Network Influences on Behavior: A Summary of Tom Valente's Keynote Address at Sunbelt XXXV: The Annual Meeting of the International Network for Social Network Analysis

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Tom Valente's 2015 keynote address overviewed his career focused on network models of the diffusion of innovations and behavior change, where he made his mark as a skilled theoretician. He is well known in the academic community as a willing collaborator and networker. He has made singular contributions to network models of the diffusion of innovations, including the role of opinion leaders, and network interventions to promote behavior change. Tom's keynote featured empirical findings from applying his theoretical models to classic diffusion datasets and current work focused on the diffusion of global tobacco policy. He concluded his talk with a summary of network interventions, which may be used to guide intervention development, evaluation, and dissemination (Valente, 2012; Valente, Palinkas, Czaja, Chu, & Brown, 2015). His keynote address emphasized not only his scientific contributions but also how his career was guided and influenced by colleagues, friends, and mentors.

Tom's work highlights the need to examine personal network exposure and thresholds in addition to exposure from the whole network when assessing behavior, behavior change, and intervention effects. Diffusion of innovation theory explains how ideas, behaviors, and products spread throughout a network (Valente & Rogers, 1995). Tom expanded upon diffusion theory for his dissertation by providing theory and techniques for integrating threshold and critical mass models with the diffusion process (Valente, 1995). Tom's network threshold model differed from Granovetter's (1983) threshold model in that Granovetter's model was predicated on people's innovativeness relative to the whole system, whereas Tom calculated thresholds relative to an individual's personal network. The novelty of Tom's dissertation was that some people are innovative relative to the whole community, but late adopters relative to their personal network and vice versa. A person's position in the network determines their exposure and people can be late adopters because their network position is such that they learn about the innovation late.

In order to complete a dissertation on network diffusion, Tom needed data. He realized that he needed to acquire secondary data to analyze as diffusion data can take years to collect since diffusion takes a long time. At this point in time (1989), few network diffusion studies had been conducted and of these some were lost. Of the studies he identified, data from three of them could be obtained and these became the three classic diffusion network datasets: Medical Innovation (Coleman, Katz, & Menzel, 1966), Brazilian Farmers (Rogers, Ascroft, & Röling, 1970), and Korean Family Planning (Rogers & Kincaid, 1981). These three datasets have been

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submitted to Connection's data exchange network and will also be made available for use in UCINET as well as in netdiffuseR, a new R package Tom is developing with George G. Vega Yon. To appreciate the challenges of obtaining these data in a pre-internet era, Tom shared some stories about how he got them. One story related to obtaining the Korean Family Planning data, which Rogers had given to Mark Granovetter, the Sunbelt X keynote speaker. Tom wrote to Granovetter who replied with a letter from Mark's colleague Dr. Roland Song (Figure 1) along with the only copy of the data which was stored on a Vax 750 tape, a data storage format that was outdated even at this point in time (1990).

Tom outlined the methods for and results from analyzing network exposure effects in the three classic diffusion datasets. The data were transformed to an event history dataset, where each person has multiple rows in the dataset, one row for each year when they did not adopt and one row for the year they did, and a binary variable indicating adoption status for each time point. Then, a discrete hazard model was calculated including effects for time, socioeconomic factors, degree, and network exposure. Using this methodology, Tom began his dissertation work assessing if cohesion or structural equivalence exposures were associated with behavioral adoption using two of the three classic diffusion network datasets. He found that the time tendencies were different for the 3 studies, as shown in Table 1. The results suggested that there was no time tendency for the medical innovation data, late adoption for the Korean family planning data, and negative, then positive time effects for the Brazilian farmers data. In Table 2, ZH VHH WKDW H[SRVXUH KDG D SRV adoption for the Brazilian farmers study, but that there was no "contagion" effect for the other two studies. (NB: For Tom's dissertation he only had acquired the Korean Family Planning and Medical Innovation data, neither of which showed network effects.) This was alarming for Tom as diffusion of innovation theory suggests that the diffusion effect, the increasing interpersonal pressure to DGRSW DQ LQQRYDWLRQ DV LW GLI 7KLV ¿QGLQJ OHG 7RP WR GHYHORS model (Valente, 1996).

Figure 1: Letter accompanying Korean Family Planning Dataset

Table 1 Time tendences for likelihoods of adoption for the three classic diffusion datasets.

