Summer 8-2023

The Effect of Viewing Different Modalities of Alcohol-Related Social Media Content Shared by Friends on Alcohol Outcomes: A Longitudinal Examination

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THE EFFECT OF VIEWING DIFFERENT MODALITIES OF ALCOHOL-RELATED SOCIAL MEDIA CONTENT SHARED BY FRIENDS ON ALCOHOL OUTCOMES: A LONGITUDINAL EXAMINATION

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A Dissertation Submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirements for the Degree of

DOCTOR OF PHILOSOPHY

PSYCHOLOGY

OLD DOMINION UNIVERSITY
August 2023

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ABSTRACT

THE EFFECT OF VIEWING DIFFERENT MODALITIES OF ALCOHOL-RELATED SOCIAL MEDIA CONTENT SHARED BY FRIENDS ON ALCOHOL OUTCOMES: A LONGITUDINAL EXAMINATION

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Social influences have robust associations with problematic alcohol use among emerging adult college students. Examinations of social influences increasingly focus on social media influences via alcohol-related content (ARC) sharing and viewing. Limited longitudinal research suggests that increased exposure to ARC is associated with increased alcohol consumption among college students over time. Most research examining exposure has not focused on who (e.g., specific friends) is sharing this content, the modality (e.g., photos) or the qualities of those sharing content and their relationship (e.g., closeness) to the viewer. The current study examined cross-sectional and longitudinal associations between alcohol consumption/consequences and: 1) sharing ARC oneself, 2) exposure to ARC shared by social network members, 3) exposure to specific modalities of ARC shared by the social network, and 4) qualities of relationships with social network members sharing ARC. Heavy/problematic college drinkers (*N*=384) completed three surveys over time (baseline, 1-month, 3-month). Each survey assessed participant social media and alcohol use as well as behaviors of their social network members (i.e., important friends). Regression analyses were conducted for cross-sectional aims and cross-lagged panel analyses were conducted for longitudinal aims. Results indicated that both self-sharing ARC (aim 1) and exposure to social network ARC (aim 2) influence consumption and consequences cross-sectionally. Longitudinal findings largely revealed that greater consumption and consequences are linked to increased self-sharing (aim 1) and social network ARC (aim 2) over time but not typically in the other direction. Only having a greater proportion of network member video ARC (aim 3) was associated with increased consumption over time. Mostly unidirectional associations between greater alcohol outcomes and increased closeness with network members sharing ARC or proportion of drinking buddies sharing ARC were observed over time (aim 4) with limited evidence for bidirectional associations. Results suggest that alcohol consumption and consequences are not only linked to sharing ARC oneself but also affect the curation of our social media feeds to feature more ARC shared by important friends over time. The role of ARC in influencing others and how to reduce its influence when viewing (i.e., media literacy strategies) should be included in existing college drinking interventions.

This dissertation is dedicated to my dad, boyfriend, and cats for their continuous love and support.

ACKNOWLEDGEMENTS

There are several people (and animals) that I would like to acknowledge who were crucial to the successful completion of this dissertation and all the requirements of the program. I want to acknowledge my advisor, Dr. Abby L. Braitman. Her tireless efforts in helping me troubleshoot my complex statistical models were greatly appreciated. Also, her insightful feedback on the theoretical rationale for my project as well as the conclusions were invaluable for not only improving my scientific writing skills but also my critical thinking skills. I am a better researcher for all her guidance over the years. I also want to acknowledge my committee members Drs. Michelle L. Kelley, Cathy Lau-Barraco, and Tony Perez. Collectively, their feedback helped me improve my project design and critically think about my findings. I would like to thank the NIAAA and the Graduate School for funding this research. I want to thank my dad continuously supporting me throughout my life including my academic career. He taught me the importance of education, hard work, and resilience. All these qualities have helped me to complete this project and program. I also want to thank my boyfriend, Jamie, for his unwavering support through the highs and lows of this program. To my cats, Sherwood and Winston, for always being there for a cuddle and providing amusement with their goofy antics.

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CHAPTER I

INTRODUCTION

Despite intervention efforts at institutions, approximately 39% of emerging adult (ages 18 to 25; Arnett, 2000) college students report they have engaged in heavy episodic drinking in the past month (Hingson et al., 2017). Negative consequences related to alcohol misuse are well documented, ranging from mild academic consequences to serious physical consequences (Conway & DiPlacido, 2015; Hingson et al., 2005; Hingson et al., 2016). Close peer influence is a well-known risk factor for problematic drinking in college student samples (for a review see Borsari & Carey, 2001). Peer influence among college students is commonly examined using social network designs in which individuals list important people in their lives and describe their qualities (Valente, 2010). There is a growing body of research showing that qualities of important peers (i.e., social networks) and qualities of their relationships to the individual are consistently related to alcohol misuse in the college student population (for reviews see Knox et al., 2019; Patterson & Goodson, 2019; Rinker et al., 2016). Although social interactions with peers take place online through social media as well as in-person, most studies examining the associations between social networks and drinking do not include assessments of exposure through online interactions (such as alcohol-related content on social media). However, exposure to alcohol-related content (ARC) on social media is a robust predictor of alcohol consumption (for a review, see Gupta et al., 2016; for a meta-analysis, see Curtis et al., 2018). To date, only one study has examined how exposure to ARC shared by specific individuals important to the participant (i.e., social networks) is related to alcohol consumption (dichotomously assessed) prospectively (Huang, Soto et al., 2014; Huang, Unger et al., 2014) among high school students, with no studies examining this association among college populations prospectively. Although much of what is known about online peer influences on drinking (via peer social network and social media) comes from both young adult and adolescent examinations, the current study focused on a college sample to address the problematic phenomenon of college drinking. In addition, the present study included more sensitive and in-depth assessments of both ARC and alcohol-related outcomes.

Prevalence of social media usage among emerging adult college students has been growing over the past few years with 95% of students reporting they use at least one platform (Heron et al., 2019; Pew Research Center, 2019) and check their social media three times per day on average (Erevik et al., 2018). Additionally, findings from a recent longitudinal study examining relationships between social media use and alcohol use over time among adolescents and young adults (ages 10-19 at start of study) indicate that being a social media non-user was a protective factor against past-month drinking or binge drinking (all ages), and that increased social media use is associated with increased alcohol consumption up to three years later (adolescents only; Ng Fat et al., 2021). Further, growing percentages of content on social media shared by users feature alcohol (Kiciman et al., 2018). Numerous studies on social media have found that sharing ARC oneself as well as exposure to ARC is related to drinking in college students (for a meta-analysis see Curtis et al., 2018; for a review see Gupta et al., 2016). However, there is a dearth of evidence examining the role of specific important peers sharing this content. As noted above, the influence of specific important peers is a robust predictor of college alcohol misuse. Moreover, although social media studies sometimes assess modality of exposure to ARC (e.g., text versus photos or videos), they often ask separate questions for different modalities then combine across modalities to create a general exposure variable. This means whether modality of exposure strengthens the relationship between specific important peers sharing ARC and alcohol consumption is underexamined. Social media studies have also revealed that exposure to ARC is associated with alcohol consumption and heavy episodic drinking up to one-year later (Boyle et al., 2016; Huang, Soto et al., 2014; Huang, Unger et al., 2014; Nesi et al., 2017). However, only one of those longitudinal studies collected information on specific peers, and only in a high school sample (Huang, Soto et al., 2014 Huang, Unger et al., 2014) leaving the influence of specific college peers unknown. Although the influence of in-person social networks has demonstrated strong associations with individual drinking, studies have shown that social networks of college students are not stable (Hallgren & Barnett, 2016; Meisel & Barnett, 2017; Reifman et al., 2006). Further, limited research has examined the stability of ARC exposure or online social networks of named specific peers over time and how this relates to individual alcohol use (Huang, Unger et al., 2014). Given the consistency in associations between social network qualities, ARC exposure, and alcohol misuse in college students, understanding how the intersection of in-person and social media social networks affects content sharing, consumption and related negative consequences is important and underexamined. Therefore, in the current study, I examined how the proportion of social network members sharing ARC, relationship qualities with members sharing ARC and modality of ARC shared by the members affect alcohol use and consequences over time to better understand what risk factors may be most impactful.

Peer Influences on Drinking Behavior

The social influence of peers has been consistently associated with individual drinking levels (see Borsari & Carey, 2001 for a review). Peer influences on drinking behavior have been most commonly examined by assessing perceptions of others' beliefs, attitudes, or behaviors (i.e., perceived norms). There are two kinds of perceived norms which dominate the alcohol literature: descriptive and injunctive. Descriptive norms are individual perceptions about how much and how often a specific reference group drinks whereas injunctive norms represent perceptions of how approving a reference group is of engaging in various drinking behaviors (Borsari & Carey, 2001). Reference groups can vary from study to study including close friend or typical student with Borsari and Carey (2001) finding up to 18 different reference groups used across the studies they reviewed. College students consistently tend to overestimate how much they believe their peers are drinking (e.g., close friends) and these misperceptions are associated with higher alcohol consumption and experiencing alcohol-related consequences (Cox et al., 2019; DiGuiseppi et al., 2018; Neighbors et al., 2007). Perceptions of drinking in proximal (e.g., close friends) versus distal (e.g., typical student) reference groups have been observed to be more accurate in terms of how much those groups are drinking (Borsari & Carey, 2001; Kenney et al., 2017; Reid et al., 2020). These perceptions may be more accurate because individuals spend more time with their close friends and are more aware of how much they drink, or individuals may have chosen friends who drink at similar levels to themselves. Although drinking can occur alone, it is more common that college students drink in groups with peers or friends (Christiansen et al., 2002). As perceptions of drinking behavior are often more accurate for proximal groups, such asclose friends, understanding how the drinking behaviors of specific members of social groups are associated with higher consumption and consequences may help to explicate how close friend drinking is related to individual drinking behavior.

College Social Network Drinking

In the past decade, it has become more common to investigate individual perceptions of specific members in their social groups or social network and how they associate with individual drinking and consequences beyond how much or how often they perceive their close friends drink (i.e., globally assessed) or approval of their own drinking behavior (for reviews see Knox et al., 2019; Rinker et al. 2016). In a recent study, which compared associations between perceived norms as captured by typical student descriptive norms versus perceived drinking among social network members (i.e., named specific peers' alcohol quantity and frequency) with individual alcohol use, perceived drinking of social network members explained 9.7% of the variance in individual alcohol use over and above perceived typical student drinking norms (Russell et al., 2020). Within the social network literature, studies have found similar relationships as those observed in perceived drinking norm studies. Namely, college students are more likely to perceive accurately how much their named important peers or close friends drank (Kenney et al., 2018; Reid et al., 2020) compared to students in the same residence hall (Kenney et al., 2017) or typical first-year students (Cox et al., 2019). Additionally, these accurate perceptions of specific social network members were associated with higher alcohol use (Cox et al., 2019; Kenney et al., 2017; Kenney et al., 2018). Findings lend support to previous research finding that perceptions of close friend drinking are more associated with individual drinking than typical student drinking norms but also suggest drinking by specific social network members who are more important to an individual may be more influential for their own drinking behavior.

Reviews of the college social network drinking literature (including both cross-sectional and longitudinal studies) have broadly found that having a larger proportion or number of social network members who drink is associated with higher alcohol consumption (Knox et al., 2019; Rinker et al., 2016). For example, having a higher percentage of drinkers in an individual's network was associated with increases in weekly drinking outcomes (i.e., drinks per drinking day and eBAC) a year later (Hallgren & Barnett, 2016; Schaefer et al., 2020). There was also some evidence to support year one participant drinking levels being positively associated with year two social network drinking levels, suggesting the relationship may be bidirectional (Hallgren & Barnett, 2016). Similarly, drinking students were more likely to name more new network members (i.e., add members) and be named by other students at subsequent assessments (Schaefer et al., 2021). Individuals who were more popular in their social group (DiGuiseppi et al., 2018) and had more social network members who they perceived drank heavily were also more likely to be heavy drinkers themselves (Rinker et al., 2016) and this relationship persisted over time (Cox et al., 2019; Schaefer et al., 2021). Thus, it appears that drinking, more specifically heavy drinking, by college student social networks appears to be a risk factor for problematic alcohol use.

Meanwhile, the composition of a college student's in-person social network is not stable (e.g., adding new friends, dropping old friends) and these changes have been found to be associated with increases in alcohol-related outcomes over time (Hallgren & Barnett, 2016; Meisel & Barnett, 2017; Reifman et al., 2006; Schaefer et al., 2021). For instance, Meisel and Barnett (2017) explicitly examined the impact of network turnover on individual drinking, and found that only 21.5% of the social network members were named at both assessments (years one and two), and 78.5% were named only once. Interestingly, both having a larger social network and adding more heavy drinkers to the network during college were associated with increased alcohol use when controlling for high school drinking (Meisel & Barnett, 2017). Meanwhile, greater changes in network members (e.g., adding or dropping) were associated with more changes in individual drinking from fall semester to the following spring semester (Reifman et al., 2006). Increases in the percentage of drinking buddies (i.e., a quality of the relationship with a social network member) in a network during a fall semester was also associated with increased alcohol use during the following spring semester (Reifman et al., 2006). Thus, not only was network turnover important as a predictor of changes in drinking for these studies, but the qualities of the individuals added or dropped were important, suggesting the importance of examining changes in specific networks over time. However, a growing body of research suggests there are also specific qualities of these drinking social network members which may strengthen the relationship between social network drinking and individual drinking.

Qualities of Social Network Members

The quality of relationships with peers' matter for college student alcohol use (for a review see Borsari & Carey, 2006) but to date, have received limited attention in the college social network literature. Transitioning to college represents a developmental shift in that there is often less parental control, students are further developing their identities, and forming new social groups (Kroger et al., 2010; Meisel & Barnett, 2017). New friendships provide incoming students with models for what is acceptable behavior in college as well as socialization opportunities which often involve drinking alcohol (Stappenbeck et al., 2010). Borsari and Carey (2006) discussed three relevant qualities of peer relationships which have been found to be associated with alcohol consumption: stability, intimacy, and social support. Stability of college social networks can be defined as how often members interact and how many members are in the network. For instance, seeing a higher proportion of social network members weekly was associated with greater alcohol use among college students (Tompsett & Colburn, 2019). Daily contact also appears to strengthen the relationship between perceptions of college social network drinking and self-reported drinking by social network members (Reid et al. 2020). Heavy drinking individuals report socializing more often with social network members than regular (i.e., drink once a month) or infrequent (i.e., drink less than once a month) drinkers (Leonard et al., 2000). Further, as previously discussed, social networks in college are often not stable and are subject to turnover (Meisel & Barnett, 2017; Reifman et al., 2006). High turnover may indicate a lack of quality relationships which has been linked to higher levels of drinking possibly due to less social support via shallow relationships and more instances of drinking alone (Pauley & Hesse, 2009). However, high turnover is also related to drinking when individuals add more heavy drinkers or drinking buddies to their social networks as well as an increase the size of their networks (Meisel & Barnett, 2017; Reifman et al., 2006). Stability through the frequency of social interactions, the size of social network, and the turnover of the social network is a relevant factor in peer relationships but most studies do not capture all aspects of stability suggesting the need for research to assess stability in multiple ways. Meanwhile, intimacy and social support are two other qualities of relationships which are theorized to be relevant to drinking among college students.

Intimacy can be thought of as how close members are with one another. Being closer with a higher proportion of the social network has been found to be associated with alcohol use (Fujimoto & Valente, 2012). Although not strictly to do with closeness, individuals who report a higher proportion or number of drinking buddies (i.e., someone you hang out with on a regular basis to do activities that center around drinking) report higher alcohol consumption (Lau-Barraco & Linden-Carmichael, 2014; Leonard et al., 2000) and this association persists over time (Lau-Barraco et al., 2012; Reifman et al., 2006). Another relationship quality that has been found to be relevant to college drinking is social support. Social support can be defined many ways, but Borsari and Carey (2006) characterized it as the individual feeling emotional supported, accepted by their social group, and free to communicate openly with their friends. Having higher proportions of emotionally supportive friends has been observed to be related to college drinking (Tompsett & Colburn, 2019). Evidence suggests that when individuals perceive a larger proportion of their network to be approving of their drinking, this proportion is associated higher alcohol use (Kenney et al., 2018; Longabaugh et al., 2010). Qualities of social network members and their relationships with individuals appear be linked to alcohol use, however, little research has examined whether they interact with other predictors of alcohol use. Several other qualities of social network members are associated with individual alcohol use beyond global perceptions of how much specific members drink which further differentiates perceived norms assessments (i.e., descriptive and injunctive norms) from social network approaches.

Social Network Approaches

Social network information is often assessed using *egocentric* or *sociocentric* approaches (Valente, 2010). With the *egocentric* approach, individuals (egos) are typically asked to list some number of individuals who have been important to them within a certain time period (their alters), then are asked to describe qualities of each alter (e.g., their gender, how much they drink) and their relationship (e.g., length of time they have been in their network, if they drink together, if they are "best friends"). Alternatively, a *sociocentric* approach involves collecting information from everyone in a given social network (usually a closed network; e.g., adolescent students in a classroom, members of a college fraternity) including the qualities of each participant (e.g., their gender, how much they drink) as well as some number of their important social ties (e.g., who the individual is friends with, who they drink with, who are their "best friends"). Using either approach, qualities of relationships with in-person social network members (e.g., having more drinking buddies in one's network; Lau-Barraco et al., 2012; Lau-Barraco & Linden-Carmichael, 2014) have been consistently associated with alcohol consumption among college students when examined using specific network approaches (for reviews, see Knox et al., 2019; Patterson & Goodson, 2019; Rinker et al., 2016). Therefore, using an egocentric social network approach whereby individuals list important people in their lives and share their perceptions on the behaviors of these important people can help researchers to gain better insight into individuals' social network composition and how these qualities relate to individual alcohol consumption and related consequences.

Social Learning and Social Norms Theories

Respectively, *social learning* and *social norms theories* can help to explain why peer influence is such a strong predictor of drinking behavior and alcohol-related consequences among college students (Bandura & McClelland, 1977; Perkins & Berkowitz, 1986; Rimal & Real, 2005). *Social learning theory* (Bandura & McClelland, 1977) suggests college students learn vicariously that drinking is acceptable and will facilitate forming new friendships through observing their peers. In turn, students are more likely to *model* the drinking behavior of peers to fit in and make friends in college. Upon, making new friends while drinking, the drinking behaviors of students are *reinforced* (i.e., social reinforcement) thus making it more likely that they will continue these behaviors to benefit socially. The roles of modeling and social reinforcement of drinking behaviors of peers can be observed in studies finding that drinking levels of individuals are often more similar to those of their social networks (Cox et al., 2019; Kenney et al., 2017; Kenney et al., 2018). Observation of peers drinking in social settings inherently aid in reinforcing *expectancies* about alcohol as a social lubricant (i.e., social cognitions) which further reinforce the likelihood of modeling peer drinking behaviors. In line with this component of social learning theory, social expectancies have been observed to mediate relationships between the proportion of drinking buddies in one's social network and alcohol use over time (Lau-Barraco et al., 2012). The last component of social learning theory is that of *reciprocal determinism* which posits that modeling, social reinforcement, and social cognitions interact with one another such that changes in one component are associated with changes in the others. The possible bidirectional relationship between individual drinking and social network drinking levels observed in Hallgren and Barnett (2016) lends support to the concept of reciprocal determinism in that changes in social network drinking were associated with changes in individual drinking, but higher individual drinking was also associated with higher social network drinking over time. Social learning theory is likely to be more relevant for formation of college social networks while social norms theories may apply more to the complex dynamics of established networks with some degree of overlap between components of each theory.

Social norms theory (also referred to as the *social ecology model*) as originally conceptualized by Perkins and Berkowitz (1986) can aid in understanding findings from studies on college social network drinking. Their theory suggests personal attitudes (i.e., liberal, moderate, conservative) towards drinking interact with perceptions of alcohol quantity consumed by typical students on campus to affect drinking behavior. Such that when students' attitudes towards drinking are congruent with their perceptions of how much they believe students are drinking on campus they tend to drink more than when discrepancies exist between their personal attitudes and perceptions of campus drinking behavior. Attitudes towards drinking as measured by participants rating their agreement to adjective pairs to describe drinking have been found to mediate the relationship between social network drinking and drinks per week consumed by individuals over time (Reid & Carey, 2018). It is worth noting that the proportion of total variance in drinking explained by alcohol attitudes was small suggesting there are other factors unaccounted for in relationships between social network drinking and individual consumption. Also, measures for attitudes differed significantly between the study which helped to validate social norms theory (Perkins & Berkowitz, 1986) and the study by Reid and Carey

(2018). The terminology (i.e., liberal, moderate, and conservative) used to describe personal attitudes towards alcohol use in the study by Perkins and Berkowitz (1986) today would be confused with descriptors of political parties and not easily understood within the context of drinking alcohol. Thus, replication of social norms theory including their measurement of attitudes is not advised. However, social norms theory only accounts for descriptive norms (e.g., perceptions of alcohol quantity being consumed by typical students at the same university). Hence, social norms theory neglects the role of injunctive norms (i.e., approval from friends for individual drinking) in explaining alcohol consumption among college students.

Rimal and Real (2005) extended social norms theory by Perkins and Berkowitz (1986) through their development and testing of their *theory of normative social behavior* (Real & Rimal, 2007; Rimal & Real, 2003). The theory of normative social behavior hypothesizes that the relationship between descriptive norms and individual alcohol consumption interacts with injunctive norms, expectations about the outcomes associated with drinking alcohol (i.e., social expectancies) and how closely students identify with members of their social network. This theory diverges from social norms theory in two key ways, by considering: 1) the role of injunctive norms, and 2) how relationships with social network members have the potential to affect alcohol consumption. For example, when students incorrectly perceive how much alcohol typical students or close friends are drinking this misperception can lead to increasing alcohol consumption as students attempt to drink at similar levels to what they believe is the norm on their particular campus. But when students believe that members of their social network are more approving of drinking behaviors (i.e., injunctive norms), expect more benefits for themselves in terms of socialization, and the individual feels more similar and look up to members to their group, the association between descriptive norms and consumption is expected to be stronger.

Indeed, we have seen in the social network drinking literature that when students perceive a larger proportion of their social network as drinkers (more specifically) heavy drinkers, they are more likely to drink heavily themselves (Hallgren & Barnett, 2016; Schaefer et al., 2021). Meanwhile, several social network qualities map on to the normative mechanisms proposed by Rimal and Real (2005) and have been found to be associated with alcohol consumption. Higher injunctive norms from social network members are associated with higher individual consumption (Kenney et al., 2018; Longabaugh et al., 2010). Although not examined in the social network literature, findings from Neighbors et al. (2007) suggest friend injunctive norms are associated with experiencing alcohol-related consequences when controlling for alcohol consumption implying injunctive norms as a normative mechanism may not only explain the relationship between descriptive norms and alcohol consumption but also the number of consequences students experience from drinking. Expectancies about receiving social benefits have also been found to mediate rather than moderate the relationship between the proportion of drinking buddies in a social network and alcohol outcomes (Lau-Barraco et al., 2012). Further, closeness and receiving emotional support from social network members is also related to alcohol consumption (Fujimoto & Valente, 2012; Tompsett & Colburn, 2019) although these social network qualities do not readily map on to the normative mechanism of group identity as defined by Rimal and Real (2005). Taken together, the framework provided by social learning and social norms theories help to explicate why perceptions of drinking behavior and qualities of social network members are associated with alcohol consumption and related consequences both cross-sectionally and over time.

Alcohol Use and ARC on Social Media

There are clear strengths in examining in-person social networks. However, it is important to recognize social interactions take place in online environments as well as in face-to-face contexts with both having the potential to expose individuals to peer drinking behaviors. Therefore, social network studies which ignore online exposure may be missing an important element of peer influence.

A burgeoning body of research conducted in adolescent and young adult populations has found associations between exposure to alcohol-related content (ARC, e.g., friends sharing photos with alcohol) on social media platforms and individual alcohol consumption, both cross-sectionally and longitudinally (for a systematic review, see Gupta et al., 2016; for a systematic review and meta-analysis, see Curtis et al., 2018). Longitudinal associations are similar among college students, with greater baseline ARC exposure associated with increased drinks per week six months later (Boyle et al., 2016). Further, in a study that followed adolescents from age 12 to 22, exposure to ARC (from various media sources including social media), alcohol descriptive norms, and frequency of alcohol use increased over time (Davis et al., 2019). Findings from Davis et al. (2019) highlight that young adulthood (i.e., adults aged 18 to 25, for a review see Arnett, 2000) may be a period when exposure to alcohol-related media is a risk factor for problematic drinking.

Similar associations have been observed between adolescents and young adults' own sharing of ARC on social media and alcohol consumption both cross-sectionally (Alhabash et al., 2020; Geusens & Beullens, 2016; Miller et al., 2014; Stoddard et al., 2012) and over time (Davis et al. 2021; Erevik et al., 2017). Geusens and Beullens (2017) found that greater self-reported drinking was linked to higher frequency of own sharing of ARC, positing drinking leads to social media sharing. However, more frequent exposure to ARC has been found to be related to subsequent more frequent personal sharing of ARC longitudinally (Erevik et al., 2018), suggesting that influence may work in the opposite direction, or be bidirectional in nature. Further, findings from Steers et al. (2019) revealed that participants continued to be heavy drinkers from sophomore year until one-year post-graduation, but they shared ARC less often over time, highlighting that as individuals transition out of young adulthood, this association may become less salient. Taken together, findings on the roles of personal sharing of and exposure to ARC suggest that each may be uniquely explaining alcohol consumption. Peer socialization versus selection theory as applied to alcohol use suggests that students may choose to socialize with peers that drink at similar levels to themselves (i.e., selection), or conversely that their consumption could be influenced by exposure to their peers drinking in-person or online via ARC (i.e., socialization; Samek et al., 2016; Windle & Windle, 2018).

It is important to note that most studies on ARC sharing and exposure have assessed subjective exposure (i.e., participants are asked to report on their exposure). Recently, LaBrie, Trager et al. (2021) found that objective ARC exposure (via objective time tracking and newsfeed sampling methods) was associated with college student alcohol use eight months later (controlling for prior drinking), replicating associations documented via subjective measures. Although individuals are typically connected with their in-person friends online, research on alcohol-related social media exposure often focuses exclusively on online content rather than who is sharing it, and studies using social network approaches often exclude assessments of online exposure. There is a dearth of research collecting detailed information on both online and in-person social ties to examine their influence on alcohol consumption among adolescents and young adults.

Perceived Norms and Social Media

Although there are several social media studies examining the association between exposure to ARC and individual alcohol use (see Curtis et al., 2018 for a meta-analysis), most do not collect specific information about who is sharing this content (i.e., social network methodology). Instead, social media studies more commonly assess descriptive and injunctive norms. In the context of social media studies, injunctive drinking norms (Geusens & Beullens, 2016; Nesi et al., 2017; Vranken et al., 2020) and descriptive drinking norms (Alhabash et al., 2020, Boyle et al., 2016; Brunelle & Hopley, 2017; Davis et al., 2019; LaBrie, Trager et al., 2021; Roberson et al., 2018; Vranken et al., 2020), are also assessed globally about groups of people (e.g., online friends, typical students) rather than specific individuals, frequently are either directly associated with individual alcohol use (Boyle et al., 2016; Davis et al., 2019) or mediate the relationship between exposure to ARC and individual alcohol use (Alhabash et al., 2020; Brunelle & Hopley, 2017; Geusens & Beullens, 2016; LaBrie, Trager et al., 2021; Nesi et al., 2017; Roberson et al., 2018; Vranken et al., 2020), both cross-sectionally and over time. Despite descriptive and injunctive drinking norms being commonly examined as predictors and mediators in social media studies, a recent study found that social network information (i.e., named specific peers' alcohol quantity and frequency) explained an additional 9.7% of the variance in individual alcohol use over and above typical student descriptive norms (Russell et al., 2020), suggesting the necessity of examining qualities of social network members sharing ARC online.

Social Network Information and Social Media

To date, only a handful of social media studies collected social network information about who is sharing the content ([sociocentric] Huang, Soto, et al., 2014; [egocentric] Cook et al., 2013; Huang, Unger et al., 2014) including qualities of alters or their relationships, such as: alcohol use status, smoking status, past month drinking (i.e., descriptive norms), acceptance of substance use (i.e., injunctive norms), if connected on specific social media platforms (i.e., Facebook, Myspace or both), risky content sharing (i.e., drinking alcohol or partying), frequency of in-person interaction, emotional closeness, discussion of substance use online (via online direct messaging), whether egos (i.e., participants) consider alters' opinions on substance use to be important, and demographics. Collectively, these studies generally found alter alcohol use status, in-person interaction, and emotional closeness with alters were associated with alcohol use among high school and college students (Cook et al., 2013; Huang, Unger, et al., 2014). Specifically, alcohol drinkers were likely to name more social ties and be named as important social ties from other network members indicating increased popularity. Students who used alcohol at similar frequencies were more likely to select each other as best friends (Huang, Soto, et al., 2014). Further, having a higher number of social network members sharing alcohol-related content was associated with individuals indicating past month alcohol use (Huang, Unger, et al., 2014). These studies demonstrate that qualities of individuals (who are connected online and in-person) included in one's social network have a strong link to individual alcohol use and may be worthwhile to examine as moderators of the relationship between exposure to ARC and consumption.

Among studies which assessed social media use behaviors by social network members, having more network members sharing risky content on social media (e.g., showing partying or drinking alcohol) was associated with individual tobacco use (Huang, Soto et al., 2014). Also, friendships were more likely to exist between members who had similar frequencies of exposure to risky content (Huang, Soto, et al., 2014). Alcohol usage by best friends moderated the relationship between having more social network members sharing photos (but not text) in which they were engaging in risky health behaviors and individual alcohol use. In other words, individuals who had fewer social network members who they drank with in-person were more likely to be influenced by the risky photo content shared by social network members (Huang, Unger, et al., 2014). These findings suggest specific qualities of social network members matter. Given prior work on how the relationship qualities of network members impact alcohol use, other qualities of relationships (e.g., emotional closeness, drinking buddy status) may also moderate the relationship between exposure to ARC and individual alcohol use and consequences experienced among college student populations.

Limited research has examined the stability of ARC exposure or online social networks of named specific peers over time and how this relates to individual alcohol use (Huang, Unger et al., 2014), but miss critical components of concern (e.g., focused on only two social media platforms, limited examination of alcohol use [ever drank versus not]), suggesting need of further examination. Social media studies that longitudinally examined associations between exposure to ARC and substance use among high school students found that having more friends who share ARC was associated with increased alcohol or cigarette use six or 12 months later (Huang Soto et al., 2014; Huang, Unger et al., 2014). Additionally, when specific sociocentric social network information was examined among high school students over six months, friend groups became more homogenous based on alcohol and tobacco use (Huang, Soto et al., 2014). Investigating changes in social network composition over time among college students, associated changes in ARC shared by network members, and alcohol outcomes could shed light on which qualities of social network members and their relationship to the individual may be considered risk factors for problematic alcohol consumption among college drinkers, which has not yet been examined.

Modalities of ARC

Although alcohol-focused social media studies sometimes assess modality (i.e., photos, text, videos), and could examine if modality moderates the associate between exposure and alcohol outcomes, this is often not done. Commonly, surveys may mention modality without assessing it, or if modality was assessed it was not reflected in the variables used for analysis. Modality assessments in ARC exposure studies often mention specific modalities or even list multiple modalities in their survey instructions but include only a single item that does not differentiate exposure across modality type. For example, studies include items such as "How often do you see text or pictures posted by peers related to alcohol, drinking, being drunk or hung-over when you check [platform name]?" (Boyle et al., 2016) or "What percentage of your Facebook friends display or post alcohol references on Facebook [for example, posting pictures of themselves drinking or status updates describing drinking experiences]?" (Geusens & Beullens, 2017; Steers et al., 2019). A few studies assessed exposure in a way that would allow for examinations across separate modality types (i.e., separate questions for different modalities), but then combined across modalities to create a general exposure variable that loses this differentiation. For example, studies include items like "How often do your friends share…1) photos or movie clips referring to alcohol use, 2) textual updates referring to alcohol use, etc." (Geusens & Beullens, 2016; Stoddard et al., 2012), or "Of the photos your friends have posted on Facebook, what percentage relate to alcohol?" versus a similar item about text (Miller et al., 2014). These items were combined to create an overall exposure variable. Although modality of exposure is mentioned or even assessed in many alcohol-focused social media studies, most studies do not examine this facet of exposure.

Only one study to date has examined the associations between exposure to specific social media content modalities and alcohol use. In an egocentric specific network study among high school students, Huang Unger et al., (2014) found that adolescent drinking was predicted by social media exposure to friends sharing photos of partying or drinking but not friends writing about partying online (i.e., text-only status updates), suggesting the importance of assessing specific modalities when examining social media content. In this study, participant drinking was assessed through asking about age of first drink, past year drinking intentions, past month drinking frequency, and past month heavy drinking frequency. These items were dichotomized to represent alcohol use status as never drank versus ever drank.

Huang, Unger, et al. (2014) was the first social media study to distinguish between modalities and collect specific social network information and made a major novel contribution to the literature. However, they dichotomized alcohol outcomes into a binary status (never drank versus ever drank) which provided less information about how modality and ARC exposure are associated with alcohol outcomes than would using the original, more precise alcohol items (e.g., age of first drink, drinking frequency and intentions) they collected, suggesting the need for a more fine-grained alcohol use assessment. Also, partying and drinking were combined in the response options, suggesting the need to assess exposure to content depicting alcohol use specifically; moreover, the study focused on content shared via photos versus text, leaving the effects of videos featuring alcohol unexamined. Further, examinations should include a more fine-grained alcohol use assessment, isolation of exposure to ARC (rather than including "partying" in general), and broader modality assessments to include videos. Given the distinction revealed between the effects of exposure to photo ARC versus text ARC, there is clearly a need to understand how specific modality of ARC shared on social media by specific close friends (i.e., their social network) helps to explain the relationship between ARC exposure and consumption in college populations. Further, Huang, Unger, et al. (2014) did not examine the effects of viewing video ARC on alcohol outcomes, suggesting the need to examine this modality as well. Finally, modality of ARC shared by specific friends on social media has been unexamined in young adult or college populations.

Summary

Taken together, exposure to alcohol-related content (ARC) on social media is associated with greater drinking across several different assessment methods, indicating a robust relationship. Findings from college social network drinking studies suggest qualities of the peers in one’s social network may be risk factors or protective factors for drinking, indicating it is important to incorporate social network assessment in studies of this phenomenon. Modalities of exposure to specific social media content may strengthen this relationship, reflecting modality as a potentially important moderator. Further, exposure to ARC appears to be associated with increased alcohol use over time when assessed longitudinally. Although the association between ARC exposure and drinking is well established in the literature, there are still several questions yet unexamined which may help explain this relationship: 1) how qualities of specific network members may moderate relationships between exposure and use, 2) effects of exposure to specific modalities of ARC on consumption, and 3) how changes in in-person and social media networks are associated with changes in exposure to content over time.

Study Purpose

The proposed research study was the first to address the dearth of research on the intersection between in-person and social media social networks and ARC exposure on problematic college drinking using a longitudinal survey design. College drinkers completed three online surveys over the course of three months, assessing their individual alcohol use and alcohol-related consequences as well as their own social media use behavior. These drinkers were also asked to list members of their close social network during each timepoint of data collection and whether each person shares ARC on social media (including content modality and frequency of sharing). In this study, I also investigated which content modalities had the strongest relationship with consumption and related consequences across a variety of social media platforms; the longitudinal survey design also elucidated whether qualities of relationships with network members who shared ARC sharing were associated with consumption. In all, the current study was a necessary first step in bridging the gap between the social network analysis and social media bodies of literature for college drinking.

Specific Aims

Aim 1

To determine if changes in frequency of participant sharing of ARC on social media over time affected consumption/consequences. Although the cross-sectional relationship between personal sharing of ARC and consumption is well established (Alhabash et al., 2020; Geusens & Beullens, 2016; Miller et al., 2014; Stoddard et al., 2012) no studies have examined how sharing this content is associated with alcohol-related consequences. Further, only two studies have examined how this relationship prospectively, finding more frequent sharing is associated with greater drinking frequency (Davis et al., 2021; Erevik et al., 2017) and a greater likelihood of hazardous or harmful alcohol consumption as measured by the Alcohol Use Disorders Identification Test (AUDIT; Saunders et al., 1993). Given the lack of the limited examinations of this relationship prospectively, in the current study, I investigated how changes in the frequency of participants sharing ARC was associated with changes in consumption/consequences both cross-sectionally and over time.

Hypothesis 1a. It was hypothesized that sharing ARC more frequently would be associated with greater (cross-sectionally) individual alcohol consumption and related consequences (see Figure 1).

Hypothesis 1b. It was hypothesized that sharing ARC more frequently would be associated with increased (longitudinally) individual alcohol consumption and related consequences (see Figure 2).

Aim 2

To determine if the proportion of social network members sharing ARC impacts consumption/consequences over time. Whereas the cross-sectional relationship between exposure to ARC shared by close friends and alcohol consumption is well-established (Alhabash et al., 2020; Erevik et al., 2017; Erevik et al., 2018; Geusens & Beullens, 2016; Geusens & Beullens, 2017; Miller et al., 2014; Roberson et al., 2018; Stoddard et al., 2012), longitudinal examinations have been limited. Although five social media studies have longitudinally examined the relationship between exposure to ARC shared by close friends on social media and alcohol use, none of these studies gathered specific social network information among college samples, or used sensitive, in-depth measures. In the current study, I investigated 1) whether the proportion of social network members sharing ARC was associated with consumption and consequences (cross-sectionally) and 2) whether the proportion of social network members sharing ARC impacted college drinking over time. Figures 1 and 2 for H1a and H1b, respectively, conceptually represent H2a and H2b as well, except that the novel predictor variable instead reflects the proportion of social network members sharing ARC.

Hypothesis 2a. It was hypothesized that having a greater proportion of social network members sharing ARC would be associated with greater individual alcohol consumption and related consequences cross-sectionally.

Hypothesis 2b. It was hypothesized that having a greater proportion of social network members sharing ARC would be associated with increased individual alcohol consumption and related consequences over time.

Aim 3

To examine how modality of ARC shared by social network members was associated with alcohol consumption/consequences. The impact of general exposure to ARC being shared on social media platforms is well-documented (Brunelle & Hopley, 2017; Cook et al., 2013; Roberson et al., 2018), but examining modalities can reveal if some content is more impactful than others on individual alcohol consumption. Although some studies have assessed modality, this has not been reflected in the variables used for analysis. However, there is evidence that modality matters; prior research found adolescent drinking was predicted by prior social media exposure to friends sharing photos of partying or drinking but not friends writing about partying online (i.e., status updates; Huang, Unger et al., 2014; Huang, Soto et al., 2014). Thus, in the current study, I examined how exposure to specific ARC modalities shared by specific social network members was associated with college drinking and related negative consequences.

Hypothesis 3a. Exposure to photos and videos depicting alcohol or its effects shared by social network members would have a stronger association with greater individual alcohol consumption and related consequences than exposure to text-only status updates. See Figure 3.

Hypothesis 3b. Increases in number of social network members sharing photos and videos would have a stronger association with increases in individual alcohol consumption and related consequences over time than increases in text-only status update exposure. See Figure 4.

Aim 4

To investigate whether qualities of relationships with social network members sharing ARC were associated with associations alcohol consumption and negative consequences after controlling for overall network proportions of these qualities of relationships. Previous research has identified specific qualities of relationships (e.g., emotional closeness, drinking buddy status) with network members that are associated with individual drinking behavior (Cook et al., 2013; Fujimoto & Valente, 2012; Lau-Barraco et al., 2012; Lau-Barraco & Linden-Carmichael, 2014; Leonard et al., 2000; Leonard & Homish, 2008; Tompsett & Colburn, 2019). To date, one study has examined the effects qualities of social network members sharing ARC and associations with individual alcohol use in a high school sample (Huang, Soto et al., 2014; Huang, Unger et al., 2014). Huang, Unger et al. (2014) found that high school students who had fewer network members who they drank with in-person were more likely to be influenced by the risky content shared online by specific social network members and this was associated with individual alcohol use. In the current study, I investigated whether the intersection of ARC sharing and qualities of social ties (i.e., relationships with the individuals sharing the content) was associated with consumption and negative consequences, above and beyond those social tie qualities in the overall network, which is underexamined in college populations. For example, I explored whether the participant being close with their network members sharing this content was associated with use and consequences or if exposure to content or general closeness with their overall network was affecting use and consequences.

Hypotheses 4a and 4b. Closeness ratings for social network members sharing ARC would be positively associated with individual alcohol consumption and related consequences, over and above overall network closeness and proportion of network sharing this content, both cross-sectionally (H4a, see Figure 5) and over time (H4b, see Figure 6).

Hypotheses 4c and 4d. Exposure to ARC shared by drinking buddies would be positively associated with consumption/related consequences, even when controlling for overall network proportion of drinking buddies and proportion of network sharing this content, both cross-sectionally (H4c) and over time (H4d). Figures 5 and 6 for H4a and H4b conceptually represent H4c and H4d as well, except that the novel predictor variable instead reflects the proportion of drinking buddies sharing alcohol-related social media content.

Aim 5

To determine if changes in participant consumption/consequences were associated with changes in self-sharing of ARC and social network qualities over time. There have been consistent associations between exposure to ARC and alcohol outcomes among college students (Alhabash et al., 2020; Erevik et al., 2017; Erevik et al., 2018; Geusens & Beullens, 2016; Geusens & Beullens, 2017; Miller et al., 2014; Roberson et al., 2018; Stoddard et al., 2012). Similarly, links between participants sharing ARC and alcohol outcomes are also well-established (Alhabash et al., 2020; Geusens & Beullens, 2016; Miller et al., 2014; Stoddard et al., 2012). However, longitudinal investigations of both participants sharing and exposure ARC on alcohol outcomes are limited (Boyle et al., 2016; Davis et al., 2021; Erevik et al., 2017). More importantly, these investigations have predominantly examined prospective associations in one direction (i.e., how participant sharing or exposure affects drinking). There is some evidence to suggest that these relationships may be bidirectional. For example, Geusens and Beullens (2017) found that greater alcohol use was linked to greater participant sharing of ARC over time. One longitudinal social network study has also found links between higher participant consumption and larger proportions of social network drinking (Hallgren & Barnett, 2016). Therefore, in the current study, I examined if the influence goes from participant consumption/consequences to participants sharing content (the opposite direction of influence from Aim 1) or to social network qualities such as sharing ARC (the opposite direction from Aim 2) over time. I also examined if consumption prospectively predicted modality of content shared by the social network (the opposite direction from Aim 3), or qualities of relationships with social network members such as drinking buddy status or closeness with members who share ARC (the opposite direction from Aim 4). There are no specific hypotheses for these associations because there is a dearth of examination for this direction of influence in the literature. Significant paths supporting this direction of influence would support that the relationships are bidirectional (if Aims 1, 2, 3, or 4 are significant) or that the direction of influence was counter to what was expected (if Aims 1, 2, 3, or 4 are not significant).

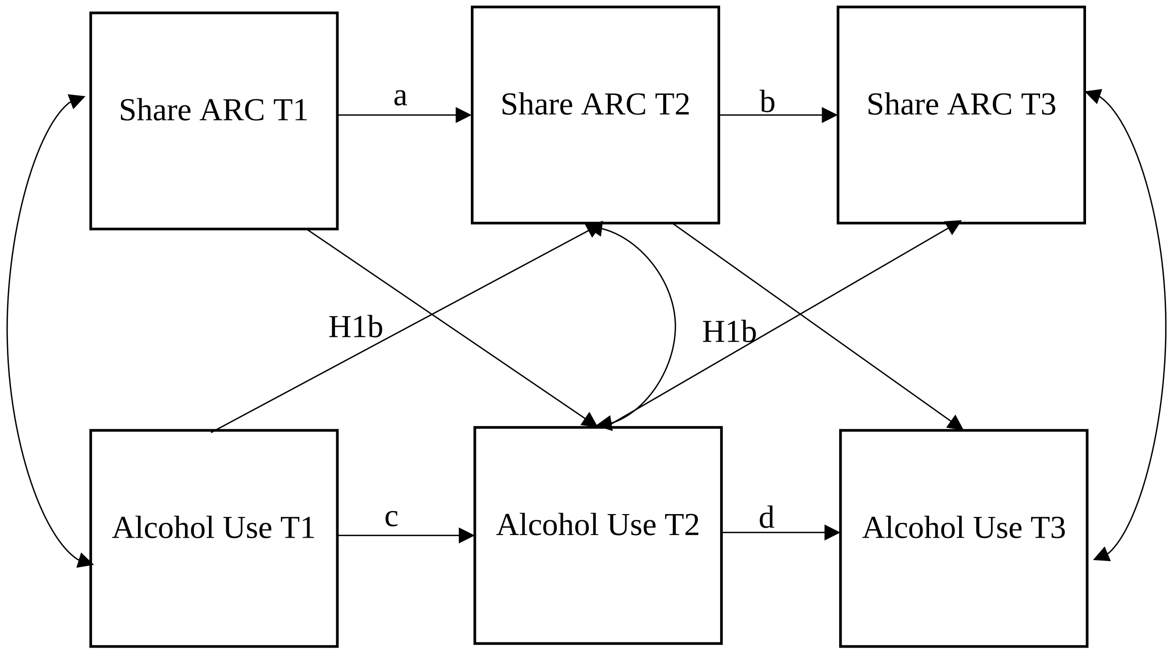
Figure 1

Cross-sectional Associations between Participants Sharing of ARC and Alcohol Use

Note. Hypothesis 1A (H1a): Participants sharing alcohol-related content (ARC) on social media will be associated with individual alcohol consumption and related consequences (examined in separate models, only use is shown above). Not pictured are the covariates included in this model (sex, frequency of checking social media, and typical quantity [only in consequences model]).

Figure 2

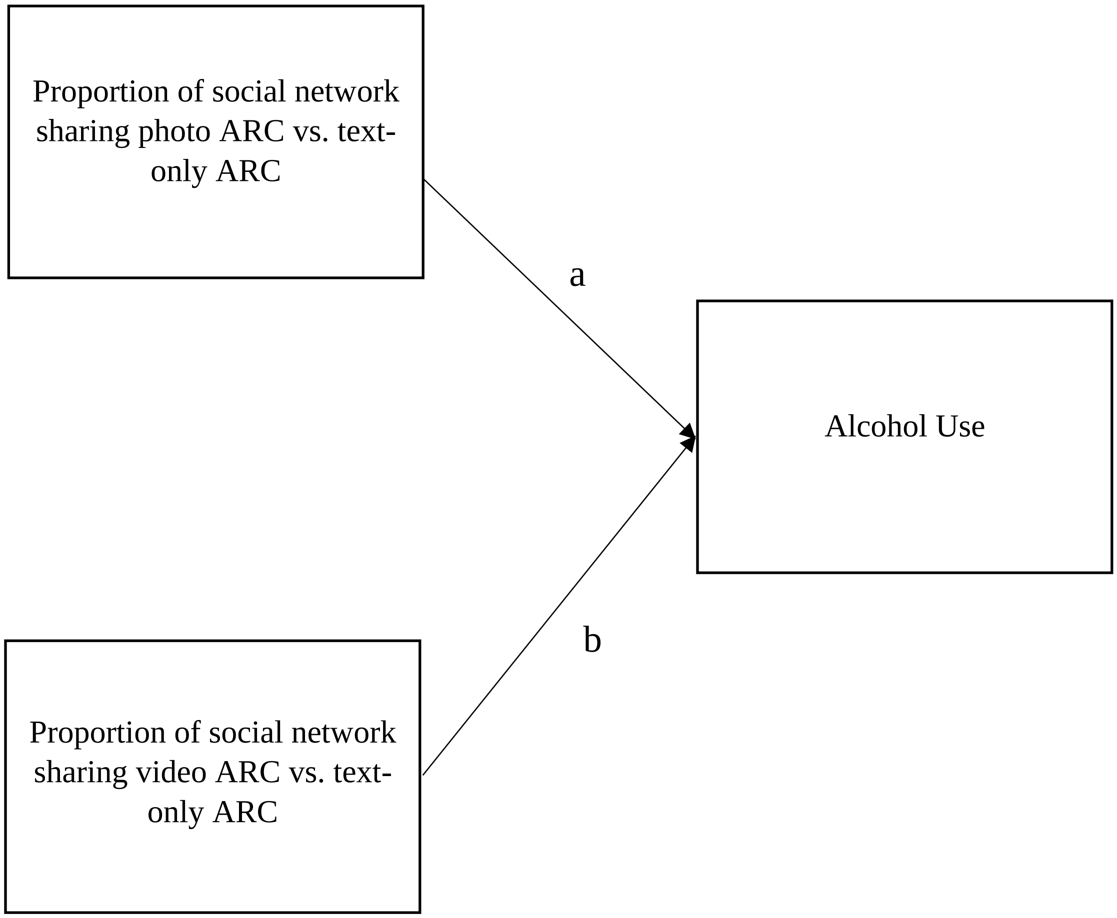
Longitudinal Associations between Sharing ARC and Alcohol Use



Note. Hypothesis 1 (H1): Changes in the frequency of sharing alcohol-related content (ARC) on social media over time affects consumption or consequences (examined in separate models, only use is shown above). The auto-regressive and cross-lagged paths are labeled for the purposes of invariance testing, as noted in the Analysis Approach section below. T# = Time point. Not pictured in this model are the covariates of participant sex, frequency of checking social media, and typical quantity (only in consequences model).

