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A dynamic network perspective on the evolution of the use of multiple mobile instant messaging apps

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ABSTRACT
Mobile instant messaging (MIM) services have emerged as digital platforms for closed and private modes of communication. The present study adopts a dynamic network approach to understanding how MIM apps are used in combination with each other. The changing patterns of cross-platform MIM use are reflected in the structural dynamics of the audience overlap network among 58 MIM apps over March 2019 to March 2021 period. The results of the separable temporal exponential random graph model indicated that the formation and persistence of audience overlap was explained by network self-organization and app reach, but not by app engagement. These effects were observed when app-level confounding factors were held constant.

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Instant messaging; mobile communication; media industry; audience overlap; network analysis; exponential random graph models

There has been a growing trend among digital media users to crave "privacy, safety, and a respite from the throngs of people on social platforms" (Wilson, 2020, para. 4). This shift toward more closed spaces for mediated communication in the current media landscape is understood as the digital campfire trend (Wilson, 2020). Mobile instant messaging (MIM) apps are instances of digital campfires, allowing users to engage in private modes of dyadic or multisided interactions (Ling & Lai, 2016; Wilson, 2020). These apps have emerged as companions to existing SNSs (e.g., Facebook Messenger) or mobile native platforms designed specifically for text- or image-based chat (e.g., Snapchat; Bayer et al., 2020; Sheer & Rice, 2017). Although traditional instant messaging services can also afford mobility, they were founded before the widespread use of smartphones and are mostly limited to one-to-one online conversations (Campbell, 2020; Ling & Lai, 2016).

MIM apps are particularly attractive to those who do not feel conformable talking about politics and controversial issues on SNSs and other open or crowded digital platforms (Valeriani & Vaccari, 2018). Context collapse is not a major concern for users of MIM apps because of the ability to "interact with individual contacts or clearly defined groups," "check whether their messages have been seen and by whom," and even specify how long a message is visible to its intended audience (Valeriani & Vaccari, 2018, p. 1718). Additionally, the intimate and private nature of MIM facilitates misinformation

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corrections (Rossini et al., 2020). Research has shown that performing, experiencing, and witnessing misinformation corrections occur more frequently on WhatsApp than on Facebook (Rossini et al., 2020). One possible explanation is that the former is perceived as a safer space for political talk than the latter.

What is largely missing from the existing literature, however, is an examination of the factors that affect the evolution of the combined use of MIM apps. This issue is worthy of investigation because mobile phone use is "an unfolding process over time" (Peng & Zhu, 2020, p. 131) triggered by personal preferences, work requirements, and app notifications. Individuals tend to launch a sequence of apps in sessions of mobile phone use and prefer to use multiple apps in the same category to enhance a certain experience (Peng & Zhu, 2020). The increasing integration of MIM apps into social life implied by the digital campfire trend (Wilson, 2020) requires a deeper understanding of the behavioral dynamics and interrelatedness of MIM use in the changing media landscape. This study explores evolutionary changes in the use of multiple MIM apps from a dynamic network perspective. Cross-platform MIM use is conceptualized as an *audience overlap* network. Audience overlap is the size or proportion of shared users between two media outlets and indicates user flows at the aggregate level (Ksiazek, 2011). A framework is proposed to explain the formation and persistence of audience overlap among MIM apps over a two-year period. The results of the network evolution model show that changes in audience overlap are explained by network self-organization and app reach. Engagement measured by time spent on the app does not drive the evolution of cross-platform MIM use.

Literature review

Cross-platform media use, audience overlap, and networked mobile communication

Given the abundance of media choices in the digital environment, communication scholars have drawn on diverse theoretical traditions (e.g., media repertoires, niche theory, and polymedia theory) to investigate how social networking or messaging platforms (e.g., Facebook and WhatsApp) are used in combination with each other via desktops or mobile devices (Bayer et al., 2020). The phenomenon of cross-platform media use within a short period of time has been conceptualized as *media multitasking*, *simultaneous media exposure*, *media multiplexing*, *media switching*, and *platform switching* (see Tandoc et al., 2019 for a review). Evidence shows that the use of multiple platforms is determined by perceived audience types, temporal rhythms, and gratification opportunities (Boczkowski et al., 2018; Tandoc et al., 2019). This growing body of literature contributes to developing a comparative perspective on how users navigate their personal media ecologies through sensemaking, calling for a shift from "a single platform at a time" to "the interrelatedness among platforms" (Boczkowski et al., 2018, p. 26). Recent work on mobile communication goes beyond traditional theoretical approaches to the multiplexity of media choices and views multi-app use as a sequential process (Peng & Zhu, 2020; Zhu et al., 2018). As a mobile phone user can initiate a sequence of activities on the screen, a transition from one app to another will create a sequence of app use at the individual level.

The focus on cross-platform media use is also reflected in audience overlap research. Rather than delve into the sensemaking process at the individual level, this stream of studies pays attention to how media outlets, especially TV channels and web domains, are linked to each other through shared audience at the aggregate level (Ksiazek, 2011; Majó-Vázquez et al., 2017; Mukerjee et al., 2018). A network approach has been adopted to explain patterns of audience overlap (Ksiazek, 2011). Specifically, media outlets are understood as network nodes. The level of overlap between nodes indicates the strength of network ties. The analysis of audience overlap as network data helps assess the degree of fragmentation in the media marketplace. For instance, Mukerjee et al. (2018) found that the network of online news consumption in the U.K. was more centralized than that in the U.S., but both networks displayed a similar core–periphery structure. The core of the networks was characterized by dense connections that varied considerably in the strength of audience overlap, providing no evidence of audience fragmentation.

Although MIM apps have emerged as an alternative coordination tool in the contemporary media landscape (Campbell, 2020; Ling & Lai, 2016), few attempts have been made to explain the evolution of the messaging platform ecosystem in the age of smartphones. Previous work has examined the use of multiple top mobile-first or mobile-only platforms such as WhatsApp and Snapchat (Boczkowski et al., 2018; Tandoc et al., 2019), but little is known about the degree to which unpopular services in the long tail share users with each other and with popular ones. This is an important issue because the focus of the current digital economy has shifted from hit products to a huge number of niche market products (Elberse, 2013). In addition, given the rapid pace of change in the media environment caused by technology innovations and external shocks (e.g., the COVID-19 pandemic), it is unclear how the patterns of cross-platform MIM use have evolved. This study fills these knowledge gaps by investigating the dynamics of the messaging platform ecosystem based on a network view of audience overlap.

