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Separating and merging professional and personal selves online: the structure and processes which shape academics' ego-networks on academic social networking sites and Twitter

Katy Jordan

Institute of Educational Technology, The Open University, Walton Hall, Milton Keynes, Buckinghamshire, UK.

katy.jordan@open.ac.uk

Abstract

Academic social networking sites seek to bring the benefits of online networking to an academic audience. The ability to make connections to others is a defining characteristic of the sites, but what types of networks are formed, and what are the implications of the structures? This study addressed this question through mixed methods social network analysis, focusing on Academia.edu, ResearchGate and Twitter, as three of the main sites used by academics in their professional lives. The structure of academics' ego-networks on social networking sites differs by platform. Networks on academic sites were smaller and more highly clustered, whereas Twitter networks were larger and more diffuse. Institutions and research interests define communities on academic sites, compared to research topics and personal interests on Twitter. The network structures reflect differences in how academics conceptualise different sites and have implications in relation to fostering social capital and research impact.

Introduction

Social network sites (SNS) have revolutionised the ways in which we connect with others online. Following the success of generic sites such as Facebook and LinkedIn, a number of academic SNS have been developed to bring the benefits of online networking to an academic audience. While the main purpose of the site may vary, the defining characteristics of SNS include being able to create a profile, make links to others, and be able to consume, produce or interact with content created by their connections on the site (Ellison & boyd, 2013). Academic SNS which fit this definition may be divided into two categories: those which have been developed primarily as a SNS, to facilitate profile creation and connection (analogous to Facebook; examples include Academia.edu and ResearchGate), and those with a primary focus on posting and sharing academic-related content and have subsequently added social networking capabilities (such as Mendeley or Zotero).

Academic SNS can incorporate a range of different functionalities. Bullinger et al. (2010) consider the functions of ten academic SNS and propose four dimensions to a typology of academic SNS: information management; collaboration; identity and network management; and communication. Espinoza Vasquez and Bastidas (2015) recently built upon this work with analysis of four SNS use by academics, identifying the following themes: collaboration, online persona management, research dissemination, documents management, and impact measurement. There is also evidence that the typologies of functions may also apply to how academics use generic SNS (Van Noorden, 2014).

Although the technical affordances of academic SNS are varied, questions remain about how they are used in practice, and what types of social network are being fostered by the sites. The profile, as a virtual representation of self, is by definition a fundamental component of any SNS (Hogan & Wellman, 2014), and identity management is consistently highlighted as one of the main affordances of academic SNS (Bullinger et al., 2010; Espinoza Vasquez & Bastidas, 2015).

As academic SNS profile fields have certain requirements about demographic information relating to academics (such as subject area, institution, and job position) as a minimum, this has provided structured data readily available via web scraping

for studies which consider identity in terms of profile characteristics. This approach has been used to address questions about the extent of uptake of services by different demographic groups, and whether this reflects existing academic hierarchies. In analysing Academia.edu profiles, activity is linked to academic seniority, with more junior academics being consistently lower in terms of a variety of profile criteria. In two studies of Academia.edu profile completion, Faculty Members were found to outperform Postdoctoral Researchers, who in turn outranked Graduate Students, in the extent of their profile completion (Almousa, 2011; Menendez, de Angeli & Menestrina, 2012). This finding applied to aspects of profiles including the amount of personal information posted, connections to others, and uploaded content, while in contrast no differences were found in terms of activities related to questions posted through the site (Almousa, 2011; Menendez et al., 2012). Similarly, Faculty Members were also found to enjoy higher levels of profile views on the site (Thelwall & Kousha, 2013). Disciplinary differences have also been reported in terms of both choice of site and user behaviour. Academia.edu is consistently reported to be more popular with academics in the Arts and Humanities while ResearchGate is preferred by the Natural and Physical Sciences (Jordan & Weller, 2018; Ortega, 2015). Almousa (2011) drew upon scholars from Anthropology, Chemistry, Computer Science and Philosophy on Academia.edu, reporting that those in Anthropology and Philosophy showed a greater level of activity on the site (Almousa, 2011). The attention that profiles receive, in terms of the number of profile views, has been shown to vary by a combination of subject area, seniority and gender (Thelwall & Kousha, 2013).

However, quantifying profile characteristics captures the product, but not the process, of academics' digital identity construction and the dynamics that shape it. Academics are constrained in their definition of identity on academic SNS as the profile fields are set by the technical design of the platform (Kimmons, 2014). Studies typically focus upon a single platform, while academics are likely to construct their identity in different ways across the range of online tools that they use in relation to their academic practice (Veletsianos, 2016). Considering the experiences of three academics with SNS more broadly (via generic sites such as Facebook), Veletsianos and Kimmons (2013) provide an insight into the tensions associated with developing an academic identity online. This is expanded in their 2014 study of 18 trainee

teachers, which introduces 'acceptable identity fragments' as a concept to think about the multiple ways that their professional and personal identities are played out online (Kimmons & Veletsianos, 2014), and reiterates the challenges of tensions between them (Kimmons & Veletsianos, 2015).

In addition to constructing a profile, being able to connect to others is a defining characteristic of SNS (boyd & Ellison, 2007). The selective construction of connections may be part of the performance of an individual's identity online; for example, Donath and boyd (2004) coined the term "public displays of connection" and Hogan and Wellman (2014) describe SNS in terms of "relational self portrait[s]". As such, personal network structures fostered by SNS occupy an interesting space in relation to online identity, being both an attribute of an individual and shaped by the social context they are embedded within.

