People Analytics: Using Digital Exhaust to Leverage Network Insights in the Algorithmically Infused Workplace

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Forbes Billionaires Innovation Leadership Money Consumer Industry

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The Geeks Arrive In HR: People Analytics Is Here

Josh Bersin Contributor

I analyze corporate HR, talent management and leadership.

The old fashioned fuddy-duddy HR department is changing. The Geeks have arrived.

Today, for the first time in the fifteen years I've been an analyst, human resources departments are getting serious about analytics. And I mean serious.

I was in a meeting several weeks ago in San Francisco and we had eight PhD statisticians, engineers, and computer scientists together, all working on people analytics for their companies. These are serious mathematicians and data scientists trying to apply data science to the people side of their businesses.

How Google Is Using People Analytics to Completely Reinvent HR

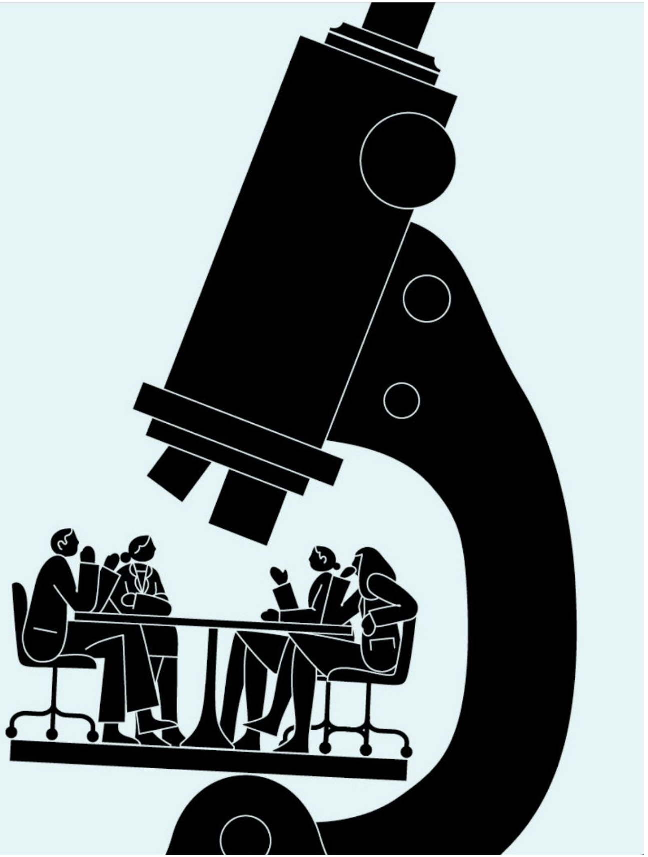
By Dr. John Sullivan February 26, 2013

Home The New York Times Magazine Share 422

What Google Learned From Its Quest to Build the Perfect Team

New research reveals surprising truths about why some work groups thrive and others falter.

BY CHARLES DUHIGG ILLUSTRATIONS BY JAMES GRAHAM FEB. 25, 2016



HOW TO HIRE THE BEST

Google Spent 2 Years Studying 180 Teams. The Most Successful Ones Shared These 5 Traits

Insights from Google's new study could forever change how teams are assembled.

1. **Psychological Safety**
   Team members feel safe to take risks and be vulnerable in front of each other.
2. **Dependability**
   Team members get things done on time and meet Google's high bar for excellence.
3. **Structure & Clarity**
   Team members have clear roles, plans, and goals.
4. **Meaning**
   Work is personally important to team members.
5. **Impact**
   Team members think their work matters and creates change.

re:Work

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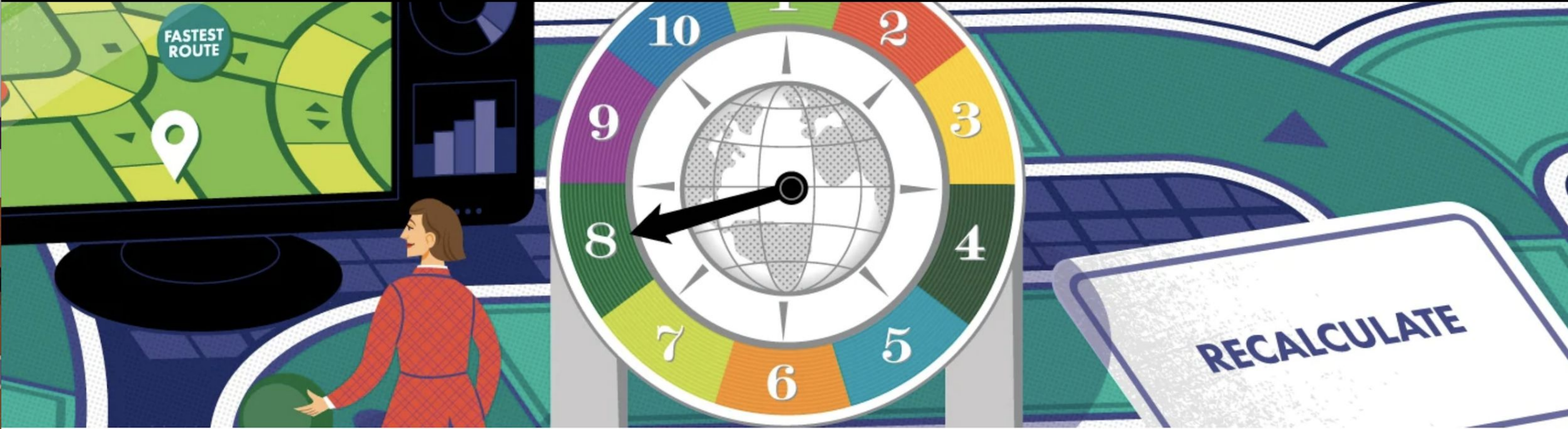

Article

February 28, 2017

People analytics: Recalculating the route

2017 Global Human Capital Trends

9%

Deloitte.

The Deloitte 2017 Human Capital Trends reported that although people analytics has become mainstream, only 9% of companies believe they have a good understanding of which talent dimensions drive performance in their organizations.

CORPORATE THEMES

HR Analytics: No Longer Just a Buzzword

Back to Blog

March 13, 2017

Arpita Vyas

At a time when the global IT and business process services industry is shifting to a value-based approach, ensuring that the right talent is hired, nurtured, and retained can be a key business enabler. According to the Deloitte Global Human Capital Trends 2016 report, 60% of the top executives surveyed hold HR accountable for business results. In 2016, 51% of companies correlated business impact to HR programs and 44% used workforce data to predict business performance. Given this trend, its easy to see why 77% of executives now rate HR analytics a key priority.

HR analytics is not about reporting standard personnel management metrics. It helps draw insights, inferences, and trends from historical data to predict future needs and behaviors, thereby ensuring that HR can truly partner with the business to achieve strategic goals. In essence, it acts as the bridge that connects HR to business. Although there is a lot of buzz around HR analytics, deploying it is not a

5%

TATA

A survey by **Tata Consultancy** Services found that just 5% of big-data **investments go to HR**, the group that typically manages **people analytics**

with Paul Leonardi
UCSB

Harvard Business Review

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ARTICLE
ANALYTICS

Better People Analytics

Measure who they know, not just who they are.
by Paul Leonardi and Noshir Contractor

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Analytics

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Noshir Contractor
Professor of behavioral sciences, Northwestern University

Better PEOPLE Analytics

Measure Who THEY KNOW, Not Just Who THEY ARE.

Illustrations by ANDY GILMORE

THE TRADITIONAL APPROACH

People Analytics

INDIVIDUALS'
TRAIT DATA

INDIVIDUALS'
STATE DATA

AGGREGATE
STATE AND TRAIT DATA

From people attribute analytics to relational analytics

THE TRADITIONAL APPROACH

People Analytics

- INDIVIDUALS' TRAIT DATA
- INDIVIDUALS' STATE DATA
- AGGREGATE STATE AND TRAIT DATA

THE NEW APPROACH

People Analytics

ATTRIBUTE ANALYTICS

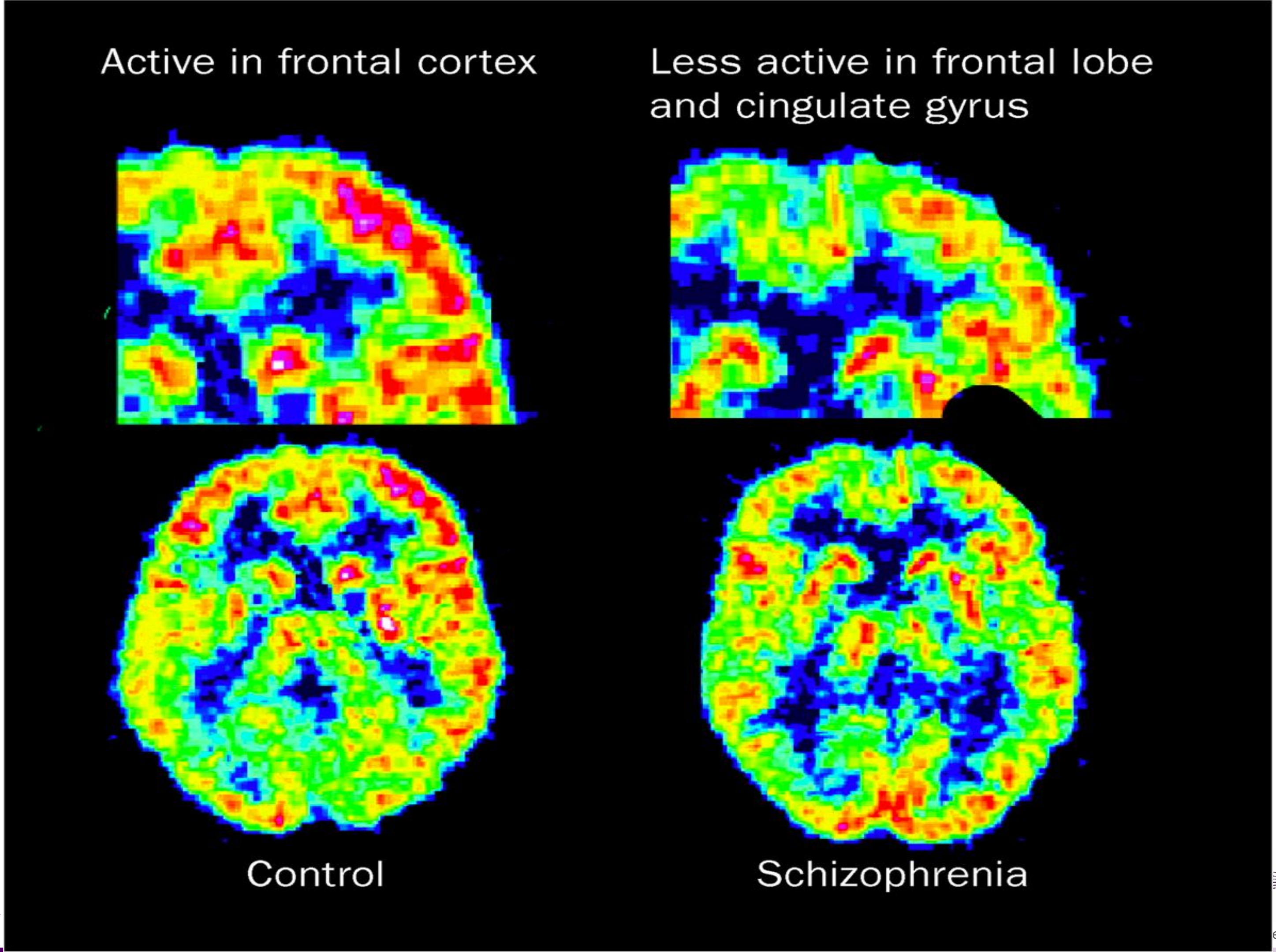
- INDIVIDUALS' TRAIT DATA
- INDIVIDUALS' STATE DATA
- AGGREGATE STATE AND TRAIT DATA

+

RELATIONAL ANALYTICS

- INDIVIDUALS' NETWORK DATA
- TEAMS' NETWORK DATA
- ORGANIZATIONS' NETWORK DATA

SOURCE Paul Leonardi and Noshir Contractor


Active in frontal cortex
Less active in frontal lobe and cingulate gyrus
Control
Schizophrenia

Pointillism

By Henri Matisse's Luxe, Calme et Volupté (1904, now in the Musée d'Orsay) is often cited as an important work of transition between the two.

STRUCTURAL

Signature

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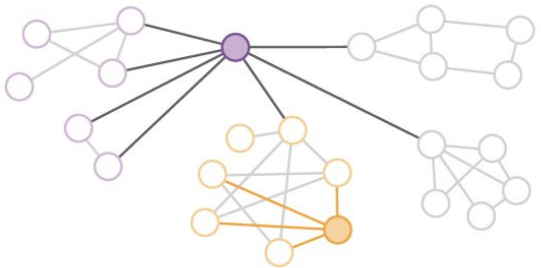
Ideation Signature

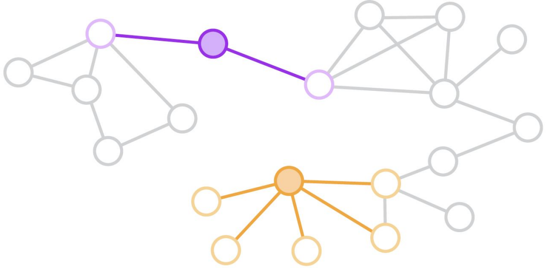
FOCUS: Individual • **PREDICTS:** Which employees will come up with good ideas



*Purple shows **low constraint:** He communicates with people in several other networks besides his own, which makes him more likely to get novel information that will lead to good ideas. Orange, who communicates only with people within his network, is less likely to generate ideas, even though he may be creative.*

Influence Signature

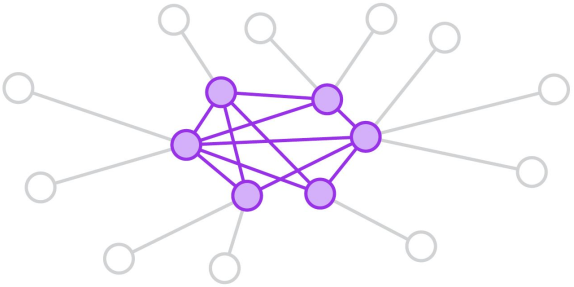
FOCUS: Individual • **PREDICTS:** Which employees will change others' behavior



*Though she connects to only two people, purple is more influential than orange, because purple's connections are better connected. Purple shows **higher aggregate prominence.** Orange may spread ideas faster, but purple can spread ideas further because her connections are more influential.*

Efficiency Signature

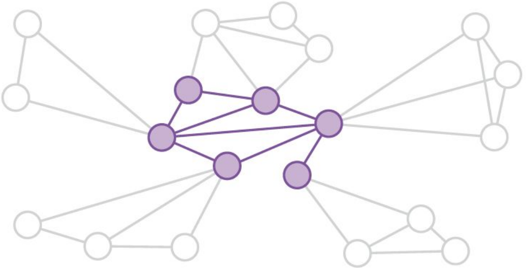
FOCUS: Team • **PREDICTS:** Which teams will complete projects on time



*The purple team members are deeply connected with one another—showing **high internal density.** This indicates that they work well together. And because members' external connections don't overlap, the team has **high external range,** which gives it greater access to helpful outside resources.*

Innovation Signature

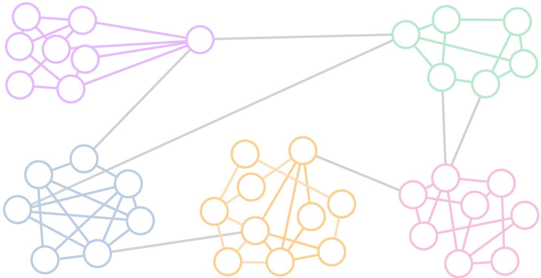
FOCUS: Team • **PREDICTS:** Which teams will innovate effectively



*Purple team members aren't deeply interconnected; their team has **low internal density.** This suggests they'll have different perspectives and more-productive debates. The members also have **high external range**, or wide, diverse connections, which will help them gain buy-in for their innovations.*

Silo Signature

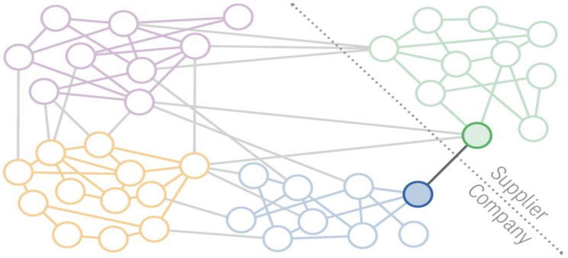
FOCUS: Group • **PREDICTS:** Whether an organization is siloed



*Each color indicates a department. People within the departments are deeply connected, but only one or two people in any department connect with people in other departments. The groups' **modularity**—the ratio of internal to external communication—is high.*

Vulnerability Signature

FOCUS: Organization • **PREDICTS:** Which employees the organization can't afford to lose



Green is a critical external supplier to company departments blue, purple, and orange. Six people at the company have relationships with green, but 30 people rely on those relationships—which puts the company at risk. If blue's one connection to green leaves, for example, the department will be cut off from the supplier. While his title may not reflect his importance, that employee is vital to information flow.

So why are we not leveraging networks insights in the workplace?

Surveys – especially those mapping social networks – are

- Time consuming
- Elicit low response rates
- Are rapidly obsolete

What if?

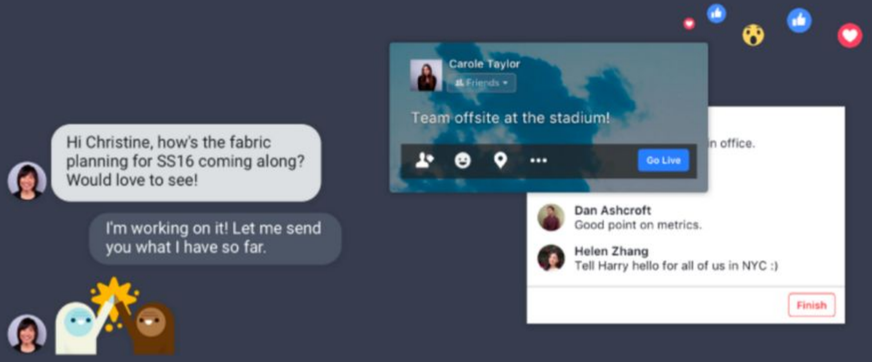
We could have survey data …

- ~~Time consuming~~ **At minimal cost**
- ~~Elicit low response rates~~ **With 100 response rate**
- ~~Are rapidly obsolete~~ **Updated 24/7**

A Digital Trace

Activity (posting, commenting, messaging, etc.) on ESM platforms leaves behind a **digital trace**.

What if we could leverage this digital trace data in order to better understand our organizations?



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JIRA

slack

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yammer

ial Network

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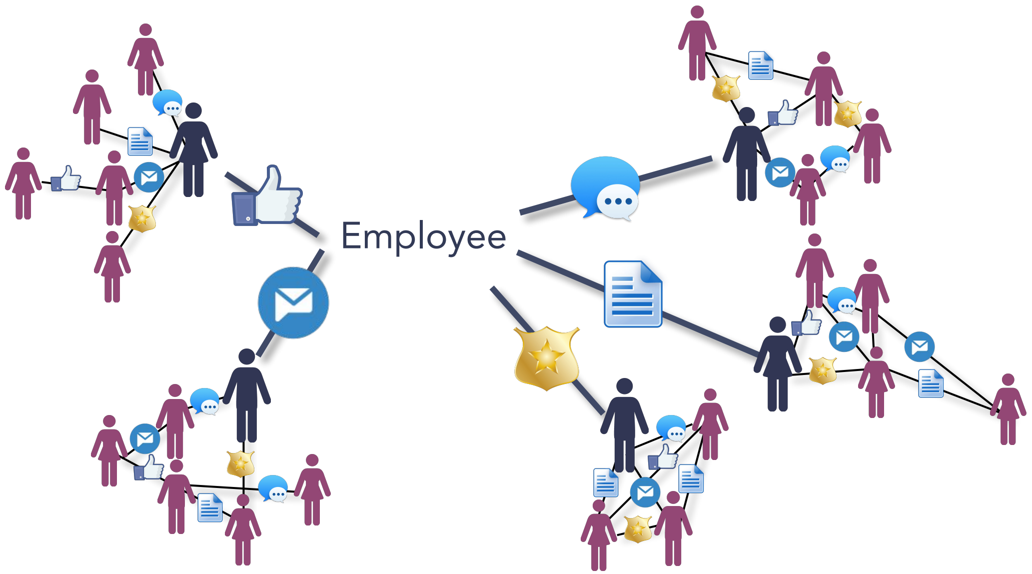
jive

Google

ORACLE®

Trello

Activity Networks from Digital Exhaust Data



Predicting Interpersonal Relationships using Enterprise Social Media

Brennan Antone[1], Dongping Zhang[1], Hui Li[2], Tony Zhang[1], Aneesh Kudaravalli[1], Yunjie Xu[2], Leslie DeChurch[1], Paul Leonardi[3], Noshir Contractor[1]

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SCHOOL OF MANAGEMENT FUDAN UNIVERSITY

This research was supported by Fudan University and Northwestern University

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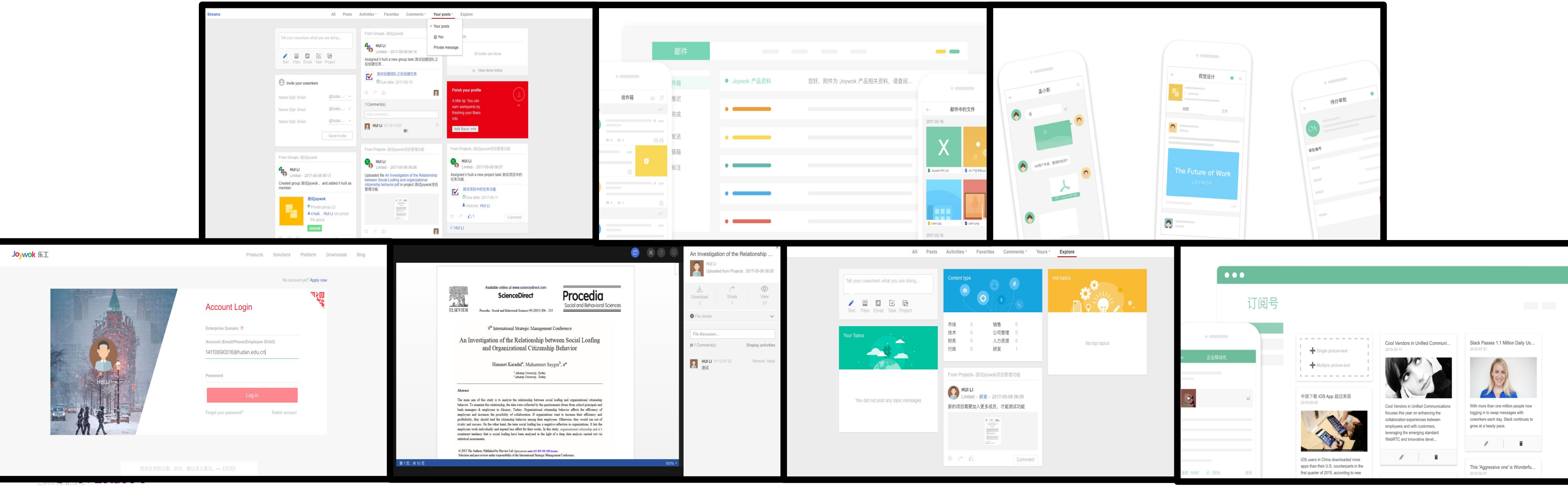
Our Data

We collected data from 66 employees at a Chinese company that uses an enterprise social media (ESM) platform



Our Data

We collected data from 66 employees at a Chinese company that uses an enterprise social media (ESM) platform.

Digital Trace Data

How people interact with one another on platform

4/13/19 – 5/31/19

Survey Data

How people describe their relationships with one another

7/3/19 – 7/28/19

Our Data

We collected data from 66 employees at a Chinese company that uses an enterprise social media (ESM) platform.

Digital Trace Data

How people interact with one another on platform

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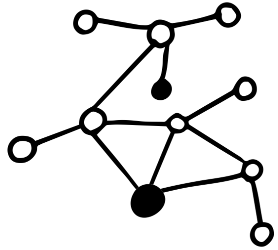
Survey Data

How people describe their relationships with one another

7/3/19 – 7/28/19

Interpersonal Relationships



Sense of Purpose

Please indicate the people at your company who give you a sense of purpose – that is, a sense that what you do at work has a positive impact and matters.

This person provides me with a sense of purpose.

Select all that apply.

Granting Leadership

Please indicate the people at your company you rely on for leadership. This can influence a formal leadership position or an informal leadership relation.

Who do you rely on for leadership?

Select all that apply.

Interpersonal Relationships

Advice Seeking

Please indicate the people at your company you go to for advice.

Who do you go to for help or advice at work?

Select all that apply.

Methodology

Modeling

Using **exponential random graph models (ERGM)**, we estimate a joint probability distribution describing which relations may occur:

$$P(Y = y) = \frac{e^{\theta S(y)}}{\sum_j e^{\theta S(j)}}$$

This is a form of statistical modeling that works when the relationships we study are, by nature, non-i.i.d.

Prediction

Based on these models, we use simulations to estimate the **probability that any hypothetical tie will occur**.

Since we can rank these ties based on their probability, by specifying some threshold value we are then able to predict which ties within a network will exist. By adjusting this threshold, we can make tradeoffs between type-I and type-2 errors.

MODELING SOCIAL RELATIONSHIPS

Key Findings: Sense of Purpose

Employees were asked to nominate others in response to:

"**This person provides me with a sense of purpose**"

Employees who send someone **1 message per day** are **15.2%** more likely to say that person provides them with a sense of purpose than those who do not.

Employees who **send someone 10% more messages than they receive** from them are **26.7%** more likely to say that person provides them with a sense of purpose, compared to a pair of people with an even split.