Telecommunication and mobile media studies have a long network tradition. Early work conceptualized telecommunications traffic between nations as an international network. The whole network analysis revealed that the structure of the world system became denser and more interdependent over time (Barnett, 2001; Monge & Matei, 2004). Another line of research conducted surveys to understand how people communicated with different social ties in personal networks (e.g., family, friends, and work colleagues) through mobile phones, traditional instant messengers, and other media channels. For instance, Kim et al. (2007) found that the social roles of communication partners varied across media types and across employment categories. More recent studies have examined the implications of mobile communication for network connectivity (Campbell, 2019; Sheer & Rice, 2017). Empirical results suggest that mobile communication serves as "an added layer of connectivity in all realms of social life" (Campbell, 2019, p. 53). In other words, bonding with strong ties through mobile media is not achieved at the expense of network diversity. The present study contributes to the literature on networked mobile communication by elucidating the evolutionary mechanism of the audience overlap network. In the present case, MIM apps (represented as nodes) are tied together if the observed audience overlap is greater than expected by chance.

Network evolution

Previous research has conceived of communication network evolution as tie changes taking place between consecutive time points (Monge et al., 2008). Such changes are manifested in two forms: the creation of previously absent ties (tie formation) and the retention of previously present ties (tie persistence; Krivitsky & Handcock, 2014). Tie formation is a result of evolutionary variation introduced by network nodes, while tie persistence reflects strong inertial forces and resistance against change (Doerfel et al., 2013; Monge et al., 2008). Evolutionary principles have also been applied to explain tie formation or persistence over an extended period of time (Hilbert et al., 2016). Recently, Xu et al. (2021) demonstrated that the evolutionary pattern of affiliation network ties between ICA subgroups and members followed the principle of the liability of newness. Specifically, a decrease in the length of ICA experience was associated with an increased likelihood that a person would terminate the existing affiliation with an ICA division or interest group.

This study adds to the literature on communication network evolution by examining the formation and persistence of the audience overlap network. Based on the taxonomy of communication relations (Shumate & Contractor, 2013), audience duplication networks can be considered the media-level projection of *affiliation networks* describing how individuals consume media outlets at a point in time (see Mukerjee et al., 2018, p. 30, for an explanation of network projection in audience overlap research). The following sections develop a series of research questions and hypotheses about the evolution of audience overlap among MIM apps.

Self-organizing features: Degree and closure effects

Informed by the concept of self-organizing systems, network scholars have viewed the emergence of structural complexity as the result of "the internal processes of the system of network ties" (Lusher & Robins, 2013, p. 23). Such network self-organization occurs independently of selection based on nodal attributes (i.e., the tendency for nodes with a certain trait to have a high probability of tie formation or persistence). The two separate processes in network evolution are in line with the distinction between position-based and trait-based selection in socio-cultural evolution (Hilbert et al., 2016).

The higher-order complex patterns of network structure can be governed by self-organizing *degree* and *closure* effects (Lusher & Robins, 2013). In network terms, degree is the number of direct ties a given node has. Researchers have found that "the likelihood of connecting to a node depends on the node's degree" (Albert & Barabási, 2002, p. 71). A new network tie has a greater chance of being attached to popular nodes with already high degrees than to unpopular nodes. This selection mechanism often results in a power-law degree distribution where a small group of nodes have a disproportionate share of ties. The increased network centralization due to initial differences in popularity is theorized as *preferential attachment* or the *Matthew effect* (Lusher & Robins, 2013). In network modeling, such degree-based processes in undirected networks are represented by star configurations with multiple ties centered on a single node (Lusher & Robins, 2013).

Evolutionary theorists argue that *random copying* (a.k.a. unbiased transmission), the socio-cultural analogy of random genetic drift, provides a more elegant explanation for the power-law degree distribution than does the theory of preferential attachment proposed by network scholars (Bentley & Shennan, 2005). The random-copying model suggests that ties in the previous generation will be picked at random for reproduction. The more popular a node is, the more likely its network ties will be copied in the next generation, making the node become even more popular over time (Bentley & Shennan, 2005). Evidence indicates that the power-law frequency distribution is a result of “pure availability” (Acerbi, 2020, p. 75), which is consistent with the prediction of the evolutionary model of random copying.

As another driving force in network evolution, closure sheds light on the transitive nature of network structure, which translates into a high probability of tie presence between nodes with shared connections (Albert & Barabási, 2002). Triangles (a.k.a. closed triads), defined as a set of three interconnected nodes, are the most basic form of network closure. According to the selection mechanism of closure, triangles will occur more frequently than expected by chance in a given network. For instance, if *a* is connected to both *b* and *c*, there is a greater chance of tie presence between *b* and *c*. Specifying the closure effect in network modeling should take into account the structural tendency against closure (Robins et al., 2012), which is often termed as network brokerage or structural equivalence (Burt, 2005). This non-closure effect in undirected networks is represented as *k-2path* (known as *4-cycle* when $k = 2$) configurations in which two nodes sharing multiple third parties do not have a direct tie to close the multiple triads. The absence of *k-2path* is interpreted as additional evidence of network closure (Robins et al., 2012).

Although self-organizing features are frequently observed in communication networks (Lusher & Robins, 2013; Monge & Contractor, 2003), cross-sectional network data are often used to infer the presence of dynamic degree and closure effects (Welles & Contractor, 2015). Additionally, few empirical research has been conducted to consider self-organizing determinants of both tie formation and persistence. This issue is worthy of investigation because tie persistence (or dissolution) is as important as tie formation in network evolution but is not a well-understood phenomenon (Kleinbaum, 2018). The objective of this study is to disentangle position-based (i.e., network self-organization) from trait-based selection in the evolution of audience overlap among MIM apps. As little attention has been paid to self-organizing features in the dynamics of audience overlap networks, the first research question asks how degree and closure effects will be responsible for tie formation and persistence. It is proposed that:

> $\boldsymbol{RQ_1}$**:** How will degree (RQ_{1a}) and closure ($RQ_{1\mathrm{b}}$) effects explain the formation and persistence of the audience overlap network among MIM apps?

