Assessing information-sharing networks within small-scale fisheries and the implications for conservation interventions

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Abstract

The effectiveness of biodiversity conservation interventions is often dependent on local resource users' underlying social interactions. However, it remains unclear how fine-scale differences in information shared between resource users can influence network structure and the success of behavior-change

interventions. Using network null models that incorporate a pre-network data permutation procedure, we compare information-sharing networks in a Peruvian fishing community where a trial conservation intervention is underway to reduce the incidental capture of sea turtles (bycatch). We show that the general network structure detailing information sharing about sea turtle bycatch differs from other fishing-related information sharing, specifically in degree assortativity and eccentricity. This finding highlights the importance of assessing social networks in contexts directly relevant to the desired intervention and that fine-scale differences in the information shared between resource users may influence network structure. Our findings also demonstrate how null model approaches developed in the ecological sciences can elucidate important differences between human networks and identify the social contexts which might be more or less appropriate for information-sharing related to conservation interventions.

Keywords: Bycatch, null model, permutation, social network analysis, sea turtle.

Introduction

The conservation and management of common-pool natural resources such as fisheries often involve behavior-change interventions with resource users[1,2]. These include interventions like the enforcement of rules, social marketing, and education campaigns[3-5]. Informed by other behavioral-change disciplines such as public health and social marketing, the fields of conservation science and natural resource management are increasingly looking to understand the social structure of communities targeted for interventions, to predict how information flows influence the transmission of pro-environmental behaviors through these networks[6,7].

One conservation issue that could be improved by better integration of social-based interventions is the management of fisheries bycatch (i.e., the non-target portion of the capture that is discarded dead or injured to the extent that death will result[8]). Bycatch remains a critical issue throughout the world's fisheries[9,10] with notable impacts to taxonomic groups with conservative life history characteristics like sea turtles,

seabirds, marine mammals, sharks, and corals[11]. Managing bycatch is a particularly challenging issue among geographically dispersed populations of resource-constrained small-scale fishers in lower- and middle-income countries[12,13]. For example, in Peru, many small-scale fisheries are economically reliant on gillnets[14], which can have significant impacts on marine megafauna populations[15-18]; the capture and subsequent mortality of sea turtles in gillnets are a particular conservation concern throughout Peru's northern ports and landing sites[16,19,20].

Social network analysis is widely used in many academic disciplines including sociology, biology, economics, psychology, and computer science to quantify individual social interactions, assess emergent structure, and potentially measure social processes[21-23]. Taking a network approach to conservation issues like mitigating bycatch in Peru's coastal fisheries can support our understanding of human behavior by providing insight into particular social processes. For example, many conservation-orientated behavior changes are complex, and adoption is through social influence[1,24,25] and social reinforcement[26], which occur through interpersonal communication, and the evaluation of credibility and social norms between peers[27-30]. In resource harvesting communities that lack institutional capacity and where state oversight is weak, such as small-scale fisheries, individual decision-makers are subject to fewer legal constraints and are more prone to influence by their peers[31]. For example, Alexander et al.[32] found that fishing experience dictates the influence among small-scale fishers in Jamaica, with older fishers and information brokers having discrete roles in shaping catch patterns for large- and small-sized fish species, respectively. In small-scale fisheries management, social network analysis has also proven useful for understanding the social dynamics of information sharing between fishers[33], considering the establishment of common rules and norms among stakeholders[34,35], identifying information brokers in communities concerning specific conservation objectives[32], and understanding complex social-ecological interactions to enhance conflict resolution strategies[36]. Now, it is becoming increasingly recognized that social networks offer a powerful lens through which to understand the social and ecological contexts in which conservation in enacted. As such, further research into understanding how network approaches developed in the social sciences relate to those

developed in ecological science, and the benefits of all types of approaches for the many questions within social networks, will now be of great benefit.

Network null models (routines that generate different types of null datasets against which the observed dataset can be compared) are a group of statistical models, commonly applied in ecology, for which developments may offer additional insights into particular questions which go beyond other statistical methods. Specifically, null models are especially useful when investigating hypotheses in datasets, control groups are difficult to establish, exogenous treatments are unavailable, and observations may be missing or biased[37-39]. As such, null model methods are important because network data is comprised of non-independent observations of multiple individuals, and small variations in how data are collected between respondents can easily generate patterns that appear as social structure[39,40]. Null models have been applied to network data in sociology since the 1970s[37] and discipline-specific developments have subsequently been made to statistical models such as exponential random graph models[41,42], conditional uniform graph tests[43-45] and quadratic assignment procedure tests [46-48]. Since the mid-1990s, the field of ecology has also made extensive use of null models to develop specialized hypothesis testing routines and treat underlying uncertainty or data collection methodology biases when interrogating non-human animal network data[49-51].

We apply null models that incorporate pre-network data permutations to fisher information-sharing data, to explore a potentially crucial, but currently untested assumption when analyzing social networks in conservation science and natural resource management – the structure of the network (i.e., which individuals are socially tied to one another, and who may share information) is consistent across different (albeit perhaps somewhat similar) information-sharing networks. This uncertain assumption implies that the social links measured in one network will also be important for spreading the conservation information of interest in another closely related network. For instance, in an exemplar and important study[52], it was intuitively assumed that information shared between fishers about fishing would be predictive of a finer-scale yet closely related environmental outcome – shark bycatch. Similarly, in a contemporary study[53]

investigating how 'key players' were positioned implementing broad conservation objectives, the social networks were based on similar information-sharing data mapping whom respondents fished with or exchange information about fishing. However, the most influential individuals in one economic or social network may not be the most influential people in a closely related information-sharing network, potentially changing expectations of individuals' influence regarding a specific conservation intervention.

When examining empirical networks, it is important to consider metrics that are relevant to the system (e.g., fishers and bycatch). The level of degree assortativity[54,55] (akin to degree homophily[56]) in a network is known to have important social implications for the operation and emergence of competition and cooperation (e.g., highly connected fishers may work together in a local fishing group). Degree assortativity can also influence the potential for social contagions to spread, given its starting point[27,57]. Suppose conservation practitioners seed information about a bycatch reduction initiative with a well-connected fisher in close contact with multiple other well-connected fishers. In that case, that information may flow more rapidly through the network than it would if it was seeded with a fisher with few social links on the network's periphery. However, evaluating who talks to who (i.e. directed network ties) has implications for how information may or may not flow. This is because individuals within a network can be highly central (generally nominated by many others) but just receive information – resulting in knowledge accumulation and the impeding rather than facilitation of information flow[28,58]. As well as assortativity-based metrics, assessing the variance in node centrality provides an informative and intuitive network measure regarding the uniformity of a network's structure, its resilience to perturbations, and the influence of start-points on social contagions[59-61] For example, node eccentricity measures how far a node is from the furthest other[62] and can be particularly informative when investigating the flow of information and transmission of behaviors across a network following an intervention.