Full Model: Sense of Purpose

Model 1: Sense of Purpose			
	Log-Odds	Odds Ratio	Interpretation
Structural Patterns			
Tie Count	-3.74 (0.27) *	0.02	Control term for the density of the network.
Reciprocity	0.11 (0.36) *	1.12	Ties tend to be reciprocated.
Outdegree 1	2.54 (0.5) *	12.68	A greater proportion of employees have an outdegree of one.
Indegree Preferential Attachment	-5.08 (1.09) *	0.01	Sense of purpose nominations tend to be spread amongst many different employees.
Outdegree Preferential Attachment	-1.51 (0.91)	0.22	Sense of purpose nominations tend to originate from many different employees.
Two Paths (GWDSP)	-0.07 (0.01) *	0.93	There is a tendency against chains of employees who are one another's sense of purpose.
Transitive Closure (GWESP)	0.96 (0.14) *	2.61	When these chains do exist, they tend to exhibit transitive closure.
Employee Information			
CEO Indegree	1.77 (0.5) *	5.87	The CEO tends to provide others with a sense of purpose.
CTO Indegree	0.04 (0.45) *	1.04	The CTO tends to provide others with a sense of purpose.
Non-Leader Homophily	-0.9 (0.19) *	0.41	Non-leaders tend not to provide a sense of purpose to other non-leaders.
Department Homophily	1.47 (0.16) *	4.35	Employees in the same department are more likely to provide one another a sense of purpose.
Less Tenure Sender Effect	0.2 (0.04) *	1.22	Employees are more likely to say those who have been at the company longer provide a sense of purpose.
Employee-to-Supervisor Ties	0.42 (0.53)	1.52	Supervisors are more likely to give those they supervise a sense of purpose
Supervisor-to-Employee Ties	0.85 (0.45)	2.34	Employees are more likely to give their immediate supervisors a sense of purpose.
Joywok Messaging (Digital Trace)			
Hundreds of Messages Sent	0.29 (0.08) *	1.34	If employees send someone messages, they are more likely to nominate that person.
Proportion Sent Relative to Received	1.3 (0.25) *	3.67	If employees send someone more messages relative to how many they receive, they are more likely to nominate that person.
AIC	1130.21		
BIC	1231.04		

Standard error in parantheses. *p<0.05

Key Findings: Granting Leadership

Employees were asked to nominate others in response to:
"**Who do you rely on for leadership?**"

Employees who send someone **1 message per day** are **10.4%** more likely to say that person provides them with a sense of purpose than those who do not.

Employees who **send someone 10% more messages than they receive** from them are **28.7%** more likely to say that person provides them with a sense of purpose, compared to a pair of people with an even split.

Full Model: Granting Leadership

Model 2: Granting Leadership			
	Log-Odds	Odds Ratio	Interpretation
Structural Patterns			
Tie Count	-2.33 (0.23) *	0.10	Control term for the density of the network.
Reciprocity	-0.43 (0.39)	0.65	Ties tend to be reciprocated.
Indegree Preferential Attachment	-5.38 (0.86) *	0.00	Granting of leadership tends to be spread amongst many different employees.
Outdegree Preferential Attachment	-1.07 (0.39) *	0.34	Granting leadership nominations tend to originate from many different employees.
Two Paths (GWDSP)	-0.22 (0.02) *	0.80	There is a tendency against chains of employees who grant one another leadership.
Transitive Closure (GWESP)	0.9 (0.09) *	2.46	When these chains do exist, they tend to exhibit transitive closure.
Employee Information			
Non-Leader to Non-Leader Ties	-0.64 (0.15) *	0.53	Non-leaders tend not to rely on other non-leaders for leadership.
Leader to Non-Leader Ties	-0.59 (0.4)	0.55	Leaders tend not to rely on non-leaders for leadership.
Leader to Leader Ties	-0.12 (0.39)	0.89	Leaders tend not to rely on others leaders for leadership.
Department Homophily	0.93 (0.11) *	2.53	Employees in the same department are more likely to rely on one another for leadership.
Less Tenure Sender Effect	0.08 (0.03) *	1.08	Employees are more likely to rely on those who have been at the company longer than them for leadership.
Employee-to-Supervisor Ties	0.25 (0.38)	1.28	Supervisors are more likely to report relying on those they supervise for leadership.
Supervisor-to-Employee Ties	0.26 (0.4)	1.30	Employees are more likely to rely on their immediate supervisors for leadership.
Joywok Messaging (Digital Trace)			
Hundreds of Messages Sent	0.2 (0.08) *	1.22	If employees send someone messages, they are more likely to rely on that person for leadership.
Proportion Sent Relative to Received	1.36 (0.19) *	3.90	If employees send someone more messages relative to how many they receive, they are more likely to rely on that person for leadership.
AIC	1589.41		
BIC	1696.53		

Standard error in parantheses. *p<0.05

Key Findings: Advice Seeking

Employees were asked to nominate others in response to:

"**Who do you go to for help or advice at work?**"

Employees who send someone **1 message per day** are **36.3%** more likely to say that person provides them with a sense of purpose than those who do not.

Employees who **send someone 10% more messages than they receive** from them are **34.7%** more likely to say that person provides them with a sense of purpose, compared to a pair of people with an even split.

Full Model: Advice Seeking

Model 3: Advice Seeking

	Log-Odds	Odds Ratio	Interpretation
Structural Patterns			
Tie Count	-1.81 (0.2) *	0.16	Control term for the density of the network.
Reciprocity	0.6 (0.12) *	1.82	Ties tend to be reciprocated.
Employee Information			
Non-Leader to Non-Leader Ties	-0.69 (0.17) *	0.50	Non-leaders tend not to rely on other non-leaders for advice.
Leader to Non-Leader Ties	-0.73 (0.25) *	0.48	Leaders tend not to rely on non-leaders for advice.
Leader to Leader Ties	2.27 (0.61) *	9.68	Leaders tend to rely on others leaders for advice.
Department Homophily	0.82 (0.1) *	2.27	Employees in the same department are more likely to go to one another for advice.
Office Homophily	0.65 (0.1) *	1.92	Employees in the same department are more likely to rely on one another for advice.
Gender Homophily	0.18 (0.08) *	1.20	Employees are more likely to go to employees of the same gender for advice.
Less Tenure Sender Effect	-0.25 (0.05) *	0.78	Employees are less likely to rely on those who have been at the company longer than them for advice.
Tenure Sender Effect	0.34 (0.04) *	1.40	Employees who have been at the company longer are more likely to seek advice.
Tenure Receiver Effect	-0.19 (0.03) *	0.83	Employees who have been at the company longer are less likely to be sought after for advice
Employee-to-Supervisor Ties	-0.14 (0.35)	0.87	Supervisors are less likely to report seeking advice from those they supervise.
Supervisor-to-Employee Ties	0.17 (0.3)	1.19	Employees are more likely to report seeking advice from their immediate supervisors.
Joywok Messaging (Digital Trace)			
Hundreds of Messages Sent	0.63 (0.1) *	1.88	If employees send someone messages, they are more likely to report seeking advice from the person.
Proportion Sent Relative to Received	1.51 (0.15) *	4.53	If employees send someone more messages relative to how many they receive, they are more likely to report seeking advice from that person.
AIC	3786		
BIC	3893.13		

Standard error in parantheses. *p<0.05

PREDICTING SOCIAL RELATIONSHIPS

Sense of Purpose

"This person provides me with a sense of purpose"

Accuracy: 89.46%

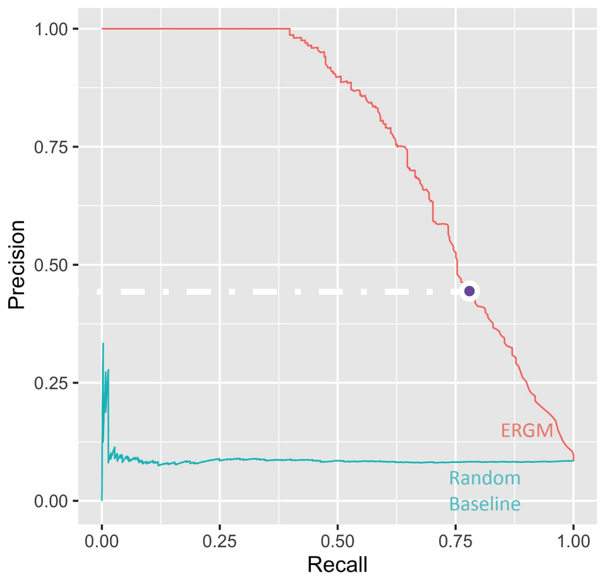
		Observed		
		0	1	
Predicted	0	**3608**	**80**	3688
	1	**379**	**289**	668
		3987	369	

Precision:
Proportion of predicted ties that actually exist
43.26%

Recall:
Proportion of existing ties predicted by our model
78.32%

Computed using a threshold of 0.1

Precision-Recall Plot



Granting Leadership

"Who do you rely on for leadership?"

Accuracy: 91.60%

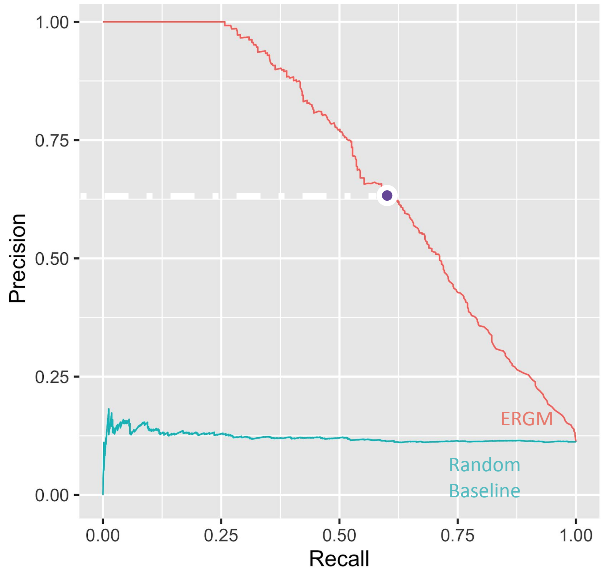
		Observed		
		0	**1**	
Predicted	**0**	**3693**	**192**	3885
	1	**174**	**297**	471
		3867	489	

Precision:
Proportion of predicted ties that actually exist
63.06%

Recall:
Proportion of existing ties captured by our model
60.74%

Computed using a threshold of 0.3

Precision-Recall Plot



Advice Seeking

"Who do you go to for help or advice at work?"

Accuracy: **78.24%**

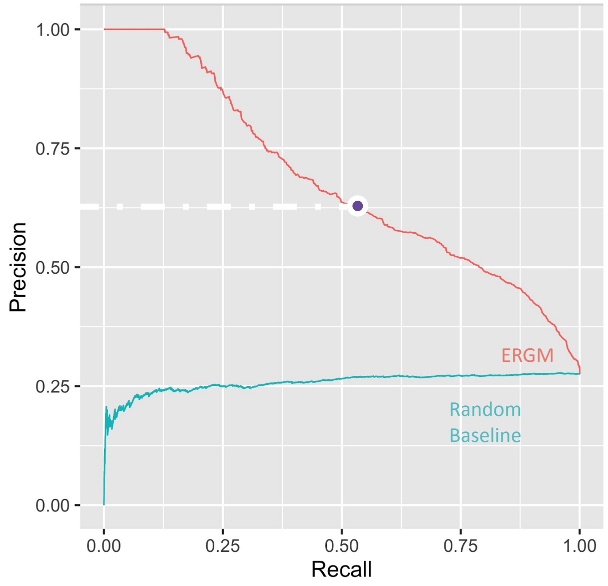
		Observed		
		0	**1**	
Predicted	**0**	**2777**	**569**	3346
	1	**379**	**631**	1010
		3156	1200	

Precision:
Proportion of predicted ties that actually exist
62.48%

Recall:
Proportion of existing ties captured by our model
52.58%

Computed using a threshold of 0.4

Precision-Recall Plot



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OBJECTIVE

- We collected survey and digital trace data from companies in the US and China
    - ***Question:*** Can we predict survey network responses using digital trace data?

We can!

Technology @ Work capture work networks ….

BUT also **change** them

Technological Affordances of Enterprise Social Media

- **Association** - Help reveal who knows who - and who knows what
- **Evaluability** - Evaluate other people’s information via recommendations, comments, liking, or tagging
- **Visibility** - See how people have responded to questions raised by others
- **Persistence** - Find information about prior interactions, decisions on a project
- **Personalization** - Include the information, photos, and other content that present personal identity

Majchrzak et al., 2013; Rice et al., 2017; Treem & Leonardi, 2013

Technological Affordances of Enterprise Social Media

- **Editability** - Revise information others provide after they have shared it
- **Pervasiveness** - Get responses to requests from others quickly
- **Awareness** - Be aware of the information and updates from others
- **Searchability** - Search for information or people by entering search words
- **Sharing** - Create groups/channels on the fly for sharing information

Majchrzak et al., 2013; Rice et al., 2017; Treem & Leonardi, 2013

Algorithmic Affordances in the Workplace

"So this software... Does it tell you to do things?"

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advancing the science of networks in communities

Algorithmic Affordances

Perspective

Measuring algorithmically infused societies

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Check for updates

Claudia Wagner[1,2,3]✉, Markus Strohmaier[1,2,3], Alexandra Olteanu[4,5], Emre Kıcıman[6], Noshir Contractor[7] & Tina Eliassi-Rad[8]

It has been the historic responsibility of the social sciences to investigate human societies. Fulfilling this responsibility requires social theories, measurement models and social data. Most existing theories and measurement models in the social sciences were not developed with the deep societal reach of algorithms in mind. The

POLICY FORUM

SOCIAL SCIENCE

Computational social science: Obstacles and opportunities

Data sharing, research ethics, and incentives must improve

By David M. J. Lazer[1,2], Alex Pentland[3], Duncan J. Watts[4], Sinan Aral[3], Susan Athey[5], Noshir Contractor[6], Deen Freelon[7], Sandra Gonzalez-Bailon[4], Gary King[2], Helen Margetts[8,9], Alondra Nelson[10,11], Matthew J. Salganik[12], Markus Strohmaier[13,14], Alessandro Vespignani[1], Claudia Wagner[14,15]

dependencies within data. A loosely connected intellectual community of social scientists, computer scientists, statistical physicists, and others has coalesced under this umbrella phrase.

MISALIGNMENT OF UNIVERSITIES

Wagner, C., Strohmaier, M., Olteanu, A., Kıcıman, E., Contractor, N., & Eliassi-Rad, T. (2021). Measuring algorithmically infused societies. *Nature*, *595*(7866), 197–204.

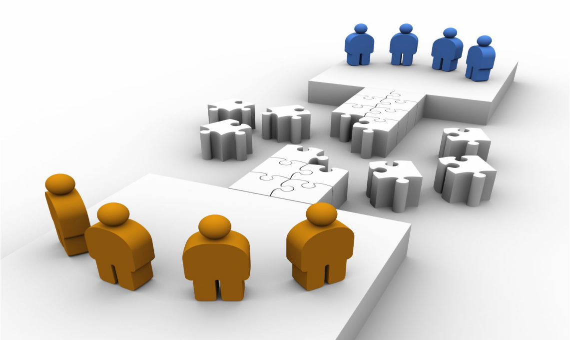
Lazer, D. M. J., Pentland, A., Watts, D. J., Aral, S., Athey, S., Contractor, N., Freelon, D., Gonzalez-Bailon, S., King, G., Margetts, H., Nelson, A., Salganik, M. J., Strohmaier, M., Vespignani, A., & Wagner, C. (2020). Computational social science: Obstacles and opportunities. *Science*, *369*(6507), 1060–1062.

Making Relational Analytics Actionable for *Teams*

Team Self-Assembly

Team Staffing

Predicting Team Performance



Predicting Team Conflict

Self-Assembled Teams

The team members have agency and are responsible for finding and selecting the other members (Hackman 1987)

How did we get here?

How did we get HERE?

How do self-designing teams assemble?

Marlon Twyman
Annenberg School for Communication
U of Southern California

Diego Gómez-Zará
Computer Science
U of Notre Dame

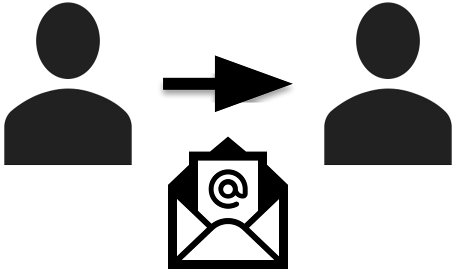
Jacqueline Ng
Harvard Business School
Harvard U

Leslie DeChurch
Communication Studies & Psychology
Northwestern U

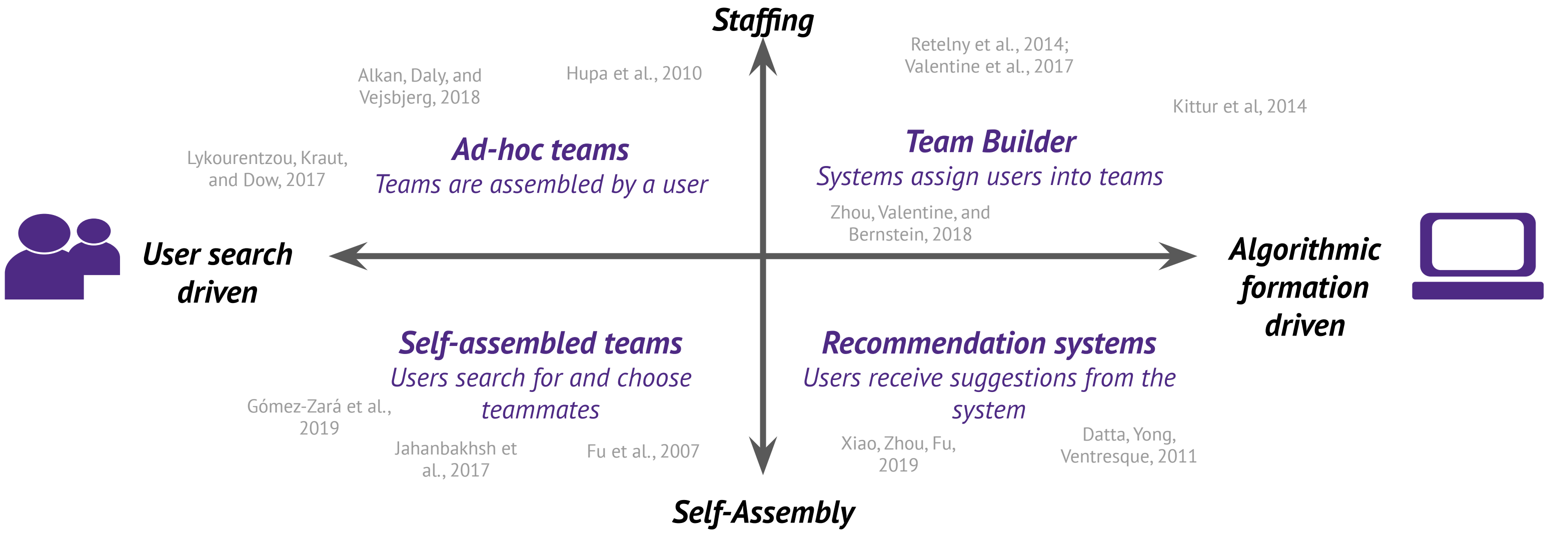
How do people decide who to invite to their team in the modern organizational landscape?

What mechanisms explain the invite process?

How does technology alter the invite process?

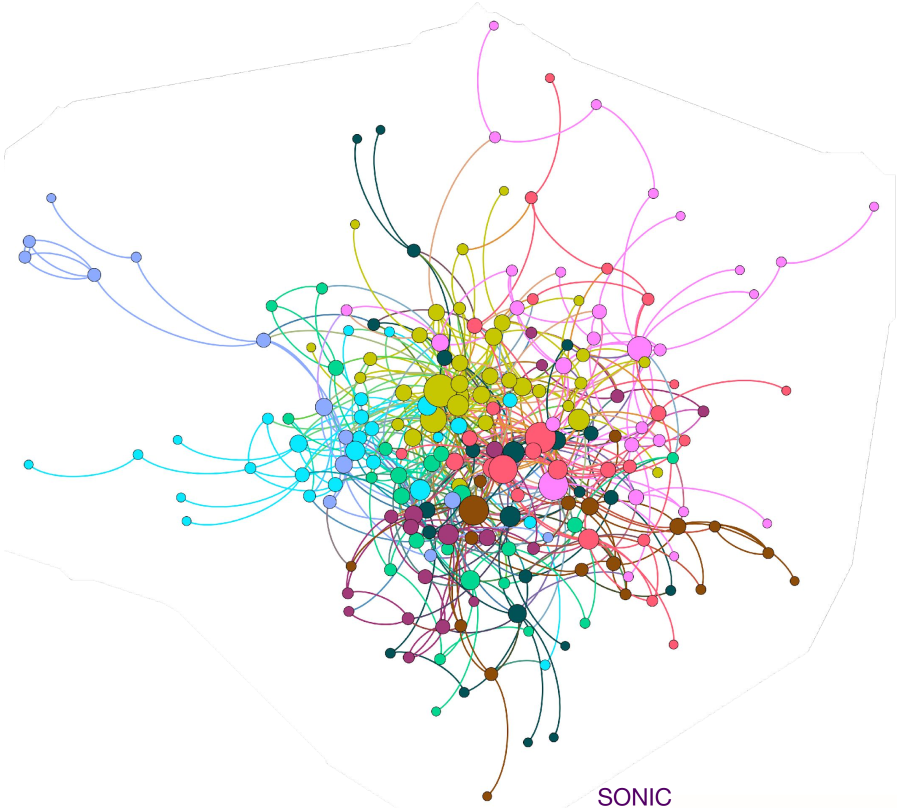


Algorithmic Affordances in the Workplace



A Technology Platform to Assemble Teams

My DreamTeam



Developers: Anup Sawant, Xiang Li

Northwestern University

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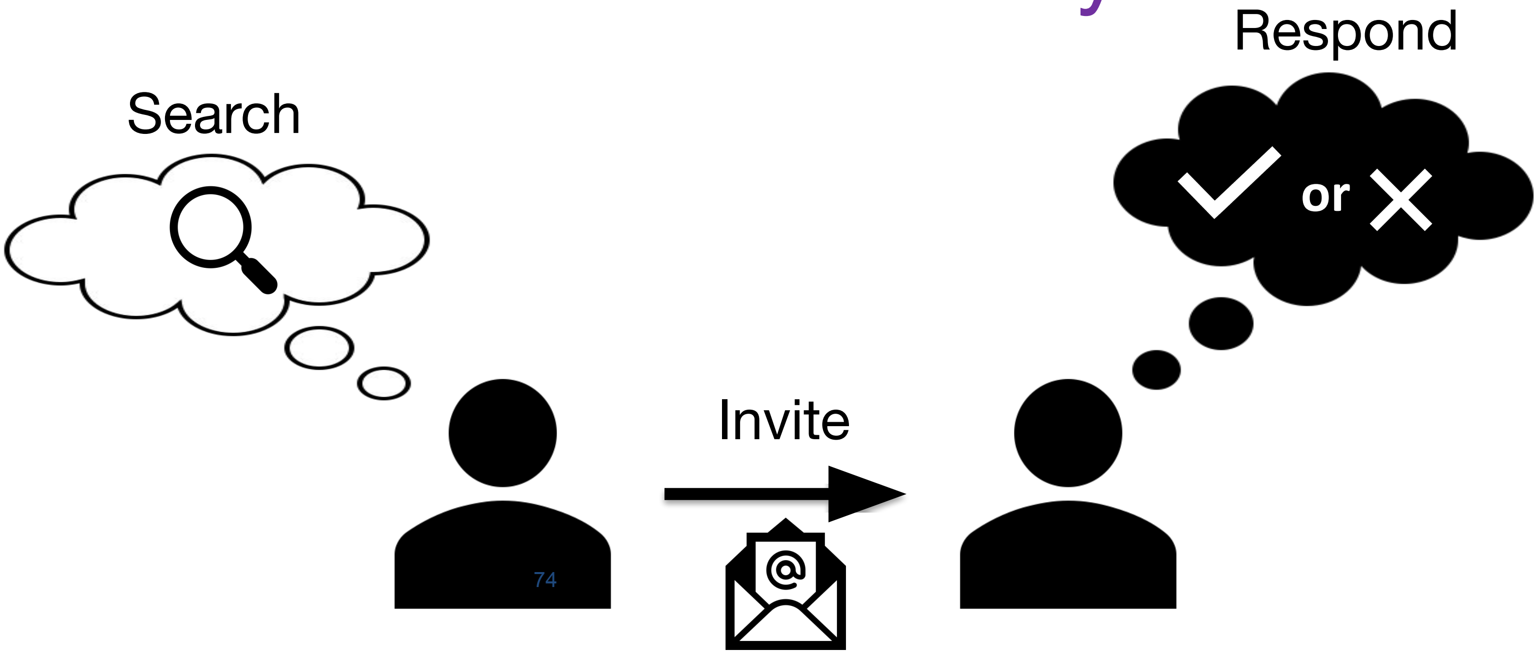
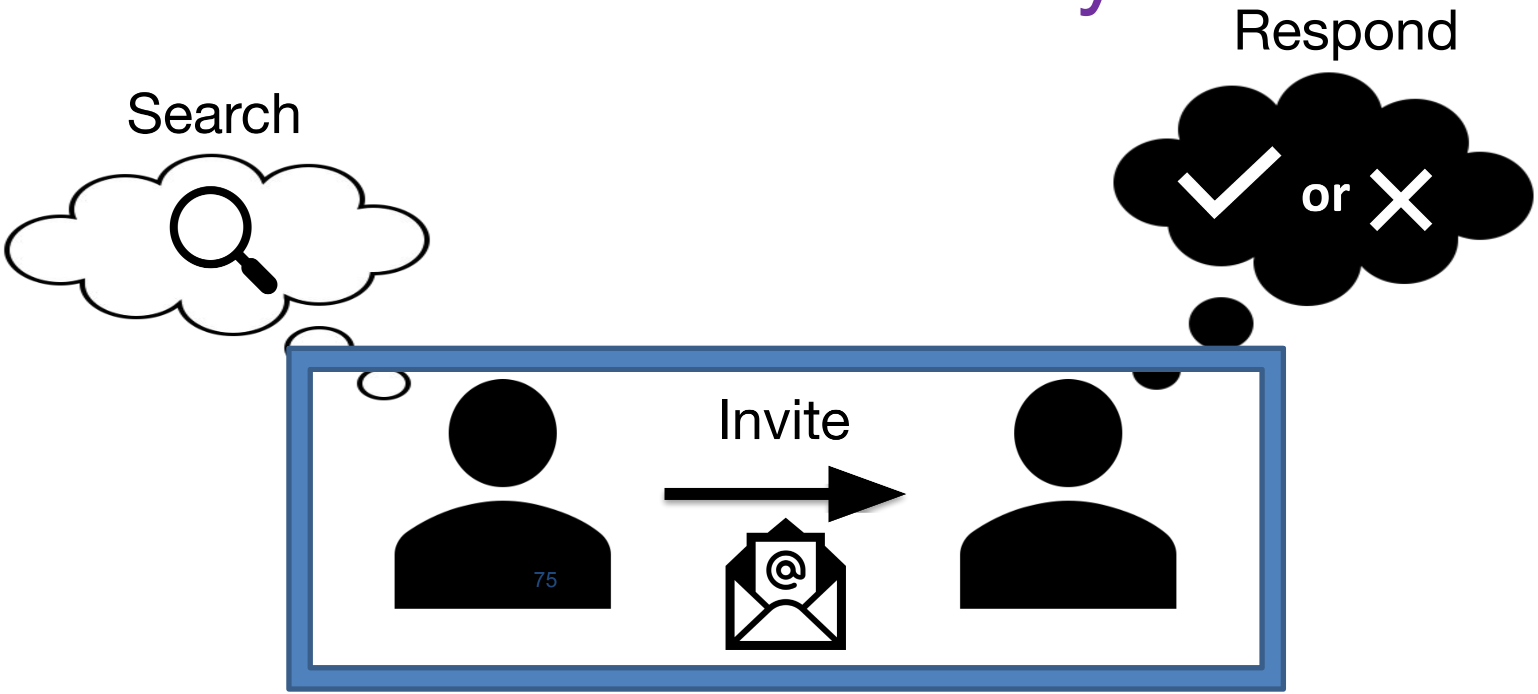
Team Assembly