App reach

Besides network self-organization, the evolutionary path of the audience overlap network can also be determined by nodal attributes (in the present case, traits of MIM apps). The present study investigates trait-based network evolution by focusing on the effects of reach and engagement, the two widely used metrics at the level of media outlets, on the formation and persistence of overlapping ties. As the traditional currency of exchange in the media marketplace, *reach* is the percentage of the population exposed to a medium within a given period (Webster et al., 2013). Researchers and practitioners have emphasized the importance of *network effects* – that is, increasing the reach of a digital platform will enhance the inherent value of the platform for everyone (Zhu & Iansiti, 2019). Unlike the conceptualization of network as nodes and ties (Monge & Contractor, 2003), media economics defines the term as a platform's scale-based advantage. Strong network effects suggest that a platform with a broader reach is more likely to retain existing users and attract additional ones because of a higher level of perceived social benefits, functional utility, and cognitive legitimacy (Centola, 2018).

Dunbar's number indicates that individuals can only maintain about 150 meaningful friendships and recognize about 1500 people at any given time (Hill & Dunbar, 2003). This theory also states that personal social networks are characterized as a sequence of successive layers reflecting "decreasing levels of emotional closeness and frequency of contact" (Dunbar, 2014, p. 110). The innermost layer consists of five contacts with the highest level of intimacy and communication frequency. This core circle is followed by cumulative layers composed of 15 (the sympathy group), 50 (friends), 150 (weak ties), 500 (acquaintances), and 1500 (faces we can put names to) individuals (Dunbar, 2014). Evidence exists that both the limit of social contacts and the structure of hierarchically inclusive layers apply to mobile communication (Mac Carron et al., 2016). Therefore, MIM services still cannot help people overcome cognitive and time constraints on the number of stable and meaningful relationships.

Mobile media research has shown that app users tend to enhance their social needs through the combined use of communication apps (Peng & Zhu, 2020). The current study predicts that the probability of sharing users is higher for a narrow-reach MIM app than for a broad-reach one. Strong network effects suggest that users of a broad-reach platform have a wide choice of available communication partners because the users' social ties have a high chance of using the same platform. This high social value makes it unnecessary to rely on other messaging platforms that provide redundant connections from any Dunbar layer. In contrast, a narrow-reach platform tends to be used in combination with other MIM services due to the difficulty of engaging in dyadic or multisided interactions with sufficient social ties across Dunbar layers on the platform. This communication purpose is especially important for working professionals who need to exchange information with friends, colleagues, business partners, and clients (Sheer & Rice, 2017). An alternative explanation is that users of narrow-reach MIM apps have lower social needs and are therefore less likely to use other messaging platforms for network connectivity. However, this explanation is inconsistent with the empirical finding that users of less popular digital media have lower levels of commitment and loyalty (Taneja, 2020). The above discussion leads to the following hypothesis:

> $\boldsymbol{H_1}$**:** An app with a broader reach will have a lower probability of tie formation (H_{1a}) and persistence (H_{1b}) in the audience overlap network among MIM apps.

As a network tie exists between a pair of nodes, attributes of both sides may affect network evolution (Lusher & Robins, 2013). There is a debate (homophily vs. heterophily) about whether nodes with similar attributes tend to be linked together. *Homophily* is the tendency for nodes with similar attributes to attach to each other (McPherson et al., 2001). Although network evolution often exhibits a strong tendency toward homophily (McPherson et al., 2001; Monge & Contractor, 2003), the opposite effect, *heterophily*, has also received empirical support (Rivera et al., 2010). For instance, Powell et al. (2005) found more evidence of heterophily than homophily in the interorganizational network dynamics of the innovation community. One theoretical explanation for heterophily is the value of complementary qualities and capabilities (Rivera et al., 2010).

The impact of app reach on cross-platform MIM use should follow the heterophily principle for three reasons. First, network effects in media economics (Zhu & Iansiti, 2019) and the applicability of Dunbar's number to mobile social networks (Mac Carron et al., 2016) suggest that narrow-reach MIM apps have a small base of potential communication partners across Dunbar layers. Users of these apps may thus be forced to rely on other messaging services for network connectivity (also implied by H_1). Empirical results have shown that the use of broad-reach messaging platforms was positively associated with (a) bridging and bonding social capital and (b) job performance and satisfaction (Sheer & Rice, 2017). Given that mobile media consumption is a rational decision (Peng & Zhu, 2020), the combined use of two apps that vary considerably in reach creates more social and professional value than does the combined use of two narrow-reach apps. Second, e-commerce research has revealed that products without mass appeal are generally used by consumers who simultaneously buy popular products in the same category (Elberse, 2013). One explanation for this co-purchase preference is that consumers of niche products are still subject to strong social pressure and consider matching their own behaviors with those of peers (Jackson, 2019). Third, the hypothesized pattern of cross-platform MIM use is complementary in nature (Rivera et al., 2010) and meets the need for both conformity and uniqueness. For instance, a person may rely on a broad-reach app for family and professional communication while choosing a narrow-reach app to connect people with similar interests in niche topics. Therefore, it is predicted that:

> ***H*$_2$:** Apps with dissimilar levels of reach will have a higher probability of tie formation (H_{2a}) and persistence (H_{2b}) in the audience overlap network than will apps with similar levels of reach.

