remedy provided under this Agreement or by law shall constitute a waiver of that or any other right or remedy, nor shall it preclude or restrict the further exercise of that or any other right or remedy. No single or partial exercise of any right or remedy shall preclude or restrict the further exercise of that or any other right or remedy.</p> <p>20</p>	<p>REMEDIES</p> <p>Except as expressly provided in this Agreement, the rights and remedies provided under this Agreement are in addition to, and not exclusive of, any rights or remedies provided by law.</p> <p>21</p>	<p>NOTICE</p> <p>21.1 Any notice given to a party under or in connection with this contract shall be in writing and shall be delivered by hand or by pre-paid first-class post or other next working day delivery service at its registered office (if a company) or its principal place of business (in any other case).</p> <p>21.2 Any notice shall be deemed to have been received:</p> <p style="padding-left: 20px;">2121 if delivered by hand, on signature of a delivery receipt or at the time the notice is left at the proper address; or</p> <p style="padding-left: 20px;">2122 if sent by pre-paid first-class post or other next working day delivery service, at 9.00 am on the second day after posting [or at the time recorded by the delivery service.</p> <p>21.3 This clause does not apply to the service of any proceedings or other documents in any legal action or, where applicable, any arbitration or other method of dispute resolution. For the purposes of this clause, "writing" shall include email.</p> <p>22</p>	<p>NON-USE OF NAMES</p> <p>Neither party may use the other's name or trademarks in any promotion, statement, advertisement, press release, or communications to the general public or any third party without the other's express written consent. Any proposed public statement, advertisement, press release, or communication by either party shall be submitted to the other party for its review and written approval at least thirty (30) days prior to the planned dissemination or publication, unless otherwise required. However, nothing shall prohibit either party from complying with Florida Statute 1004.22(2)</p>
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- regarding sponsored research activities.
- 23 ENTIRE AGREEMENT**
- 23.1 This Agreement constitutes the entire agreement between the parties and supersedes all previous discussions, correspondence, negotiations, arrangements, understandings and agreements between them relating to its subject matter.
- 23.2 Each party acknowledges that in entering into this Agreement it does not rely on, and shall have no remedies in respect of, any representation or warranty (whether made innocently or negligently) that is not set out in this Agreement.
- 23.3 Each party agrees that it shall have no claim for innocent or negligent misrepresentation or negligent misstatement based on any statement in this Agreement.
- 24 VARIATION**
- Except as expressly provided in this Agreement, no variation of this Agreement shall be effective unless it is in writing and signed by the parties (or their authorized representatives).
- 25 SEVERANCE**
- 25.1 If any provision or part-provision of this Agreement is or becomes invalid, illegal or unenforceable, it shall be deemed modified to the minimum extent necessary to make it valid, legal and enforceable. If such modification is not possible, the relevant provision or part-provision shall be deemed deleted. Any modification to or deletion of a provision or part-provision under this clause shall not affect the validity and enforceability of the rest of this Agreement.
- 26**
- If one party gives notice to the other of the possibility that any provision or part-provision of this Agreement is invalid, illegal or unenforceable, the parties shall negotiate in good faith to amend such provision so that, as amended, it is legal, valid and enforceable, and, to the greatest extent possible, achieves the intended commercial result of the original provision.
- 27 NO PARTNERSHIP OR AGENCY**
- 27.1 Nothing in this Agreement is intended to, or shall be deemed to, establish any partnership or joint venture between any of the parties, constitute any party the agent of another party, or authorize any party to make or enter into any commitments for or on behalf of any other party.
- 27.2 Each party confirms it is acting on its own behalf and not for the benefit of any other person.
- 28 THIRD-PARTY RIGHTS**
- A person who is not a party to this Agreement shall not have any rights under the Contracts (Rights of Third Parties) Act 1999 to enforce any term of this Agreement.
- 29 DISPUTES**
- 29.1 Any disputes, questions or differences regarding the interpretation or the implementation of this Agreement should be resolved through good faith discussions between both Parties (or their designees). If resolution through discussions is impossible, the dispute shall be submitted for arbitration administered by the International Centre for Dispute Resolution in accordance with its International Arbitration Rules. Jurisdiction and applicable law shall be determined in consultation with the Parties in the event a dispute arises. Arbitration shall be conducted in the English language." .