We focus on a coastal fishing community in Peru with problematic sea turtle bycatch. At our study site, a local not-for-profit is undertaking a trial community co-management bycatch reduction scheme[63]. This

initiative intends to create direct incentives for the sea turtle bycatch reduction by giving price premiums to fish caught by fishers that follow bycatch reduction guidelines such as using light-emitting diodes on nets[64]. Timely bycatch information is conveyed to fishers by the not-for-profit[65], which has a vision of expanding the community co-management scheme, first to more fishers within the target community, and second to similar communities along Peru's coast. This expansion could be more cost-efficient if the not-for-profit better understood how messages about the bycatch-reduction initiative's existence and aims might spread.

In this study, we assess whether networks of information-sharing about sea turtle bycatch are structurally similar to networks for other information related to fishing (Table 1). We test the assumption that knowledge about information-sharing social networks should be transferable to a related information-sharing network of interest (other fishing issues and sea turtle bycatch, in our case). We illustrate how null model analysis techniques used in the ecological sciences may offer more in-depth insights into the fine-scale structure of human networks than could be gained from simple centrality measurement methods, and we provide insight into comparing information-sharing networks within a social system of high conservation interest. We conclude by discussing our findings in the context of research priorities for conservation science and highlight how our result can contribute to predicting how new information and behaviors may spread socially.

Results

We constructed nine full fishing-related information-sharing networks (Methods). Of the 165 skippers surveyed, 151 nominated at least one gillnet skipper from the site as a key contact they talk to about fishing success, while 116 fishers from the site were nominated at least once by other fishers surveyed. The networks resulted in a total of 427 fisher-to-fisher nominations (i.e., links between the 165 skippers interviewed) for one network or more (Supplementary Table 1). On average, fishers had 2.8 fisher-to-fisher contacts with whom they had formed communication links specific to fishing. Information-sharing networks per nomination averaged 7.7 (range 1-9). Fishers received on average 3.7 links (range 1–15) for one or more information-sharing network. Across the nine information-sharing networks evaluated (Table

1), sea turtle bycatch was discussed by fishers the least (61.6% of possible fisher-fisher links). In contrast, fishing location and fishing activity were discussed by fishers most frequently (both in 97.9% of the possible fisher-to-fisher links; Supplementary Table 1).

Structural differences between information-sharing networks

We separately assessed degree assortativity and node eccentricity of the sea turtle bycatch information-sharing networks and each of the other networks of information sharing related to fishing (Table 2). Across these networks, we compared how the observed statistics differed from edge-permutated versions of themselves. We considered the observed statistic to be significantly different from that expected under the null models when it fell outside the 95% range of the distribution of the statistics generated by the permutations (i.e., equivalent to significantly different at $p<0.05$ level in a two-tailed test).

Degree assortativity

For each fishing-related information-sharing network, we evaluated degree assortativity (the propensity for a fisher to be connected to others who are similarly (dis-)connected; referred to as degree homophily in the social sciences), as this is a primary structural component of the network[54,55] (Table 2). We found that networks of sea turtle bycatch information-sharing nominations show no significant degree assortativity in comparison to the edge permutation null models (Observed stat: 0.038, edge null model 1: mean ± SD = -0.005 ± 0.059; $p = 0.512$, edge null model 2: mean ± SD = -0.011 ± 0.059; $p = 0.39$). As such, there was no evidence for a non-random tendency for highly nominated nodes to be disproportionately connected to other highly nominated nodes, nor for rarely nominated nodes to be disproportionately connected to other rarely nominated nodes. The sea turtle bycatch information-sharing network differed markedly in this regard from all of the other information-sharing networks' (Fig. 2c), all of which had significantly higher degree assortativity scores than expected from edge permutation null model 1. In addition, all the other information-sharing networks' had significantly higher degree assortativity scores than expected from edge permutation null model 2 apart from the 'weather' and 'technology' networks, which fell outside the top

5% of the null network degree assortativity coefficients but were not significantly different in the two-tailed test (edge permutation model 2 two-tailed p=0.06) (Fig. 2d).

Eccentricity

We found that sharing of information regarding sea turtle bycatch had a significantly lower variance in node eccentricity than expected under the null models controlling for simple properties such as the number of nominations and degree distributions (Observed stat: 14.71, edge null model 1: mean ± SD = 41 ± 13.5; $p<0.01$, edge null model 2: mean ± SD = 22.66 ± 5.335; $p<0.05$). Importantly, sea turtle bycatch information sharing was again unique in this sense (Fig. 2d), as none of the other information-sharing networks were significantly lower than expected under null permutations of themselves (Supplementary Table 2). Six of the eight other networks showed significantly higher variance in node eccentricity than expected from a null model of their structure, which illustrates a particularly stark contrast from the sea turtle bycatch information-sharing network. These results demonstrate less variation in individuals' centralities across the gillnet skippers than expected in terms of sea turtle bycatch information sharing. In other words, gillnet skippers are more similar in how they share information about sea turtle bycatch with one another than expected, while this is not true for any other networks of information sharing. This conclusion also held when considering other measures of centrality. For supplementary information, we examined the variance in betweenness (as an alternative measure of centrality; Supplementary Fig. 3) and mean eccentricity for each network's nodes (rather than the variance; Supplementary Fig. 4). We also investigated the observed variance in node eccentricity in comparison to the null distributions (generated from the cross-network permutations; Supplementary Fig. 5) and the observed mean node eccentricity in comparison to the null distributions

(Supplementary Fig. 6). The findings demonstrated that the sea turtle bycatch information-sharing network generally held some structural dissimilarities to all other fishing-related information-sharing networks.