App engagement

The notion of *engagement* has gained popularity in the media industry over the past decade. However, there is little industry-wide consensus on how to define the concept (Steensen et al., 2020). Engagement has thus been criticized as an umbrella term due to its inherent ambiguity and a lack of contrast (Napoli, 2011). Another major concern is that engagement is often equated with quantitative and behavioral media metrics in practice (Steensen et al., 2020). This reductionist view of engagement has led the media industry to rely heavily on metrics "not only to monitor audience behaviour but also, increasingly, as the preferred way to analyze the inner and perhaps unconscious motivations driving audience engagement" (Steensen et al., 2020, p. 1663). To promote engagement as an alternative currency of exchange in the media marketplace, many industry stakeholders have advocated quantifying engagement as time spent with media (e.g., average minutes per visitor; Nelson & Taneja, 2018; Nelson & Webster, 2016). Empirical research has conferred legitimacy on the exposure-based metric of engagement in online environments. For instance, engagement (measured by time spent on the site) was found to be uncorrelated with reach (measured by unique visitors to the site; Nelson & Webster, 2016). This result supports the idea that the engagement metric goes beyond the traditional audience currency (i.e., reach) and adds value to buying and selling online media. Although engagement and reach capture different aspects of user behavior, little research has been conducted to distinguish the effect of engagement from that of reach on the evolution of audience overlap.

Previous research has two conflicting views on media substitution: displacement and complementarity (Dimmick, 2003; Kim et al., 2020). Given that media outlets compete for a limited amount of audience attention, the displacement argument suggests that people will spend time on one MIM app at the expense of using another in the same category, leading to a low probability of audience overlap. By contrast, the complementarity argument suggests that the total amount of time spent on MIM apps will increase over time because MIM apps are superior to existing media forms. Additionally, people will incorporate multiple MIM apps into their media diet to maximize supplementary benefits. The use of one MIM app will enhance that of another MIM app, producing a spillover effect. Hence, a high probability of audience overlap is expected. As there is no consensus on media substitution (Dimmick, 2003; Kim et al., 2020), the present study explores how app engagement affects tie formation and persistence in the audience overlap network. As previously mentioned, trait-based evolution operates at either the level of a single node (main effect) or the level of a node pair (homophily/heterophily effect; Lusher & Robins, 2013), so the following research question considers main and homophily/heterophily effects simultaneously.

> ***RQ*$_2$:** Will app engagement explain the formation and persistence of the audience overlap network?

Method

Data collection

The tracking data were acquired from Comscore Mobile Metrix® in the U.S. market. Comscore monitors app performance across smartphones and tablets through a user-centric measurement approach. As of May 2021, Comscore collected media consumption data from a panel of 18,115 Android users, 3915 iPhone users, and 3451 iPad users who installed tracking software on their mobile devices. Individual level information on media exposure is unavailable to Comscore subscribers. Only aggregate monthly measures of online media outlets are provided (Taneja, 2016). It was not until January 2019 that Comscore started to provide a comprehensive report of monthly estimates of app use.

The MIM apps in the sample met the following two criteria. First, a given app was on Comscore's list of "Instant Messengers" or was assigned to the "Communication" category by the Google Play Store. The Apple App Store was not considered because there was no platform-specific label for MIM apps. Most MIM apps defined by Comscore and the Google Play Store were affiliated with the "Social Networking" (e.g., WhatsApp) or "Photo & Video" (e.g., Snapchat) category on the Apple App Store. Second, the app reached at least 0.01% of the total digital population in the U.S. across the five time points (March 2019 [t_1], September 2019 [t_2], March 2020 [t_3], September 2020 [t_4], and March 2021 [t_5]). Otherwise, monthly estimates of audience overlap would be unreliable (Mukerjee et al., 2018). The two requirements led to a total of 58 apps (see Online Supplemental Table S1 for the full list).

The next step was to construct the longitudinal audience overlap network among the same set of 58 MIM apps over the two-year period. Estimates of audience overlap reported by Comscore were organized in the form of symmetric matrices, where diagonal entries were left blank and off-diagonal entries were the size of the duplicated audience between pairs of apps at a given time point. As the observed audience overlap may not be greater than chance, the *phi* coefficient was computed to filter out audience overlap attributed to random browsing behavior (Majó-Vázquez et al., 2017; Mukerjee et al., 2018). This thresholding approach offers an assessment of statistical significance and is necessary for cleaning audience overlap data. Without a formal statistical test, there is no way to determine whether the difference between the observed and expected overlap was a significant departure from zero. Unlike the iterative proportional scaling algorithm (Rice, 1982), the *phi* coefficient approach uses a formula (Majó-Vázquez et al., 2017, p. 291; Mukerjee et al., 2018, p. 35) to calculate estimated cell frequencies (in the present case, expected overlap between pairs of apps).

The current study followed the standard procedure (Majó-Vázquez et al., 2017; Mukerjee et al., 2018) and eliminated the weakest overlapping ties that did not reach statistical significance at the 0.01 level (with a t value smaller than 2.58). The significance test removed 18%, 19%, 16%, 19%, and 18% of all the overlapping ties at each time point. After eliminating the non-significant ties, the weighted entries that had a t value greater than or equal to 2.58 were recoded as "1" to indicate tie presence in the observed network. The remaining off-diagonal entries were recoded as "0." In other words, undirected ties after dichotomization show that the observed audience overlap between two MIP apps (represented as network nodes) is significantly greater than the expected overlap. The binary transformation is necessary because the method for modeling network dynamics, which is introduced in the analysis section, does not apply to weighted ties (Krivitsky & Handcock, 2014). Table 1 provides a summary of the binary network data. Panel A describes the observed network through commonly used metrics, including average degree centrality (the count of a node's direct ties), density (the ratio of the number of actual ties to the number of possible ties), average clustering

Table 1. Summary of the binary network data.