Figure 3

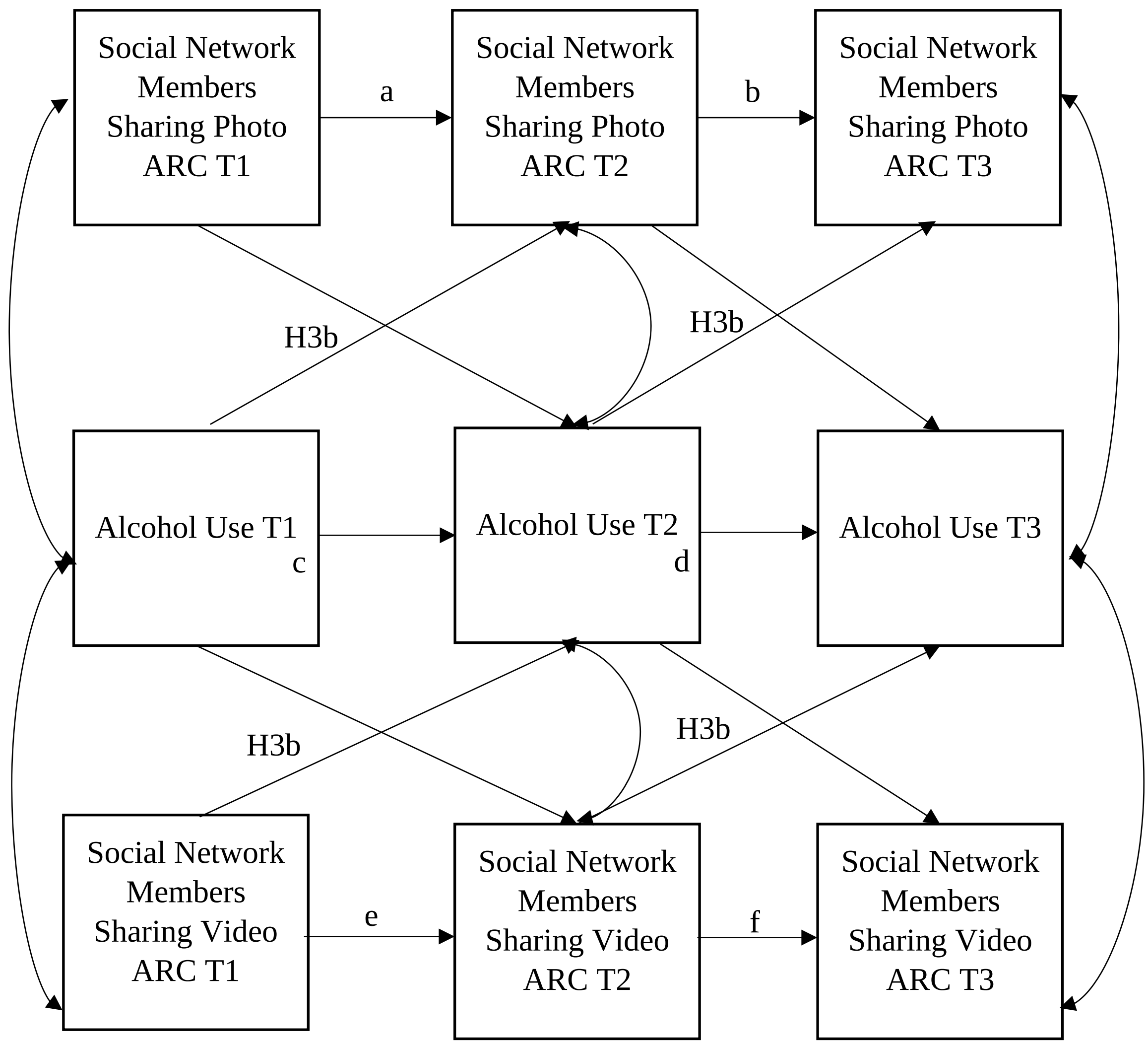
Cross-sectional Associations between Exposure to Various Modalities of ARC Shared by Network Members and Alcohol Use



Note. Hypothesis 3a (H3a): a > b. Exposure to photos and videos vs. text-only content depicting alcohol (ARC) or its effects shared by social network members will be associated with greater individual alcohol consumption and consequences (examined in separate models, only use is shown above). Not pictured in this model are the covariates of participant sex, frequency of checking social media, and typical quantity (only in consequences model).

Figure 4

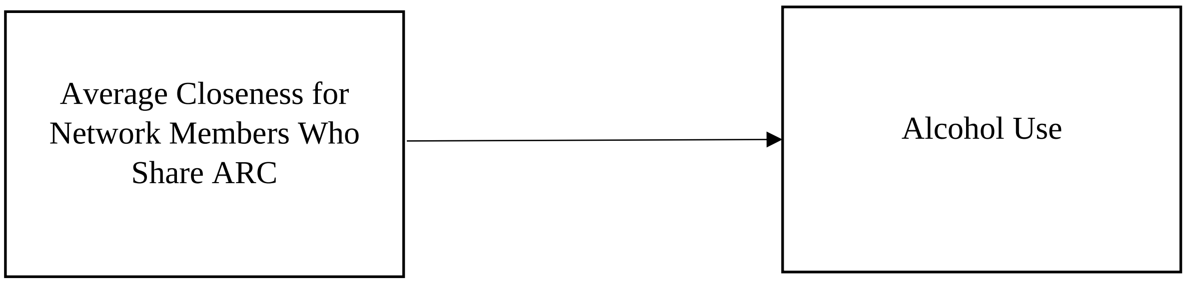
Longitudinal Associations between Network Members Sharing Alcohol-related Photos, Videos, Text and Alcohol Use



Note. Hypothesis 3b (H3b): Changes in the proportion of network members sharing alcohol-related photos and videos (ARC) rather than text-based status updates on social media over time affects consumption or consequences (examined in separate models). T# = Time point. Not pictured in this model (for clarity) are the proportions of the social network sharing text at each time point, select within-time correlations, as well as the covariates of participant sex, frequency of checking social media, and typical quantity (only in consequences model).

Figure 5

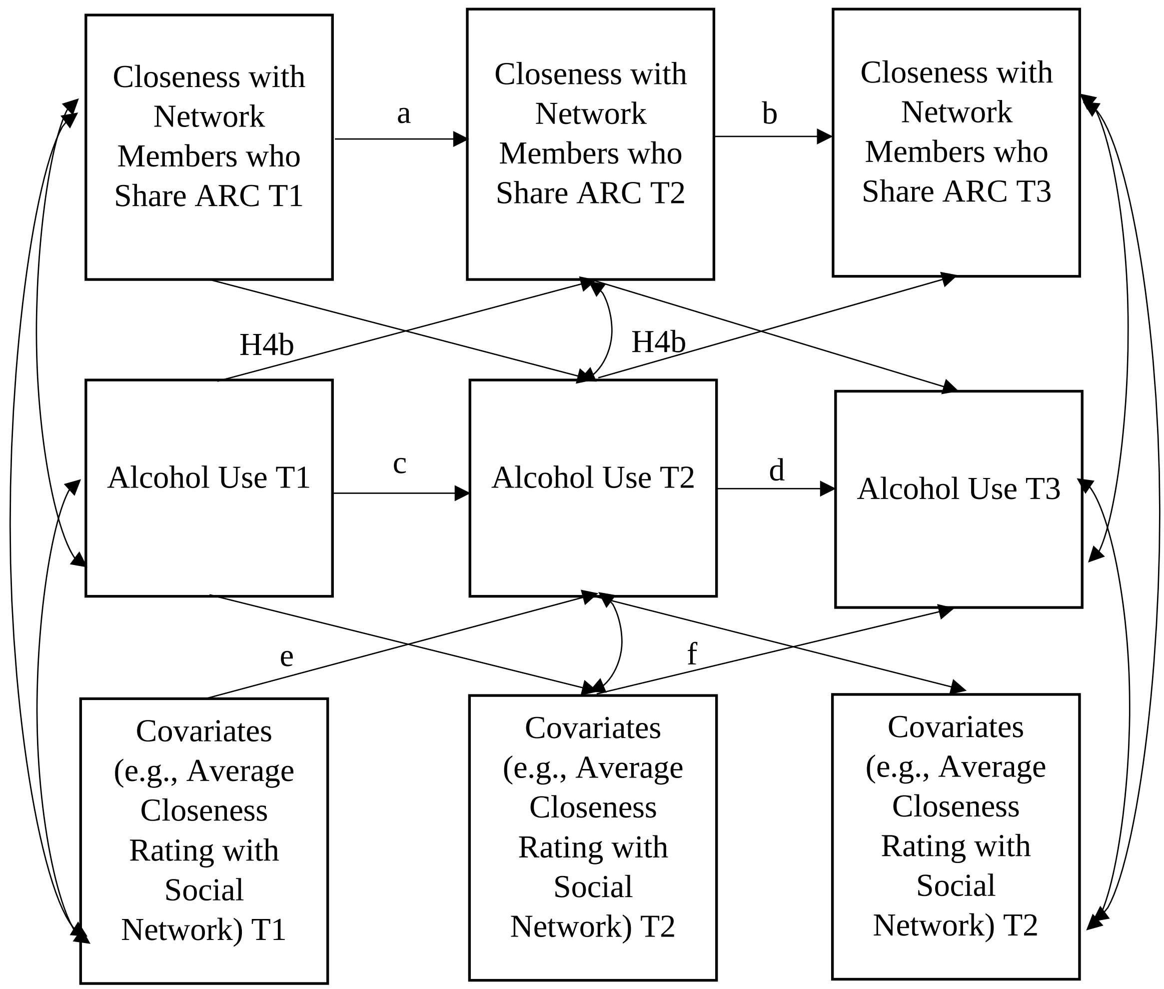
Cross-sectional Associations between Closeness for Network Members Sharing ARC and Alcohol Use



Note. Hypothesis 4A (H4a): Average closeness with social network members who share alcohol-related content on social media (ARC) will be associated with individual alcohol consumption and related consequences (examined in separate models, only use is shown above). Not pictured are the covariates included in this model (average closeness rating for network members, proportion of network members sharing alcohol-related content, participant sex, frequency of checking social media, and typical quantity [only in consequences model]).

Figure 6

Longitudinal Associations Between Closeness with Network Members Sharing ARC and Alcohol Use



Note. Hypothesis 4b (H4b): Average closeness with social network members who share alcohol-related social media content (ARC) will be associated with individual alcohol consumption and related consequences (examined in separate models, only use is shown above) over time, controlling for covariates (average closeness rating with social network, proportion of social network members sharing ARC, participant sex, frequency of checking social media, and typical quantity [only in consequences model]). Not pictured in this figure is the cross-sectional correlation between average closeness with network members who share ARC at Time 2 and

Figure 6 (*continued*)

average closeness with social network at Time 2. This correlation will be included in the model but was omitted from the figure for clarity. Additionally, not all associations between covariates and predictors and/or outcomes are pictured but will be included in the model as detailed in the Analysis Approach section. T# = Time point.

CHAPTER II

METHOD

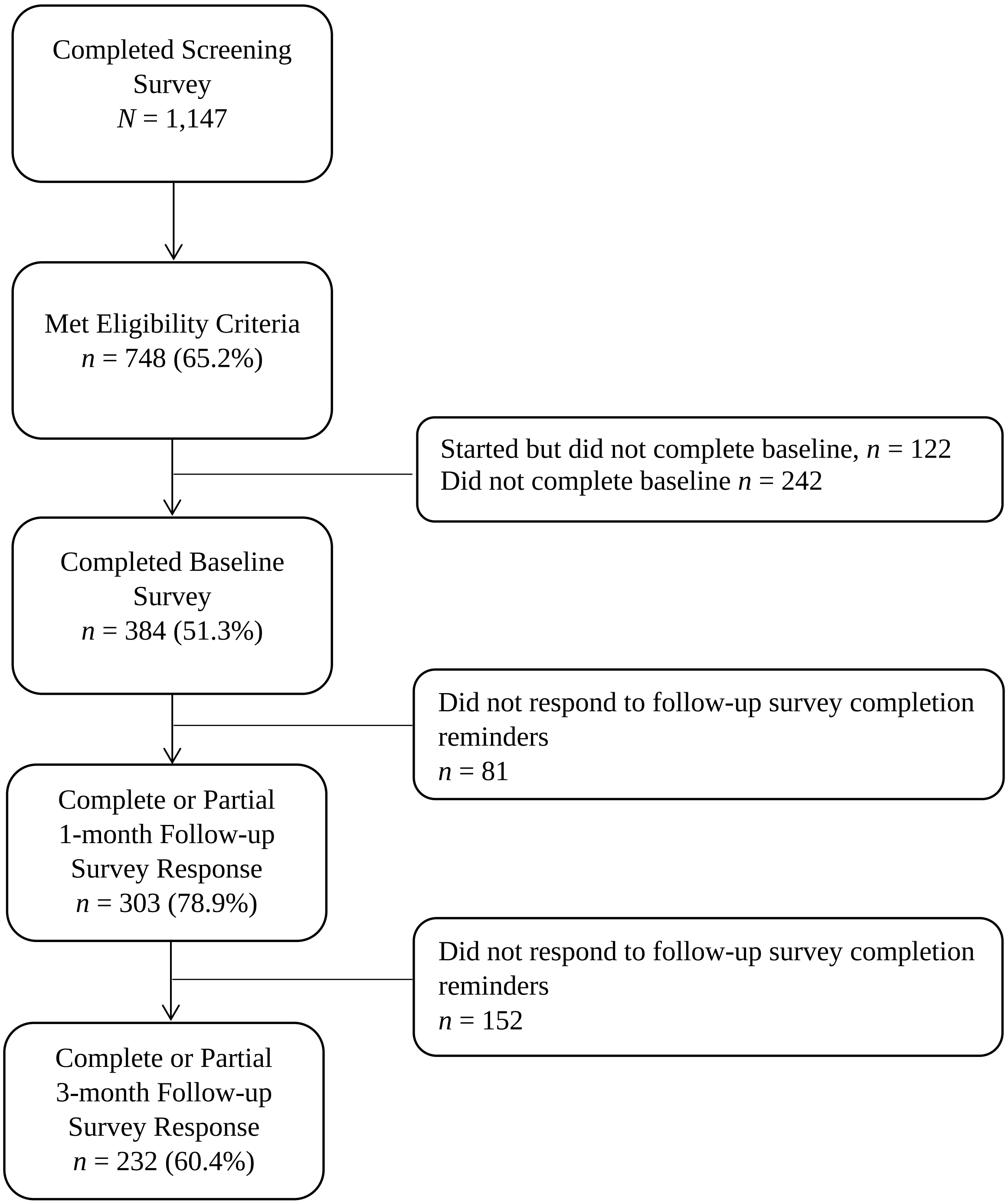
Participants

Participants were 384 undergraduate college drinkers (see power analysis section below). Participants were recruited from William & Mary University through mass emails to the general student body. Although recruiting from two universities was originally proposed, due to non-response from potential participants at Old Dominion University over the first few weeks of recruitment, this recruitment site was dropped. Recruitment materials included a brief description of the study (i.e., that it was interested in examining social media use, peer networks, and drinking behavior among college students). The recruitment materials also informed students this was a three-part study that consisted of completing three 30-minute online surveys over the course of three months (baseline, 1-month, 3-month), and that compensation would be provided (see Compensation section below).To be eligible, participants had to 1) be between the ages of 18-25 (more likely to engage in heavy episodic drinking and use social media; Heron et al., 2019; Hingson et al., 2017), 2) have an active account on at least one social media platform, 3) have consumed alcohol on at least 2+ days in the past 30 days, and either 4a) have consumed 4+/5+ alcoholic drinks (for women/men) on at least one drinking occasion in the past 30 days, or 4b) have experienced at least one negative consequence related to drinking alcoholic beverages in the past 30 days. These criteria were chosen to reflect emerging adults who drink regularly and are heavy or problematic drinkers, in addition to being active on social media.

In total, 1,147 individuals completed the screening survey (see Figure 7). Of those who completed the screening survey, 65.2% were eligible to participate in the current study and 51.3% of those who were eligible completed the baseline survey. Of those who completed the baseline survey, 78.9% fully or partially completed the 1-month survey and 60.4% fully or partially completed the 3-month survey.

Figure 7

Recruitment Flow Across Timepoints



Note. Completing baseline allowed participants to skip items but participants had to reach the end of the survey and provide contact information to be eligible for the follow-up surveys.

For the complete baseline sample (*N* = 384), participants were on average 20.04 years old (*SD* = 1.26), mostly identified as female (69.3%) with 74.2% reporting their biological sex was female, and the majority identified as White (79.6%). For more details, see Table 1.

Table 1

Demographic Information for Full Baseline Sample

Variables	*M* (*SD*)
Age	20.04 (1.26)
GPA	3.24 (1.05)
	n (%)
Gender Identity	
Man	90 (23.4)
Woman	266 (69.3)
Nonbinary/genderqueer/genderfluid	27 (7.0)
Other	1 (0.3)
Sex	
Male	99 (25.8)
Female	285 (74.2)
Ethnicity – Hispanic or Latino/a/x	
Yes	36 (9.4)
No	348 (90.6)
Racial Identity	
Black	18 (4.7)
Asian	35 (9.2)
Hawaiian Native and/or Pacific Islander	1 (0.3)
White	304 (79.6)
Middle Eastern or North African	2 (0.5)
Other	22 (5.8)
Class Year	
Freshman	84 (21.9)
Sophomore	86 (22.4)
Junior	105 (27.3)
Senior	96 (25.0)
Graduate	4 (1.0)
Transfer	5 (1.3)
Other	4 (1.0)
Typical Grades	
Mostly A’s	236 (61.6)
Mostly B’s	107 (27.9)
Mostly C’s	10 (2.6)
Mostly D’s	0 (0.0)
Mostly F’s	0 (0.0)
I don’t know yet	30 (7.8)
In-state or Out-of-state Student Status	
In-state	252 (65.6)
Out-of-state	132 (34.4)
Sexual Identity	

Table 1 (*continued*)

Variables	*n* (%)
Gay	21 (5.5)
Lesbian	23 (6.0)
Bisexual	119 (31.0)
Queer	44 (11.5)
Asexual	11 (2.9)
Pansexual	10 (2.6)
Questioning	25 (6.5)
Heterosexual/Straight	206 (53.6)
Other	2 (0.5)
Suspect Mother Had a Drinking Problem	
Yes	42 (11.0)
No	341 (89.0)
Suspect Father Had a Drinking Problem	
Yes	97 (25.3)
No	286 (74.7)
Greek Life Involvement	
A current member	111 (28.9)
Currently pledging	12 (3.1)
Not a member, but regularly or occasionally attend Greek social events	109 (28.4)
Not a member, and do not attend Greek events	142 (37.0)
Deactivated (former member)	10 (2.6)

Note. Sex was coded 0 = *female* and 1 = *male*. Percentages for sexual identity do not add up to 100% because participants were allowed to select all that applied.

Procedure

Overview

Data collection began in March 2022 and was completed in March 2023. The current study consisted of participants completing three online surveys (for a summary of measures included, see Appendix A) over the course of three months (i.e., baseline, 1-month, 3-month). Although originally planned for baseline, 6 weeks, and 12 weeks, the survey management software did not allow for a week-based schedule, and so this was adjusted to baseline, 1-month, and 3-months to be compatible with the survey platform. Several studies have observed variability in social network composition and alcohol-related social media content exposure, respectively, when using similar follow up periods and intervals between follow-up assessments have been used in several studies (two time points, 6-month interval, Boyle et al., 2016; three time points, 3-month intervals, Graupensperger et al., 2020; two time points, 6-month interval, Huang, Unger, et al., 2014). In the initial correspondence (i.e., recruitment email, posted announcement) a link was included for an online screening survey (see Appendix B) to determine eligibility and collect their William & Mary email address. To discourage participants from re-taking the screening survey, several unrelated distractor items were included. Participants were screened until target enrollment was reached (see power analysis section below). Eligible participants were given the choice to complete the baseline survey immediately after completing the screening survey or were asked if they would like to receive an email later with the link to complete their baseline survey. The first page of the baseline online survey displayed the consent form (see Appendix C) which told participants that the purpose of this study was to examine changes in social media exposure, social networks of peers, and drinking behavior among college students over time and that participation in this study would involve completing three 30-minute surveys over the course of three months (i.e., baseline, 1-month, 3-month). To continue and complete the baseline survey, participants indicated that they would like to participate by typing their name in a box at the end of the consent form and then clicking the arrow button at the bottom of the first page of the baseline survey acknowledging they had read and understood the consent form. In each survey (see Appendices D-I), participants were asked about their social media usage, specific members of their social network (and qualities of each individual, including their social media posts), alcohol consumption, alcohol-related consequences, contact information (only at baseline), and demographics (only at baseline). Contact information (i.e., email address that participant checks most often) was collected so that Qualtrics could be used to send emails to participants which included Qualtrics-generated unique survey links for each participant to ensure the data was automatically linked across the three surveys. Several types of correspondence between the researcher and participants took place over the course of the study (see Appendix J for all correspondence with participants). Reminders to complete each survey were be sent every two days via text message (if selected by the participant) and email (using the preferred email address and phone number provided in the baseline survey) for a period of up to two weeks (or until the appropriate survey was completed).

Compensation

Participants were given the option to receive either a $5 Amazon gift card, $5 added to their Tribe Card (student) account, or a raffle entry to win one of five $10 Amazon gift cards or one for $50 after completing each of the three surveys, and received an additional $5 bonus or additional raffle entry they completed all three surveys. Thus, there was a max of $20 in direct payments or participants could win up to $40 or $200 depending on raffle amount chosen). There were 24 total raffles (6 for each wave of data collection, and 6 for the bonus).

This compensation structure (i.e., $5 Amazon gift cards for each survey completed) was consistent with a prior longitudinal study of social networks and drinking with college athletes which achieved 77% retention of those enrolled (Graupensperger et al., 2020). Additionally, raffle incentives have been used to successfully recruit and retain participants for survey designs both cross-sectionally (Laguilles et al., 2011) and longitudinally (Göritz & Wolff, 2007). Across four surveys, Laguilles et al. (2011) yielded response rates averaging 55.5% for participants offered raffle entry as incentive; raffle incentives ranged from $50 gift cards for the dining hall on campus to an iPod touch. A four-wave longitudinal survey study demonstrated that those who participated in the first survey with a raffle incentive or no incentive had high retention for follow-up surveys with the same incentive structure (Göritz & Wolff, 2007). In the study conducted by Göritz and Wolff (2007), college students were randomly assigned to either be entered in a raffle to win one of five 20-euro gift certificates or no incentive. Participants who completed the first survey were invited to complete the second survey (sent one month later) and participants who completed the second survey were invited to complete the third survey (sent one year after survey two) and this same process was used for the fourth survey (sent one year after survey three). Of the participants invited to participate in each wave, retention rates (averaged across all four waves) for the raffle incentive participants (90.7%) were slightly higher than the no incentive participants (87.9%).

Measures

At each timepoint, participants completed a series of questionnaires about their alcohol consumption, alcohol-related consequences experienced, members of their social network (and qualities of each member), individual social media usage, and demographics (only during the baseline survey). For any questions which used branching logic, time-balance items were included to ensure surveys were the same approximate length for all participants. Additionally, four attention check questions (e.g., “Please select ‘Agree’ for this item”) were included throughout the questionnaires as they have been found to help identify participants who are satisficing (i.e., not fully reading items in questionnaires) which can decrease statistical power (Maniaci & Rogge, 2014; Oppenheimer et al., 2009). Participants who were found to be satisficing at any time point were reminded to read items carefully via live feedback automatically generated during the survey if they responded with an incorrect answer to one of the attention check questions. Participants had to select the correct response for each attention check item in order to proceed with completing the survey.

Alcohol Consumption

Participant alcohol consumption was assessed using a modified version of the Daily Drinking Questionnaire (DDQ; Collins et al., 1985; see Appendix C). Participants were presented with a chart describing standard drink amounts based on type of alcoholic beverage. They were asked to consider a typical week in the past 30 days and report how many standard drinks they had each day and how many hours they spent consuming those drinks using a series of drop-down menus for each day of the week. This measure was used to calculate alcohol quantity by summing the number of drinks consumed in a typical week. The DDQ has been demonstrated to have adequate convergent validity with other measures of alcohol consumption among college students as well as good reliability based on collateral reports on participant drinking behavior from their friends or roommates (Collins et al., 1985; Marlatt et al., 1998).

Alcohol-related Consequences

The Brief Young Adult Alcohol Consequences Questionnaire (B-YAACQ; Kahler et al., 2005; see Appendix D) was used to assess the number of negative consequences experienced while drinking alcohol in the past 30 days. The B-YAACQ consists of 24 items presented as a checklist where participants endorsed which items they experienced. One item was added for 'none of the above' if a participant had not experienced any consequences related to drinking alcohol. A total score was then computed by summing the number of endorsed responses for the 24 items. Higher scores indicated that participants had experienced more negative consequences associated with drinking alcohol in the past 30 days. The B-YAACQ has been shown to have good internal consistency among college student samples, convergent validity with other measures of alcohol consequences, and test-retest reliability (Kahler et al., 2005; Kahler et al., 2008).

Social Network

Social network characteristics were assessed using a modified, briefer version of the Important People Interview (IPI; Clifford & Longabaugh, 1991). The IPI was modified to create the Brief Important People Interview (BIPI; DeMartini et al., 2013; Zywiak et al., 2002; Zywiak & Longabaugh, 2002) for use in studies which examined perceived levels of support for drinking in adult alcohol treatment seeking samples (Anton et al., 2006; Project Match Research Group, 1998). The IPI was changed in the following ways to create the BIPI: shortened to only ask questions which were most predictive of treatment outcomes in the COMBINE and Project Match studies (e.g., network member drinking status, reactions to drinking; Anton et al., 2006; Project Match Research Group, 1998), format was changed from an interview to a computerized questionnaire (Hallgren & Barnett, 2016), and some questions were changed to make the questionnaire more relevant for college students (DeMartini et al., 2013; Reid et al., 2015). For example, the question "How has this person reacted to your drinking? 1 = *Encouraged to* 4 = *Left, or made you leave when you were drinking*" was changed to "How accepting would this person be if you decided to drink much less? 1 = *Not very accepting* to 4 = *Very accepting*".

In the current study, the BIPI was modified further such that instead of asking participants to name 10 network members as in the original BIPI, participants identified five network members. Previous research has found administering a version of the IPI asking for five network members versus 10 network members yields similar variability in score distributions for network drinking, percentage of drinking network members, and percentage of heavy drinking network members (Hallgren & Barnett, 2016). Further, the network variables defined with five members versus 10 also had similar associations with drinking, both concurrently and a year later. In the current study, participants were asked the following, “Please list the first names and last initials for up to five (5) friends you have been in contact with regularly and who have been the most significant in your life in the past 30 days. These might have been people you hung out with in-person, texted, video chatted, messaged online, or talked to on the phone.” The first half of the instructions blends language from Cook et al. (2013), where participants were asked to identify five people they interacted the most frequently online, as well as from Reid and Carey (2018) which asked participants to list friends they had had regular contact with in the last month. The second half of the instructions in previous studies typically list, “These might be people you socialized with, studied with, or regularly had fun with. These people might be parents, friends, roommates, people from work, or anyone that you see as having had a significant impact on your life, regardless of whether or not you liked them” (Barnett et al., 2014; Cox et al., 2019; Meisel & Barnett, 2017), but were modified in the current study to reflect the ways participants may have socialized with their friends. Then, participants were asked to describe each person they listed, answering questions about the qualities of their relationship as well as questions about qualities of that individual. Additionally, the BIPI used in the current study included several new questions to assess the key phenomena of interest in the proposed specific aims. These questions and their response options included, “How close do you feel to [person name]? 1 = *Not very close* to 3 = *Very close*”, “Is [person name] a “drinking buddy”, meaning a person with whom you get together on a regular basis to do activities that center around drinking and/or going to bars or clubs? *Yes*/*No*, “Do you think [person name] posts/shares content on social media where alcohol is present or posts about alcohol (alcohol posts)? *Yes*/*No*”, “How often do you think [person name] posts/shares content that features alcohol? 1 = *Never* to 7 = *Daily or Almost Daily*” or “Are the alcohol posts [person name] shares usually…? (Select only one) 1 = *Videos (with or without text)*, 2 = *Photos (with or without text)*, 3 = *Text-only status updates*, 4 = *Other (Please describe)*”. For the full list of questions used in the BIPI for the current study see Appendix E. The BIPI has shown good external validity, concurrent validity with the full IPI and test-retest reliability with year 1 network drinking predicting year 2 participant drinking and vice versa (Hallgren & Barnett, 2016).

For continuous social network variables (e.g., average closeness rating for the social network), responses were averaged across all network members. For categorical social network variables (0/1 responses; e.g., if network member is a drinking buddy or if network member shares alcohol-related content [ARC]), a proportion of network members meeting this description was calculated. Calculating proportion of network variables is a common practice in analyzing social network data (for a review, see Rinker et al., 2016). As the question assessing the typical modality of ARC shared by each named network member is nominal with four response options, this question was recoded into two new variables reflecting the comparisons between photo vs. text (1 = *photo*, 0 = *text*) and video vs. text (1 = *video*, 0 = *text*) with the other response option set to missing, consistent with hypotheses 3a and 3b.

Further, social network variables which reflect the intersection of qualities of relationships with participants (e.g., average closeness rating, drinking buddy status) and whether social network members share ARC were computed. Computing continuous intersection social network variables involved computing an average closeness rating only for the network members that share ARC. Computing categorical intersection social network variables involved computing the proportion of the network who possessed both qualities (e.g., shared ARC and were considered a drinking buddy) compared to individuals who shared this content but did not have this other quality (e.g., 0 = *drinking buddy who does not share ARC*, 1 = *drinking buddy who shares ARC*).

Social Media Use

Questions (see Appendix F) were asked to gather descriptive information about social media platforms participants use, whether participants shared alcohol-related social media content (1 = *Yes*, 0 = *No*), which modality of alcohol-related content participants shared most often (1 = *Videos (with or without text)*, 2 = *Photos (with or without text)*, 3 = *Text-only status updates*, 4 = *Other (Please describe)*), what social media platforms they shared alcohol-related content on, and frequency of sharing alcohol-related social media content (1 = *Never* to 7 = *Daily or Almost Daily*). Participants were asked how often they checked the social media platforms they had accounts on (1 = *Less than once per week* to 5 = *7 or more times per day*).

Demographics

General information about age, gender identity, sexual identity, sex, race, ethnicity, class standing, GPA, typical grades, in-state/out-of-state student status, whether parents were suspected to have a drinking problem, and Greek life involvement was collected during the baseline survey (see Appendix G).

Analysis Approach

To analyze the proposed aims of the current study, structural equation modeling was used, with path analyses used to assess cross-sectional hypotheses (aim 1: if participant sharing of ARC was linked to drinking/consequences [2 models]; aim 2: if the proportion of the social network sharing ARC was associated with drinking/consequences [2 models]; aim 3: if individual drinking/consequences varied by modality of ARC shared by social network members [2 models]; aim 4: if qualities of relationships with network members sharing ARC were associated with drinking/consequences [4 models]). These path analysis models were fully saturated, therefore model fit statistics are not reported. Cross-lagged panel models assessed longitudinal hypotheses (i.e., aim 1: if participants sharing ARC was associated with alcohol consumption and consequences over time [2 models]; aim 2: if social network ARC sharing was associated with alcohol outcomes over time [2 models]; aim 3: if social network members sharing photo and video ARC were associated with alcohol outcomes over time [2 models]; aim 4: if qualities of relationships with network members sharing ARC were associated with drinking/consequences longitudinally [4 models]; aim 5: if participant alcohol outcomes were linked to participant sharing ARC or social network qualities sharing ARC [no additional models models]). All hypothesis examinations for the proposed study were conducted in Mplus version 8 (Muthén & Muthén, 1998-2017). Standardized effects (i.e., betas or βs) and unstandardized effects (i.e., B-values) are reported for all examinations. Betas for constrained paths are based on standard deviations for estimates of predictors at baseline associated with outcomes at the 1-month follow-up or within-timepoint baseline associations, respectively. Standard errors and *p*-values for the unstandardized effects are reported.

Sex (time-invariant) was controlled for in all analyses (1 = *male*, 0 = *female*), as sex differences in alcohol consumption and consequences experienced are well established in the college drinking literature (e.g., Murphy et al., 2005; O'Hare, 1990; Sugarman et al., 2009). Additionally, sex differences have emerged in frequency of social media checking, time spent using social media platforms, and exposure to ARC shared on social media by peers (Alhabash et al., 2020; Boyle et al., 2016; Brunelle & Hopley, 2017; Geusens & Beullens, 2016; Geusens & Beullens, 2017; LaBrie, Boyle, et al., 2021; LaBrie, Trager, et al., 2021; Miller et al., 2014; Nesi et al., 2017; Scott et al., 2020). Among social media studies which have examined relationships between alcohol-related content exposure and alcohol use, frequency of checking social media platforms has also been found to be related to consumption (Boyle et al., 2016; Brunelle & Hopley, 2017; Miller et al., 2014; Nesi et al., 2017; Scott et al., 2020; Stoddard et al., 2012), and was included as a time-varying covariate in all models. Thus, frequency of checking social media was specified as a time-varying covariate in all models. Given that alcohol quantity is commonly associated with alcohol-related consequences (e.g., Barnett et al., 2014), it was controlled for as a time-varying covariate in all consequences models. Additionally, compensation (i.e., guaranteed $5 Amazon gift card or Tribe Card money versus non-guaranteed raffle entry to win one of five $10 or one $50 Amazon gift cards or Tribe Card money) was also included as a time-varying covariate to account for potential differences in participant compensation. Similarly, as data collection occurred over multiple semesters, semester when each survey was completed (i.e., spring 2022, summer 2022, fall 2022, spring 2023) was also included as a time-varying covariate.

Prior to testing longitudinal hypotheses via cross-lagged panel models, invariance of the autoregressive and cross-lagged paths, respectively, was tested for each model, to identify the most parsimonious model to test hypotheses. For the autoregressive paths, whether the path from the Time 1 predictor (e.g., frequency of participants sharing content) to the same construct at

Time 2 (labeled path a in Figure 2) was significantly different from the path from the same Time 2 construct to the same Time 3 construct (labeled path b in Figure 2) was examined. If they were not significantly different, these two autoregressive paths were constrained to equality in the final model. If they were significantly different, these paths were freely estimated in the final model. The same process was followed for the autoregressive paths for outcomes (e.g., comparing the path from Time 1 to Time 2 alcohol outcomes to the path for Time 2 to Time 3 alcohol outcomes; paths c and d, respectively, in Figure 2). For the cross-lagged paths, I examined whether the path from the Time 1 predictor to the Time 2 outcome (e.g., frequency of participating sharing content predicting alcohol outcomes) was significantly different from the path from the Time 2 predictor to the Time 3 outcome. I also examined if the relationships for influence that were in the opposite direction were invariant (e.g., whether the path between Time 1 alcohol outcomes to Time 2 frequency of participants sharing content was significantly different from the path from Time 2 alcohol outcomes to Time 3 frequency of participants sharing content). If they were not significantly different, these two cross-lagged paths were constrained to equality in the final model. If they were significantly different, these paths were freely estimated in the final model. Note that the cross-lagged paths were the hypothesized paths of interest (e.g., H1b), which means the hypothesis could be examined with one estimate (if invariant) or two estimates (if not). Model fit varied depending on the invariance testing, therefore fit statistics were not reported.

Aim 1

For H1a (cross-sectional), two path analysis models (one for consumption and one for consequences) were conducted with participant sharing of ARC as the observed predictor variable. To assess if H1a was supported, a significant association between participant sharing of

ARC and consumption and consequences would be observed (see Figure 1). In the cross-lagged panel models for H1b (see Figure 2), whether the frequency of participants sharing ARC was associated with participant consumption and consequences was examined over time. The frequency of participants sharing ARC for Time 1, 2, and 3 were included as observed predictor variables in the model as well as observed variables for participant alcohol consumption or consequences (separate models) at Time 1, 2, and 3 as outcome variables. Cross-lagged paths for Time 1 frequency of participants sharing ARC predicting Time 2 participant alcohol outcomes as well as Time 2 frequency of content shared predicting Time 3 participant alcohol outcomes (see paths labeled H1b in Figure 2) were examined. The model also included autoregressive paths (see paths a, b, c, d in Figure 1; e.g., Time 2 frequency of participants sharing ARC was predicted by Time 1 frequency of participants sharing ARC). As is standard with panel models, within-time correlations (e.g., Time 1 frequency of participants sharing ARC and Time 1 alcohol outcomes, Time 2 frequency of participants sharing ARC and Time 2 alcohol outcomes, etc.) were included, but these were not examined as part of the current study's aims. If H1b was supported, this estimate (or these estimates) would be significantly greater than zero.

Aim 2

For H2a (cross-sectional), two path analysis models (one for consumption and one for consequences) with the proportion of network members sharing ARC as the observed predictor variable were conducted. To assess if H2a was supported, a significant association between the proportion of network members sharing of ARC and consumption and consequences (see Figure 1) would be observed. In the cross-lagged panel models for H2b (see Figure 2), whether the proportion of network members sharing ARC was associated with participant consumption and consequences over time was examined. The proportions of network members sharing ARC for

Time 1, 2, and 3 were included as observed predictor variables in the model as well as observed variables for participant alcohol consumption or consequences (separate models) at Time 1, 2, and 3 as outcome variables. Cross-lagged paths for whether Time 1 proportion of network members sharing ARC predicted Time 2 participant alcohol outcomes as well as whether Time 2 proportion of content shared predicted Time 3 participant alcohol outcomes (see paths labeled H1b in Figure 2) were examined. The model also included autoregressive paths (see paths a, b, c, d in Figure 2; e.g., Time 2 proportion of ARC shared by networks was predicted by Time 1 proportion of ARC shared by networks). As is standard with panel models, within-time correlations (e.g., Time 1 proportion of network members sharing ARC and Time 1 alcohol outcomes, Time 2 proportion of network members sharing ARC and Time 2 alcohol outcomes, etc.) were included, but these were not examined as part of the current study's aims. Auto-regressive invariance and cross-lagged invariance were examined before the significance of H2b was determined. If H2b was supported, the estimate (or estimates) of the cross-lagged paths between the proportion of network members sharing ARC and alcohol outcomes would be significantly greater than zero.

Aim 3

Aim 3 examined if modality (e.g., photo, video, text) of ARC shared on social media platforms by social network members (see Social Network in the Measures section above) was associated with participant alcohol consumption and related consequences cross-sectionally. For H3a (cross-sectional), two path analysis models (one for consumption and one for consequences) were run with the proportion of network members sharing alcohol-related photos versus text and the proportion of network members sharing alcohol-related videos versus text included in the same model as observed predictor variables (see Figure 3). To assess if H3a was supported, I used the model constraint command in Mplus was used and parameter estimates were subtracted for path c from a and c from b. Then whether these new estimates representing the difference in the strength of associations were significant different from zero was examined. For H3b (longitudinal), two panel models (one for consumption and one for consequences) were conducted with the proportion of network members sharing alcohol-related photos, videos, and text (separate variables) at Time 1, 2, and 3 included in the same models as observed predictor variables (see Figure 4). For H3b, whether the cross-lagged paths for Time 1 proportions of network members sharing alcohol-related photos and videos (separate paths) were more strongly associated with Time 2 participant alcohol outcomes than the Time 1 proportion of network members sharing alcohol-related text was examined using the model constraint command in Mplus. Similarly, whether Time 2 proportions of network members sharing alcohol-related photos and videos (separate paths) were more strongly associated with Time 3 participant alcohol outcomes than the Time 2 proportions of network members sharing alcohol-related text was examined. Auto-regressive invariance and cross-lagged invariance were examined before the significance of H3b was determined. If H3b was supported, the cross-lagged paths for proportion of network members sharing alcohol-related videos or photos) would be stronger than the cross-lagged paths for proportion of network members sharing alcohol-relate text, after accounting for time-varying and time-invariant covariates.

Aim 4

For H4a (closeness of network members sharing ARC) and H4c (drinking buddy status of network members sharing ARC), a path analysis (see Figure 5) examined if there was an association between the average closeness rating for social network members sharing ARC and participant drinking outcomes (quantity and consequences examined in separate models), after controlling for the average closeness rating for the full social network and proportion of social network sharing ARC cross-sectionally (so above and beyond the effects of general closeness with network members, and generally how many members share ARC on social media). A similar model was executed for H4c, with proportion of drinking buddies sharing content versus not as the main predictor of interest, and with proportion of drinking buddies in the full network replacing average closeness for the full network as a covariate. H4a would be supported if there was a significant association between average closeness with network members sharing ARC and alcohol outcomes when controlling for covariates. H4c would be supported if there was a significant association between the proportion of drinking buddies sharing content and alcohol outcomes after accounting for the covariates.

To examine H4b and H4d, cross-lagged panel models were conducted (similar to other longitudinal hypotheses; see Figure 6). The predictor variables, average closeness rating for social network members who share ARC (H4b) or the proportion of drinking buddies who share ARC (H4d) were included as observed variables with cross-lagged paths that examined if these qualities were longitudinally associated with participant alcohol outcomes (consumption and related consequences in separate models). For H4b (closeness), Time 2 participant alcohol outcomes would be predicted by the Time 1 average closeness rating with social network members who share ARC (H4a), controlling for Time 1 average closeness rating of the social network and Time 1 proportion of social network members sharing ARC. These associations would be modeled identically for Time 3, controlling for Time 2. A similar model was executed for H4d (drinking buddies who share ARC) but controlled for the previous timepoint’s proportion of social network members who share ARC and the proportion of drinking buddies in social network as the covariates. All timepoints for the social network quality of relationship variables (e.g., average closeness with social network members sharing content) and alcohol outcome variables were regressed on the time-varying covariates of average closeness of network (within and across timepoints; see paths e and f in Figure 6 as examples) and the proportion of network sharing content (within and across time points). The same approach used for all longitudinal models assessing whether or not to constrain or freely estimate autoregressive or cross-lagged paths over time, respectively, were followed for Aim 4. H4b would be supported if the cross-lagged paths from average closeness with network members sharing ARC (T1 and T2) and alcohol outcomes (T2 and T3) were significant when controlling for time-varying and time-invariant covariates. H4d would be supported if the cross-lagged paths from the proportion of drinking buddies sharing content (T1 and T2) and alcohol outcomes (T2 and T3) were significant after controlling for time-varying and time-invariant covariates.

Aim 5

Aim 5 consisted of exploring if the influence goes in the opposite direction from the directions hypothesized in longitudinal Aims 1-4 (i.e., from participant alcohol use/consequences to participant sharing of ARC for Aim 1, social network sharing of ARC for Aim 2, modality of content shared for Aim 3, and qualities of social network members sharing content for Aim 4) by examining the cross-lags in the non-hypothesized directions in previously run models.

Power Analysis

For the main effects of longitudinal aims (aims 1-5), a series of Monte Carlo Simulation power analyses were conducted using Mplus (Muthén & Muthén, 1998-2017) using standardized effect size estimates for alcohol use outcomes from the longitudinal social network literature as starting values for the autoregressive and cross-lagged paths. Large effect sizes ($\beta > 0.50$) for the autoregressive paths and medium effect sizes ($\beta = 0.20 – 0.50$) for the cross-lagged paths were estimated based on rates from previous longitudinal social network research ($\beta = 0.11 – 0.40$; Hallgren & Barnett, 2016; $\beta = -0.10 – 0.06$; Huang, Unger et al., 2014; $\beta = 0.10 – 0.23$; Meisel & Barnett, 2017; $\beta = 0.10 – 0.26$; Reid & Carey, 2018). A conservative rate of attrition (20% by the end of time 3 with lower attrition expected at time 2) was accounted for based on rates from previous longitudinal social network research (9.1% attrition, Huang, Unger et al., 2014; 9.1% attrition, Meisel & Barnett; 2017; 12.5% attrition, Reid & Carey, 2018). To obtain power of .80 with an alpha of .05 for the proposed analyses, 350 people were needed.

Monte Carlo simulation power analyses were also conducted for the cross-sectional aims (H3a, H4a, H4c), revealing that a sample of 350 was sufficient to yield power of .80 with an alpha of .05 for effect sizes as low as .16 for the intersection social network variables (e.g., proportion of network sharing alcohol-related videos vs. text, average closeness rating for social network members who share ARC), which is on the lower end of range from prior cross-sectional social network literature. Effect sizes from previous cross-sectional social network studies which have used intersection variables have ranged from .16 to .69 (with an average of .35, across six effect sizes; Bartel et al., 2020; Tompsett & Colburn, 2019). Large effect sizes ($\beta > 0.50$) were specified for the social network quality or quality of relationship with the participant variables (e.g., proportion of social network sharing ARC, average closeness rating for social network). There is substantial variability in the literature surrounding social network qualities and qualities of relationships with participants affecting alcohol outcomes, with previously reported effect sizes ranging from .08 to .77, cross-sectionally (with an average of 0.29 across 13 effect sizes observed in the literature; Barnett et al., 2014; Bartel et al., 2020; Cook et al., 2013; Lorant & Nicaise, 2014; Kenney et al., 2017; Russell et al., 2020; Tompsett & Colburn, 2019) and from -0.10 to 0.40, longitudinally (with an average of .17 across 22 effect sizes observed in the literature; Hallgren & Barnett, 2016; Homish & Leonard, 2008; Huang, Unger et al., 2014; Meisel & Barnett, 2017; Reifman et al., 2006, Reid & Carey, 2018). Thus, a sample of 350 should yield power above .80 for the anticipated effect sizes for these associations.

CHAPTER III

RESULTS

Data Cleaning

All continuous predictor and control variables of interest were examined for normality and outliers by examining skewness and kurtosis values, histograms, and boxplots. Most variables were normally distributed with an absence of outliers; however, boxplots revealed the presence of 7 outliers for baseline quantity and 3 outliers for 1-month quantity. These outliers were winsorized to the next highest value. Although alcohol consequences at the 3-month follow-up were kurtotic but not skewed, there were an increasing percentage of participants at each follow-up survey who said they experienced no alcohol consequences (1-month 23% reported no consequences, 3-month 37% reported no consequences). Conversely, only 5.7% of participants reported experiencing no consequences at baseline. These percentages suggest it is appropriate to proceed with the cross-sectional analyses with baseline consequences being treated as normally distributed but for the longitudinal analyses a new approach must be taken given the number of individuals who reported no consequences. To understand how the study aims differ for those who experience any alcohol consequences versus those who experience no consequences, for longitudinal examinations, the consequences outcome was examined in two ways: those that experienced any consequences versus those that experienced none (coded as 0 = *none* and 1 = *1 or more consequences*) and a second outcome examining the number of consequences continuously (only among those reporting values other than 0). Initially, I attempted to examine these two outcomes simultaneously via zero-inflated negative binomial models, but due to the complexity of the hypothesized models, the models did not converge. However, I was able to examine these two outcomes (consequences versus none; number of consequences among those who reported them) in separate models, which is what I presented here.