Cross-network correlations of dyadic links

If individuals' social behavior remains consistent across different aspects of their social lives, in terms of which individuals they form links with and the number of links they form, then the social networks across these contexts are expected to be correlated [66,67]. As individuals who share information to a particular topic, they may be more likely than a non-connected pair of individuals (dyad) to share a different topic of information (i.e., two gillnet skippers who know each other versus two that do not know each other). We, therefore, expected that information-sharing networks across the assessed information types that relate to fishing would be correlated. However, specific networks may be strongly correlated to one another, while other networks may be less correlated.

Gillnet skippers in our survey were asked to nominate individuals that they exchange useful information with about fishing and that they considered valuable to their fishing success. Respondents were then asked which type of fishing-related information they talk to each nominated individual about (Table 1). Given this system, we intuitively expected that information-sharing networks across the assessed information types would be correlated with one another, assuming that pairs of skippers (dyads) who share information within a specific network would be more likely to share information in another network. As such, we expected all the other networks to significantly predict information-sharing within the network of particular interest (sea turtle bycatch information). Indeed, the sea turtle bycatch information-sharing network significantly correlated with all other networks (unfolded corr; $r = >0.7$; standard $p<0.01$). We also tested this observed correlation against that expected under the general social structure (cross-network null model 1 - who gains information from whom overall; Fig. 1c) as well as controlling for the probability of nomination within each network (cross-network null model 2; Fig. 1d). Under these null models, we found that the dyadic directed links within the sea turtle bycatch information-sharing network were significantly

228 more correlated with four information sharing networks (regarding gear, locations, technology, and
229 regulations – see Table 1) than expected under the general social structure (Fig. 3). Although the sea turtle
230 bycatch information-sharing network held the highest raw correlation with networks of information
231 regarding fishing locations (unfolded corr; r = 0.78), the largest difference between the correlation expected
232 under the null models and the observed correlation was with information sharing regarding fishing
233 regulations (unfolded corr; r = 0.78; mean expected corr cross-network null model 1 r= 0.65, mean expected
234 corr cross-network null model 2 r= 0.65), suggesting that the fishing regulations network was particularly
235 predictive of sea turtle bycatch information links given the underlying social structure of the system.
236

237 **Discussion**

238 By combining a fine-scale survey of a small-scale fishing community with a network null model approach
239 that incorporates a pre-network data permutation procedure, we show that information-sharing networks
240 about an issue of conservation concern (sea turtle bycatch) are structurally dissimilar from other closely
241 related information-sharing networks that relate to fishing (Fig. 2), more so than expected by simple
242 differences in an individual's degree (how many people they are connected to). We also demonstrate that
243 specific fishing-related information-sharing networks can still be predictive of how information about sea
244 turtle bycatch is shared between fishers, even more so than expected under the nomination structure of
245 who nominated whom (Fig. 3).
246

247 ***Structural differences between information-sharing networks***

248 We found that the sea turtle bycatch network did not show any degree assortativity (i.e. homophily - gillnet
249 skippers talking to other gillnet skippers with a similar number of connections) despite the positive degree
250 assortativity patterns across all other fishing-related information-sharing networks (Fig. 2c and
251 Supplementary Table 1). This finding indicates that the usual mechanisms that drive information sharing
252 between gillnet skippers in the other fishing-related networks (and potentially social networks generally)
253 are not at play in the sea turtle bycatch information-sharing network[54,55]. The lack of discussion about sea

turtle bycatch between gillnet skippers with similar levels of bycatch may potentially occur if some San Jose gillnet skippers with higher rates of sea turtle bycatch do not realize or appreciate that they have higher bycatch than other gillnet skippers in the community[68]. Indeed, previous research and field observations have suggested that fishers with higher bycatch rates tend not to put much effort into actively avoiding sea turtles captures unless they are specifically incentivized to do so (i.e., through the local not-for-profit's trial bycatch reduction initiative)[63]. Our degree assortativity results suggest that managers should incorporate an educational discussion with fishers on the local variations in sea turtle bycatch rates, prior to undertaking the planned expansion of the bycatch reduction strategy on trial, to improve how information about the sea turtle bycatch reduction intervention is shared between fishers.

We also found that the sea turtle bycatch information-sharing network has less variance in node centrality than expected, i.e., a more uniform individual-level network structure (Fig. 2d and Table 2). The low variance in node eccentricity indicates that the sea turtle bycatch network has a more homogenous network structure than the other networks (and many observed social networks, where high variability in node centrality is common and can result in high-degree nodes forming[69,70]). This finding indicates that information about sea turtle bycatch will have less variation in the rate of diffusion throughout the San Jose skipper community, regardless of which skipper first started talking to other skippers in the community about the capture, compared to information-sharing in a network with higher variance in node eccentricity (e.g., the weather, fishing locations, fishing activity, and finance).

As an addition to the above points, we found less variance in node centrality (Fig. 2d) and less variance in mean eccentricity (Supplementary Fig. 4) in the sea turtle bycatch information-sharing network when comparing to the cross-network null models (Supplementary Fig. 5, 6). This lower variance shows that the variance and mean eccentricity is lower than expected, not just in comparison to the edge null models, but also lower than expected given the underlying social structure of who is connected to whom. This lower variance found when comparing the cross-network null models reinforces the hypothesis that the

network's fine-scale structure (beyond who talks to whom) is contributing to these patterns. For example, certain personality traits that gillnet skippers hold, such as whether they would be willing to work with a local not-for-profit organization to implement sea turtle bycatch reduction strategies on their boats in future, may be contributing to skipper centrality within the network. This finding demonstrates a particularly interesting use of comparing results across various null models that randomize different processes. Conservation scientists and practitioners can use this information to guide research into the underlying differences in attitudes, beliefs, and knowledge between gillnet skippers and other natural resource users in local communities of conservation focus[30]. These findings could inform the design of interventions that could be tailored to particular perspectives about conservation interventions and sustainable harvesting practices more widely than the marine conservation focus of the current study.