Panel A. Metrics of the audience overlap network among 58 MIM apps at each time point

Time point	Average degree centrality	Density	Average clustering coefficient	Average path length
t_1 (March 2019)	21.83	.38	.64	1.63
t_2 (September 2019)	22.10	.39	.62	1.63
t_3 (March 2020)	21.93	.39	.64	1.65
t_4 (September 2020)	24.55	.43	.64	1.59
t_5 (March 2021)	24.86	.44	.67	1.58

Panel B. Number and proportion of tie changes in the observed network in each period

Period	$0 \rightarrow 0$	$0 \rightarrow 1$	$1 \rightarrow 0$	$1 \rightarrow 1$	Number of possible ties
$t_1 \rightarrow t_2$	823 (50%)	197 (12%)	189 (11%)	444 (27%)	1653 (100%)
$t_2 \rightarrow t_3$	799 (48%)	213 (13%)	218 (13%)	423 (26%)	1653 (100%)
$t_3 \rightarrow t_4$	760 (46%)	257 (16%)	181 (11%)	455 (28%)	1653 (100%)
$t_4 \rightarrow t_5$	739 (45%)	202 (12%)	193 (12%)	519 (31%)	1653 (100%)

Note: In the first row, "0" indicates tie absence, and "1" indicates tie presence.

coefficient (an indicator of how nodes cluster together), and average path length (average shortest distance between pairs of nodes). Panel B reports the number and proportion of tie changes in each period. About 70% of previously present ties would persist in the next period, while there was a 20% chance that an absent tie at t_n would be transformed into a present tie at t_{n+1}.

Measures

Dependent variables

Tie formation (i.e., the creation of previously absent ties) and *tie persistence* (i.e., the retention of previously present ties) were measured by observing tie changes in the dynamic network of audience overlap from t_{n} to $t_{\mathrm{n+1}}$.

Independent variables

Self-organizing features. *Degree effects* were represented as the *2-star* and *3-star* parameters (Lusher & Robins, 2013). A *2-star* consists of three nodes $\{i, j, k\}$ such that i is linked to both j and k while there is no audience overlap between j and k. A *3-star* is a set of four nodes $\{i, j, k, h\}$ in which i (with a degree of 3) shares traffic with the remaining three (with a degree of 1). The two degree-based parameters measure the extent to which the formation and persistence of overlapping ties are directed to a few highly connected apps in the audience overlap network. *Closure effects* were represented as the *triangle* and *4-cycle* (*2-2path*) parameters (Lusher & Robins, 2013). A *triangle* is a closed triad, meaning that a set of three apps are fully connected in the audience overlap network. The presence of *triangle* indicates that nodes have a strong tendency to share third parties in network evolution. A *4-cycle*, which can be interpreted as a structural tendency against network closure (Robins et al., 2012), is a set of four nodes $\{i, j, k, h\}$ in which four ties $\{(i, k), (i, h), (j, k), (j, h)\}$ are present. The absence of *4-cycle* provides additional evidence of closure (Robins et al., 2012).

Nodal attributes. *App reach* ($M = 2.54$, SD = 7.15, Min = 0.01, Max = 48.93) was measured as 100 multiplied by the percentage of the entire U.S. online population who used a given app at time t_n. *App engagement* ($M = 168.59$, SD = 270.50, Min = 1.04, Max = 2158.26) was operationalized as the average number of minutes spent on the app per unique visitor in the same month (Nelson & Taneja, 2018; Nelson & Webster, 2016). These two metrics were obtained from the Comscore database. Correlation coefficients between the two independent variables were .08 ($p = .57$), .13 ($p = .35$), .20 ($p = .12$), .34 ($p = .009$), and .38 ($p = .003$) in five waves. The growing correlation and significance of the relationship might also result from network effects in the digital environment (Zhu & Iansiti, 2019). As a platform's user reach is positively associated with the platform's perceived value, users tend to spend more time on a MIM app that has gained more popularity in the population.

Control variables

The *edges* parameter, which is analogous to the constant term in traditional regression analysis, estimates the baseline probability of tie formation or persistence. This parameter must be included in dynamic network modeling (Morris et al., 2008). Several app attributes were manually coded. A company (e.g., Facebook, Google, Microsoft, and TextMe) can implement a multi-product strategy to offer more than one MIM app. It was possible that the formation and persistence of audience overlap was driven by the company's efforts to promote products in the same category through advertising and recommender systems. *App developer* was thus included as a control. *Developer location* was the country where the company was headquartered during the observation period. The variable considered the possibility that Comscore's panelists in the U.S. preferred to use multiple MIM apps developed by U.S. companies. The 58 apps in the sample were developed by 46 companies in 10 countries including U.S. ($n = 44$), China ($n = 3$), Australia ($n = 2$), Israel ($n = 2$), and South Korea ($n = 2$). *App age* ($M = 88.33$, SD = 32.11, Min = 12.00, Max = 148.00) was the number of months since the app's first appearance on the Apple App Store or the Google Play Store. *Corporate app* ($M = .09$) indicated whether a given app was designed specifically for workplace communication (1 = Yes, 0 = No). The app was coded as 1 if its description in app stores included keywords such as "work," "workforce," "business," "professional," and "employees." This variable considered the possibility that the evolution of audience overlap was determined by an app's target groups. *App cost* ($M = .71$) was whether a given app offered in-app purchases (1 = Yes, 0 = No). *App availability* ($M = .81$) indicated whether users could download the app from both the Apple App Store and the Google Play Store (1 = Yes, 0 = No). All MIM apps in the sample were available on the latter platform. A total of 11 apps did not exist on the Apple App Store. Besides the economic and availability constraints, another alternative explanation was that an app's technical features predicted the likelihood that the app would share users with other MIM services. *Instant video chat* ($M = .59$) was thus used as a control variable. It was coded as 1 if the app description indicated the presence of a video conferencing feature. Apps without this technical feature were coded as 0. Two coders independently coded each of the 58 apps and agreed on at least 93% of their decisions. The few disagreements were resolved through discussion.

Analysis

As a simulation-based tool for analyzing unweighted networks observed at discrete points in time, the separable temporal exponential random graph model (STERGM) was employed to investigate the dynamics of the audience overlap network among 58 MIM apps. Tracking tie changes in each pair of MIM apps once every six months during March 2019 to March 2021 period led to five waves. This is a reasonable wave number for the STERGM. As a temporal extension of exponential random graph models (ERGMs), the STERGM analyzes network change between discrete time steps and separates the processes of tie formation and persistence. A fundamental assumption is that the two processes are interdependent over time but occur independently within a time step (Krivitsky & Handcock, 2014). Suppose that apps i and j are connected (or disconnected) in the observed network at time t_n. The STERGM allows tie formation and persistence to be determined by previous network states. However, it excludes the possibility that the retention (or creation) of a previously present (or absent) tie from t_n to t_{n+1} depends on whether either i or j forms new (or dissolves existing) ties with other apps during the same period. It is unlikely that this independent assumption would bias the findings because the temporal order of newly formed and dissolved overlapping ties from t_n to t_{n+1} is unavailable in the Comscore database. There is no way to know how the processes of tie formation and persistence are interdependent within the t_n to t_{n+1} period.