Team Assembly



The structure of invites sent within a large group of people

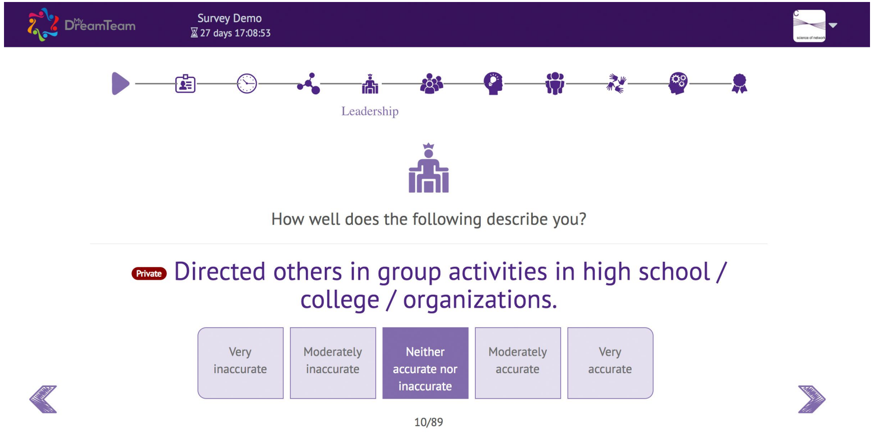
Designing Teams for Innovation

- Environmental ecology and social psychology majors (from 2 universities) assembling project teams
  - Each team was required to have members from each university
- **<u>Goal of project</u>**: simulating an advertising campaign to mitigate an environmental sustainability issue
- Participants assembled into teams over the course of one week using technology platform
- 213 participants (32 teams) in Sample 1
- 197 participants (31 teams) in Sample 2

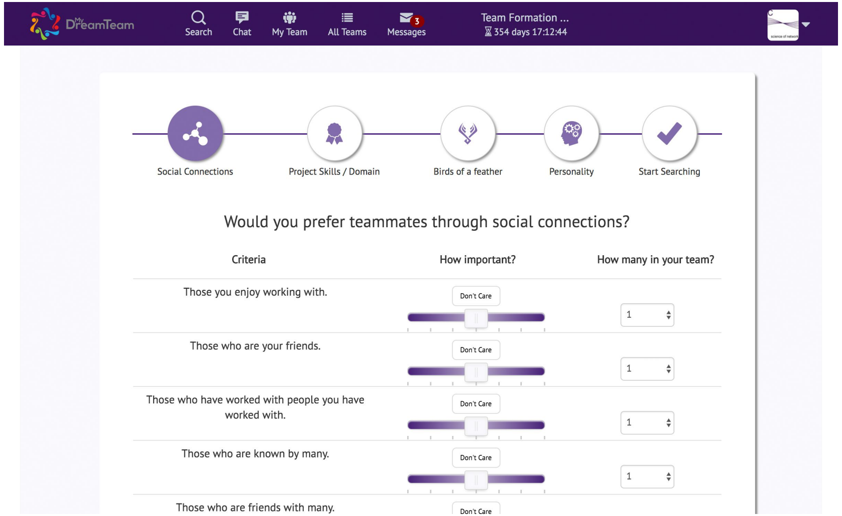
(DeChurch, Zaccaro, & Kanfer NSF Grant No. SMA 1262474)

Building User Profiles and Stating Preferences

1. Responding to Personal Surveys



2. Stating Teammate Preferences



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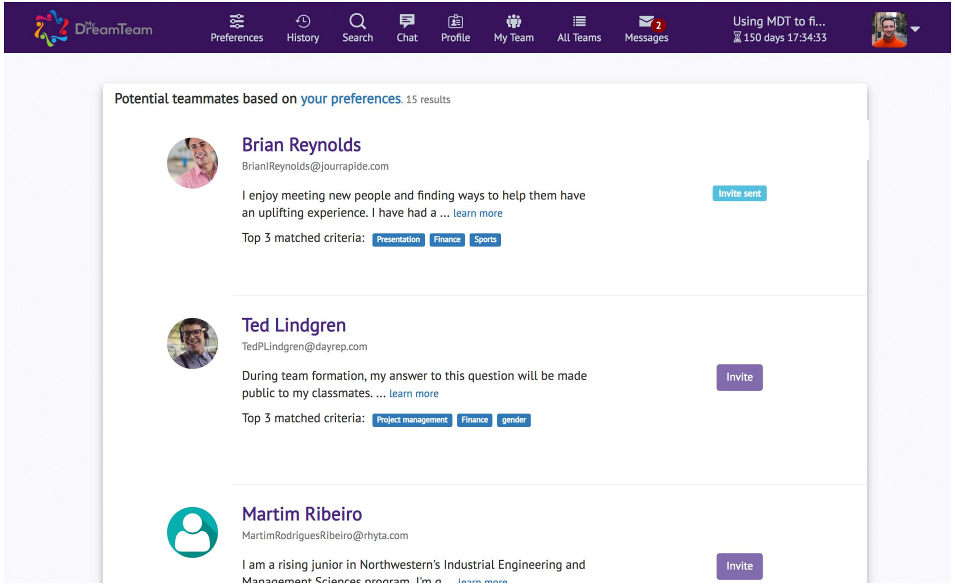
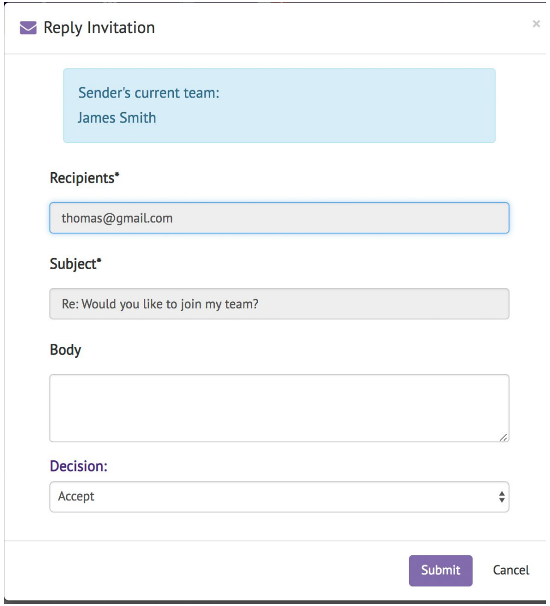
Interacting with Potential Teammates

3. Reviewing Recommendations



4. Sending Invitations



Behavioral Data: Recommendations and Invites

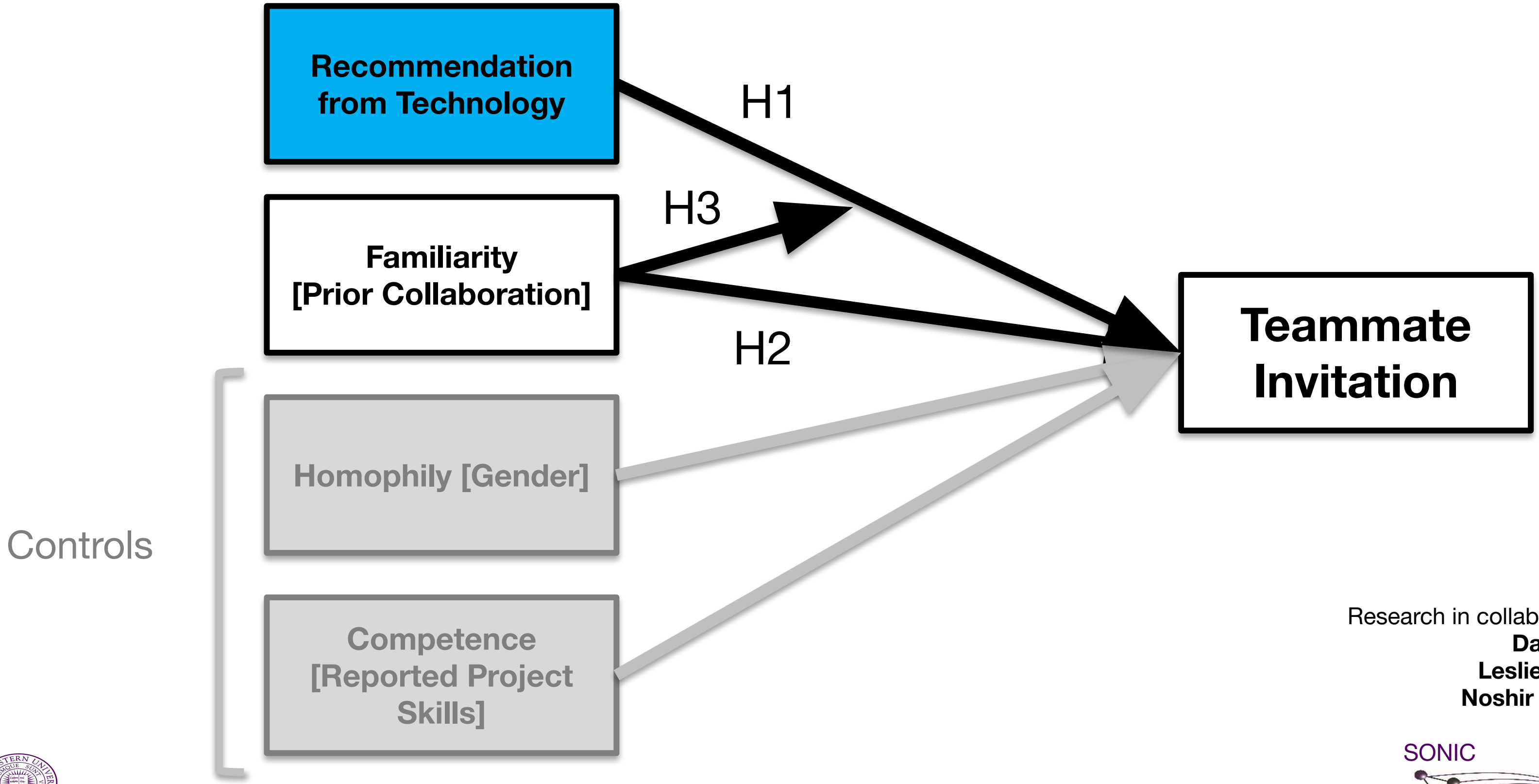
Recommendations

- Who was recommended to whom?
  - Rank-ordered list of potential teammates
  - Converted to directed binary network (1 = ranked 1 to 10, 0 = greater than 10)

Invites (DV)

- Who invited whom to a team?
  - Invitations sent during team assembly
  - Directed binary network
- **The network of invites**

Inviting Teammates in Online Recommender Systems:
The Roles of Online Recommendations and Prior Collaboration



Research in collaboration with
Dan Newman
Leslie DeChurch
Noshir Contractor

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ERGM Results for Main Effects (H1 & H2)

Hypotheses 1 and 2 supported in both samples

Hypothesis	Sample 1 Coefficients	Sample 2 Coefficients
H1: Recipient with Top 10 Recommendation	**1.67*** **	**1.42*** **
H2: Prior Collaboration with Recipient	**2.85*** **	**3.86*** **

Control variables were also included

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

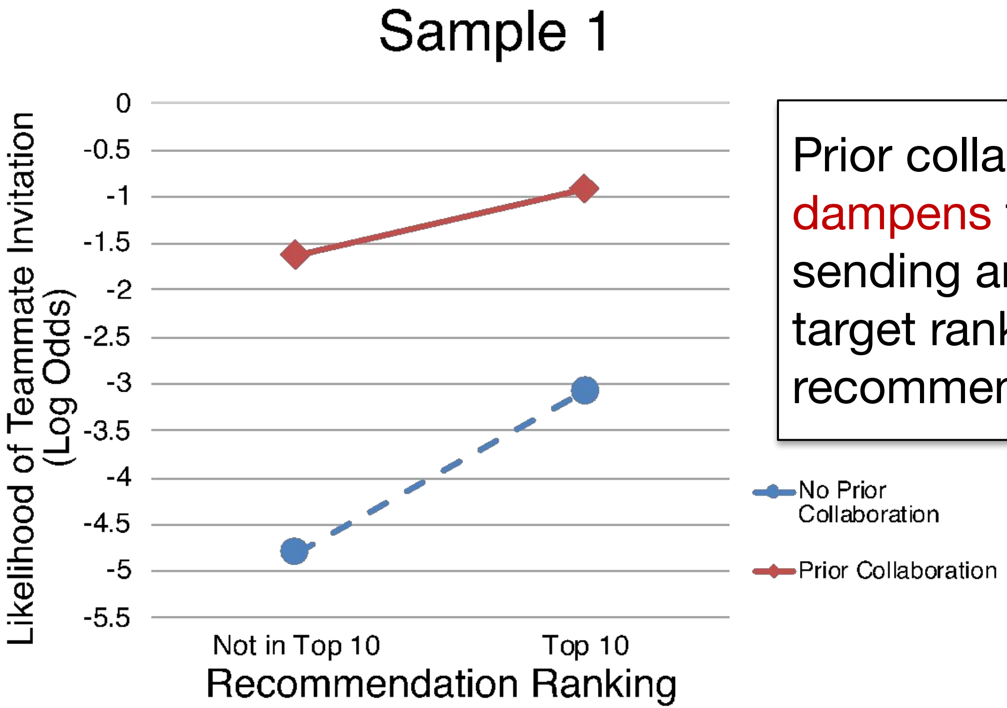
Hypothesis 3 supported in both samples

Hypothesis	Sample 1 Coefficients	Sample 2 Coefficients
H1: Recipient with Top 10 Recommendation	**1.74*****	**1.49*****
H2: Prior Collaboration with Recipient	**3.18*****	**3.98*****
H3: Prior Collaboration X Top 10 Recommendation Interaction	**-1.03****	**-1.11***

Control variables were also included

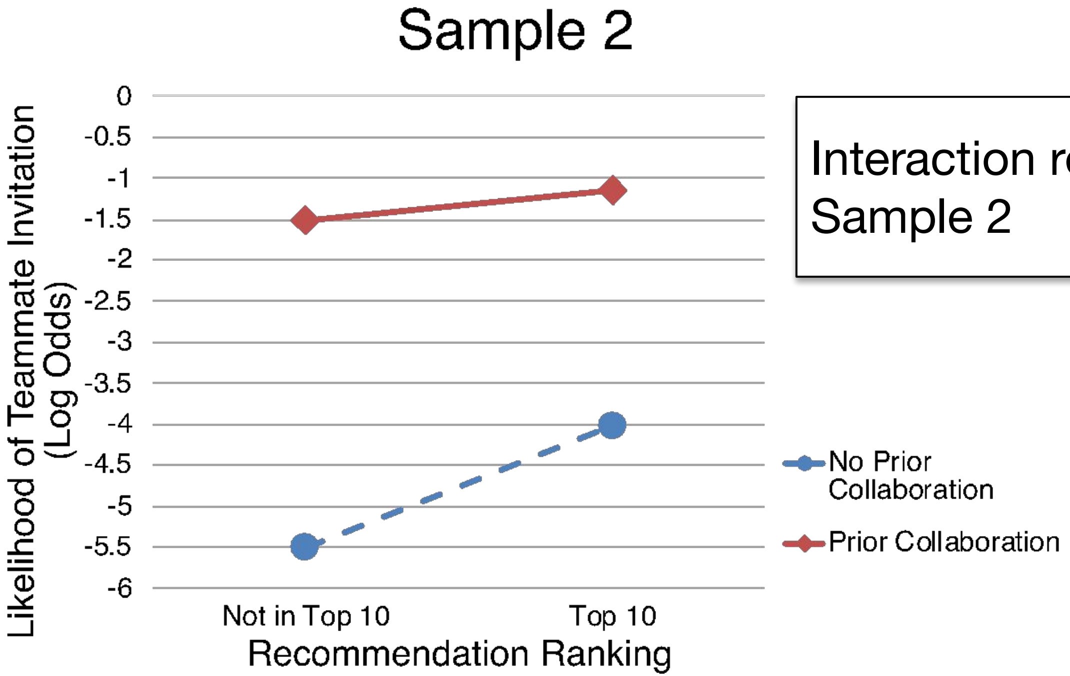
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Interaction: Recommendation X Prior Collaboration



Prior collaboration dampens the likelihood of sending an invitation to a target ranked in the Top 10 recommendations

Interaction: Recommendation X Prior Collaboration



Interaction replicates in Sample 2

Nudging Assembly of Diverse Teams

Genetic Algorithm to Find Team Combinations (NSGA-II)
Max Identity Diversity
&
Max Cognitive Diversity

NSGA-II: Non-dominated Sorting Genetic Algorithm II

Algorithmic Diversity

Agency

Agency	No	Yes
No	Random Teams	Teams assembled by an algorithm
Yes	Informational Nudges Normal MDT	Algorithmic Nudges Diverse MDT

Query Score

Matthew Dvorak
90% match

Kelsey Fontanetta
87% match

Query Score * Diversity Score

Brandon Williams
93% match

Kelsey Fontanetta
87% match

Nudging Assembly of Diverse Teams

Informational nudges

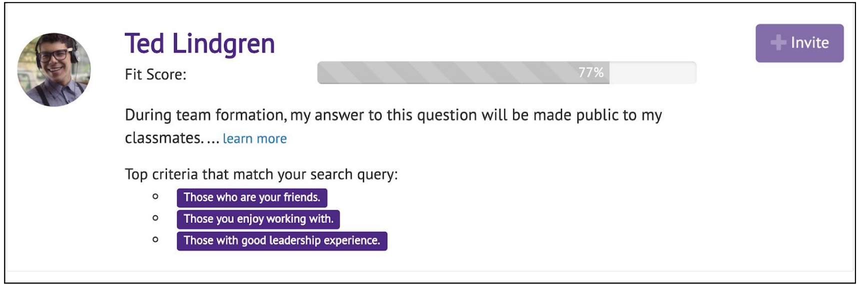
- Provide information to accompany each of the search results:
  - *Adding X to your team will change the diversity of your team on Y dimension by +/- percent*

Algorithmic Nudges

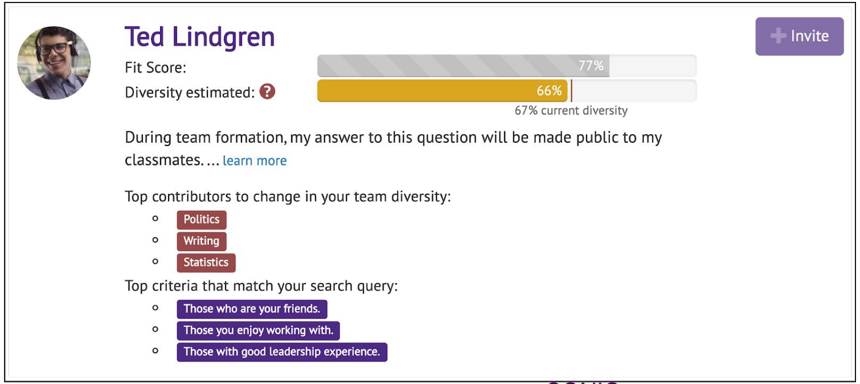
- Weighting rank order of search results with the extent to which an individual increases diversity of the team on multiple dimensions.

Informational Nudges for Assembly of Diverse Teams

- The system calculated a diversity score for each potential teammate based on demographic attributes and project skills disparity.
- In the control condition, the score was calculated but not displayed to the user.
- In the treatment condition, the score was calculated and displayed to the user.



Control condition (no diversity information displayed)



Treatment condition (diversity information displayed)

Informational Nudges for Assembly of Diverse Teams

- We conducted two studies. One in an **onsite** undergraduate class at a university in the US (46 students), and the other in an **online** course for 70 faculty members at a university in Argentina.
- For the **onsite** course, we conducted a <u>pre-post treatment</u>: the system displayed the diversity score only for the second project.
- For the **online** course, we did a <u>randomized field experiment</u>: we randomly assigned participants to control and treatment conditions.

Source: iStock

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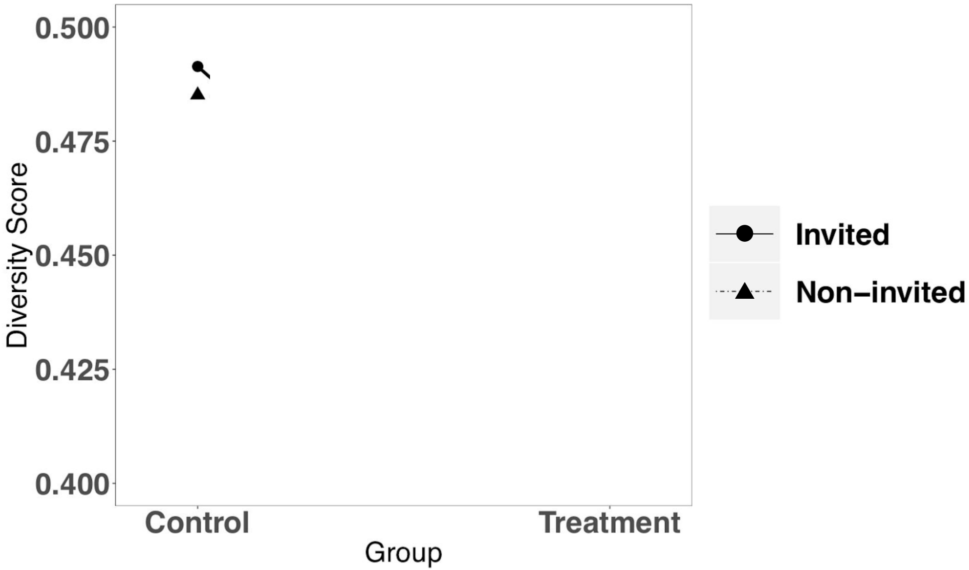
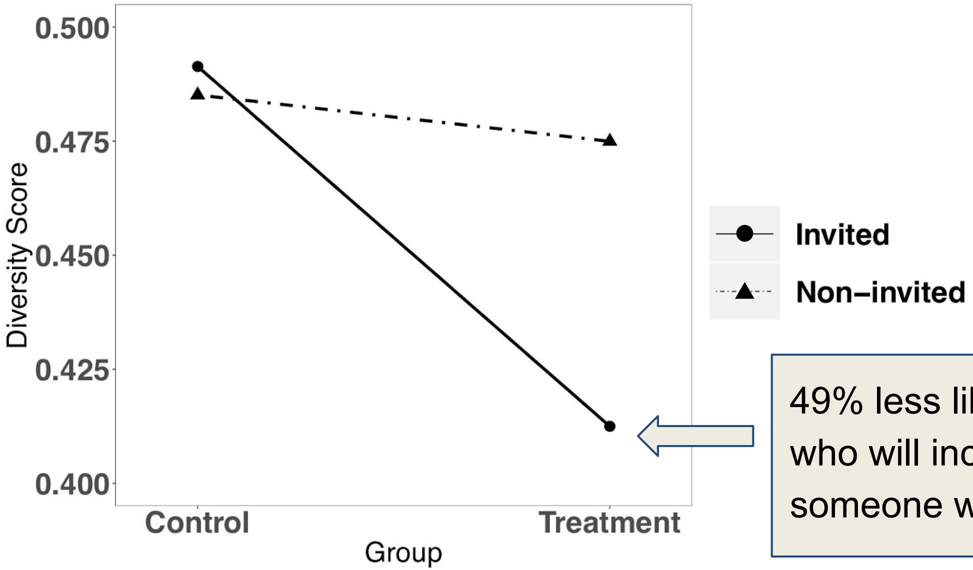
Informational Nudges for Assembly of Diverse Teams

No difference in diversity score between those invited and those not invited in the control condition



Informational Nudges for Assembly of Diverse Teams

Big difference in diversity score between those invited and those not invited in the treatment condition



49% less likely to invite someone who will increase diversity than someone who will reduce it.

Nudging Assembly of Diverse Teams

Algorithmic Diversity

Agency	No	Yes
No	Random Teams	Teams assembled by an algorithm
Yes	**Informational Nudges** Normal MDT	**Algorithmic Nudges** Diverse MDT

Genetic Algorithm to Find Team Combinations (NSGA-II)
Max Identity Diversity
&
Max Cognitive Diversity

NSGA-II: Non-dominated Sorting Genetic Algorithm II

Query Score

Matthew Dvorak 90% match
Kelsey Fontanetta 87% match

Query Score * Diversity Score

Brandon Williams 93% match
Kelsey Fontanetta 87% match

Nudging Assembly of Diverse Teams

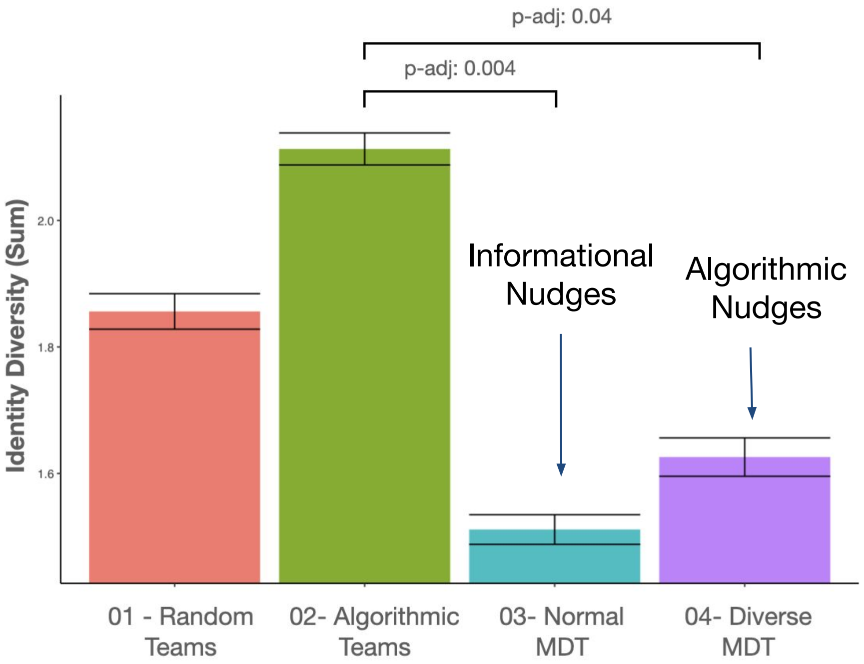
- In a third study, we studied the effect of the team formation strategy on team diversity and performance.
- We conducted a 2x2 between-subject experiment, manipulating **personal agency** and **inclusion of diversity criteria**.
- We recruited 386 participants and 52 teams were assembled.
- Participants had to complete a creativity task: they designed recruitment materials for an NGO.