The lack of positive incentives for fishers to mitigate bycatch in the study system[63], coupled with a lack of fishers' understanding of vessel-level bycatch rates[68], leaves the possibility that some fishers may take sea turtle bycatch and not discuss it with anyone. Fishing practices in general will affect rates of bycatch, for example, discussions about gear, fishing location, weather, or fishing finances (which can influence decisions about when and what to fish), despite whether bycatch itself is the topic discussed. Further, social theory tells us that people are more likely to be influenced by those they have multiple overlapping or strong information-sharing ties with, rather than those they share only one type of information-sharing tie with[71]. Thus, exploration of whether weighted social ties comprised of multiple fine-scale information topics that relate to a conservation intervention (e.g., ties where fishers talk about sea turtle bycatch, gear, fishing location, weather, and fishing finances) are better at predicting behavioral change than a social network of a single higher-level information topic (e.g., fishing) warrants investigation. The application of null models that preform pre-network data permutations offers scope for direct comparisons of different underpinning processes, and also for encapsulating information on the weighting of edges when comparing networks between one another, a task various other approaches such as standard exponential random graph models[41,42] are not currently well suited.

306

307 ***Cross-network correlations of dyadic links***

308 Understanding correlations between networks allows for assessing skipper-to-skipper (dyadic link)
309 information-sharing differences between multiple networks. Insight into these differences helps identify
310 social contexts suited to conservation interventions, and more broadly, offers insight into the
311 generalizability of network research[72].

312

313 Using null model network-based approaches, we demonstrate that across all the networks assessed, the fine-
314 scale structures of our information-sharing networks are more similar than otherwise expected based on the
315 number of links or even who is linked to whom. While this similarity assures that in San Jose's gillnet
316 skipper network, knowledge about a social network based on general information spread should be
317 transferable into understanding how novel information spreads, the similarity also demonstrates that relying
318 on simple network measures without the use of the null model comparisons could potentially result in an
319 improper assessment of network structure. This result demonstrates the broad applicability of our network
320 null model approach. We also show the networks that are most closely related to the specific network of
321 conservation interest, offering a greater understanding of how information flows relevant to the broader
322 topic of information-sharing about fishing are structured and relate to one another (Fig. 3). Both these points
323 support the value of conservationist investing time and resources in more robust and comprehensive null
324 model network-based analyses when gathering and assessing network data.

325

326 Our results indicate that the fishing regulations network, followed by the vessel technology and
327 maintenance, fishing gear, and fishing location networks, are more correlated with the sea turtle bycatch
328 network structure than expected under the cross-network null models (Fig. 3). This finding gives insight
329 into how fishers perceive information relating to sea turtle bycatch. For example, the correlation between
330 sea turtle bycatch and the fishing regulation network could be because fishers perceive sea turtle bycatch
331 as something they must abide by, similar to fishing regulations (related to the business and governance of

332 fishing; Table 1). This correlation is supported by a supplementary structural analysis that shows that the
333 sea turtle bycatch and regulation networks are structurally dissimilar concerning node variance to all other
334 information sharing (Supplementary Results; Supplementary Fig. 3, 9, 10). While these results begin to
335 provide a more in-depth insight into how sea turtle bycatch information-sharing relates to other fishing-
336 related information and how this information is perceived by fishers, further exploration is needed to
337 determine the process underlying the structural differences identified.
338
339 ***Applying network models in conservation science***
340 Building on the foundations presented in this study, further investigation into the drivers of the differences
341 between the sea turtle bycatch network and other networks is warranted. For instance, how might individual-
342 level traits influence the information-sharing networks' structure and the transmission of conservation-
343 orientated behaviors? Structured network experiments offer significant potential in this area of research.
344 Centola[57] experimentally assessed an online fitness group to show that increasing the demographic similarity
345 of contacts directly increased the adoption of an online dieting program among both healthy and obese
346 participants. This study demonstrated that degree assortativity (homophily) between network neighbors not
347 only provides social reinforcement but can be a significant factor in spreading behavioral contagions.
348
349 Another immediate research need is to understand whether skippers' attitudes and behaviors govern the
350 social network links (e.g., measuring the relation through which influence flows will affect specific
351 behavior[73]) or whether the social network positions govern skippers' propensity to adopt positive attitudes
352 and behaviors towards sea turtle bycatch (e.g., using social selection models to examine whether attribute-
353 related processes affect network ties[74])? If the former is true, then interventions that seek to change the
354 group-level social norm about bycatch could be useful as a way of bringing peripheral fishers into the
355 intervention, for example, through campaigns to engender pride in conserving sea turtles. Whereas if the
356 latter is true, then interventions that seek to improve communication between peripherally located and
357 more central fishers could be a more effective strategy, such as setting up networking events to talk about

the issues around bycatch. Thus, research that assesses individual nodes' network positions, followed by the implementation of interventions in an experimental setting, and then a reassessment of nodes' network positions would be informative for conservation intervention design.

Finally, the future focus on the mode and extent of information transmission dynamics across different networks would be particularly useful. For instance, simulating the transmission of information under different scenarios could provide insight into how the mode in which behaviors may spread, and the network structure can alter information flow in natural populations[27]. More specifically, diffusion simulations could establish how different information-sharing networks differ in which nodes are of particular importance, and which strategies may be optimal for spreading new conservation initiatives.

Conclusion

We quantified the underlying structure of a small-scale fishery social system across nine information-sharing networks relating to fishing. We demonstrated how networks of information-sharing regarding a conservation-relevant topic (sea turtle bycatch) are structurally dissimilar from other fishing-related information-sharing networks, and the extent to which dyadic links can be non-randomly predicted from other information-sharing networks. Our results show how emerging network approaches (specifically null models that incorporate a pre-network data permutation procedure) allow identification of the extent of structural differences between networks and provides information about which other networks are best correlated with the conservation-relevant information sharing. Our findings highlight the need for further research on the use of network null modeling and cross-network comparisons to understand how information relating to a planned conservation intervention may spread through a network, which in turn could help inform messaging about conservation interventions that are salient to community members targeted for conservation interventions.