ERGMs can be treated as autoregressive models in the sense that all predictors are functions of the dependent variable (Morris et al., 2008). In ERGMs, predictors are chosen from a list of *structural* and *attribute parameters* that describe position-based and trait-based network evolution, respectively. Each parameter represents a specific network configuration (see Shumate & Palazzolo, 2010, for an introduction of ERGMs in communication research). *Structural parameters* (e.g., *edges*, *2-star*, *3-star*, *triangle,* and *4-cycle*) capture the process of network self-organization and assess the extent to which the change of a tie depends on the state of other ties. In contrast, *attribute parameters* consider how nodal attributes (e.g., *app reach*, *app engagement, app developer*, *developer location*, *app age*, *corporate app*, *app cost*, *app availability*, and *instant video chat*) are responsible for network evolution. For undirected networks, there are two types of attribute parameters. First, the *nodecov* (or *nodefactor*) parameter tests whether a node's quantitative (or categorical) attribute is related to the node's tendency to be linked to others. Second, a negative (or positive) and significant *absdiff* (or *nodematch*) parameter shows evidence of the homophily effect: a high probability of tie formation or persistence between two nodes with similar quantitative (or categorical) characteristics. By contrast, a positive (or negative) and significant *absdiff* (or *nodematch*) parameter indicates the heterophily effect.

This study incorporated both structural and attribute parameters in the STERGM estimation. Both the *nodecov* (or *nodefactor*) and *absdiff* (or *nodematch*) parameters were specified for each nodal attribute. The only exception was *app developer* because the inclusion of 45 dummies did not improve model fit. The dichotomous *developer location* (1 = U.S., 0 = others, $M = .76$) was entered as a *nodefactor* parameter. Network analysis was performed using the tergm package (version 3.7.0) in R.

Results

Table 2 summarizes the results of the STERGM estimation. All coefficients are expressed as the conditional log odds of the creation of previously absent ties (Model 1) and the retention of previously present ties (Model 2). A parameter reaches statistical significance when the ratio of the coefficient to the standard error is greater than 1.96 in magnitude. A positive sign of the coefficient indicates that a given configuration is more likely to form or persist over time. The two models explained 33% ([5531–3690]/5531) and 29% ([3635–2599]/3635) of the total deviance, respectively. There was no warning message of linear combinations of predictors.

RQ_1 asked how self-organizing features would explain the formation and persistence of the audience overlap network among MIM apps. RQ_{1a} focused on degree effects. Model 1 showed that the configuration represented by the *3-star* parameter occurred more frequently than expected by chance in tie-formation processes (log odds = 0.002, SE = 0.0003, $p < .001$). Additionally, neither of the degree-based parameters (i.e., the *2-star* and *3-star* parameters) produced a significant effect on tie persistence in Model 2. Taken together, there was growing network centralization over time, which was consistent with the prediction of preferential attachment, the Matthew effect, or the random-copying model.

Table 2. Formation and persistence mechanisms of the audience overlap network among 58 MIM apps over March 2019 to March 2021 period.

	Model 1: tie formation		Model 2: tie persistence	
	Log odds	SE	Log odds	SE
Structural parameters				
Edges	−2.49***	0.02	−1.78***	0.20
***RQ_1*: 2-star**	−0.008	0.01	0.04	0.02
***RQ_1*: 3-star**	0.002***	0.0003	0.001	0.001
***RQ_1*: Triangle**	0.25***	0.03	0.48***	0.05
***RQ_1*: 4-cycle**	−0.006***	0.001	−0.02***	0.003
Attribute parameters				
***H_1*: App reach (nodecov)**	−0.07**	0.03	−0.03	0.04
***H_2*: App reach (absdiff)**	0.07*	0.03	0.05	0.04
***RQ_2*: App engagement (nodecov)**	−0.0003	0.0002	0.0001	0.0003
***RQ_2*: App engagement (absdiff)**	0.0003	0.0003	−0.0002	0.0004
App developer (nodematch)	0.34***	0.02	0.85*	0.43
Developer location (nodefactor)	−0.13***	0.04	−0.19	0.21
Developer location (nodematch)	0.07*	0.03	0.38	0.26
App age (nodecov)	0.001	0.001	0.0002	0.001
App age (absdiff)	0.001	0.002	−0.001	0.002
Corporate app (nodefactor)	−0.04	0.05	−0.13	0.21
Corporate app (nodematch)	0.001	0.05	0.17	0.22
App cost (nodefactor)	−0.23**	0.08	−0.09	0.09
App cost (nodematch)	0.01	0.10	0.28*	0.11
App availability (nodefactor)	−0.31**	0.12	−0.46**	0.14
App availability (nodematch)	0.28*	0.13	0.60***	0.17
Instant video chat (nodefactor)	−0.05	0.06	0.05	0.07
Instant video chat (nodematch)	0.01	0.08	0.10	0.10
Null Deviance	5531		3635	
Residual Deviance	3690		2599	
Akaike Information Criterion	3734		2643	
Bayesian Information Criterion	3872		2772	

*$p < .05$.
**$p < .01$.
***$p < .001$.

RQ_{1b} focused on closure effects. The positive effect of the *triangle* parameter on tie formation (log odds = 0.25, SE = 0.03, $p < .001$) and persistence (log odds = 0.48, SE = 0.05, $p < .001$) indicated a strong tendency for nodes to share third parties over time. Specifically, when new ties were formed, triangles appeared more frequently than expected by chance. The newly formed triangles were also more likely to be retained in the network. In addition, there was no evidence of the structural tendency against network closure. Results showed that the configuration represented by the *4-cycle* parameter occurred less often than expected (log odds = −0.006, SE = 0.001, $p < .001$). Once established, the *4-cycle* structure was less stable over time (log odds = −0.02, SE = 0.003, $p < .001$).