The network structures formed will have implications for the flow of information within the network, which is of particular relevance to academics seeking to use social media to enhance the reach and impact of their research. The concept of social capital can provide a lens for considering social network structures in terms of power and hierarchy. Social capital can be defined as the advantages conferred to an individual through their position within a social structure and linked to where an individual sits in relation to different communities (Burt, 2005). Greater bonding social capital is associated with being part of denser, more cohesive network structures, while bridging social capital is related to positions (such as brokers) linking different communities (Crossley, Bellotti, Edwards, Everett, Koskinen & Tranmer, 2015). Both bring attendant benefits and constraints; for example, those with high bonding capital may experience the benefits of solidarity but be constrained by social norms, while those with high bridging social capital may lack support but gain benefits from performing brokerage roles (Burt, 2005). Ways in which academic SNS can capture and metricise 'scholarly reputation' have become a focus for research on the topic (Jordan, 2018a), although metrics currently appear to rely on traditional publishing-related measures such as the journal impact factor (Jordan, 2015; Orduna-Malea, Martín-Martín, Thelwall & López-Cózar, 2017) rather than utilising the networks fostered by the sites.

Three existing studies have examined the social network structure of academic SNS, the first two of which examined the networks of connections between academics affiliated with particular universities. Jordan (2014) sampled the networks of academics associated with The Open University via Academia.edu, Mendeley and Zotero, while Hoffmann, Lutz and Meckel (2015) sampled a Swiss university on the ResearchGate platform. The results suggested clustering according to subject area or department (Jordan, 2014), and correlation between academic hierarchy and position within networks (Hoffmann et al., 2015; Jordan, 2014). Hoffmann and Lutz (2017) confirmed this finding and further tested the relationships between network structures and a range of research impact metrics through a larger sample of ResearchGate users. Some network metrics (principally follower and following counts) have been examined at a much larger scale through analysis of information harvested from the profiles of 87,083 ResearchGate users across 61 U.S. universities (Yan & Zhang, 2018; Yan, Zhang & Bromfield, 2018). Grouping institution according to their level of research activity for comparison, academics from higher ranked institutions are associated with greater numbers of followers and fewer followees, and connections are commonly made to other academics at the same institution (Yan & Zhang, 2018). By expressing the number of followers and followees as a ratio, the users' data is according to a typology of three behaviours; Information Source users (high followers, low following; 38.0%), Friend users (similar followers and following; 54.2%), and Information Seeker users (low followers, high following; 7.8%) (Yan et al., 2018). The prevalence of different user types is also shown to differ according to the research activity level of institutions (Yan et al., 2018).

This study therefore sought to gain a greater understanding of the structures of academics' social networks online. It advances the research agenda initiated by looking at academic SNS network structures at the institutional level (Hoffmann et al., 2015; Jordan, 2014) by focusing on the ego-networks of a sample of academics, and exploring the processes which shape the networks by discussing the structures with participants. The following research questions guided the study:

1. What are the structural characteristics of academics' online ego-networks on social networking sites?
2. How do academics construct and understand their ego-networks?

Methods

In order to both elucidate the network structures and explore the processes which led to their development, a mixed methods social network analysis approach was used (Dominguez & Hollstein, 2014; Edwards, 2010). Participants were drawn from a pool of academics who had previously completed an online survey and had indicated willingness to participate in network data collection and interviews (Jordan, 2017; Jordan & Weller, 2018).

Prior to launching the online survey, approval was sought and granted from the Open University Human Research Ethics Committee. As the research design involved multiple sources of data, informed consent was sought at each stage. The first page of the survey set out the projects' ethical policies, including data storage, anonymization and withdrawal from the study. The final page of the survey introduced the network data and interview stage, with an example of an ego-network visualisation, and asked participants to indicate if they would be willing to take part in the next phase. Finally, an interview consent form was sent to interview participants ahead of the interviews and discussed before starting each interview. This included additional ethical issues related to protecting identities as much as possible through removal of personally-identifiable information (including name, institution, specific subject area, for example) while not being possible to completely guarantee anonymity due to the public nature of the network data.

A purposive sampling approach (Arber, 2001; Teddlie & Yu, 2007) was applied in order to ensure that a range of different perspectives were included in the sample for network analyses. The following criteria were applied: those who use Twitter and an academic SNS (either Academia.edu or ResearchGate), and are based in the UK. The decision to sample from UK-based academics was primarily practical, in order to schedule follow-up interviews online but within the same time zone. It also controlled for variation according to difference Higher Education systems. Sampling was also stratified to ensure representation across three disciplinary areas (Arts & Humanities, Natural Sciences and Social Sciences) and job positions (PhD students, researchers, lecturers and professors). A total of 55 academics were included in the

sample on this basis. An overview of the demographic characteristics of the network analysis sample is shown in Table 1.

Table 1: Characteristics of the 55 academics included in the network sample. In addition to one academic SNS (specified below), Twitter networks were sampled for all participants except the eight shown in bold, due to having larger networks.