Materials and Methods

384 ***Study system***

385 San Jose, Lambayeque, Peru (6°46' S, 79°58' W) is home to 168 small-scale commercial gillnet skippers
386 that fish throughout the year. We surveyed 165 fishers representing 98.2% of the gillnet skippers at the site
387 between July–September 2017 (Supplementary Fig. 2b, Supplementary Table 1). Gillnet skippers in San
388 Jose are known to capture sea turtles in high numbers[19,20,75]. Green turtles (*Chelonia mydas*) are captured
389 most frequently, followed by olive ridley turtles (*Lepidochelys olivacea*), and leatherback turtles
390 (*Dermochelys coriacea*)[63]. Five gillnet skippers and their crew are currently involved in a trial community
391 co-management bycatch reduction scheme operating from San Jose that requires fishers to use light-emitting
392 diodes on their nets (Supplementary Materials). Skippers were deemed active if they fished from the San
393 Jose port with gillnets in the winter of 1 July – 30 September 2017. The network was surveyed during
394 winter as skippers actively fishing during these months are established fishers in the San Jose community
395 throughout the year. We define gillnets as encompassing surface drift gillnets and fixed bottom gillnets in
396 single or trammel net configurations. The total San Jose gillnet skipper population (n=168) was determined
397 using a combination of membership lists of the two main fishing groups in San Jose, lists of boats towed in
398 and out of the water with tractors, and key informant interviews (Supplementary Materials).

399

400 ***Data collection***

401 We collected social network data using a structured questionnaire with a fixed choice survey design,
402 where fishers were asked to consider up to ten individuals with whom they exchange useful information
403 about fishing and whom they considered valuable to their fishing success. Fishers were not asked who
404 they receive information from (Supplementary Materials). We developed our questionnaire based on key
405 informant interviews and relevant conservation science and social network analysis literature[76,77].
406 Questionnaires were trialed with fishers (n=8) in the Santa Rosa fishing community 17 km down the coast
407 from San Jose (Fig. 2a). In classifying fishing-related information, we classified two broad categories
408 about which we expect gillnet skippers to exchange fishing related information. These include 1) the
409 process of fishing, and 2) the business and governance of fishing. We then disaggregated these two broad

categories into nine fine-scale information-sharing types that relate to fishing (Table 1). Fishers were then asked to highlight which fishing-related information they discussed with each nominee. For each fishing-related information network, fishers were asked to consider relationships that they have had with other skippers, vessel owners, crew members, other fishery leaders, fishery management officials, members of the scientific community, boat launching/landing support, fish sellers/market operators, family members, and any other stakeholders they fished or shared information with about fishing (Supplementary Materials). Prior informed consent was obtained from all participants in this study. Pilot study data were not included in this study's analysis. Fishers were interviewed in their native language (Spanish). This research has Research Ethics Approval (CUREC 1A; Ref No: R52516/RE001 and R52516/RE002).

Statistics and Reproducibility

Social network construction

A social network was created for each fishing-related information type (Table 1). In each network, the nodes were the individuals, and the binary directed edges were the nominations by one node (sender) of another node (receiver) for this information type. All analysis was carried out in R[78] using the igraph package[79] for visualizing and processing the analysis and carrying out the network comparisons using the null models.

Structural differences across information-sharing networks

To investigate whether networks of information-sharing between individuals were similar across different information types, we examined the networks' structural properties in terms of their degree assortativity and the variance and mean of individual centrality (Table 2). To account for the effect of basic characteristics of the networks (e.g., number of links, degree distributions) we compared these observed summary statistics to null models, which allowed inference of structural differences and similarities over and above that expected from these simple differences using null models (Fig. 1).

Degree assortativity

436 The degree assortativity (or homophily) coefficient[55] measures the extent to which central nodes are
437 connected to other central nodes, and peripheral nodes are connected to other peripheral nodes based on a
438 particular trait. Positive values demonstrate degree assortativity, with perfectly homophilous networks
439 scoring 1, and negative values representing disassortment. When nodes of similar centrality are randomly
440 distributed in a network (i.e., fully disassorted), those networks do not always score -1 due to the
441 minimum value depending on the number of node types and the relative number of links within each
442 group[55]. For each of the information-sharing networks, we first calculated the assortativity by in-degree
443 (the number of nominations each interviewed skipper received). Degree assortativity measures the extent
444 to which 'individuals that are highly nominated are disproportionately connected to others that are highly
445 nominated' and 'individuals that are rarely nominated are disproportionately connected to others that are
446 rarely nominated'. This is the primary assortativity measure of interest as in-degree provides the measure
447 of which individuals provide information to others. However, as individuals differed in the number of
448 nominations they made within each information-sharing network, we also calculated the assortativity by
449 out-degree (the number of nominations each interviewed skipper made) to examine whether individuals
450 were also disproportionately connected to others who make a similar number of nominations as
451 themselves. As social networks often show assortativity by degree, we predicted that all the information
452 sharing networks would be positively homophilous by nominations made and nominations received (i.e.,
453 highly nominating and nominated individuals would be closely associated with highly nominating and
454 nominated individuals, whilst peripheral individuals would be more likely to be connected).
455
456 Eccentricity
457 We aimed to consider node-level properties that depend on the structure of the social network (Table 2).
458 For this purpose, we used node eccentricity (igraph package[79]) that measures how far a node is from the
459 furthest other[62]. Although this metric describes a node's position within the wider network, the range of
460 potential values it can take is not overly affected by permutations of the network structure in comparison
461 to other more vulnerable metrics (e.g., betweenness, clustering) which are innately dependent on multiple

aspects of the set structure of the network and are intuitively expected to differ largely from permutations by default. Finally, this metric is also relatively fast to compute; this is particularly useful when calculating it for many iterations of null networks. As such, we computed the variation in eccentricity in 'received nominations' (in-eccentricity) for each of the information sharing networks.

Null models for structural differences

Drawing comparisons of network structure, correlations, and node positions across different networks requires particular consideration because the general structure of the network (such as the number of links or degree distributions) has a large effect on the observed values obtained from standard summary statistics. This structure can be taken into consideration by comparing networks to null permutations (controlled randomizations) of themselves and recalculating the same summary statistics on the null networks. Through comparing the observed values of the summary statistics to the distribution of those statistics generated from the null networks, insight can be gained into the actual differences between observed networks across other networks, over and above what is expected from simple properties such as the number of links.

When calculating summary statistics (in-/out-degree assortativity, eccentricity) of each of the information-sharing networks, we also compared these to the values generated from permuting each of the networks separately. Specifically, we carried out edge permutations. The first edge permutation simply allowed the randomization of all in-going links, while maintaining the number of nominations (out-going links) each individual made within this information-sharing network (termed edge null model 1 - Fig. 1a). The second edge permutation was a more conservative version of this, allowing swaps of links (which individuals nominated which other individuals in this information-sharing network) but maintaining the number of nominations each individual made in this information-sharing network (termed edge null model 2- Fig. 1b). Separately, for each of the information-sharing networks, 1000 permuted networks (of both of these permutation types) were generated and the distribution of the summary statistics were calculated for them.