Missing Data

A series of chi-squares and *t*-tests were conducted to examine if there were any demographic differences (see Table 2) among participants who completed only baseline (n = 73), completed the baseline and 1-month follow-up surveys only (n = 83), completed the baseline and 3-month follow-up surveys only (n = 12), and completed all three surveys (n = 216). The only significant demographic difference among study completion status was for participant sex, p = .010, such that female participants completed more surveys than male participants. Participant sex was already a planned covariate based on prior research. Due to small cell sizes for class year response options, chi-square test statistics could not be computed even after dropping “Graduate”, “Transfer”, and “Other” cases. Additionally, participants were allowed to select all that applied for sexual identity; as such chi-square test statistics could not be computed because at least one variable in each 2-way table was a constant. Also, due to small cell sizes for some of the Greek Life involvement question response options, several categories were collapsed to compare to the category “Not a member, and do not attend Greek events”.

Table 2

Demographic Differences by Study Completion Status

Variable	Completed Baseline Survey Only *n* = 73	Completed Baseline and 1-month Surveys *n* = 83	Completed Baseline and 3-month Surveys *n* = 12	Completed All 3 Surveys *n* = 216	*p*
Age *M* (*SD*)	20.15 (1.39)	20.11 (1.23)	19.67 (1.61)	20.00 (1.22)	.560
GPA *M* (*SD*)	3.37 (0.80)	3.28 (0.89)	2.93 (1.43)	3.20 (1.16)	.461
Gender Identity *n* (%)					.092
Man	22 (30.1)	25 (30.1)	4 (33.3)	39 (18.1)	
Woman	48 (65.8)	50 (60.2)	8 (66.7)	160 (74.1)	
Nonbinary/genderqueer/genderfluid	3 (4.1)	7 (8.4)	0 (0.0)	17 (7.9)	
Other	0 (0.0)	1 (1.2)	0 (0.0)	0 (0.0)	
Sex *n* (%)					**.010**
Male	25 (34.2)	27 (32.5)	5 (41.7)	42 (19.4)	
Female	48 (65.8)	56 (67.5)	7 (58.3)	174 (80.6)	
Ethnicity – Hispanic or Latino/a/x *n* (%)					.263
Yes	7 (9.6)	11 (13.3)	2 (16.7)	16 (7.4)	
No	66 (90.4)	72 (86.7)	10 (83.3)	200 (92.6)	
Racial Identity *n* (%)					.276
Black	4 (5.5)	2 (2.4)	1 (8.3)	11 (5.1)	
Asian	8 (11.0)	7 (8.4)	1 (8.3)	19 (8.9)	
Hawaiian Native and/or Pacific Islander	0 (0.0)	0 (0.0)	1 (8.3)	0 (0.0)	
White	58 (79.5)	71 (85.5)	8 (66.7)	167 (78.0)	
Middle Eastern or North African	0 (0.0)	1 (1.2)	0 (0.0)	1 (0.5)	
Other	3 (4.1)	2 (2.4)	1 (8.3)	16 (7.5)	
Class Year *n* (%)					-
Freshman	19 (26.0)	16 (19.3)	4 (33.3)	45 (20.8)	
Sophomore	16 (21.9)	19 (22.9)	1 (8.3)	50 (23.1)	
Junior	17 (23.3)	19 (22.9)	5 (41.7)	64 (29.6)	

Table 2 (*continued*)

Variable	Completed Baseline Survey Only *n* = 73	Completed Baseline and 1-month Surveys *n* = 83	Completed Baseline and 3-month Surveys *n* = 12	Completed All 3 Surveys *n* = 216	*p*
Senior	20 (27.4)	26 (31.3)	2 (0.5)	48 (22.2)	
Graduate	0 (0.0)	0 (0.0)	0 (0.0)	4 (1.9)	
Transfer	0 (0.0)	1 (1.2)	0 (0.0)	4 (1.9)	
Other	1 (1.4)	2 (2.4)	0 (0.0)	1 (0.5)	
Typical Grades *n* (%)					.102
Mostly A’s	46 (63.0)	45 (54.2)	6 (50.0)	139 (64.7)	
Mostly B’s	20 (27.4)	33 (39.8)	4 (33.3)	50 (23.3)	
Mostly C’s	3 (4.1)	0 (0.0)	1 (8.3)	6 (2.8)	
Mostly D’s	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	
Mostly F’s	0 (0.0)	0 (0.0)	0 (0.0)	0 (0.0)	
I don’t know yet	4 (5.5)	5 (6.0)	1 (8.3)	20 (9.3)	
In-state or Out-of-state Student Status *n* (%)					.725
In-state	44 (60.3)	54 (65.1)	8 (66.7)	146 (67.6)	
Out-of-state	29 (39.7)	29 (34.9)	4 (33.3)	70 (32.4)	
Sexual Identity *n* (%)					-
Gay	5 (23.8)	4 (19.0)	0 (0.0)	12 (57.1)	
Lesbian	4 (17.4)	2 (8.7)	0 (0.0)	17 (73.9)	
Bisexual	20 (16.8)	29 (24.4)	3 (2.5)	67 (56.3)	
Queer	10 (22.7)	10 (22.7)	1 (2.3)	23 (52.3)	
Asexual	3 (27.3)	3 (27.3)	0 (0.0)	5 (45.5)	
Pansexual	2 (20.0)	2 (20.0)	1 (10.0)	5 (50.0)	
Questioning	3 (12.0)	6 (24.0)	0 (0.0)	16 (64.0)	
Heterosexual/Straight	42 (20.4)	41 (19.9)	9 (4.4)	114 (55.3)	
Other	0 (0.0)	0 (0.0)	0 (0.0)	2 (100.0)	
Suspect Mother Had a Drinking Problem *n* (%)					.083
Yes	4 (5.5)	15 (18.1)	1 (8.3)	22 (10.2)	
No	69 (94.5)	68 (81.9)	11 (91.7)	193 (89.8)	

Table 2 (*continued*)

Variable	Completed Baseline Survey Only *n* = 73	Completed Baseline and 1-month Surveys *n* = 83	Completed Baseline and 3-month Surveys *n* = 12	Completed All 3 Surveys *n* = 216	*p*
Suspect Father Had a Drinking Problem *n* (%)					.525
Yes	16 (21.9)	21 (25.3)	5 (41.7)	55 (25.6)	
No	57 (78.1)	62 (74.7)	7 (58.3)	160 (74.4)	
Greek Life Involvement *n* (%)					.842
Involved in Greek Life	49 (67.1)	50 (60.2)	8 (66.7)	135 (62.5)	
Not involved in Greek Life	24 (32.9)	33 (39.8)	4 (33.3)	81 (37.5)	

Note. Bold values indicate significance.

Two participants did not complete the Brief Important People Interview (BIPI) at baseline (time 1). This means they were missing responses for key predictor variables of interest for aims 2-4 (i.e., all the social network questions). For this reason, data for these two participants were not included in the cross-sectional analyses for those aims. There were no missing data for any other key variables of interest at baseline.

As evidenced in Figure 7, there was attrition at the 1-month and 3-month follow-up time points. To identify whether the data were missing completely at random (MCAR) versus missing at random (MAR), a series of *t*-tests and chi-squares were conducted to examine if the key variables of interest (dependent variables) differed by whether surveys were missing or not (1 vs. 0) at the 1-month and 3-month time points (independent variables), which would reflect whether the data were missing at random (MAR), meaning missingness is related to another variable in the dataset. In the current study, missing data for the 1-month and 3-month surveys was only due to non-completion of a survey and not due to skipping items for key variables. Therefore, the values for the *t*-tests and chi-squares for missingness reflect missing the entire survey.

As seen in Table 3, missing the survey at 1-month was associated with the semester participants completed their baseline survey, modality of network members sharing ARC, and drinking quantity. Participants who completed their baseline survey earlier (e.g., spring 2022) were more likely to be missing the 1-month survey than those who completed their baseline survey later (e.g., summer 2022, fall 2022). The proportion of social network members sharing video ARC (versus photo ARC) at baseline was lower for participants who were missing the survey at 1-month than for those who were not missing. Most importantly, participants who did not complete the 1-month follow-up survey reported more alcohol consumption than those who completed the 1-month survey. Semester the baseline survey was completed and baseline quantity are already included as planned covariates in the proposed models of interest. The proportion of social network members sharing video ARC at baseline was added as a covariate in the proposed aim 3 models as well.

As seen in Table 4, missing the 3-month survey was associated with participant sex, baseline compensation, and baseline quantity. Female participants and those who selected direct payment were less likely to miss the 3-month survey than male participants or those who selected raffle as their compensation. Similar to the 1-month missing data analyses, participants who were missing at the 3-month follow-up survey consumed more alcohol than those who completed the 3-month survey. Missingness on the 3-month follow-up survey was not associated with any key variables of interest at the 1-month follow-up survey. Participant sex, baseline compensation and baseline quantity are already included as covariates in the proposed models.

Table 3

Missing the 1-month Follow-up Survey

	1-month Survey		
Variable	Not missing	Missing	*p*
Baseline			
Age *M* (*SD*)	20.03 (1.23)	20.06 (1.36)	.885
Sex *n* (%)			.082
Female	213 (76.6)	72 (67.9)	
Male	65 (23.4)	34 (32.1)	
Social Media Checking Frequency Baseline *M* (*SD*)	6.23 (0.90)	6.30 (0.90)	.508
Semester Baseline *M* (*SD*)	1.61 (0.86)	1.42 (0.77)	**.044**
Compensation Baseline *n* (%)			.085
Raffle	196 (70.5)	84 (79.2)	
Direct Payment	82 (29.5)	22 (20.8)	
Participant Sharing ARC Baseline *n* (%)			.528
No	182 (65.5)	73 (68.9)	
Yes	96 (34.5)	33 (31.1)	
Frequency of Participant Sharing ARC Baseline *M* (*SD*)	2.63 (0.92)	2.73 (0.91)	.582
Proportion of SN Sharing ARC Baseline *M* (*SD*)	0.31 (0.28)	0.33 (0.30)	.510
Average Frequency of SN Sharing ARC Baseline *M (SD)*	3.18 (1.04)	3.14 (1.08)	.794
Proportion of SN Share Mostly Video ARC Baseline *M* (*SD*)	0.29 (0.40)	0.17 (0.31)	**.010**
Average Closeness with SN Baseline *M* (*SD*)	2.62 (0.33)	2.68 (0.34)	.112
Average Closeness with SN Who Share ARC Baseline *M* (*SD*)	2.61 (0.48)	2.63 (0.45)	.807
Proportion of DB in SN Baseline *M* (*SD*)	0.49 (0.32)	0.53 (0.35)	.244
Proportion of DB Sharing ARC Baseline *M* (*SD*)	0.29 (0.32)	0.33 (0.36)	.320
Participant Quantity Baseline *M* (*SD*)	8.26 (6.21)	10.74 (7.81)	**.002**
Participant Consequences Baseline *M* (*SD*)	4.22 (3.13)	4.42 (3.14)	.567

Note. Quantity = number of drinks consumed in a typical week in the past 30 days, Consequences = number of consequences experienced in the past 30 days, ARC = alcohol-related content on social media, SN = social network, DB = drinking buddy. Sex was coded 0 = *female* and 1 = *male*. Semester was coded 1 = *spring 2022*, 2 = *summer 2022*, 3 = *fall 2022*, and 4 = *spring 2023*. Bold values indicate significance.

Table 4

Missing the 3-month Follow-up Survey

	3-month Survey		
Variable	Not missing	Missing	*p*
<u>Baseline</u>			
Age *M* (*SD*)	20.00 (1.24)	20.10 (1.30)	.456
Sex *n* (%)			**.002**
Female	176 (80.4)	109 (28.4)	
Male	43 (19.6)	56 (33.9)	
Social Media Checking Frequency Baseline *M* (*SD*)	6.27 (0.90)	6.23 (0.90)	.674
Semester Baseline *M* (*SD*)	1.63 (0.85)	1.47 (0.81)	.064
Compensation Baseline *n* (%)			**.007**
Raffle	148 (67.6)	132 (80.0)	
Direct Payment	71 (32.4)	33 (20.0)	
Participant Sharing ARC Baseline *n* (%)			.732
No	147 (67.1)	108 (65.5)	
Yes	72 (32.9)	57 (34.5)	
Frequency of Participant Sharing ARC Baseline *M* (*SD*)	2.65 (0.91)	2.65 (0.94)	.982
Proportion of SN Sharing ARC Baseline *M* (*SD*)	0.31 (0.28)	0.33 (0.29)	.496
Average Frequency of SN Sharing ARC Baseline *M (SD)*	3.22 (1.07)	3.10 (1.03)	.351
Proportion of SN Share Mostly Video ARC Baseline *M* (*SD*)	0.26 (0.38)	0.25 (0.38)	.954
Average Closeness with SN Baseline *M* (*SD*)	2.63 (0.33)	2.64 (0.35)	.851
Average Closeness with SN Who Share ARC Baseline *M* (*SD*)	2.63 (0.46)	2.60 (0.49)	.604
Proportion of DB in SN Baseline *M* (*SD*)	0.49 (0.32)	0.51 (0.33)	.565
Proportion of DB Sharing ARC Baseline *M* (*SD*)	0.30 (0.33)	0.30 (0.34)	.891
Participant Quantity Baseline *M* (*SD*)	8.32 (6.74)	9.78 (6.74)	**.036**
Participant Consequences Baseline *M* (*SD*)	4.22 (3.23)	4.35 (3.01)	.707
<u>1-month</u>			
Social Media Checking Frequency 1-month *M* (*SD*)	6.15 (0.94)	6.20 (0.92)	.674
Semester 1-month *M* (*SD*)	1.77 (0.83)	1.63 (0.84)	.169
Compensation 1-month *n* (%)			.201
Raffle	120 (57.4)	45 (66.2)	
Direct Payment	89 (42.6)	23 (33.8)	
Participant Sharing ARC 1-month *n* (%)			.370
No	148 (70.8)	55 (65.5)	
Yes	61 (29.2)	29 (34.5)	
Frequency of Participant Sharing ARC 1-month *M* (*SD*)	2.72 (0.99)	2.75 (1.11)	.903
Proportion of SN Sharing ARC 1-month *M* (*SD*)	0.30 (0.28)	0.35 (0.31)	.218
Average Frequency of SN Sharing ARC 1-month *M* (*SD*)	3.24 (1.07)	3.13 (1.19)	.550
Proportion of SN Share Mostly Video ARC 1-month *M* (*SD*)	0.22 (0.35)	0.20 (0.33)	.794
Average Closeness with SN 1-month *M* (*SD*)	2.62 (0.32)	2.61 (0.33)	.722
Average Closeness with SN Who Share ARC 1-month *M* (*SD*)	2.59 (0.51)	2.55 (0.49)	.615
Proportion of DB in SN 1-month *M* (*SD*)	0.45 (0.34)	0.45 (0.35)	.998
Proportion of DB Sharing ARC 1-month *M* (*SD*)	0.35 (0.34)	0.39 (0.39)	.411
Participant Quantity 1-month *M* (*SD*)	6.85 (5.46)	8.35 (6.06)	.055
Participant Consequences 1-month *M* (*SD*)	3.06 (3.23)	3.46 (3.55)	.383

Note. Quantity = number of drinks consumed in a typical week in the past 30 days, Consequences = number of consequences experienced in the past 30 days, ARC = alcohol-related content on social media, SN = social network, DB = drinking buddy. Sex was coded 0 =

Table 4 (*continued*)

female and 1 = *male*. Semester was coded 1 = *spring 2022*, 2 = *summer 2022*, 3 = *fall 2022*, and 4 = *spring 2023*. Bold values indicate significance.

To explore whether the data were missing not at random (MNAR), sensitivity analyses were also conducted to examine whether missingness was affecting the results of the analyses (i.e., impacting the findings of the aims; 21 models). Selection models were used as outcome variables are approximately normal and there were not relatively large sample sizes for each pattern of missingness (e.g., complete only baseline, complete time 1 and time 2, complete timepoints 1 and 3, complete all timepoints; Enders, 2011).

The selection models for the sensitivity analyses consisted of adding indicators of missingness to the existing planned models, essentially serving as a series of logistic regressions predicting the likelihood of missingness at timepoints 2 or 3 based on model predictors or outcomes. If there was a significant association between missingness at time 2 and any predictor or outcome at time 2, over and above the effects of the predictor or outcome at time 1, this would provide evidence for MNAR (missingness at a timepoint is associated with another variable from the same timepoint, controlling for observed variables at the prior timepoint). If the results of the planned analyses without missingness indicators were comparable to the results of the analyses which included indicators of missingness, then one can be more confident in the conclusions drawn from the findings (i.e., the findings are not sensitive to missingness). If the patterns of results changed substantially, then the models were likely sensitive to missingness, and the data were potentially MNAR. Also, if the key variables of interests were associated with missingness within the same time point this provided evidence that the data in this model may be MNAR.

To run the sensitivity analyses using selection models, indicators of missingness for the 1-month and 3-month surveys were created. Next, the models (after invariance testing) were run with and without missingness indicators. The estimates and *p*-values differed for the key variables of interest across the models with and without missingness indicators, and some within-timepoint missingness associations were significant, suggesting the data may be MNAR. Therefore, the final models reported for all longitudinal aims included the missingness indicators. Additionally, all analyses were run with full information maximum likelihood estimation, which minimizes any possible bias introduced by missing data patterns (Enders, 2013; Hallgren & Witkiewitz, 2013; Witkiewitz et al., 2014).

Descriptive Statistics

Bivariate correlation analyses among all variables of interest were conducted (see Table 5). Covariates (sex, compensation, semester, social media checking frequency) were only included from baseline. All covariates held significant associations (mix of positive and negative) with at least some of the key predictors and outcomes of interest across all timepoints suggesting it was important to include them in the final models. There were positive associations between participants sharing ARC themselves and the friends in their social network sharing ARC across all timepoints implying that if participants shared ARC, it was likely they had more friends that did as well. These associations also persisted for modality of ARC shared by friends and relationship qualities with those friends sharing ARC such as closeness and drinking buddy status. Further, there were also a number of positive significant associations between participants sharing ARC, friends sharing ARC (including modality and qualities of relationships), and alcohol outcomes across all timepoints.

Table 5

Correlation Analyses Among All Variables of Interest

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.
1. Sex	-																			
2. Comp	.00	-																		
3. Semester	-.00	**.72**	-																	
4. SM Frq	-.07	-.03	.01	-																
5. Pt Share ARC	-.09	-.02	-.01	**.13**	-															
6. Pt Share ARC 1m	-.05	-.11	-.02	**.14**	**.51**	-														
7. Pt Share ARC 3m	-.11	-.00	.06	**.19**	**.54**	**.62**	-													
8. Pt ARC Frq	-.10	-.13	-.09	.14	-	**.23**	.13	-												
9. Pt ARC Frq 1m	-.17	-.02	.09	.19	**.34**	-	**.43**	**.58**	-											
10. Pt ARC Frq 3m	.23	.04	.10	.21	.24	.16	-	.28	**.73**	-										
11. SN Share ARC	-.10	-.04	-.03	**.14**	**.41**	**.41**	**.29**	**.18**	**.33**	**.28**	-									
12. SN Share ARC 1m	-.06	**-.13**	-.07	**.17**	**.40**	**.46**	**.34**	.11	**.33**	**.32**	**.66**	-								
13. SN Share ARC 3m	-.08	-.02	-.03	.13	**.39**	**.31**	**.38**	.20	**.56**	**.25**	**.54**	**.60**	-							
14. SN ARC Frq	**-.13**	-.07	-.01	.06	.09	.05	-.08	**.25**	**.37**	.11	**.22**	.12	.13	-						
15. SN ARC Frq 1m	.001	.06	.06	-.02	.13	.04	.05	**.30**	**.38**	**.44**	**.19**	**.17**	**.25**	**.43**	-					
16. SN ARC Frq 3m	-.12	**-.16**	-.11	-.03	.07	.01	.11	.01	.27	**.28**	.01	.04	.16	**.26**	**.45**	-				
17. SN Vid ARC	-.05	-.06	.04	.05	.04	-.06	.01	.04	.11	.20	.02	.05	-.04	**.24**	.12	.07	-			
18. SN Vid ARC 1m	-.03	-.05	.01	.02	-.04	-.03	-.13	-.19	-.17	.17	.12	**.16**	-.02	**.19**	**.23**	.03	**.36**	-		
19. SN Vid ARC 3m	.11	.07	-.06	.01	.08	-.03	.02	.06	.18	.24	.16	.13	.02	**.19**	.11	.10	**.22**	**.21**	-	
20. SN Clse	-.05	-.02	-.07	.01	.08	**.12**	.11	.10	.12	**-.28**	-.01	.02	.07	.08	-.09	-.06	.03	-.07	-.05	-

Table 5 (*continued*)

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.
21. SN Clse 1m	-.08	.02	.02	.11	.04	.01	.10	.06	.07	-.06	.06	.04	.05	.03	**-.15**	-.03	.02	-.01	.02	**.51**
22. SN Clse 3m	**-.16**	-.03	-.03	**.15**	.06	.10	.10	.16	.13	.02	-.01	.08	-.04	.03	-.09	-.14	.08	.05	.06	**.47**
23. SN Clse ARC	-.12	.07	.03	.06	.11	.06	.05	.09	.17	-.06	-.02	.05	.04	.04	-.08	-.07	**.13**	-.04	-.05	**.67**
24. SN Clse ARC 1m	-.04	.12	.05	**.15**	**.14**	**.16**	**.17**	.12	-.01	.02	**.15**	.12	.09	.01	-.07	-.00	.06	.06	.05	**.38**
25. SN Clse ARC 3m	-.14	.02	.01	**.25**	.15	**.20**	**.25**	**.26**	.19	.15	**.17**	**.24**	.14	.10	.06	-.12	.08	-.00	.08	**.41**
26. DB SN	.02	-.02	-.06	.02	**.14**	**.28**	**.20**	.02	.17	**.29**	**.17**	**.23**	**.20**	**.17**	.11	.11	.01	.04	.10	**.19**
27. DB SN 1m	-.02	**-.15**	**-.17**	.03	**.13**	**.20**	**.18**	.10	.12	.16	**.16**	**.29**	**.19**	.10	-.02	.07	-.01	.01	.06	**.19**
28. DB SN 3m	-.06	-.06	-.08	.03	.06	**.25**	**.22**	.07	**.26**	.17	**.21**	**.25**	**.18**	-.12	-.07	.03	-.14	-.14	-.01	.11
29. DB ARC	**-.12**	-.09	-.10	.08	**.27**	**.41**	**.27**	.14	.19	**.29**	**.59**	**.42**	**.42**	**.19**	.11	.06	-.04	.05	.03	.08
30. DB ARC 1m	**-.15**	**-.16**	**-.14**	**.15**	**.30**	**.36**	**.24**	.14	**.24**	.17	**.46**	**.69**	**.47**	.06	.06	.01	.08	.08	-.00	.11
31. DB ARC 3m	**-.22**	-.08	-.05	**.22**	**.33**	**.29**	**.37**	.07	**.39**	.13	**.40**	**.45**	**.67**	.03	.18	.14	-.09	.01	.06	.06
32. Quant	**.21**	-.07	-.03	.06	**.25**	**.33**	**.21**	**27**	**.40**	**.42**	.08	**.26**	**.22**	**.24**	**.15**	.12	.04	-.02	.08	**.12**
33. Quant 1m	**.12**	-.05	.09	.09	**.27**	**.29**	**.25**	**.30**	**.42**	**.36**	**.17**	**.27**	**.16**	**.19**	.13	.09	**.18**	-.07	.001	**.13**
34. Quant 3m	.09	**.17**	**.18**	.05	**.18**	**.19**	**.19**	**.25**	.05	**.43**	.09	.07	**.15**	.03	.12	.06	.12	-.01	.03	.08
35. Any Conseq	-.09	-.05	.00	.06	.08	.10	.11	.13	.11	.14	.05	.08	.09	**.12**	.13	.05	.06	.11	-.13	.06
36. Any Conseq 1m	-.02	-.06	.04	.04	**.15**	**.16**	**.22**	.15	.13	.12	.08	.04	.05	.02	.14	.07	.01	.01	-.10	.07
37. Any Conseq 3m	-.00	.13	.12	.03	**.17**	**.23**	**.31**	.13	-.06	.10	**.15**	.11	**.15**	-.07	**.17**	.09	.09	.09	-.00	.08
38. Num Conseq	.01	-.08	-.05	**.11**	**.22**	**.28**	**.22**	**.28**	**.35**	.27	**.16**	**.25**	**.24**	**.21**	**.16**	-.01	.11	-.00	.12	.03
39. Num Conseq 1m	-.04	.03	.10	.05	**.15**	**.23**	.14	.22	**.37**	**.35**	**.22**	**.28**	**.30**	**.25**	.13	-.03	**.22**	-.04	.15	-.01
40. Num Conseq 3m	-.10	-.03	.08	.09	.16	.14	**.22**	**.38**	**.61**	.26	**.18**	**.24**	**.24**	.12	.12	-.03	-.01	-.10	-.01	.04

Table 5 (*continued*)

Variable	21.	22.	23.	24.	25.	26.	27.	28.	29.	30.	31.	32.	33.	34.	35.	36.	37.	38.	39.	40.
1. Sex	-.08	**-.16**	-.12	-.04	-.14	.02	-.02	-.06	**-.12**	**-.15**	**-.22**	**.21**	**.12**	.09	-.09	-.02	-.00	.01	-.04	.10
2. Comp	.02	-.03	.07	.12	.02	-.02	**-.15**	-.06	-.09	**-.16**	-.08	-.07	-.05	**.17**	-.05	-.06	.13	-.08	.03	-.03
3. Semester	.02	-.03	.03	.05	.01	-.06	**-.17**	-.08	-.10	**-.14**	-.05	-.03	.09	**.18**	.00	.04	.12	-.05	.10	.08
4. SM Frq	.11	**.15**	.06	**.15**	**.25**	.02	.03	.03	.08	**.15**	**.22**	.06	.09	.05	.06	.04	.03	**.11**	.05	.09
5. Pt Share ARC	.04	.06	.11	**.14**	.15	**.14**	**.13**	.06	**.27**	**.30**	**.33**	**.25**	**.27**	**.18**	.08	**.15**	**.17**	**.22**	**.15**	.16
6. Pt Share ARC 1m	.01	.10	.06	**.16**	**.20**	**.28**	**.20**	**.25**	**.41**	**.36**	**.29**	**.33**	**.29**	**.19**	.10	**.16**	**.23**	**.28**	**.23**	.14
7. Pt Share ARC 3m	.10	.10	.05	**.17**	**.25**	**.20**	**.18**	**.22**	**.27**	**.24**	**.37**	**.21**	**.25**	**.19**	.11	**.22**	**.31**	**.22**	.14	**.22**
8. Pt ARC Frq	.06	.16	.09	.12	**.26**	.02	.10	.07	.14	.14	.07	**.27**	**.30**	**.25**	.13	.15	.13	**.28**	.22	**.38**
9. Pt ARC Frq 1m	.07	.13	.17	-.01	.19	.17	.12	**.26**	.19	**.24**	**.39**	**.40**	**.42**	.05	.11	.13	-.06	**.35**	**.37**	**.61**
10. Pt ARC Frq 3m	-.06	.02	-.06	.02	.15	**.29**	.16	.17	**.29**	.17	.13	**.42**	**.36**	**.43**	.14	.12	.10	**.27**	**.35**	.26
11. SN Share ARC	.06	-.01	-.02	**.15**	**.17**	**.17**	**.16**	**.21**	**.59**	**.46**	**.40**	.08	**.17**	.09	.05	.08	**.15**	**.16**	**.22**	**.18**
12. SN Share ARC 1m	.04	.08	.05	.12	**.24**	**.23**	**.29**	**.25**	**.42**	**.69**	**.45**	**.26**	**.27**	.07	.08	.04	.11	**.25**	**.28**	**.24**
13. SN Share ARC 3m	.05	-.04	.04	.09	.14	**.20**	**.19**	**.18**	**.42**	**.47**	**.67**	**.22**	**.16**	**.15**	.09	.05	**.15**	**.24**	**.30**	**.24**
14. SN ARC Frq	.03	.03	.04	.01	.10	**.17**	.10	-.12	**.19**	.06	.03	**.24**	**.19**	.03	**.12**	.02	-.07	**.21**	**.25**	.12
15. SN ARC Frq 1m	**-.15**	-.09	-.08	-.07	.06	.11	-.02	-.07	.11	.06	.18	**.15**	.13	.12	.13	.14	**.17**	**.16**	.13	.12
16. SN ARC Frq 3m	-.03	-.14	-.07	-.00	-.12	.11	.07	.03	.06	.01	.14	.12	.09	.06	.05	.07	.09	-.01	-.03	-.03
17. SN Vid ARC	.02	.08	**.13**	.06	.08	.01	-.01	-.14	-.04	.08	-.09	.04	**.18**	.12	.06	.01	.09	.11	**.22**	-.01
18. SN Vid ARC 1m	-.01	.05	-.04	.06	-.00	.04	.01	-.14	.05	.08	.01	-.02	-.07	-.01	.11	.01	.09	-.00	-.04	-.10
19. SN Vid ARC 3m	.02	.06	-.05	.05	.08	.10	.06	-.01	.03	-.00	.06	.08	.00	.03	-.13	-.10	-.00	.12	.15	-.01
20. SN Clse	**.51**	**.47**	**.67**	**.38**	**.41**	**.19**	**.19**	.11	.08	.11	.06	**.12**	**.13**	.08	.06	.07	.08	.03	-.01	.04

Table 5 (*continued*)

Variable	21.	22.	23.	24.	25.	26.	27.	28.	29.	30.	31.	32.	33.	34.	35.	36.	37.	38.	39.	40.
21. SN Clse 1m	-																			
22. SN Clse 3m	**.49**	-																		
23. SN Clse ARC	**.40**	**.38**	-																	
24. SN Clse ARC 1m	**.68**	**.36**	**.55**	-																
25. SN Clse ARC 3m	**.48**	**.76**	**.49**	**.53**	-															
26. DB SN	**.15**	.13	**.15**	**.24**	**.17**	-														
27. DB SN 1m	**.19**	**.17**	.10	**.29**	**.21**	**.67**	-													
28. DB SN 3m	.06	.13	-.01	.15	.15	**.61**	**.73**	-												
29. DB ARC	**.13**	.11	**.18**	**.18**	**.22**	**.34**	**.23**	**.23**	-											
30. DB ARC 1m	**.17**	.08	**.17**	**.27**	.11	**.29**	**.22**	**.16**	**.45**	-										
31. DB ARC 3m	.09	.06	.05	.11	**.20**	**.16**	.10	.12	**.47**	**.58**	-									
32. Quant	.09	-.05	.05	**.17**	.10	**.37**	**.34**	**.22**	**.14**	**.25**	.07	-								
33. Quant 1m	**.16**	**.14**	**.15**	**.22**	**.22**	**.40**	**.48**	**.36**	**.15**	**.19**	.02	**.75**	-							
34. Quant 3m	.12	-.01	.10	**.17**	.15	**.37**	**.31**	**.29**	**.15**	-.03	**-.01**	.55	**.61**	-						
35. Any Conseq	-.00	.01	-.01	.10	**.18**	**.13**	**.14**	**.21**	-.08	.05	-.01	**.11**	**.17**	**.21**	-					
36. Any Conseq 1m	.02	.05	.09	.09	.12	**.17**	**.18**	**.25**	.09	-.05	.00	**.20**	**.35**	**.28**	**.34**	-				
37. Any Conseq 3m	.02	-.07	.08	.15	.06	**.17**	**.15**	**.24**	.07	-.01	.10	**.24**	**.33**	**.50**	**.29**	**.48**	-			
38. Num Conseq	.05	.01	.09	.12	.10	**.24**	**.24**	**.25**	**.23**	**.26**	.14	**.49**	**.38**	**.26**	**-**	**.18**	**.30**	-		
39. Num Conseq 1m	.03	.03	.11	**.16**	**.20**	**.29**	**.23**	**.26**	**.22**	**.31**	**.26**	**.52**	**.47**	**.39**	.09	-	**.30**	**.60**	-	
40. Num Conseq 3m	-.01	.04	.03	.15	.14	.14	**.19**	.14	.13	.13	.13	**.20**	**.37**	**.32**	.08	**.17**	-	**.39**	**.45**	-

Note. SM = social media, frq = frequency, pt = participant, ARC = alcohol-related content, 1m = 1-month follow-up, SN = social network, 3m = 3-month follow-up, vid = video, clse = closeness, DB = drinking buddy, quant = alcohol quantity, conseq = alcohol consequences, num = number. Sex was coded 0 = *female* and 1 = *male*. Semester was coded 1 = *spring 2022*, 2 = *summer 2022*, 3 = *fall 2022*, and 4 = *spring 2023*. Compensation was coded 0 = *raffle entry* and 1 = *direct payment*. Bold values represent significant associations ($p < .05$).

Participant Social Media Usage

As seen in Table 6, Instagram, Snapchat, and Facebook were the most commonly used social media platforms among participants at all three timepoints. Further, participants most frequently reported checking their social media accounts seven or more times per day. When it came to participants sharing ARC, only about a third of participants reported posting. Of those that posted, they mostly reported posting less than once a month. Photo ARC was the most popular modality for participants to share with video ARC being the second most common. The majority of ARC was posted by participants to Snapchat, with Instagram being the second most popular destination.

Table 6

Participant Social Media Usage Across All Three Timepoints

Variable	Baseline *n* (%)	1-month Follow-up *n* (%)	3-month Follow-up *n* (%)
Social Media Platforms Used			
Facebook	298 (77.6)	220 (57.3)	156 (40.6)
Instagram	367 (95.6)	291 (75.8)	218 (56.8)
Snapchat	348 (90.6)	270 (70.3)	198 (51.6)
Twitter	227 (59.1)	178 (46.4)	123 (32.0)
TikTok	283 (73.7)	218 (56.8)	155 (40.4)
Other	28 (7.3)	24 (6.3)	17 (4.4)
Do not have a social media account	0 (0.0)	0 (0.0)	2 (0.5)
Frequency of Checking Social Media			
Never	0 (0.0)	0 (0.0)	3 (0.8)
Once a month or less	0 (0.0)	0 (0.0)	0 (0.0)
2-3 times a month	4 (1.0)	3 (1.0)	1 (0.4)
1-6 times a week	12 (3.1)	13 (4.3)	14 (6.0)
1-3 times a day	59 (15.4)	54 (17.8)	52 (22.4)
4-6 times a day	117 (30.5)	93 (30.7)	71 (30.6)
7 or more times a day	192 (50.0)	140 (46.2)	91 (39.2)
Do not have a social media account	0 (0.0)	0 (0.0)	0 (0.0)
Participant Shares ARC			
Yes	129 (33.6)	90 (30.7)	66 (29.2)
No	255 (66.4)	203 (69.3)	160 (70.8)
ARC Modality			
Videos (with or without text)	22 (17.1)	19 (21.3)	13 (19.7)
Photos (with or without text)	105 (81.4)	68 (76.4)	52 (78.8)
Text-only status updates	1 (0.8)	1 (1.1)	1 (1.5)
Other	1 (0.8)	1 (1.1)	0 (0.0)
Frequency of Sharing ARC			
Never	0 (0.0)	1 (1.1)	0 (0.0)
Less than once a month	79 (61.2)	52 (58.4)	33 (50.0)
Every month	20 (15.5)	11 (12.4)	17 (25.8)
A couple times a month	27 (20.9)	21 (23.6)	11 (16.7)
Every week	2 (1.6)	3 (3.4)	3 (4.5)
A couple times a week	1 (0.8)	1 (1.1)	2 (3.0)
Daily or almost daily	0 (0.0)	0 (0.0)	0 (0.0)
Platforms Used to Share ARC			
Facebook	5 (1.3)	1 (0.3)	1 (0.3)
Instagram	65 (16.9)	48 (12.5)	37 (9.6)
Snapchat	95 (24.7)	63 (16.4)	49 (12.8)
Twitter	5 (1.3)	4 (1.0)	1 (0.3)

Table 6 (*continued*)

Variable	Baseline *n* (%)	1-month Follow-up *n* (%)	3-month Follow-up *n* (%)
TikTok	12 (3.1)	7 (1.8)	3 (0.8)
Other	5 (1.3)	4 (1.0)	3 (0.8)

Note. ARC = alcohol-related content on social media. Percentages do not add to 100% for the social media platform questions because participants were able to select all responses that applied.

Social Network Characteristics

As seen in Table 7, across all three timepoints, participants, on average named four to five social network members. Further, approximately a third of participants' social network members shared ARC which equates to about one to two network members. Further, across all three timepoints, about 70% of participants said they had at least one network member sharing ARC. On average, participants reported their social network members shared ARC every month to a couple of times a month. Participants reported that most of their social network members shared photo ARC with video ARC being the second most common. Text-only ARC was the least common with less than one network member sharing this content and only about 5-9% of participants saying they had at least one network member sharing this modality of content. Further social network characteristics can be viewed in Table 7.

Table 7

Social Network Characteristics Across All Three Timepoints

Variable	Baseline	1-month Follow-up	3-month Follow-up
Total Number of SN Members Named *M* (*SD*)	4.76 (0.73)	4.55 (0.97)	4.52 (1.06)
Proportion of SN Sharing ARC *M* (*SD*)	0.32 (0.28)	0.31 (0.29)	0.32 (0.30)
Proportion of 0.00 *n* (%)	111 (29.1)	91 (32.6)	67 (30.9)
Proportion > 0.00 *n* (%)	271 (70.9)	188 (67.4)	150 (69.9)
Average Frequency of SN Sharing ARC *M* (*SD*)	3.17 (1.05)	3.21 (1.10)	3.05 (1.05)
Proportion of SN Sharing Mostly Video ARC *M* (*SD*)	0.24 (0.37)	0.20 (0.33)	0.23 (0.36)
Proportion of 0.00 *n* (%)	175 (64.8)	123 (66.1)	100 (66.7)
Proportion > 0.00 *n* (%)	95 (35.2)	63 (33.9)	50 (33.3)
Proportion of SN Sharing Mostly Photo ARC *M* (*SD*)	0.70 (0.39)	0.75 (0.36)	0.75 (0.38)
Proportion of 0.00 *n* (%)	52 (19.3)	27 (14.5)	24 (16.0)
Proportion > 0.00 *n* (%)	218 (80.7)	159 (85.5)	126 (84.0)
Proportion of SN Sharing Mostly Text ARC *M* (*SD*)	0.06 (0.20)	0.04 (0.19)	0.03 (0.15)
Proportion of 0.00 *n* (%)	246 (91.1)	175 (94.1)	143 (95.3)
Proportion > 0.00 *n* (%)	24 (8.9)	11 (5.9)	7 (4.7)
Average Closeness with SN *M* (*SD*)	2.63 (0.34)	2.62 (0.32)	2.66 (0.33)
Average Closeness with SN Sharing ARC *M* (*SD*)	2.62 (0.47)	2.58 (0.50)	2.55 (0.50)
Proportion of Drinking Buddies in SN *M* (*SD*)	0.50 (0.33)	0.45 (0.34)	0.45 (0.34)
Proportion of 0.00 *n* (%)	65 (17.0)	68 (24.3)	47 (21.5)
Proportion > 0.00 *n* (%)	317 (83.0)	212 (75.7)	172 (78.5)
Proportion of Drinking Buddies in SN Sharing ARC *M* (*SD*)	0.30 (0.33)	0.32 (0.35)	0.30 (34)
Proportion of 0.00 *n* (%)	162 (45.5)	83 (38.6)	71 (41.3)
Proportion > 0.00 *n* (%)	194 (54.5)	132 (61.4)	101 (58.7)

Note. SN = social network, ARC = alcohol-related content. The responses options for frequency of SN sharing ARC were 1 (*Never*), 2 (*Less than once a month*), 3 (*Every month*), 4 (*A couple times a month*), 5 (*Every week*), 6 (*A couple times a week*), and 7 (*Daily or almost daily*). The response options for closeness with SN were 1 (*Not very close*), 2 (*Somewhat close*), and 3 (*Very close*).

Participant Alcohol Use and Consequences

As seen in Table 8, participants drank the greatest quantity at baseline. A larger proportion of the sample reported experiencing any consequences versus no consequences at baseline with those who reported experiencing consequences on average reporting between four and five. Conversely lower proportions of participants reported consequences and lower numbers of consequences in the follow-up surveys.

Table 8

Participant Alcohol Quantity and Consequences Across All Three Time Points

Variable	Baseline *M* (*SD*)	1-month Follow-up *M* (*SD*)	3-month Follow-up M (*SD*)
Quantity	8.94 (6.77)	7.22 (5.64)	5.95 (5.38)
Consequences Yes/No	0.94 (0.23)	0.77 (0.42)	0.63 (0.48)
Number of Consequences	4.54 (3.04)	4.11 (3.22)	3.53 (2.98)

Note. Quantity = total number of drinks consumed in a typical week in the past 30 days. Consequences Yes/No = participants who experienced any consequences were recoded as a “1” while those who did not experience any consequences were recoded as a “0”, Number of Consequences = for participants who did experience consequences this variable reflected the total number of consequences they had experienced.

Aim 1: Participant Sharing of ARC

Aim 1a: Cross-sectional Participant Sharing of ARC

As seen in Table 9, after controlling for participant sex, social media checking frequency, semester survey was completed, compensation chosen and quantity (in consequences model only), participants sharing ARC was associated with their alcohol quantity as well as consequences. When controlling for the same variables as above, frequency of participants sharing ARC was only associated with alcohol quantity but not consequences.

Table 9

Cross-sectional Aim 1 Models: Participants Sharing ARC Predicts Alcohol Outcomes

	Quantity				Consequences			
Variable	β	*B*	*SE*	*p*	β	*B*	*SE*	*p*
Aim 1a: Participant ARC (Y/N)								
Semester	0.04	0.36	0.56	.523	0.01	0.05	0.24	.847
Compensation	-0.10	-1.44	1.05	.170	-0.06	-0.43	0.45	.343
Social Media Frequency	0.04	0.30	0.36	.410	0.07	0.24	0.15	.127
Sex	**0.24****	**3.65****	**0.74**	**<.001**	**-0.11***	**-0.77***	**0.33**	**.017**
Quantity	-	-	-	-	**0.47****	**0.22****	**0.02**	**<.001**
Participant Share ARC	**0.27****	**3.83****	**0.69**	**<.001**	**0.09***	**0.62***	**0.31**	**.044**
Aim 1b: Frequency of Participant ARC								
Semester	0.14	1.31	1.08	.225	0.01	0.03	0.45	.944
Compensation	-0.22	-3.82	2.05	.063	-0.12	-1.00	0.86	.244
Social Media Frequency	0.07	0.68	0.79	.393	0.11	0.51	0.33	.118
Sex	**0.24***	**4.57***	**1.58**	**.004**	-0.04	-0.32	0.67	.633
Quantity	-	-	-	-	**0.49****	**0.23****	**0.04**	**<.001**
Frequency ARC	**0.26***	**2.25***	**0.70**	**.001**	0.14	0.55	0.30	.067

Note. ARC = alcohol-related content, Y/N = yes/no, social media checking frequency = frequency of checking social media (across all platforms), quantity = number of alcoholic drinks consumed in a typical day, consequences = number of alcohol-related consequences experienced. Sex was coded 0 = *female* and 1 = *male*. Only the models examining consequences controlled for quantity. Significant associations are in bold. **p* < .05 ***p* < .001.

Aims 1b and 5: Longitudinal Participant Sharing of ARC

As seen in Table 6, the numbers of participants reporting they shared ARC were low across all three timepoints. Therefore, a second set of models was conducted to examine if the frequency of their sharing ARC was associated with alcohol quantity and consequences over time.

Alcohol Quantity. Details of invariance testing are included in Table 10. In the model examining participants sharing ARC as the key predictor, no paths of interest significantly varied over time and all were therefore constrained to equality within relevant pairs. In the model examining frequency of participants sharing ARC, only the cross-lagged paths from frequency of sharing ARC to quantity were found to significantly vary over time and were therefore freely estimated in the final model while all other paths within relevant pairs were constrained to equality.

For the model examining participants sharing ARC (yes/no), both pairs of cross-lagged paths between alcohol quantity and the likelihood of participants later sharing ARC were not significant. Both pairs of cross-lagged paths between participants sharing ARC and later alcohol quantity were also not significant (see Table 11 and Figure 8).

For the model examining frequency of participants sharing ARC, both sets of cross-lagged paths were significant. Greater alcohol quantity was associated with greater frequency of participants sharing ARC over time, and also greater frequency of participants sharing ARC was associated with greater alcohol quantity (both from baseline to the 1-month follow-up and 1-month to 3-month (see Table 11 and Figure 8).

Table 10

Longitudinal Aim 1 For Alcohol Quantity: Invariance Testing for Cross-lagged and Auto-regressive Paths

Paths	Paths Compared	χ^2_{diff}	df_{diff}	p	Conclusion
Participant Shares ARC					
Cross-lagged					
Quantity T1 → Share ARC T2	A	1.550	1	.213	Constrain
Quantity T2 → Share ARC T3	A				
Share ARC T1 → Quantity T2	B	0.317	1	.574	Constrain
Share ARC T2 → Quantity T3	B				
Auto-regressive					
Share ARC T1 → Share ARC T2	C	0.098	1	.754	Constrain
Share ARC T2 → Share ARC T3	C				
Quantity T1 → Quantity T2	D	0.211	1	.646	Constrain
Quantity T2 → Quantity T3	D				
Freq Participant Shares ARC					
Cross-lagged					
Quantity T1 → Freq Share ARC T2	E	0.240	1	.624	Constrain
Quantity T2 → Freq Share ARC T3	E				
Freq Share ARC T1 → Quantity T2	F	5.516	1	**.019**	Free
Freq Share ARC T2 → Quantity T3	F				
Auto-regressive					
Freq Share ARC T1 → Freq Share ARC T2	G	1.583	1	.208	Constrain
Freq Share ARC T2 → Freq Share ARC T3	G				
Quantity T1 → Quantity T2	H	2.003	1	.157	Constrain
Quantity T2 → Quantity T3	H				

Note. ARC = alcohol-related content on social media, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up], Quantity = number of alcoholic drinks consumed in a typical week in the past 30 days, Freq = frequency. Letter pairs reflect which paths were freely estimated versus constrained to equality for each chi-square comparison. Although not listed in the table, invariance testing was also conducted for all covariate paths.