H_1 stated that an app with a broader reach would have a lower probability of tie formation (H_{1a}) and persistence (H_{1b}). Evidence indicated that the *nodecov* parameter of reach was a negative and significant predictor of tie formation (log odds = −0.07, SE = 0.03, $p = .007$), supporting H_{1a}. However, the same parameter did not explain tie persistence (log odds = −0.03, SE = 0.04, $p = .40$), rejecting H_{1b}.

H_2 predicted that apps with dissimilar levels of reach would have a higher probability of tie formation (H_{2a}) and persistence (H_{2b}) than would apps with similar levels of reach. Model 1 revealed that the larger the absolute difference in reach between two apps (represented by the *absdiff* parameter of app reach), the greater the likelihood that a tie would be created (log odds = 0.07, SE = 0.03, p = .012). This result lent support to H_{2a}. Model 2 showed that the same parameter did not exert a significant influence on tie persistence (log odds = 0.05, SE = 0.04, p = .18). Thus, H_{2b} was rejected.

RQ_2 asked whether app engagement would explain the formation and persistence of audience overlap. The results demonstrated that app engagement was unrelated to either tie formation or persistence. The main and homophily/heterophily effects of the variable, represented by the *nodecov* and *absdiff* parameters respectively, were not statistically significant. RQ_2 was then answered.

Traditional fit indices such as R-squared were unavailable in the STERGM. Instead, model fit (a.k.a. goodness-of-fit) is assessed by higher-order statistics. GoF checks were performed to evaluate the extent to which the two models in Table 2 reproduced higher-order structural characteristics of the observed network. The GoF statistics for degree, edgewise shared partners, and minimum geodesic distance showed that the STERGM estimation provided a nearly perfect fit to the network data. As illustrated in Figure 1, all solid black lines were within the boundaries of the simulated distribution represented by boxplots. Additionally, the Monte Carlo p-value of each statistic (available upon request) was not below the 0.05 threshold. These results provided evidence of the validity of the results.

Discussion

The purpose of this study was to identify factors affecting changes in the use of multiple MIM apps from a dynamic network perspective. The changing patterns of cross-platform MIM use were reflected in the structural dynamics of the audience overlap network. Shared traffic data among 58 MIM apps over March 2019 to March 2021 period were retrieved from Comscore Mobile Metrix®. The STERGM was used to elucidate the

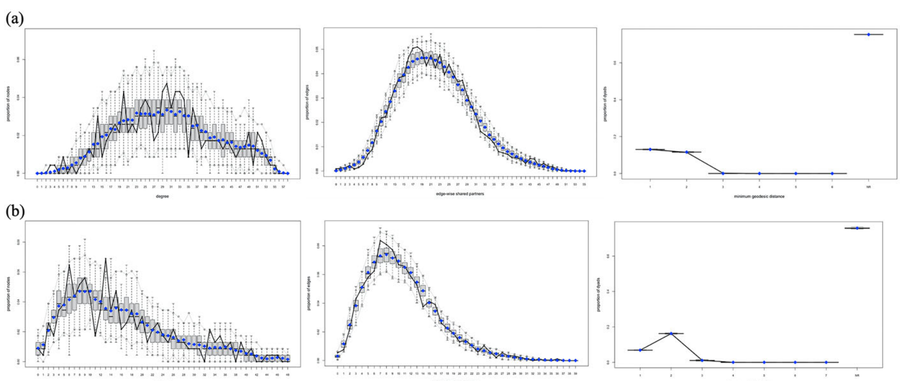

Figure 1. Plots of GoF statistics for degree, edgewise shared partners, and minimum geodesic distance. Notes: Panels (a) and (b) display the GoF plots for Models 1 and 2 in Table 2, respectively. Black lines represent the distribution of higher-order statistics of the observed network. Boxplots represent the same statistic from the simulated networks generated by the STERGM. Gray lines mark the 95% confidence limits of the simulated distribution. In the STERGM, model fit is assessed by GoF statistics such as degree, edgewise shared partners, and minimum geodesic distance. Model fit is good if all solid black lines are within the boundaries of the simulated distribution represented by boxplots.

formation and persistence mechanisms of audience overlap. The results showed that the evolution of cross-platform MIM use was determined by self-organizing forces and app reach, but not by app engagement.

The current study adds an evolutionary component to comparative studies of mobile media (Boczkowski et al., 2018; Tandoc et al., 2019) and network studies of audience overlap (Ksiazek, 2011; Mukerjee et al., 2018). This evolutionary view holds that network change proceeds via the *formation* and *persistence* of ties observed at discrete points in time (Krivitsky & Handcock, 2014). An evolutionary interpretation of tie presence in the observed network is that connected MIM apps occupy similar positions in a multidimensional resource space and compete for the same set of users (Monge et al., 2008). Previous studies have demonstrated that network evolution is governed by both position-based and trait-based selection (Lusher & Robins, 2013; Monge & Contractor, 2003). The present study advances this stream of literature by confirming that tie changes in the audience overlap network among MIM apps were driven by both selection mechanisms.

The evolution of the audience overlap network exhibited self-organizing features and was explained by degree and closure effects. Empirical results supported the growing network centralization suggested by preferential attachment, the Matthew effect, or the evolutionary model of random copying. Specifically, MIM apps that were already central in the audience overlap network would share users with even more messaging platforms at a later point in time, as evidenced by the positive effect of *3-star* on tie formation and the null effect of degree-based parameters on tie persistence. The increased network centralization does not translate into a high degree of concentration or monopoly in the MIM app market. The best indicator of this market characteristic is the Herfindahl–Hirschman Index based on the distribution of app reach. Because a MIM app with a broader reach shared users with fewer MIM services, the central nodes in the audience overlap network were unlikely hit products, suggesting that users of narrow-reach MIM apps relied increasingly on other products in the same category to satisfy needs.

Closure was another defining structural feature of the evolution of audience overlap. As a negative and significant *4-cycle* parameter can be interpreted as evidence of network closure, the positive effect of *triangle* on tie formation and persistence was consistent with the negative effect of *4-cycle*. The observed patterns indicated the emergence of closed triads where all involved MIM apps shared audience with each other over time. Once formed, the triadic configuration was also more stable than expected by chance.