Session with participants on Zoom

Impact of Nudging Assembly of Diverse Teams on Diversity

Agency negatively affected the assembly of identity diverse teams.

Self-assembled teams had lower identity diversity compared to random and algorithmic teams

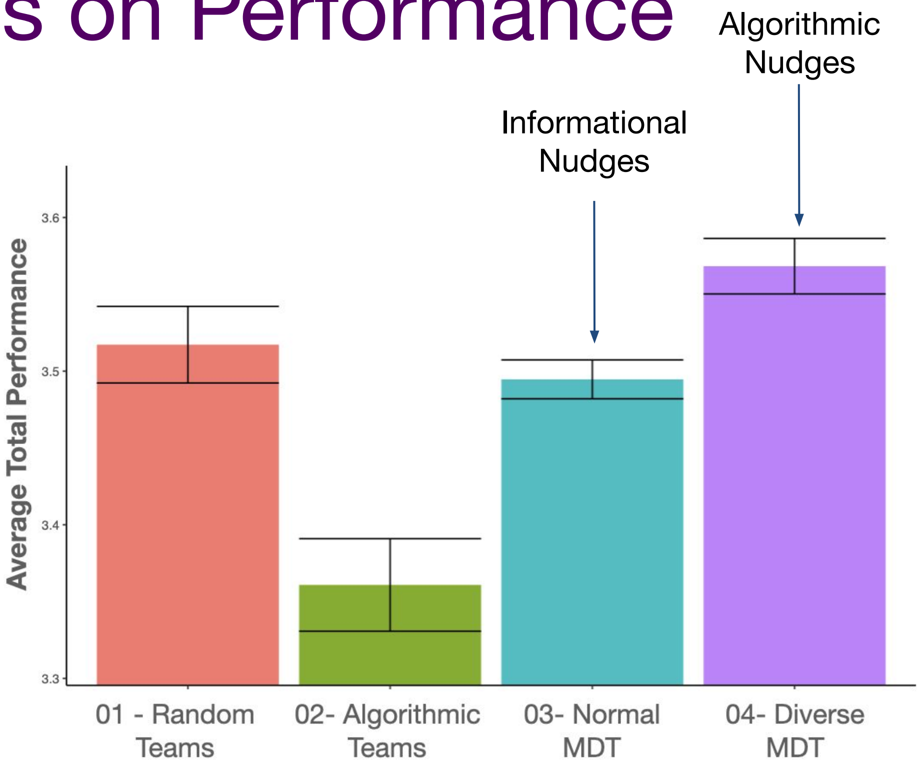


Impact of Nudging Assembly of Diverse Teams on Performance

When checking team's total performance, the Diverse MDT teams achieved the highest scores.

Algorithmic teams scored the lowest.

Self-assembled teams scored lower than Random and Diverse teams.



Nudging Assembly of Diverse Teams

Informational nudges

- Provide information to accompany each of the search results:
    - *Adding X to your team will change the diversity of your team on Y dimension by +/- percent*
- ***People assembled into LESS diverse teams!***

Algorithmic Nudges

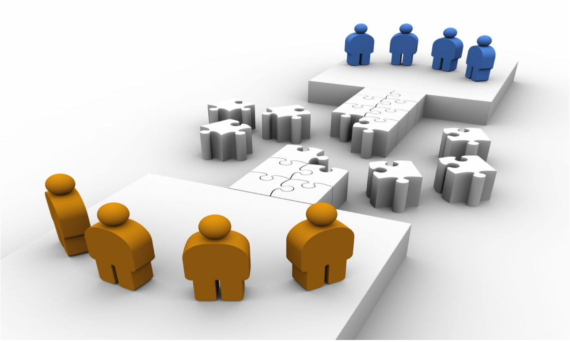
- Weighting rank order of search results with the extent to which an individual increases diversity of the team on multiple dimensions.
-
- ***People assembled into MORE diverse teams!***
- ***And they performed better than teams assembled by Informational Nudges***

Making Relational Analytics Actionable for *Teams*

Team Self-Assembly

Team Staffing

Predicting Team Performance



Predicting Team Conflict

Relational Analytics for Predicting Effective Space Crews:

Brennan Antone
Cornell U

Alina Lungeanu
Northwestern University

Jacqueline Ng Lane
Harvard University

Leslie DeChurch
Northwestern University

Suzanne Bell
NASA

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Humans
will become an
interplanetary
species

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NASA
NASA
NASA'S JOURNEY TO MARS

Distance

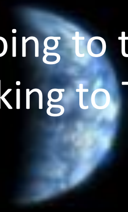
ISS orbits 250 miles above earth, Moon is 250,000 miles (1000 times farther).

If the International Space Station is two steps away, the moon is a mile away.

If the International Space Station is a mile away, the moon is like going to Europe.

Mars is 250 million miles - 1000 times farther than Moon and a million times farther than space station.

If the moon is a step away, Mars is 3000 miles away,



If going to the moon is walking across the living room, going to Mars is like walking to Tibet.

Travel Time: 259 Days

Travel Time: 259 Days

Travel Time: 259 Days

Depart from	AU	Years	AU/Year	J2000
Earth	1.0000	1.0000	6.2832	100.4644
Arrive at				
Mars	1.5237	1.8808	5.0902	355.4533

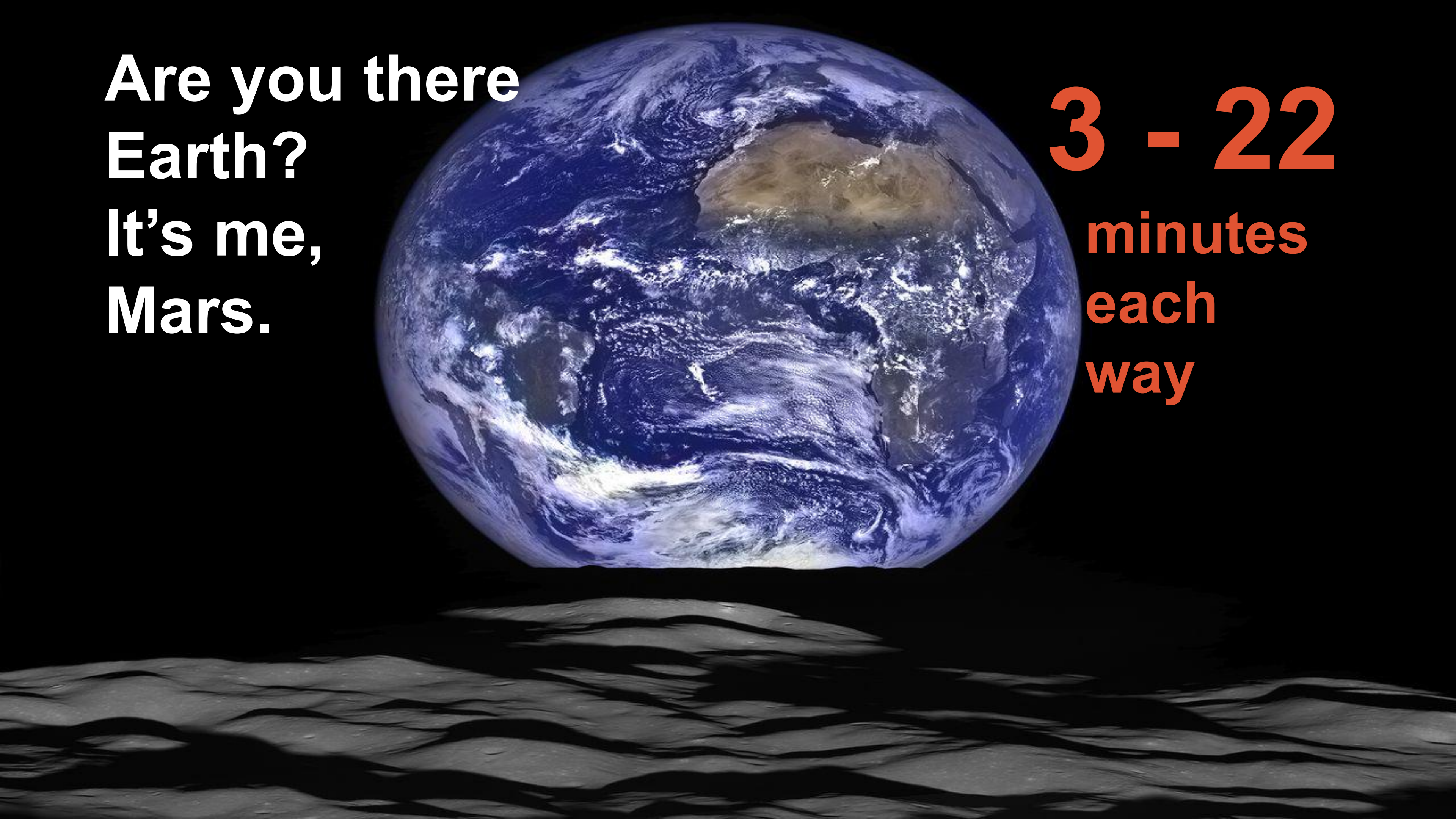
Synodic			Perihelion DV	2.9448	km/sec
Period	2.1354	Years	Aphelion DV	2.6490	km/sec
Trip Time	0.7087	Years	Total DV	5.5937	km/sec

Leave	Month	Day	Year	Arrive	Month	Day	Year
2001.2495	3	30	2001	2001.9582	12	15	2001
2003.3849	5	19	2003	2004.0936	2	4	2004
2005.5202	7	7	2005	2006.2290	3	22	2006
2007.6556	8	26	2007	2008.3643	5	11	2008
2009.7910	10	15	2009	2010.4997	6	30	2010
2011.9264	12	4	2011	2012.6351	8	19	2012
2014.0618	1	22	2014	2014.7705	10	7	2014
2016.1972	3	11	2016	2016.9059	11	26	2016
2018.3326	4	30	2018	2019.0413	1	15	2019
2020.4679	6	18	2020	2021.1767	3	4	2021
2022.6033	8	7	2022	2023.3120	4	22	2023
2024.7387	9	26	2024	2025.4474	6	11	2025
2026.8741	11	15	2026	2027.5828	7	30	2027
2029.0095	1	3	2029	2029.7182	9	19	2029
2031.1449	2	22	2031	2031.8536	11	7	2031
2033.2803	4	11	2033	2033.9890	12	26	2033
2035.4156	5	30	2035	2036.1244	2	15	2036
2037.5510	7	18	2037	2038.2597	4	4	2038
2039.6864	9	7	2039	2040.3951	5	22	2040
2041.8218	10	26	2041	2042.5305	7	11	2042
2043.9572	12	15	2043	2044.6659	8	30	2044
2046.0926	2	3	2046	2046.8013	10	18	2046
2048.2280	3	22	2048	2048.9367	12	7	2048
2050.3633	5	11	2050	2051.0721	1	26	2051
2052.4987	6	30	2052	2053.2074	3	15	2053
2054.6341	8	18	2054	2055.3428	5	3	2055
2056.7695	10	7	2056	2057.4782	6	22	2057
2058.9049	11	26	2058	2059.6136	8	11	2059
2061.0403	1	14	2061	2061.7490	9	30	2061
2063.1756	3	3	2063	2063.8844	11	18	2063
2065.3110	4	22	2065	2066.0198	1	7	2066
2067.4464	6	11	2067	2068.1551	2	26	2068
2069.5818	7	29	2069	2070.2905	4	15	2070
2071.7172	9	18	2071	2072.4259	6	3	2072
2073.8526	11	7	2073	2074.5613	7	22	2074
2075.9880	12	26	2075	2076.6967	9	11	2076
2078.1233	2	14	2078	2078.8321	10	30	2078
2080.2587	4	3	2080	2080.9674	12	18	2080
2082.3941	5	22	2082	2083.1028	2	7	2083
2084.5295	7	11	2084	2085.2382	3	26	2085
2086.6649	8	29	2086	2087.3736	5	14	2087
2088.8003	10	18	2088	2089.5090	7	3	2089
2090.9357	12	7	2090	2091.6444	8	22	2091
2093.0710	1	26	2093	2093.7798	10	11	2093
2095.2064	3	14	2095	2095.9151	11	29	2095
2097.3418	5	3	2097	2098.0505	1	18	2098
2099.4772	6	22	2099	2100.1859	3	7	2100
2101.6126	8	11	2101	2102.3213	4	26	2102

Travel Time: 259 Days

2009.7910	10	15	2009	2010.4997	6	30	2010
2011.9264	12	4	2011	2012.6351	8	19	2012
2014.0618	1	22	2014	2014.7705	10	7	2014
2016.1972	3	11	2016	2016.9059	11	26	2016
2018.3326	4	30	2018	2019.0413	1	15	2019
2020.4679	6	18	2020	2021.1767	3	4	2021
2022.6033	8	7	2022	2023.3120	4	22	2023
2024.7387	9	26	2024	2025.4474	6	11	2025
2026.8741	11	15	2026	2027.5828	7	30	2027
2029.0095	1	3	2029	2029.7182	9	19	2029
2031.1449	2	22	2031	2031.8536	11	7	2031
2033.2803	4	11	2033	2033.9890	12	26	2033
2035.4156	5	30	2035	2036.1244	2	15	2036
2037.5510	7	18	2037	2038.2597	4	4	2038
2039.6864	9	7	2039	2040.3951	5	22	2040
2041.8218	10	26	2041	2042.5305	7	11	2042
2043.9572	12	15	2043	2044.6659	8	30	2044
2046.0926	2	3	2046	2046.8013	10	18	2046

NASA'S JOURNEY TO MARS


Are you there
Earth?
It’s me,
Mars.
3 - 22
minutes
each
way

Distance

...means CREW Autonomy

Risk Statement

Given that the conditions of space missions may lead to inadequate functioning within a team (inadequate cooperation, coordination, communication and/or psychosocial adaptation), which includes flight crew and ground support, there is a possibility that performance and behavioral health decrements will occur.

DRM Categories	Mission Type and Duration	Operations	
		LxC	Risk Disposition *
Low Earth Orbit	Short (<30 days)	3x2	Accepted with Monitoring
	Long (30 days-1 year)	3x2	Accepted with Monitoring
Lunar Orbital	Short (<30 days)	3x2	Accepted with Monitoring
	Long (30 days-1 year)	3x3	Requires Mitigation
Lunar Orbital + Surface	Short (<30 days)	3x2	Accepted with Monitoring
	Long (30 days-1 year)	3x2	Accepted with Monitoring
Mars	Preparatory (<1 year)	3x3	Requires Mitigation
	Mars Planetary (730-1224 days)	3x4	Requires Mitigation

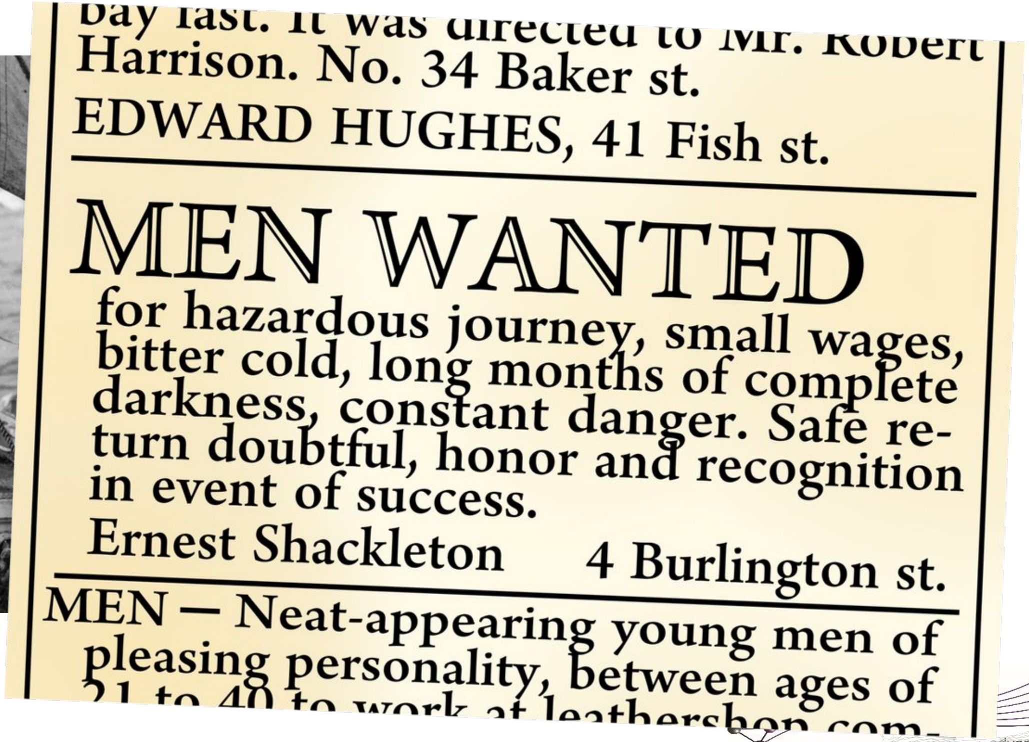
“All the conditions necessary for murder are met if you shut two men in a cabin measuring 18 by 20 and leave them together for two months.”

-Valery Ryumin, Cosmonaut

advancing the
etworks in communities

Shackleton’s approach to team assembly for the South Pole

UK, 1914, Shackleton's crew sets out for the South Pole



Harrison. No. 34 Baker st.

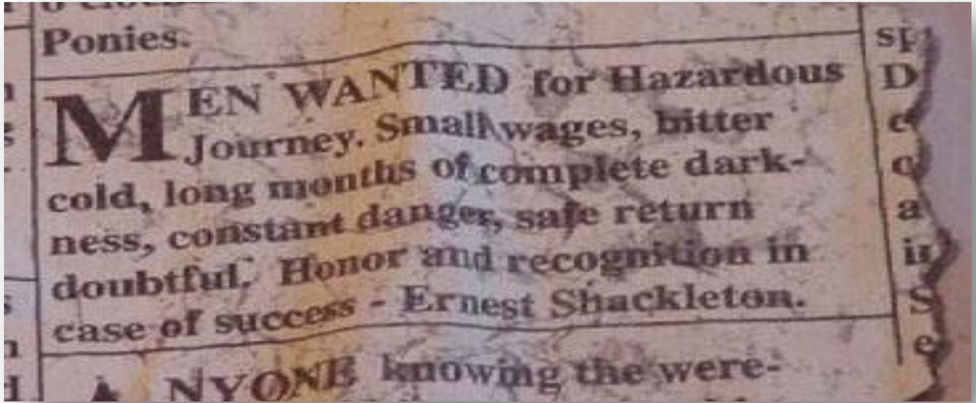
EDWARD HUGHES, 41 Fish st.

MEN WANTED

for hazardous journey, small wages, bitter cold, long months of complete darkness, constant danger. Safe return doubtful, honor and recognition in event of success.

Ernest Shackleton 4 Burlington st.

MEN — Neat-appearing young men of pleasing personality, between ages of



Ponies.

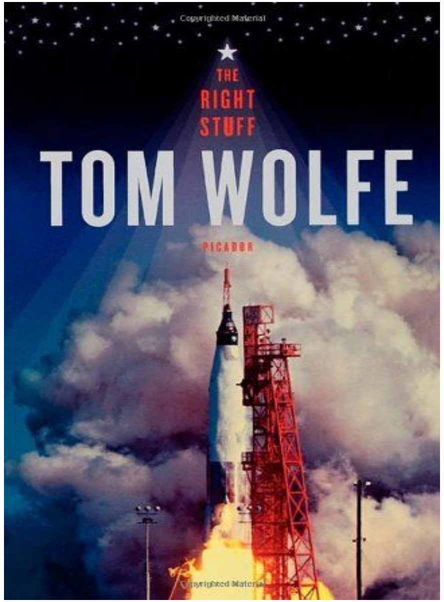
MEN WANTED for Hazardous Journey. Small wages, bitter cold, long months of complete darkness, constant danger, safe return doubtful. Honor and recognition in case of success - Ernest Shackleton.

ANYONE knowing the were-

"The most positive peer nominations were received by those who scored <u>low on self-reflection and emotional expressiveness</u>" (Biersner & Hogan, 1984).

"..the Antarctic station thus becoming a haven for the technically competent individual who is <u>deficient in social skills</u>" (Natani & Shurley, 1974, p. 90)

NASA's approach to team assembly for the Moon



USA, 1959, NASA announces "The Mercury 7" first astronaut class

An Alternative View:

"X is a master of good natured fun. I think when he leaves we will see a shift in the enjoyment of the people working the ground jobs. <u>He is brilliant at knowing the perfect balance of fun with professionalism</u>. I am in awe constantly. My love of joking around is immense but I am a mere child next to the talents of my commander. He is gifted (Stuster, 2016, p.78)."

Peggy Whitson, Chair
Astronaut Selection Board
(2009)

- Changed emphasis for astronaut selection:
  “plays well with others”

Astronaut Job Analysis Reveals:

"Teamwork makes the dream work at NASA"

NASA's approach to team assembly for Mars

Space as a place for the interpersonally gifted

I like to think about this along the lines of a camping trip and who you would like to have along with you … someone that is competent and can take good care of themselves and their equipment, someone that **contributes to the team** and **helps with group tasks**, someone that is **good natured** and **pleasant to be around**, etc., someone fun!

- Jessica Meir

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How can we help teams foster beneficial social networks?

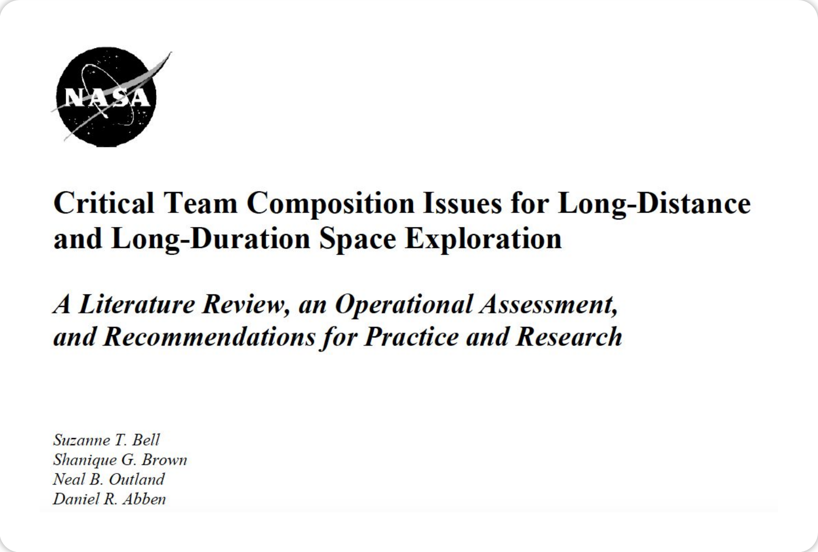
RQ1: Given everything we know about networks and teams, can we accurately model team networks?

RQ2: How can we use the network model to intervene in teams?

RQ1:

Given everything we know about networks and teams, can we accurately model team networks?

Which characteristics predict social integration?


Critical Team Composition Issues for Long-Distance and Long-Duration Space Exploration

A Literature Review, an Operational Assessment, and Recommendations for Practice and Research

Suzanne T. Bell
Shanique G. Brown
Neal B. Outland
Daniel R. Abben

- Shared Values (e.g., benevolence, traditionalism)
- Personality (e.g., facets of extraversion, agreeableness)
- Coping styles
- Emotion regulation
- National background
- Military background
- Sex
- Age
- Etc.