Cross-network correlations

To reveal the extent to which the sea turtle bycatch information-sharing networks can be predicted from the other networks evaluated, we examined the dyadic similarity between the different information-sharing networks. We used cross-network null models to compare the expected correlation between each network and subsequently determined how the observed correlation between each network was driven by fine-scale structure over-and-above that expected from the system's general social structure. To examine the relationship between each network of dyadic information-sharing nominations, we calculated the correlation between the dyadic nominations on the unfolded network matrices. This approach is somewhat analogous to the Mantel test[80] (that tests the correlation between two matrices), yet as the networks were directed (and non-symmetrical), this was applied to the entire matrix rather than the lower triangle part (but excluding the diagonals because 'self-nominations' were not possible). The calculated correlation statistic represented the similarity/dissimilarity in the directed dyadic nominations amongst networks (who nominates whom), and these were compared to the distribution of the correlation statistic generated from the null models. To infer the extent to which networks are more, or less, similar than expected under the general dyadic social structure, we carried out a cross-network null model: For each dyadic nomination across any of the networks, we randomized the networks that these nominations were made within (termed 'cross-network null model 1' – Fig. 1c). As an even more conservative version of a cross-network null model, we created a new version of these permutations and controlled for the number of nominations that took place overall within each network (termed cross-network null model 2 – Fig. 1d; Supplementary Fig. 7, 8).

Data availability

The data and R scripts that support the findings of this study are available at https://github.com/JoshFirth/bycatch_information_flow.

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696 **Competing financial interests.** The authors declare no competing financial interests

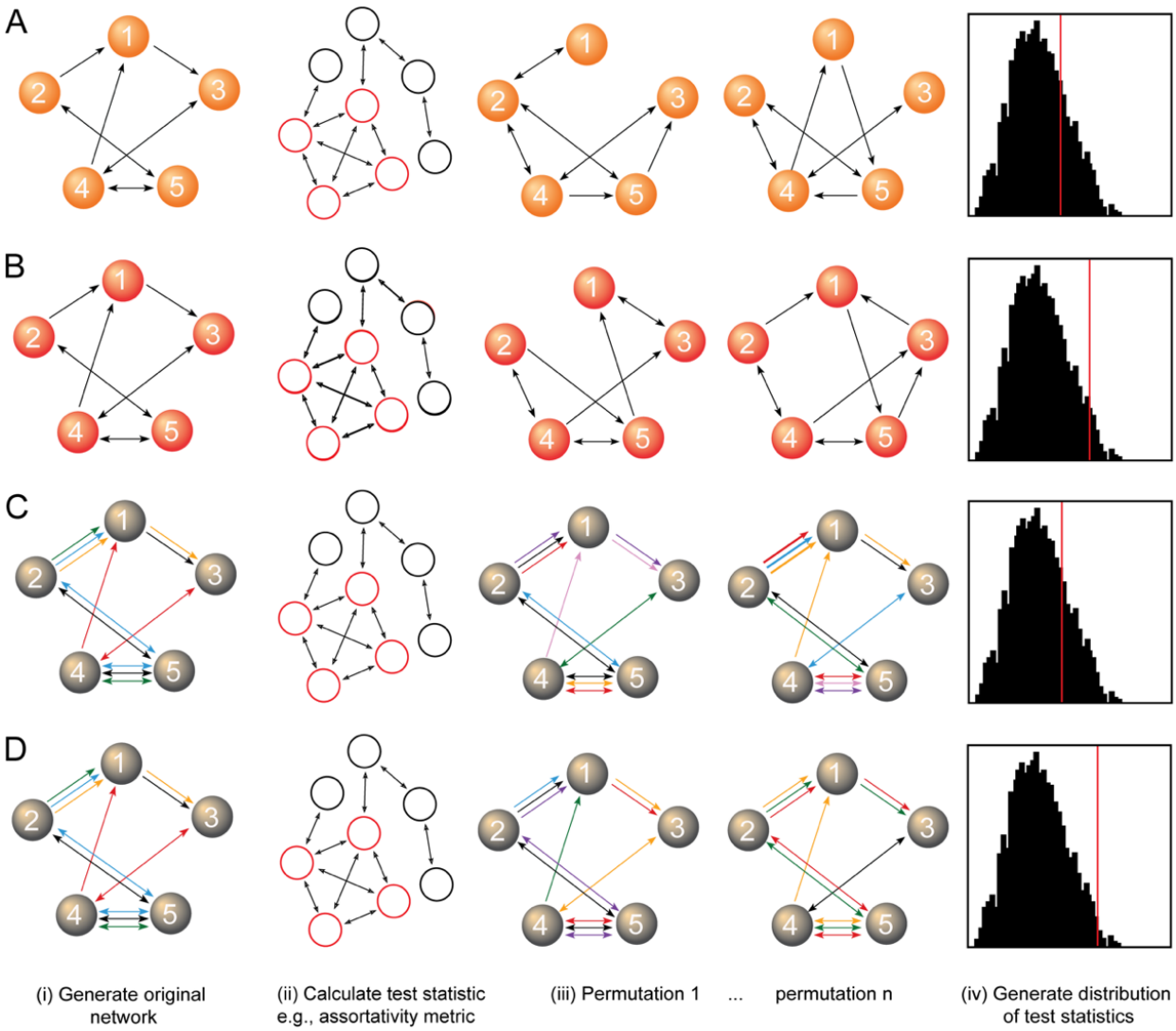


Figure 1. Schematic representation of edge-based permutation models with directed network data. Four main null model steps include (i) creating a social network from the observed data, (ii) calculating a test statistic, for example, a network-level metric like degree assortativity (high-degree nodes that are colored red primarily connect to other high-degree nodes), (iii) randomizing the observation data (typically with 1000 permutations), and (iv) recording the distribution of possible test statistics. Conclusions can then by drawn by comparing the observed test statistics to the distribution test statistics, and the *P*-value calculated. Throughout the edge swap permutations, the node positions remain the same, but the configuration of edges between nodes change based on select criteria. The four null model examples shown are all used in this paper's analysis. Edge permutation **(A)** allows the randomization of

all in-going links, whilst maintaining the number of nominations (out-going links) each individual made, **(B)** only allows the swap of links, by maintaining the number of nominees (in-going links) and nominations (out-going links) each individual made in this information-sharing network. The cross-network permutation **(C)** maintains each dyadic nomination, but randomizes the networks that these nominations were made in (i.e., when individual X nominated individual Y for information sharing within three different information-sharing networks (represented by different colored arrows), the cross-network permutation allows these three nominations to be reassigned to any of the nine possible networks), and **(D)** maintains each dyadic nomination, but randomizes the networks that these nominations were made in, while also controlling for the number of nominations that took place overall within each network (i.e., when individual X nominated individual Y for information sharing within three different information-sharing networks, these three nominations were reassigned amongst the networks in a way that was equal to the number of nominations in each network).