ID	Job	Discipline	Academic SNS sampled
3, 52	Professor	Social Sciences	Academia.edu
4, 51	Professor	Social Sciences	ResearchGate
5, 8 , 49	Lecturer	Social Sciences	Academia.edu
6, 50	Lecturer	Social Sciences	ResearchGate
9, 12, 47 , 48, 54	Researcher	Social Sciences	Academia.edu
11	Researcher	Social Sciences	ResearchGate
14, 44, 45, 46	PhD student	Social Sciences	Academia.edu
15, 16	PhD student	Social Sciences	ResearchGate
17, 18, 19	Professor	Natural Sciences	ResearchGate
20	Professor	Natural Sciences	Academia.edu
21, 22, 23	Lecturer	Natural Sciences	ResearchGate
24	Lecturer	Natural Sciences	Academia.edu
7	Lecturer	Natural Sciences	ResearchGate
10, 25, 26	Researcher	Natural Sciences	ResearchGate
27, 28	PhD student	Natural Sciences	ResearchGate
29, 30	PhD student	Natural Sciences	Academia.edu
1, 2, 31	Professor	Arts & Humanities	Academia.edu
32, 33, 34, 35, 53	Lecturer	Arts & Humanities	Academia.edu
36, 37, 38, 39, 55	Researcher	Arts & Humanities	Academia.edu
13, 40, 41, 42, 43	PhD student	Arts & Humanities	Academia.edu

Ego-networks were sampled from two platforms per participant: one specifically academic SNS (either Academia.edu or ResearchGate, and Twitter). The decision to sample from these platforms was informed by a recent large-scale survey undertaken by Nature, which highlighted the importance of Twitter use by academics for a range of purposes in their professional lives (Van Noorden, 2014).

Academia.edu and ResearchGate were included as the most well-known academic SNS, and disciplinary differences in the extent of uptake on one site or the other (Jordan & Weller, 2018; Van Noorden, 2014). In instances where participants use both Academia.edu and ResearchGate, the platform which they use more extensively was selected. The survey data indicated that Academia.edu and ResearchGate show a similar profile of purposes for use (Figure 1, redrawn from raw data and excluding non-users; NPG, 2014) so on this basis both Academia.edu and ResearchGate were included in the academic SNS network data sample. Table 1 shows the extent to which Academia.edu and ResearchGate were present within the

sample. During analysis, nonparametric (median) tests were carried out on the network metrics to examine whether any significant differences existed between the two sites, however all yielded non-significant results.

Figure 1: Percentage of respondents who are users of academic SNS and use them for particular purposes. Data for Academia.edu is shown in grey, and ResearchGate in black. Redrawn from raw data (NPG, 2014).

Automated tools were used to collect network data, between March and July 2015. Twitter data was obtained via their API using NodeXL (Smith et al., 2009); data from Academia.edu was collected using Mozenda, a commercial web scraping programme, while data from ResearchGate was collected directly by the researcher copying-and-pasting follower lists from all users in each ego-network as the service terms and conditions prohibit automated means. Data collection began in March 2015 and concluded within four weeks for the academic SNS; due to rate limiting, Twitter data collection carried on until July. In each case, the networks collected were directed graphs representing follower-following relationships. As nodes, this included the participant ('ego'), their followers (in-degree), and those who they are following themselves (out-degree). Edges represent any follower-following relationships which existed between the group of nodes.

Due to the restrictions that NodeXL places upon its access to the Twitter API, it was not possible to collect accurate network data for the largest networks. At the time of

data collection, NodeXL would not return the full list of users for followers or following values over 2,000 people. This was verified by comparing the size of the list of users returned by collecting data through NodeXL to the number of followers and following as stated on the participants' Twitter profile page. Eight participants were affected by this; data about degree, in-degree and out-degree was collected manually from their profile pages, but no network graphs could be created for these participants so they were excluded from the other network metric analyses. The restrictions also imply that there would be a risk of edges within the ego-networks not being collected. It is not possible to calculate the extent of data loss, but it is likely to be low, as any given edge would have two chances to be collected. Only instances where edges exist between nodes which both have in excess of 2,000 followers and following would carry a risk of being affected (Jordan, 2018b).

Network data was collected in the form of edges tables in Excel spreadsheets and imported into Gephi (Bastian, Heymann & Jacomy, 2009) in order to perform network analyses and generate visualisations. Additional analysis, principally in relation to determining brokerage roles, was carried out using Pajek (De Nooy, Mrvar & Batagelj, 2005). The nature of the social network data collected (i.e. ego-networks) defines the types of available analyses and metrics to an extent; analyses suitable for ego-networks are either topological (concerned with the size and structure of the network) or compositional (focusing for example upon the characteristics of network participants) (DeJordy & Halgin, 2008). An overview of the analyses and metrics suitable for ego-networks is shown in Table 2.

Table 2: Social network analyses appropriate for use in relation to ego-networks (Borgatti, Everett & Johnson, 2013; DeJordy & Halgin, 2008; Prell, 2012).