Development of the CREWS Model
Crew Recommender for Effective Work in Space

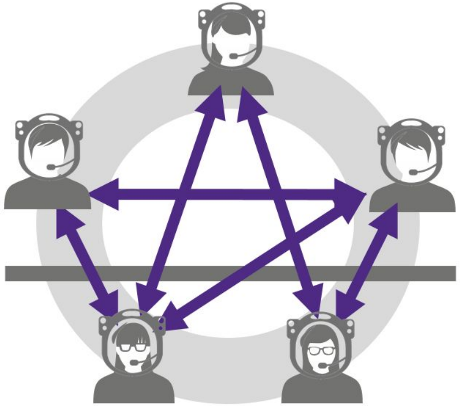
Step 1: Conceptual Model

Step 2: Observation

Step 3: Estimation

Step 4: Validation

Step 5: Application



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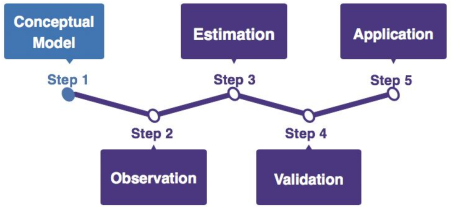
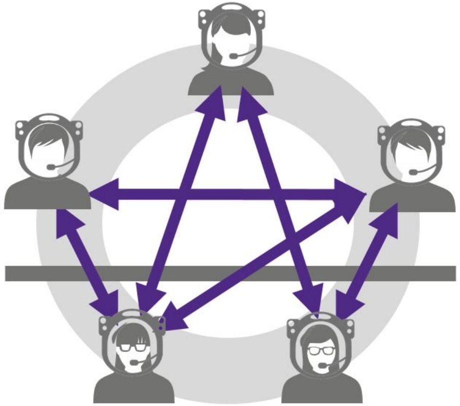
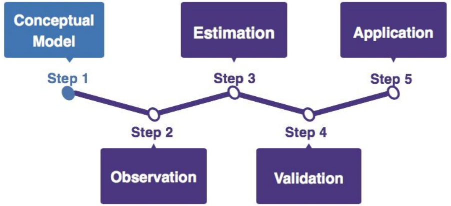


Networks in Teams

Working Relationships:

- **Task Affect**: *"With whom do you enjoy working?"*
- **Hindrance**: *"Who makes tasks difficult to complete?"*





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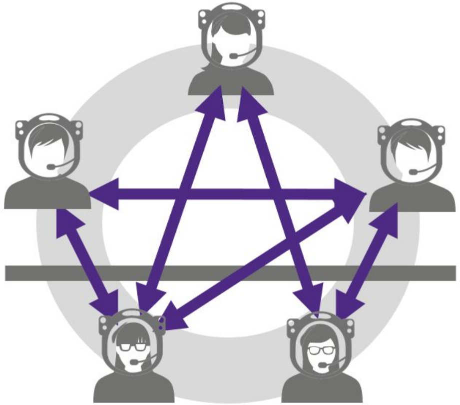

Informal Leadership:

- **Claim Leadership**: *“Who do you rely on for leadership?”*
- **Grant Leadership**: *“To whom do you provide leadership?”*

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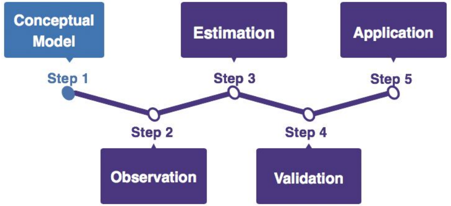
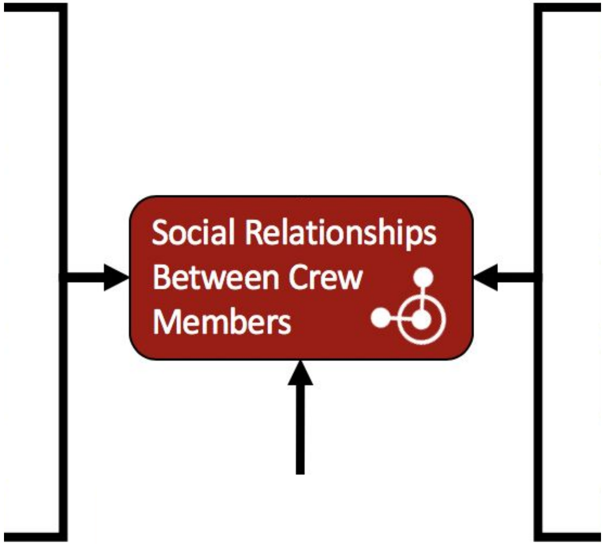
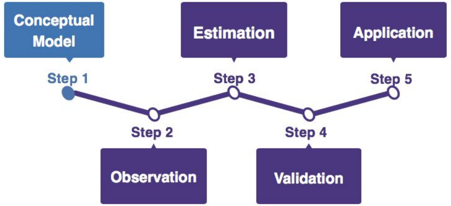
Factors shaping team networks in space - Theoretical





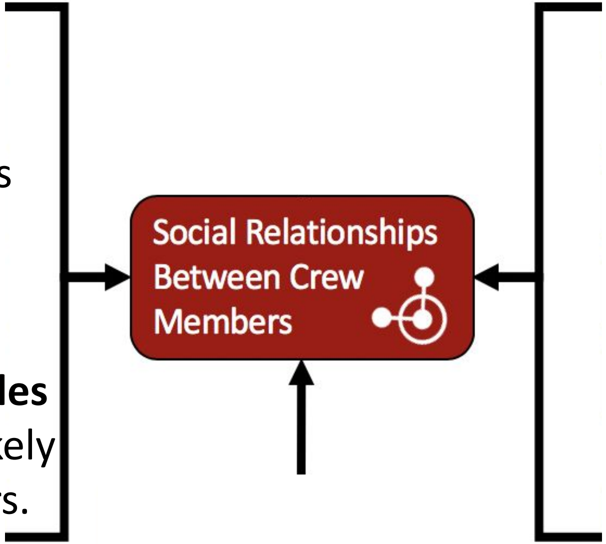
Factors shaping team networks in space - Theoretical



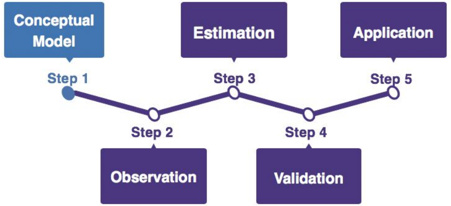
Space Context

Time in isolation
Task schedule and attributes
Communication delay
etc.

e.g., **High workload schedules** make crew members less likely to enjoy working with others.



Factors shaping team networks in space - Theoretical



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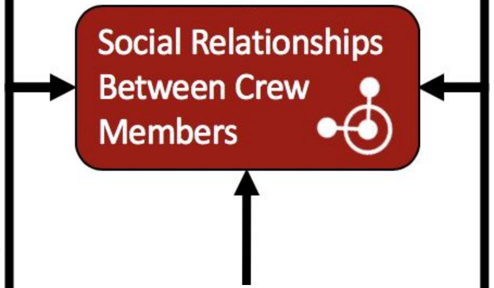
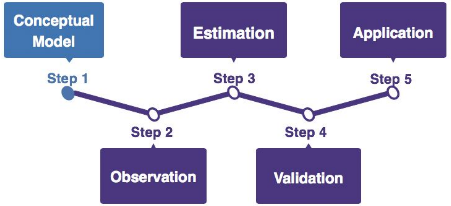


Crew Attributes

Personality and values
Personality compatibility
Demographic faultlines
etc.

e.g., Crew members high in **self-monitoring** have fewer negative relationships.

Factors shaping team networks in space - Theoretical



Space Context

Time in isolation
Task schedule and attributes
Communication delay
etc.

e.g., **High workload schedules** make crew members less likely to enjoy working with others.

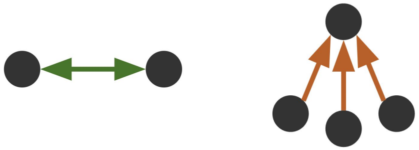
Social Relationships Between Crew Members

Crew Attributes

Personality and values
Personality compatibility
Demographic faultlines
etc.

e.g., Crew members high in **self-monitoring** have fewer negative relationships.

Network Effects



Observe these factors and networks in space analog teams - Measurement

Conceptual Model — Step 1

Step 2 — **Observation**

Estimation — Step 3

Step 4 — **Validation**

Application — Step 5

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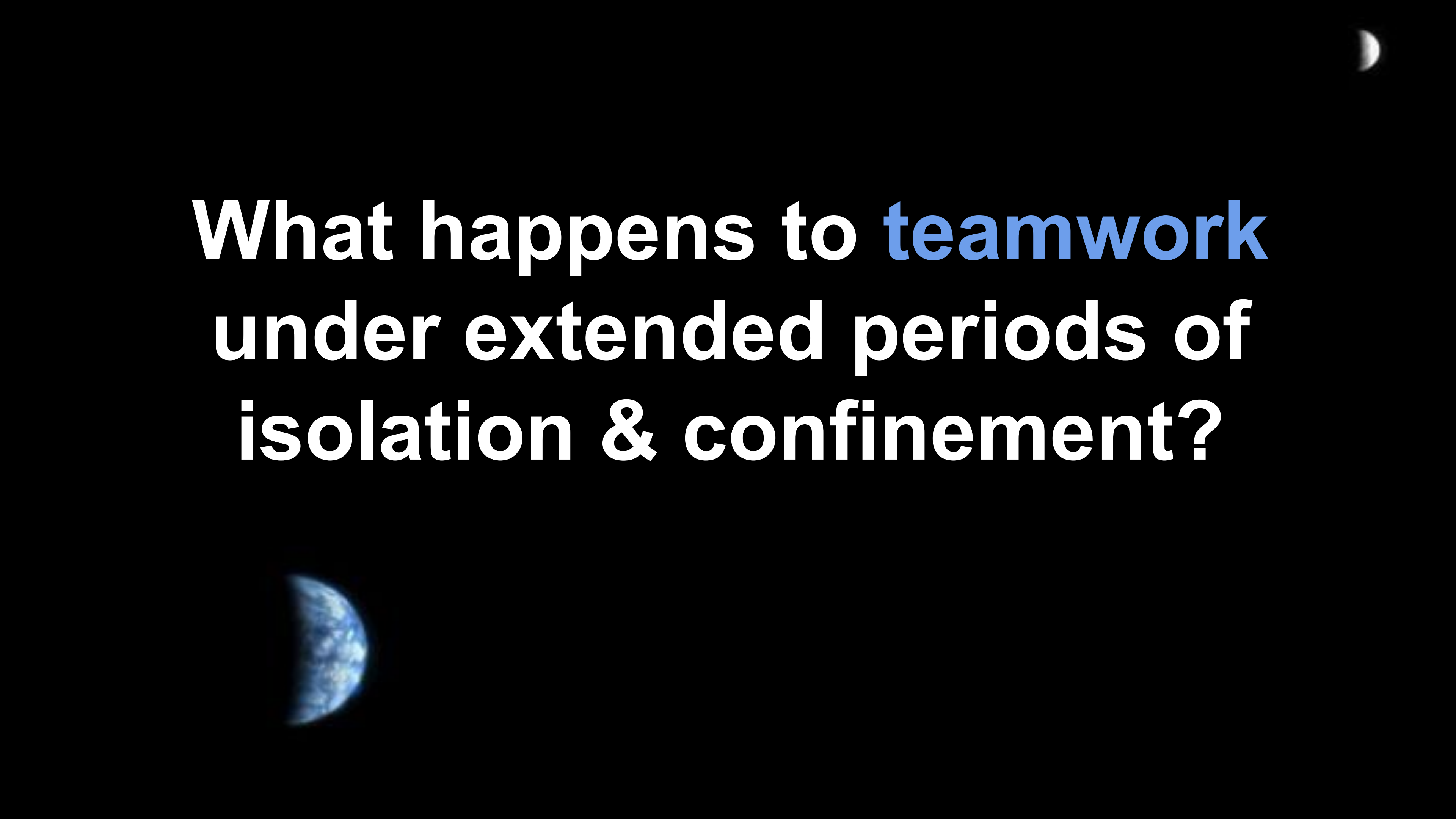

What happens to teamwork
under extended periods of
isolation & confinement?

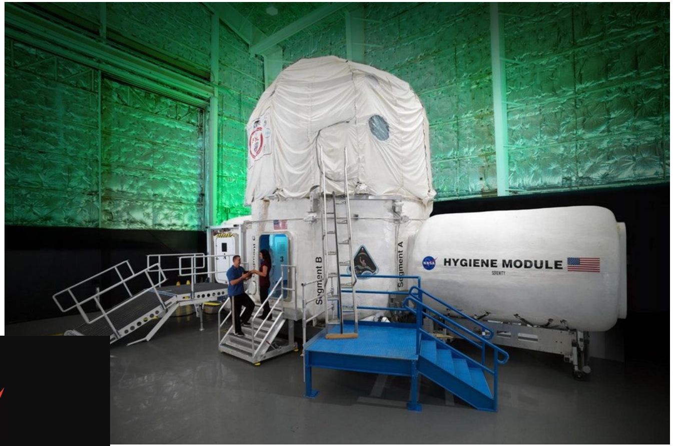
Wouldn’t it be nice to have a human petri dish?

A human petri dish?

- … where we could manipulate people's isolation and sensory deprivation for 100s of days
- … while making them do complex and boring tasks and
- … monitoring them 24/7 physiologically and via audio/video, administering unlimited surveys?
- … *Zimbardo's dream .. our nightmare?*

That’s **exactly** what we are doing

USA's HERA Space Analog




NASA's HERA XIV crew, inside the habitat
Copyright 2017 Dr. Shelley Cazares.
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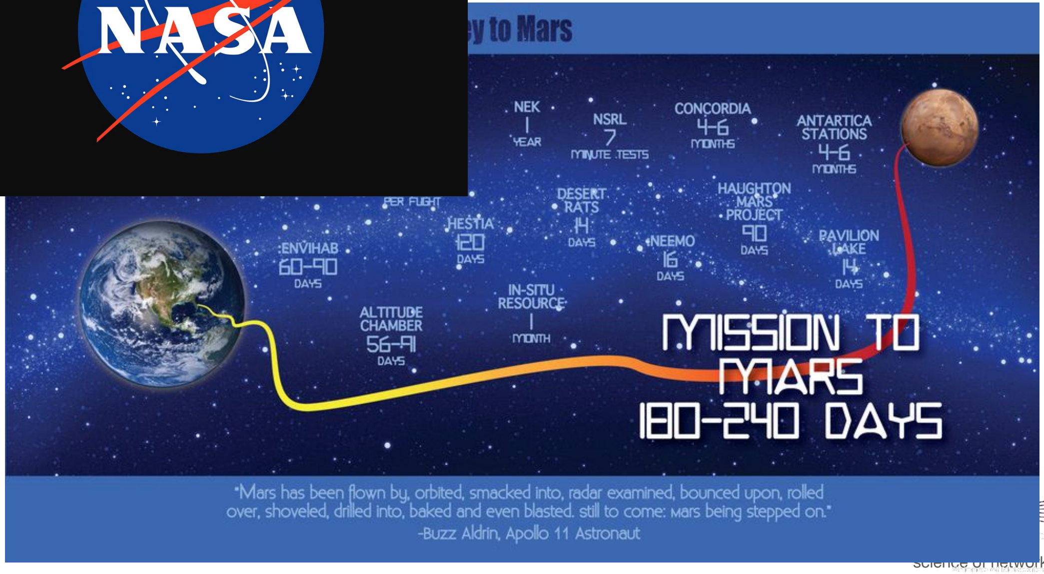
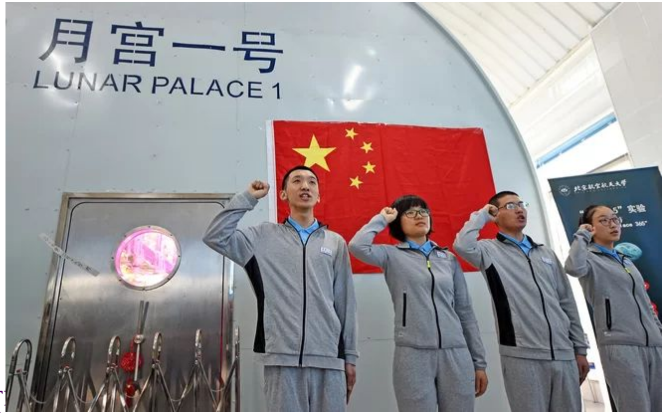


Chinese Lunar Palace



Russia's NEK

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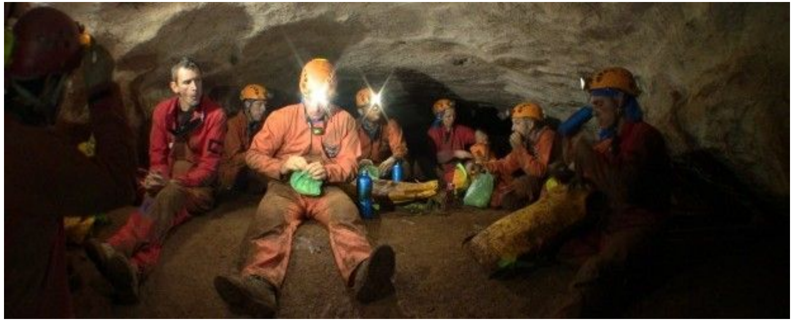
Japan’s Isolation Chamber

Concordia (S. Pole)



Caves (Sardinia)

Pangaea-X Moon base (Canary Islands)

European Space Agency

Ground-Based Analogs

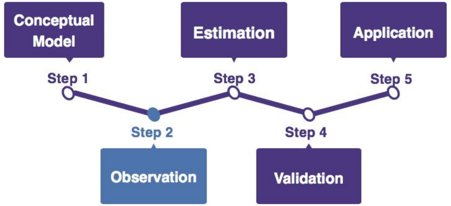
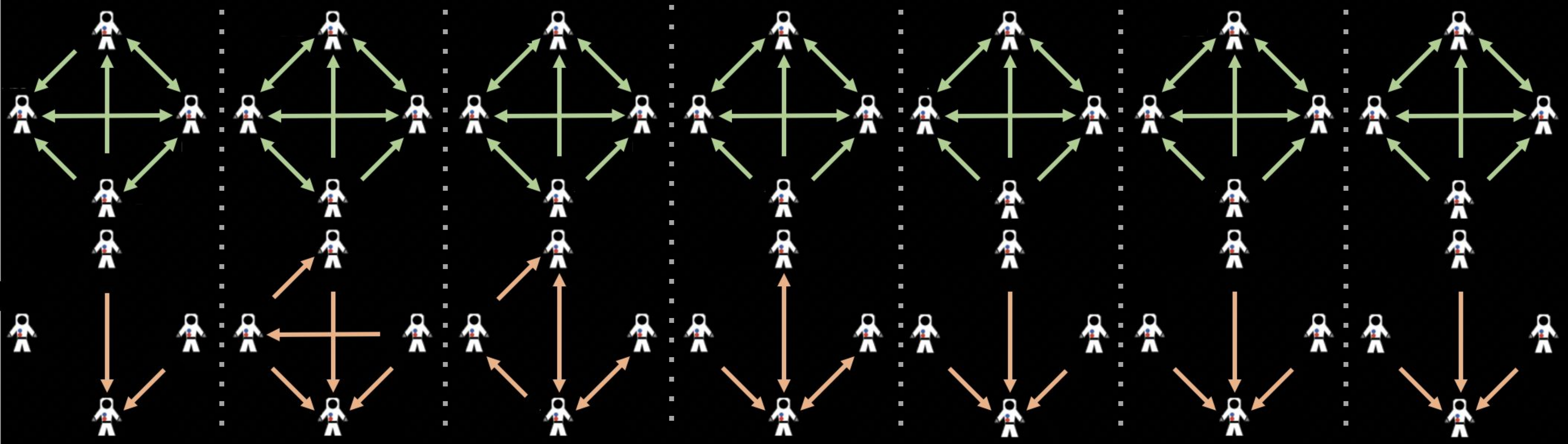


Image credit: NASA

Teams complete **30 or 45 day missions**

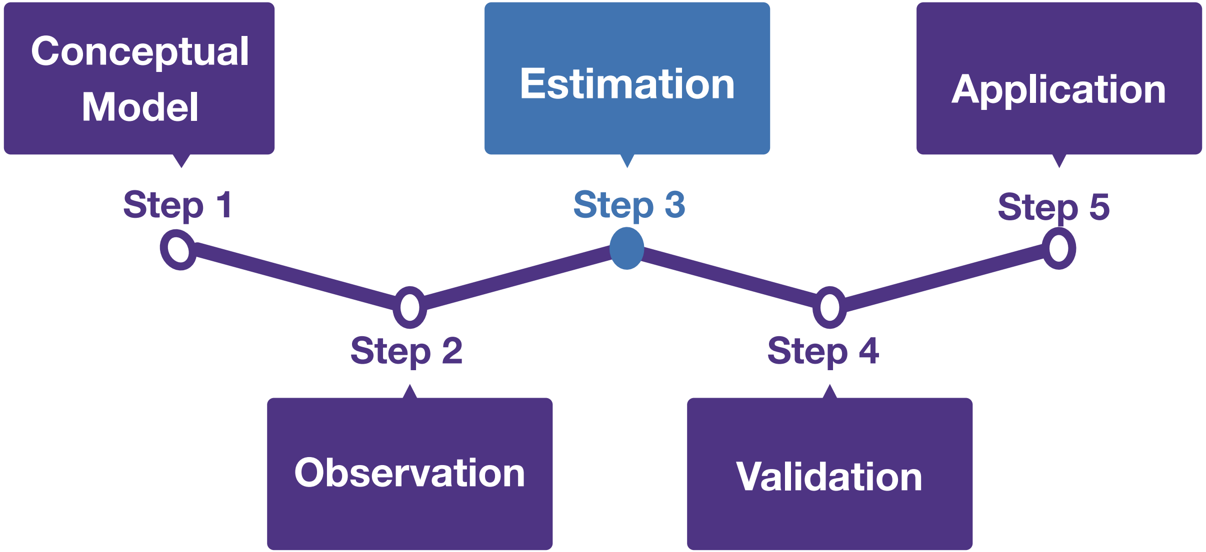
Isolation	Heavily scheduled days
Sleep Deprivation	Slam shifts
Communication delay	Emergency simulations

Task Affect: *"With whom do you work effectively?"*

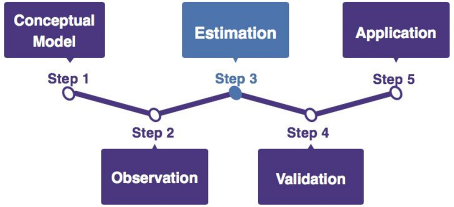


Hindrance: *"Who makes tasks difficult to complete?"*

Calibrate the model based on data - Estimation



Computational modeling

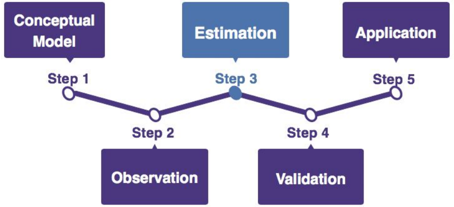


Computational model predicts how social networks develop over time in space crews.

Empirical data collected over the course of **8 analog missions** was used to calibrate the model.

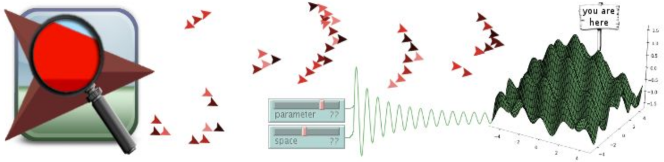
Antone, B., Lungeanu, A., Bell, S. T., DeChurch, L. A., & Contractor, N. (2020). Computational Modeling of Long-Distance Space Exploration: A Guide to Predictive and Prescriptive Approaches to the Dynamics of Team Composition. In *Psychology and Human Performance in Space Programs* (pp. 107-130). CRC Press.

Step 3 - Estimation



Model development

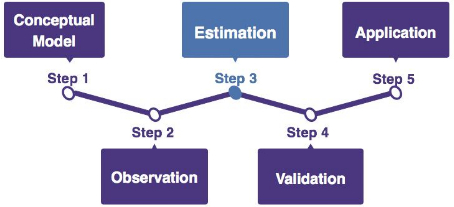
- NetLogo agent-based model platform *(Wilensky, 1999)*

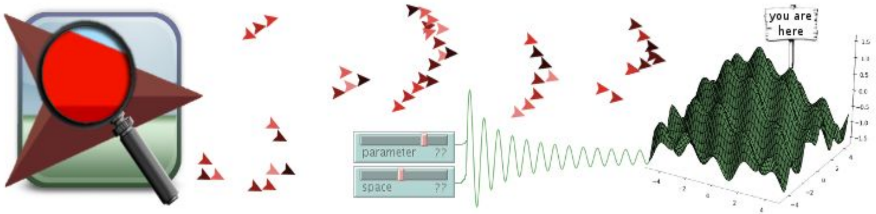


Parameter estimation

- BehaviorSearch tool *(Stonedahl & Wilensky, 2010)*
  - A tool to conduct evolutionary search in parameter-spaces for agent-based models build in NetLogo
  - Genetic algorithms to search over the set of possible parameters
  - Objective is to select parameters that maximize the ability of the model to replicate the trends observed in a set of training data (using random oversampling due to class imbalance)

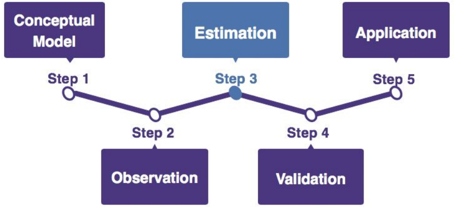
Step 3 - Estimation





- Estimation:
  - For each set of parameters, we ran 15 different searches that each used 20,000 model runs
  - 4 model runs were used to estimate the performance at each point. 15 additional runs were used to check solutions that were candidates for the best
  - Independently estimated models for four network ties: task affect, hindrance, granting leadership, and claiming leadership

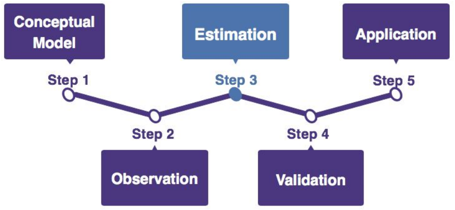
Step 3 – Estimation
Task Affect and Hindrance



	Task Affect	Hindrance
ICC Context		
Cumulative Sleep Deprivation	0.35	0.31
Communication Delay	0.08	-0.38
Social Network Trends		
Density	-0.79	-0.27
Tie Persistence	0.21	0.81
Reciprocity	-0.27	-0.96
Transitivity	0.72	-0.23
Task and Scheduling		
Task Workload	0.90	0.25
Task Interdependence	-0.26	-0.17
Task Importance	-0.88	-0.11
Similarity		
Demographic Homophily	0.34	-0.38
Military Background Homophily	-0.73	0.18
Cognitive Styles Similarity	-0.72	
Psych. Col. Similarity		-0.89
Humor (Coping) Similarity		0.89
Team Identity Similarity		0.17

	Task Affect	Hindrance
Sender Attributes		
Humor (Cope) Sender	-0.97	
Reliance (Psy. Col.) Sender	0.57	
Emotional Regulation Reappraisal Sender	0.46	
Cumulative Workload Sender	-0.78	0.08
Emotionality Sender		-0.17
Self-Monitoring Motivation Sender		-0.98
Conservation Sender		0.88
Receiver Attributes		
Self-Monitoring Motivation Receiver	0.56	-0.85
Self-Direction Receiver	0.83	
Norm Acceptance Receiver	0.97	
Conscientiousness Receiver	-0.73	0.26
Neuroticism Receiver	-0.53	0.37
Cheerfulness Receiver	0.69	
Friendliness Receiver		-1.00
Emotionality Receiver		0.84
Psych. Col. Receiver		0.24
Instrumental Support (Coping) Receiver		0.75

Step 3 – Estimation
Task Affect and Hindrance



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Crew members tend to enjoy working with individuals who are high in self-monitoring motivation.

These individuals are less likely to be viewed as making tasks difficult to complete.

	Task Affect	Hindrance
Sender Attributes		
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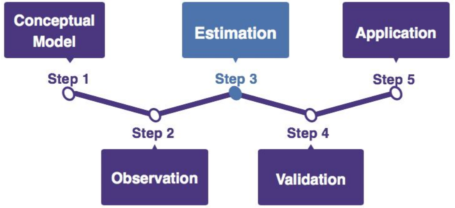
Step 3 – Estimation
Task Affect and Hindrance



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High workload schedules make crew members less likely to enjoy working with others.