Table 11

Longitudinal Cross-lagged Panel Model Results for Aim 1: Self-sharing ARC and Alcohol Quantity

	β	*B*	*SE*	*p*
Participant Sharing ARC				
Auto-regressive Paths				
Sharing ARC Y/N (T1 → T2, T2 → T3)	**0.77****	**1.23****	**0.14**	**<.001**
Quantity (T1 → T2, T2 → T3)	**0.79****	**0.64****	**0.03**	**<.001**
Cross-lagged Paths				
Sharing ARC Y/N → Quantity (T1 → T2, T2 → T3)	0.03	0.18	0.19	.347
Quantity → Sharing ARC Y/N (T1 → T2, T2 → T3)	0.06	0.02	0.01	.235
Covariates and Missingness				
Sex → Sharing ARC Y/N (T1 → T1, T1 → T2, T1 → T3)	**-0.10***	**-0.23***	**0.11**	**.046**
Sex → Quantity (T1 → T1)	**0.23****	**3.50****	**0.72**	**<.001**
Sex → Quantity (T1 → T2)	-0.04	-0.45	0.67	.505
Sex → Quantity (T1 → T3)	-0.01	-0.13	0.78	.870
Semester → Sharing ARC Y/N (T1 → T1, T2 → T2, T3→T3)	0.05	0.07	0.13	.597
Semester → Quantity (T1 → T1, T2 → T2, T3→T3)	0.12	1.00	0.62	.105
Compensation → Sharing ARC Y/N (T1 → T1, T2 → T2, T3→T3)	-0.14	-0.33	0.19	.086
Compensation → Quantity (T1 → T1, T2 → T2, T3→T3)	-0.10	-1.54	0.86	.073
SM Check Freq → Sharing ARC Y/N (T1 → T1, T2 → T2, T3→T3)	**0.24****	**0.27****	**0.07**	**<.001**
SM Check Freq → Quantity (T1 → T1, T2 → T2, T3→T3)	**0.06***	**0.48***	**0.23**	**.034**
Sharing ARC Y/N → Miss 1-month follow-up (T1 → T2)	**-0.32***	**-0.32***	**0.15**	**.030**
Sharing ARC Y/N → Miss 3-month follow-up (T2 → T3)	-0.17	-0.10	0.07	.152
Sharing ARC Y/N → Miss 1-month follow-up (T2 → T2)	0.16	0.10	0.06	.121
Sharing ARC Y/N → Miss 3-month follow-up (T3 → T3)	0.10	0.04	0.04	.243
Quantity → Miss 1-month follow-up (T1 → T2)	**0.48***	**0.08***	**0.03**	**.013**
Quantity → Miss 3-month follow-up (T2 → T3)	0.21	0.04	0.02	.088
Quantity → Miss 1-month follow-up (T2 → T2)	**-0.32***	**-0.06***	**0.03**	**.035**
Quantity → Miss 3-month follow-up (T3 → T3)	-0.12	-0.02	0.01	.118
Freq Participant Sharing ARC				
Auto-regressive Paths				
Freq Sharing ARC (T1 → T2, T2 → T3)	**0.51****	**0.60****	**0.10**	**<.001**
Quantity (T1 → T2, T2 → T3)	**0.81****	**0.67****	**0.03**	**<.001**
Cross-lagged Paths				
Freq Sharing ARC → Quantity (T1 → T2)	**0.17***	**1.08***	**0.44**	**.014**
Freq Sharing ARC → Quantity (T2 → T3)	**-0.21***	**-1.08***	**0.34**	**.001**
Quantity → Freq Sharing ARC (T1 → T2, T2 → T3)	**0.18***	**0.03***	**0.01**	**.008**
Covariates and Missingness				
Sex → Freq Sharing ARC (T1 → T1)	-0.17	-0.33	0.21	.117

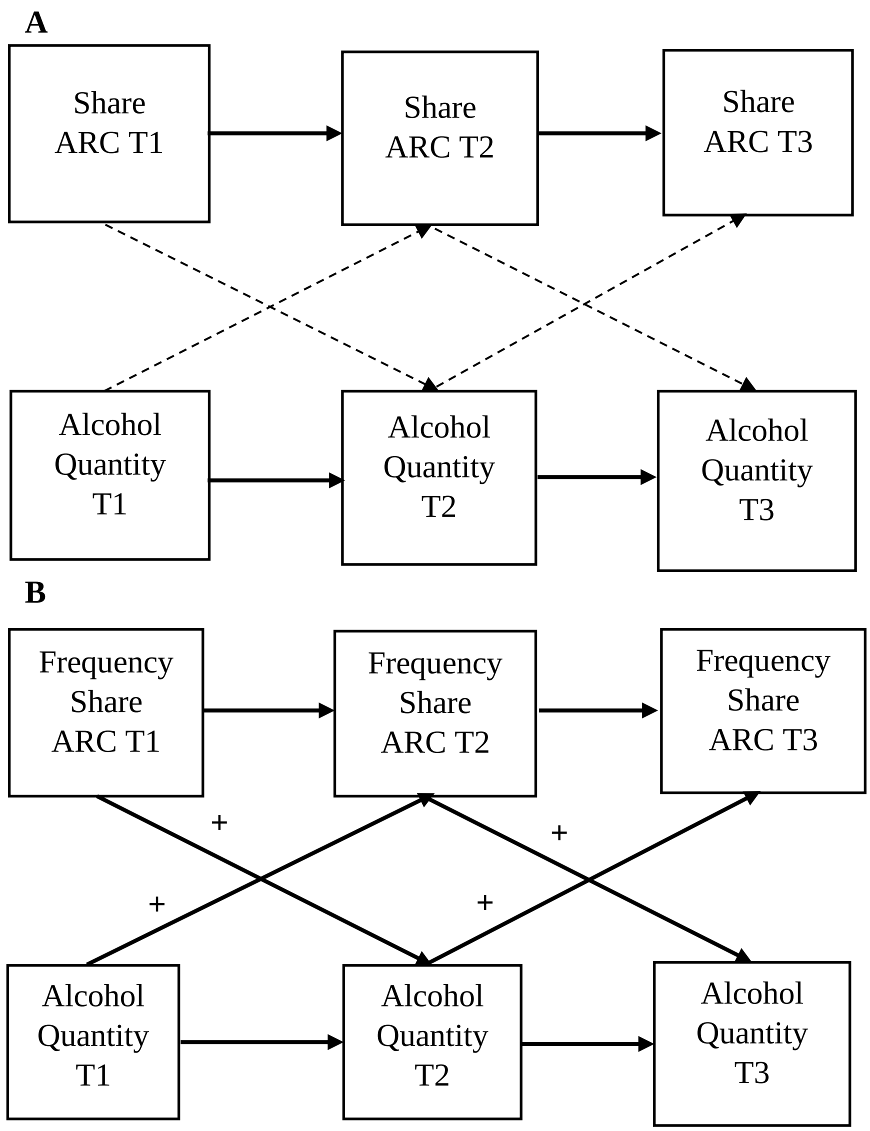
Table 11 (*continued*)

	β	*B*	*SE*	*p*
Sex → Freq Sharing ARC (T1 → T2)	-0.16	-0.38	0.31	.223
Sex → Freq Sharing ARC (T1 → T3)	**0.42***	**0.97***	**0.39**	**.013**
Sex → Quantity (T1 → T1)	**0.22****	**3.42****	**0.71**	**<.001**
Sex → Quantity (T1 → T2)	-0.02	-0.29	0.79	.719
Sex → Quantity (T1 → T3)	-0.06	-0.66	0.80	.415
Semester → Freq Sharing ARC (T1 → T1, T2 → T2, T3→T3)	0.09	0.09	0.13	.469
Semester → Quantity (T1 → T1)	0.15	1.17	0.64	.070
Semester → Quantity (T2 → T2)	-0.11	-1.68	1.23	.171
Semester → Quantity (T3 → T3)	-0.00	-0.02	1.16	.988
Compensation → Freq Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.16	-0.32	0.18	.075
Compensation → Quantity (T1 → T1, T2 → T2, T3→T3)	-0.03	-0.50	0.61	.410
SM Check Freq → Freq Sharing ARC (T1 → T1, T2 → T2, T3→T3)	**0.18***	**0.18***	**0.07**	**.008**
SM Check Freq → Quantity (T1 → T1, T2 → T2, T3→T3)	**0.08***	**0.56***	**0.22**	**.012**
Freq Sharing ARC → Miss 1-month follow-up (T1 → T2)	-0.19	-0.22	0.14	.118
Freq Sharing ARC → Miss 3-month follow-up (T2 → T3)	-0.25	-0.26	0.15	.088
Freq Sharing ARC → Miss 1-month follow-up (T2 → T2)	0.07	0.07	0.05	.152
Freq Sharing ARC → Miss 3-month follow-up (T3 → T3)	0.18	0.19	0.12	.119
Quantity → Miss 1-month follow-up (T1 → T2)	0.21	0.03	0.02	.090
Quantity → Miss 3-month follow-up (T2 → T3)	**0.32***	**0.06***	**0.02**	**.013**
Quantity → Miss 1-month follow-up (T2 → T2)	-0.12	-0.02	0.01	.122
Quantity → Miss 3-month follow-up (T3 → T3)	**-0.29***	**-0.06***	**0.03**	**.024**

Note. ARC = alcohol-related content, Y/N = yes/no, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up], quantity = number of alcoholic drinks consumed in a typical week in the past 30 days, Freq = frequency, SM = social media. Sex was coded 0 = *female* and 1 = *male*. Betas for constrained paths are based on standard deviations for estimates of predictors at baseline associated with outcomes at the 1-month follow-up or within-timepoint baseline associations, respectively. Significant path estimates are in bold, **p* < .05, ***p* < .001.

Figure 8

Longitudinal Associations between Sharing ARC and Alcohol Quantity



Note. ARC = alcohol-related content, Alcohol Quantity = number of alcoholic drinks consumed in a typical week in the past 30 days. Significant paths are in bold, while dashed lines represent non-significant paths. Although not pictured, all models controlled for participant sex, social media checking frequency, semesters, and compensation chosen.

Any Alcohol Consequences. Details of invariance testing are included in Table 12. For the model examining participants sharing ARC (yes/no), no paths of interest were found to significantly vary over time. Therefore, all were constrained to equality. For the model examining the frequency of participants sharing ARC, the cross-lagged paths from frequency of sharing ARC to experiencing alcohol consequences (versus not experiencing any alcohol consequences) and the auto-regressive paths for alcohol consequences were found to significantly vary over time. These paths were then freely estimated in the final model, while all other paths were constrained to equality within relevant pairs as indicated in Table 12.

As seen in Table 13, experiencing any alcohol consequences was significantly associated with a greater likelihood of sharing ARC over time. Sharing ARC was not significantly linked to likelihood of experiencing any alcohol consequences over time (see also Figure 9). The same pattern of findings was observed in the model examining the frequency of participants sharing ARC in that experiencing any alcohol consequences was associated with greater frequency of sharing ARC over time. Frequency of ARC sharing was not significantly associated with likelihood of experiencing any alcohol consequences (see Table 13 and Figure 9).

Table 12

Longitudinal Aim 1 For Reporting Any Alcohol Consequences: Invariance Testing for Cross-lagged and Auto-regressive Paths

Paths	Paths Compared	χ^2_{diff}	df_{diff}	p	Conclusion
Participant Shares ARC					
Cross-lagged					
Any Conseq T1 → Share ARC T2	A	0.042	1	.837	Constrain
Any Conseq T2 → Share ARC T3	A				
Share ARC T1 → Any Conseq T2	B	0.185	1	.667	Constrain
Share ARC T2 → Any Conseq T3	B				
Auto-regressive					
Share ARC T1 → Share ARC T2	C	0.298	1	.585	Constrain
Share ARC T2 → Share ARC T3	C				
Any Conseq T1 → Any Conseq T2	D	3.719	1	.054	Constrain
Any Conseq T2 → Any Conseq T3	D				
Freq Participant Shares ARC					
Cross-lagged					
Any Conseq T1 → Freq Share ARC T2	E	0.119	1	.730	Constrain
Any Conseq T2 → Freq Share ARC T3	E				
Freq Share ARC T1 → Any Conseq T2	F	4.272	1	**.039**	**Free**
Freq Share ARC T2 → Any Conseq T3	F				
Auto-regressive					
Freq Share ARC T1 → Freq Share ARC T2	G	3.144	1	.076	Constrain
Freq Share ARC T2 → Freq Share ARC T3	G				
Any Conseq T1 → Any Conseq T2	H	4.913	1	**.027**	**Free**
Any Conseq T2 → Any Conseq T3	H				

Note. Any Conseq = experience any alcohol consequences where 1 = *yes* and 0 = *no*. ARC = alcohol-related content on social media, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up], Freq = frequency. Letter pairs reflect which paths were freely estimated versus constrained to equality for each chi-square comparison. Although not listed in the table, invariance testing was also conducted for all within-timepoint covariate paths.

Table 13

Longitudinal Cross-lagged Panel Model Results for Aim 1: Self-sharing ARC and Reporting Any Alcohol Consequences

	β	*B*	*SE*	*p*
Participant Sharing ARC				
Auto-regressive Paths				
Sharing ARC Y/N (T1 → T2, T2 → T3)	**0.71****	**1.28****	**0.20**	**<.001**
Any Consequences (T1 → T2, T2 → T3)	**0.78****	**0.96***	**0.35**	**.006**
Cross-lagged Paths				
Sharing ARC Y/N → Any Consequences (T1 → T2, T2 → T3)	**0.20***	0.27	0.17	.109
Any Consequences → Sharing ARC Y/N (T1 → T2, T2 → T3)	**0.42****	**0.70***	**0.21**	**.001**
Covariates and Missingness				
Sex → Sharing ARC Y/N (T1 → T1, T1 → T2, T1 → T3)	**-0.14***	**-0.34***	**0.13**	**.008**
Sex → Any Consequences (T1 → T1, T1 → T2, T1 → T3)	-0.06	-0.14	0.12	.243
Semester → Sharing ARC Y/N (T1 → T1, T2 → T2, T3→T3)	-0.02	-0.03	0.13	.825
Semester → Any Consequences (T1 → T1, T2 → T2, T3→T3)	0.18	0.24	0.14	.082
Compensation → Sharing ARC Y/N (T1 → T1, T2 → T2, T3→T3)	-0.05	-0.11	0.18	.553
Compensation → Any Consequences (T1 → T1, T2 → T2, T3→T3)	-0.09	-0.24	0.21	.268
SM Check Freq → Sharing ARC Y/N (T1 → T1, T2 → T2, T3→T3)	**0.18***	**0.21***	**0.08**	**.005**
SM Check Freq → Any Consequences (T1 → T1, T2 → T2, T3→T3)	0.05	0.07	0.07	.333
Quantity → Any Consequences (T1 → T1)	**0.44****	**0.07****	**0.01**	**<.001**
Quantity → Any Consequences (T2 → T2)	**0.48****	**0.18***	**0.06**	**.004**
Quantity → Any Consequences (T3 → T3)	**0.43****	0.21	0.14	.138
Sharing ARC Y/N → Miss 1-month follow-up (T1 → T2)	-0.16	-0.15	0.10	.135
Sharing ARC Y/N → Miss 3-month follow-up (T2 → T3)	-0.03	-0.02	0.05	.736
Sharing ARC Y/N → Miss 1-month follow-up (T2 → T2)	0.12	0.07	0.05	.142
Sharing ARC Y/N → Miss 3-month follow-up (T3 → T3)	0.03	0.01	0.03	.693
Any Consequences → Miss 1-month follow-up (T1 → T2)	**-0.09***	**-0.08***	**0.04**	**.043**
Any Consequences → Miss 3-month follow-up (T2 → T3)	-0.04	-0.03	0.03	.236
Any Consequences → Miss 1-month follow-up (T2 → T2)	0.01	0.004	0.03	.877
Any Consequences → Miss 3-month follow-up (T3 → T3)	0.01	0.01	0.02	.714
Freq Participant Sharing ARC				
Auto-regressive Paths				
Freq Sharing ARC	**0.27***	**0.33****	**0.09**	**<.001**
Any Consequences (T1 → T2)	**0.96****	**0.48****	**0.11**	**<.001**
Any Consequences (T2 → T3)	**0.72****	**1.03****	**0.26**	**<.001**
Cross-lagged Paths				
Freq Sharing ARC → Any Consequences (T1 → T2)	-0.29	-0.19	0.13	.133
Freq Sharing ARC → Any Consequences (T2 → T3)	-0.02	-0.02	0.08	.811
Any Consequences → Freq Sharing ARC	**0.76****	**0.69****	**0.13**	**<.001**
Covariates and Missingness				
Sex → Freq Sharing ARC (T1 → T1, T1 → T2, T1 → T3)	-0.05	-0.09	0.12	.486
Sex → Any Consequences (T1 → T1, T1 → T2, T1 → T3)	-0.04	-0.09	0.06	.157

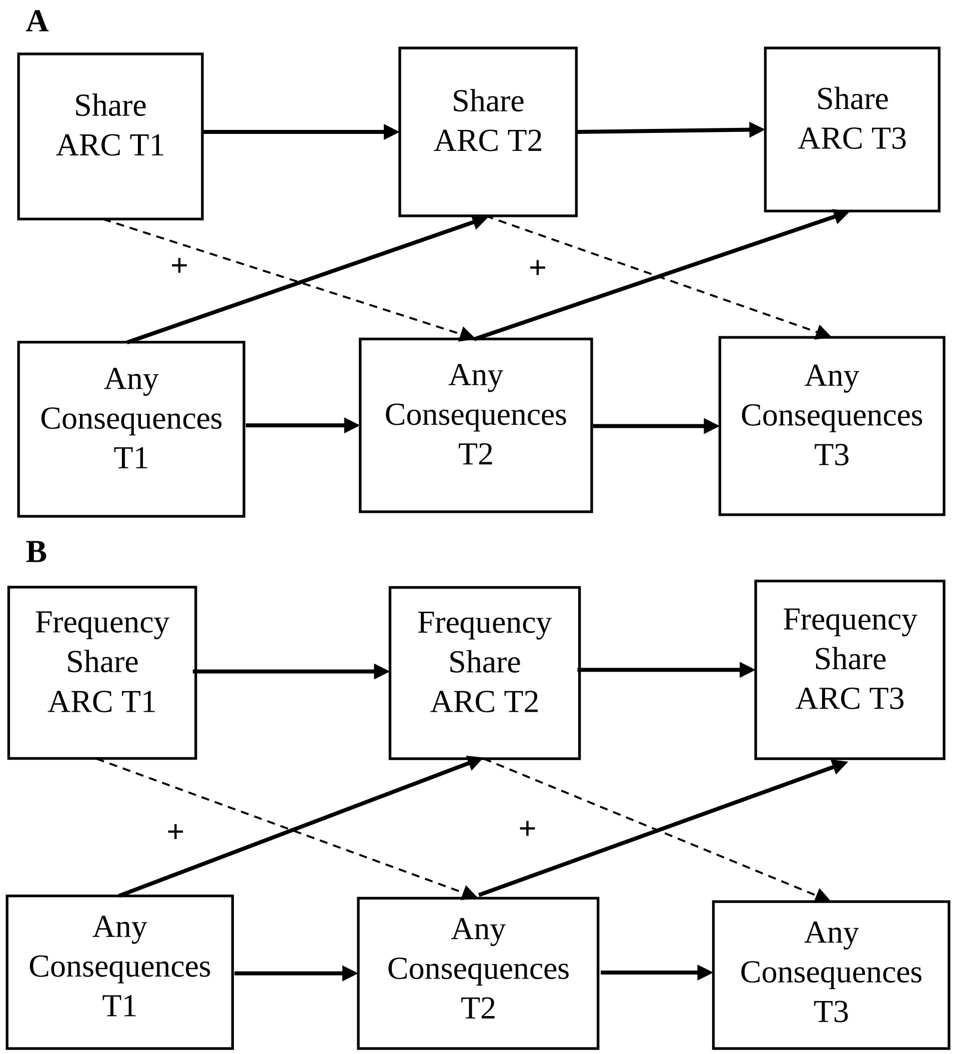
Table 13 (*continued*)

	β	*B*	*SE*	*p*
Semester → Freq Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.09	-0.09	0.13	.499
Semester → Any Consequences (T1 → T1, T2 → T2, T3→T3)	0.13	0.17	0.11	.129
Compensation → Freq Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.07	-0.14	0.18	.454
Compensation → Any Consequences (T1 → T1, T2 → T2, T3→T3)	-0.07	-0.18	0.14	.210
SM Check Freq → Freq Sharing ARC (T1 → T1, T2 → T2, T3→T3)	**0.16***	**0.15***	**0.07**	**.032**
SM Check Freq → Any Consequences (T1 → T1, T2 → T2, T3→T3)	0.05	0.06	0.04	.123
Quantity → Any Consequences (T1 → T1, T2 → T2, T3→T3)	**0.42****	**0.07****	**0.01**	**<.001**
Freq Sharing ARC → Miss 1-month follow-up (T1 → T2)	0.02	0.02	0.13	.891
Freq Sharing ARC → Miss 3-month follow-up (T2 → T3)	0.15	0.15	0.11	.149
Freq Sharing ARC → Miss 1-month follow-up (T2 → T2)	0.08	0.08	0.05	.149
Freq Sharing ARC → Miss 3-month follow-up (T3 → T3)	-0.04	-0.05	0.05	.337
Any Consequences → Miss 1-month follow-up (T1 → T2)	**-0.10***	**-0.09***	**0.04**	**.037**
Any Consequences → Miss 3-month follow-up (T2 → T3)	-0.03	-0.06	0.08	.464
Any Consequences → Miss 1-month follow-up (T2 → T2)	0.00	-0.001	0.06	.989
Any Consequences → Miss 3-month follow-up (T3 → T3)	0.02	0.02	0.03	.453

Note. ARC = alcohol-related content, Y/N = yes/no, ever consequences = if participant reported any alcohol consequences (1) versus no alcohol consequences (0) in the past 30 days, Freq = frequency, quantity = number of alcoholic drinks consumed in a typical week in the past 30 days, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Sex was coded 0 = *female* and 1 = *male*. Betas for constrained paths are based on standard deviations for estimates of predictors at baseline associated with outcomes at the 1-month follow-up or within-timepoint baseline associations, respectively. Significant path estimates are in bold, **p* < .05, ***p* < .001.

Figure 9

Longitudinal Associations between Sharing ARC and Reporting Any Alcohol Consequences



Note. ARC = alcohol-related content, any consequences = if participant reported any alcohol consequences (1) versus no alcohol consequences (0) in the past 30 days. Significant path estimates are in bold, while dashed lines represent non-significant paths. Although not pictured, all models controlled for participant sex, social media checking frequency, semesters, compensation, and alcohol quantity.

Number of Alcohol Consequences. Details of invariance testing are included in Table 14. The autoregressive paths for the number of alcohol consequences were found to significantly vary over time in the model examining participants sharing ARC as well as the model examining the frequency of participants sharing ARC. These paths were freely estimated in the final model while all other paths of interest were constrained to equality within relevant pairs.

In the model examining participants sharing ARC, reporting more alcohol consequences was associated with a greater likelihood of sharing ARC over time. Sharing ARC was not associated with number of alcohol consequences over time (see Table 15 and Figure 10). In the model examining the frequency of participants sharing ARC, reporting more alcohol consequences was associated with sharing ARC more frequently over time, and sharing more ARC was associated reporting more alcohol consequences over time (see Table 15 and Figure 10).

Table 14

Longitudinal Aim 1 For Number of Alcohol Consequences: Invariance Testing for Cross-lagged and Auto-regressive Paths

Paths	Paths Compared	χ^2_{diff}	df_{diff}	p	Conclusion
Participant Shares ARC					
Cross-lagged					
Conseq T1 → Share ARC T2	A	1.386	1	.239	Constrain
Conseq T2 → Share ARC T3	A				
Share ARC T1 → Conseq T2	B	0.216	1	.642	Constrain
Share ARC T2 → Conseq T3	B				
Auto-regressive					
Share ARC T1 → Share ARC T2	C	0.159	1	.690	Constrain
Share ARC T2 → Share ARC T3	C				
Conseq T1 → Conseq T2	D	6.952	1	**.008**	Free
Conseq T2 → Conseq T3	D				
Freq Participant Shares ARC					
Cross-lagged					
Conseq T1 → Freq Share ARC T2	E	0.450	1	.502	Constrain
Conseq T2 → Freq Share ARC T3	E				
Freq Share ARC T1 → Conseq T2	F	2.467	1	.116	Constrain
Freq Share ARC T2 → Conseq T3	F				
Auto-regressive					
Freq Share ARC T1 → Freq Share ARC T2	G	0.955	1	.328	Constrain
Freq Share ARC T2 → Freq Share ARC T3	G				
Conseq T1 → Conseq T2	H	8.306	1	**.004**	Free
Conseq T2 → Conseq T3	H				

Note. Conseq = number of alcohol consequences experienced in the past 30 days. ARC = alcohol-related content on social media, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up], Freq = frequency. Letter pairs reflect which paths were freely estimated versus constrained to equality for each chi-square comparison. Although not listed in the table, invariance testing was also carried out for all within-timepoint covariate paths.

Table 15

Longitudinal Cross-lagged Panel Model Results for Aim 1: Self-sharing ARC and Number of Alcohol Consequences

	β	*B*	*SE*	*p*
Participant Sharing ARC				
<u>*Auto-regressive Paths*</u>				
Sharing ARC Y/N (T1 → T2, T2 → T3)	**0.73***	**1.20****	**0.14**	**<.001**
Consequences (T1 → T2)	**0.71****	**0.69****	**0.06**	**<.001**
Consequences (T2 → T3)	**0.44****	**0.45****	**0.07**	**<.001**
<u>*Cross-lagged Paths*</u>				
Sharing ARC Y/N → Consequences (T1 → T2, T2 → T3)	0.05	0.14	0.13	.276
Consequences → Sharing ARC Y/N (T1 → T2, T2 → T3)	**0.26****	**0.15****	**0.04**	**<.001**
<u>*Covariates and Missingness*</u>				
Sex → Sharing ARC Y/N (T1 → T1, T1 → T2, T1 → T3)	**-0.14***	**-0.34***	**0.12**	**.003**
Sex → Consequences (T1 → T1, T1 → T2, T1 → T3)	**-0.08***	**-0.55***	**0.27**	**.038**
Semester → Sharing ARC Y/N (T1 → T1, T2 → T2, T3→T3)	0.02	0.02	0.13	.871
Semester → Consequences (T1 → T1, T2 → T2, T3→T3)	0.07	0.25	0.26	.334
Compensation → Sharing ARC Y/N (T1 → T1, T2 → T2, T3→T3)	-0.10	-0.24	0.18	.199
Compensation → Consequences (T1 → T1, T2 → T2, T3→T3)	0.00	0.03	0.32	.930
SM Check Freq → Sharing ARC Y/N (T1 → T1, T2 → T2, T3→T3)	**0.21***	**0.24***	**0.08**	**.002**
SM Check Freq → Consequences (T1 → T1, T2 → T2, T3→T3)	0.06	0.20	0.13	.119
Quantity → Consequences (T1 → T1)	**0.60****	**0.27****	**0.02**	**<.001**
Quantity → Consequences (T2 → T2)	**0.16***	**0.12***	**0.04**	**.001**
Quantity → Consequences (T3 → T3)	**0.22****	**0.15***	**0.05**	**.001**
Sharing ARC Y/N → Miss 1-month follow-up (T1 → T2)	-0.12	-0.12	0.08	.128
Sharing ARC Y/N → Miss 3-month follow-up (T2 → T3)	-0.04	-0.02	0.04	.524
Sharing ARC Y/N → Miss 1-month follow-up (T2 → T2)	0.06	0.04	0.04	.402
Sharing ARC Y/N → Miss 3-month follow-up (T3 → T3)	0.02	0.01	0.02	.680
Consequences → Miss 1-month follow-up (T1 → T2)	0.05	0.02	0.02	.463
Consequences → Miss 3-month follow-up (T2 → T3)	0.07	0.02	0.03	.382
Consequences → Miss 1-month follow-up (T2 → T2)	-0.01	-0.01	0.02	.748
Consequences → Miss 3-month follow-up (T3 → T3)	-0.03	-0.01	0.01	.387
Freq Participant Sharing ARC				
<u>*Auto-regressive Paths*</u>				
Freq Sharing ARC (T1 → T2, T2 → T3)	**0.40****	**0.46****	**0.09**	**<.001**
Consequences (T1 → T2)	**0.70****	**0.68****	**0.07**	**<.001**
Consequences (T2 → T3)	**0.42****	**0.43****	**0.08**	**<.001**
<u>*Cross-lagged Paths*</u>				
Freq Sharing ARC → Consequences (T1 → T2, T2 → T3)	**0.18***	**0.62***	**0.19**	**.001**

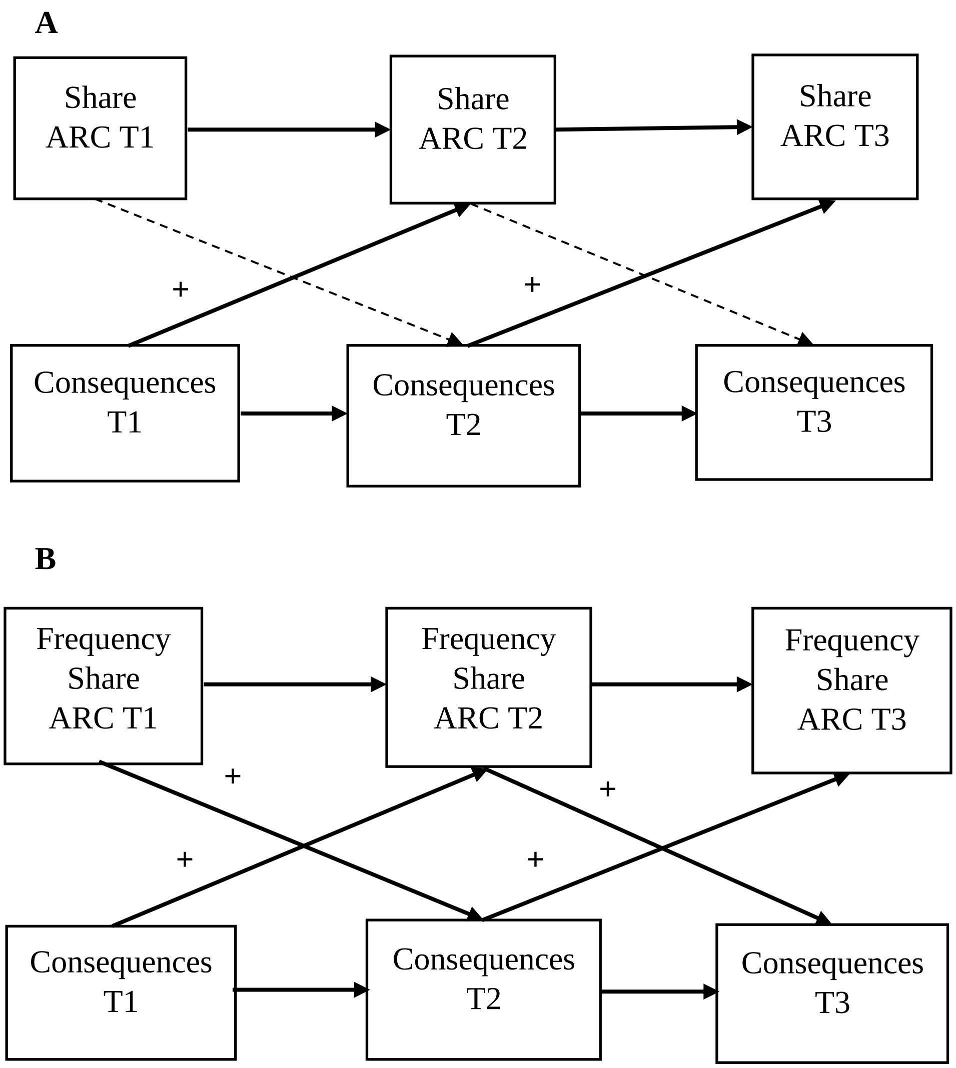
Table 15 (*continued*)

	β	*B*	*SE*	*p*
Consequences → Freq Sharing ARC (T1 → T2, T2 → T3)	**0.29***	**0.09****	**0.02**	**<.001**
<u>*Covariates and Missingness*</u>				
Sex → Freq Sharing ARC (T1 → T1, T1 → T2, T1 → T3)	-0.18	-0.10	0.11	.357
Sex → Consequences (T1 → T1, T1 → T2, T1 → T3)	-0.07	**-0.52***	**0.26**	**.045**
Semester → Freq Sharing ARC (T1 → T1, T2 → T2, T3→T3)	0.01	0.01	0.14	.925
Semester → Consequences (T1 → T1)	0.03	0.11	0.28	.688
Semester → Consequences (T2 → T2)	0.03	0.28	0.58	.634
Semester → Consequences (T3 → T3)	-0.04	-0.58	1.38	.674
Compensation → Freq Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.12	-0.23	0.19	.231
Compensation → Consequences (T1 → T1)	-0.04	-0.26	0.56	.638
Compensation → Consequences (T2 → T2)	0.08	0.65	0.47	.165
Compensation → Consequences (T3 → T3)	-0.08	-0.56	0.46	.228
SM Check Freq → Freq Sharing ARC (T1 → T1, T2 → T2, T3→T3)	**0.18***	**0.18***	**0.08**	**.018**
SM Check Freq → Consequences (T1 → T1)	0.04	0.14	0.16	.375
SM Check Freq → Consequences (T2 → T2)	0.10	0.47	0.29	.103
SM Check Freq → Consequences (T3 → T3)	-0.00	-0.03	0.30	.925
Quantity → Consequences (T1 → T1)	**0.60****	**0.26****	**0.02**	**<.001**
Quantity → Consequences (T2 → T2)	**0.16****	**0.13***	**0.04**	**.001**
Quantity → Consequences (T3 → T3)	**0.22****	**0.15***	**0.04**	**.001**
Freq Sharing ARC → Miss 1-month follow-up (T1 → T2)	-0.05	-0.05	0.11	.678
Freq Sharing ARC → Miss 3-month follow-up (T2 → T3)	-0.12	-0.06	0.08	.403
Freq Sharing ARC → Miss 1-month follow-up (T2 → T2)	0.02	0.02	0.04	.657
Freq Sharing ARC → Miss 3-month follow-up (T3 → T3)	0.04	0.02	0.03	.516
Consequences → Miss 1-month follow-up (T1 → T2)	0.03	0.01	0.02	.691
Consequences → Miss 1-month follow-up (T2 → T3)	0.08	0.02	0.02	.463
Consequences → Miss 1-month follow-up (T2 → T2)	-0.00	-0.001	0.01	.962
Consequences → Miss 3-month follow-up (T3 → T3)	-0.01	-0.002	0.01	.807

Note. ARC = alcohol-related content, Y/N = yes/no, Consequences = number of alcohol consequences reported in the past 30 days, Freq = frequency, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up], quantity = number of alcoholic drinks consumed in a typical week in the past 30 days. Sex was coded 0 = *female* and 1 = *male*. Betas for constrained paths are based on standard deviations for estimates of predictors at baseline associated with outcomes at the 1-month follow-up or within-timepoint baseline associations, respectively. Significant path estimates are in bold, *p < .05, **p < .001.

Figure 10

Longitudinal Associations between Sharing ARC and Number of Alcohol Consequences



Note. ARC = alcohol-related content, Consequences = number of alcohol consequences experienced in the past 30 days. Significant path estimates are in bold, while dashed lines represent non-significant paths. Although not pictured, all models controlled for participant sex, social media checking frequency, semesters, compensation chosen, and alcohol quantity.

Aim 2: Social Network Sharing of ARC

Aim 2a: Cross-sectional Social Network Sharing of ARC

As seen in Table 16, after controlling for participant sex, social media checking frequency, semester survey was completed, compensation method, and alcohol quantity (only consequences model), a greater proportion of social network members sharing ARC was associated with reporting more alcohol-related consequences but was not significantly associated with quantity. After controlling for the same variables as above, social network members sharing ARC more frequently was associated with greater quantity but was not associated with consequences.

Table 16

Cross-sectional Aim 2 Models: Friend Social Network Members Sharing ARC Predicts Alcohol Outcomes

	Quantity				Consequences			
Variable	β	*B*	*SE*	*p*	β	*B*	*SE*	*p*
Aim 2a: Social Network Share ARC (Y/N)								
Semester	0.05	0.39	0.58	.498	0.01	0.05	0.24	.826
Compensation	-0.10	-1.56	1.09	.152	-0.06	-0.43	0.45	.338
Social Media Frequency	0.06	0.48	0.38	.203	0.06	0.22	0.16	.150
Sex	**0.23****	**3.51****	**0.77**	**<.001**	**-0.11***	**-0.76***	**0.33**	**.021**
Quantity	-	-	-	-	**0.49****	**0.23****	**0.02**	**<.001**
Prop SN Share ARC	0.09	2.16	1.19	.070	**0.10***	**1.12***	**0.49**	**.024**
Aim 2b: Frequency of Social Network ARC								
Semester	0.08	0.68	0.73	.353	0.10	0.39	0.31	.211
Compensation	-0.13	-1.97	1.33	.139	**-0.17***	**-1.24***	**0.58**	**.032**
Social Media Frequency	0.03	0.24	0.45	.596	0.03	0.12	0.19	.544
Sex	**0.17***	**2.62***	**0.92**	**.005**	-0.08	-0.59	0.40	.142
Quantity	-	-	-	-	**0.43****	**0.20****	**0.03**	**<.001**
Frequency SN ARC	**0.25****	**1.56****	**0.37**	**<.001**	0.11	0.31	0.16	.056

Note. ARC = alcohol-related content, Y/N = yes/no, Prop = proportion, SN = social network, social media frequency = frequency of checking social media (across all platforms), quantity = number of alcoholic drinks consumed in a typical day, consequences = number of alcohol-related consequences experienced. Sex was coded 0 = *female* and 1 = *male*. Only the models examining consequences controlled for quantity. Significant associations are in bold. **p* < .05, ***p* < .001.

Aims 2b and 5: Longitudinal Social Network Sharing of ARC

Alcohol Quantity. Details of invariance testing are included in Table 17. In the model examining the proportion of the social network sharing ARC, both pairs of cross-lagged paths were found to significantly vary over time. They were therefore freely estimated in the final model while all other paths were constrained to equality within relevant pairs over time. In the model examining the frequency of social network members sharing ARC, none of the cross-lagged or auto-regressive paths were found to vary over time and were constrained to equality in the final model.

In the model examining the proportion of social network members sharing ARC, greater alcohol quantity at baseline was significantly associated with higher proportion of social network sharing ARC at 1-month, and higher proportion of social network sharing ARC at baseline was associated with greater alcohol quantity at 1-month. However, the cross-lagged path from alcohol quantity at 1-month to the proportion sharing ARC at 3-month was not significant nor was the cross-lagged path from the proportion of sharing ARC at 1-month to alcohol quantity at 3-month (see Table 18 and Figure 11). In the model examining the frequency of social network members sharing ARC, alcohol quantity was not significantly associated with frequency of sharing ARC by network members over time. The cross-lagged paths between frequency of social network members sharing ARC to alcohol quantity were also not significant (see Table 18 and Figure 11).

Table 17

Longitudinal Aim 2 for Alcohol Quantity: Invariance Testing for Cross-lagged and Auto-regressive Paths

Paths	Paths Compared	χ^2_{diff}	df_{diff}	*p*	Conclusion
Prop SN shares ARC					
Cross-lagged					
Quantity T1 → Prop SN Share ARC T2	A	4.812	1	**.028**	Free
Quantity T2 → Prop SN Share ARC T3	A				
Prop SN Share ARC T1 → Quantity T2	B	5.871	1	**.015**	Free
Prop Share ARC T2 → Quantity T3	B				
Auto-regressive					
Prop SN Share ARC T1 → Prop SN Share ARC T2	C	0.399	1	.528	Constrain
Prop SN Share ARC T2 → Prop SN Share ARC T3	C				
Quantity T1 → Quantity T2	D	1.594	1	.207	Constrain
Quantity T2 → Quantity T3	D				
Freq SN shares ARC					
Cross-lagged					
Quantity T1 → Freq SN Share ARC T2	E	0.067	1	.796	Constrain
Quantity T2 → Freq SN Share ARC T3	E				
Freq SN Share ARC T1 → Quantity T2	F	0.050	1	.823	Constrain
Freq Share ARC T2 → Quantity T3	F				
Auto-regressive					
Freq SN Share ARC T1 → Freq SN Share ARC T2	G	0.081	1	.776	Constrain
Freq SN Share ARC T2 → Freq SN Share ARC T3	G				
Quantity T1 → Quantity T2	H	2.099	1	.147	Constrain
Quantity T2 → Quantity T3	H				

Note. Prop = proportion, SN = social network, ARC = alcohol-related content on social media, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up], Quantity = number of alcoholic drinks consumed in a typical week in the past 30 days, Freq = frequency. Letter pairs reflect which paths were freely estimated versus constrained to equality for each chi-square comparison. Although not listed in the table, invariance testing was also carried out for all within-timepoint covariate paths.

Table 18

Longitudinal Cross-lagged Panel Model Results for Aim 2: SN Sharing ARC and Alcohol Quantity

	β	*B*	*SE*	*p*
Prop SN Sharing ARC				
Auto-regressive Paths				
Prop SN Sharing ARC (T1 → T2, T2 → T3)	**0.73****	**0.70****	**0.04**	**<.001**
Quantity (T1 → T2, T2 → T3)	**0.81****	**0.67****	**0.03**	**<.001**
Cross-lagged Paths				
Prop SN Sharing ARC → Quantity (T1 → T2)	**0.11***	**2.24***	**0.91**	**.014**
Prop SN Sharing ARC → Quantity (T2 → T3)	-0.10	-1.86	1.18	.113
Quantity → Prop SN Sharing ARC (T1 → T2)	**0.26****	**0.01****	**0.00**	**<.001**
Quantity → Prop SN Sharing ARC (T2 → T3)	-0.01	0.00	0.00	.905
Covariates and Missingness				
Sex → Prop SN Sharing ARC (T1 → T1, T1 → T2, T1 → T3)	-0.06	-0.04	0.02	.051
Sex → Quantity (T1 → T1)	**0.23****	**3.48****	**0.71**	**<.001**
Sex → Quantity (T1 → T2)	-0.07	-0.85	0.70	.227
Sex → Quantity (T1 → T3)	0.02	0.27	0.78	.727
Semester → Prop SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.05	-0.02	0.03	.533
Semester → Quantity (T1 → T1)	**0.15***	1.22	0.63	.051
Semester → Quantity (T2 → T2)	0.02	0.39	0.91	.673
Semester → Quantity (T3 → T3)	-0.04	-1.08	1.67	.517
Compensation → Prop SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.08	-0.05	0.03	.117
Compensation → Quantity (T1 → T1, T2 → T2, T3→T3)	-0.10	-1.46	0.87	.095
SM Check Freq → Prop SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	**0.13****	**0.04****	**0.01**	**<.001**
SM Check Freq → Quantity (T1 → T1, T2 → T2, T3→T3)	**0.09****	**0.65***	**0.24**	**.007**
Prop SN Sharing ARC → Miss 1-month follow-up (T1 → T2)	-0.14	-0.51	0.32	.113
Prop SN Sharing ARC → Miss 3-month follow-up (T2 → T3)	0.16	0.59	0.43	.169
Prop SN Sharing ARC → Miss 1-month follow-up (T2 → T2)	0.09	0.32	0.21	.132
Prop SN Sharing ARC → Miss 3-month follow-up (T3 → T3)	-0.10	-0.32	0.23	.173
Quantity → Miss 1-month follow-up (T1 → T2)	0.17	0.03	0.02	.097
Quantity → Miss 3-month follow-up (T2 → T3)	-0.06	-0.01	0.02	.477
Quantity → Miss 1-month follow-up (T2 → T2)	-0.13	-0.02	0.02	.109
Quantity → Miss 3-month follow-up (T3 → T3)	0.04	0.01	0.01	.444
Freq SN Sharing ARC				
Auto-regressive Paths				
Freq SN Sharing ARC (T1 → T2, T2 → T3)	**0.46****	**0.48****	**0.05**	**<.001**
Quantity (T1 → T2, T2 → T3)	**0.81****	**0.65****	**0.03**	**<.001**
Cross-lagged Paths				
Freq SN Sharing ARC → Quantity (T1 → T2, T2 → T3)	-0.01	-0.02	0.19	.901
Quantity → Freq SN Sharing ARC (T1 → T2, T2 → T3)	0.06	0.01	0.01	.317
Covariates and Missingness				
Sex → Freq SN Sharing ARC (T1 → T1, T1 → T2, T1 → T3)	-0.07	-0.16	0.10	.120

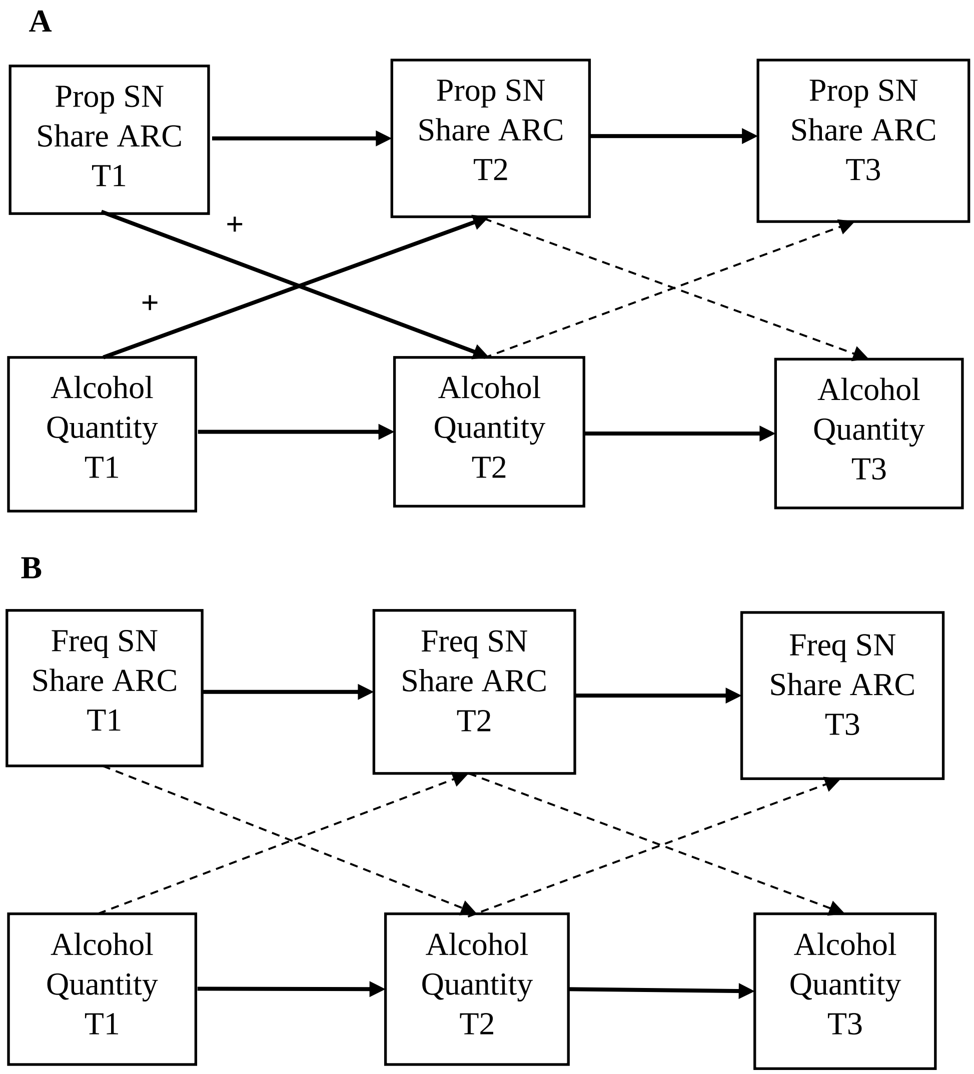
Table 18 (*continued*)

	β	*B*	*SE*	*p*
Sex → Quantity (T1 → T1)	**0.22****	**3.33****	**0.70**	**<.001**
Sex → Quantity (T1 → T2)	-0.02	-0.27	0.70	.695
Sex → Quantity (T1 → T3)	-0.03	-0.33	0.76	.668
Semester → Freq SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	0.08	0.10	0.11	.372
Semester → Quantity (T1 → T1)	0.15	1.22	0.65	.063
Semester → Quantity (T2 → T2)	-0.10	-1.53	1.30	.240
Semester → Quantity (T3 → T3)	-0.02	-0.65	1.64	.692
Compensation → Freq SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.07	-0.17	0.14	.231
Compensation → Quantity (T1 → T1, T2 → T2, T3→T3)	-0.06	-0.83	0.79	.291
SM Check Freq → Freq SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	0.04	0.04	0.05	.374
SM Check Freq → Quantity (T1 → T1, T2 → T2, T3→T3)	0.06	0.44	0.23	.057
Freq SN Sharing ARC → Miss 1-month follow-up (T1 → T2)	-0.05	-0.05	0.09	.589
Freq SN Sharing ARC → Miss 3-month follow-up (T2 → T3)	-0.15	-0.14	0.11	.204
Freq SN Sharing ARC → Miss 1-month follow-up (T2 → T2)	0.02	0.02	0.04	.562
Freq SN Sharing ARC → Miss 3-month follow-up (T3 → T3)	0.07	0.06	0.06	.284
Quantity → Miss 1-month follow-up (T1 → T2)	0.02	0.00	0.00	.566
Quantity → Miss 3-month follow-up (T2 → T3)	0.18	0.03	0.02	.064
Quantity → Miss 1-month follow-up (T2 → T2)	-0.01	-0.00	0.00	.797
Quantity → Miss 3-month follow-up (T3 → T3)	-0.11	-0.02	0.01	.083

Note. Prop = proportion, SN = social network, ARC = alcohol-related content, quantity = number of alcoholic drinks consumed in a typical week in the past 30 days, Freq = frequency, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Sex was coded 0 = *female* and 1 = *male*. Betas for constrained paths are based on standard deviations for estimates of predictors at baseline associated with outcomes at the 1-month follow-up or within-timepoint baseline associations, respectively. Significant path estimates are in bold, **p* < .05, ***p* < .001.