Besides network self-organization, app attributes played an important role in determining the evolutionary trajectory of audience overlap. Guided by research on network effects (Zhu & Iansiti, 2019), mobile social networks (Mac Carron et al., 2016), and e-commerce (Elberse, 2013), this study identified the mechanism through which app reach affected the formation and persistence of audience overlap. The MIM apps in the sample consisted not only of broad-reach messaging platforms with strong network effects, but also of unpopular platforms in the long tail. The analysis revealed that an app with a broader reach had a lower probability of tie formation. The heterophily effect (Rivera et al., 2010) was also supported in the context of networked mobile communication. Specifically, audience overlap was likely to occur between MIM apps with dissimilar levels of reach due to complementary benefits. These effects were observed after controlling for commercial, technical, and design features of mobile apps. Given that app reach did not influence tie persistence, narrow-reach apps were increasingly connected in the audience overlap network over time. Users of narrow-reach apps relied heavily on other MIM apps, especially broad-reach ones, for communication purposes.

Furthermore, the current study deepens our understanding of audience evolution and the media marketplace (Napoli, 2011; Nelson & Taneja, 2018; Nelson & Webster, 2016) by distinguishing the effect of reach from that of engagement on changes in audience overlap among MIM apps. The network evolution model indicated that app engagement was not a significant predictor of tie formation and persistence. Additionally, although reach and engagement (measured by time spent with media) captured different aspects of audience behavior in online environments (Nelson & Webster, 2016), the positive association between the two metrics became significant after the outbreak of COVID-19. This result suggests that the ongoing pandemic may affect the routine use of MIM apps. The effects of exogenous shocks on the evolution of personal media ecologies warrant further investigation.

Contributions

This study contributes to the literature on instant messaging by analyzing how MIM apps are used in combination with each other over time. Previous research mainly used a cross-sectional design and focused on single MIM services (Dogruel & Schnauber-Stockmann, 2021). Even when cross-platform MIM use was considered, little attention was paid to the interrelatedness among MIM services (Sheer & Rice, 2017; Valeriani & Vaccari, 2018).

In addition, the present study bridges across communication subfields, including cross-platform media use (Boczkowski et al., 2018; Tandoc et al., 2019), audience overlap (Ksiazek, 2011; Mukerjee et al., 2018), networked mobile communication (Campbell, 2019, 2020), media economics (Kim et al., 2020; Nelson & Webster, 2016), and communication network evolution (Monge et al., 2008; Xu et al., 2021). The evolutionary framework provides a novel approach to understanding user behavior in the mobile media market. This analytical approach can guide future efforts in theorizing and modeling dynamic changes in media systems.

Limitations and directions for future research

Several limitations need to be addressed in future research. First, media consumption data purchased from commercial firms like Comscore do not include individual level information (Taneja, 2016). Inferring individual choices from aggregate level data is challenging because cross-platform media use may vary significantly across gender, age, ethnic, education, income, occupational, political, and cultural groups. Future research can use other mobile tracking tools (see Christner et al., 2021, for an overview) to answer the question of how individual attributes affect the formation and persistence of the use of multiple apps.

Second, the narrow focus on MIM apps does not necessarily mean that similar effects would be observed in the audience overlap networks of other app types. However, previous research has shown that individuals are more likely to use multiple apps in the same category than those in different categories (Peng & Zhu, 2020), suggesting that the structure of audience overlap among apps in another category (e.g., Games) can be similar to that observed in this study. Another reasonable inference is that two apps in the same category would have a higher probability of tie formation and persistence in the audience overlap network than two apps in different categories. If recent findings on global Internet structure apply to app use (Ng & Taneja, 2019), it is expected that the patterns of the combined use of MIM apps in this study would be generalized to countries that share borders and languages with the U.S. or that have a much smaller Internet market size than the U.S. Future studies can test the above propositions to determine the generalizability of the empirical results.

Third, the analysis of audience overlap data provides little information on the extent to which the personal social network on one app overlaps with that on another app. As a result, the social implications of audience overlap require further investigation. For instance, does a high degree of audience overlap necessarily translate into a high degree of personal network overlap? How is the structure of hierarchically inclusive layers (Dunbar, 2014) reflected in audience overlap? The coevolution of personal network characteristics (e.g., size, centrality, brokerage, cohesion, diversity, and average tie strength) and cross-platform MIM use is another fruitful area for future research.

Fourth, a methodological limitation is that the STERGM analyzes only unweighted ties. Previous research has shown a significant difference in the centrality distribution between the weighed and unweighted versions of the same audience overlap network (Mukerjee et al., 2018), suggesting that dichotomizing network data may reduce significant effects of greater overlap. It is necessary to determine if the findings apply weighted ties when more sophisticated statistical techniques are available. The ordered stochastic actor-oriented model (SAOM) and the relational event model (REM) can both handle weighted ties and consider self-organizing properties in network evolution, but both techniques are incompatible with the Comscore network data. Specifically, the observed network is a media-level projection of user choices of MIM apps, so app owners have little agency in initiating, maintaining, and dissolving network ties, violating the assumption of the SAOM. By contrast, the STERGM does not assume high degrees of node agency and is therefore a better option than the SAOM. The REM requires that each relational event has a place in the ordinal or continuous sequence. However, Comscore provides no information about the temporal order of audience overlap within a month. For instance, there is no way to know whether the overlap between app *i* and app *j* occurred earlier than that between app *j* and app *k* in September 2020. Hence, the REM cannot be used to analyze the evolution of the observed network.

Conclusion

As instances of digital campfires (Wilson, 2020) in the contemporary media landscape, MIM services afford more closed and private modes of communication than do traditional social platforms. This study investigates changes in the use of multiple MIM apps from a dynamic network perspective. The analysis of audience overlap as network data reveals that the evolution of cross-platform MIM use is explained by self-organizing features and app reach, but not by app engagement. These findings shed light on the evolutionary dynamics of the messaging platform ecosystem in the age of smartphones.

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