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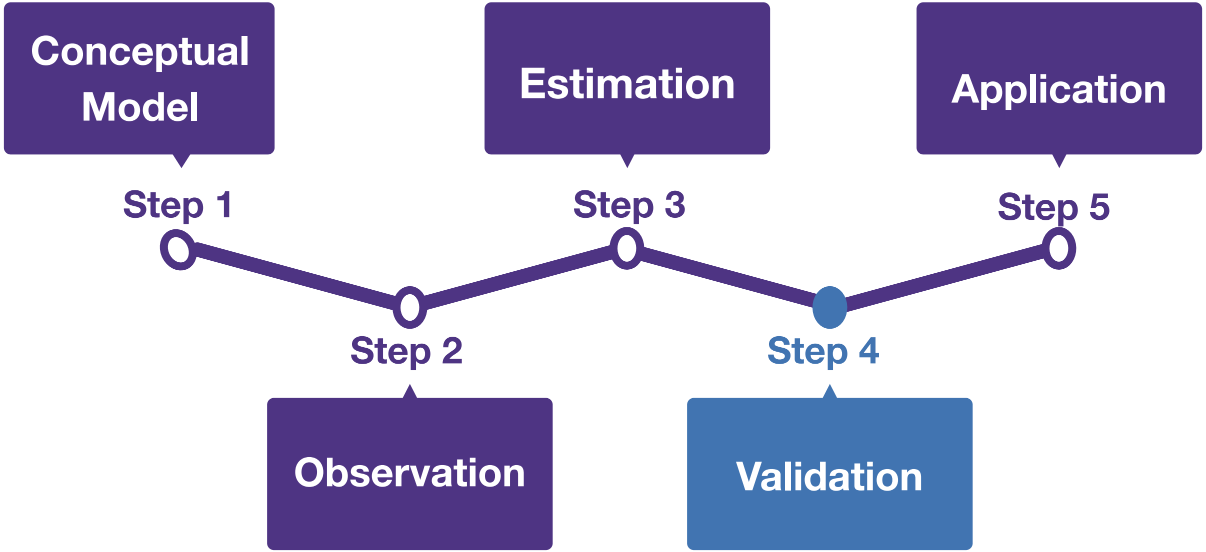
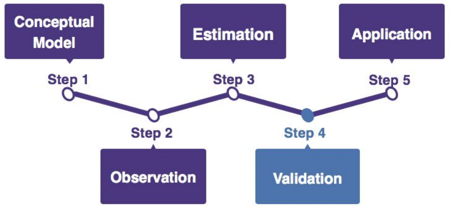
Psych. Col. Receiver		0.24

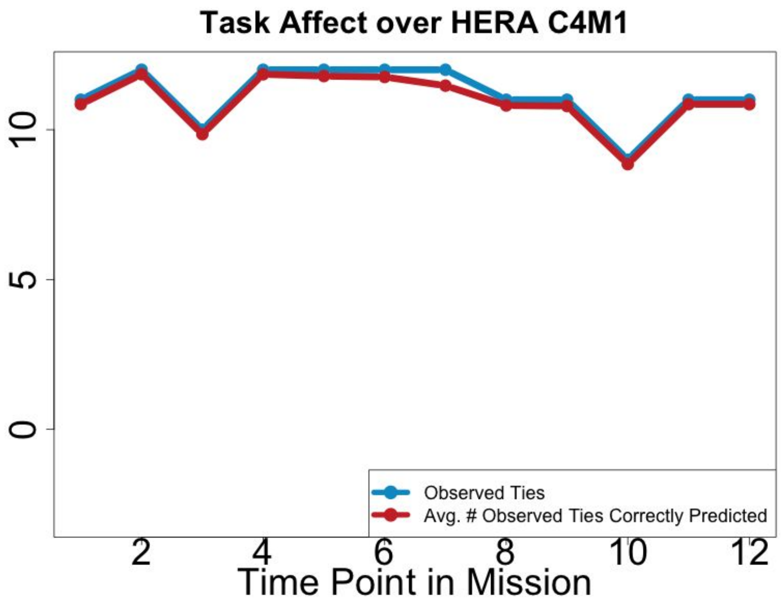
Can we use a model trained on data from one team to predict networks in another team?

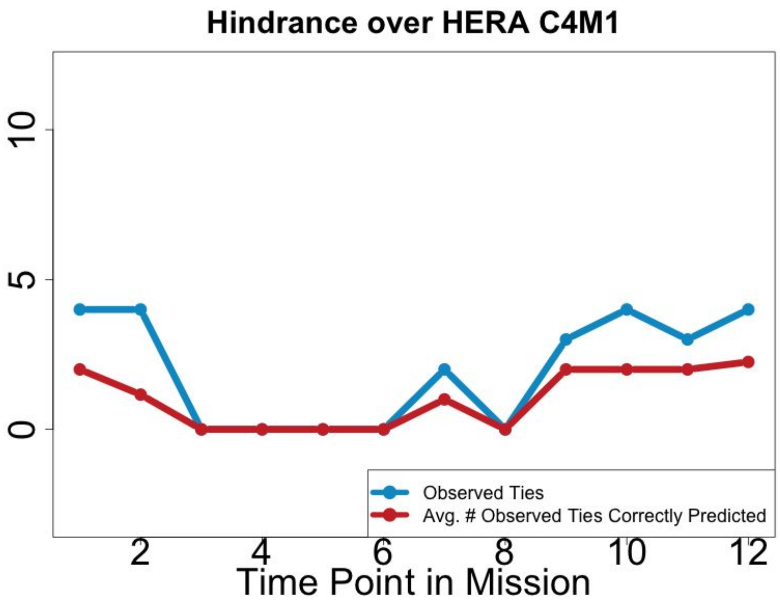


Internal Validation



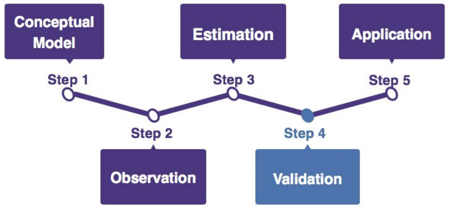
"<u>How can we be sure</u> of what we know?"





Maximum of 12 ties is possible in a four-person crew.

Internal Validation



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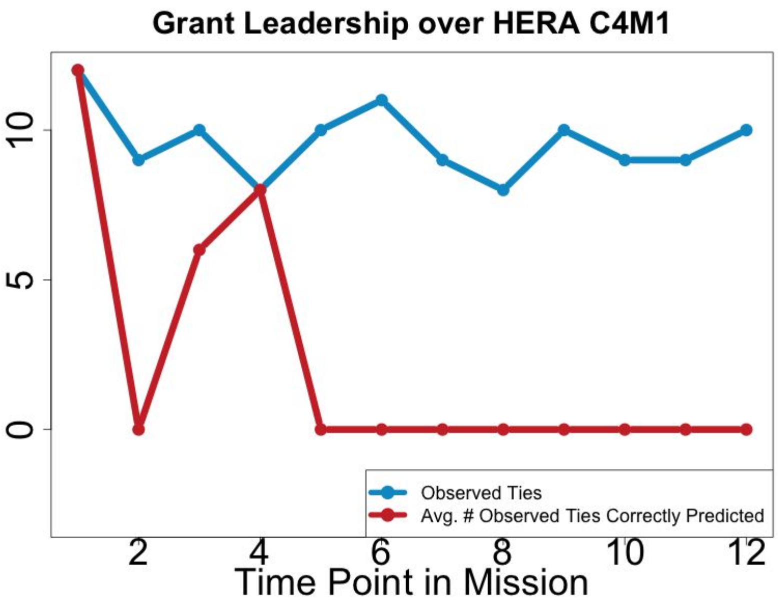
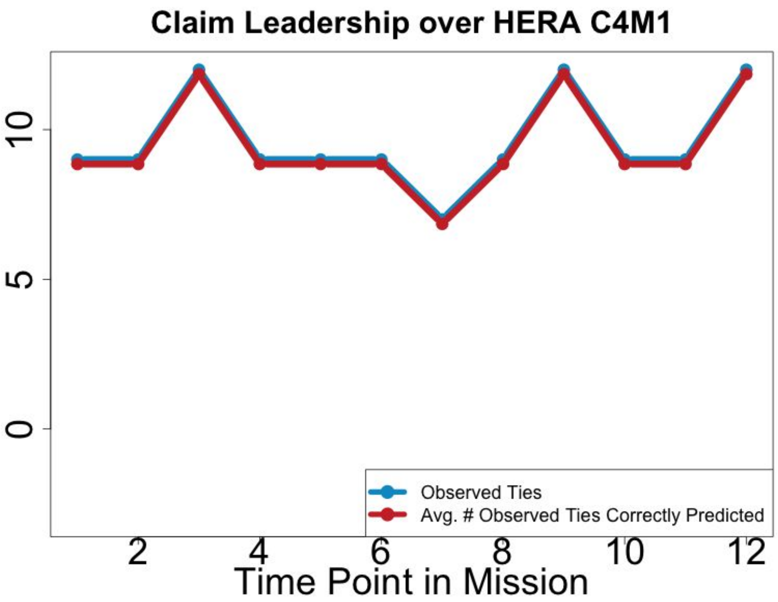
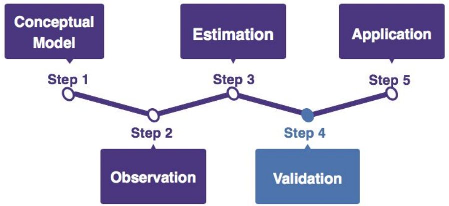




Maximum of 12 ties is possible in a four-person crew

External Validation

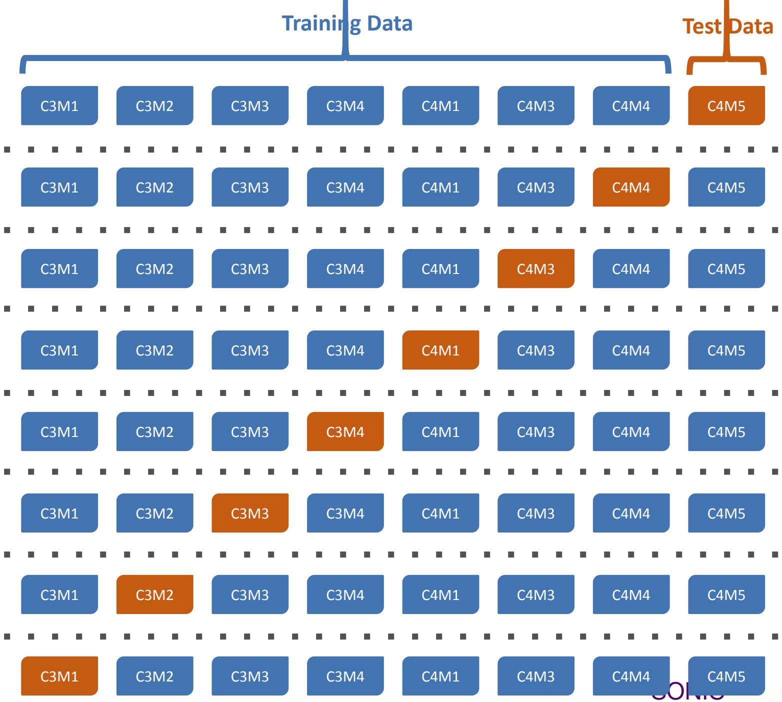


How well will our model perform on new data?

Examine average performance of the model on test data, by using <u>8-fold cross validation</u>.

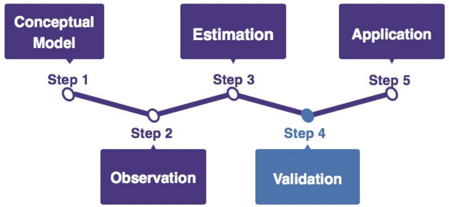
Crew used for training the model

Crew used for testing the model



avg. testing performance computed across 8 different models

External Validation

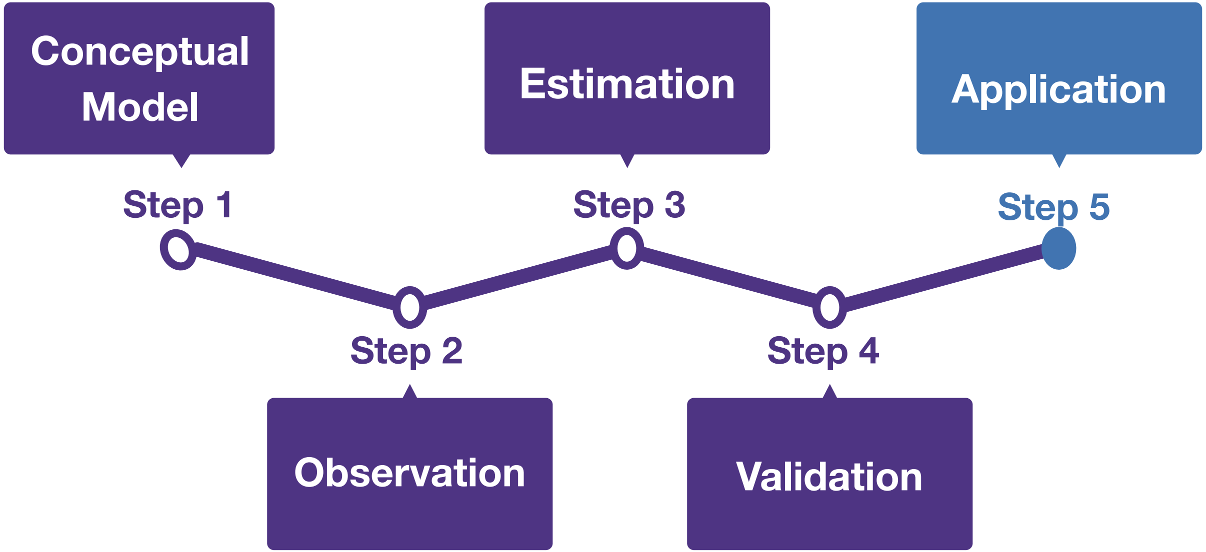


Summary:

Avg. Performance on Test Data

Ranking Network Models by F_1-Score	
Task Affect	*0.808*
Claim Leadership	*0.705*
Hindrance	*0.373*
Grant Leadership	*0.291*

How can we use the network model to intervene in teams?

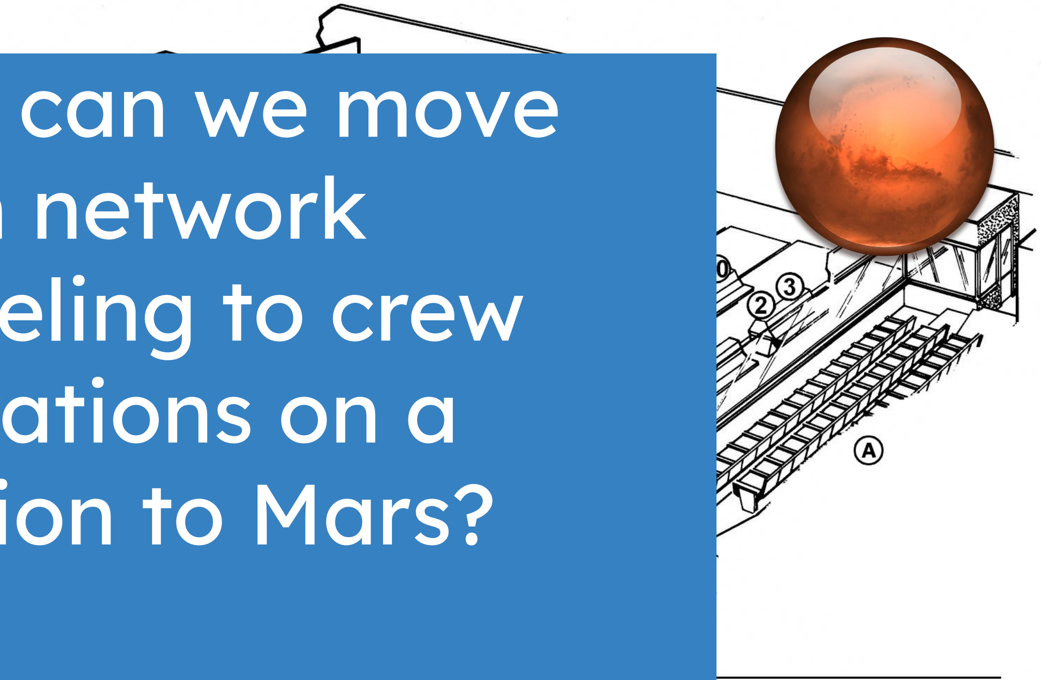


RQ2:

How can we use the network model to intervene in teams?

How can we move from network modeling to crew operations on a Mission to Mars?

An Experiment with Humans



tion and Communications Officer
nd Procedures
t Flight Director
ctor
es Officer
ork Controller

Third row:
11: SURGEON – Life Systems Officer/Flight Surgeon
12: CAPCOM – Capsule Communicator
13: EECOM – Electrical, Environmental, and Communications
14: GNC – Guidance, Navigation, and Control
15: TELMU – Telemetry, Electrical, and EVA Mobility Unit (LM EECOM)
16: CONTROL – LM Guidance & Navigation

First row:
4: PAO – Public Affairs Office
1: DFO – Director of Flight Operations
2: HQ – NASA headquarters (Mission Operations Directorate)
3: DOD – Department of Defense

A: Glass fronted viewing room seating 74 authorized visitors

How can we use the network model to intervene in teams?

3 year team timeframe

✗ Choose which people to send

✗ Veto who NOT to send

✗ Add or drop a member if needed

✗ Design the team for homophily

✗ Redesign the work

How can we use the network model to intervene in teams?

3 year team timeframe

Choose which people to send
Veto who NOT to send
Add or drop a member if needed
Design the team for homophily
Redesign the work
Change the work schedule

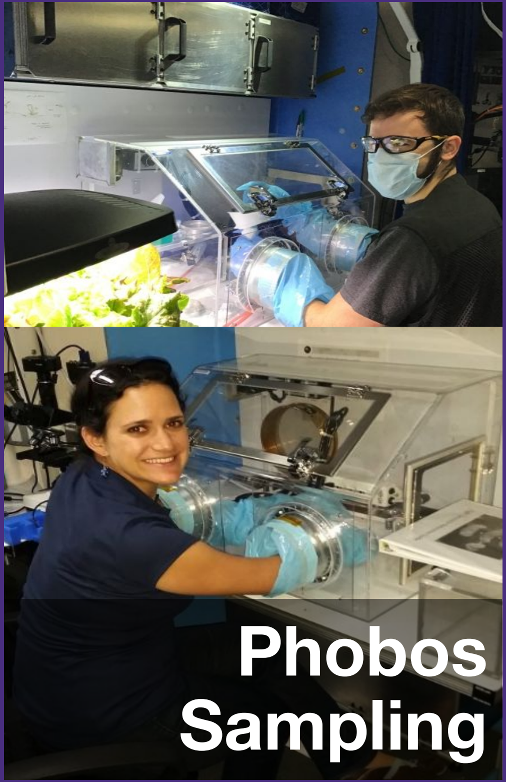
Method - Participants & Procedure

- 4, 4-person analog teams
- Each team lived in HERA for 45 days
- NASA selected the team members
- NASA determined the work schedule
- Once the crew was chosen, Northwestern ran our model and determined who to pair up on the most interdependent tasks during the mission
- NASA study team was blind to the NU study design and purpose

Method - Interdependent Task Selection

82nd percentile in terms of **workload** (NASA-TLX scale; Hart & Staveland, 1988).

84th percentile in terms of **team interdependence** (TTA scale; Arthur et al., 2005).



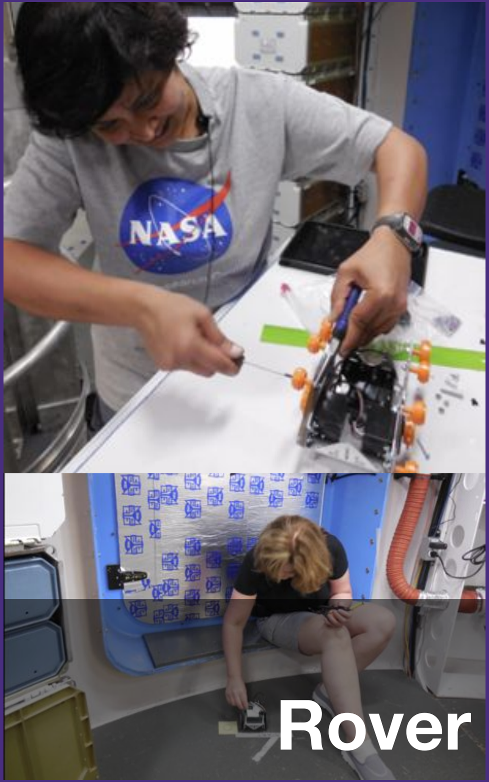


Image credit: NASA

95th percentile in terms of **workload** (NASA-TLX scale; Hart & Staveland, 1988).

77th percentile in terms of **team interdependence** (TTA scale; Arthur et al., 2005).

Method - The Network Intervention

<u>Maximize</u> the # of days where the crew members like working together

<u>Minimize</u> the # of days where crew members find others difficult to work with

Image credit: "Away", Netflix

Select a **"Recommended" pairing** (best) and a **"Disadvised" pairing** (worst) <u>based on our computational model's predictions</u>

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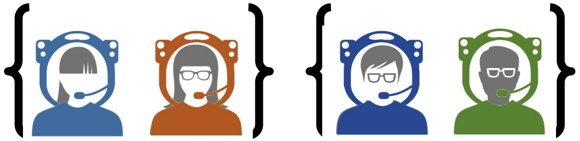
Method - Network Intervention

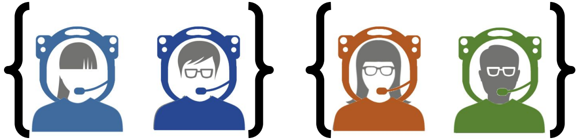
Recommend one of three ways to split the crew into pairs:



Pairing 1:

{ Commander & Flight Engineer}

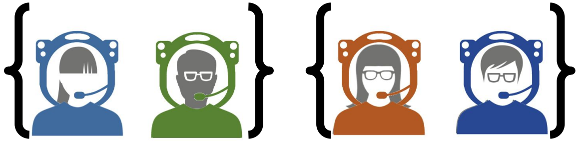
{ Mission Specialist 1 & Mission Specialist 2}



Pairing 2:

{Commander & Mission Specialist 1}

{ Flight Engineer & Mission Specialist 2}



Pairing 3:

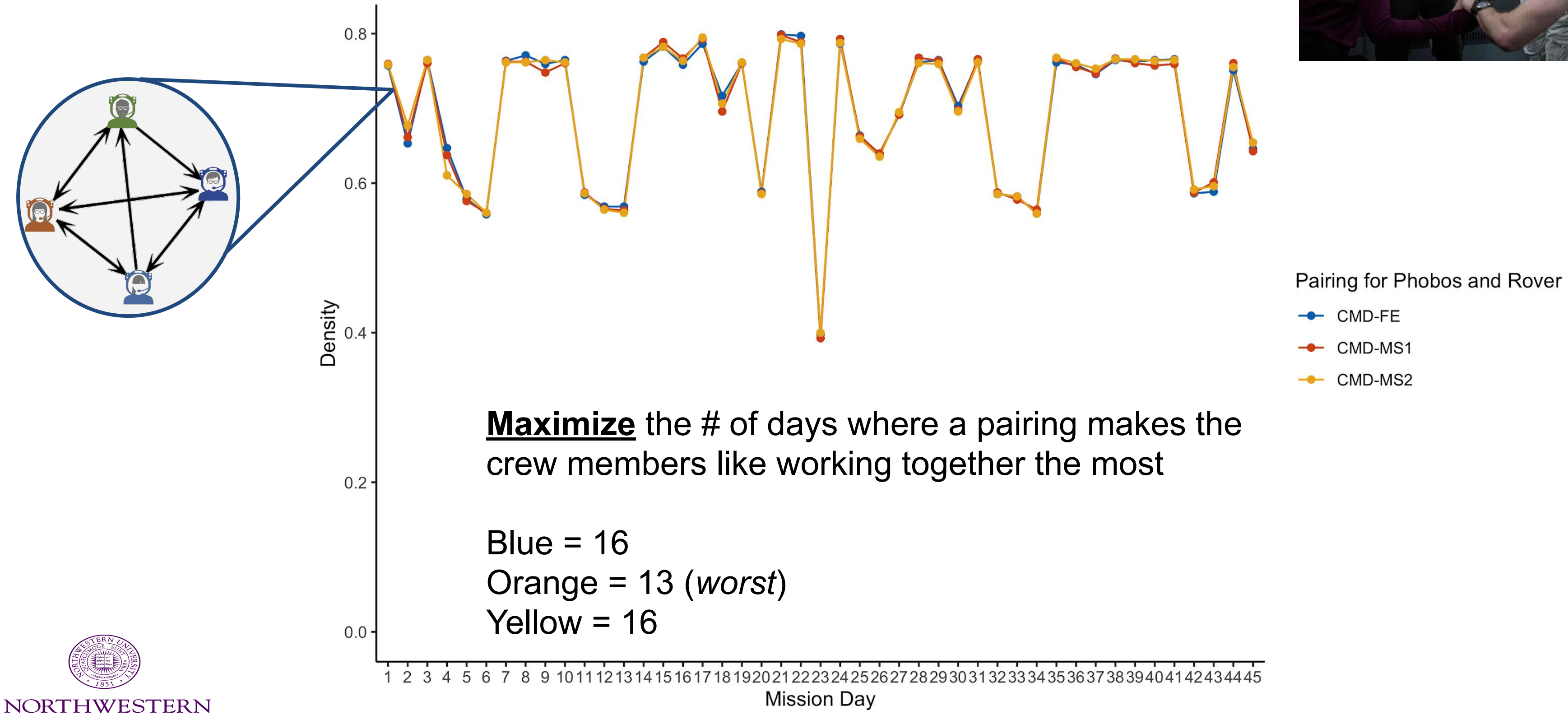
{Commander & Mission Specialist 2}

{ Flight Engineer & Mission Specialist 1}

Method - Experimental Design

	Quarter 1: MD 1-11	Quarter 2: MD 12-22	Quarter 3: MD 23-34	Quarter 4: MD 35-45
Crew 1	**Best pairing** (CMD-MS1) (FE-MS2)	**Disadvised pairing** (CMD-FE) (MS1-MS2)	**Best pairing** (CMD-MS1) (FE-MS2)	**Disadvised pairing** (CMD-FE) (MS1-MS2)
Crew 2	**Disadvised pairing** (CMD-MS2) (FE-MS1)	**Best pairing** (CMD-MS1) (FE-MS2)	**Disadvised pairing** (CMD-MS2) (FE-MS1)	**Best pairing** (CMD-MS1) (FE-MS2)
Crew 3	**Best pairing** (CMD-FE) (MS1-MS2)	**Disadvised pairing** (CMD-MS1) (FE-MS2)	**Best pairing** (CMD-FE) (MS1-MS2)	**Disadvised pairing** (CMD-MS1) (FE-MS2)
Crew 4	**Disadvised pairing** (CMD-MS2) (FE-MS1)	**Best pairing** (CMD-FE) (MS1-MS2)	**Disadvised pairing** (CMD-MS2) (FE-MS1)	**Best pairing** (CMD-FE) (MS1-MS2)