Figure 11

Longitudinal Associations between the Proportion/Frequency of the Social Network Sharing ARC and Alcohol Quantity



Note. Prop = proportion, SN = social network, ARC = alcohol-related content, quantity = number of alcoholic drinks consumed in a typical week in the past 30 days. Although not pictured, all models controlled for participant sex, social media checking frequency, semesters, and compensation chosen. Significant path estimates are in bold, while dashed lines represent non-significant paths.

Any Alcohol Consequences. Details of invariance testing are included in Table 19. In the model examining the proportion of the social network sharing ARC, the cross-lagged paths from experiencing any alcohol consequences to the proportion of the social network sharing ARC and the auto-regressive paths for consequences were found to significantly vary over time and were freely estimated in the final model while all other paths of interest were constrained to equality within relevant pairs over time. In the model examining the frequency of social network members sharing ARC, the cross-lagged paths from frequency of sharing ARC to experiencing any alcohol consequences and the auto-regressive paths for consequences were found to significantly vary over time. These paths were freely estimated in the final model while all other paths were constrained to equality within relevant pairs over time.

In the model examining the proportion of social network members sharing ARC, reporting experiencing any alcohol consequences at baseline was significantly associated with a higher proportion of network members sharing ARC at 1-month. The cross-lagged path from experiencing any alcohol consequences at 1-month to the proportion sharing at 3-month was not significant. The cross-lagged paths from the proportion sharing to experiencing any alcohol consequences over time were not significant (see Table 20 and Figure 12).

In the model examining the frequency of social network members sharing ARC, more frequent sharing at baseline was associated with lower likelihood of alcohol consequences at 1-month, while the cross-lagged path from the proportion sharing at 1-month to experiencing any alcohol consequences at 3-month was not significantly associated. The cross-lagged paths from experiencing any alcohol consequences to the frequency of sharing were also not significantly associated over time (see Table 20 and Figure 12).

Table 19

Longitudinal Aim 2 for Reporting Any Alcohol Consequences: Invariance Testing for Cross-lagged and Auto-regressive Paths

Paths	Paths Compared	χ^2_{diff}	df_{diff}	p	Conclusion
Prop SN shares ARC					
Cross-lagged					
Any Conseq T1 → Prop SN Share ARC T2	A	5.931	1	**.015**	Free
Any Conseq T2 → Prop SN Share ARC T3	A				
Prop SN Share ARC T1 → Any Conseq T2	B	.087	1	.768	Constrain
Prop Share ARC T2 → Any Conseq T3	B				
Auto-regressive					
Prop SN Share ARC T1 → Prop SN Share ARC T2	C	0.008	1	.930	Constrain
Prop SN Share ARC T2 → Prop SN Share ARC T3	C				
Any Conseq T1 → Any Conseq T2	D	4.971	1	**.026**	Free
Any Conseq T2 → Any Conseq T3	D				
Freq SN shares ARC					
Cross-lagged					
Any Conseq T1 → Freq SN Share ARC T2	E	3.735	1	.053	Constrain
Any Conseq T2 → Freq SN Share ARC T3	E				
Freq SN Share ARC T1 → Any Conseq T2	F	5.099	1	**.024**	Free
Freq Share ARC T2 → Any Conseq T3	F				
Auto-regressive					
Freq SN Share ARC T1 → Freq SN Share ARC T2	G	0.009	1	.923	Constrain
Freq SN Share ARC T2 → Freq SN Share ARC T3	G				
Any Conseq T1 → Any Conseq T2	H	7.200	1	**.007**	Free
Any Conseq T2 → Any Conseq T3	H				

Note. Any Conseq = experience any alcohol consequences where 1 = *yes* and 0 = *no*, SN = social network, ARC = alcohol-related content on social media, Freq = frequency, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Letter pairs reflect which paths were freely estimated versus constrained to equality for each chi-square comparison. Although not listed in the table, invariance testing was also carried out for all within-timepoint covariate paths.

Table 20

Cross-lagged Panel Model Results for Aim 2: SN Sharing ARC and Reporting Any Consequences

	β	*B*	*SE*	*p*
Prop SN Sharing ARC				
Auto-regressive Paths				
Prop SN Sharing ARC (T1 → T2, T2 → T3)	**0.70****	**0.68****	**0.05**	**<.001**
Any Consequences (T1 → T2)	**0.81****	**0.43****	**0.10**	**<.001**
Any Consequences (T2 → T3)	**0.71****	**0.97****	**0.24**	**<.001**
Cross-lagged Paths				
Prop SN Sharing ARC → Any Consequences (T1 → T2, T2 → T3)	0.13	0.26	0.14	.065
Any Consequences → Prop SN Sharing ARC (T1 → T2)	**0.47****	**0.11****	**0.03**	**<.001**
Any Consequences → Prop SN Sharing ARC (T2 → T3)	0.01	0.00	0.04	.931
Covariates and Missingness				
Sex → Prop SN Sharing ARC (T1 → T1, T1 → T2, T2 → T3)	**-0.07***	**-0.04***	**0.02**	**.040**
Sex → Any Consequences (T1 → T1, T1 → T2, T2 → T3)	-0.04	-0.09	0.07	.196
Semester → Prop SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.05	-0.02	0.02	.448
Semester → Any Consequences (T1 → T1, T2 → T2, T3→T3)	0.11	0.15	0.11	.161
Compensation → Prop SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.05	-0.03	0.03	.289
Compensation → Any Consequences (T1 → T1, T2 → T2, T3→T3)	-0.06	-0.14	0.14	.298
SM Check Freq → Prop SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	**0.12***	**0.04***	**0.01**	**.001**
SM Check Freq → Any Consequences (T1 → T1, T2 → T2, T3→T3)	0.05	0.06	0.04	.173
Quantity → Any Consequences (T1 → T1, T2 → T2, T3→T3)	**0.45****	**0.07****	**0.01**	**<.001**
Prop SN Sharing ARC → Miss 1-month follow-up (T1 → T2)	-0.06	-0.20	0.25	.438
Prop SN Sharing ARC → Miss 3-month follow-up (T2 → T3)	0.15	0.54	0.34	.114
Prop SN Sharing ARC → Miss 1-month follow-up (T2 → T2)	0.08	0.29	0.18	.111
Prop SN Sharing ARC → Miss 3-month follow-up (T3 → T3)	-0.09	-0.31	0.20	.118
Any Consequences → Miss 1-month follow-up (T1 → T2)	**-0.09***	**-0.08***	**0.03**	**.011**
Any Consequences → Miss 3-month follow-up (T2 → T3)	-0.04	-0.08	0.06	.195
Any Consequences → Miss 1-month follow-up (T2 → T2)	0.00	0.01	0.06	.913
Any Consequences → Miss 3-month follow-up (T3 → T3)	0.02	0.03	0.03	.351
Freq SN Sharing ARC				
Auto-regressive Paths				
Freq SN Sharing ARC (T1 → T2, T2 → T3)	**0.41****	**0.45****	**0.05**	**<.001**
Any Consequences (T1 → T2)	**0.89****	**0.38****	**0.09**	**<.001**
Any Consequences (T2 → T3)	**0.68****	**1.06****	**0.28**	**<.001**
Cross-lagged Paths				
Freq SN Sharing ARC → Any Consequences (T1 → T2)	**-0.27***	**-0.12***	**0.06**	**.032**
Freq SN Sharing ARC → Any Consequences (T2 → T3)	0.11	0.07	0.06	.252
Any Consequences → Freq SN Sharing ARC (T1 → T2, T2 → T3)	0.22	0.21	0.12	.065

Table 20 (*continued*)

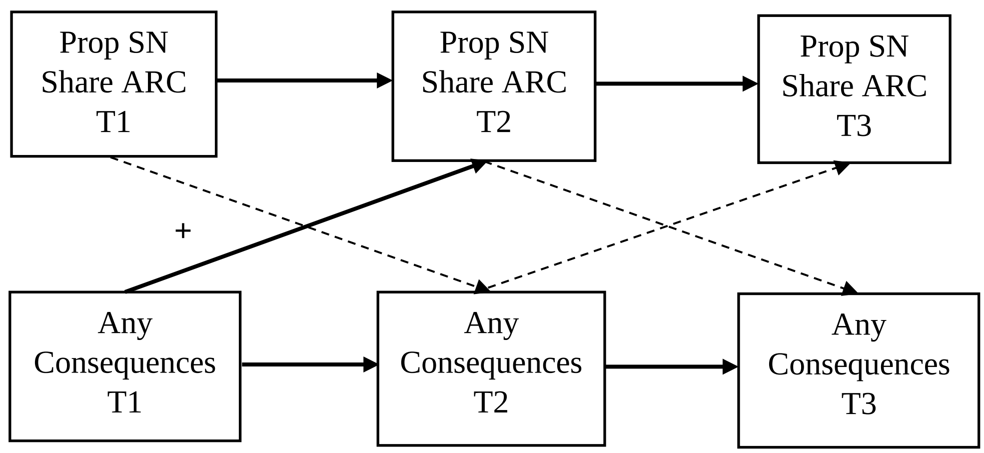
	β	*B*	*SE*	*p*
<u>*Covariates and Missingness*</u>				
Sex → Freq SN Sharing ARC (T1 → T1, T1 → T2, T2 → T3)	**-0.09***	**-0.20***	**0.10**	**.044**
Sex → Any Consequences (T1 → T1, T1 → T2, T2 → T3)	-0.04	-0.09	0.06	.140
Semester → Freq SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	0.05	0.06	0.11	.575
Semester → Any Consequences (T1 → T1, T2 → T2, T3→T3)	0.12	0.16	0.12	.179
Compensation → Freq SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.05	-0.12	0.12	.346
Compensation → Any Consequences (T1 → T1, T2 → T2, T3→T3)	-0.06	-0.15	0.14	.280
SM Check Freq → Freq SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	0.02	0.02	0.04	.574
SM Check Freq → Any Consequences (T1 → T1, T2 → T2, T3→T3)	0.03	0.04	0.04	.234
Quantity → Any Consequences (T1 → T1, T2 → T2, T3→T3)	**0.39****	**0.06****	**0.01**	**<.001**
Freq SN Sharing ARC → Miss 1-month follow-up (T1 → T2)	-0.06	-0.06	0.10	.569
Freq SN Sharing ARC → Miss 3-month follow-up (T2 → T3)	-0.17	-0.16	0.09	.084
Freq SN Sharing ARC → Miss 1-month follow-up (T2 → T2)	0.06	0.05	0.05	.345
Freq SN Sharing ARC → Miss 3-month follow-up (T3 → T3)	0.07	0.07	0.04	.081
Any Consequences → Miss 1-month follow-up (T1 → T2)	**-0.14***	**-0.13***	**0.04**	**.001**
Any Consequences → Miss 3-month follow-up (T2 → T3)	0.05	0.11	0.14	.404
Any Consequences → Miss 1-month follow-up (T2 → T2)	0.02	0.05	0.09	.560
Any Consequences → Miss 3-month follow-up (T3 → T3)	-0.02	-0.03	0.04	.536

Note. Prop = proportion, SN = social network, ARC = alcohol-related content, any consequences = if participant reported any alcohol consequences (1) versus no alcohol consequences (0) in the past 30 days, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up], Freq = frequency, quantity = number of alcoholic drinks consumed in a typical week in the past 30 days. Sex was coded 0 = *female* and 1 = *male*. Betas for constrained paths are based on standard deviations for estimates of predictors at baseline associated with outcomes at the 1-month follow-up or within-timepoint baseline associations, respectively. Significant path estimates are in bold, *$p < .05$, **$p < .001$.

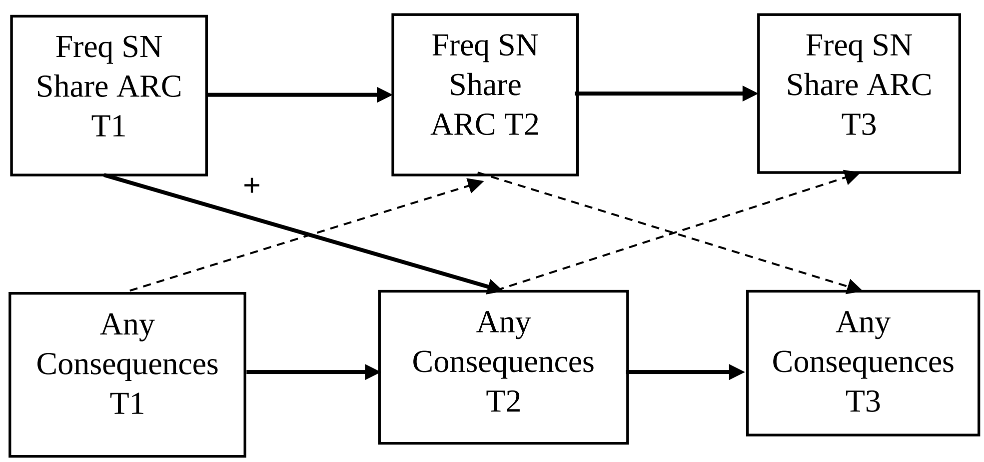
Figure 12

Longitudinal Associations between the Proportion/Frequency of the Social Network Sharing ARC and Reporting Any Alcohol Consequences

A



B



Note. Prop = proportion, SN = social network, ARC = alcohol-related content, any consequences = if participant reported any alcohol consequences (1) versus no alcohol consequences (0) in the past 30 days. Although not pictured, all models controlled for participant sex, social media checking frequency, semesters, compensation chosen, and alcohol quantity. Significant path estimates are in bold, while dashed lines represent non-significant paths.

Number of Alcohol Consequences. Details of invariance testing are included in Table 21. In both models, only the auto-regressive paths for the number of alcohol consequences were found to significantly vary over time. Therefore, they were freely estimated in the final model while all other paths of interest were constrained to equality within relevant pairs. In the model examining the proportion of social network members sharing ARC, greater number of alcohol consequences was significantly associated with higher proportion of network members sharing ARC over time. Also, a higher proportion of network members sharing ARC was associated with a greater number of alcohol consequences over time (see Table 22 and Figure 13). In the model examining the frequency of social network members sharing ARC, none of the cross-lagged paths were significantly associated over time (see Table 22 and Figure 13).

Table 21

Longitudinal Aim 2 for Number of Alcohol Consequences: Invariance Testing for Cross-lagged and Auto-regressive Paths

Paths	Paths Compared	χ^2_{diff}	df_{diff}	*p*	Conclusion
Prop SN shares ARC					
Cross-lagged					
Conseq T1 → Prop SN Share ARC T2	A	0.00	1	1.00	Constrain
Conseq T2 → Prop SN Share ARC T3	A				
Prop SN Share ARC T1 → Conseq T2	B	0.00	1	1.00	Constrain
Prop Share ARC T2 → Conseq T3	B				
Auto-regressive					
Prop SN Share ARC T1 → Prop SN Share ARC T2	C	0.665	1	.415	Constrain
Prop SN Share ARC T2 → Prop SN Share ARC T3	C				
Conseq T1 → Conseq T2	D	5.799	1	**.016**	Free
Conseq T2 → Conseq T3	D				
Freq SN shares ARC					
Cross-lagged					
Conseq T1 → Freq SN Share ARC T2	E	3.535	1	.060	Constrain
Conseq T2 → Freq SN Share ARC T3	E				
Freq SN Share ARC T1 → Conseq T2	F	1.027	1	.311	Constrain
Freq Share ARC T2 → Conseq T3	F				
Auto-regressive					
Freq SN Share ARC T1 → Freq SN Share ARC T2	G	0.000	1	1.00	Constrain
Freq SN Share ARC T2 → Freq SN Share ARC T3	G				
Conseq T1 → Conseq T2	H	5.894	1	**.015**	Free
Conseq T2 → Conseq T3	H				

Note. Conseq = total number of alcohol consequences experienced in the past 30 days for participants who said they had experienced any consequences, SN = social network, ARC = alcohol-related content on social media, Freq = frequency, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Letter pairs reflect which paths were freely estimated versus constrained to equality for each chi-square comparison. Although not listed in the table, invariance testing was also carried out for all within-timepoint covariate paths.

Table 22

Longitudinal Cross-lagged Panel Model Results for Aim 2: SN Sharing ARC and Number of Alcohol Consequences

	β	*B*	*SE*	*p*
Prop SN Sharing ARC				
Auto-regressive Paths				
Prop SN Sharing ARC (T1 → T2, T2 → T3)	**0.67****	**0.64****	**0.04**	**<.001**
Consequences (T1 → T2)	**0.71****	**0.69****	**0.06**	**<.001**
Consequences (T2 → T3)	**0.43****	**0.44****	**0.07**	**<.001**
Cross-lagged Paths				
Prop SN Sharing ARC → Consequences (T1 → T2, T2 → T3)	**0.10***	**1.07***	**0.52**	**.038**
Consequences → Prop SN Sharing ARC (T1 → T2, T2 → T3)	**0.19***	**0.02****	**0.00**	**<.001**
Covariates and Missingness				
Sex → Prop SN Sharing ARC (T1 → T1, T1 → T2, T1 → T3)	**-0.07***	**-0.04***	**0.02**	**.036**
Sex → Consequences (T1 → T1, T1 → T2, T1 → T3)	**-0.08***	**-0.58***	**0.26**	**.028**
Semester → Prop SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.03	-0.01	0.03	.669
Semester → Consequences (T1 → T1, T2 → T2, T3→T3)	0.06	0.20	0.26	.446
Compensation → Prop SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.06	-0.04	0.03	.225
Compensation → Consequences (T1 → T1, T2 → T2, T3→T3)	0.01	0.06	0.32	.843
SM Check Freq → Prop SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	**0.13***	**0.04***	**0.02**	**.001**
SM Check Freq → Consequences (T1 → T1, T2 → T2, T3→T3)	0.06	0.20	0.13	.139
Quantity → Consequences (T1 → T1)	**0.59****	**0.26****	**0.02**	**<.001**
Quantity → Consequences (T2 → T2)	**0.14***	**0.11***	**0.04**	**.005**
Quantity → Consequences (T3 → T3)	**0.24****	**0.16****	**0.05**	**<.001**
Prop SN Sharing ARC → Miss 1-month follow-up (T1 → T2)	-0.05	-0.17	0.27	.513
Prop SN Sharing ARC → Miss 3-month follow-up (T2 → T3)	0.06	0.21	0.27	.454
Prop SN Sharing ARC → Miss 1-month follow-up (T2 → T2)	0.03	0.13	0.20	.525
Prop SN Sharing ARC → Miss 3-month follow-up (T3 → T3)	-0.04	-0.13	0.15	.397
Consequences → Miss 1-month follow-up (T1 → T2)	0.04	0.01	0.03	.567
Consequences → Miss 3-month follow-up (T2 → T3)	0.02	0.01	0.02	.804
Consequences → Miss 1-month follow-up (T2 → T2)	-0.02	-0.01	0.02	.734
Consequences → Miss 3-month follow-up (T3 → T3)	-0.01	-0.00	0.01	.740
Freq SN Sharing ARC				
Auto-regressive Paths				
Freq SN Sharing ARC (T1 → T2, T2 → T3)	**0.43****	**0.46****	**0.05**	**<.001**
Consequences (T1 → T2)	**0.70****	**0.67****	**0.06**	**<.001**
Consequences (T2 → T3)	**0.45****	**0.45****	**0.07**	**<.001**
Cross-lagged Paths				
Freq SN Sharing ARC → Consequences (T1 → T2, T2 → T3)	0.06	0.17	0.15	.252
Consequences → Freq SN Sharing ARC (T1 → T2, T2 → T3)	0.04	0.01	0.02	.474
Covariates and Missingness				
Sex → Freq SN Sharing ARC (T1 → T1, T1 → T2, T1 → T3)	**-0.09***	**-0.20***	**0.10**	**.040**
Sex → Consequences (T1 → T1, T1 → T2, T1 → T3)	**-0.08***	**-0.58***	**0.27**	**.031**
Semester → Freq SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	0.07	0.08	0.11	.454
Semester → Consequences (T1 → T1, T2 → T2, T3→T3)	0.06	0.20	0.26	.447
Compensation → Freq SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.06	-0.13	0.11	.240
Compensation → Consequences (T1 → T1, T2 → T2, T3→T3)	0.01	0.09	0.33	.774

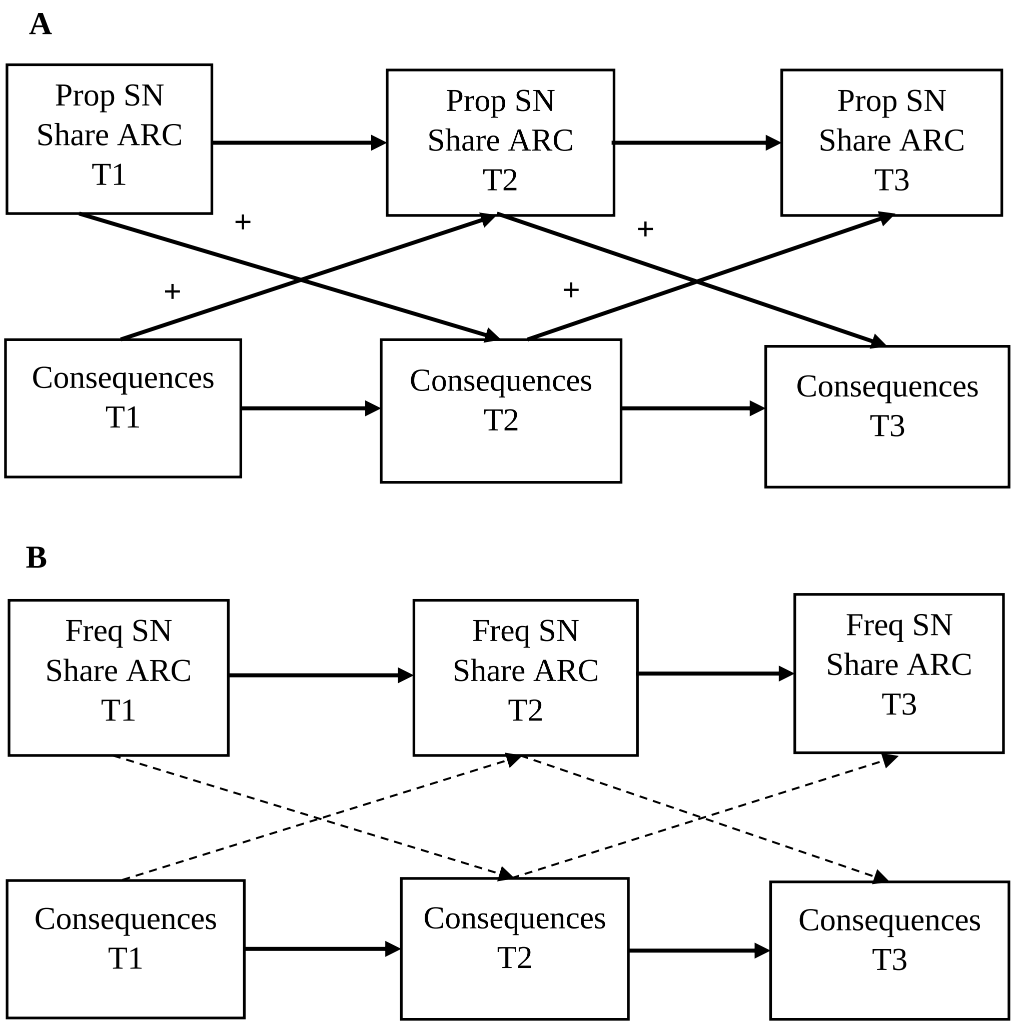
Table 22 (*continued*)

	β	*B*	*SE*	*p*
SM Check Freq → Freq SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	0.03	0.03	0.04	.473
SM Check Freq → Consequences (T1 → T1, T2 → T2, T3→T3)	0.06	0.20	0.13	.123
Quantity → Consequences (T1 → T1)	**0.58***	**0.26****	**0.02**	**<.001**
Quantity → Consequences (T2 → T2)	**0.15***	**0.12***	**0.04**	**.002**
Quantity → Consequences (T3 → T3)	**0.23****	**0.16****	**0.05**	**<.001**
Freq SN Sharing ARC → Miss 1-month follow-up (T1 → T2)	-0.13	-0.13	0.10	.184
Freq SN Sharing ARC → Miss 3-month follow-up (T2 → T3)	-0.13	-0.12	0.09	.188
Freq SN Sharing ARC → Miss 1-month follow-up (T2 → T2)	0.05	0.05	0.04	.244
Freq SN Sharing ARC → Miss 3-month follow-up (T3 → T3)	0.06	0.06	0.05	.209
Consequences → Miss 1-month follow-up (T1 → T2)	0.05	0.02	0.03	.542
Consequences → Miss 3-month follow-up (T2 → T3)	0.07	0.02	0.03	.363
Consequences → Miss 1-month follow-up (T2 → T2)	-0.00	-0.00	0.02	.957
Consequences → Miss 3-month follow-up (T3 → T3)	-0.01	-0.01	0.01	.637

Note. Prop = proportion, SN = social network, ARC = alcohol-related content, consequences = number of alcohol consequences reported in the past 30 days, quantity = number of alcoholic drinks consumed in a typical week in the past 30 days, Freq = frequency, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Sex was coded 0 = *female* and 1 = *male*. Betas for constrained paths are based on standard deviations for estimates of predictors at baseline associated with outcomes at the 1-month follow-up or within-timepoint baseline associations, respectively. Significant path estimates are in bold, **p* < .05, ***p* < .001.

Figure 13

Longitudinal Associations between the Proportion/Frequency of the Social Network Sharing ARC and Number of Alcohol Consequences



Note. Prop = proportion, SN = social network, ARC = alcohol-related content, consequences = number of alcohol consequences experienced in the past 30 days. Although not pictured, all models controlled for participant sex, social media checking frequency, semesters, compensation chosen, and alcohol quantity. Significant path estimates are in bold.

Aim 3: Modality of ARC Shared

Aim 3a: Cross-sectional Modality of ARC Shared

As seen in Table 7, the average proportion of social network members sharing text-only ARC was quite low at baseline (*M* = 0.06, *SD* = 0.20). This was originally proposed as the category of reference (i.e., I would examine photo versus text only and video versus text only). However, because of this low endorsement for text-only ARC, a new dummy variable was created with video (with or without text) ARC coded as a "1" and photo (with or without text) ARC coded as a "0". Aim 3a now examines whether video ARC versus photo ARC is associated with alcohol quantity and consequences (separate models).

As seen in Table 23, after controlling for participant sex, social media checking frequency, semester survey was completed, compensation method, and alcohol quantity (only in alcohol consequences model), the proportion of social network members sharing mostly video ARC (compared to photo ARC) was not associated with alcohol quantity or consequences.

Table 23

Cross-sectional Aim 3 Models: Friend Social Network Members Sharing Different Modalities of ARC Predicting Alcohol Outcomes

	Quantity				Consequences			
Variable	β	*B*	*SE*	*p*	β	*B*	*SE*	*p*
Semester	0.09	0.74	0.78	.342	0.08	0.32	0.33	.335
Compensation	-0.14	-2.15	1.44	.136	-0.15	-1.11	0.60	.066
Social Media Frequency	0.05	0.35	0.48	.465	0.05	0.17	0.20	.401
Sex	**0.14***	**2.25****	**0.98**	**.021**	-0.10	-0.77	0.41	.063
Quantity	-	-	-	-	**0.45****	**0.21****	**0.03**	**<.001**
SN Share Video ARC	0.04	0.65	1.09	.553	0.08	0.63	0.46	.166

Note. ARC = alcohol-related content, social media frequency = frequency of checking social media (across all platforms), quantity = number of alcoholic drinks consumed in a typical day, consequences = number of alcohol-related consequences reported. Sex was coded 0 = *female* and 1 = *male*. Only the model examining consequences controlled for quantity. Significant associations are in bold. *$p < .05$, **$p < .001$.

Aims 3b and 5: Longitudinal Modality of ARC Shared

As seen in Table 7, the proportions of social network members sharing text-only ARC were quite low across all three timepoints (*M*s = 0.03-0.06, *SD*s = 0.15-0.20). Similar to what was done at baseline for the cross-sectional examination, new dummy variables were calculated where video ARC was coded as a “1” and photo ARC was coded as a “0” for each follow-up timepoint. Aim 3b now examines the associations between sharing video ARC versus photo ARC and alcohol quantity and consequences (separate models) over time.

Alcohol Quantity. Details of invariance testing are included in Table 24. No paths of interest were found to significantly vary over time and were all constrained to equality within relevant pairs in the final model. In the final model, a higher proportion of social network members sharing video ARC (compare to photo ARC) was associated with greater alcohol quantity over time. All other cross-lagged paths were not significant (see Table 25 and Figure 14).

Table 24

Longitudinal Aim 3 for Alcohol Quantity: Invariance Testing for Cross-lagged and Auto-regressive Paths

Paths	Paths Compared	χ^2_{diff}	df_{diff}	p	Conclusion
Cross-lagged					
Quantity T1 → Prop SN Video ARC T2	A	0.285	1	.593	Constrain
Quantity T2 → Prop SN Video ARC T3	A				
Prop SN Video ARC T1 → Quantity T2	B	0.00	1	1.00	Constrain
Prop SN Video ARC T2 → Quantity T3	B				
Auto-regressive					
Prop SN Video ARC T1 → Prop SN Video ARC T2	C	0.264	1	.607	Constrain
Prop SN Video ARC T2 → Prop SN Video ARC T3	C				
Quantity T1 → Quantity T2	D	1.549	1	.213	Constrain
Quantity T2 → Quantity T3	D				

Note. Prop = proportion, SN = social network, ARC = alcohol-related content, quantity = number of alcoholic drinks consumed in a typical week in the past 30 days, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Letter pairs reflect which paths were freely estimated versus constrained to equality for each chi-square comparison. Although not listed in the table, invariance testing was also carried out for all within-timepoint covariate paths.

Table 25

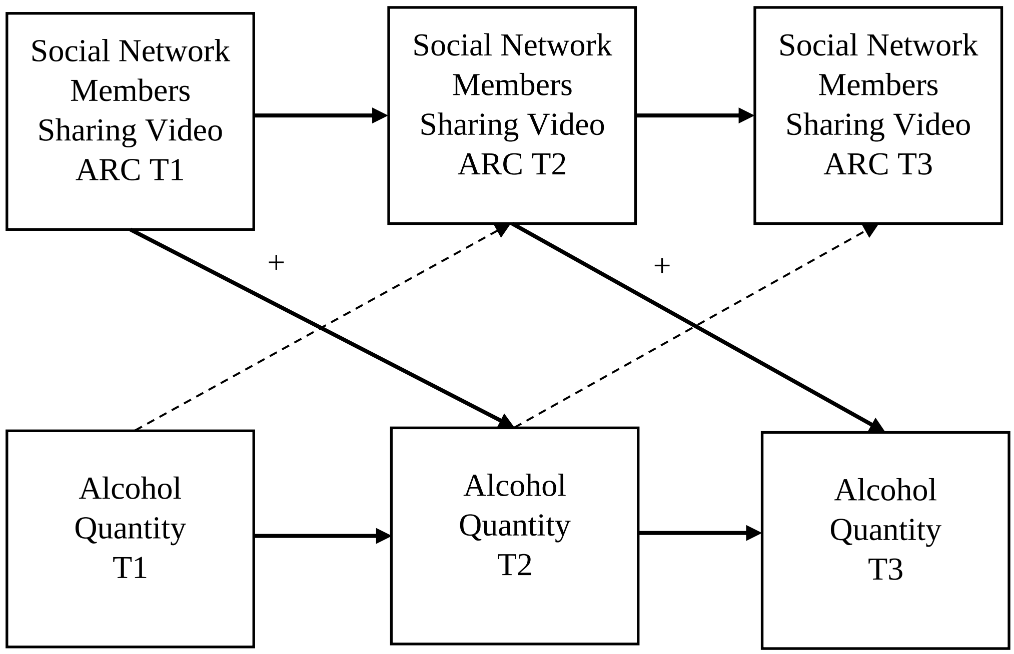
Longitudinal Cross-lagged Panel Model Results for Aim 3: SN Sharing Video versus Photo ARC and Alcohol Quantity

	β	*B*	*SE*	*p*
Auto-regressive Paths				
Prop SN Sharing Video ARC (T1 → T2, T2 → T3)	**0.38****	**0.31****	**0.07**	**<.001**
Quantity (T1 → T2, T2 → T3)	**0.82****	**0.66****	**0.03**	**<.001**
Cross-lagged Paths				
Prop SN Sharing Video ARC → Quantity (T1 → T2, T2 → T3)	**0.15****	**0.22***	**0.06**	**.001**
Quantity → Prop SN Sharing Video ARC (T1 → T2, T2 → T3)	0.05	0.02	0.03	.502
Covariates and Missingness				
Sex → Prop SN Sharing Video ARC (T1 → T1, T1 → T2, T1 → T3)	-0.02	-0.01	0.03	.702
Sex → Quantity (T1 → T1)	**0.21****	**0.33****	**0.07**	**<.001**
Sex → Quantity (T1 → T2)	-0.01	-0.01	0.07	.885
Sex → Quantity (T1 → T3)	-0.03	-0.04	0.08	.589
Semester → Prop SN Sharing Video ARC (T1 → T1, T2 → T2, T3→T3)	**0.23***	**0.11***	**0.04**	**.004**
Semester → Quantity (T1 → T1)	0.12	0.10	0.06	.116
Semester → Quantity (T2 → T2)	**-0.15***	**-0.24***	**0.11**	**.033**
Semester → Quantity (T3 → T3)	-0.03	-0.07	0.16	.652
Compensation → Prop SN Sharing Video ARC (T1 → T1, T2 → T2, T3→T3)	0.01	0.01	0.03	.733
Compensation → Quantity (T1 → T1, T2 → T2, T3→T3)	-0.04	-0.06	0.04	.154
SM Check Freq → Prop SN Sharing Video ARC (T1 → T1, T2 → T2, T3→T3)	-0.05	-0.02	0.01	.185
SM Check Freq → Quantity (T1 → T1, T2 → T2, T3→T3)	**0.06***	**0.04***	**0.02**	**.029**
Prop SN Sharing Video ARC → Miss 1-month follow-up (T1 → T2)	**-0.32***	**-0.87***	**0.37**	**.017**
Prop SN Sharing Video ARC → Miss 3-month follow-up (T2 → T3)	-0.08	-0.27	0.29	.355
Prop SN Sharing Video ARC → Miss 1-month follow-up (T2 → T2)	0.13	0.42	0.23	.075
Prop SN Sharing Video ARC → Miss 3-month follow-up (T3 → T3)	0.03	0.07	0.08	.371
Quantity → Miss 1-month follow-up (T1 → T2)	-0.03	-0.05	0.12	.700
Quantity → Miss 3-month follow-up (T2 → T3)	0.18	0.33	0.19	.084
Quantity → Miss 1-month follow-up (T2 → T2)	0.09	0.18	0.16	.255
Quantity → Miss 3-month follow-up (T3 → T3)	-0.11	-0.21	0.13	.100

Note. Prop = proportion, SN = social network, ARC = alcohol-related content, quantity = number of alcoholic drinks consumed in a typical week in the past 30 days, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Sex was coded 0 = f*emale* and 1 = *male*. Betas for constrained paths are based on standard deviations for estimates of predictors at baseline associated with outcomes at the 1-month follow-up or within-timepoint baseline associations, respectively. Significant path estimates are in bold, **p* < .05, ***p* < .001.

Figure 14

Longitudinal Associations between Network Members Sharing Alcohol-related Videos versus Photos and Alcohol Quantity



Note. ARC = alcohol-related content, alcohol quantity = number of alcoholic drinks consumed in a typical week in the past 30 days. Although not pictured, all models controlled for participant sex, social media checking frequency, semesters, and compensation chosen. Significant path estimates are in bold, while dashed lines represent non-significant paths.

Any Alcohol Consequences. Details of invariance testing are included in Table 26. None of the cross-lagged or autoregressive paths of interest were found to significantly vary over time. Therefore, they were all constrained to equality within relevant pairs in the final model. In the final model, none of the cross-lagged paths were significantly associated over time (see Table 27 and Figure 15).

Table 26

Longitudinal Aim 3 for Reporting Any Alcohol Consequences: Invariance Testing for Cross-lagged and Auto-regressive Paths

Paths	Paths Compared	χ^2_{diff}	df_{diff}	p	Conclusion
Cross-lagged					
Any Conseq T1 → Prop SN Video ARC T2	A	1.840	1	.175	Constrain
Any Conseq T2 → Prop SN Video ARC T3	A				
Prop SN Video ARC T1 → Any Conseq T2	B	3.040	1	.081	Constrain
Prop SN Video ARC T2 → Any Conseq T3	B				
Auto-regressive					
Prop SN Video ARC T1 → Prop SN Video ARC T2	C	0.101	1	.750	Constrain
Prop SN Video ARC T2 → Prop SN Video ARC T3	C				
Any Conseq T1 → Any Conseq T2	D	3.723	1	.054	Constrain
Any Conseq T2 → Any Conseq T3	D				

Note. Any Conseq = experience any alcohol consequences where 1 = *yes* and 0 = *no*, SN = social network, ARC = alcohol-related content on social media, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Letter pairs reflect which paths were freely estimated versus constrained to equality for each chi-square comparison. Although not listed in the table, invariance testing was also carried out for all within-timepoint covariate paths.

Table 27

Longitudinal Cross-lagged Panel Model Results for Aim 3: SN Sharing Video versus Photo ARC and Reporting Any Alcohol Consequences

	β	*B*	*SE*	*p*
Auto-regressive Paths				
Prop SN Sharing Video ARC (T1 → T2, T2 → T3)	**0.32****	**0.28****	**0.06**	**<.001**
Any Consequences (T1 → T2, T2 → T3)	**0.87****	**0.57****	**0.07**	**<.001**
Cross-lagged Paths				
Prop SN Sharing Video ARC → Any Consequences (T1 → T2, T2 → T3)	0.08	0.15	0.14	.274
Any Consequences → Prop SN Sharing Video ARC (T1 → T2, T2 → T3)	-0.06	-0.02	0.03	.548
Covariates and Missingness				
Sex → Prop SN Sharing Video ARC (T1 → T1, T1 → T2, T1 → T3)	-0.01	-0.01	0.04	.733
Sex → Any Consequences (T1 → T1, T1 → T2, T1 → T3)	-0.04	-0.11	0.07	.132
Semester → Prop SN Sharing Video ARC (T1 → T1, T2 → T2, T3→T3)	0.19	0.09	0.05	.060
Semester → Any Consequences (T1 → T1, T2 → T2, T3→T3)	0.11	0.15	0.13	.247
Compensation → Prop SN Sharing Video ARC (T1 → T1)	-0.19	-0.17	0.10	.090
Compensation → Prop SN Sharing Video ARC (T2 → T2)	0.07	0.07	0.10	.453
Compensation → Prop SN Sharing Video ARC (T3 → T3)	0.19	0.61	0.52	.236
Compensation → Any Consequences (T1 → T1, T2 → T2, T3→T3)	-0.10	-0.25	0.20	.203
SM Check Freq → Prop SN Sharing Video ARC (T1 → T1)	0.04	0.02	0.03	.627
SM Check Freq → Prop SN Sharing Video ARC (T2 → T2)	**-0.19***	**-0.10***	**0.03**	**.003**
SM Check Freq → Prop SN Sharing Video ARC (T3 → T3)	0.10	0.04	0.04	.352
SM Check Freq → Any Consequences (T1 → T1, T2 → T2, T3→T3)	0.05	0.06	0.04	.147
Quantity → Any Consequences (T1 → T1, T2 → T2, T3→T3)	**0.41****	**0.07****	**0.01**	**<.001**
Prop SN Sharing Video ARC → Miss 1-month follow-up (T1 → T2)	-0.14	-0.37	0.21	.074
Prop SN Sharing Video ARC → Miss 3-month follow-up (T2 → T3)	-0.03	-0.10	0.13	.419
Prop SN Sharing Video ARC → Miss 1-month follow-up (T2 → T2)	0.03	0.08	0.08	.301
Prop SN Sharing Video ARC → Miss 3-month follow-up (T3 → T3)	0.01	0.02	0.04	.688
Any Consequences → Miss 1-month follow-up (T1 → T2)	**-0.15***	**-0.14***	**0.04**	**.001**
Any Consequences → Miss 3-month follow-up (T2 → T3)	-0.02	-0.03	0.03	.247
Any Consequences → Miss 1-month follow-up (T2 → T2)	0.06	0.08	0.07	.250
Any Consequences → Miss 3-month follow-up (T3 → T3)	0.00	0.01	0.03	.833

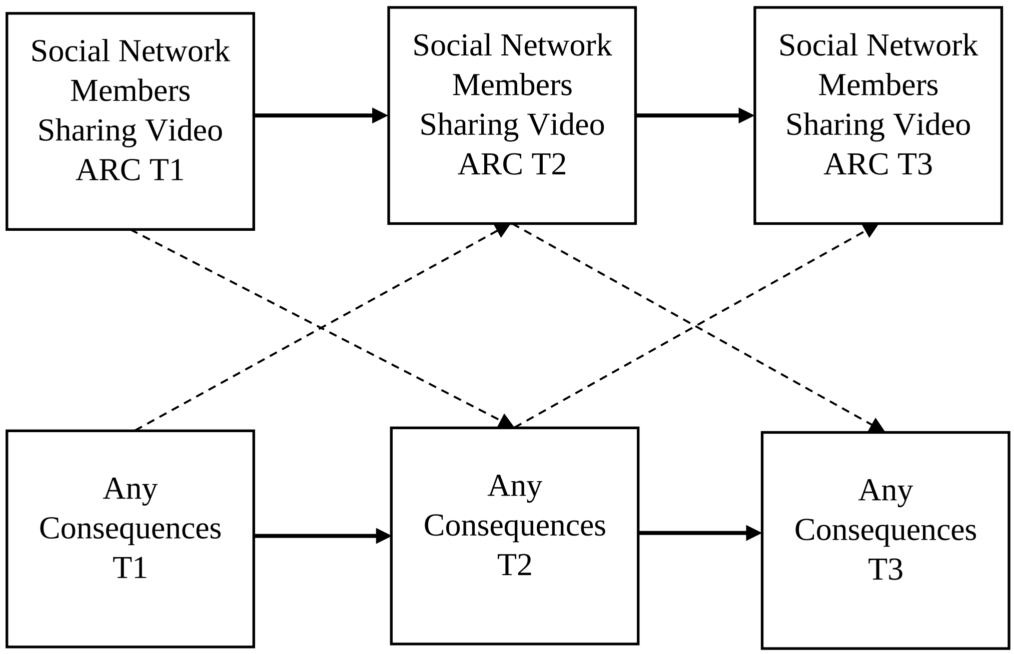
Note. Prop = proportion, SN = social network, ARC = alcohol-related content, any consequences = if participant reported any alcohol consequences (1) versus no alcohol consequences (0) in the past 30 days, quantity = number of alcoholic drinks consumed in a typical week in the past 30 days, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Sex was coded 0 = *female* and 1 = *male*. Betas for constrained paths are based on standard deviations for estimates of predictors at baseline associated with outcomes at the 1-

Table 27 (*continued*)

month follow-up or within-timepoint baseline associations, respectively. Significant path estimates are in bold, *$p < .05$, **$p < .001$.

Figure 15

Longitudinal Associations between Network Members Sharing Alcohol-related Videos versus Photos and Reporting Any Alcohol Consequences



Note. ARC = alcohol-related content, any consequences = if participant reported any alcohol consequences (1) versus no alcohol consequences (0) in the past 30 days. Although not pictured, all models controlled for participant sex, social media checking frequency, semesters, compensation chosen, and alcohol quantity. Significant path estimates are in bold, while dashed lines represent non-significant paths.

Number of Alcohol Consequences. Details of invariance testing are included in Table 28. Only the auto-regressive paths for the number of alcohol consequences were found to significantly vary over time. These paths were then freely estimated in the final model while all other paths of interest were constrained to equality within relevant pairs over time. In the final model, none of the cross-lagged paths were significantly associated over time (see Table 29 and Figure 16).

Table 28

Longitudinal Aim 3 for Number of Alcohol Consequences: Invariance Testing for Cross-lagged and Auto-regressive Paths

Paths	Paths Compared	χ^2_{diff}	df_{diff}	*p*	Conclusion
Cross-lagged					
Conseq T1 → Prop SN Video ARC T2	A	1.964	1	.161	Constrain
Conseq T2 → Prop SN Video ARC T3	A				
Prop SN Video ARC T1 → Conseq T2	B	2.446	1	.118	Constrain
Prop SN Video ARC T2 → Conseq T3	B				
Auto-regressive					
Prop SN Video ARC T1 → Prop SN Video ARC T2	C	0.539	1	.463	Constrain
Prop SN Video ARC T2 → Prop SN Video ARC T3	C				
Conseq T1 → Conseq T2	D	4.669	1	**.031**	Free
Conseq T2 → Conseq T3	D				

Note. Conseq = total number of alcohol consequences reported in the past 30 days for participants who said they had experienced any consequences, SN = social network, ARC = alcohol-related content on social media, Freq = frequency, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Letter pairs reflect which paths were freely estimated versus constrained to equality for each chi-square comparison. Although not listed in the table, invariance testing was also carried out for all within-timepoint covariate paths.