Types of analysis	Types of question	Appropriate metrics
Size	How many people is the participant connected to?	Degree; In-degree and out-degree for directed graphs
	How many communities is the participant part of?	Modularity
Structure	Does the participant connect people who would otherwise be unconnected?	Structural holes (betweenness centrality)
	How does the location of the participant mediate information flow between communities?	Brokerage roles (Gould & Fernandez, 1989)
	Are there many connections within the network, relative to its size?	Density
	To what extent are follower-following relationships mutual between ego and the others in their networks?	Reciprocity
Composition	Does ego connect to others like herself?	Homophily
	Are the alters similar?	Homogeneity

As the research questions are specifically focused upon eliciting the structure of academics' ego-networks, the metrics relating to the size and structure of the networks were implemented. Issues of network composition, including homophily and homogeneity, were also addressed to an extent through the interview discussion. While it would have been possible to address homophily and homogeneity to an extent by collecting further data from the alters' profiles, this was not undertaken for three reasons. First, for ethical reasons, as it would not have been practical to gain informed consent from all members of the networks. Second, differences in the extent of profile completion or frequency of profile updates would mean that the data were not guaranteed to be accurate. Third, the focus of the study is on how the participants perceive their networks, so the significance of the alters to

ego is of greater importance here. This approach did rely upon participants' recollection of individuals in the interviews. While the extent of recollection at the level of individuals varied, particularly with larger networks, participants could confidently identify the defining characteristics of different modularity classes throughout. Metrics which were implemented across the full sample of ego-networks and platforms were analysed via nonparametric statistical tests (Kruskal-Wallis and median tests), as a number of SNA metrics are not well described by Poisson or normal distributions (Barabasi, 2011; Field, 2009).

While the network analyses provided an indication of trends in network structure, it in itself could not explain the processes which led to the networks' creation. To address this, co-interpretive interviews were held with a sub-sample of participants. The combination of network analyses and co-interpretive interviews represented a mixed methods design striving for 'completeness', with the purposes of the qualitative data being to provide insight into the quantitative component (Venkatesh, Brown & Bala, 2013). The decision not to interview the full 55 network participants was made after considering the goals of the interviews within the research design and practical constraints. Determining how many qualitative interviews is appropriate is not a question which has a definitive answer but rather depends upon a combination of issues relating to the epistemology of the study and practical issues concerning the particular research setting (Baker & Edwards, 2012).

For practical reasons, considering the time involved in arranging, conducting, transcribing and analysing interviews, it was not possible to interview the full sample of 55 academics within the scope of the study. As the purpose of the interviews was to illuminate the quantitative network analysis findings through qualitative inquiry and open coding, it was not possible to know at the outset how many interviews would be required to achieve saturation (Ragin, in Baker & Edwards, 2012). However, the number of interviews required may not be large in practice; for example, reflecting on an earlier study, Guest, Bunce and Johnson (2006) suggest that the main themes were established after 12 interviews (although they caution that this figure would need to be greater if the sampled population were more heterogeneous). The decision was made to invite 24 academics to interview, in order to ensure that a range of perspectives in relation to discipline and job position were present (see Table 3), with the possibility of holding further interviews if necessary. In practice, a

sense of approaching theoretical saturation (Morse, 2007) was gained after the ninth interview.

The interview sample was constructed in order to include participants across a range of three disciplines and four job positions (Table 3). In instances where more than two eligible survey participants had indicated that they would be willing to take part in interviews, participants were selected at random. In some instances, there were insufficient respondents to be able to achieve two participants per combination due to not having more than one in the original sample, or non-response to the email invitation. 24 participants were invited to take part; two declined (one due to time constraints, and the other having left academia since the survey had been undertaken) and four did not respond, giving an interview sample of 18 participants. Interview participants were assigned pseudonyms which reflected their gender, alphabetically according to the order in which interviews were held.

Table 3: Pseudonyms assigned to interview participants, crosstabulated by job position and discipline.

		Job position			
		Professor	Lecturer	Researcher	Graduate student
Discipline	Humanities	Oliver	Nicola, Pippa	Carol	Isaac
	Natural Sciences	Harriet, Marilyn	Alice, David	Gillian, Kieran	Emily
	Social Sciences	Lucy	Frances, Rachael	Quentin, Beth	Jacob

For the participants selected to take part in interviews, the network visualisations were exported as web pages from Gephi using the Sigma.js exporter (Hale, 2012). These pages were then hosted on password-protected web space; links and login details were shared with participants ahead of interviews. The interviews were semi-structured in format (DiCicco-Bloom & Crabtree, 2006; Wengraf, 2001); a pre-planned interview schedule was used to ensure that key topics were discussed, informed by the results of the network analysis, but with enough flexibility to explore unexpected aspects if they emerged. The interview schedule is included in Appendix A. Each took place online via Skype; screen sharing was used so that both the interviewer and participant could see the network under discussion. Both audio and

screen video were recorded during each interview, using Camtasia; interviews were subsequently transcribed and imported into nVivo for analysis.

A grounded theory-based approach was used to analyse the interview data (Charmaz, 2014; Glaser & Strauss, 1967). This was chosen because of the lack of comprehensive pre-existing categories appropriate to the research topic, and to allow themes to emerge from the data and participants' perspectives without imposing assumptions at the outset. Initially, open coding was used. Open codes closely reflected the phrases and words used by participants, using constant comparison during the process. Second, open codes were combined into emergent categories. At this point, the emergent categories were applied to a fresh set of transcripts in nVivo, to check that the categories were applied consistently to the whole sample. Emergent codes in turn underwent axial coding into themes (Charmaz, 2014; Strauss & Corbin, 1998). A graphical representation of the process is shown in Figure 2.