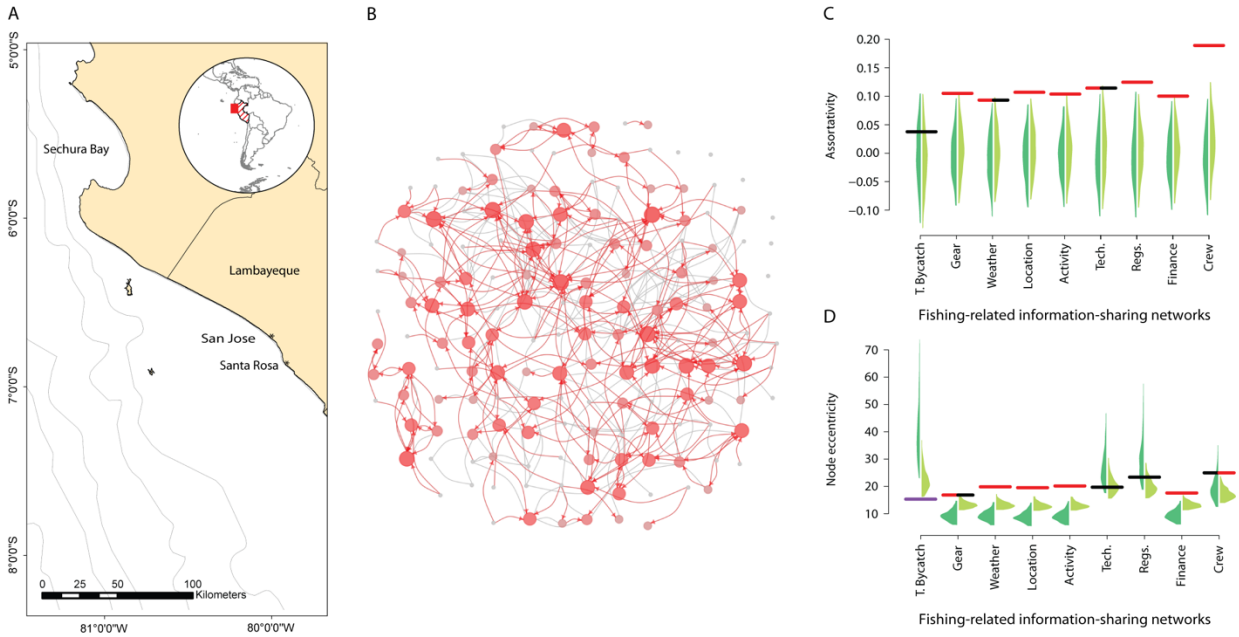


Figure 2. Structure of information-sharing in relation to sea turtle bycatch. (A) A map of the study site, San Jose, Lambayeque, Peru (6°46' S 79°58' W) and the surrounding coastline. Depth contours show 200, 1000, 3000, and 5000 meters **(B)** Illustrative network of the structure of information-sharing in relation to sea turtle bycatch. The nodes show each of the skippers and the adjoining lines show which dyads shared information in at least one information-sharing network, and nominations within the sea turtle bycatch network is highlighted as a directed red arrow here (arrow points to the one that was nominated). Node size and shading shows the number of nominations each individual received for sea turtle bycatch information (largest and most red = most nominations, small and grey = no nominations). Layout was set as a spring layout of edges across any network (to minimize overlap) and then expanded into a circular setting. See Supplementary Fig. 1 for illustrative comparisons across networks. **(C)** The observed in-degree assortativity (homophily) in comparison to the null distributions for the different information-sharing networks, and **(D)** the observed variance in the node eccentricity in comparison to the null distributions for the different information-sharing networks. Horizontal lines show the observed values from the actual networks (red = observed values are above the permutations, black = observed

values are within the range of the permutations, purple = observed values are below the permutations). Polygon distributions show those generated by permutations (dark green = outgoing edge permutation that maintains the no. of nominations each individual makes, light green = edge swap that maintains the no. of nominations each individual makes and also the number of times each individual was nominated). Due to differences in network factors, direct comparisons between the observed values are not informative. For details on each fishing-related information-sharing network assessed refer to Table 1.