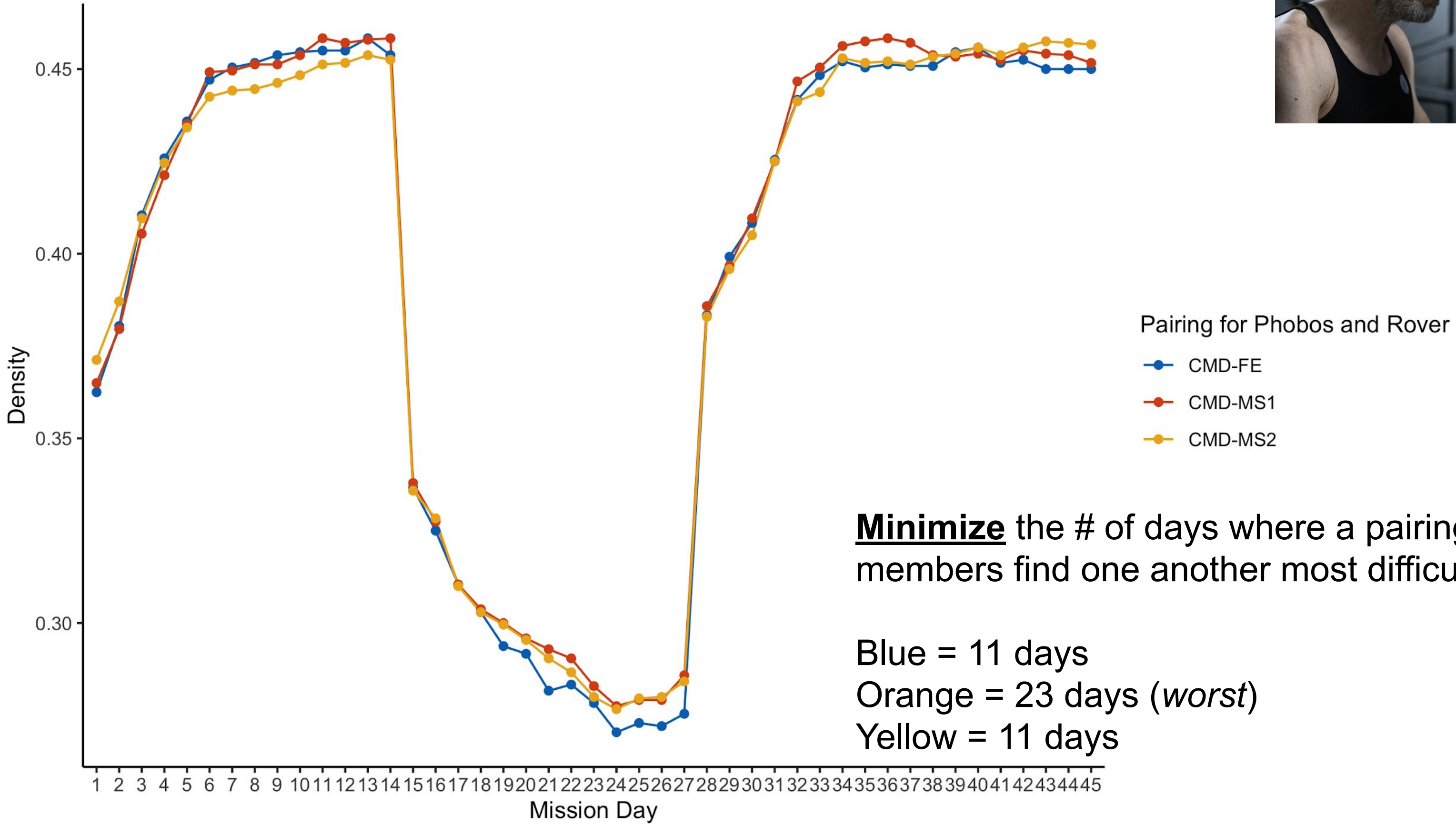
Pre mission: Ran 200 simulations per crew to predict:
Task Affect: "With whom do you enjoy working?"



Maximize the # of days where a pairing makes the crew members like working together the most

Blue = 16
Orange = 13 (*worst*)
Yellow = 16

Ran 200 simulations per crew to predict:
Hindrance: "Who makes tasks difficult to complete?"



<u>Minimize</u> the # of days where a pairing makes crew members find one another most difficult to work with...

Blue = 11 days
Orange = 23 days (*worst*)
Yellow = 11 days

1. IV: Network pairing (Advised, Disadvised); Observed over 11 task episodes per team

	Tasks	Surveys
Quarter 1: Day 1-11	**Rover** (Day 4) **Rover** (Day 6)	**Survey** (Day 5) **Survey** (Day 7)
Quarter 2: Day 12-22	**Rover** (Day 13) **Rover** (Day 19) **Rover** (Day 21)	**Survey** (Day 13) **Survey** (Day 20) **Survey** (Day 21)
Quarter 3: Day 23-34	**Rover** (Day 25) **Phobos** (Day 32) **Rover** (Day 33)	**Survey** (Day 25) **Survey** (Day 33) **Survey** (Day 33)
Quarter 4: Day 35-45	**Rover** (Day 35) **Phobos** (Day 38) **Rover** (Day 42)	**Survey** (Day 38) **Survey** (Day 38) **Survey** (Day 42)

2. Manipulation Checks:

Working with __ was a positive experience.

Working with __ added friction to our relationship.

3. DVs: Affective & Hindrance ties

Surveys administered on the day of/after each treatment

1. Manipulation Checks:
Did crew members perceive differences between working in the recommended or disadvised pairs?

Image credit: NASA

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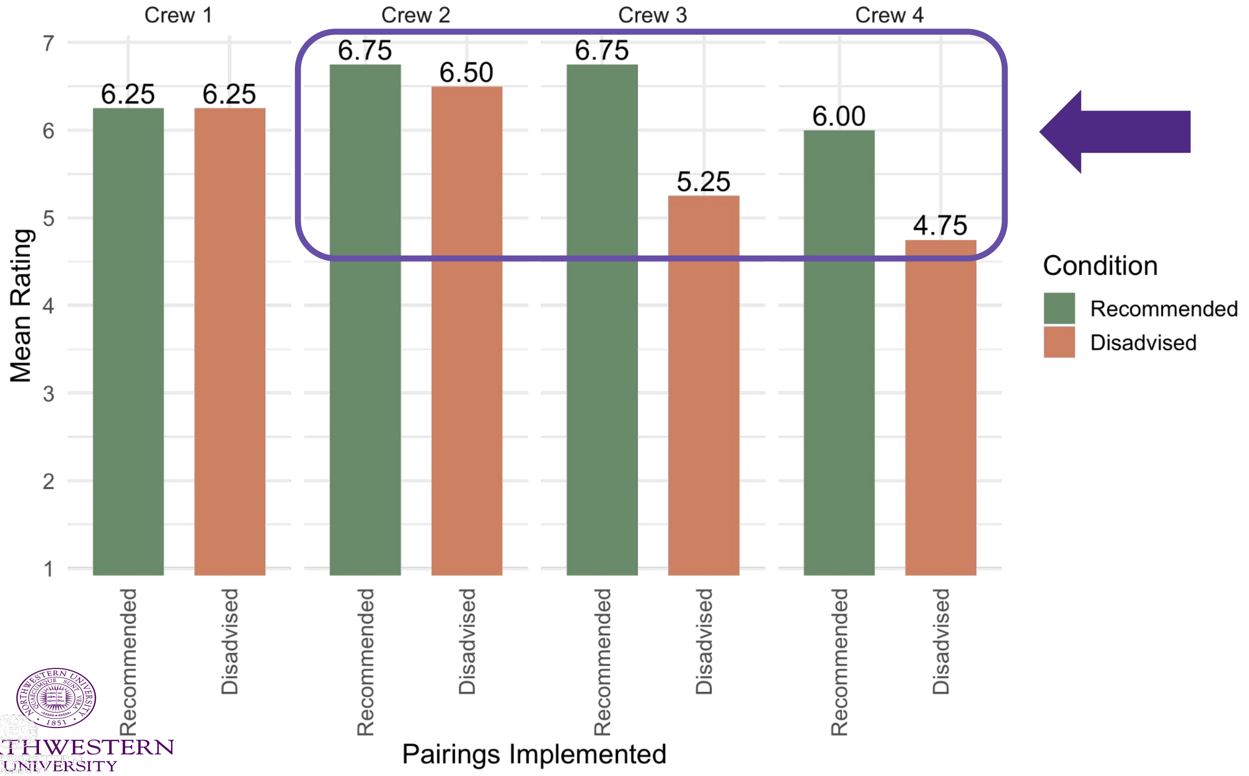
"Working with my partner on the Phobos task was a positive experience."



"Recommended" vs. "Disadvised" Pairs

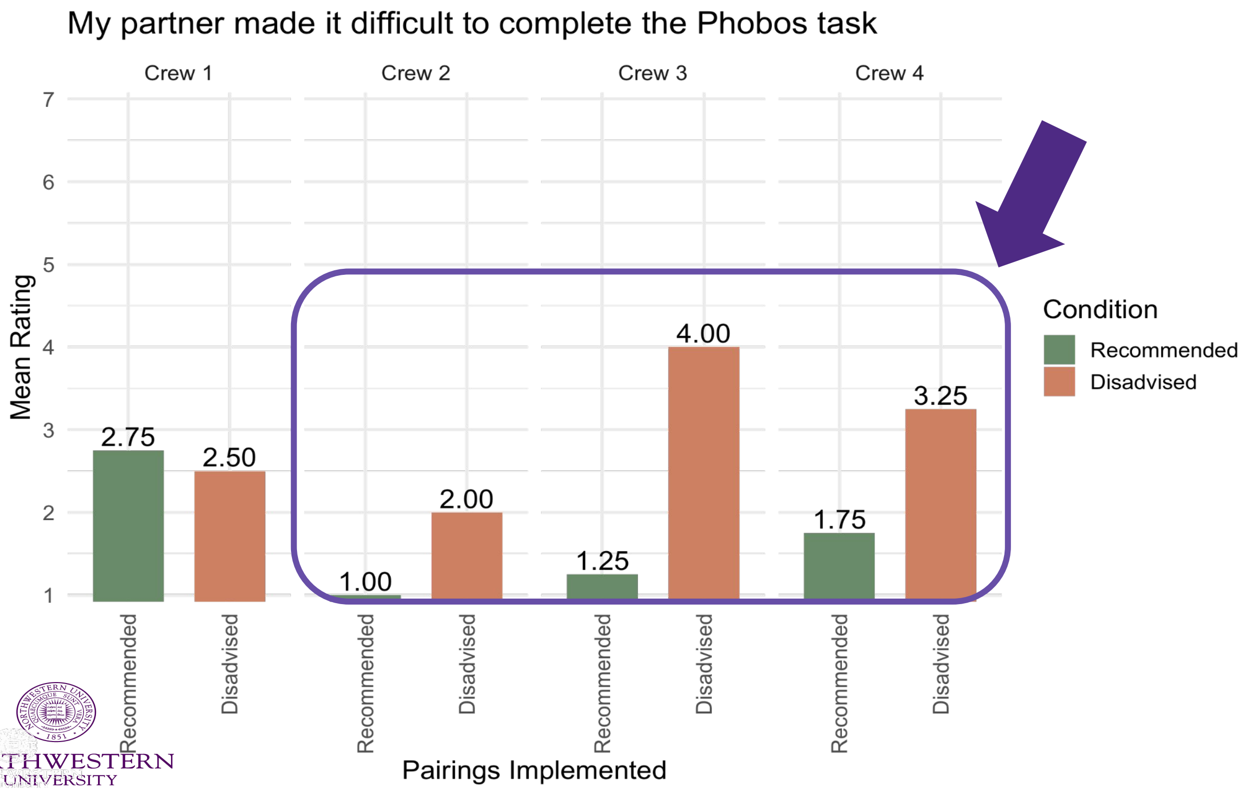
Mean difference:

$\boldsymbol{\mu = 0.75}$

Wilcoxon Paired Samples Nonparametric Test:

$\boldsymbol{p = 0.07}$

“My partner made it difficult to complete the Phobos task.”



“Recommended” vs. “Disadvised” Pairs

Mean difference:

μ **= -1.25**

Wilcoxon Paired Samples Nonparametric Test:

p **= 0.09**

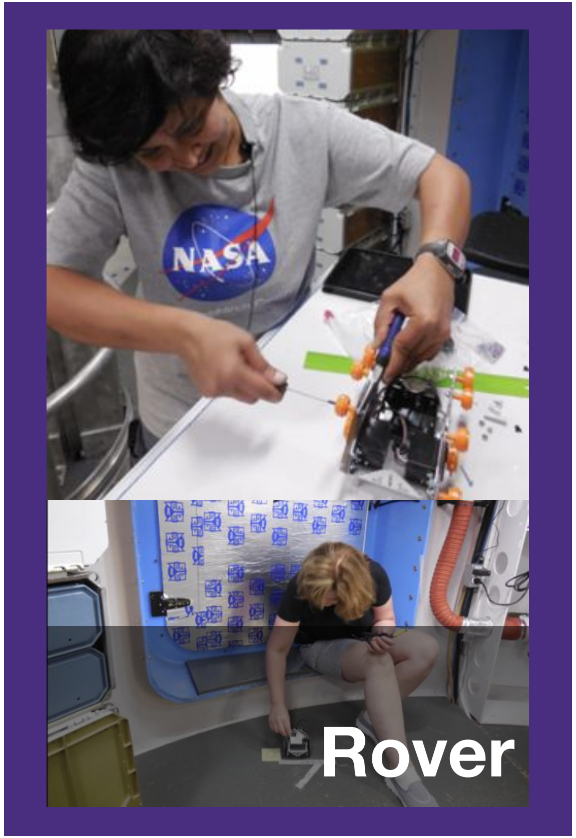
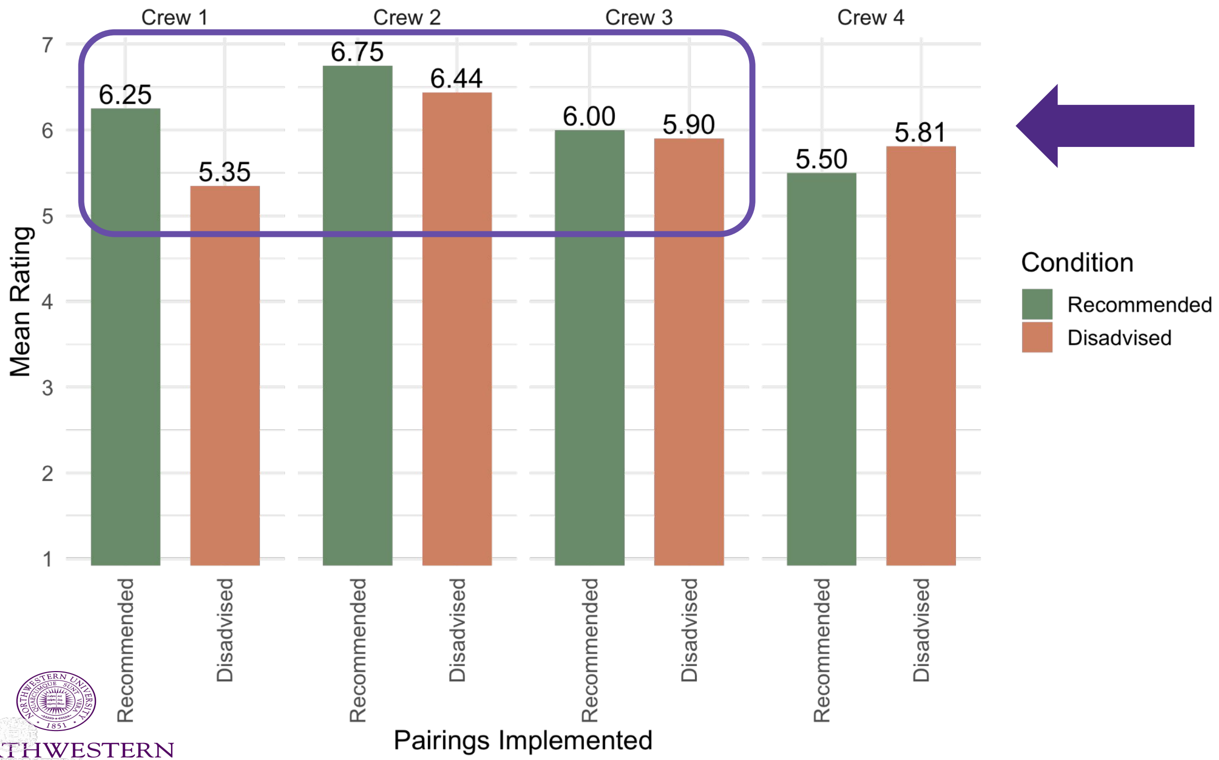


Image credit: NASA

"Working with my partner on the Rover task was a positive experience."



"Recommended" vs. "Disadvised" Pairs

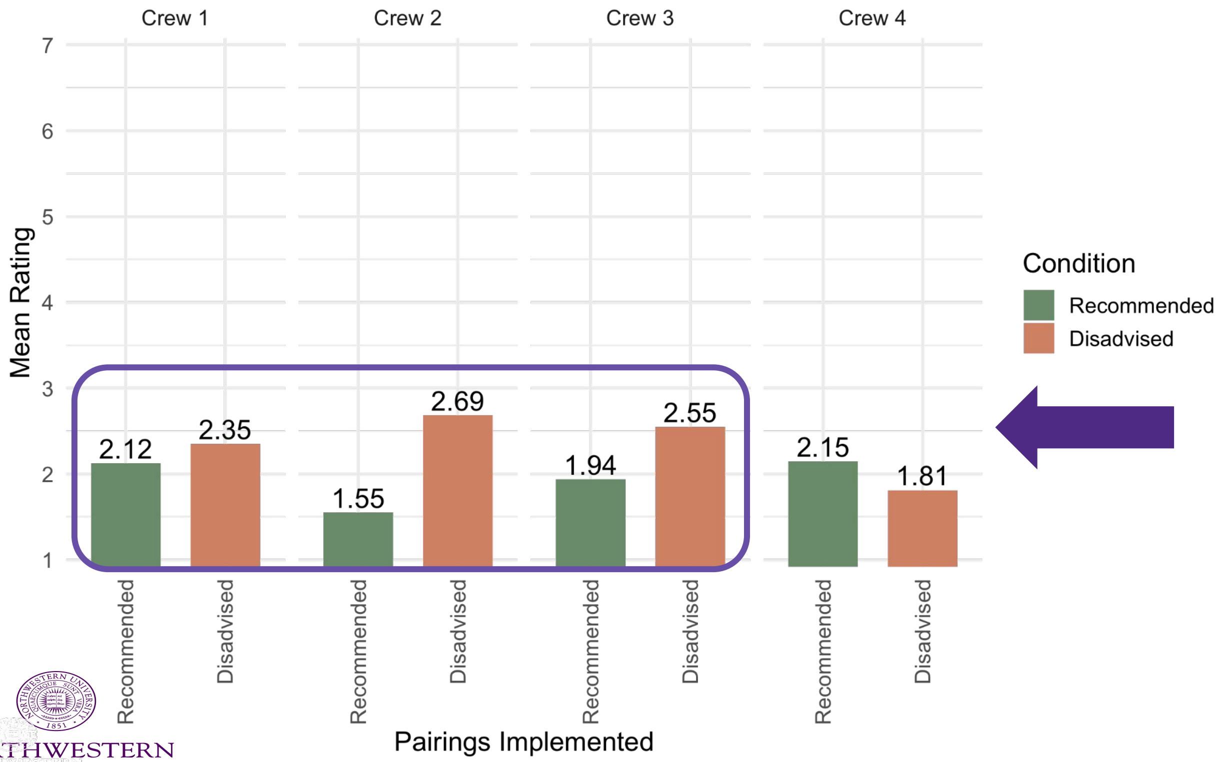
Mean difference:

$\boldsymbol{\mu}$ **= 0.25**

Wilcoxon Paired Samples Nonparametric Test:

$\boldsymbol{p}$ **= 0.26**

“My partner made it difficult to complete the Rover task.”



“Recommended” vs. “Disadvised” Pairs

Mean difference:

***μ* = -0.41**

Wilcoxon Paired Samples Nonparametric Test:

***p* = 0.14**

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Did crew members perceive differences?

Yes, and they prefer working with the model-predicted teammate

2. Results:
How did crew pairings affect the observed crew networks during the mission?

Task Affect: **"With whom do you enjoy working?"**

Proportion of Task Affect ties between each type of partner

	Task Affect ties felt towards ...			Total
	"__Recommended__" Partner	"Middle" Partner	*"__Disadvised__"* Partner	
Measured in quarters under *"Recommended"* Pairings	1.00	0.94	0.94	0.96
Measured in quarters under *"Disadvised"* Pairings	0.99	0.97	0.97	0.98
Total	0.99	0.96	0.96	

Observed positive ties follow the model predictions

Task Affect: “With whom do you enjoy working?”

Proportion of Task Affect ties between each type of partner

	Task Affect ties felt towards …			Total
	“Recommended” Partner	“Middle” Partner	*“Disadvised”* Partner	
Measured in quarters under *“Recommended”* Pairings	1.00	0.94	0.94	0.96
Measured in quarters under *“Disadvised”* Pairings	0.99	0.97	0.97	0.98
Total	0.99	0.96	0.96	

More positive relations between “disadvised” partners when they worked together than when they did not.

Hindrance: “Who makes tasks difficult to complete?”

Proportion of Hindrance ties between each type of partner

	Hindrance ties felt towards ...			Total
	“Recommended” Partner	**“Middle”** Partner	***“Disadvised”*** Partner	
Measured in quarters under *“Recommended”* Pairings	0.02	0.05	0.09	0.05
Measured in quarters under *“Disadvised”* Pairings	0.02	0.05	0.04	0.03
Total	0.02	0.05	0.07	

Observed negative ties follow the model predictions

Hindrance: "Who makes tasks difficult to complete?"

Proportion of Hindrance ties between each type of partner

	Hindrance ties felt towards ...			
	"Recommended" Partner	"Middle" Partner	*"Disadvised"* Partner	Total
Measured in quarters under *"Recommended"* Pairings	0.02	0.05	0.09	0.05
Measured in quarters under *"Disadvised"* Pairings	0.02	0.05	0.04	0.03
Total	0.02	0.05	0.07	

Fewer negative relations between "disadvised" partners when they worked together than when they did not.

Did the model accurately predict?

Yes, crew-reported affect and hindrance match model predictions

However...

Did the model accurately predict?

Yes, crew-reported affect and hindrance match model predictions

However...disadvised pairings resulted in more positive/ fewer negative ties among the disadvised duos, and in the crew in general

Conclusions

CREWS offers some prediction of positive and negative ties. Crew members had **better overall relationships** with, and **preferred working with, their recommended partners**.

Pairing the disadvised pairings on highly interdependent tasks could ***improve* relations between disadvised partners** & benefit the crew networks overall.

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From Understanding to Enabling

Tool for Evaluating And Mitigating Space Team Risks (TEAMSTAR)

DEMO

Recent Related Publications

Lungeanu, A., DeChurch, L.A., Niler, A., Mesmer-Magnus, J.R., Contractor, N.S. (in press). **Organizing for Mars:** A task management perspective on work within spaceflight multiteam systems. ***Human Factors***.

Lungeanu, A., DeChurch, L. A., & Contractor, N. S. (2022). **Leading teams over time through space:** Computational experiments on leadership network archetypes. ***The Leadership Quarterly*.**

Larson, L., Wojcik, H., Gokhman, I., DeChurch, L., Bell, S., & Contractor, N. (2019). **Team performance in space crews**: Houston, we have a teamwork problem. ***Acta Astronautica***, *161*, 108-114.

NASA Collaborators

Lauren Landon
Brandon Vessey
James Garrett
Sarah Huppman
Ashley Johnson

HOUSTON | WE HAVE A PODCAST

If you're fascinated by the idea of humans traveling through space and curious about how that all works, you've come to the right place.

"Houston We Have a Podcast" is the official podcast of the NASA Johnson Space Center from Houston, Texas, home for NASA's astronauts and Mission Control Center. Listen to the brightest minds of America's space agency – astronauts, engineers, scientists and program leaders – discuss exciting topics in engineering, science and technology, sharing their personal stories and expertise on every aspect of human spaceflight. Learn more about how the work being done will help send humans forward to the Moon and on to Mars in the Artemis program.

On Episode 175, team science experts Noshir Contractor, Suzanne Bell, and Leslie DeChurch discuss team composition research at NASA and the role teams play in human spaceflight and space exploration. This episode was recorded on October 28, 2020.