Figure 2: Representation of the open codes, emergent categories and themes during the process of qualitative analysis.

The resulting coding scheme (shown in Figure 3) was applied in nVivo by a second coder to half of the transcripts in order to assess inter-coder reliability. This yielded a Cohen's Kappa value of 0.59 (Cohen, 1960). According to the most frequently used categorisations of Cohen's Kappa, this value falls within 'fair to good (0.40 to 0.75)' levels of agreement (Fleiss, 1981). While the full coding scheme comprises three levels, including network structure and connections, conceptualising platforms and role, and strategies and relationships with formal academia, the analysis and discussion here will focus upon the first two levels, as they relate directly to the two research questions at hand. The third level is less focus upon network structure and rather upon reasons for using the sites; see Jordan (2017) for further discussion.

Figure 3: Emergent coding scheme derived from qualitative analysis of co-interpretive interviews.

Results and Discussion

First considering the research question of ‘What are the structural characteristics of academics’ online ego-networks on social networking sites?’, the structural characteristics of academics’ ego-networks on academic SNS have been examined here in two principal ways: through metrics related to both network size and network structure. These basic measures can indicate how wide a pool of people ego can draw upon, and how widely information can be transmitted (Prell, 2012). An overview of the metrics is shown in Table 4.

Table 4: Overview of metrics for the SNA tests undertaken on the Twitter and academic SNS personal networks. IQR denotes interquartile range, and SD standard deviation.

Metrics			Twitter	Academic SNS
Network size	Number of nodes	Median	894	91
		IQR	936	122
	Degree	Median	1293	119
		IQR	1623	168
	In-degree	Median	777	68
		IQR	880	90
	Out-degree	Median	580	53
		IQR	626	86
	Modularity	Mean	4.79	4.29
		SD	1.06	1.26
Network structure	Network density	Mean	0.05	0.08
		SD	0.04	0.06

Reciprocity	Mean	0.36	0.41
	SD	0.08	0.13
Ego betweenness centrality	Mean	0.43	0.46
	SD	0.14	0.17
Brokerage	Modal type	Liaisons	Representatives

While the size of the networks involved shows a good deal of variation, there are structural features which are common across the dataset and social networks more broadly. Networks on both platforms show degree distributions which are steeply unequal with fat tails; that is, a large proportion of academics have relatively few connections, while a small proportion exhibit very high degree. This is a classic characteristic of social networks more generally (Barabasi, 2011). However, the number of people in the participants' ego-networks spans a wide range of values, and average network size is considerably larger on Twitter compared to academic SNS. Overall, participants have a higher average in-degree than out-degree (i.e. they have more 'followers' than they are 'following'), although there is variation in the data according to job position (Figures 4 and 5). An independent samples Kruskal-Wallis test confirmed that the distribution of in-degree on academic SNS varied significantly according to job position, $X^2(3, N = 55) = 11.834, p = 0.008$, with Professors demonstrating the highest in-degree (Figure 4).

Figure 4: Median average in-degree (grey bars) and out-degree (black bars) for academic SNS networks according to job position.

Figure 5: Median average in-degree (grey bars) and out-degree (black bars) for Twitter networks according to job position.

In addition to significant differences in network size in relation to job position, significant differences were found in terms of both discipline and job position for reciprocity. As the relationships between nodes in the network graphs are directed, reciprocity is a measure of the extent to which pairs of nodes are both following each other (mutual) rather than existing only in one direction. This gives us an indication of how strong the participants' ties are with the people in their ego-networks. It is measured here by calculating the proportion of mutual ties in terms of the total number of pairs of connected nodes in the network (Hanneman & Riddle, 2005). As

a proportion, values exist between zero and one; a reciprocity measure closer to one would indicate a high level of reciprocal ties within the network.

On academic SNS, significant differences in reciprocity were found according to discipline, with Arts and Humanities exhibiting higher levels of reciprocity (independent samples Kruskal-Wallis test, $X^2(2, N = 55) = 8.049, p = 0.018$). This trend was also seen in the Twitter data, although the differences were not statistically significant. On the other hand, the Twitter data did show significant differences in reciprocity according to job position, with graduate students showing the highest levels of reciprocity and professors the lowest (independent samples Kruskal-Wallis test, $X^2(2, N = 55) = 8.087, p = 0.044$). The trend is also reflected in the academic SNS, to an extent; professors show lower levels of reciprocity than the other categories, although the difference is not statistically significant. Note that reciprocity is measured here for the entire ego-network surrounding each participant, so reflects the level of reciprocity in the community surrounding them, rather than the participant alone. However, the disparity between in-degree and out-degree seen according to job position would suggest that personal levels of reciprocity are reflected in a similar way.

The number of communities within the networks was assessed by applying the modularity algorithm in Gephi (Blondel, Guillaume, Lambiotte & Lefebvre, 2008). The algorithm is a way of mathematically detecting communities, as defined by subgroups of highly-connected nodes within a network. Resolution was set to 1 (Lambiotte, Delvenne & Barahona, 2009). Modularity, a scalar value between -1 and 1, is a measure of the quality of communities detected within a network, based upon the difference between the density of links within and between different communities. The modularity algorithm uses an iterative process to assign nodes to different communities in order to maximise the modularity (Blondel et al., 2008).