Table 29

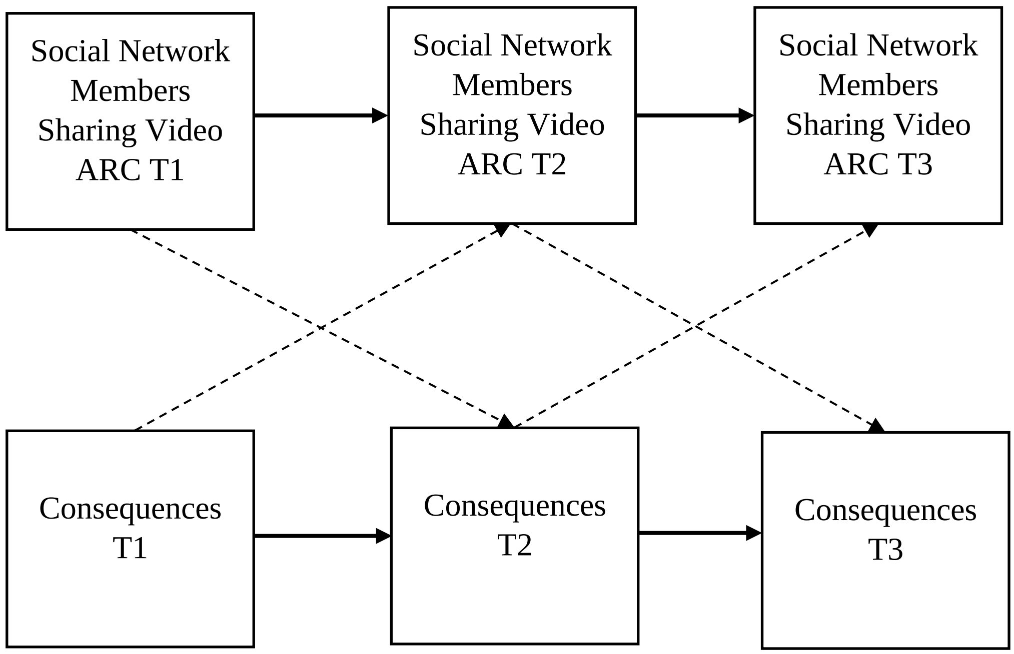
Longitudinal Cross-lagged Panel Model Results for Aim 3: SN Sharing Video versus Photo ARC and Number of Alcohol Consequences

	β	*B*	*SE*	*p*
Auto-regressive Paths				
Prop SN Sharing Video ARC (T1 → T2, T2 → T3)	**0.33****	**0.28****	**0.06**	**<.001**
Consequences (T1 → T2)	**0.70****	**0.68****	**0.06**	**<.001**
Consequences (T2 → T3)		**0.45****	**0.07**	**<.001**
Cross-lagged Paths				
Prop SN Sharing Video ARC → Consequences (T1 → T2, T2 → T3)	0.07	0.54	0.44	.217
Consequences → Prop SN Sharing Video ARC (T1 → T2, T2 → T3)	0.10	0.01	0.01	.117
Covariates and Missingness				
Sex → Prop SN Sharing Video ARC (T1 → T1, T1 → T2, T1 → T3)	-0.01	-0.01	0.04	.767
Sex → Consequences (T1 → T1, T1 → T2, T1 → T3)	**-0.09***	**-0.59***	**0.27**	**.029**
Semester → Prop SN Sharing Video ARC (T1 → T1, T2 → T2, T3→T3)	**0.24***	**0.11***	**0.04**	**.009**
Semester → Consequences (T1 → T1, T2 → T2, T3→T3)	0.06	0.20	0.26	.425
Compensation → Prop SN Sharing Video ARC (T1 → T1, T2 → T2, T3→T3)	0.01	0.01	0.04	.870
Compensation → Consequences (T1 → T1, T2 → T2, T3→T3)	0.01	0.10	0.31	.759
SM Check Freq → Prop SN Sharing Video ARC (T1 → T1, T2 → T2, T3→T3)	-0.05	-0.02	0.02	.272
SM Check Freq → Consequences (T1 → T1, T2 → T2, T3→T3)	0.06	0.21	0.13	.101
Quantity → Consequences (T1 → T1)	**0.57****	**0.26****	**0.02**	**<.001**
Quantity → Consequences (T2 → T2)	**0.14***	**0.11***	**0.04**	**.003**
Quantity → Consequences (T3 → T3)	**0.23****	**0.16***	**0.05**	**.001**
Prop SN Sharing Video ARC → Miss 1-month follow-up (T1 → T2)	-0.13	-0.32	0.22	.143
Prop SN Sharing Video ARC → Miss 3-month follow-up (T2 → T3)	-0.10	-0.30	0.25	.228
Prop SN Sharing Video ARC → Miss 1-month follow-up (T2 → T2)	0.02	0.07	0.10	.480
Prop SN Sharing Video ARC → Miss 3-month follow-up (T3 → T3)	0.02	0.06	0.06	.374
Consequences → Miss 1-month follow-up (T1 → T2)	0.08	0.03	0.03	.334
Consequences → Miss 3-month follow-up (T2 → T3)	0.07	0.02	0.03	.364
Consequences → Miss 1-month follow-up (T2 → T2)	-0.02	-0.01	0.02	.681
Consequences → Miss 3-month follow-up (T3 → T3)	-0.02	-0.01	0.01	.430

Note. Prop = proportion, SN = social network, ARC = alcohol-related content, consequences = number of alcohol consequences reported in the past 30 days among those who reported experiencing any consequences, quantity = number of alcoholic drinks consumed in a typical week in the past 30 days, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Sex was coded 0 = *female* and 1 = *male*. Betas for constrained paths are based on standard deviations for estimates of predictors at baseline associated with outcomes at the 1-month follow-up or within-timepoint baseline associations, respectively. Significant path estimates are in bold, *$p < .05$, **$p < .001$.

Figure 16

Longitudinal Associations between Network Members Sharing Alcohol-related Videos versus Photos and Number of Alcohol Consequences



Note. ARC = alcohol-related content, consequences = number of alcohol consequences reported in the past 30 days. Although not pictured, all models controlled for participant sex, social media checking frequency, semesters, compensation chosen, and alcohol quantity. Significant path estimates are in bold, while dashed lines represent non-significant paths.

Aim 4: Qualities of Relationships with Social Network Members

Aim 4a: Cross-sectional Closeness with Social Network Sharing ARC

As seen in Table 30, after controlling for participant sex, social media checking frequency, semester survey was completed, compensation method, average closeness with social network members, the proportion of social network members sharing ARC, and alcohol quantity (only in alcohol consequences models), average closeness with social network members sharing ARC was not associated with alcohol quantity or consequences.

Table 30

Cross-sectional Aim 4a Model: Average Closeness with Social Network Members Sharing ARC Predicting Alcohol Outcomes

	Quantity				Consequences			
Variable	β	*B*	*SE*	*p*	β	*B*	*SE*	*p*
Semester	0.10	0.82	0.74	.264	0.10	0.37	0.31	.231
Compensation	-0.16	-2.37	1.35	.079	**-0.18***	**-1.31***	**0.57**	**.022**
Social Media Frequency	0.03	0.24	0.46	.606	0.02	0.05	0.20	.782
Sex	**0.16***	**2.47***	**0.94**	**.008**	-0.08	-0.60	0.40	.136
Quantity	-	-	-	-	**0.43****	**0.21****	**0.03**	**<.001**
Closeness SN	0.11	2.04	1.54	.186	-0.09	-0.77	0.65	.239
SN Share ARC	**0.16***	**4.39***	**1.66**	**.008**	**0.13***	**1.71***	**0.71**	**.016**
Closeness SN Share ARC	0.01	0.10	1.13	.932	0.12	0.79	0.48	.100

Note. ARC = alcohol-related content, social media frequency = frequency of checking social media (across all platforms), SN = social network, quantity = number of alcoholic drinks consumed in a typical day, consequences = number of alcohol-related consequences reported. Sex was coded 0 = *female* and 1 = *male*. Only the models examining alcohol consequences controlled for quantity. Significant associations are in bold. *$p < .05$, **$p < .001$.

Aims 4b and 5: Longitudinal Closeness with Social Network Sharing ARC

Alcohol Quantity. Details of invariance testing are included in Table 31. None of the paths of interest were found to significantly vary over time and were all constrained to equality within relevant pairs. In the final model, none of the cross-lagged paths between alcohol quantity and average closeness with social network members sharing ARC were associated over time (see Table 32 and Figure 17).

Table 31

Longitudinal Aim 4b for Alcohol Quantity: Invariance Testing for Cross-lagged and Auto-regressive Paths

Paths	Paths Compared	χ^2_{diff}	df_{diff}	p	Conclusion
Cross-lagged					
Quantity T1 → Close SN Share ARC T2	A	0.066	1	.798	Constrain
Quantity T2 → Close SN Share ARC T3	A				
Close SN Share ARC T1 → Quantity T2	B	0.404	1	.525	Constrain
Close Share ARC T2 → Quantity T3	B				
Auto-regressive					
Close SN Share ARC T1 → Close SN Share ARC T2	C	0.109	1	.741	Constrain
Close SN Share ARC T2 → Close SN Share ARC T3	C				
Quantity T1 → Quantity T2	D	2.115	1	.146	Constrain
Quantity T2 → Quantity T3	D				

Note. Close = closeness, SN = social network, ARC = alcohol-related content, quantity = number of alcoholic drinks consumed in a typical week in the past 30 days, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Letter pairs reflect which paths were freely estimated versus constrained to equality for each chi-square comparison. Although not listed in the table, invariance testing was also carried out for all within-timepoint covariate paths.

Table 32

Longitudinal Cross-lagged Panel Model Results for Aim 4b: Closeness with SN Sharing ARC and Alcohol Quantity

	β	*B*	*SE*	*p*
Auto-regressive Paths				
Closeness SN Sharing ARC (T1 → T2, T2 → T3)	**0.66****	**0.67****	**0.10**	**<.001**
Quantity (T1 → T2, T2 → T3)	**0.81****	**0.66****	**0.03**	**<.001**
Cross-lagged Paths				
Closeness SN Sharing ARC → Quantity (T1 → T2, T2 → T3)	0.07	0.85	0.84	.309
Quantity → Closeness Sharing ARC (T1 → T2, T2 → T3)	0.09	0.01	0.004	.092
Covariates and Missingness				
Closeness SN → Closeness SN Sharing ARC (T1 → T2, T2 → T3)	**-0.46****	**-0.66****	**0.16**	**<.001**
Closeness SN → Closeness SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	**0.69****	**1.04****	**0.11**	**<.001**
Closeness SN → Quantity (T1 → T2, T2 → T3)	-0.05	-0.86	1.27	.498
Closeness SN → Quantity (T1 → T1)	**0.12***	**2.43***	**1.02**	**.017**
Closeness SN → Quantity (T2 → T2)	0.12	2.06	1.20	.087
Closeness SN → Quantity (T3 → T3)	-0.03	-0.51	1.06	.631
Prop SN Sharing ARC → Closeness SN Sharing ARC (T1 → T2, T2 → T3)	0.12	0.21	0.12	.083
Prop SN Sharing ARC → Closeness SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.02	-0.03	0.11	.755
Prop SN Sharing ARC → Quantity (T1 → T2)	**-0.14***	**-2.90***	**1.36**	**.033**
Prop SN Sharing ARC → Quantity (T2 → T3)	**-0.29****	**-5.35****	**1.34**	**<.001**
Prop SN Sharing ARC → Quantity (T1 → T1, T2 → T2, T3→T3)	**0.18****	**4.53****	**1.04**	**<.001**
Sex → Closeness SN Sharing ARC (T1 → T1, T1 → T2, T2 → T3)	**-0.08***	**-0.08***	**0.04**	**.041**
Sex → Quantity (T1 → T1)	**0.22****	**3.33****	**0.70**	**<.001**
Sex → Quantity (T1 → T2)	-0.01	-0.15	0.69	.834
Sex → Quantity (T1 → T3)	-0.03	-0.39	0.76	.612
Semester → Closeness SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.07	-0.04	0.05	.410
Semester → Quantity (T1 → T1)	**0.15***	1.24	0.64	.053
Semester → Quantity (T2 → T2)	-0.05	-0.79	1.21	.514
Semester → Quantity (T3 → T3)	-0.05	-1.55	1.55	.316
Compensation → Closeness SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	0.10	0.10	0.07	.153
Compensation → Quantity (T1 → T1, T2 → T2, T3→T3)	-0.07	-1.12	0.78	.153
SM Check Freq → Closeness SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	**0.10***	**0.05***	**0.02**	**.010**
SM Check Freq → Quantity (T1 → T1, T2 → T2, T3→T3)	0.06	0.46	0.23	.052
Closeness SN Sharing ARC → Miss 1-month follow-up (T1 → T2)	-0.01	-0.03	0.09	.777
Closeness SN Sharing ARC → Miss 3-month follow-up (T2 → T3)	-0.12	-0.26	0.16	.111
Closeness SN Sharing ARC → Miss 1-month follow-up (T2 → T2)	0.01	0.02	0.05	.778
Closeness SN Sharing ARC → Miss 3-month follow-up (T3 → T3)	0.02	0.04	0.08	.608
Quantity → Miss 1-month follow-up (T1 → T2)	0.01	0.002	0.003	.555
Quantity → Miss 3-month follow-up (T2 → T3)	**0.28***	**0.05***	**0.02**	**.015**
Quantity → Miss 1-month follow-up (T2 → T2)	-0.01	-0.001	0.003	.698
Quantity → Miss 3-month follow-up (T3 → T3)	**-0.17***	**-0.03***	**0.02**	**.025**

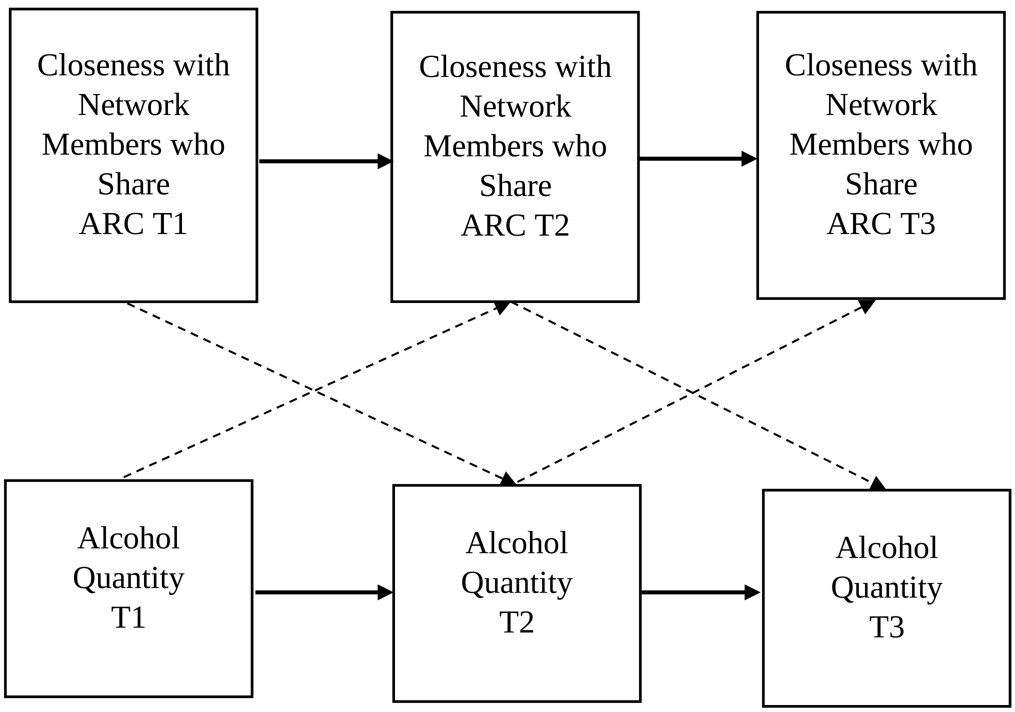
Note. SN = social network, ARC = alcohol-related content, quantity = number of alcoholic drinks consumed in a typical week in the past 30 days, T1 = timepoint 1 [baseline], T2 =

Table 32 (*continued*)

timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Sex was coded 0 = *female* and 1 = *male*. Betas for constrained paths are based on standard deviations for estimates of predictors at baseline associated with outcomes at the 1-month follow-up or within-timepoint baseline associations, respectively. Significant path estimates are in bold, *$p < .05$, **$p < .001$.

Figure 17

Longitudinal Associations between Closeness with Network Members Sharing ARC and Alcohol Quantity



Note. ARC = alcohol-related content, Alcohol Quantity = number of alcoholic drinks consumed in a typical week in the past 30 days. Although not pictured, all models controlled for participant sex, social media checking frequency, semesters, compensation chosen, average closeness with social network members, and the proportion of social network members sharing alcohol-related content. Significant path estimates are in bold, while dashed lines represent non-significant paths.

Any Alcohol Consequences. Details of invariance testing are included in Table 33. None of the paths of interest were found to significantly vary over time and were all constrained to equality within relevant pairs in the final model. In the final model, reporting any alcohol consequences was associated with higher average closeness with social network members sharing ARC over time. All other cross-lagged paths were not significant (see Table 34 and Figure 18).

Table 33

Longitudinal Aim 4b for Reporting Any Alcohol Consequences: Invariance Testing for Cross-lagged and Auto-regressive Paths

Paths	Paths Compared	χ^2_{diff}	df_{diff}	p	Conclusion
Cross-lagged					
Any Conseq T1 → Close SN Share ARC T2	A	1.173	1	.279	Constrain
Any Conseq T2 → Close SN Share ARC T3	A				
Close SN Share ARC T1 → Any Conseq T2	B	0.785	1	.376	Constrain
Close Share ARC T2 → Any Conseq T3	B				
Auto-regressive					
Close SN Share ARC T1 → Close SN Share ARC T2	C	0.078	1	.780	Constrain
Close SN Share ARC T2 → Close SN Share ARC T3	C				
Any Conseq T1 → Any Conseq T2	D	3.500	1	.061	Constrain
Any Conseq T2 → Any Conseq T3	D				

Note. Any Conseq = experience any consequences where 1 = *yes* and 0 = *no*, Close = closeness, SN = social network, ARC = alcohol-related content on social media, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Letter pairs reflect which paths were freely estimated versus constrained to equality for each chi-square comparison. Although not listed in the table, invariance testing was also carried out for all within-timepoint covariate paths.

Table 34

Longitudinal Cross-lagged Panel Model Results for Aim 4b: Closeness with SN Sharing ARC and Reporting Any Alcohol Consequences

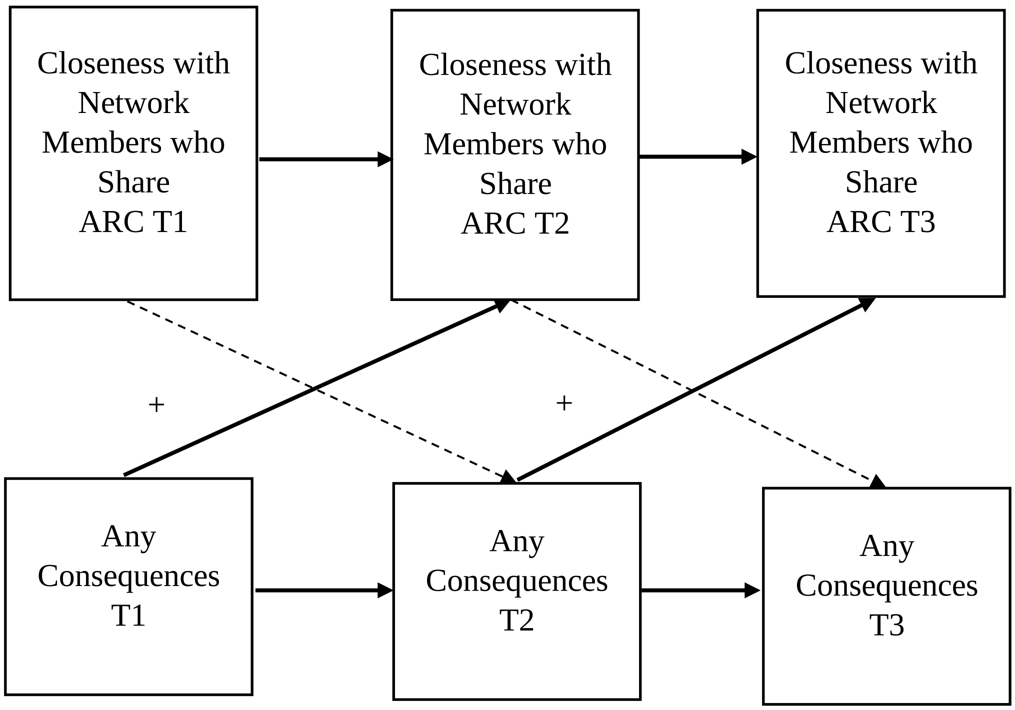
	β	*B*	*SE*	*p*
<u>*Auto-regressive Paths*</u>				
Closeness SN Sharing ARC (T1 → T2, T2 → T3)	**0.69****	**0.71****	**0.11**	**<.001**
Any Consequences (T1 → T2, T2 → T3)	**0.88****	**0.95***	**0.39**	**.015**
<u>*Cross-lagged Paths*</u>				
Closeness SN Sharing ARC → Any Consequences (T1 → T2, T2 → T3)	**0.34***	0.88	0.55	.113
Any Consequences → Closeness Sharing ARC (T1 → T2, T2 → T3)	**0.18***	**0.08***	**0.03**	**.007**
<u>*Covariates and Missingness*</u>				
Closeness SN → Closeness SN Sharing ARC (T1 → T2, T2 → T3)	**-0.52****	**-0.74****	**0.17**	**<.001**
Closeness SN → Closeness SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	**0.68****	**1.04****	**0.10**	**<.001**
Closeness SN → Any Consequences (T1 → T2, T2 → T3)	-0.24	-0.87	0.64	.178
Closeness SN → Any Consequences (T1 → T1)	0.14	0.46	0.27	.092
Closeness SN → Any Consequences (T2 → T2)	-0.16	-0.59	0.41	.144
Closeness SN → Any Consequences (T3 → T3)	-0.16	-0.81	0.85	.342
Prop SN Sharing ARC → Closeness SN Sharing ARC (T1 → T2, T2 → T3)	0.12	0.21	0.11	.062
Prop SN Sharing ARC → Closeness SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.02	-0.04	0.11	.748
Prop SN Sharing ARC → Any Consequences (T1 → T2, T2 → T3)	-0.02	-0.09	0.41	.822
Prop SN Sharing ARC → Any Consequences (T1 → T1, T2 → T2, T3→T3)	0.04	0.16	0.26	.545
Sex → Closeness SN Sharing ARC (T1 → T1, T1 → T2, T1 → T3)	-0.07	-0.07	0.04	.072
Sex → Any Consequences (T1 → T1, T1 → T2, T1 → T3)	-0.05	-0.13	0.11	.231
Semester → Closeness SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.11	-0.06	0.05	.214
Semester → Any Consequences (T1 → T1, T2 → T2, T3→T3)	0.18	0.23	0.14	.086
Compensation → Closeness SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	0.14	0.14	0.07	.058
Compensation → Any Consequences (T1 → T1, T2 → T2, T3→T3)	-0.13	-0.32	0.23	.169
SM Check Freq → Closeness SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	**0.08***	**0.04***	**0.02**	**.039**
SM Check Freq → Any Consequences (T1 → T1, T2 → T2, T3→T3)	0.06	0.07	0.07	.285
Quantity → Any Consequences (T1 → T1)	**0.38****	**0.06****	**0.01**	**<.001**
Quantity → Any Consequences (T2 → T2)	**0.46****	**0.15***	**0.06**	**.020**
Quantity → Any Consequences (T3 → T3)	**0.43****	0.16	0.13	.222
Closeness SN Sharing ARC → Miss 1-month follow-up (T1 → T2)	-0.02	-0.03	0.17	.842
Closeness SN Sharing ARC → Miss 3-month follow-up (T2 → T3)	-0.05	-0.11	0.11	.305
Closeness SN Sharing ARC → Miss 1-month follow-up (T2 → T2)	0.02	0.05	0.09	.616
Closeness SN Sharing ARC → Miss 3-month follow-up (T3 → T3)	0.03	0.07	0.05	.195
Any Consequences → Miss 1-month follow-up (T1 → T2)	**-0.13***	**-0.12***	**0.04**	**.001**
Any Consequences → Miss 3-month follow-up (T2 → T3)	-0.01	-0.01	0.02	.567
Any Consequences → Miss 1-month follow-up (T2 → T2)	0.03	0.03	0.04	.458
Any Consequences → Miss 3-month follow-up (T3 → T3)	0.00	0.00	0.01	.881

Table 34 (*continued*)

Note. SN = social network, ARC = alcohol-related content, any consequences = if participant reported any alcohol consequences (1) versus no alcohol consequences (0) in the past 30 days, quantity = number of alcoholic drinks consumed in a typical week in the past 30 days, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Sex was coded 0 = *female* and 1 = *male*. Betas for constrained paths are based on standard deviations for estimates of predictors at baseline associated with outcomes at the 1-month follow-up or within-timepoint baseline associations, respectively. Significant path estimates are in bold, *p < .05, **p < .001.

Figure 18

Longitudinal Associations Between Closeness with Network Members Sharing ARC and Reporting Any Alcohol Consequences



Note. ARC = alcohol-related content, Any consequences = if participant experienced any alcohol consequences (1) versus no alcohol consequences (0) in the past 30 days. Although not listed in the table, all models controlled for participant sex, social media checking frequency, semesters, compensation chosen, average closeness with social network members, the proportion of social network members sharing alcohol-related content, and alcohol quantity. Significant path estimates are in bold, while dashed lines represent non-significant paths.

Number of Alcohol Consequences. Details of invariance testing are included in Table 35. Only the auto-regressive paths for the number of alcohol consequences experienced were found to significantly vary over time. These were freely estimated in the final model while all other paths of interest were constrained to equality within relevant pairs over time. In the final model, none of the cross-lagged paths were significant (see Table 36 and Figure 19).

Table 35

Longitudinal Aim 4b for Number of Alcohol Consequences: Invariance Testing for Cross-lagged and Auto-regressive Paths

Paths	Paths Compared	χ^2_{diff}	df_{diff}	*p*	Conclusion
Cross-lagged					
Conseq T1 → Close SN Share ARC T2	A	0.025	1	.874	Constrain
Conseq T2 → Close SN Share ARC T3	A				
Close SN Share ARC T1 → Conseq T2	B	0.746	1	.388	Constrain
Close Share ARC T2 → Conseq T3	B				
Auto-regressive					
Close SN Share ARC T1 → Close SN Share ARC T2	C	0.078	1	.780	Constrain
Close SN Share ARC T2 → Close SN Share ARC T3	C				
Conseq T1 → Conseq T2	D	5.620	1	**.018**	Free
Conseq T2 → Conseq T3	D				

Note. Close = closeness, SN = social network, ARC = alcohol-related content, consequences = number of alcohol consequences reported in the past 30 days, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Letter pairs reflect which paths were freely estimated versus constrained to equality for each chi-square comparison. Although not listed in the table, invariance testing was also carried out for all within-timepoint covariate paths.

Table 36

Longitudinal Cross-lagged Panel Model Results for Aim 4b: Closeness with SN Sharing ARC and Number of Alcohol Consequences

	β	*B*	*SE*	*p*
Auto-regressive Paths				
Closeness SN Sharing ARC	**0.63****	**0.65****	**0.10**	**<.001**
Consequences (T1 → T2)	**0.70****	**0.67****	**0.06**	**<.001**
Consequences (T2 → T3)	**0.45****	**0.45****	**0.07**	**<.001**
Cross-lagged Paths				
Closeness SN Sharing ARC → Consequences	0.02	0.12	0.71	.864
Consequences → Closeness SN Sharing ARC	0.07	0.01	0.01	.191
Covariates and Missingness				
Closeness SN → Closeness SN Sharing ARC (T1 → T2, T2 → T3)	**-0.44****	**-0.63****	**0.15**	**<.001**
Closeness SN → Closeness SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	**0.76****	**1.05****	**0.11**	**<.001**
Closeness SN → Consequences (T1 → T2, T2 → T3)	-0.03	-0.24	0.94	.796
Closeness SN → Consequences (T1 → T1, T2 → T2, T3→T3)	-0.02	-0.16	0.38	.678
Prop SN Sharing ARC → Closeness SN Sharing ARC (T1 → T2, T2 → T3)	0.09	0.16	0.12	.178
Prop SN Sharing ARC → Closeness SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	0.01	0.01	0.12	.913
Prop SN Sharing ARC → Consequences (T1 → T2, T2 → T3)	-0.02	-0.18	0.65	.782
Prop SN Sharing ARC → Consequences (T1 → T1, T2 → T2, T3→T3)	**0.11***	**1.23***	**0.45**	**.006**
Sex → Closeness SN Sharing ARC (T1 → T1, T1 → T2, T1 → T3)	**-0.08***	**-0.09***	**0.04**	**.043**
Sex → Consequences (T1 → T1, T1 → T2, T1 → T3)	**-0.09***	**-0.60***	**0.27**	**.026**
Semester → Closeness SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.09	-0.05	0.05	.318
Semester → Consequences (T1 → T1, T2 → T2, T3→T3)	0.02	0.05	0.25	.833
Compensation → Closeness SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	0.09	0.09	0.07	.164
Compensation → Consequences (T1 → T1)	-0.04	-0.29	0.54	.589
Compensation → Consequences (T2 → T2)	0.12	0.97	0.54	.071
Compensation → Consequences (T3 → T3)	-0.06	-0.41	0.49	.400
SM Check Freq → Closeness SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	**0.10***	**0.05***	**0.02**	**.017**
SM Check Freq → Consequences (T1 → T1, T2 → T2, T3→T3)	0.06	0.21	0.13	.098
Quantity → Consequences (T1 → T1)	**0.58****	**0.26****	**0.02**	**<.001**
Quantity → Consequences (T2 → T2)	**0.15***	**0.11***	**0.04**	**.002**
Quantity → Consequences (T3 → T3)	**0.22****	**0.15****	**0.04**	**<.001**
Closeness SN Sharing ARC → Miss 1-month follow-up (T1 → T2)	0.01	0.02	0.13	.880
Closeness SN Sharing ARC → Miss 3-month follow-up (T2 → T3)	-0.05	-0.10	0.10	.321
Closeness SN Sharing ARC → Miss 1-month follow-up (T2 → T2)	-0.01	-0.01	0.07	.857
Closeness SN Sharing ARC → Miss 3-month follow-up (T3 → T3)	0.02	0.05	0.05	.320
Consequences → Miss 1-month follow-up (T1 → T2)	0.03	0.01	0.02	.658
Consequences → Miss 1-month follow-up (T2 → T3)	0.06	0.02	0.02	.404
Consequences → Miss 1-month follow-up (T2 → T2)	-0.01	-0.00	0.02	.808
Consequences → Miss 3-month follow-up (T3 → T3)	-0.02	-0.01	0.01	.434

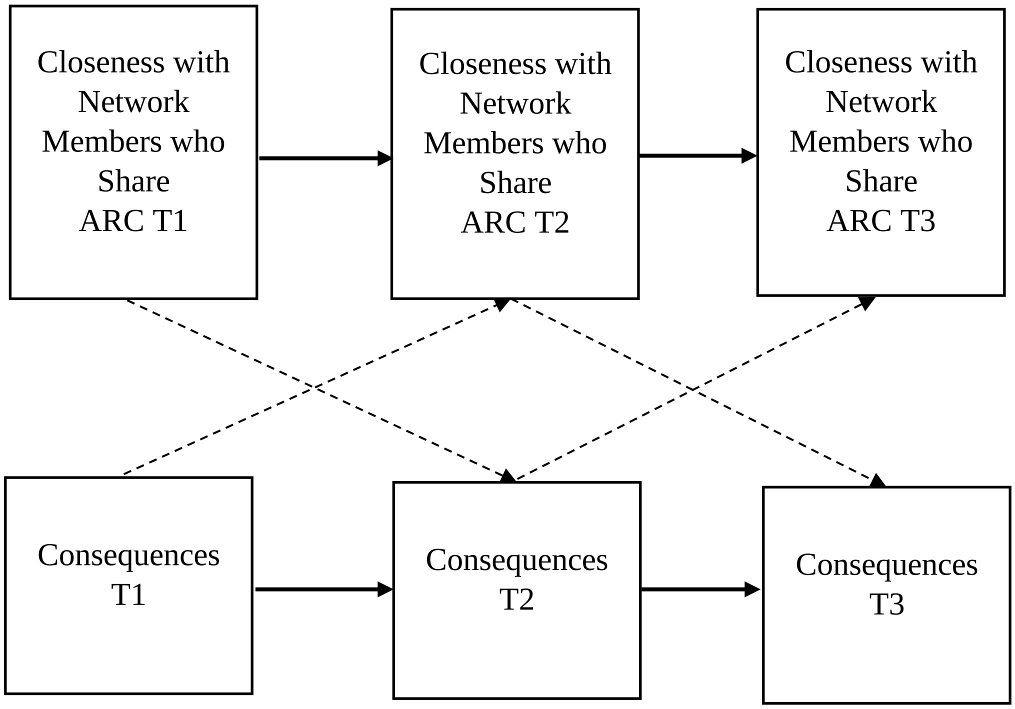
Note. SN = social network, ARC = alcohol-related content, consequences = number of alcohol consequences reported in the past 30 days, quantity = number of alcoholic drinks consumed in a

Table 36 (*continued*)

typical week in the past 30 days, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Sex was coded 0 = *female* and 1 = *male*. Betas for constrained paths are based on standard deviations for estimates of predictors at baseline associated with outcomes at the 1-month follow-up or within-timepoint baseline associations, respectively. Significant path estimates are in bold, *p < .05, **p < .001.

Figure 19

Longitudinal Associations between Closeness with Network Members Sharing ARC and Number of Alcohol Consequences



Note. ARC = alcohol-related content, Consequences = number of alcohol consequences reported in the past 30 days. Although not pictured, all models controlled for participant sex, social media checking frequency, semesters, compensation chosen, average closeness with social network members, the proportion of social network members sharing alcohol-related content, and alcohol quantity. Significant path estimates are in bold, while dashed lines represent non-significant paths.

Aim 4c: Cross-sectional Drinking Buddies Sharing ARC

As seen in Table 37, after controlling for participant sex, social media checking frequency, semester survey was completed, compensation method, the proportion of drinking buddies in the social network, the proportion of social network members sharing ARC, and alcohol quantity (only in alcohol consequences model), the proportion of drinking buddies sharing ARC was not significantly associated with alcohol quantity or consequences. However, after controlling for all other variables in the model, the proportion of drinking buddies in the social network was positively associated with alcohol quantity but not consequences.

Table 37

Cross-sectional Aim 4c Model: Proportion of Drinking Buddies in Social Network Sharing ARC Predict Alcohol Outcomes

	Quantity				Consequences			
Variable	β	*B*	*SE*	*p*	β	*B*	*SE*	*p*
Semester	0.11	0.93	0.61	.125	0.05	0.19	0.27	.485
Compensation	**-0.15***	**-2.35***	**1.12**	**.036**	-0.12	-0.81	0.49	.097
Social Media Frequency	0.07	0.55	0.37	.140	0.08	0.28	0.16	.086
Sex	**0.23****	**3.65****	**0.77**	**<.001**	**-0.10***	**-0.69***	**0.34**	**.044**
Quantity	-	-	-	-	**0.45****	**0.21****	**0.02**	**<.001**
Drink Buddy SN	**0.32****	**7.09****	**1.15**	**<.001**	0.05	0.55	0.53	.296
SN Share ARC	-0.01	-0.19	1.48	.895	0.06	0.64	0.64	.319
Drink Buddy SN Share ARC	0.06	1.12	1.33	.397	0.05	0.48	0.58	.407

Note. ARC = alcohol-related content, social media frequency = frequency of checking social media (across all platforms), SN = social network, quantity = number of alcoholic drinks consumed in a typical day, consequences = number of alcohol-related consequences reported. Only the model examining consequences controlled for alcohol quantity. Sex was coded 0 = *female* and 1 = *male*. Significant associations are in bold. *$p < .05$, **$p < .001$.

Aims 4d and 5: Longitudinal Drinking Buddies Sharing ARC

Alcohol Quantity. Details of invariance testing are included in Table 38. Only the cross-lagged paths from alcohol quantity to the proportion of drinking buddies sharing ARC were found to significantly vary over time. These paths were freely estimated in the final model while all other paths of interest were constrained to equality within relevant pairs over time. In the final model, greater alcohol quantity at baseline was associated with a higher proportion of drinking buddies sharing ARC at 1-month, but the path from alcohol quantity at 1-month was not significantly associated with the proportion of drinking buddies sharing ARC at 3-month. All other cross-lagged paths were not significant (see Table 39 and Figure 20).

Table 38

Longitudinal Aim 4d for Alcohol Quantity: Invariance Testing for Cross-lagged and Auto-regressive Paths

Paths	Paths Compared	χ^2_{diff}	df_{diff}	p	Conclusion
Cross-lagged					
Quantity T1 → DB SN Share ARC T2	A	6.993	1	**.008**	Free
Quantity T2 → DB SN Share ARC T3	A				
DB SN Share ARC T1 → Quantity T2	B	2.767	1	.096	Constrain
DB Share ARC T2 → Quantity T3	B				
Auto-regressive					
DB SN Share ARC T1 → DB SN Share ARC T2	C	0.416	1	.519	Constrain
DB SN Share ARC T2 → DB SN Share ARC T3	C				
Quantity T1 → Quantity T2	D	2.049	1	.152	Constrain
Quantity T2 → Quantity T3	D				

Note. DB = drinking buddy, SN = social network, ARC = alcohol-related content, quantity = number of alcoholic drinks consumed in a typical week in the past 30 days, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Letter pairs reflect which paths were freely estimated versus constrained to equality for each chi-square comparison. Although not listed in the table, invariance testing was also carried out for all within-timepoint covariate paths.

Table 39

Longitudinal Cross-lagged Panel Model Results for Aim 4d: DB in SN Sharing ARC and Alcohol Quantity

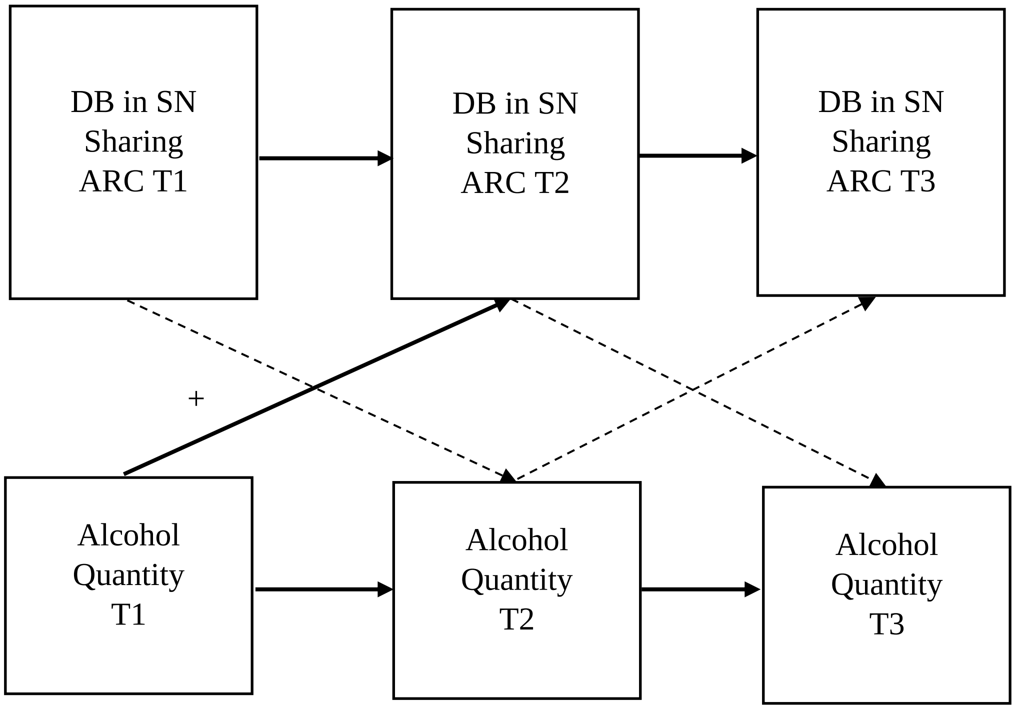
	β	*B*	*SE*	*p*
Auto-regressive Paths				
DB SN Sharing ARC (T1 → T2, T2 → T3)	__0.51**__	__0.57**__	__0.09__	__<.001__
Quantity (T1 → T2, T2 → T3)	__0.74**__	__0.62**__	__0.03__	__<.001__
Cross-lagged Paths				
DB SN Sharing ARC → Quantity (T1 → T2, T2 → T3)	0.13	2.21	1.17	.058
Quantity → DB SN Sharing ARC (T1 → T2)	__0.16*__	__0.01*__	__0.00__	__.032__
Quantity → DB SN Sharing ARC (T2 → T3)	-0.04	-0.00	0.01	.601
Covariates and Missingness				
DB SN → DB SN Sharing ARC (T1 → T2, T2 → T3)	__-0.17*__	__-0.19*__	__0.09__	__.032__
DB SN → DB SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	0.07	0.07	0.07	.287
DB SN → Quantity (T1 → T2, T2 → T3)	__-0.20*__	__-3.58*__	__1.69__	__.034__
DB SN → Quantity (T1)	__0.42**__	__9.09**__	__1.01__	__<.001__
DB SN → Quantity (T2)	__0.33**__	__5.60**__	__1.50__	__<.001__
DB SN → Quantity (T3)	__0.37**__	__5.99*__	__1.81__	__.001__
Prop SN Sharing ARC → DB SN Sharing ARC (T1 → T2, T2 → T3)	__-0.38**__	__-0.49**__	__0.12__	__<.001__
Prop SN Sharing ARC → DB SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	__0.69**__	__0.80**__	__0.08__	__<.001__
Prop SN Sharing ARC → Quantity (T1 → T2)	__-0.16*__	__-3.39*__	__1.65__	__.040__
Prop SN Sharing ARC → Quantity (T2 → T3)	__-0.31*__	__-5.77*__	__1.85__	__.002__
Prop SN Sharing ARC → Quantity (T1 → T1, T2 → T2, T3→T3)	__0.10*__	__2.57*__	__0.92__	__.005__
Sex → DB SN Sharing ARC (T1 → T1, T1 → T2, T2 → T3)	__-0.12*__	__-0.09*__	__0.03__	__.004__
Sex → Quantity (T1 → T1)	__0.23**__	__3.54**__	__0.72__	__<.001__
Sex → Quantity (T1 → T2)	-0.04	-0.45	0.69	.518
Sex → Quantity (T1 → T3)	0.02	0.21	0.78	.789
Semester → DB SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.04	-0.02	0.03	.629
Semester → Quantity (T1 → T1)	0.15	1.21	0.66	.065
Semester → Quantity (T2 → T2)	0.06	0.97	0.91	.286
Semester → Quantity (T3 → T3)	-0.04	-1.12	1.60	.483
Compensation → DB SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.00	-0.00	0.04	.952
Compensation → Quantity (T1 → T1, T2 → T2, T3→T3)	-0.09	-1.40	0.88	.112
SM Check Freq → DB SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	__0.08*__	__0.03*__	__0.01__	__.043__
SM Check Freq → Quantity (T1 → T1, T2 → T2, T3→T3)	0.05	0.34	0.21	.105
DB SN Sharing ARC → Miss 1-month follow-up (T1 → T2)	0.18	0.61	0.43	.154
DB SN Sharing ARC → Miss 3-month follow-up (T2 → T3)	0.21	0.60	0.36	.094
DB SN Sharing ARC → Miss 1-month follow-up (T2 → T2)	-0.14	-0.44	0.27	.108
DB SN Sharing ARC → Miss 3-month follow-up (T3 → T3)	-0.12	-0.39	0.24	.100
Quantity → Miss 1-month follow-up (T1 → T2)	__0.51*__	__0.08*__	__0.03__	__.008__
Quantity → Miss 3-month follow-up (T2 → T3)	0.09	0.02	0.02	.384
Quantity → Miss 1-month follow-up (T2 → T2)	__-0.39*__	__-0.07*__	__0.03__	__.014__
Quantity → Miss 3-month follow-up (T3 → T3)	-0.09	-0.02	0.02	.245

Table 39 (*continued*)

Note. DB = drinking buddies, SN = social network, ARC = alcohol-related content, quantity = number of alcoholic drinks consumed in a typical week in the past 30 days, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Sex was coded 0 = *female* and 1 = *male*. Betas for constrained paths are based on standard deviations for estimates of predictors at baseline associated with outcomes at the 1-month follow-up or within-timepoint baseline associations, respectively. Significant path estimates are in bold, $^{*}p < .05$, $^{**}p < .001$.

Figure 20

Longitudinal Associations between Drinking Buddies in the Social Network Sharing ARC and Alcohol Quantity



Note. DB = drinking buddies, SN = social network, ARC = alcohol-related content, Alcohol quantity = number of drinks consumed in a typical week in the past 30 days. Although not pictured, all models controlled for participant sex, social media checking frequency, semesters, compensation chosen, the proportion of drinking buddies in the social network, and the proportion of social network members sharing ARC. Significant path estimates are in bold, while dashed lines represent non-significant paths.

Any Alcohol Consequences. Details of invariance testing are included in Table 40. Only the cross-lagged paths from experiencing any alcohol consequences to the proportion of drinking buddies sharing ARC were found to vary significantly over time. These paths were freely estimated in the final model while all other paths of interest were constrained to equality within relevant pairs. In the final model, reporting any alcohol consequences at baseline was associated with a higher proportion of drinking buddies sharing ARC at 1-month, while the cross-lagged path from experiencing any alcohol consequences at 1-month to the proportion of drinking buddies sharing ARC at 3-month was not significant. A greater proportion of drinking buddies sharing ARC was associated with a greater likelihood of reporting any alcohol consequences over time (see Table 41 and Figure 21).

Table 40

Longitudinal Aim 4d for Reporting Any Alcohol Consequences: Invariance Testing for Cross-lagged and Auto-regressive Paths

Paths	Paths Compared	χ^2_{diff}	df_{diff}	*p*	Conclusion
Cross-lagged					
Any Conseq T1 → DB SN Share ARC T2	A	5.044	1	**.025**	Free
Any Conseq T2 → DB SN Share ARC T3	A				
DB SN Share ARC T1 → Any Conseq T2	B	2.303	1	.129	Constrain
DB Share ARC T2 → Any Conseq T3	B				
Auto-regressive					
DB SN Share ARC T1 → DB SN Share ARC T2	C	0.125	1	.723	Constrain
DB SN Share ARC T2 → DB SN Share ARC T3	C				
Any Conseq T1 → Any Conseq T2	D	0.471	1	.493	Constrain
Any Conseq T2 → Any Conseq T3	D				

Note. Any Conseq = experience any alcohol consequences where 1 = *yes* and 0 = *no*, DB = drinking buddy, SN = social network, ARC = alcohol-related content on social media, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Letter pairs reflect which paths were freely estimated versus constrained to equality for each chi-square comparison. Although not listed in the table, invariance testing was also carried out for all within-timepoint covariate paths.