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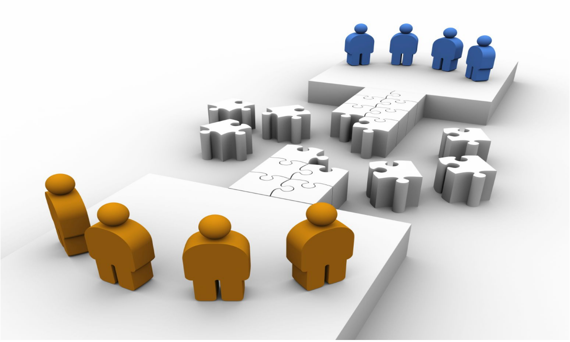
Making Relational Analytics Actionable for *Teams*

Team Self-Assembly

Team Staffing

Predicting Team Performance



Predicting Team Conflict

nature human behaviour

LETTERS

https://doi.org/10.1038/s41562-018-0460-y

Prior shared success predicts victory in team competitions

Satyam Mukherjee[1,2,3*], Yun Huang[4], Julia Neidhardt[5], Brian Uzzi[1,2] and Noshir Contractor[1,2,4,6]

Kolkata Knight Riders –
2 players who play for India,
Rest All-Star players from Australia,
South Africa, New Zealand …

IPL Year	Final Standing
2008	League stage
2009	League stage
2010	League stage
2011	Playoffs: 4th
2012	Champions
2013	League stage
2014	Champions
2015	League stage

INDIAN PREMIER LEAGUE

Chennai Super Kings –
6 players who play for India

Year	Indian Premier League
2008	Runners-up
2009	Playoffs
2010	Champions
2011	Champions
2012	Runners-up
2013	Runners-up
2014	Playoffs
2015	Runners-up

Data

NBA 2012 & 2013
30 National level teams

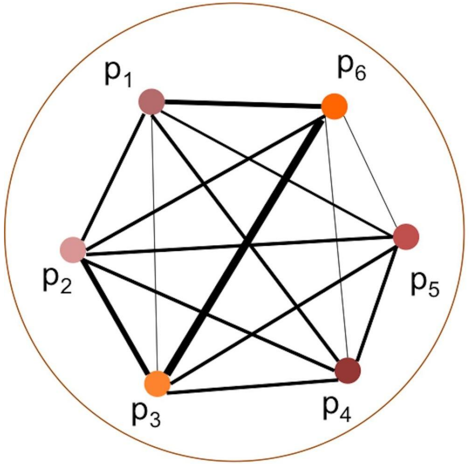
Soccer – EPL 2012, 2013
23 club teams

Cricket – IPL 2012, 2013
9 teams at city level

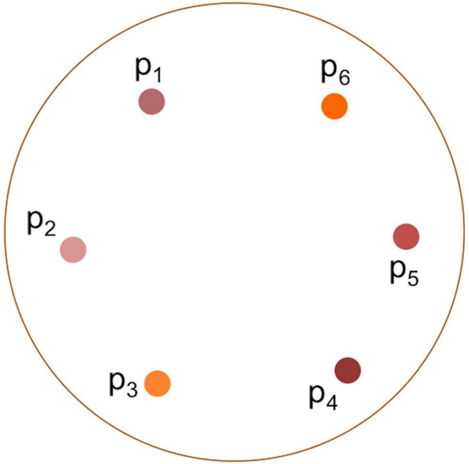
Baseball – MLB 2012, 2013
30 National teams

Online Games
Two teams - Radiant & Dire
4357 games

Team Interactions and Team Skills



a. Team Interactions



b. Team skills

(a) The links represent the successful prior repeated interactions among the players. Thickness of a link being proportional to the number of such interactions.

(b) Every team member possesses individual attributes like skills. The color of the nodes is as per the individual skills of every player. Team skill is measured as the average of individual skills, with stronger teams having a higher average.

	Sports and e-Sports				
	NBA	EPL	IPL	MLB	Dota2
Number of Teams	30	20	8 (2008-2010); 10 (2011); 9 (2012 - 2013)	30	8,714
Team scores	Team points	Team goals	Team run rates	Team runs	Tower scores
Team skills C_1	Average BPM	Average number of goals scored	Average strike rate of batsmen	Average of pitching WAR	Average death rate
Team skills C_2	Average Points	Average number of shots	Average economy rate of bowlers	Average of Batting OPS	Average assist rate
Team skills C_3	Average Assists	Average number of Assists	NA	NA	NA
Prior shared success	Average number of successful prior interactions in a team				

Prior Shared Success

For each team, we define the weighted density of its network of past successful interactions (S) of teammates, i.e.,

$$S_i = \frac{1}{N_i(N_i - 1)} \sum_{k=1}^{N_i} \sum_{j=1}^{N_i} w_{kj}$$

where N_i is the number of players a team used in match i and w_{kj} is the number of matches that team member k and j played together and won in the past.

The prior shared success variable δS_i^{12} measures the difference of two teams' past successful interactions in a match i:

$$\delta S_i^{12} = S_i^1 - S_i^2$$

where S_i^1 and S_i^2 are the average numbers of past successful interactions in Team1 and Team2, respectively.

Results

	NBA 2013-2014		EPL 2013-2014		IPL 2013		MLB 2013		Dota2	
Ind. Var.										
δS		0.021** (0.006)		0.093** (0.034)		0.210** (0.074)		0.057*** (0.005)		0.114*** (0.015)
Control variables										
δC_1	0.320 (0.135)	0.251 (0.136)	0.234 (0.131)	0.302* (0.135)	0.0008 (0.013)	-0.008 (0.016)	0.064 (0.049)	0.036 (0.050)	-0.347*** (0.056)	-0.35*** (0.056)
δC_2	0.034 (0.094)	0.062 (0.093)	0.008 (0.191)	0.087 (0.194)	0.017 (0.582)	-0.103 (0.620)	-0.729 (0.505)	-1.322* (0.523)	0.182*** (0.049)	0.102* (0.050)
δC_3	-0.262 (0.265)	-0.125 (0.267)	-0.586 (0.892)	-0.791 (0.916)	NA	NA	NA	NA	NA	NA
Team Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y	N	N
BIC	1922	1915	607	604	163	155	3737	3582	6012	5959
Pseudo-R^2	0.158	0.166	0.17	0.196	0.20	0.32	0.038	0.086	0.013	0.032
Prob > chi^2	<0.0001	<0.0001	0.0016	0.0010	0.27	0.026	<0.0001	<0.0001	<0.0001	<0.0001
% of games, correctly predicted	69%	71%	73%	76%	71%	78%	59%	65%	54%	56%
N_{obs}	1315	1315	380	380	74	74	2422	2422	4357	4357

Conclusions

Individual brilliance played very modest impacts on the outcome of a Cricket, Soccer, NBA match and Dota2

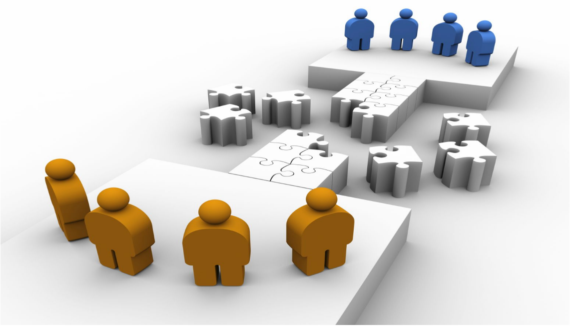
Prior relationships in team victories between players has a much more significant effect on the outcome

Making Relational Analytics Actionable for *Teams*

Team Self-Assembly

Team Staffing

Predicting Team Performance



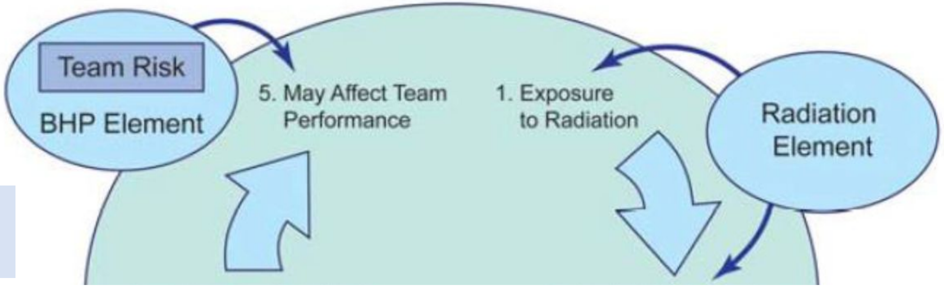
Predicting Team Conflict

Predicting Conflict – in Space

Michael Schultz, Indiana University

with Leslie DeChurch & Noshir Contractor
Northwestern University

TEAM RISK



Risk of Performance and Behavioral Health Decrements Due to Inadequate Cooperation, Coordination, Communication, and Psychosocial Adaptation within a Team

MARS 500

Q: What was the biggest teamwork challenge you experienced?

A: “Mind Reading…we had to try to read each others’ minds…mindreading with the crew members speaking Russian, but you can communicate more easily with them in Russian than with the ground.”

Team Cognition

- Teams - shared cognition linked to team stability, efficiency, performance, positive responses to stress (DeChurch & Mesmer-Magnus 2010)

- Multiteam systems - shared cognition between teams positively related to inter-team coordination & multiteam performance (DeChurch, 2002; Murase, Carter, DeChurch, Marks, 2014)

Team Cognition

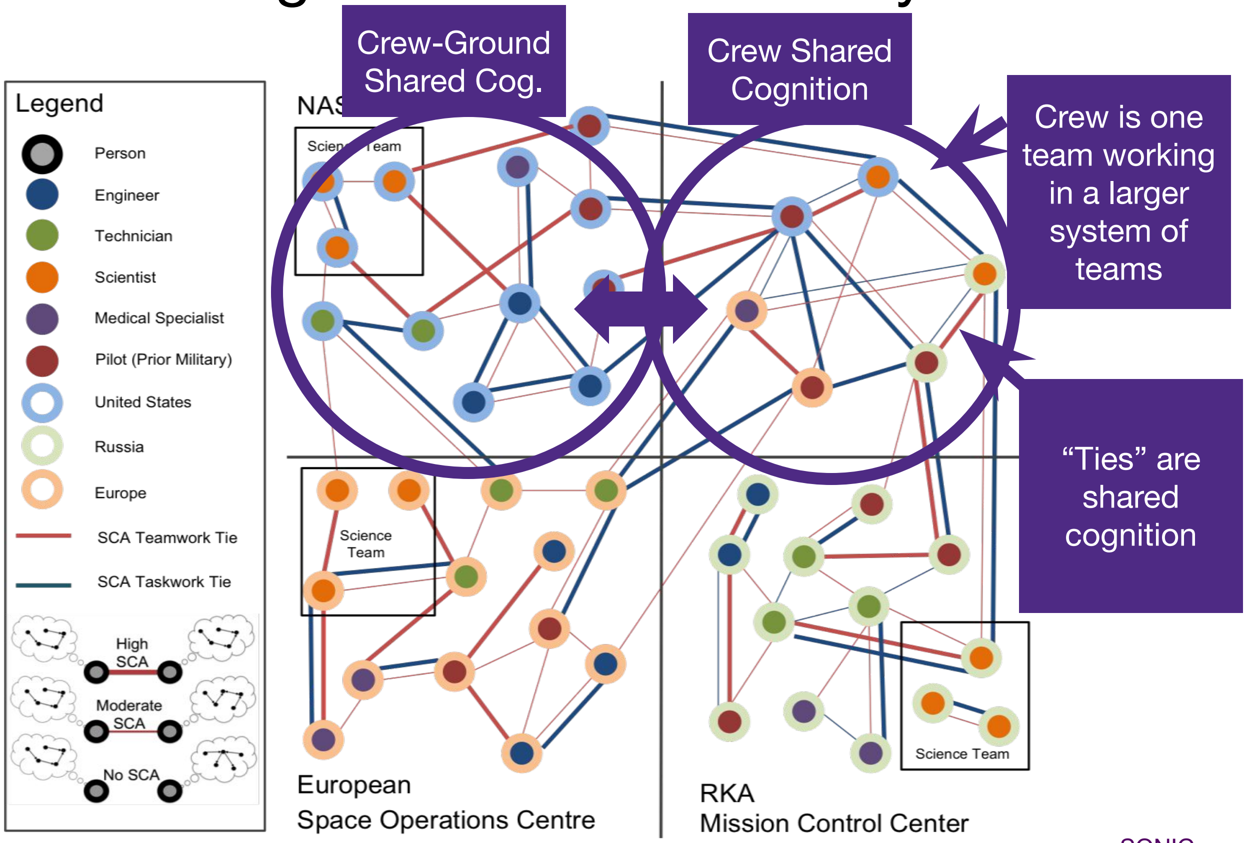
- *Team cognition* is the **strongest** correlate of team process & performance (DeChurch & Mesmer-Magnus, 2010; Updated in 2016)

Meta-Analysis of 128 studies

- Rho(Process) =.38;
- Rho (Perf) = .35

DeChurch, L. A., & Mesmer-Magnus, J. R. (2010). The cognitive underpinnings of effective teamwork: A meta-analysis. The Journal of Applied Psychology, 95(1), 32–53.

Shared Cognition in Multiteam Systems



Research Question 1:

- What pattern of shared cognition is needed within and between teams, at different points in time, and under different conditions?

Research Question 2:

- How can we accurately detect, in real-time, critical shifts in shared cognition that indicate increased levels of team risk?

CASE STUDY: SKYLAB

The First U.S. Space Station
5.14.1973

Cognition within and between teams

Ground Control

Space Crew

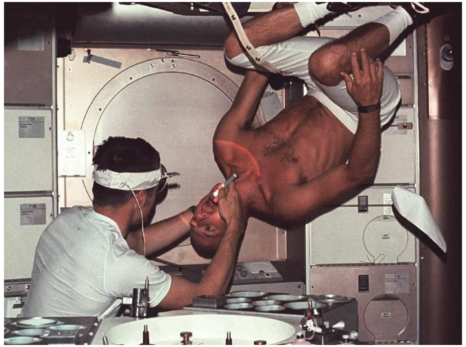
Skylab Crews

Three manned missions with three crewmembers:

- Commander (CDR), Pilot (PLT), Scientist pilot (SPT)



Mission Details: Skylab 1



- Duration: 28 days
- Working in space, Solar observations
- 3 EVAs (one for docking)
- Deployment of solar parasol
- Technical difficulties and high involvement with mission control

Mission Details: Skylab 2

- Duration: 59 days
- Biological experiments, health research
- 3 EVAs
- Lost thruster, potentially mission threatening
- “Low” involvement with mission control

Mission Details: Skylab 3

- Duration: 84 days
- Comet and solar observations
- 4 EVAs
- Space sickness hidden from ground control
- Complaints about busy work schedule
- Tension between mission control and crew
  - “Mutiny in space”

Astronauts Went on Strike in Space to Get Weekends Off

Celebrate International Workers Day by remembering that one time astronauts went on strike and spent the day goofing off.

SHARE TWEET

Daniel Oberhaus
May 1 2017, 8:00pm

We would never work 16 hours a day for 84 straight days on the ground, and we should not be expected to do it here in space.

— SKYLAB 4 COMMANDER JERRY CARR TO NASA, JUST BEFORE THE CREW WENT ON STRIKE

Skylab mutiny

From Wikipedia, the free encyclopedia

The **Skylab mutiny** was a day-long mutiny held by the crew of Skylab 3 on December 28, 1973, the last of the U.S. National Aeronautics and Space Administration's Skylab missions. The three-man crew, Gerald P. Carr, Edward G. Gibson, and William R. Pogue, turned off radio communications with NASA ground control for a full day, spending the day relaxing and looking at the Earth before resuming communication with NASA.

They refused communications from mission control during this period.[4] Once communications resumed, there were discussions between the crew and NASA, and the mission continued for several more weeks before the crew returned to Earth in 1974.[4] The 84-day mission was Skylab's last crew, and last time American astronauts set foot in a space station for two decades, until Shuttle–*Mir* in the 1990s.

The event, which is the only strike to have occurred in space,[has been extensively studied as case study in various fields of endeavor including space medicine, **team management**, and psychology.[6] Man-hours in space was, and continued to be into the 21st century, a profoundly expensive undertaking; a single day on Skylab was worth about $22.4 million in 2017 dollars. The mutiny also impacted the planning of future space missions, especially long-term missions.

Harvard Business School

9-481-008

Rev. November 1, 1981

Strike in Space

On December 27, 1973, the third crew of the Skylab space station turned off the radio and refused to talk with Houston Mission Control. For highly trained and disciplined astronauts, this refusal to work was an unprecedented move. How and why the first strike in space came about is perhaps one of the most interesting questions thus far generated by the space program.

Measuring Shared Cognition with Text

Conventional measurement of mental models requires elaborate survey instruments (Cooke et al. 2004):

- Time-consuming; survey fatigue
- Intrusive; potential response bias
- Not “real-time” nor continuous

Diaries (auto-biographical) versus **Conversational** Analysis

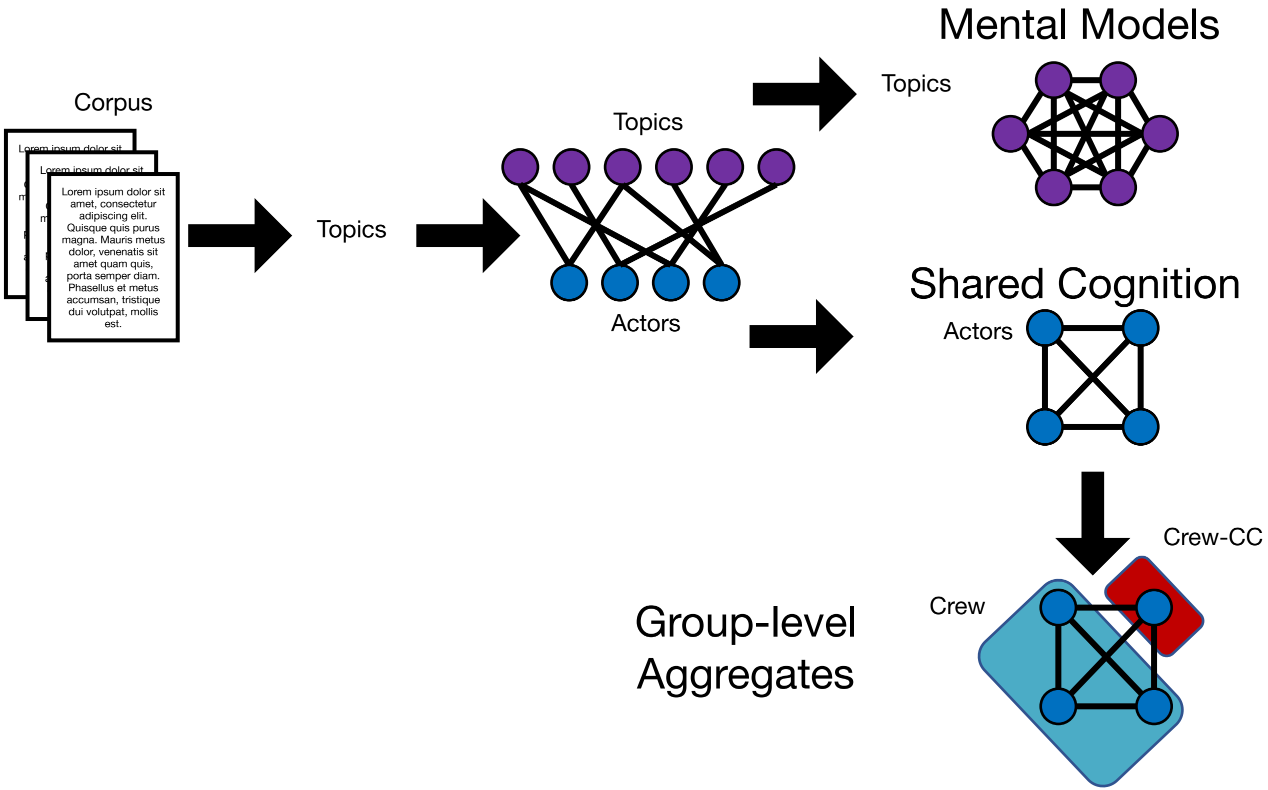
Conversation-based measures:

- Non-intrusive, do not require attention, and can be run continually
- Useful for analysis of cognition, interactions, and discourse (Evans & Aceves 2016)

Data - Transcripts

- 2 channels: Air to ground communications & onboard voice transcription
- ~15,000 pages of spoken communication, ~3,800 tapes
- Identify time, speaker, and verbatim utterance
    - Trimmed to four most prevalent speakers: Commander (CDR), Pilot (PLT), Scientist pilot (SPT), & CapCom (CC) – voice of Mission Control

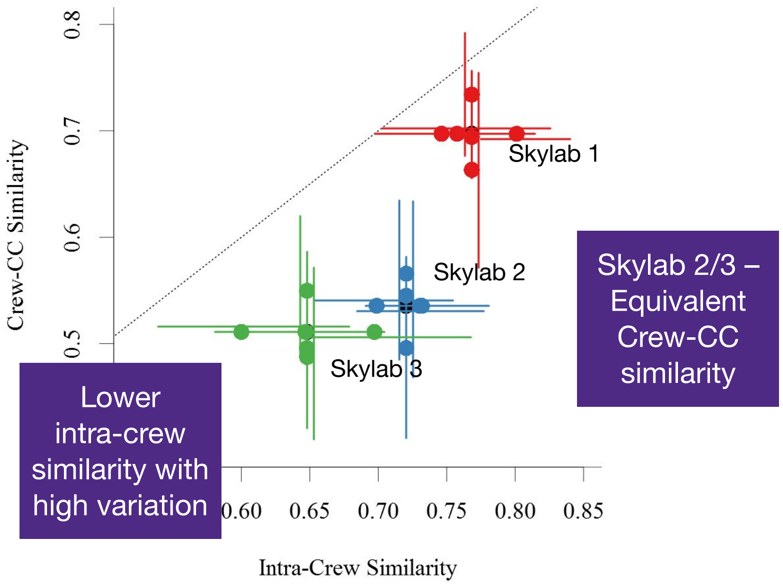
From Conversation to Cognitive Networks



Topics Identified in LDA

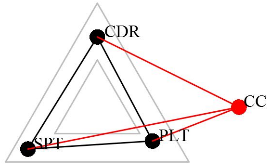
Topic Label	Words	Topic Label	Words
Capsule	deorbit service, evaporation	**Maintenance**	exchanger condensate, lights
Communication	legible chat, howdy	**Medical**	bicep systolic, scans
Consumption	afrin biscuit, whiskey	**News**	Nixon Kissinger, congress
Earth Observation	intervalometer Boston, airfield	**Personal**	Jane birthday, dad
EVA	visor tether, EVA	**Piloting**	thrust pitch, yaw
Experiments	striation seed	**Repair**	cutter foil, meteroid
Hygiene	washcloth spoon, trash	**Solar Observation**	raster aperture, sunspot
Instruments	scatterometer radiometer, malfunction	**Space Observation**	procyon rigel, airglow
		Other	

Average Shared Cognition

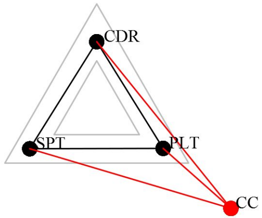


Shared Cognition – Day 15

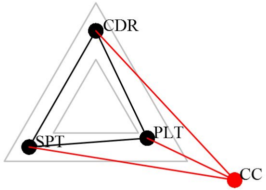
Skylab 1



Skylab 2

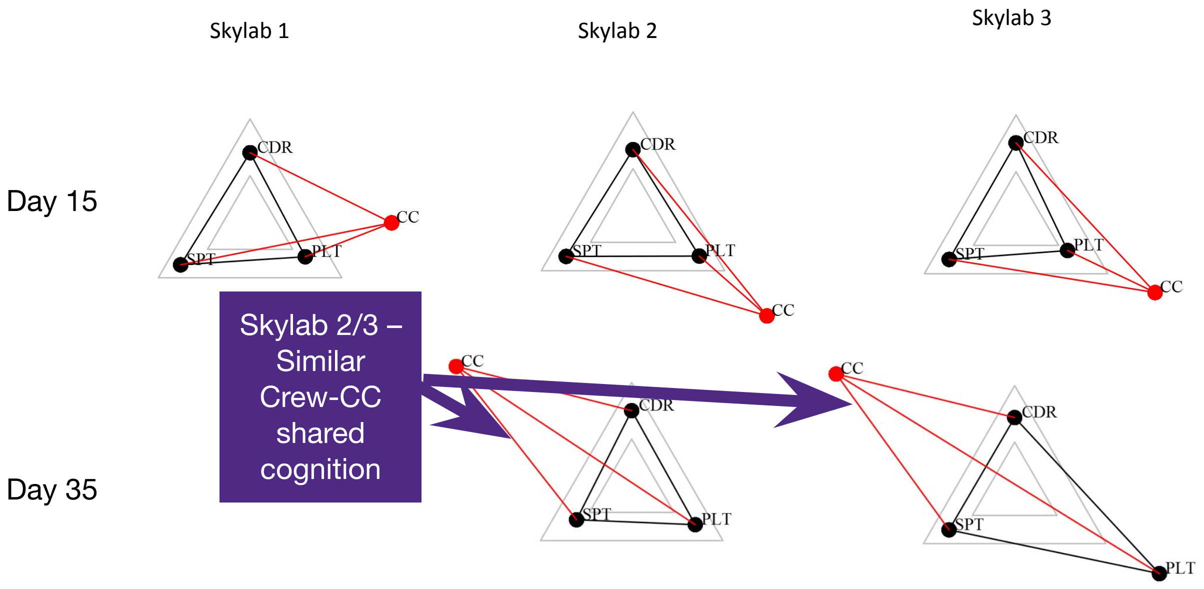


Skylab 3



Skylab 2 Crew More Similar to CC than 3/4

Shared Cognition – Day 35



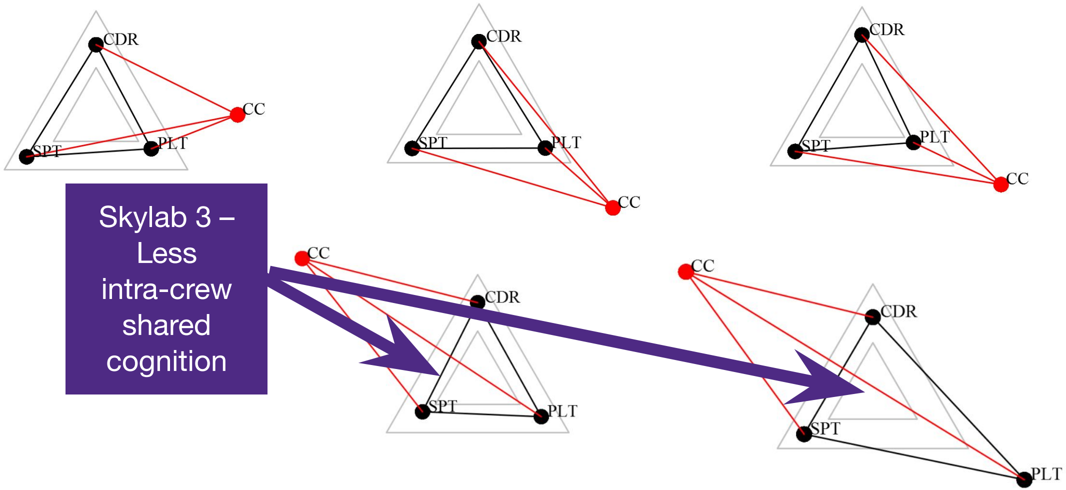
Skylab 3 Mutiny Day 46

Shared Cognition – Day 35

Skylab 1 Skylab 2 Skylab 3

Day 15

Day 35



Skylab 3 – Less intra-crew shared cognition

Skylab 3 Mutiny Day 46

NORTHWESTERN UNIVERSITY

NIC

advancing the science of networks in communities

People Analytics &
The Changing Nature of Work

- People Analytics enables <u>researchers</u> and <u>practitioners</u> to get new insights into communication in the workplace
- **The BIG questions?**
  - *Just because we can, should we?*
  - *Who gets to see these insights?*
  - *What protections do workers have against misuse/abuse of their data?*

Acknowledgements

National Science Foundation
WHERE DISCOVERIES BEGIN

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