Likelihood of Adoption			
	Medical Innovation N=868	Korean Fam. Planning N=6,356	Brazilian Farmers N=10,085
Time 2	1.11	1.27	0.10*
Time 3	1.31	1.26	0.10*
Time 4	1.61	1.14	0.59
Time 5	2.20	1.47	3.37**
Time 6	2.80	1.60*	0.29
Time 7	3.71*	1.66*	0.29
Time 8	2.09	1.48	1.41
Time 9	1.52	2.65**	0.29
Time 10	0.53	1.96**	11.4**
Time 11	3.14		0.70
Time 12	2.20		5.65**
Time 13	1.55		2.26*
Time 14	3.73		6.01**
Time 15	4.85*		11.54
Time 16	1.17		11.67**
Time 17	1.24		18.1**
Time 18			16.9**
Time 19			22.26**

Note: *indicates $p < .05$, ** indicates $p < .01$

Table 2: Predictors of likelihood of adoption for the three classic diffusion studies (controlling for time dummies (Table 1)).

	Likelihood of Adoption		
	Medical Innovation N=868	Korean Fam. Planning N=6,356	Brazilian Farmers N=10,085
Detail Agents	1.27		
Science Orientation	0.60**		
Journals Subs.	1.63*		
# Sons		1.43**	
Media Camp. Exp.		1.10**	
Income			1.18**
Visits to City			1.00
Out Degree	0.96	1.05	0.98
In Degree	1.04	1.06**	1.02*
Exposure (Cohesion)	0.94	1.16	2.16**

Note: * indicates p < .05, ** indicates p < .01

While working on an evaluation of a media campaign to promote family planning in Bolivia, Tom found that the campaign did not increase contraceptive use. He had hypothesized that the combined effect of mass media and interpersonal communication exposures would be associated with contraceptive use, but the data did QRW VXSSRUW WKLV $W WKLV SRLQW 7RP ZDV DW KLV ¿UVW MRE working in a staff evaluation position at the Center for Communication Programs at Johns Hopkins University. Not wanting to report back to the program developers that their program was not effective, Tom applied the threshold model from his dissertation. Table 3 presents the results of the Bolivian campaign analysis when the GDWD DUH VWUDWL¿HG E\ SHUVRQDO QHWZRUN WKUHVKROG OHYH The Bolivia data showed that women with low thresholds to adoption reported higher exposures to the media campaign. The campaign was effective primarily for the women with low thresholds, in both panel and cross-sectional analyses. The threshold model provides a way WR PHDVXUH WKH WZR VWHS ÀRZ K\SRWKHVLV RI PHGLD HIIHFWV (Valente & Saba, 1998). More than just modeling a theory, this research suggests that intervention effects may be missed if network thresholds to adoption are ignored. Tom's analysis found that health media campaigns are effective, but mostly worked by increasing contraceptive use for those people lacking contraceptive users in their network (Valente & Saba, 1998). This study suggested that media interventions may interact with social network characteristics: Exposure, position, embeddedness, and so on. Many media interventions may be effective through peer communication and assessing media effects using the threshold model may prove useful when conducting such studies.

Tom pointed out that the problem with network diffusion studies conducted to date is that they have used static measures of networks and adoption data are often retrospective recall or from incomplete records. One of his recent projects is attempting to correct this shortcoming by analyzing diffusion with complete adoption data and multiple, dynamic networks. This project was instigated when Tom heard about GLOBALink, an electronic forum which was developed to facilitate communication on global tobacco control issues. One of the outcomes of tobacco control advocates' work has been the creation, UDWL¿FDWLRQ DQG LPSOHPHQWDV Convention on Tobacco Control (FCTC) Treaty. GLOBALink consisted of about 7,000 members over its 20-year history, providing a large dataset with multiple networks for diffusion network analysis.

The advantages of the FCTC diffusion data are that the adoption data are accurate, there is no missing data, and there are multiple, dynamic networks. The LQÀXHQFHV RI FRXQWU\ DWWULEXW UDWL¿FDWLRQV RI RWKHU FRXQWU international trade and GLOBALink networks using similar methodology to that used on the classic diffusion datasets. Results of this study indicate that exposure to WUHDW\ UDWL¿FDWLRQ LV SUHGLFW for some networks.

Tom wanted to do something more interesting with this dataset than just test prior theories. This inspired him to develop a dynamic model of diffusion effects)LJXUH ZKLFK LQFOXGHV SHHU H[WHUQDO LQÀXHQFH DQG WKH U DJJUHJDWLQJ UHVHDUFK ¿QGLQJV I

Table 3: Campaign exposure as a predictor of likelihood of adoption IRU %ROLYLDQ FRQWUDFHSWLRQ VWXG\ VW & Saba, 1998).