Table 41

Longitudinal Cross-lagged Panel Model Results for Aim 4d: DB in SN Sharing ARC and Reporting Any Alcohol Consequences

	β	*B*	*SE*	*p*
Auto-regressive Paths				
DB SN Sharing ARC (T1 → T2, T2, → T3)	**0.59****	**0.60****	**0.11**	**<.001**
Any Consequences (T1 → T2, T2, → T3)	**0.86****	**0.64****	**0.08**	**<.001**
Cross-lagged Paths				
DB SN Sharing ARC → Any Consequences (T1 → T2, T2, → T3)	**0.24***	**0.66***	**0.25**	**.010**
Any Consequences → DB SN Sharing ARC (T1 → T2)	**0.41****	**0.11****	**0.03**	**<.001**
Any Consequences → DB SN Sharing ARC (T2 → T3)	0.00	0.00	0.03	.994
Covariates and Missingness				
DB SN → DB SN Sharing ARC (T1 → T2, T2 → T3)	**-0.21***	**-0.25***	**0.09**	**.006**
DB SN → DB SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	0.07	0.08	0.07	.281
DB SN → Any Consequences (T1 → T2, T2 → T3)	**-0.64****	**-1.98****	**0.56**	**<.001**
DB SN → Any Consequences (T1 → T1, T2 → T2, T3→T3)	**0.33****	**1.36****	**0.38**	**<.001**
Prop SN Sharing ARC → DB SN Sharing ARC (T1 → T2, T2 → T3)	**-0.36****	**-0.43****	**0.12**	**<.001**
Prop SN Sharing ARC → DB SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	**0.67****	**0.78****	**0.09**	**<.001**
Prop SN Sharing ARC → Any Consequences (T1 → T2, T2 → T3)	-0.07	-0.22	0.35	.540
Prop SN Sharing ARC → Any Consequences (T1 → T1, T2 → T2, T3→T3)	-0.02	-0.10	0.21	.621
Sex → DB SN Sharing ARC (T1 → T1, T1 → T2, T2 → T3)	**-0.14***	**-0.10***	**0.03**	**.001**
Sex → Any Consequences (T1 → T1, T1 → T2, T2 → T3)	-0.02	-0.05	0.08	.543
Semester → DB SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.09	-0.03	0.03	.269
Semester → Any Consequences (T1 → T1, T2 → T2, T3→T3)	0.12	0.17	0.12	.152
Compensation → DB SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	0.02	0.01	0.04	.717
Compensation → Any Consequences (T1 → T1, T2 → T2, T3→T3)	-0.05	-0.13	0.13	.332
SM Check Freq → DB SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	0.05	0.02	0.01	.140
SM Check Freq → Any Consequences (T1 → T1, T2 → T2, T3→T3)	0.04	0.05	0.04	.273
Quantity → Any Consequences (T1 → T1, T2 → T2, T3→T3)	**0.42****	**0.07****	**0.01**	**<.001**
DB SN Sharing ARC → Miss 1-month follow-up (T1 → T2)	0.10	0.31	0.31	.313
DB SN Sharing ARC → Miss 3-month follow-up (T2 → T3)	0.23	0.70	0.38	.066
DB SN Sharing ARC → Miss 1-month follow-up (T2 → T2)	-0.04	-0.13	0.19	.482
DB SN Sharing ARC → Miss 3-month follow-up (T3 → T3)	-0.15	-0.44	0.26	.088
Any Consequences → Miss 1-month follow-up (T1 → T2)	-0.03	-0.03	0.04	.493
Any Consequences → Miss 3-month follow-up (T2 → T3)	-0.04	-0.04	0.05	.381
Any Consequences → Miss 1-month follow-up (T2 → T2)	-0.02	-0.03	0.05	.548
Any Consequences → Miss 3-month follow-up (T3 → T3)	0.03	0.05	0.05	.334

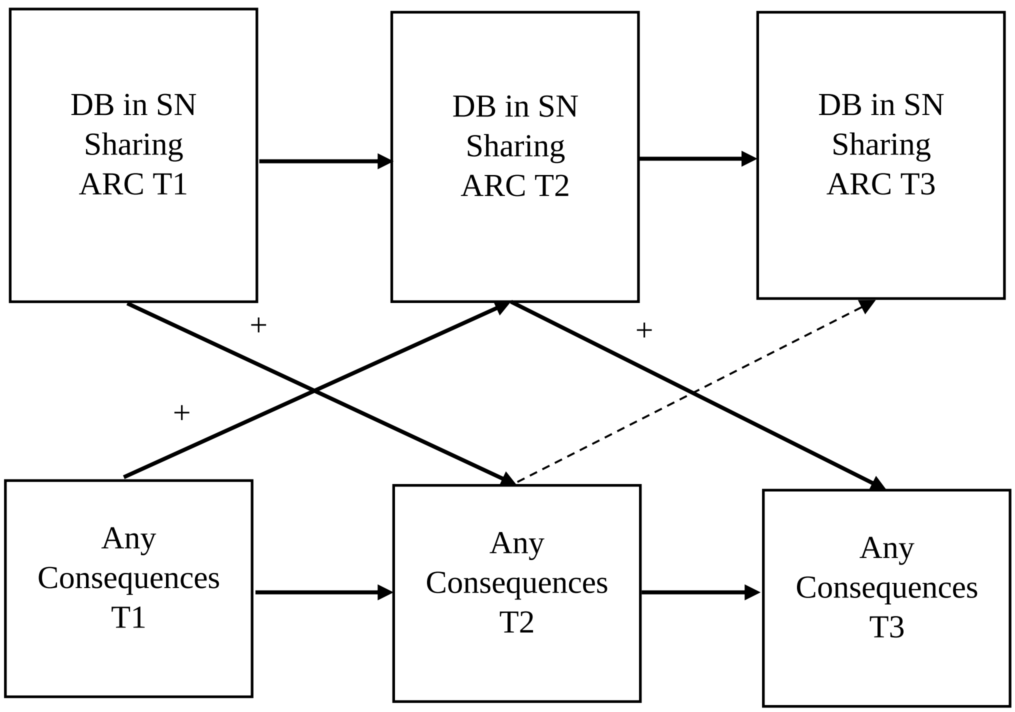
Note. DB = drinking buddies, SN = social network, ARC = alcohol-related content, any consequences = if participant reported any alcohol consequences (1) versus no alcohol consequences (0) in the past 30 days, quantity = number of alcoholic drinks consumed in a typical week in the past 30 days, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-

Table 41 (*continued*)

up], T3 = timepoint 3 [3-month follow-up]. Sex was coded 0 = *female* and 1 = *male*. Betas for constrained paths are based on standard deviations for estimates of predictors at baseline associated with outcomes at the 1-month follow-up or within-timepoint baseline associations, respectively. Significant path estimates are in bold, *p < .05, **p < .001.

Figure 21

Longitudinal Associations between Drinking Buddies in the Social Network Sharing ARC and Reporting Any Alcohol Consequences



Note. DB = drinking buddies, SN = social network, ARC = alcohol-related content, any consequences = if participant reported any alcohol consequences (1) versus no alcohol consequences (0) in the past 30 days. Although not pictured, all models controlled for participant sex, social media checking frequency, semesters, compensation chosen, the proportion of drinking buddies in the social network, the proportion of social network members sharing ARC, and alcohol quantity. Significant path estimates are in bold, while dashed lines represent non-significant paths.

Number of Alcohol Consequences. Details of invariance testing are included in Table 42. The cross-lagged paths from the proportion of drinking buddies sharing ARC to the number of alcohol consequences as well as the auto-regressive paths for the number of alcohol consequences were found to significantly vary over time. These were freely estimated in the final model while all other paths of interest were constrained to equality within relevant pairs. In the final model, reporting a greater number of alcohol consequences was associated with a higher proportion of drinking buddies sharing ARC over time. None of the other cross-lagged paths were significant (see Table 43 and Figure 22).

Table 42

Longitudinal Aim 4d for Number of Alcohol Consequences: Invariance Testing for Cross-lagged and Auto-regressive Paths

Paths	Paths Compared	χ^2_{diff}	df_{diff}	p	Conclusion
Cross-lagged					
Conseq T1 → DB SN Share ARC T2	A	0.515	1	.473	Constrain
Conseq T2 → DB SN Share ARC T3	A				
DB SN Share ARC T1 → Conseq T2	B	4.257	1	**.039**	Free
DB SN Share ARC T2 → Conseq T3	B				
Auto-regressive					
DB SN Share ARC T1 → DB SN Share ARC T2	C	0.709	1	.400	Constrain
DB SN Share ARC T2 → DB SN Share ARC T3	C				
Conseq T1 → Conseq T2	D	5.137	1	**.023**	Free
Conseq T2 → Conseq T3	D				

Note. DB = drinking buddy, SN = social network, ARC = alcohol-related content, consequences = number of alcohol consequences reported in the past 30 days, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Letter pairs reflect which paths were freely estimated versus constrained to equality for each chi-square comparison. Although not listed in the table, invariance testing was also carried out for all within-timepoint covariate paths.

Table 43

Longitudinal Cross-lagged Panel Model Results for Aim 4d: DB in SN Sharing ARC and Number of Alcohol Consequences

	β	*B*	*SE*	*p*
Auto-regressive Paths				
DB SN Sharing ARC	**0.39****	**0.42****	**0.08**	**<.001**
Consequences (T1 → T2)	**0.71****	**0.69****	**0.06**	**<.001**
Consequences (T2 → T3)	**0.46****	**0.46****	**0.07**	**<.001**
Cross-lagged Paths				
DB SN Sharing ARC → Consequences (T1 → T2)	-0.10	-0.93	0.72	.196
DB SN Sharing ARC → Consequences (T2 → T3)	-0.14	-1.22	0.73	.095
Consequences → DB SN Sharing ARC (T1 → T2, T2 → T3)	**0.11***	**0.01***	**0.01**	**.033**
Covariates and Missingness				
DB SN → DB SN Sharing ARC (T1 → T2, T2 → T3)	0.19	0.22	0.13	.095
DB SN → DB SN Sharing ARC (T1 → T1)	0.16	0.17	0.09	.051
DB SN → DB SN Sharing ARC (T2 → T2)	**-0.27***	**-0.30***	**0.15**	**.044**
DB SN → DB SN Sharing ARC (T3 → T3)	-0.34	-0.35	0.21	.102
DB SN → Consequences (T1 → T2, T2 → T3)	-0.05	-0.51	0.62	.417
DB SN → Consequences (T1 → T1, T2 → T2, T3→T3)	0.07	0.66	0.43	.124
Prop SN Sharing ARC → DB SN Sharing ARC (T1 → T2, T2 → T3)	**-0.26***	**-0.32***	**0.10**	**.001**
Prop SN Sharing ARC → DB SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	**0.66****	**0.77****	**0.08**	**<.001**
Prop SN Sharing ARC → Consequences (T1 → T2, T2 → T3)	0.08	0.85	0.75	.255
Prop SN Sharing ARC → Consequences (T1 → T1, T2 → T2, T3→T3)	**0.10***	**1.06***	**0.44**	**.015**
Sex → DB SN Sharing ARC (T1 → T1, T1 → T2, T1 → T3)	**-0.15****	**-0.11***	**0.03**	**.001**
Sex → Consequences (T1 → T1, T1 → T2, T1 → T3)	**-0.09***	**-0.66***	**0.27**	**.014**
Semester → DB SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	-0.12	-0.05	0.03	.134
Semester → Consequences (T1 → T1, T2 → T2, T3→T3)	0.06	0.20	0.26	.448
Compensation → DB SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	0.00	0.003	0.04	.928
Compensation → Consequences (T1 → T1, T2 → T2, T3→T3)	0.01	0.08	0.31	.800
SM Check Freq → DB SN Sharing ARC (T1 → T1, T2 → T2, T3→T3)	0.06	0.02	0.01	.108
SM Check Freq → Consequences (T1 → T1, T2 → T2, T3→T3)	0.06	0.20	0.13	.123
Quantity → Consequences (T1 → T1)	**0.58****	**0.26****	**0.02**	**<.001**
Quantity → Consequences (T2 → T2)	0.09	0.07	0.04	.062
Quantity → Consequences (T3 → T3)	**0.22****	**0.15***	**0.05**	**.001**
DB SN Sharing ARC → Miss 1-month follow-up (T1 → T2)	0.08	0.26	0.26	.314
DB SN Sharing ARC → Miss 3-month follow-up (T2 → T3)	0.17	0.49	0.37	.190
DB SN Sharing ARC → Miss 1-month follow-up (T2 → T2)	-0.05	-0.13	0.13	.326
DB SN Sharing ARC → Miss 3-month follow-up (T3 → T3)	-0.10	-0.30	0.23	.182
Consequences → Miss 1-month follow-up (T1 → T2)	0.09	0.03	0.04	.393
Consequences → Miss 3-month follow-up (T2 → T3)	0.05	0.02	0.03	.539
Consequences → Miss 1-month follow-up (T2 → T2)	-0.05	-0.02	0.02	.478
Consequences → Miss 3-month follow-up (T3 → T3)	-0.02	-0.01	0.01	.620

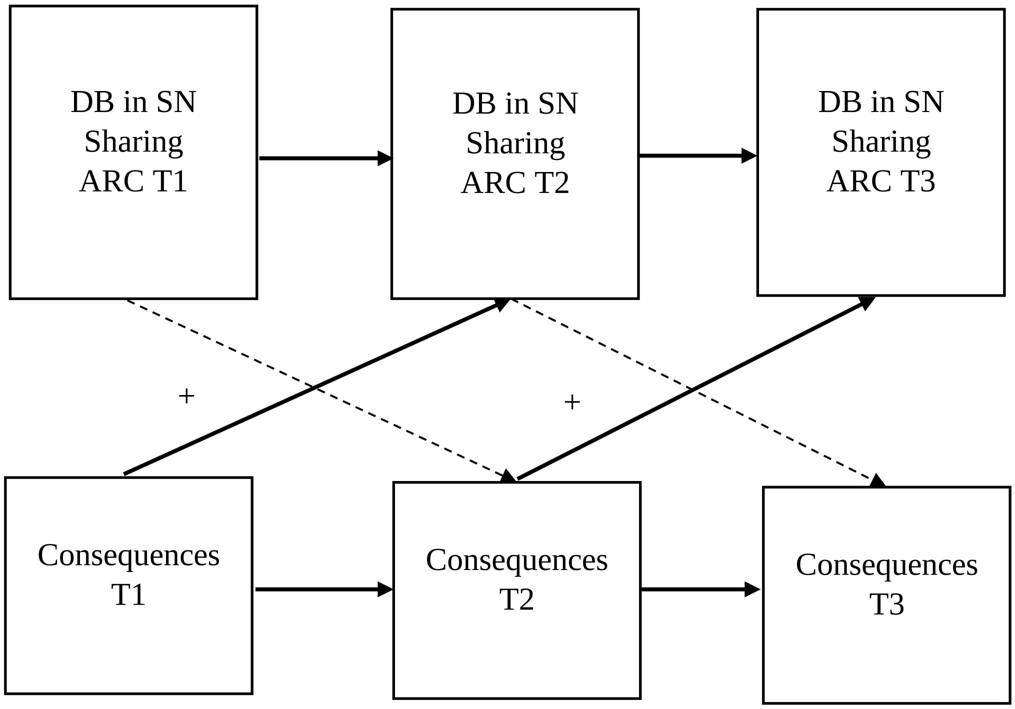
Note. DB = drinking buddies, SN = social network, ARC = alcohol-related content, consequences = number of alcohol consequences reported in the past 30 days, quantity = number

Table 43 (*continued*)

of alcoholic drinks consumed in a typical week in the past 30 days, T1 = timepoint 1 [baseline], T2 = timepoint 2 [1-month follow-up], T3 = timepoint 3 [3-month follow-up]. Sex was coded 0 = *female* and 1= *male*. Betas for constrained paths are based on standard deviations for estimates of predictors at baseline associated with outcomes at the 1-month follow-up or within-timepoint baseline associations, respectively. Significant path estimates are in bold, *p < .05, **p < .001.

Figure 22

Longitudinal Associations between Drinking Buddies in the Social Network Sharing ARC and Number of Alcohol Consequences



Note. DB = drinking buddies, SN = social network, ARC = alcohol-related content, consequences = number of alcohol consequences reported in the past 30 days. Although not pictured, all models controlled for participant sex, social media checking frequency, semesters, compensation chosen, the proportion of drinking buddies in the social network, the proportion of social network members sharing ARC, and alcohol quantity. Significant path estimates are in bold, while dashed lines represent non-significant paths.

CHAPTER IV

DISCUSSION

The current study addressed several critical gaps in the literature by assessing both cross-sectional and longitudinal associations between alcohol quantity and consequences (separate models) and self-sharing ARC (aim 1), exposure to ARC shared by social network members (aim 2), exposure to video ARC versus photo ARC (aim 3), and closeness with (aims 4a and 4b) and drinking buddy status of (aims 4c and 4d) social network members sharing ARC among heavy or problematic college drinkers.

Self-sharing ARC

Aim 1a examined if the frequency of self-sharing ARC was cross-sectionally associated with alcohol quantity and related consequences cross-sectionally. Additional analyses were also conducted to see if participants self-sharing ARC measured dichotomously (i.e., yes or no response) was associated with alcohol outcomes. This hypothesis was partially supported in that participants sharing any ARC was associated with simultaneous greater alcohol quantity and consequences while greater frequency of participants sharing ARC was only associated with higher simultaneous alcohol quantity but not consequences (though the significance for consequences was marginal; $p = .067$). These findings are in line with literature examining self-sharing ARC and alcohol outcomes (e.g., Alhabash et al., 2020). The non-significant but marginal association between frequency of participants sharing ARC and consequences could be due to controlling for participant alcohol quantity to examine problematic drinking after controlling for drinking level, especially given these are heavy or problematic drinkers. Only one study (Richner et al., 2021) has examined the association between self-sharing ARC and consequences, but these researchers did not control for alcohol quantity. Notably, most studies examining self-sharing either examine alcohol quantity as the only alcohol-related outcome (e.g., Alhabash et al., 2020) or use the Alcohol Use Disorders Identification Test (AUDIT; Saunders et al., 1993) which conflates quantity and consequences into a single indicator of hazardous drinking (e.g., Geusens & Beullens, 2016).

Aim 1b examined if the frequency of self-sharing ARC was associated with alcohol quantity and consequences over time while Aim 5 simultaneously examined in the same model if alcohol quantity and consequences were associated with frequency of self-sharing ARC over time. As with Aim 1a, models examining the association between sharing any ARC and alcohol outcomes were also conducted. These hypotheses were partially supported for frequency of self-sharing and sharing any ARC. Bidirectional associations were observed between both pairs of timepoints (baseline to 1-month and 1-month to 3-month), such that participants sharing ARC more frequently was associated with greater alcohol quantity and reporting more alcohol-related consequences over time, and greater drinking and consequences associated with participants sharing ARC more often over time. No longitudinal associations in either direction were observed for sharing any ARC and quantity. However, unidirectional associations were observed for consequences, with participants who reported any alcohol consequences and a greater number of consequences (separate models) associated with sharing any ARC across time.

The findings of the current study are mostly in line with the literature. Few studies have examined unidirectional versus bidirectional associations over time between self-sharing ARC and alcohol use. Like my college student sample, Geber et al. (2021) found bidirectional associations between greater frequency of self-sharing ARC and higher drinking frequency four months later with an adolescent sample. Unlike my study, Geusens and Beullens (2020) did not find any significant longitudinal associations between the frequency of self-sharing ARC and later alcohol consumption as measured by the AUDIT-C (Saunders et al., 1993; which examined alcohol quantity and frequency) from baseline to two years later among adolescents. However, in another study by Geusens and Beullens (2017) bidirectional associations were observed between greater frequency of self-sharing ARC and frequency of binge drinking one year later among adolescents which are like the current study's findings. Like my study, Geusens et al. (2022) found that college students who shared more intoxication ARC (show/discuss intoxication or problematic drinking) but not general ARC (show/discuss alcohol or drinking but not intoxication) decreased their alcohol consumption from their sophomore year to their junior year. Conversely, the current study found that heavy or problematic college drinkers who drank more also shared more ARC three months later and vice versa (i.e., those who shared ARC drank more later). This discrepancy in the findings of my study and those of Geusens et al. (2022) could be because the Geusens et al. (2022) study distinguished between general alcohol posts versus intoxication posts on Facebook (facilitated by a content analysis approach to count the number of posts on each participant's feed) whereas my study only asked about alcohol posts globally and across all platforms. Overall, the findings from prior studies are mostly in line with my findings and show a consistent association between the frequency of sharing ARC and alcohol consumption among adolescents and young adults alike.

Exposure to ARC Shared by Social Network Members

Aim 2a examined if the proportion of social network members (i.e., important friends) sharing ARC as well as the frequency of social network members sharing ARC (separate models) was associated with alcohol quantity and consequences cross-sectionally. These hypotheses were partially supported. The proportion of social network members sharing ARC was not associated alcohol quantity, though the significance was marginal (*p* = .070). However, having a larger proportion of social network members sharing ARC was associated with reporting more alcohol-related consequences. Social network members sharing ARC more frequently was associated with higher alcohol quantity, but social network members sharing ARC more frequently was not associated with reporting more consequences, though significance was marginal (*p* = .056).

These findings are mostly in line with prior literature. Research examining the effects of exposure on alcohol quantity cross-sectionally without using a social network approach (i.e., non-specific norms approach) have mostly used frequency of exposure rather than exposure to posts by specific important friends. Like my findings, frequency of exposure to peer ARC (assessed as non-specific peers, such as "close friends") has been consistently associated with alcohol quantity among college students (e.g., Alhabash et al., 2020; Boyle et al., 2016). The current examination moved the literature forward not just in this more precise assessment of who is posting ARC, but also more precise and sensitive measure of alcohol-related consequences among heavy or problematic college drinkers. Most previous studies used either alcohol quantity as an outcome or the AUDIT (Saunders et al., 1993) total score, which assesses both alcohol consumption and consequences; moreover, the only previous study that used consequences as an outcome did not control for participant alcohol quantity in its consequences model, thus, the researchers did not isolate problematic drinking from how much one drinks (Richner et al., 2021). The marginal significance for proportion of ARC exposure and alcohol quantity versus significant association between frequency of ARC posting and alcohol quantity could convey that how often your friends post ARC (frequency of posting) influences alcohol quantity but how often the participant sees ARC (frequency of exposure) does not. For example, participants may have friends that post ARC occasionally, however, ARC is likely to be posted on different days and on different social media platforms, thus, the participants are exposed to ARC daily.

Aim 2b examined if the proportion of social network members sharing ARC or how frequently social network members share ARC (separate models) was associated with alcohol quantity and consequences over time. Aim 5 simultaneously examined in the same model if alcohol quantity or consequences were associated with the ARC posting proportion or frequency over time (separate models). This hypothesis was partially supported for the models examining the proportion of social network members sharing ARC. Positive bidirectional associations were observed with having more social network members sharing ARC associated with greater alcohol quantity over time, and greater drinking was associated with more friends later sharing ARC, providing evidence for socialization and selection. Only unidirectional associations were observed between reporting any alcohol-related consequences and seeing more friends later sharing ARC but not vice versa. However, neither of these trends were maintained over time, with the only significant paths going from baseline to 1-month (but not later). On the other hand, bidirectional associations between the proportion of social network members sharing ARC and the number of consequences experienced were observed from baseline to 3-months suggesting that those who experience more consequences may also see more of their friends share ARC and vice versa. For how frequently friends share ARC, this aim was not supported. The majority of relationships were not significant, with the only significant association in an unanticipated direction; more frequent ARC sharing by friends at baseline was associated with a lower likelihood of reporting later alcohol consequences.

These findings overall are mostly in line with previous literature. Only two studies have examined unidirectional or bidirectional associations between exposure to peer ARC and alcohol consumption over time, with all using a non-specific norms approach and focusing on frequency of exposure (Geber et al., 2021; Geusens & Beullens, 2020), suggesting my examination of specific important peers (i.e., social network approach) and focus on how many of these peers post this type of content makes a unique contribution. Also, prior studies examined these associations only in adolescents, and did not examine consequences as an outcome. Both the current examination and Geber et al. (2021) found ARC exposure was associated with drinking over time, but while the current examination was bidirectional (more network members posting ARC associated with greater drinking at 1 month, and vice versa), Geber et al. (2021) documented only a unidirectional association whereby more frequent exposure to ARC from any source (i.e., no source, such as friends, was specified in the question) was associated with drinking more frequently four months later among adolescents; the association from drinking frequency to frequency to exposure was not significant. Like my study, Geusens and Beullens (2020) found that adolescent alcohol consumption was associated with frequency of exposure to ARC one year later. However, they found only a unidirectional association with a non-significant association between frequency of exposure to ARC and alcohol consumption while I found a bidirectional association. Discrepancies between the findings of the Geusens and Beullens (2020) study and the current study may also lie in the non-specific approach the researchers used to assess ARC in which they assessed general and friend exposure separately then averaged them together whereas the current study used a social network approach.

Modality of ARC

Aim 3a examined if the proportion of social network members sharing mostly video ARC with or without text (compared to photo ARC with or without text) was associated with alcohol quantity or consequences cross-sectionally. Hypotheses were not supported in that the proportion of social network members sharing mostly video ARC was not significantly associated with alcohol quantity or consequences. Aim 3b examined if the proportion of social network members sharing mostly video ARC was associated with quantity or consequences over time. Aim 5 simultaneously examined (in the same models) whether quantity, experiencing any consequences, or the number of consequences (separate models for each outcome) were associated with the proportion of social network members sharing mostly video ARC. These hypotheses were partially supported. The alcohol quantity model indicated unidirectional associations, with more friends sharing video ARC being associated with later drinking but not vice versa. Further, there were no significant longitudinal associations between the proportion of friends sharing video ARC and alcohol-related consequences in either direction.

Only one study has examined the effects of exposure to specific modalities of ARC on alcohol use finding that adolescents who reported they had more social network members posting photo ARC (but not text-only ARC) at baseline were more likely to endorse any alcohol use (dichotomously assessed) six months later (Huang, Unger, et al., 2014). Unlike my study, Huang, Unger, et al. (2014) did not examine video ARC, meaning the unidirectional associations in the current study between having a greater proportion of social network members sharing mostly video ARC and later alcohol quantity are novel and extend prior findings. Thus, the current study makes a unique contribution not only by also examining the effects of video ARC exposure (as well as photo ARC) on alcohol use with a sample of heavy or problematic college drinkers but it also examined alcohol-related consequences as an outcome albeit the latter examinations were not significant.

Closeness with Social Network Members Sharing ARC

Aim 4a examined if average closeness with social network members sharing ARC was associated with alcohol quantity or consequences cross-sectionally. This hypothesis was not supported in that average closeness with social network members sharing ARC was not significantly associated with quantity or consequences. Aim 4b examined if average closeness with social network members sharing ARC was associated with quantity, experiencing any consequences, or the number of consequences over time. Aim 5 simultaneously examined in the same models whether quantity, experiencing any consequences, or the number of consequences was associated with average closeness with social network members sharing ARC over time. This hypothesis was partially supported. The consequences model indicated unidirectional associations, with a higher likelihood of reporting any consequences found to be associated with greater average closeness with friends who shared ARC later; the association between average closeness with friends who shared ARC and the likelihood of reporting any consequences was not significant. There were no significant associations between quantity and closeness with friends who shared ARC in either direction.

These hypotheses were exploratory in nature as non-specific norms approaches for examining ARC exposure are not able to assess relationship qualities between the ARC poster and viewer. Thus, support for the current study findings comes from the social network drinking literature. Only five other studies to date aside from the current study have examined associations between closeness (and related constructs such as emotional support) with social network members and substance use outcomes (including alcohol use) among adolescents and college students (Cruz et al., 2012; Mason et al., 2014, 2017; Tompsett & Colburn, 2019). Unlike the current study which found associations between alcohol-related consequences and closeness with friends sharing ARC, closeness was found to moderate associations between having peers in one's social network using substances (e.g., tobacco, alcohol) and alcohol use (e.g., frequency of alcohol use and alcohol consequences) such that greater closeness with substance using peers was associated with increased alcohol use from early adolescence to late adolescence as well as continued use into early adulthood (Cruz et al., 2012).

Although not called closeness per se, Tompsett and Colburn (2019) found that greater emotional support among friends who binge drink was associated with higher alcohol risk (e.g., higher alcohol frequency, cravings, and consequences) cross-sectionally. Tompsett and Colburn (2019) did assess alcohol-related consequences but unlike the current study they did not examine associations in the other direction, that is, from consequences to emotional support from friends who binge drink. However, in Mason et al. (2017), closeness was found to moderate associations between peer substance use as well as offers to use substances and tobacco use two years later but not alcohol use or cannabis use two years later among adolescents. In Mason et al. (2014) perceived closeness with peers in one's network was associated with cannabis use but not alcohol use or tobacco use among college students cross-sectionally. The findings in Mason et al. (2014, 2017) diverge from those of the current study in that they found no associations between closeness and alcohol outcomes and instead found them with use of other substances. Given the findings of prior studies, future research should examine associations between closeness with friends who share ARC (or content featuring other substances) and using other substances. My study was novel in its use of a subset approach to examine two social network variables simultaneously (i.e., closeness and ARC sharing) and how these affect later alcohol use and consequences.

Drinking Buddies Sharing ARC

Aim 4c examined if the proportion of drinking buddies sharing ARC was associated with quantity or consequences cross-sectionally. This hypothesis was not supported. The proportion of drinking buddies sharing ARC was not significantly associated with alcohol quantity or consequences. Aim 4d examined if the proportion of drinking buddies sharing ARC was associated with quantity, experiencing any consequences, or the number of consequences over time. Aim 5 simultaneously examined in the same models if quantity, experiencing any consequences, or the number of consequences were associated with the proportion of drinking buddies sharing ARC over time. These hypotheses were partially supported. The alcohol quantity model indicated unidirectional associations, with greater alcohol quantity at baseline associated with more drinking buddies sharing ARC at 1-month, but this trend was not maintained over time. The reporting any consequences model indicated bidirectional associations from baseline to 1-month, with reporting any alcohol-related consequences associated with having more drinking buddies sharing ARC later and having more drinking buddies sharing ARC associated with later consequences. From 1-month to 3-month only unidirectional associations were found, with having more drinking buddies sharing ARC associated with later likelihood of reporting consequences. On the other hand, unidirectional associations persisted over time with reporting a higher number of alcohol-related consequences being associated with having more drinking buddies share ARC but not vice versa.

Aims 4c and 4d were exploratory in nature. Only one study to date has found that having a greater proportion of drinking buddies sharing ARC is associated with greater drinking frequency among college students cross-sectionally (Strowger et al., 2022). Previous research has examined associations between the number/proportion of drinking buddies in one’s social network and alcohol use among college students cross-sectionally (Lau-Barraco & Linden, 2014) and longitudinally (Reifman et al., 2006). In Lau-Barraco and Linden (2014), close friend descriptive drinking norms (i.e., perceptions of alcohol quantity consumed by close friends) significantly moderated associations between the number of drinking buddies and participant alcohol outcomes such that those with low and moderate norms, but larger numbers of drinking buddies had higher levels of alcohol use. These findings suggest that having more drinking buddies in one's social network generally is an important influence on college drinking. In the current study, no significant cross-sectional associations were found for the proportion of drinking buddies sharing ARC and participant quantity or consequences. However, having more drinking buddies in one's network was associated with greater quantity but not consequences (after controlling for quantity) suggesting that the strength of the proportion of drinking buddies' effect was stronger than the effect of the proportion of drinking buddies sharing ARC on quantity while participant alcohol quantity was stronger than the effects of both drinking buddy proportion variables in the consequences model.

As for prior longitudinal findings, Reifman et al. (2006) found that having a higher proportion of drinking buddies at baseline was associated with increased alcohol misuse later (approximately 5 months later). However, this trend did not maintain over time. However, unlike the current study, Reifman et al. (2006) did not explore associations in the other direction (i.e., from alcohol misuse to the proportion of drinking buddies). Their findings are mostly in line with those in the current study which found similar longitudinal associations between having more drinking buddies sharing ARC and alcohol quantity and consequences from baseline to 1-month but not from 1-month to 3-month. Although the current study used shorter lags than Reifman et al. (2006), it is possible associations between alcohol quantity and related consequences and the proportion of drinking buddies sharing ARC may not persist over longer periods of time. Also, Reifman et al. (2006) focused only on in-person networks whereas the current study focused on both in-person and online networks, suggesting that the in-person influence of drinking buddies may be longer term than the influence of those drinking buddies sharing ARC which might be more impactful in the short term. Further, only one previous study (Strowger et al., 2022) examined the association between drinking buddies in one's social network sharing ARC and college drinking, suggesting the current study makes a novel contribution by examining these associations longitudinally among heavy or problematic heavy drinkers.

Implications

Theoretical

The findings of the current study both support and expand existing theories about associations between social influences and alcohol consumption (i.e., social learning, social norms, theory of normative social behavior). In line with *social learning theory* (Bandura & McClelland, 1977), the current study found that students who saw more ARC shared by their important friends drank more later suggesting these students may be *modeling* the drinking behavior seen online via ARC. We also observed significant correlations between students having more friends sharing ARC and their sharing it themselves suggesting they not only modeled the drinking behavior they saw online but also shared the same content themselves. It is possible that by engaging in more alcohol consumption and sharing ARC they may have received validation from their important friends which *reinforced* these behaviors thus providing some evidence for *reciprocal determinism* (i.e., interaction between modeling and reinforcement). The bidirectional associations observed between participants sharing ARC and drinking as well as seeing ARC from important friends and drinking also lend support for reciprocal determinism in that these behaviors appeared to reinforce one another over time thus perpetuating the cycle. The remaining component of this theory, *social expectancies*, were not assessed or examined directly in the current study. However, given that most ARC features people and positive consequences of drinking (e.g., having fun with friends; Hendriks et al., 2018), it may be that seeing this content shared by important friends online may increase the likelihood of modeling in a similar way to observing friends drinking in social settings in person. Thus, it appears social learning theory can serve as an important model for explorations into ARC on social media and its involvement with college drinking. Future research should aim to also assess social expectancies along with drinking and ARC sharing by important friends to understand their interactive effects on college drinking.

The findings of the current study also have theoretical implications for *social norms theory* and the *theory of normative social behavior* (Perkins & Berkowitz, 1986; Rimal & Real, 2005). Ultimately, ARC represents another source of normative alcohol information that young people are exposed to, and which can potentially influence their own drinking behavior. Before social media, alcohol was depicted in the media in movies, for example, and still is (Patsouras et al., 2023). However, prior literature has found that more proximal influences like close friends are more impactful on drinking behavior than more distal influences (e.g., typical student or actors portraying students in movies; Kenney et al., 2017, 2018; Reid et al., 2020; Russell et al., 2020). Additionally, whereas in the past students likely knew their friends drank by drinking with them or socializing with them, with the introduction of social media, students now learn about drinking events their friends are involved in that they themselves were not present at, thus representing another way of learning about others' drinking behaviors (informing normative perceptions).

Descriptive and *injunctive drinking norms* have been consistently found to explain associations between close friend ARC exposure (assessed globally not for specific friends) and college student drinking both cross-sectionally and over time (e.g., Alhabash et al., 2020; Geusens & Beullens, 2016) suggesting that seeing drinking behavior online may be contributing to shaping students' normative perceptions about how much and how often their friends are drinking, and approval by their friends and other reference groups for drinking alcohol. Similar to social learning theory, the bidirectional associations found in the current study between participants seeing important friends share ARC and their own drinking may be explained by this content shaping their normative perceptions of how much their friends drink (descriptive) and how socially acceptable this behavior is in their friend group (injunctive).

The *strength or quality of the relationship* among students with members of their social group is another component of social norms theories that is hypothesized to interact with descriptive drinking norms to affect individual alcohol consumption. The current study found that having more drinking buddies sharing ARC was associated with increased alcohol consequences later, suggesting that this relationship quality (drinking together with specific friends who also shared content which depicts drinking) was impactful on their experiencing alcohol-related harms above and beyond participants' own drinking levels. Drinking with specific friends and those friends sharing ARC also may be contributing to students' beliefs that their friends approve of drinking alcohol and sharing ARC. *Personal attitudes* towards drinking as well as social expectancies (also apart of social learning theory) are other components of social norms theories which were not directly assessed in the current study but having positive attitudes towards drinking could contribute to sharing ARC oneself and seeing ARC shared by important friends could also affect one's attitudes through normalization of drinking. As such, future research attempting to understand where ARC shared by important friends fits into existing social norms theories as a source of online drinking information in addition to in person drinking may also wish to examine alcohol attitudes and social expectancies. Moreover, the current findings confirm close friends sharing ARC on social media is a relevant construct in addressing heavy or problematic college drinking, and moves existing theories forward into this contemporary phenomenon.

Clinical

The findings of the current study have important clinical implications for updating existing college drinking interventions (in-person and online) which have previously demonstrated mostly short- to long-term efficacy (depending on the format) in reducing alcohol use (for reviews see, Carey et al., 2009, 2012, 2016; Cole et al., 2016; Hennessy et al., 2019; Moreira et al., 2009; Samson & Tanner-Smith, 2015). These interventions typically include content on alcohol education, personalized feedback about risk level as well as how one's drinking levels compare to those of same age peers and typical students at the same university (Hennessy et al., 2019). The latter describes content on descriptive norms or how much student perceive others drinking or approve of drinking. These norms are likely partially shaped by seeing peers post ARC on social media. As such, updating these interventions to include content about ARC posted by important peers could help improve their efficacy. A recent study found that students who reported higher ARC exposure did not reduce their alcohol use as much as students with lower ARC exposure when receiving a personalized normative feedback intervention designed to correct students' perceptions of how much/often others drink (Boyle et al., 2021). It may be that interventions addressing general perceptions about how much others drink do not address the social influences (e.g., in-person interactions, ARC exposure) from important individuals in students' lives which could be more influential than acquaintances or strangers. The bidirectional associations from the current findings between ARC sharing by important friends and alcohol quantity and consequences suggest that content discussing social media as another form of social influence would be beneficial to add to existing brief alcohol interventions.

This content could include presenting norms for how often students on campus post ARC on social media to dispel potential discrepancies between students' perceptions of how normative this behavior is and the reality. Much in the same way that campus drinking norms are assessed for use in these brief interventions, ARC posting norms could also be collected to establish true rates on campus. There is some evidence to support that students think their peers post ARC more than they do (Litt et al., 2021; Meisel et al., 2022). Including this content could potentially lower students' rates of their own ARC posting. It is important to remember that the association between students' alcohol quantity and consequences and their posting ARC later suggests that the ARC they post is likely a reflection of their own offline drinking experiences. While college drinking interventions help with reducing overall use, adding content to correct ARC posting norms may help to reduce the link between their own drinking experiences and posting about them on social media.

To help reduce the influence of ARC exposure on student drinking behavior, social media literacy skills could be taught to help them critically evaluate commercial- and peer-generated ARC. Skills that would be relevant would be assessing the perceived realism (e.g., are the peers really drinking alcohol or is the post staged to look like they may be, is the post only showing the positives of alcohol use and not the negatives) as well as considering the motives of the poster (e.g., to look cool, popular, fit in). To date, only one social media literacy program which focuses on evaluating substance-related content shared by peers has been piloted among high school students (Dunn et al., 2020). Thinking critically about the content was associated with eliciting more negative feelings about peers who post this content. Participants also expressed a desire to help change substance use norms by sharing non-substance-related content.

Although Dunn et al. (2020) developed the first social media alcohol-specific literacy program for social media specifically, alcohol-specific literacy programs for general media (e.g., movies, commercials) have been shown to be effective (small to medium effect sizes) at reducing alcohol use, cognitions (e.g., attitudes, expectancies), and intentions among children, adolescents, and young adults (for a meta-analysis, see Xie et al., 2019; for a meta-analytic review, see Vahedi et al., 2018; for a systematic review, see Gordon et al., 2015). However, existing alcohol-related media literacy programs predominantly focus on exposure to alcohol advertising, which as the findings of the current study and prior research show, is not the only source of ARC exposure. They also focus on traditional media (e.g., TV, movies, magazines) which lacks the interactivity that social media possesses. This key difference between traditional and social media underscores the need to develop social media focused literacy programs that conceptualizes young people not only as passive consumers of social media but also as active participants through engaging with others' content or creating their own. These findings suggest that ARC-specific social media literacy skills not only could help reduce use but could also shift alcohol use cognitions which would fit well in the context of being supplemental content included in an existing brief alcohol intervention.

The findings of the current study also suggested that participants' own drinking was associated with their exposure to ARC shared by important friends later, suggesting that they may be curating their social media feeds by following these friends and engaging with their

ARC. Engagement in their friends' ARC by viewing, liking, commenting, sharing may also be informing the algorithms underlying these platforms that participants enjoy this content, and the algorithms may direct that more of this content be shown. Thus, knowledge about how algorithms work and how to reduce their influence may be useful to include. Although not focused on alcohol, a qualitative study by Swart et al. (2021) examining how algorithms curate news on social media found that adolescents and young adults varied in their understanding of what an algorithm was and how it may curate their social media feed, differed in how beneficial or harmful they believed algorithms were, and reported low self-efficacy when it came to counteracting algorithms. Participants described some skills they used for counteracting algorithms such as unfollowing certain accounts or setting up notifications for accounts they wanted to see content from but generally felt the algorithm was more powerful and these strategies would take more work on their part. These findings suggest that young people would like to have greater algorithmic literacy as well as less burdensome ways to have more control over their feeds. For example, in the context of ARC, this could involve "hiding" this content when shared by friends to tell the algorithm they do not wish to see this content.

Limitations

There were several limitations with the current study which span multiple areas, including sample, design, measurement, and technology. In terms of generalizability, the sample consisted of college students from one institution and was not particularly diverse (79.6% White, 74.2% female), and may not represent college students nationwide or globally. Students at William & Mary come from families with median household incomes in the top 20% of incomes in the country on average (The New York Times, 2017) and previous research has found that there are higher percentages of drinkers among those with higher incomes (Widbrodt et al., 2014). Higher household income for William & Mary students could mean these students had greater access when it came to purchasing alcohol than students at other institutions. The predominance of White women in the sample is also a limitation. Further prior literature suggests that not only do men drink more than women, but they also perceive that other men drink more and approve of drinking more (Neighbors et al., 2008; White et al., 2020; Widbrodt et al., 2014). Similarly non-Hispanic White college students drink more and perceive other White students to drink more and approve of drinking more than students who identify as other ethnic or racial identities (Hagler et al., 2017; LaBrie et al., 2012; McCabe et al., 2019; Witbrodt et al., 2014). There is limited literature to date suggesting that men also see more ARC on social media, and this affects their drinking levels and perceptions of how much other men drink more than women (Boyle et al., 2016). Also, exposure to ARC affects drinking rates among men during the transition to college whereas exposure appears to affect drinking among women during the first semester, suggesting men and women may be differentially impacted by exposure during their first year of college (Davis et al., 2021). Greater exposure to ARC in movies has also been found to associated with greater drinking among White and Black adolescents but was stronger among White adolescents (Gibbons et al., 2010). Taken together, if the sample in the current study had been more balanced in sex, race, and ethnicity, the associations between ARC, alcohol quantity, and consequences could have differed by intersectional identities and possibly been weaker in strength or non-significant. Future research should aim to oversample men, Hispanic, and non-White racial identities to further understand how associations between not only between ARC and drinking behavior but also perceptions of/approval for drinking may vary by sex, ethnicity, and race.

Use of self-report measures for frequency of social media checking and sharing of/exposure to ARC could have been subject to recall biases. Previous research has found that accuracy is low for recalling how much time is spent on social media compared to objective measures such as passive sensing; individuals often report spending more time on social media than they actually do (for a systematic review and meta-analysis see Parry et al., 2021). Although not social media-specific, a recent study found that adults tend to underestimate the number of times alcoholic beverages or drinking is shown in movies (e.g., movie ARC; Patsouras et al., 2023). Similarly, college students tend to overestimate how much they share ARC compared to objective estimates from a content analysis of their social media accounts (Geusens & Beullens, 2023). However, self-reported frequency of sharing ARC was found to be a stronger predictor of frequency of alcohol consumption and frequency of binge drinking than objective estimates of alcohol posts shared (Geusens & Beullens, 2021). Overestimation of time spent on social media and frequency of sharing ARC could be related to social desirability biases as social media use and drinking are often viewed as normative behaviors among college students (Lee et al., 2021; Yildiz Durak et al., 2019).

Further, although the study used a longitudinal study design which is a strength, the length of time between surveys may not have been ideal for accurate participant recall or for the timing of social influence. Given that young adults spend several hours a day on multiple social media platforms and check those platforms at least daily (Pew Research Center, 2021), an ecological momentary assessment (EMA) design where participants were assessed daily or multiple times per day may have been better for more accurate recall of viewing ARC and drinking behaviors. Recall biases have been noted not only for remembering how much time was spent on social media broadly but also for estimating alcohol quantity, and EMA designs have been found to be more accurate (for review see Griffioen et al., 2020; Wray et al., 2014). Moreover, the fact that findings tended to be stronger for the baseline to 1-month interval than the 1-month to 3-month interval suggests these associations may be linked for shorter time periods; daily or moment level research should be explored. Another limitation concerns the intervals between the surveys. I originally proposed to have equally spaced intervals (i.e., baseline, 6 weeks, 12 weeks) but I needed to change to baseline, 1-month, and 3-months because of data collection platform limitations. The findings of the current study may have been impacted by the different lengths of time between the assessments.

The assessment of closeness with a specific friend listed, which has been used in prior research (e.g., Lau-Barraco & Linden, 2014; Mason et al., 2014, 2017), had narrow response options (e.g., from 1-3 or *not very close* to *very close*); it could be that a wider range could have reflected more nuances in perceived closeness. The majority of social network studies focused on alcohol use have not commonly assessed perceived closeness but some of the few that did assessed frequency of behaviors that imply closeness, such as “How often have you gone to [friend name] for help with personal problems, like advice about your friends or parents, or if you just wanted someone to talk to?” with responses ranging from “About once a year or less” to “About daily” (Tompsett & Colburn, 2019). It is possible that using other operationalizations of closeness may have yielded different results.

Retention was also an issue for the current study and may have impacted the ability to test some of the longitudinal aims. Moreover, data that were retained was associated with the variables being reported; specifically, for some of the longitudinal models, there was evidence that the variables of interest (e.g., alcohol quantity) were associated with missingness, suggesting missing at random and/or missing not at random (i.e., changes in *p*-values observed when comparing models with and without missingness indicators, or significant within timepoint associations between variables of interest and a missingness indicator for that timepoint, controlling for previous levels). It is possible that compensation rate was not enough to incentivize students to complete all three surveys over three months. Indeed, our missing data analyses testing for missing at random (MAR) associations found that 80% of participants who chose raffle entry at baseline versus 20% who chose direct payment at baseline skipped the 3-month survey, suggesting raffle entry may not have been as incentivizing for continuing in the study. Prior social network drinking studies typically provided between $5 to $25 for each survey for longitudinal survey designs (Graupensperger et al., 2020; Meisel & Barnett, 2017; Reifman et al., 2006), so the direct payments of $5 for the current study are on the lower end of that range.

Academic schedules could have also impacted retention as some of the follow-up surveys encompassed holidays (e.g., Thanksgiving) and periods of breaks from classes (e.g., winter or summer breaks). During these times, it is possible that students were not checking their school emails as frequently as when classes were in session. Only 49% of the current study sample provided non-school emails, and 71% of the sample provided a phone number for text message reminders. Additionally, there were a few technology-related limitations. The data collection site (William & Mary) transitioned from emails ending in "@email.wm.edu" to those ending in "@wm.edu" during the data collection period. These two emails were not merged into one inbox and likely meant that students were either mostly checking one of those emails or could have been checking one of them less often. The platforms used to send emails (Qualtrics) and texts (Google Voice) track if messages are sent but not if they are received or viewed, so it is not known how many of the email and text message follow-ups were read.

Future Directions

Both the current study findings and limitations lend themselves to several future directions for this line of research. In terms of design, more studies using EMA approaches are needed to help understand the effects of viewing ARC on alcohol use in the moment. To date, only one study has investigated the effects of viewing ARC on next-day drinking, finding that exposure to at least one alcohol post increased the likelihood of drinking the next day as well as increased the number of drinks consumed (Hendriks et al., 2021). However, this study had several limitations including requiring participants to check a separate app each day to see the social media posts from other study participants which had been transferred there from established social media platforms. This separate app limits the ecological validity of their findings as it does not reflect how content naturally appears in their various feeds (e.g., devoid of platform algorithms and only includes study participants who may or may not be friends). Moreover, the other study participants were likely not close friends, which means the ARC viewed may not have had as much influence on participant drinking levels. Research is needed conducting a naturalistic social network EMA study to not only understand how viewing ARC on social media impacts drinking but also if the source of this content (e.g., closer social network members versus others) affects this association in-the-moment. Use of a social network design would also allow for examination of how other relationship qualities with members who share ARC may impact drinking.

Given the inaccuracies in self-reporting on social media use and sharing of ARC previously found in the literature, future research should also seek to assess these constructs objectively. For time spent on and frequency of checking social media, passive sensing approaches could be used whereby a separate app records these metrics in the background and sends them to the researchers directly (Bessenyei et al., 2021; Domoff et al., 2021; Yuan et al., 2019). It would be ideal to also employ methods to capture actual rates of sharing and viewing ARC, of which there are a few available, but they range in the amount of research team burden. For ARC sharing, quantitative content analyses can be conducted whereby participants give researchers access to their social media accounts and researchers then go through the accounts and code posts shared by the participant as alcohol or non-alcohol according to an established codebook (e.g., D'Angelo & Moreno, 2021; Geusens & Beullens, 2023; Hendriks et al., 2018). Artificial intelligence (AI) can also be used to conduct content analyses whereby participants provide researchers with access to their social media accounts so a researcher-developed app can download their alcohol-related posts, then the AI models could be applied to these posts to code the quantity and frequency of ARC shared (Bergman et al., 2020; Hassanpour et al., 2019; Marengo et al., 2019; Russell, Valdez, et al., 2022; Stevens et al., 2022). A gap in the literature remains for methods to capture all ARC that participants see, with one study having college students first provide their login information for Instagram, then using a Python macro to log into their account and randomly capture posts from their feed (LaBrie et al., 2021). Altogether, use of objective assessments coupled with self-reports would result in improved understanding of the importance of perceptions versus actual sharing/viewing in predicting drinking behavior.