APPENDIX B

TALKLIFE COMMENT CODING MANUAL

Spreadsheet

Data File Location

/Dropbox/SRCD_JF_Peer_Support/quant_coding/
<https://www.dropbox.com/sh/2sio71ne39vkw0v/AADTPmHwxovkJXikFcjULmiZa?dl=0>

Emily's current file: emily_coding_08_2021-07-05.xlsx

Alialani's current file: alialani_coding_08_2021-07-05.xlsx

Column Names

coding_id – unique number for each comment that you can use to point me to comments you have questions about, etc.

comment_id – unique number for each comment that will be used to link the data back to the original huge dataset; you can ignore this column and leave it alone

comment – comment by platform user in response to a post in the Self-Harm category

emotional – rating for emotional support in the comment; can be 0, 1, or 2

informational – rating for informational support in the comment; can be 0, 1, or 2

tricky – especially difficult-to-code comments should be marked with a 1

pii – comments with personally identifiable information should be marked with a 1

notes – document anything you want to remember or ask about here, e.g., if you made a tricky rating and you want to remember how you made the decision, note it here

Rating Protocol

You will use the 2-Way Social Support Scale to rate all comments for the amount of both **emotional support** and **informational support**.

Emotional support (ES) messages provide understanding, encouragement, affirmation, sympathy, or caring.

Informational support (IS) messages provide advice, referrals or knowledge.

All comments will receive ratings of both ES and IS. Possible ratings are:

0 = none

1 = some

2 = a lot

For each comment, you should start by determining the presence or absence of ES and IS. If ES or IS is absent, rate the comment a zero in that column. If ES or IS is present, determine its amount or strength. If ES or IS is generic or brief, rate it a one. If ES or IS is present with more elaboration or specificity, rate it a two.

Here are the **decision rules** we have agreed on:

1. "Don't do it!" or similar should be coded as emotional support (encouragement).
2. "It gets better" or similar should be coded as emotional support (encouragement).
3. "That's good," "It really is," "Me too," or similar should be coded as emotional support (affirmation).
4. Offers to talk that demonstrate some awareness of the other person's needs or state of mind should be coded as emotional support (caring). For example, "You can Kik me at #####" is *not* supportive, while "Kik me if you want to talk #####" is supportive.
5. Emoji and symbols (e.g., xxx, :), :(, <3) should not be coded as emotional support on their own. A comment that would otherwise be coded ES 0, IS 0 (e.g., "What's happened?") should still be ES 0, IS 0 even if it has a symbol or emoji (e.g., "What's happened? Xxx").
6. Most questions (i.e., those that solicit information or clarification or seem random) should be coded as ES 0, IS 0. Questions that offer something (e.g., an offer to talk about the problem/emotion or a suggestion) should be coded as supportive.
7. Informational Support should offer information or insight that is plausibly not obvious to the original poster.
8. In comments that offer advice, we are not assessing the quality of the advice. We should rate the comment, "Just forget about your past," Informational Support level 1, even though it's potentially not helpful advice.
9. Comments with multiple types of Emotional Support (e.g., affirmation + encouragement + caring) or Informational Support (e.g., knowledge + referral) should be coded at level 2.

If you find a comment to be particularly confusing or difficult to rate, mark it with a one in the *tricky* column. You should aim to rate no more than 5% of comments as tricky.

Personally Identifiable Information (PII)

Personally identifiable information (PII) is information that can be used to identify a person, e.g., name, phone number, email address, social media username, etc. The dataset has been largely scrubbed of PII; PII has been replaced with "#####." If you do encounter some unscrubbed PII, you should mark it with a one in the *pii* column.