In keeping with social networks more generally, communities (defined as clusters of highly inter-connected nodes, calculated using modularity) are seen within the network graphs on both platform, the median number of modularity classes within each network being four. Annotating the networks with information from the interviews revealed that in academics' ego-networks, modularity classes are more

frequently defined by institutions and research interests on academic SNS, compared to research interests and personal interests on Twitter (Figure 6).

Figure 6: Frequency of different types of community on each platform. Black bars represent academic SNS, and grey bars represent Twitter.

Higher average ego betweenness centrality suggests more structural holes may exist in the academic SNS (0.46) compared to Twitter (0.43). The platforms show a clear contrast in terms of the types of brokerage roles academics play. Brokerage roles provide a formal characterisation of where ego sits in relation to different groups (defined by modularity class) within their ego-network and how information is likely to flow between ego given the directionality of edges between them. Five possible brokerage types were identified by Gould and Fernandez (1989), illustrated in Figure 7.

Coordinator	Itinerant broker	Representative	Gatekeeper	Liaison
Broker is part of a community and mediates between other members of the same community	Broker mediates between members of the same community without being a member herself.	Broker mediates flow of information out of a community.	Broker mediates flow of information into a community.	Broker mediates between two different groups, neither of which she belongs to.

Figure 7: Typology of brokerage roles (Gould and Fernandez, 1989; Prell, 2012). Node 'A' is the broker in each; nodes are colour-coded according to membership of different communities.

For academic SNS, the modal brokerage type is 'representatives', a role which places academics in an outward-facing role mediating flow of information from a group. In contrast, ego most frequently plays a 'liaison' type brokerage role (that is, linking groups while not being closely affiliated with either) observed in Twitter networks. These results would fit with a characterisation of academic SNS as being used primarily as a form of dissemination network, while Twitter is a richer source of gaining novel information from diverse sources.

Overall, the trends in the data show that academics' personal networks developed on academic SNS are smaller, more dense, more highly clustered around discrete modularity classes and showing greater reciprocity. In contrast, Twitter networks are larger and more diffuse. To illustrate these differences in network structure, the networks of an approximately 'average' academic in the sample are shown in Figure 8.

Figure 8: Personal networks of an Arts and Humanities lecturer whose personal networks on both platforms are approximately average size overall according to degree. Left, Academia.edu, ranked 21st; right, Twitter, ranked 27th. Nodes are colour-coded according to modularity class.

Academic hierarchy is reflected in network structures, with seniority and institutional affiliations playing a greater role in influencing network structure in academic SNS

compared to Twitter. On both types of platform, professors show the highest average in-degree (number of followers), and the largest disparity with out-degree (the number of people that they choose to follow). In stark contrast, while graduate students have the fewest average in-degree and out-degree on academic SNS, they have the highest out-degree on Twitter, and have second highest average in-degree after professors. Researchers and lecturers show intermediate levels of both in-degree and out-degree on both platforms, with lecturers exhibiting a greater in-degree than out-degree on average compared to researchers on both platforms. This reinforces findings from analysis of Academia.edu profiles (Menendez et al., 2012) and ResearchGate network analysis (Hoffmann et al., 2015), which both suggest that academic SNS serve to preserve formal academic hierarchies. These trends in network structure suggest that academic SNS may preserve offline relationships and existing academic hierarchies to a greater extent than Twitter, reflecting differences in social capital more broadly facilitated by the different sites.

In addressing the question ‘How do academics construct and understand their ego-networks?’, participants accounted for structural differences in their ego-nets through differences in how they conceptualise the roles of different platforms in relation to their professional life. Academic SNS are regarded as a more formal academic identity, akin to a business card, or as a personal repository. As such, the network of connections formed is a largely a reflection of pre-existing professional relationships, such as co-authors and former colleagues:

[Academia.edu] “Yeah, they’re people that I kind of know of, or have been in a department with, or I’ve been a student with, or I’ve worked closely with. [...] it’s people that I know, not people who I want to get to know.” - Carol

Metaphors for academic SNS conceptualise the sites as either a virtual CV, or personal repository, or a combination of both roles. As such, academic SNS are viewed as ‘static’ and not sites which foreground social interaction. This confirms and elaborates upon Bukvova’s (2012) characterisation of academic SNS being used mainly as ‘visit card, curriculum vitae’, or an online ‘presence’. This perception is likely to be highly influenced by the design of the platform itself (Papacharissi, 2009), with the design of profile structure dictated by academic SNS reflecting expectations

of content associated with academic CVs and how their conception of authentic academic identity has been written into the platforms (Kimmons, 2014).

Twitter is viewed as a space where personal and professional are mixed, similar to a conference coffee break. A complementary metaphor emerged describing Twitter as being akin to social break times, such as cigarette breaks at work or coffee breaks at conferences. In contrast to academic SNS, Twitter both reinforces existing professional relationships and fosters novel connections. This is often linked to a perception that connections from in-person events may be pre-empted or reified by connecting via Twitter, or that Twitter provides a space akin to social events at conferences, creating connections that will then be drawn upon when the academics do meet in person.