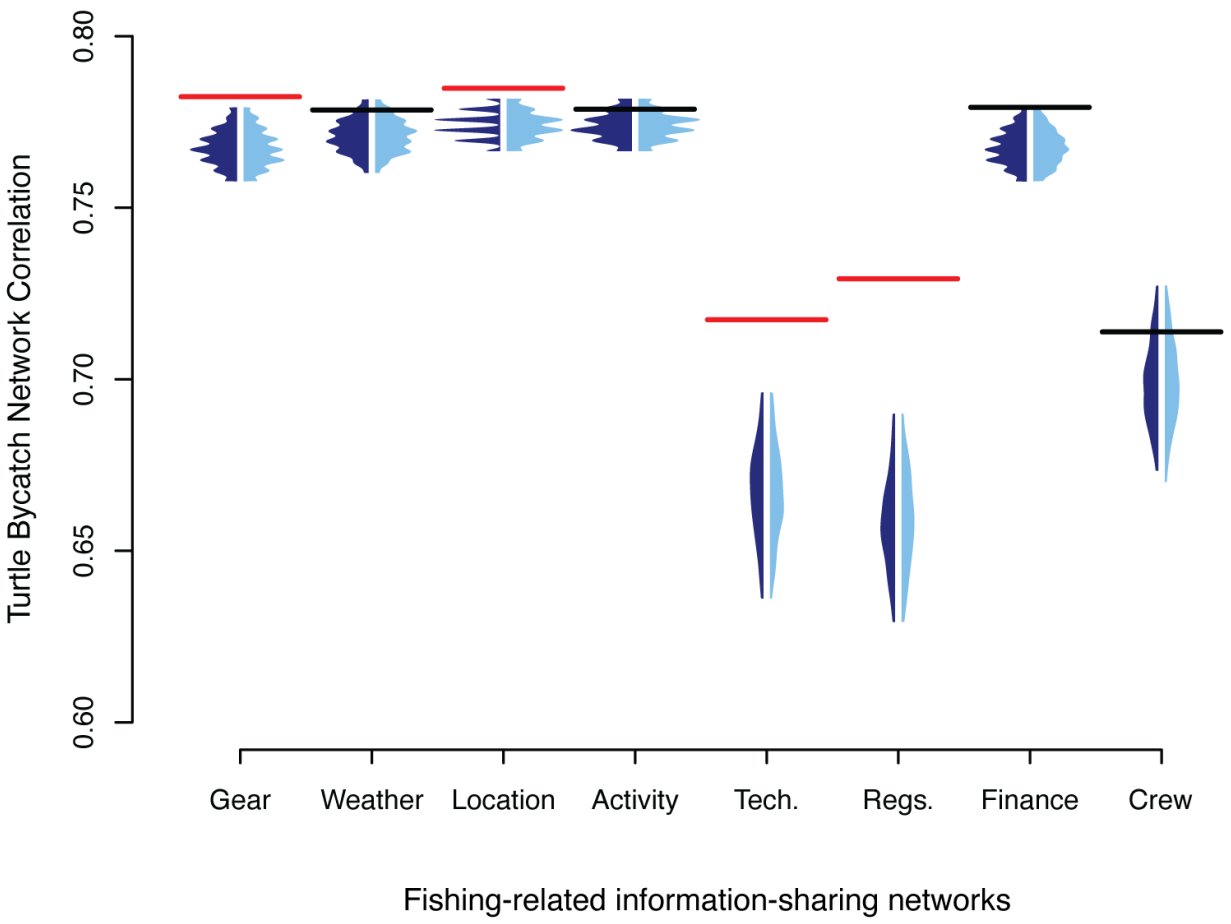


Figure 3. The observed correlation (and the correlations expected under the null models) between the sea turtle bycatch information-sharing network with all the other information networks. Horizontal lines show the observed values from the actual networks (red = observed values are above the permutations, black = observed values are within the range of the permutations, purple = observed values are below the permutations). Polygon distributions show those generated by permutations (dark blue = network swap that maintains the no. of nominations each individual makes and also the number of times each individual was nominated, but swaps the network these were made within whilst maintain the number of times each network was nominated as overall, light blue = conservative network swap that is the same as dark blue, but also maintains the number of networks each dyad nominated each other for – but changes those networks (same as a gbi permutation but on the dyad-by-network edges). Comparison between networks can be made by comparing the distance between the observed values from the actual

755 networks (horizontal lines) and their associated permutation distribution (polygon) to the distance
756 between the observed and associated permutation for each network. Due to differences in network factors,
757 direct comparisons between the observed values are not informative. For details on each fishing-related
758 information-sharing network assessed refer to Table 1.

759

760 **Table 1.** Information-sharing networks that relate to fishing.

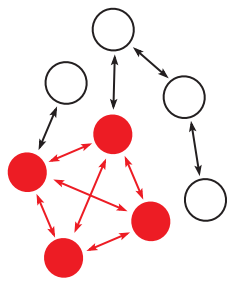
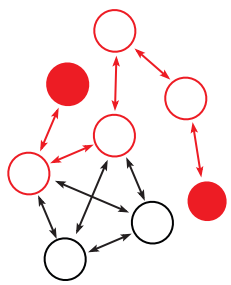
Full name	Short name	Description	Broad categorization
Sea turtle bycatch	T.Bycatch	Sea turtle bycatch encounters including live releases and mortalities in nets.	Process of fishing, Business and governance of fishing
Gillnet type & maintenance	Gear	Changes made to net configuration (shifting rigging configurations from surface drift net to mid-water drift net or bottom-set net), and net maintenance.	Process of fishing
Weather conditions	Weather	Ocean and weather conditions (e.g., wind, swell).	
Fish location & catch sites	Location	Where fish might be located and where they have been travelling to fish.	
Fishing activity	Activity	How many people fishing, who is fishing, who caught what.	
Vessel technology & maintenance	Tech	Existing and new technologies used onboard the vessel (e.g., echo sounder, compass) and vessel maintenance (e.g., hull repairs, painting).	
Fishing regulations	Regs	Fishery policy and legislation.	Business and governance of fishing
Fishing finances	Finance	Market prices, loans, fines, penalties.	
Crew management	Crew	The hiring and instructing of crew onboard the vessel.	

761

762 **Table 2.** Network metrics used to assess information-sharing network structure. For network structure, red nodes (circles) and links (arrows)

763 outline the represented metric in the network.

764

Metric	Network structure	Definition	Theoretical use in conservation-relevant systems	Example
Degree assortativity (homophily)		A preference for nodes to attach to others that are similar in some way (e.g., high-degree) [55]	Identifies individuals and pathways of individuals that could facilitate widespread diffusion of information about conservation initiatives in a community of conservation interest.	The authors use simulations of animal data to assess how variation in simple social association rules between individuals can determine their positions within emerging social networks. The results show that simple differences in group size cause positive assortativity and that metrics of individuals' indirect links can be more strongly related to underlying simple social differences than metrics of their dyadic links[81].
Node eccentricity		The furthest network distance between a node and all other nodes in the networks [62]. The equivalent to the inverse of some definitions of 'node closeness'	Can inform whether or not information relevant to a conservation initiative is shared in an even or clustered manner throughout a community on interest. This can inform how social norms and personal beliefs might affect information flow, which in turn can allow for conservation practitioners to tailor interventions to particular perspectives about a harmful activity (e.g., bycatch).	Using social network analysis and several centrality measures including 'node closeness' (also equivalent to the inverse of some definitions of 'node eccentricity') the authors assess the structural nature and expanse of climate-based communication between professionals across sectors in the Pacific Islands region. Their results show a simultaneously diffuse and strongly connected network, with no isolated spatial or sectoral groups. The most central network members were shown to be those with a strong networking component to their professions [82].

765