Another burgeoning area of research is examining the prevalence of ARC promoting safety, moderation, or abstinence among college students (Moreno et al., 2021) or sobriety and recovery among adults (Russell, Ou et al., 2022; Russell et al., 2021). Russell, Valdez et al. (2022) conducted a content analysis of over 200,000 Dry January tweets across three years (including during the pandemic) using AI finding that discussion of health benefits, resources, and updates about progress were consistent themes over time. Russell et al. (2021) also conducted a content analysis of 82 of the most watched TikTok videos on recovery finding they each had over 2 million views and over 300,000 likes with common themes being discussing individual recovery journeys, having a strong identity as a person in recovery, and celebrating milestones. Among college students specifically, abstinence posts (about being sober, sobriety, stopping, avoiding, or quitting alcohol) were rare on Facebook and constituted only 100 posts or less per year compared to four alcohol posts a semester on average (Moreno et al., 2021). Russell, Ou et al. (2022) found that exposure to content highlighting positive experiences with alcohol treatment or recovery was associated with higher treatment seeking intentions among adult viewers, along with more positive attitudes towards treatment effectiveness and lower treatment seeking stigma. These findings suggest there is promise in harnessing the impact of these types of posts for prevention and intervention, yet a gap in the literature in understanding this phenomenon among college students.

CHAPTER V

CONCLUSION

This study added to the limited longitudinal research examining the effects of self-sharing ARC as well as exposure to ARC and alcohol quantity and consequences among heavy or problematic college drinkers. Further, this study was the first to employ a social network approach to examine associations between alcohol outcomes and exposure to ARC shared by important friends specifically, including the effects of modality of ARC shared and relationship qualities. Cross-sectionally, greater self-sharing of ARC and exposure to important friend ARC were associated with higher alcohol quantity and consequences. However, no cross-sectional associations were observed for associations between the proportion of important friends sharing video (versus photo) ARC, closeness with important friends sharing ARC, or the proportion of drinking buddies sharing ARC and alcohol outcomes (quantity or consequences). In terms of longitudinal findings, although some bidirectional associations were observed, unidirectional associations were common between greater alcohol quantity and consequences and later increased self-sharing of ARC or exposure to close friend ARC, as well as heightened relationship qualities (e.g., greater closeness with important friends or higher proportion of drinking buddies sharing ARC) over time. Also, having a higher proportion of important friends sharing video ARC (compared to photo ARC) was also associated with increased alcohol quantity but not consequences over time. Taken together, these findings suggest that ARC is clearly related to college student drinking, whether students are sharing it themselves or viewing their close friends' ARC. Taking steps to correct ARC posting norms and including social media literacy skills specific to ARC in existing brief alcohol interventions are important areas to explore, as they may help to reduce the association between ARC and drinking behavior. Future research should use EMA designs to better understand how viewing ARC affects alcohol cognitions and behavior in the moment. They should also assess who is sharing ARC (including important friends) to discern which sources may be exerting a stronger influence.

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APPENDIX A

SUMMARY OF STUDY MEASURES

Construct	Measure
Screening Assessment	Determine if participant meets eligibility criteria, namely: 1) aged 18-25, 2) has consumed one alcoholic drink in the past seven days, and 3) has an account on at least one social media platform and collect William & Mary email address to send baseline survey if eligible
Assessment Battery	The following questionnaires were included in the baseline, 3-month, and 3-month surveys (except demographics and contact information which were only be assessed at baseline)
Alcohol Use	Daily Drinking Questionnaire (DDQ; Collins et al., 1985)
Alcohol Consequences	Brief Young Adult Alcohol Consequences Questionnaire (B-YAACQ; Kahler et al., 2005)
Social Network Characteristics	Brief Important People Questionnaire (BIPI; DeMartini et al., 2013; Zwyiak et al., 2002)
Social Media Use	General questions about social media use
Demographics	General background questions (only at baseline)
Contact Information	First name, alternative email address, phone number (only at baseline)

APPENDIX B

SCREENING QUESTIONNAIRE

1. What is your age? [ ]
2. Was there an occasion in the past 30 days where you consumed either 4+ alcoholic drinks (for women) or 5+ alcoholic drinks (for men)?
   - o Yes
   - o No
3. How many days in the past 30 days have you consumed at least one alcoholic drink?
   - o Drop down (0-30)
4. Have you experienced at least one of the following consequences listed below after consuming alcoholic drinks in the past 30 days?
   - o Yes
   - o No

While drinking, I have said or done embarrassing things.
The quality of my work or schoolwork has suffered because of my drinking.
I have felt badly about myself because of my drinking.
I have driven a car when I knew I had too much to drink to drive safely.
I have had a hangover (headache, sick stomach) the morning after I had been drinking.
I have passed out from drinking.
I have taken foolish risks when I have been drinking.
I have felt very sick to my stomach or thrown up after drinking.
My drinking has created problems between myself and my boyfriend/girlfriend/spouse, parents, or other near relatives.
I have spent too much time drinking.
I have not gone to work or missed classes at school because of drinking, a hangover, or illness caused by drinking.
I have felt like I needed a drink after I'd gotten up (that is, before breakfast).
I have become very rude, obnoxious or insulting after drinking.
I have woken up in an unexpected place after heavy drinking.
I have found that I needed larger amounts of alcohol to feel any effect, or that I could no longer get high or drunk on the amount that used to get me high or drunk.
I have neglected my obligations to family, work, or school because of drinking.
I often have ended up drinking on nights when I had planned not to drink.
When drinking, I have done impulsive things that I regretted later.
I have often found it difficult to limit how much I drink.
My drinking has gotten me into sexual situations I later regretted.
I've not been able to remember large stretches of time while drinking heavily.
My physical appearance has been harmed by my drinking.
I have been overweight because of drinking.

I have had less energy or felt tired because of my drinking.

5. Do you have an account on at least one social media platform (ex. TikTok, Instagram, Snapchat, Facebook)?
   - Yes
   - No
6. What is your student status?
   - Full-time
   - Part-time
   - No longer a student
7. Where is your current residence?
   - On-campus dormitory
   - On-campus living-learning community
   - On-campus themed community
   - Off-campus house or apartment (with roommates or on your own)
   - With family or partner
8. What is your involvement in social fraternities or sororities?
   - A current member
   - Currently pledging
   - Not a member, but regularly or occasionally attend Greek social events
   - Not a member, and do not attend Greek events
9. What is your relationship status?
   - Single, not in a committed relationship
   - In a committed relationship
   - Married
   - Divorced
   - Other [Please describe]
10. There are many ways that individuals think of their sexual identity. Choose all the identity(ies) that best describe you:
    - Gay
    - Lesbian
    - Bisexual
    - Queer
    - Asexual
    - Pansexual
    - Questioning
    - Heterosexual/straight
    - Other [Please describe]

If participants are eligible, the following message will be displayed if the proposal is funded.

You are eligible to participate in this three-part study!

As a reminder, this study will look at how social media usage and drinking behaviors of students change over their college career. Three surveys will be sent over three months, and each survey will take about 30 minutes to complete.

For each survey you complete you will receive either a $5 Amazon gift card (total of $15) or have the same amount added to your ConnectPoints account. If you complete all three surveys, you will receive either an additional $5 Amazon gift card or the same amount added to your ConnectPoints account.

Would you like to complete the first survey now or would you like to be emailed the link to complete the survey at a later time?

- Now
- Later

If participants select “later”, the following items will appear.

1. What is your email address (including “@wm.edu”/ “@email.wm.edu”)? ______________________________
2. Please repeat your email address. ____________________________

APPENDIX C

CONSENT FORM

INFORMED CONSENT DOCUMENT

OLD DOMINON UNIVERSITY

PROJECT TITLE: College Student Social Networks, Social Media Use, and Drinking Behavior

INTRODUCTION

The purposes of this form are to give you information that may affect your decision whether to say YES or NO to participation in this research, and to record the consent of those who say YES. The research project titled "College Student Social Media Use and Drinking Behavior" will take place online.

This study will involve you completing up to three online surveys that ask you about your social relationships, social media use, and alcohol consumption. There will be a 1-month delay period between completing the first and second surveys, and 2-month delay period between the second and third surveys. In other words, after this first survey, you will be invited to completed follow-up surveys 1 and 3 months later. After each survey is sent out, we will send daily text and email reminders starting the following day for a period of up to two weeks (or until the survey is completed). As compensation for completing each survey, you will be entered into separate raffles to win either one of ten $10 Amazon gift cards (you could win up to $30 across all three surveys) or one $50 Amazon gift card (you could win up to $150 for all three surveys). Additionally, if you complete all three surveys you will be entered into an additional raffle for one of ten $10 Amazon gift cards (you can win an additional $10) or one $50 gift card (you can win an additional $50). Alternatively, you may choose to have the same amount added to your MonarchPlus/ConnectPoints account if you are selected as a winner for at least one of the raffles. Last, obtaining high quality data is critical for determining the reliability of our findings. For this reason, we may provide live automatically generated feedback during the study if we notice you are not reading items carefully, asking you to read the items more carefully.

RESEARCHERS

Principal Investigator: Abby Braitman, Ph.D., Assistant Professor, Psychology Department, abraitma@odu.edu

Co-investigator: Megan Strowger, M.S., Graduate Research Assistant,

Psychology Department, mstro006@odu.edu

Co-investigator: Adrian Bravo, Ph.D., Assistant Professor, Psychological Sciences Department, ajbravo@wm.edu

DESCRIPTION OF RESEARCH STUDY

The current study seeks to explore the relationship between exposure to content featuring alcohol on social media, qualities of who is sharing the content, and subsequent alcohol use in college students.

If you decide to participate, then you will join a study that involves you completing up to three online surveys that ask you about your social relationships, social media use, and alcohol consumption. There will be a 1-month delay period between completing the first and second, and a 2-month delay period between the second and third surveys. In other words, after this first survey, you will be invited to completed follow-up surveys 1 and 3 months later. Each survey will last approximately 30 minutes. If you say YES, then your participation will last for up to three months for this online study. Approximately 350 Old Dominion University and William & Mary University students will be participating in this study.

EXCLUSIONARY CRITERIA

You must be at least 18 years old but not more than 25 years old to be eligible for this study.

You must also have an active account on at least 1 social media platform.

In addition, you must have consumed alcohol on at least 2+ days in the past 30 days, and either have consumed 4+/5+ alcoholic drinks (for women/men) on at least one occasion in the past 30 days or have experienced at least one negative consequence from drinking alcohol in the past 30 days.

RISKS AND BENEFITS

RISKS: If you decide to participate in this study, then you may face a risk of psychological discomfort from answering some of the survey questions. The researcher tried to reduce these risks by allowing you to not complete any questions that may make you uncomfortable. And, as with any research, there is some possibility that you may be subject to risks that have not yet been identified.

BENEFITS: There are no direct benefits for participating in this study.

COSTS AND PAYMENTS

The researchers want your decision about participating in this study to be absolutely voluntary. The researchers are unable to give you any guaranteed payment for participating in this study. Yet they recognize that your participation may pose some inconvenience and requires your time. As compensation for completing each survey, you will be given the option to receive a direct payment of a $5 gift card or be entered into separate raffles to win either one of five $10 gift cards (you could win up to $30 across all three surveys) or one $50 gift card (you could win up to $150 for all three surveys). Additionally, if you complete all three surveys you will be given the option to receive an additional direct payment of a $5 gift card or be entered into an additional raffle for one of five $10 gift cards (you can win an additional $10) or one $50 gift card (you can win an additional $50). If you win any of these raffles, you can choose to receive payment as an Amazon gift card, or to have the amount added to your Tribe Card (William & Mary students) account. Direct payments will only be issued as Amazon gift cards.

NEW INFORMATION

If the researchers find new information during this study that would reasonably change your decision about participating, then they will give it to you.

CONFIDENTIALITY

The researchers will take reasonable steps to keep private information, such as your questionnaire responses confidential. Data collected will be stored on a password-protected survey platform account prior to its processing and when it is downloaded for analyzing it will be stored on a password-protected computer. The researcher will remove identifying information at the end of the data collection period. De-identified information may be used for future research. The results of this study may be used in reports, presentations, and publications; but the researcher will not identify you.

WITHDRAWAL PRIVILEGE

It is OK for you to say NO. Even if you say YES now, you are free to say NO later, and walk away or withdraw from the study -- at any time. Your decision will not affect your relationship with Old Dominion University, or otherwise cause a loss of benefits to which you might otherwise be entitled. The researchers reserve the right to withdraw your participation in this study, at any time, if they observe potential problems with your continued participation.

COMPENSATION FOR ILLNESS AND INJURY

If you say YES, then your consent in this document does not waive any of your legal rights. However, in the event of harm arising from this study, neither Old Dominion University nor the researchers are able to give you any money, insurance coverage, free medical care, or any other compensation for such injury. In the event that you suffer injury as a result of participation in this research project, you may contact Abby Braitman, Ph.D., Principal Investigator at abraitma@odu.edu or Megan Strowger, M.S., Co-Investigator, at mstro006@odu.edu, Dr. Tancy Vandecar-Burdin the current IRB chair at 757-683-3802 at Old Dominion University, or the Old Dominion University Office of Research at 757-683-3460 who will be glad to review the matter with you.

VOLUNTARY CONSENT

If you have any questions about the study and would like them answered before you provide your consent, please click on the link below to schedule a brief Zoom meeting with the co-investigator, Megan Strowger.

https://calendly.com/socialmediaalcoholstudy/15-minute-study-q-a-session

By agreeing to participate in this study by clicking the next arrow button to continue on to the main survey, you are saying that you have read this information, that you are satisfied that you understand the information, the research study, and its risks and benefits. If you have any questions about this research study now or in the future, please contact the co-investigator, Megan Strowger, at mstro006@odu.edu or the principal investigator, Dr. Abby Braitman, at abraitma@odu.edu. If at any time you feel pressured to participate, or If you have any questions about your rights as a study participant, then you should call Dr. Tancy Vandecar-Burdin, the current IRB chair, at 757-683-3802, or the Old Dominion University Office of Research, at 757-683-3460.

And importantly, by typing your name in the box below, you are telling the researcher YES, that you agree to participate in this study.

Your name: ____

You may choose to print a copy of this page for your own records.

APPENDIX D

DAILY DRINKING QUESTIONNAIRE

ALCOHOL USE

The following questions are about your alcohol use. For all questions that ask, **standard drinks** will be equal to roughly 14 grams of pure alcohol, which is found in:

- 12 oz of hard seltzer at 5% alcohol
- 12 oz of regular beer at 5% alcohol
- 8-9 oz of craft beer at about 7% alcohol
- 4-5 oz of wine at about 13% alcohol
- 1.5 oz of liquor in a mixed drink at 40% alcohol
- 1.5 oz of 80 proof liquor at 40% alcohol

The following questions refer to your alcohol use **in the past 30 days.**

On a ***typical Monday…***

how many drinks do you have? (drop down 0-30+)

how many hours typically pass while you are drinking? (0-24)

On a ***typical Tuesday…***

how many drinks do you have? (drop down 0-30+)

how many hours typically pass while you are drinking? (0-24)

On a ***typical Wednesday…***

how many drinks do you have? (drop down 0-30+)

how many hours typically pass while you are drinking? (0-24)

On a ***typical Thursday…***

how many drinks do you have? (drop down 0-30+)

how many hours typically pass while you are drinking? (0-24)

On a ***typical Friday…***

how many drinks do you have? (drop down 0-30+)

how many hours typically pass while you are drinking? (0-24)

On a ***typical Saturday…***

how many drinks do you have? (drop down 0-30+)

how many hours typically pass while you are drinking? (0-24)

On a ***typical Sunday…***

how many drinks do you have? (drop down 0-30+)

how many hours typically pass while you are drinking? (0-24)

Think of the one day you consumed the most alcohol in the past month. How many standard drinks did you consume that day? [dropdown menu; range from 0-30+ drinks]

On this heaviest drinking day, approximately how many hours passed from the beginning of the first drink to the finishing of the last? [dropdown menu; range from 0-24]

How many days in the past month did you have difficulty remembering things you said or did or events that happened while you were drinking? [dropdown menu; range from 0-30+]

How many days in the past month did you pass out during or after drinking? [dropdown menu; range from 0-30+]

APPENDIX E

BRIF YOUNG ADULT ALCOHOL CONSEQUENCES QUESTIONNAIRE

Below is a list of things that sometimes happen to people either during, or after they have been drinking alcohol. Next to each item below, please check each box to indicate whether that item describes something that has happened to you **IN THE PAST 30 DAYS.**

In the **past 30 days**...

1. While drinking, I have said or done embarrassing things.	
2. The quality of my work or schoolwork has suffered because of my drinking.	
3. I have felt badly about myself because of my drinking.	
4. I have driven a car when I knew I had too much to drink to drive safely.	
5. I have had a hangover (headache, sick stomach) the morning after I had been drinking.	
6. I have passed out from drinking.	
7. I have taken foolish risks when I have been drinking.	
8. I have felt very sick to my stomach or thrown up after drinking.	
9. My drinking has created problems between myself and my boyfriend/girlfriend/spouse, parents, or other near relatives.	
10. I have spent too much time drinking.	
11. I have not gone to work or missed classes at school because of drinking, a hangover, or illness caused by drinking.	
12. I have felt like I needed a drink after I'd gotten up (that is, before breakfast).	
13. I have become very rude, obnoxious or insulting after drinking.	
14. I have woken up in an unexpected place after heavy drinking.	
15. I have found that I needed larger amounts of alcohol to feel any effect, or that I could no longer get high or drunk on the amount that used to get me high or drunk.	
16. I have neglected my obligations to family, work, or school because of drinking.	
17. I often have ended up drinking on nights when I had planned not to drink.	
18. When drinking, I have done impulsive things that I regretted later.	
19. I have often found it difficult to limit how much I drink.	
20. My drinking has gotten me into sexual situations I later regretted.	
21. I've not been able to remember large stretches of time while drinking heavily.	
22. My physical appearance has been harmed by my drinking.	
23. I have been overweight because of drinking.	
24. I have had less energy or felt tired because of my drinking.	
25. None of the above.	

APPENDIX F

BRIEF IMPORTANT PEOPLE INTERVIEW

Please list the first names and last initials for up to five (5) friends you have been in contact with regularly and who have been the most significant in your life **in the past 30 days**. These might have been people you hung out with in-person, texted, video chatted, messaged online, or talked to on the phone.

When listing your friends, you can either provide their first name and last initial (ex. Jane S.) or you can provide the first two letters of both names (ex. JaSm). **PLEASE DO NOT ENTER FRIEND'S FULL FIRST AND FULL LAST NAME.** The purpose of listing your friends' names is so that you remember who you are referring to. We will not contact any of your friends and will follow the same secure data storage procedures that we will use for the other sections of this survey.

______Person 1______________[string fill in the blank]

______Person 2______________[string fill in the blank]

______Person 3______________ [string fill in the blank]

______Person 4______________[string fill in the blank]

______Person 5______________[string fill in the blank]

We are now going to ask you a few questions about qualities of each of the friends you named as well as the kinds of content they share on their social media profiles.

All questions below will appear for each person listed.

1. What gender does [person name] identify as?

    1 = Male

    2 = Female

    3 = Trans*

    4 = Nonbinary

    5 = Other [Please describe]

2. What is [person name]'s age in years?

____

3. What racial group best describes [person name]?

    African-American or Black

Asian

Native Hawaiian or other Pacific Islander

White

Native American/Alaskan Native

Middle Eastern or North African

More than one race

Other [Please describe]

4. We would like to ask you about [person names]'s alcohol use. How many drinks do you think [person name] consumes in a typical week?

___________________(drop down 0-30+)

5. On how many days do you think [person name] drinks in a typical week?

___________________(drop down 0-7)

6. Is [person name] a "drinking buddy", meaning a person with whom you get together on a regular basis to do activities that center around drinking and/or going to bars or clubs?

1 = Yes

2 = No

7. How close do you feel to [person name]?

1=Not very close
2=Sort of close
3=Very close

8. How long have you known [person name] (in years)?

____________________________ (numeric fill in the blank)

9. In a typical week, how often do you communicate with [person name] in-person, via text, via social media messaging or on the phone?

1=Never or hardly ever

2=Less than once a day

3=Once a day

4 =Several times a day

10. Are you friends/connected with [person name] on social media?

1 = Yes

2 = No

11. Do you think [person name] posts/shares content on social media where alcohol is present or posts about alcohol (alcohol posts)?

1 = Yes

2 = No

If ‘Yes’ to item 11 then participant will see the following questions.

12. Are the alcohol posts [person name] shares usually…? (Select only one)

1 = Videos (with or without text)

2 = Photos (with or without text)

3 = Text-only status updates

4 = Other [Please describe]

5 = [person name] does not share alcohol posts

13. How often do you think [person name] posts/shares content which features alcohol?

1 = Never

2 = Less than once a month

3 = Every month

4 = A couple of times a month

5 = Every week

6 = A couple of times a week

7 = Daily or almost daily

14. In posts about alcohol that [person name] shares, do they typically feature other people?

1 = Yes, 2 or more other people

2 = Yes, 1 other person

3 = No, they only feature [person name]

4 = No, there are no people featured in the posts

5 = [person name] does not share alcohol posts

15. Do alcohol posts from [person name] typically show:

1 = Positive experiences with drinking alcohol (for example, having fun)

2 = Negative experiences with drinking alcohol (for example, having a hangover)

3 = Neutral alcohol content (for example, just a post about alcohol without any context)

4 = [person name] does not share alcohol posts

16. Do you ever engage with the alcohol posts [person name] shares?

1 = Yes, I will comment, like, and share with my other friends/followers

2 = Yes, I will comment and like

3 = Yes, I will like

4 = Yes, I will share with my other friends/followers

5 = No, I will just view while scrolling

6 = [person name] does not share alcohol posts

17. On what social media platforms do you think [person name] posts/shares content which features alcohol? (Select all that apply)

1 = Facebook

2 = Instagram

3 = Snapchat

4 = Twitter

5 = TikTok

6 = Other [Please describe]

7 = [person name] does not share alcohol posts

If 'No' to item 11 then participant will see the following questions.

12. Are the non-alcohol posts [person name] shares usually…? These are posts where alcohol is not present, or they are not about alcohol (ex. daily life, health, travel).

1 = Videos (with or without text)

2 = Photos (with or without text)

3 = Text-only status updates

4 = Other [Please describe]

5 = [person name] does not share non-alcohol posts

13. How often do you think [person name] posts/shares non-alcohol posts?

1 = Never

2 = Less than once a month

3 = Every month

4 = A couple of times a month

5 = Every week

6 = A couple of times a week

7 = Daily or almost daily

14. In the non-alcohol posts that [person name] shares, do they typically feature other people?

1 = Yes, 2 or more other people

2 = Yes, 1 other person

3 = No, they only feature [person name]

4 = No, there are no people featured in the posts

5 = [person name] does not share non-alcohol posts

15. Do non-alcohol posts from [person name] typically show:

1 = Positive experiences (for example, having fun, enjoying themselves)

2 = Negative experiences (for example, sharing sad stories)

3 = Neutral content (for example, pictures/text/videos without any context)

4 = [person name] does not share non-alcohol posts

16. Do you ever engage with the non-alcohol posts [person name] shares?

1 = Yes, I will comment, like, and share with my other friends/followers

2 = Yes, I will comment and like

3 = Yes, I will like

4 = Yes, I will share with my other friends/followers

5 = No, I will just view while scrolling

6 = [person name] does not share non-alcohol posts

17. Which social media platforms do you see [person name] share non-alcohol posts on most frequently?

1 = Facebook

2 = Instagram

3 = Snapchat

4 = Twitter

5 = TikTok

6 = Other [Please describe]

APPENDIX G

SOCIAL MEDIA USE

The following questions will ask you to describe your usage of social media including how much time you spend on the platforms you have accounts on, the content you share, and the content you see.

1. What social media platforms do you have accounts on? (select all that apply)

    1 = Facebook

    2 = Instagram

    3 = Snapchat

    4 = Twitter

    5 = TikTok

    6 = Other ________

2. How often do you typically "check" your social media account(s) (total across all platforms)?

    0 = Never

    1 = Once a month or less

    2 = 2-3 times per month

    3 = 1-6 times per week

    4 = 1-3 times per day

    5 = 4-6 times per day

    6 = 7 or more times per day

    7 = Do not have a social media account

3. Do you own a smartphone (for example, iPhone, Android)?

    1 = Yes

    2 = No

4. What type of smartphone do you own?

    1 = iPhone

    2 = Android

    3 = Other (Please describe)

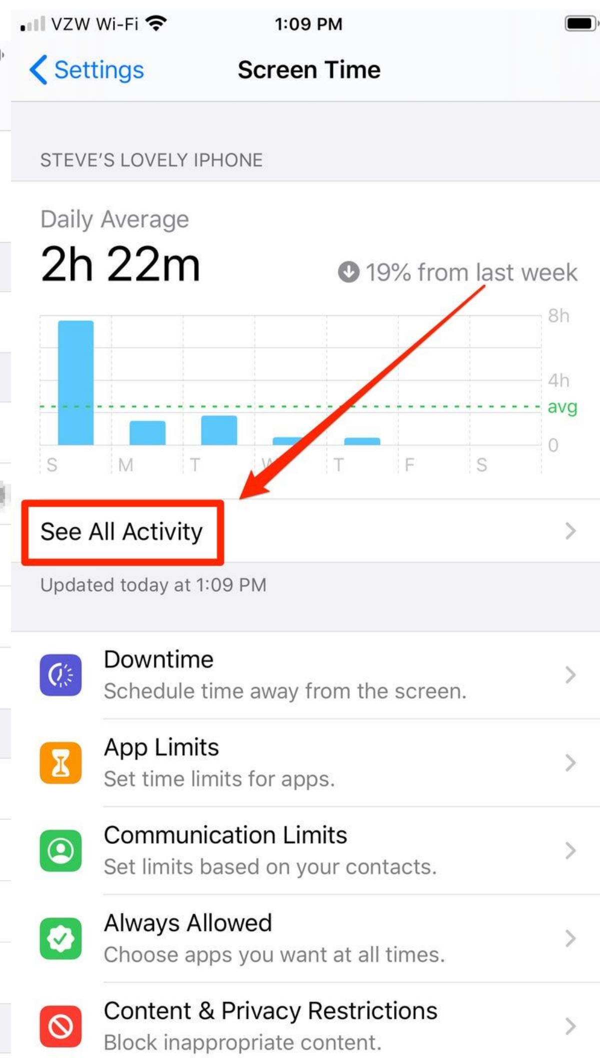
Using your smartphone, please follow the instructions on the next page to locate and record how much time (in hours), on average, you spent in the past week using the social media platforms you have accounts on.

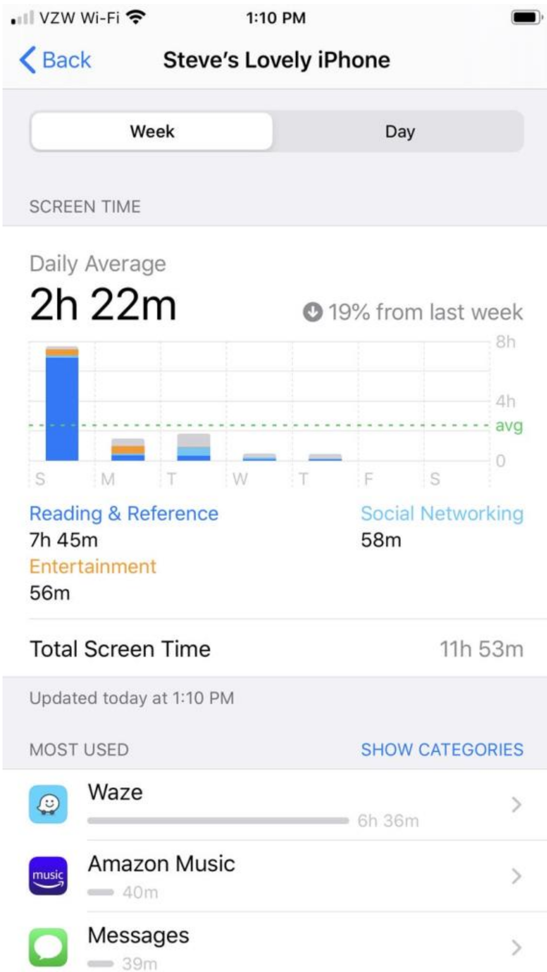
For each social media platform participants indicate they have an account on, they will be shown instructions on how to look up their average time spent on that platform in the past week.

iPhone

If you own an iPhone, please follow these instructions to find out how much type you spent (in hours), on average, using specific social media platforms in the past week.

1. Launch the settings app
2. Scroll down to the words "Screen Time" (beside an hourglass icon in a purple square)
3. Tap "See All Activity"
4. Now scroll down to check out app usage, and tap "Show More" to see all the apps, as only the most used few will initially display.





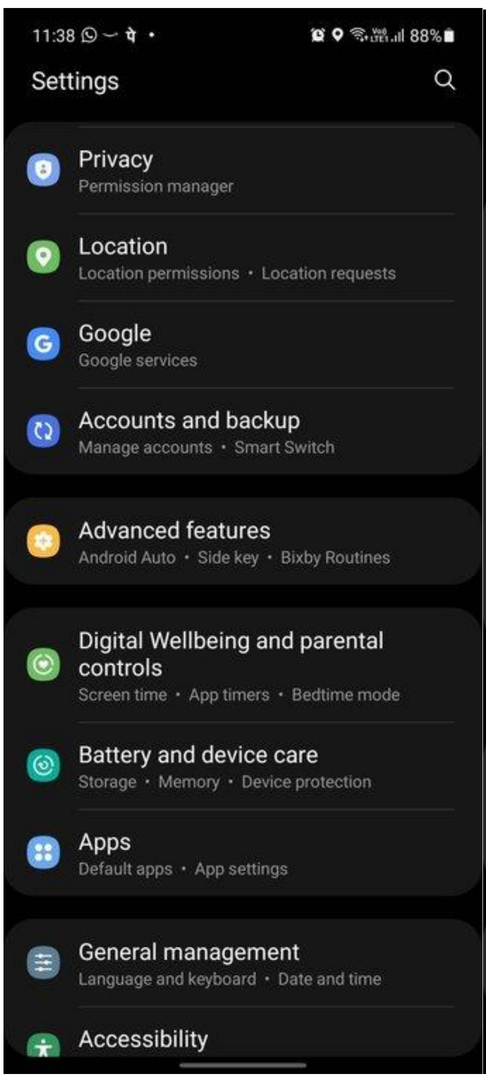
5. How much time per day (in hours and minutes, if applicable) did you spend checking [social media platform name] this past week?

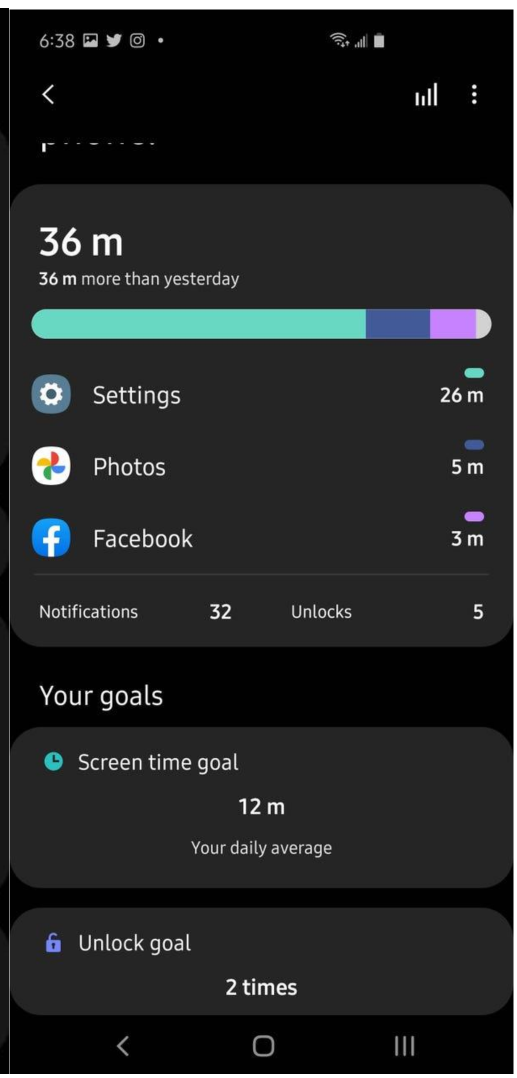
____

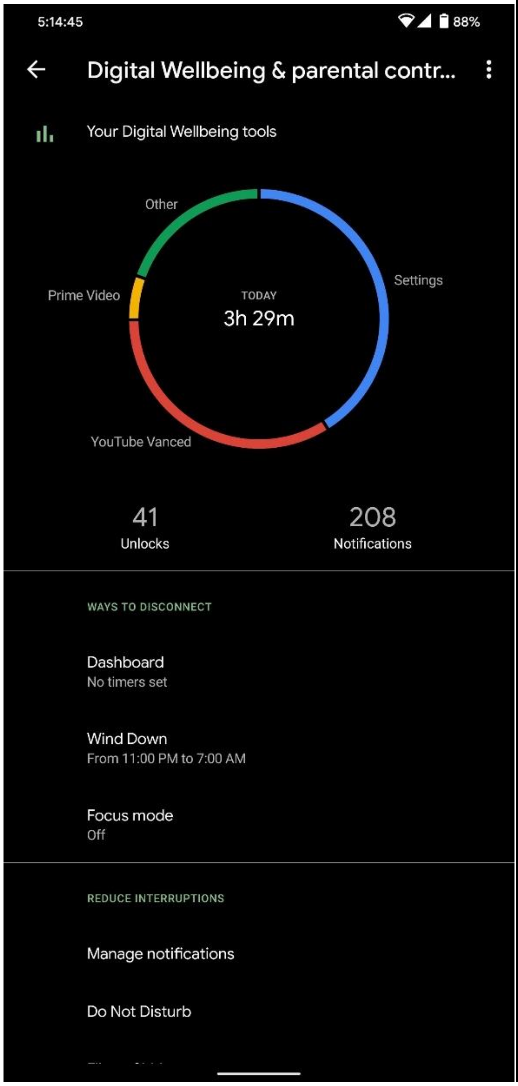
Android

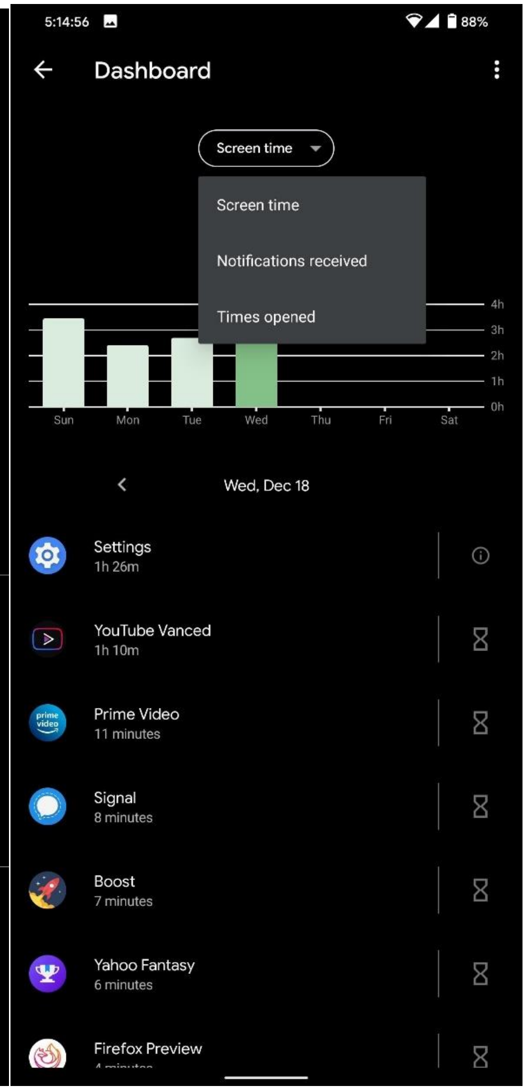
If you own an Android smartphone, please follow these instructions to find out how much time you spent (in hours), on average, using specific social media platforms in the past week.

1. Start the Settings app and tap "Digital Wellbeing and parental controls." Some Android phones may just have "Digital Wellbeing".
2. Tap "Show your data" in the Your Digital Wellbeing tools section at the top of the page. If this is not an option, select "Dashboard".
3. If you selected, "Show your data", then you should now see your current app usage statistics front-and-center on the screen. Tap the graph icon at the top right of the screen to see a weekly report of your screen time in apps.
4. If you selected, "Dashboard" during step 2, select "Screen time" from the dropdown menu above the graph of your weekly usage. Tap on each app to get a graph of your weekly usage for a particular app.









5. After following the instructions, were you able to find information on your smartphone about your average time spent on the social media platforms you use?

1 = Yes

2 = No

6. How many hours (and minutes, if applicable) did you spend on [social media platform name] on [day of the week] in the past week?

____

7. Do you post/share content on social media where alcohol is present or posts about alcohol (alcohol posts)?

1 = Yes

2 = No

If ‘Yes’ to item 7 then participant will see the following questions.

8. Are the alcohol posts you share usually…?

1 = Videos (with or without text)

2 = Photos (with or without text)

3 = Text-only status updates

4 = Other _________

9. On what social media platforms do you post/share content which features alcohol?

1 = Facebook

2 = Instagram

3 = Snapchat

4 = Twitter

5 = TikTok

6 = Other _______

10. How often do you post/share this content which features alcohol?

0 = Never

1 = Rarely

2 = Occasionally

3 = Often

4 = Always

Branching logic will be used to ask the following questions if participants select “No” to item 7.

8. Are the non-alcohol posts you share usually…?

1 = Videos (with or without text)

2 = Photos (with or without text)

3 = Text-only status updates

4 = Other _________

9. How often do you share non-alcohol posts?

1 = Never

2 = Less than once a month

3 = Every month

4 = A couple of times a month

5 = Every week

6 = A couple of times a week

7 = Daily or almost daily

10. On what social media platforms do you <u>share non-alcohol posts</u>? [Select all that apply]

1 = Facebook

2 = Instagram

3 = Snapchat

4 = Twitter

5 = TikTok

6 = Other ________

All participants will see the following questions.

11. Do you see alcohol posts or media content shared by any of the following on social media: (select all that apply)

1 = Friends

2 = Brands/stores

3 = Social media influencers or content creators

4 = Other [Please describe] ______________

5 = I do not see this content on social media

12. How often do you see alcohol posts **shared by friends**?

1 = Never

2 = Less than once a month

3 = Every month

4 = A couple of times a month

5 = Every week

6 = A couple of times a week

7 = Daily or almost daily

13. How often do you see alcohol posts **shared by alcohol brands or stores**?

1 = Never

2 = Less than once a month

3 = Every month

4 = A couple of times a month

5 = Every week

6 = A couple of times a week

7 = Daily or almost daily

14. How often do you see alcohol posts shared by **social media influencers or content creators**?

Influencers are individuals with large numbers of followers, many whom they have never met in real life. They can be celebrities, musicians, athletes, or only famous on social media platforms.

1 = Never

2 = Less than once a month

3 = Every month

4 = A couple of times a month

5 = Every week

6 = A couple of times a week

15. How often do you see alcohol posts shared by **[Other listed source]**?

1 = Never

2 = Less than once a month

3 = Every month

4 = A couple of times a month

5 = Every week

6 = A couple of times a week

APPENDIX H

DEMOGRAPHICS

1. What is your age? [ ] – numeric validation allowing 18-99

2. What is your class standing?

- Freshman
- Sophomore
- Junior
- Senior
- Undergraduate/Graduate student (combined program)
- Graduate
- Other (Please describe): ______________________

3. What is your GPA on a 4.0 scale? (First semester students enter 0.0)

____

4. What grades do you typically receive in your classes? (First semester students select "I don't know yet")

- Mostly A's
- Mostly B's
- Mostly C's
- Mostly D's
- Mostly F's
- I don't know yet

4. What university do you attend?

- Old Dominion University
- William & Mary College

5. Are you an in-state or out-of-state student? In-state means you are a resident of Virginia and out-of-state means you are not a resident of Virginia (i.e., you are a resident of another state).

- In-state
- Out-of-state
- I don't know

6. Are you Hispanic or Latino/a/x?

- Yes
- No

7. Which racial group best describes you?

- African American/Black
- Asian or Asian American
- Native Hawaiian or other Pacific Islander
- White
- Middle Eastern or North African
- Native American
- Other (Please describe): ____________________

8. What is your gender?

- Man
- Woman
- Nonbinary
- Other (Please describe): ____________________

9. What is your biological sex (assigned at birth)?

- Male
- Female
- Other [Please describe]: ____________________

10. There are many ways that individuals think of their sexual identity. Choose all the identity(ies) that best describe you:

- Gay
- Lesbian
- Bisexual
- Queer
- Asexual
- Pansexual
- Questioning
- Heterosexual/Straight
- Other [Please describe]: ________________

11. What is your weight in pounds? (only enter the number): ______________________

12. What is your height in feet and inches? (drop down menu [0-12] for both)

13. Did you ever suspect that your mother had a drinking problem?
- Yes
- No

14. Did you ever suspect that your father had a drinking problem?
- Yes
- No

15. What is your involvement in social fraternities or sororities?

- A current member
- Currently pledging
- Not a member, but regularly or occasionally attend Greek social events
- Not a member, and do not attend Greek events

APPENDIX I

CONTACT INFORMATION

1. What is your first name? ________________________
2. What is your last name? ________________________
3. As part of this study, you may also be invited to complete follow-up surveys. You would be paid/entered into separate raffles for completing each of these surveys. If you are willing to receive text message reminders for follow-up assessments, please provide your mobile phone number. ___________________________
4. Even if you entered your email address at the end of the screening survey, please enter your email address again below as this will be used to link your responses across surveys. What is your email address (including "@wm.edu"/ "@email.wm.edu")? ___________________________
5. Please repeat your email address. __________________________
6. If you check another email address more often than your William & Mary email OR leave William & Mary before the study is over, you are still eligible to complete follow-up surveys (and still be paid/entered into raffles to complete them). If there is another email address, we could use to contact you with survey invitations, please list it here: ___________________________

APPENDIX J

RECRUITMENT AND CORRESPONDENCE

Recruitment Email (sent to general student body)
Hello!

You are invited to participate in our three-part online research study to receive $5 Amazon gift cards. The study titled "College Student Social Networks, Social Media Use, and Drinking Behavior" will look at how social media usage and drinking behaviors of students change over time. The three surveys will be sent over three months and for each survey you complete you will receive a $5 Amazon gift card or the same amount added to your ConnectPoints account (total of $15). Each survey will take about 30 minutes to complete. If you complete all three surveys, you will receive an additional $5.

You must be between 1) 18-25 years old, 2) have an account on at least one social media platform, 3) have consumed alcohol on at least 2+ days in the past 30 days, and either 4a) have consumed 4+ or 5+ alcoholic drinks (for women/men) on at least one drinking occasion in the past 30 days, or 4b) have experienced at least one negative consequence related to drinking alcoholic beverages in the past 30 days.

If you are interested, let us know by filling out this brief 3-5 minute eligibility survey.

Link to the survey:

If you have any questions, feel free to reply to this email address.

Thank you!
Megan Strowger

Recruitment Post (shared in student announcements)
Do you drink alcohol with your friends? Do you use social media? Have you ever seen your friends post about alcohol on social media? Participate in a study to earn up to $20

If you answered yes to any of these questions, you may be eligible to participate in a **three-part** online survey study. This study will look at how social media usage and drinking behaviors of students change over their college career.

Three surveys will be sent **over three months**. Each survey will last approximately 30 minutes. For each survey you complete you will receive either **a $5 Amazon gift card or the same amount of money in MonarchPlus/ConnectPoints** (total of $15). If you complete ***all three surveys***, you will receive an **additional $5**.

Still interested? Click on the link below to complete a brief 3-5 minute screening survey.

Baseline Survey Email (sent if participants want to complete baseline later)

Hello [First Name],

Thank you for completing the brief screening survey for the study titled “College Student Social Networks, Social Media Use, and Drinking Behavior”. You are eligible to participate in this study. Please click on your unique link below and be sure to read the consent form on first page of the study carefully to ensure you understand the details of the study. If you have any questions before consenting to participate, feel free to email me.

If you wish to consent to participate, please type you name in the box at the end of the consent form and click the arrow button at the bottom right corner of the screen and continue to complete the first survey which is estimated to take 30 minutes to complete. After completing the first survey you will receive either a $5 Amazon gift card or the same amount added to your ConnectPoints account. Then, 6 and 12 weeks (3 months) after completing the first survey you will be sent links to complete the second and third surveys. For completing each of those you will receive either $5 Amazon gift cards or ConnectPoints (total of $10). Finally, if you complete all three surveys you will receive an additional $5 (you could earn up to $20).

Link to the survey:

Best,
Megan Strowger

1-month, 3-month Survey Email
Hello [First Name],

Thank you for your participation and completing the first survey in the study titled “College Student, Social Networks, Social Media Use, and Drinking Behavior”!

It’s time for your second/third survey! As a reminder, for completion of the second/third survey will receive a either a $5 Amazon gift card or the same amount added to your ConnectPoints account. And if you complete all three surveys, you will receive an additional $5.

Here's your unique link:

Best,
Megan Strowger

Reminder to Complete Surveys Email
Hello [First Name],

Just as a reminder you have up to two weeks to complete your survey for the study titled “College Student Social Networks, Social Media Use, and Drinking Behavior” in order to receive a either a $5 Amazon gift card or the same amount added to your ConnectPoints account. Reminders will be sent each day during this two-week period. If you wish to discontinue your participation at any time, please reply to let me know and I will remove you from our email/text reminder list.

Here's your unique link:

Best,
Megan Strowger

Text Message Reminder to Complete Surveys
Hi [First Name], this is a reminder that you have two weeks to complete your survey for the study called "College Student Social Networks, Social Media Use, and Drinking Behavior". After completing, you will receive a either a $5 Amazon gift card or the same amount added to your ConnectPoints account. Here's your unique link: Thanks! Megan Strowger

Compensation Email for Baseline, 1-month, 3-month Surveys
Hello [First Name],

Thank you for your participation in the study titled "College Student Social Networks, Social Media Use, and Drinking Behavior"! For completing your first/second/third survey you will receive either a $5 Amazon gift card or the same amount added to your ConnectPoints account.

Here is the code:

Best,
Megan Strowger

Compensation Email for Bonus Raffle for Completing All Three Surveys
Hello [First Name],

Thank you for your participation in the study titled "College Student Social Networks, Social Media Use, and Drinking Behavior" and completing all three surveys! As a bonus for completing all three surveys, you will receive an additional $5 Amazon gift card or the same amount added to your ConnectPoints account.

Here is the code:

Best,
Megan Strowger

VITA

Megan E. Strowger
Email: mstro006@odu.edu

Department of Psychology
250 Mills Godwin Life Sciences Bldg.
Norfolk, VA 23529

EDUCATION

Old Dominion University, Norfolk, VA 2023
Doctor of Philosophy in Psychology
Dissertation: *The effect of viewing different modalities of alcohol-related social media content shared by friends on alcohol outcomes: A longitudinal examination*
Major Area Paper: *How is the intersection of social media and in-person social networks associated with alcohol consumption among young adults and adolescents: A critical review*
Faculty advisor: Abby Braitman, Ph.D.

University of the Sciences in Philadelphia, Philadelphia, PA 2016
Master of Science in Health Psychology
Thesis: *Interoceptive Sounds and Emotion Recognition*
Thesis Advisor: Stephen Moelter, Ph.D.

Drexel University, Philadelphia, PA
Bachelor of Science, *Cum Laude* 2014
Major: Psychology; Minor: Arabic Language
Honor's Thesis: *Political Orientation and Religiosity Predict Rape Myth Beliefs*
Honor's Thesis Advisor: James Herbert, Ph.D.