“I found that being at the relevant conferences where those people are and also having that connection on Twitter as I said just nailed that first contact that people might recognise you from your profile and then there is a connection there [...] you almost kind of have a friendship before you get to events sometimes because you’ve exchanged opinions or resources on Twitter and then you go to a conference and you’ve almost got a ready made friendship in a way. It’s quite interesting and quite pleasant.” - Quentin

While academic SNS were described in purely professional terms, the merging of professional and personal creates a different environment for interactions on Twitter. Negotiating the divide between personal and professional can be seen as potentially problematic, but an expectation of some personal expression and authenticity is a defining part of Twitter to an extent.

“I think the hard thing for Twitter is to get the tone because I think it’s something less serious, but it’s not Facebook [...] but you should try to be a little more light-hearted when you can be, ‘cos I think people like to have this kind of mix, that there’s an element of a personal connection [...] as a researcher people want something a little bit more than the only thing you ever say is ‘here’s my latest paper’. - Frances

Expectations of authenticity and negotiating the balance between mixing and dividing the personal and private on Twitter reflect concepts of ‘context collapse’ and

'microcelebrity' (boyd, 2011; Marwick, 2010). In the context of Twitter, the interviews showed that the academics in this study are aware of these issues, and have developed strategies for negotiating them. It is also notable that these issues were absent from discussions on academic SNS.

"If you wouldn't say it in small talk at a conference, don't post it on Twitter." - Frances

Striking the right balance between personal and professional is challenging and an issue which the academics in this study are highly aware of. Strategies involved in presenting an authentic, professional yet personal, academic are a mix of choosing which information to divulge, the language used to do so, and awareness of how different audiences will perceive the tweets.

"I sort of enter into jokey conversations with people on Twitter, where there are levels of irony and sarcasm which you wouldn't use in an academic paper or something [...] in that sense there is sort of different registers of tone and language and presentation which kind of straddle that boundary between the personal and professional, and there are sort of ways of policing that boundary that don't just exist at the edge of social media."- Kieran

Several of the participants here discussed having considered or set up separate Twitter accounts for personal and professional identities (this was not perceived to be an issue for the exclusively professional academic SNS), although this practice often proved cumbersome and time consuming, and for the academics here at least, the professional identity would prevail but in combination with personal elements.

Perception of potential risk was coupled with academics' describing a range of personal mechanisms they had developed to mitigate these risks, using criteria based on imagined audiences (e.g. whether a grandparent would react badly to the content) or not openly discussing particular topics (e.g. politics). Such mantras touch upon all three dynamics of context collapse, invisible audiences and blurring public and private (boyd, 2008), and also to processes of managing microcelebrity which sit at their intersection (Marwick, 2010). The phenomenon of microcelebrity examines the processes by which individuals tailor their content on SNS in response to perceived audiences (Marwick, 2010). For example, if Isaac had a new paper out, he

would upload it to Academia.edu but not tweet about it; “I’m conscious of the fact that a lot of these people wouldn’t be interested in it”.

Conclusions

Together, the network structures and co-interpretive interviews support the idea that network structures on academic SNS are more hierarchical and preserve traditional academic power structures in comparison with Twitter, which affords greater opportunity for academics at all levels to connect with a wider range of individuals and audiences. For the academic SNS-based ego-networks in the sample, differences in in-degree and out-degree steeply favour following the most senior academics. Identification of clusters within the network using modularity and characterised through interviews with participants show that connections are largely based on existing working relationships and affiliations. Examination of brokerage roles most frequently observed in the academic SNS networks show that academics are typically aligned with outward transmission of information. In contrast, Twitter networks are larger, more diffuse, defining clusters identified by modularity class in relation to interests rather than institutions, and facilitating novel connections and information gathering. The interviews uncovered links between the contrasting ways in which academics conceptualise the roles of different platforms, and the network structures observed.

The characteristics of network structures observed on Twitter suggest that this platform may offer more potential for novel connections and opportunities for academics, which would help explain why it may be a better platform for generating social capital. The interviews allowed the network structures to be examined in these terms. By discussing the community structures with participants, academic affiliations and research specialisms define modularity classes, while institutional affiliations are less frequently present in Twitter modularity classes, which align with research topics and personal interests. The types of brokerage role performed by ego (that is, how the participant is positioned in relation to the communities they are linked to) is contrasted on different sites, with academics most frequently being 'representatives' on academic SNS, and 'liaisons' on Twitter. Representatives

mediate flow of information out of a community, while being in liaison-type positions mean that academics on Twitter are mediating the flow of information between communities which they are not strongly integrated into themselves (Prell, 2012).

The results clarify and extend findings from previous studies which have derived academic social network metrics directly from sites without user involvement. The finding that academics mainly connect to those with whom they have a pre-existing working relationship on academic SNS explains the observations of modularity in relation to departments in the Open University sample (Jordan, 2014), and homophily in terms of institutional affiliation in the US-based sample (Yan & Zhang, 2018). The sampled academic SNS ego-networks also provide a more detailed characterisation of trends observed in in-degree, out-degree and centrality measures according to different levels of academic seniority (Hoffmann, Lutz & Meckel, 2015; Jordan, 2014; Lutz & Hoffmann, 2017). This may provide an alternative explanation for some of the trends reported within the large ResearchGate dataset and analysis (Yan & Zhang, 2018; Yan, Zhang & Bromfield, 2018); while a range of metrics, including follower and followee counts, are reported to correlate with the research activity level of institutions, this may simply reflect differing staff to student ratios, as users' academic positions and demographic information were not considered in the analysis.