	Cross-Sectional		Panel	
	Low Threshold	High Threshold	Low Threshold	High Threshold
Education	1.35**	1.75**	1.31	1.4
Income	1.35**	1.17	1.13	0.97
Age	0.92**	0.92**	0.98	0.98
# Children	1.15	1.2	1.05	1.21
Campaign Exposure	2.36**	1.92	1.71*	1.26

Note: * indicates p < .05, ** indicates p < .01

diffusion research. The model proposes that external LQÀXHQFH GHFD\V RYHU WLPH DQG GHFD\V RYHU WLPH SHHU role of opinion leaders varies. We have tested the model on the FCTC diffusion data and found partial support for its components. This work is currently being expanded upon in the Global Diffusion of Tobacco Control study 9DOHQWH '\DO &KX :LSÀL)

Tom has translated his empirical and theoretical work from network diffusion research to provide a framework for the use of social network data to design, adopt, implement and sustain behavior change interventions (Valente, 2012; Valente, Palinkas, et al., 2015). Research documenting the association between networks and behavior spurred researchers in the 1990s to pose this question: “If networks are so important how can they be used to accelerate change?” Many interventions have used the opinion leader model where opinion OHDGHUV DUH LGHQWL¿HG WKUR recruited to be change agents who give talks and promote a new practice during informal conversations. Tom and his wife, Dr. Rebecca Davis expanded on the opinion leader model with their observation that leaders aren't necessarily leaders for everyone. They published a paper proposing the optimal Leader/Learner model in which OHDGHUV DUH LGHQWL¿HG DQG who nominated them (Valente & Davis, 1999). This model was tested in a randomized control trial and found to be more effective than when leaders are chosen via network nominations but groups constructed randomly (Valente, Hoffman, Ritt-Olson, Lichtman, & Johnson, 2003; Valente, Unger, Ritt-Olson, Cen, & Johnson, 2006). Tom proposed that many research avenues remain unexplored in network interventions, such as whether it is [illegible] WKHP RU LGHQWLI\ OHDGHUV ¿UVW them, comparing different network approaches, and how contextual factors affect network interventions.

Tom's approach to his work focuses on examining the whole by looking at the parts. That is, in order to understand the behavior of a network, he considers how each individual node views its network and that each node FDQ KDYH D XQLTXH UHVSRQVH WR Calculating thresholds from nodes' personal networks, PRGHOLQJ HIIHFWV RI SXEOLF KHDO threshold, and acknowledging that leaders are only leaders for some nodes in a network all suggest attention paid to heterogeneity in nodes' perceptions of their network and QRGHV¶ VXVFHSWLELOLW\ DQG LQÀX individual variation within networks, Tom would not [illegible] on innovation adoption in the classic diffusion studies, or in his later research.

Tom proves that his theories are applicable to the real world with his work in network interventions and evaluations of health campaigns. Many interventions are evaluated without considering thresholds. Some interventions may have been deemed ineffective when [illegible] they actually made a difference for people with low thresholds and low exposure. If we know that media interventions may not affect those people with high thresholds, what is the best intervention design to reach these people? Similarly, how do we identify those people likely to have low thresholds prior to diffusion occurring

Figure 2 Hypothesized dynamic model of diffusion effects (from Valente et al., 2015).

in order to design campaign advertising to reach these people?

Tom's research has spanned from studying societies where interpersonal communication occurs in person to studying communication enabled by the internet. Understanding how technology affects communication may prove important in future diffusion research. Work by Tom and his former graduate student Dr. Grace Huang suggests that exposure through social networking sites to photos of friends participating in risky activities may LQÀXHQFH DQ DGROHVFHQW¶V RZQ ULVN EHKDYLRUV +XDQJ et al., 2014). It is unclear how technology affects explicit and implicit endorsement, how people interpret information received through social media in comparison to in person, and how exposure and thresholds may be affected by technology.

In sum, Tom has provided theoretical models, empirical research, and practical intervention applications for diffusion of innovation theory. He stated that we NQRZ QHWZRUNV LQÀXHQFH EHKDYLRUV LQ SURIRXQG DQG diverse ways, and diffusion theory provides a way to FRPSDUH QHWZRUN LQÀXHQFHV RQ EHKDYLRU DQG EHKDYLRUDO LQÀXHQFHV RQ QHWZRUNV +LV UHVHDUFK H[HPSOL¿HV WKH QHHG to guide network research with theories and frameworks. However, his speech highlighted more than just his research contributions. Tom detailed how his career was LQÀXHQFHG E\ KLV RZQ VRFLDO QHWZRUN ¿OOHG ZLWK PHQWRUV colleagues, and collaborators. His mentor, Dr. Everett Rogers, encouraged him to connect with other scholars and made sure he realized there were people behind the authors. Tom and Everett even conducted oral history interviews with about a dozen diffusion scholars from which Tom learned more about diffusion research than he ever did reading about it. Tom summarized his career so IDU E\ VD\LQJ WKDW QHWZRUN PDWWHU ¿QGLQJ JRRG PHQWRUV and colleagues is critically important, and that it takes time to build a career. Tom has certainly demonstrated these ideals as a researcher.

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