Examples

ES: 0, IS: 0 – "Kik me #####" // "What's the disease?" // "I no I do it in front of my parents they don't care"

ES: 1, IS: 0 – “That's exactly how I feel” // “No struggling makes you stronger” // “I'm so sorry. How old are you?” // “Don't do it honey! :(“ // “It really is” // “That's good” // “Me too” // “Same <3” // “It gets better” // “Store of my life!” // “My kik is ##### if you need to talk <3”

ES: 2, IS: 0 – “One slip up does not mean you're a failure, it just means you were able to go that many days without hurting yourself. Whether its one or a hundred, any amount of time is an accomplishment.” // “It's hard but you seem like a strong girl and I believe in you. You are so strong anyone who cuts them self are the strongest people yet just know in the future everything will be better stay strong ❤️” // “This is great! Keep up the good work Samantha”

ES: 0, IS: 1 – “distraction distraction 😊” // “Babe, you have to eat. There are a millions ways to be skinny.” // “I can't answer that. Do you honestly love it? You might want to try focusing your energy someplace else.”

ES: 0, IS: 2 – “When you have the urge distract yourself. Watch a movie, work out, talk to friends. To get your mind off of it.” // “Take a red marker and draw on your arm where you would cut. It obviously will not have the EXACT same effect as cutting, the actions will be the same enough that your urge to cut will hopefully be satisfied.” // “Try and find a psychologist for free or most universities have student counsellors or pyschologist to help those who are going through a rough time so maybe find out about the student support services”

ES: 1, IS: 1 – “They are not your friends. You are worth so much more than that try and find opportunities to meet genuine people who will become real friend good luck dear.x” // “Stay strong, don't do it!!! ❤️❤️ distract yourself!! Kik me if you want, #####” // “It's okay. A lot of people do sick things but just focus on something else.”

ES:1, IS: 2 – “Hang in there! Hold a cloth on the cuts and put pressure on them to stop the bleeding! Tell your parents or call the ambulance please tell somebody!! If you need to talk I'm here but please tell an adult!” // “I can tell you that some days it will be easier to control those urges, and you'll feel great! Other days it will be harder, and when it gets hard, you'll question if you're going backwards. You're not. This is just a rough day on the road to happiness. I promise, it gets better.“

ES: 2, IS: 1 – “You're not weak. We all relapse. Me? I just relapsed after a year. It feels like a failure. It's just a bump in the road. Just take it one day at a time. Xx” // “please stay strong, don't cut yourself. you are too beautiful and important to be hurting yourself. tell a parent or someone you can trust about how you're feeling. I love you xx” // “Awe im sriry im glad u didnt cut ik how hard it is not to i do it everyday i hate my scars but it shows my past was hard and painful u should put ice on your knuckles to numb the pain plz keep your head up im here if u need someone”

ES: 2, IS: 2 – “I've been here. I've said these exact words. I've even acted on it. I want you to think about everyone that has had an impact on your life. Anyone that you have impacted. You probably don't know half of the people that you have touched. Be strong. Even if you feel that you're at rock bottom, you can only go up. Find someone to vent to, even if it's a complete

stranger. You are loved and you only have one life, your future holds so much. Think, imagine, believe that you will have better days. Because you will. I promise.”

tricky – “Hey! Don't hate life. It's precious <3. Hold on pain ends {hope}” // “Don't, stay strong, keep your mind off of it. You will be happier later for not cutting” // “You hate yourself because you put too much value on the opinions of others! If that's how your friends treat you then you need to find better friends mate, don't turn it inward onto yourself! ;)” // “You could try to hide them with waterproof makeup, also up until this weekend try putting lotion or something on the cuts”

Kik

When you review comments that refer to the Kik messaging app (or any other means of communicating off the platform), you should rate the portion of the comment that is not related to communicating off the platform. For example, a comment that says, “Kik me: ##### *hugs*” should be rated a 1 for ES and a 0 for IS based on the “*hugs*” portion of the comment. A comment that only contains Kik information, e.g., “Kik me #####,” should be rated as a 0 on both ES and IS because the entire comment is focused on talking off the platform. We do not see this as supportive because we do not know the commenter’s intention or behavior on Kik.

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