The finding that academic SNS largely replicate existing working relationships resonates with conceptualisations of self through SNS as 'public displays of connection' (Donath & boyd, 2004) or 'relational self-portraits' (Hogan & Wellman, 2014). However, in contrast to these concepts, the interviews place strong emphasis on existing relationships as connections rather than imagining a future academic self. This recasts their role as a 'relational CV', with implications for how users interact with network structures on academic SNS, and how academic SNS may usefully use network structures to enhance the experiences of using the sites for academics (network structure not being exploited by the sites at present).

The blurring of public and private (boyd, 2008) was found to be strongly influential on how academics conceptualise their use of different sites, the networks they foster, and how their personal and professional identities are expressed via different sites. The distinction between personal and professional identities being modulated by

different sites links to other work on academic identity online. Expression of professional identity online and its necessity to be tied to an authentic name contrasts with influential early work on digital identity, which emphasises identity construction, anonymity and pseudonymity (e.g. Turkle, 1996). While generic SNS platforms (such as Facebook) have enacted 'real name' encouraging policies in recent years (Ellison, 2013), expressing professional identity online arguably necessitates a singular (or at least primary), recognisable identity, to accrue professional reputation. These issues may go hand in hand, but as Kimmons (2014) argues, the concept of what constitutes an authentic identity varies according to different platforms, and digital literacies are required in order to prevent identity being prescribed entirely by the platform.

The findings of this study have practical implications, both for academics who wish to develop their online professional identity and use online social networks, and also for developers of academic SNS platforms. For academics, a major barrier to uptake of social media for professional use is a perception that sites are not useful, or lacking awareness of the roles that different platforms can play (NPG, 2014). The findings here emphasise that not all social media tools have the same affordances, and particularly the roles played by academic SNS and Twitter. For an academic wishing to develop their online presence, the choice of which academic SNS to use to host their formal identity and papers may be informed by the disciplinary differences observed between Academia.edu and ResearchGate. However, the potential for connecting with new professional connections and audiences through academic SNS is limited in comparison with Twitter, so it is recommended that academics host their identity and files on academic SNS but also share links to them through Twitter. The study highlights how the tools are particularly helpful for early career academics, and that for those who actively engage with the platforms, this can go some way to raising their profile beyond the academic hierarchy.

For those seeking to develop or enhance academic SNS platforms, the findings here show that the ways that academics conceptualise the sites and build their networks may be at odds with what the sites themselves seek to achieve. Academic SNS do appear to succeed as a way of hosting a formal academic identity and publications, and as such provide an important platform particularly to early career academics and are succeeding in their goals to act as a type of publishing platform. However, if the

social network structure is an important part of an academic SNS, further attention may be needed to assist in mechanisms to help academics connect, as the social network that grows organically largely reflects pre-existing connections rather than new ones.

To encourage network building, a greater emphasis could be placed on the contribution that connections make to the reward structures within academic SNS, such as the ResearchGate score. Current mechanisms for recommending who to connect to are largely based on pre-existing relationships such as co-authorship, citations, and shared institutions. Recommendations based on second-order network connections may be a useful way of surfacing beneficial latent ties.

There is also a question of whether academic SNS seek to replicate existing academic social hierarchies (as the network structure reflects at present), or to promote the flow of information through the network in novel and more equitable ways. If their goal is the latter, a rethink of the nature of connections may be beneficial. Having directed connections at present preserves hierarchy and one-way flow of information, which could be ameliorated if relationships were redefined as undirected, mutual ties (as is currently the case with Facebook and LinkedIn).

The characteristics of networks could also be used to the advantage of academic SNS platforms. At ResearchGate, the RG Score is described as a novel way of measuring academic reputation, although in practice it largely reflects impact factors of the journals in which an individual has published (Jordan, 2015; Orduna-Malea et al., 2017). Given that connections are frequently current or former colleagues, they would be well placed to verify the academics' reputation, which could be drawn upon through recommendation or testimonial features such as those current used by LinkedIn.

The study presented here has limitations, particularly in relation to the sampling. A relatively small sample was necessary in order to explore the network structures in greater detail and seek co-interpretation with participants. While the sample was constructed in order to ensure that a range of perspectives were included, the sample was self-selecting and only included UK-based academics. A combination of web-scraped and survey-based follow-up work would be valuable in order to confirm the findings with a larger sample. As academic SNS have been shown to vary in

popularity and importance in different countries (Thelwall & Kousha, 2015), exploring network structures with users from a wider range of locations would also be valuable. As the present study highlights the contrasting value of academic SNS and Twitter for academics building their online professional networks, there is also a question of how other parts of the social media ecosystem relate to these distinctions. Further work is currently underway to examine how academics' information sharing and perceptions of audience vary according to a wider range of platforms (Jordan, forthcoming).

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Appendix A

Semi-structured interview schedule for co-interpretive interviews.

Ice breaking:

Thank participant for survey participation

Recap on research progress so far

Recap on participants' job position

For each network (academic SNS first, followed by Twitter):

When did they start using the site? Why?

What were your impressions of the network graphs? Did they raise any questions?

How would you explain the communities (clusters) within the networks?

How would you explain the nodes which do not fit into communities?

As an academic, are there particular parts of the networks which you would consider to be more important? Why?

Are there any aspects of the visualisations which strike you as surprising or unexpected?

How would you explain differences in structure between the different networks?