Human-Autonomy Teaming: Can Autonomy be a Good Team Player?

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Center for Human/Artificial Intelligence/Robot Teaming (CHART)

Global Security Initiative
Arizona State University

CHART assembles **multidisciplinary** teams to address **human-machine integration issues** in transportation, emergency response, manufacturing, medicine, and defense.

Launched: 2017

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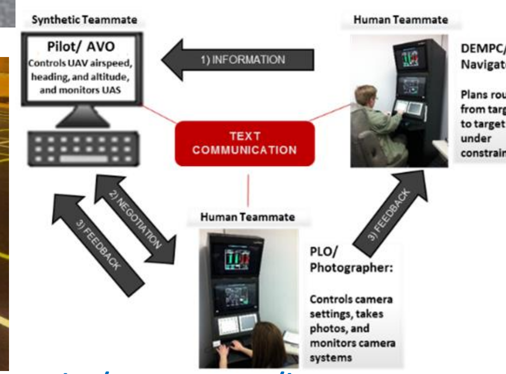


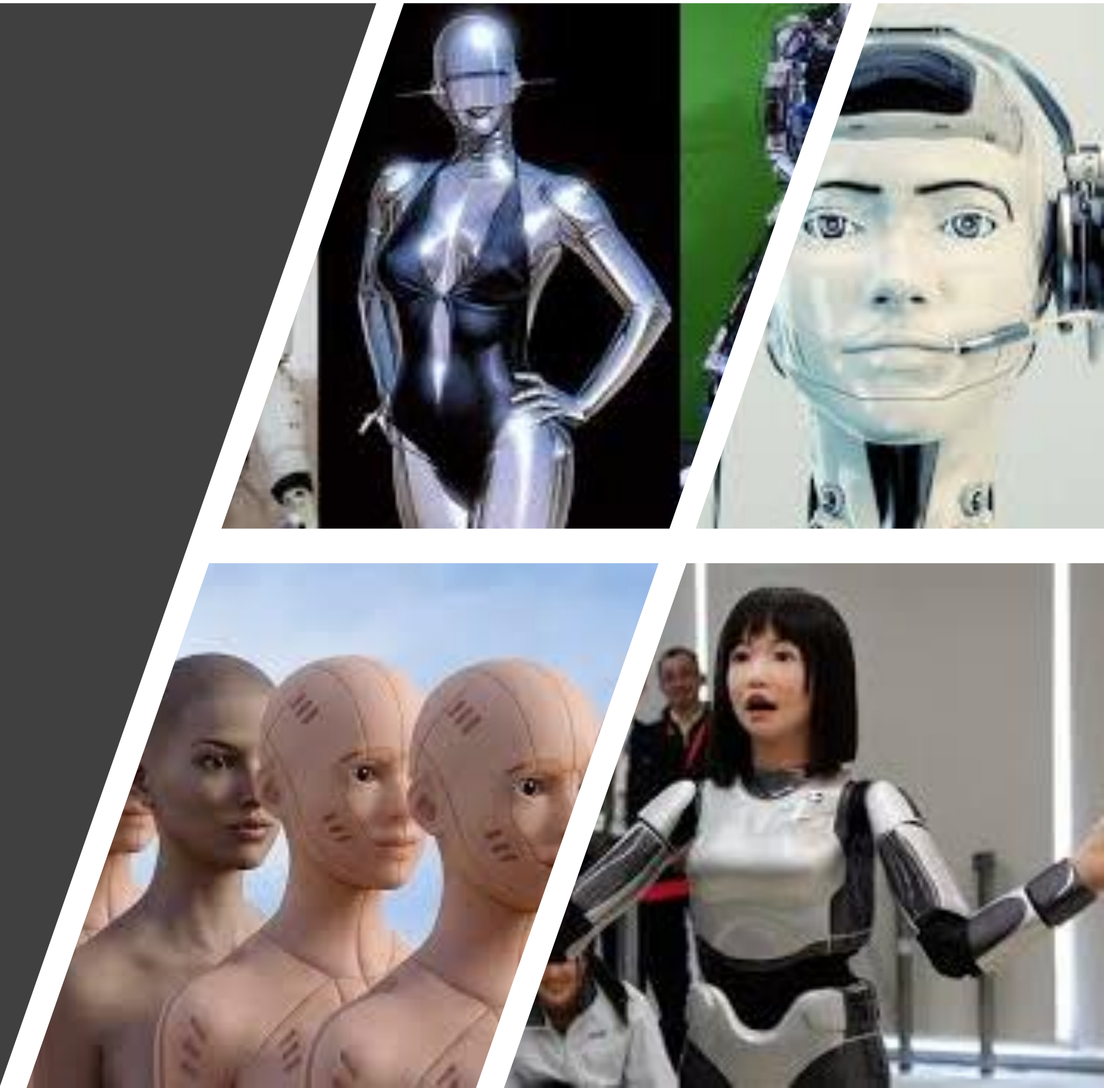
https://globalsecurity.asu.edu/expertise/human-artificial-intelligence-and-robot-teaming

Overview

- Taking Teaming Seriously in Human-Autonomy Teaming
- CHART Human-Autonomy Teaming Research
  - ❖Complex Team Tasks
  - ❖Testbeds/Synthetic Task Environments
  - ❖Wizard of OZ
- In Depth: The Synthetic Teammate Project

Taking Teaming Seriously in Human Autonomy Teams

Team members have different roles and responsibilities – do not replicate humans and their roles. Exceptions?



Taking Teaming Seriously in Human Autonomy Teams

Effective teams understand that each team member has different roles and responsibilities and avoid role confusion, but back each other up as necessary - autonomy needs understanding of whole task. What does this mean?

Taking Teaming Seriously in Human Autonomy Teams

Effective teams <u>share knowledge</u> about the team goals and the current situation and this facilitates coordination and implicit communication – human-autonomy team training?

Taking Teaming Seriously in Human Autonomy Teams

Effective teams have team members who are interdependent and thus need to *<u>interact/communicate</u>* *even when direct communication is impossible– some other communication model than natural language?*

Taking Teaming Seriously in Human Autonomy Teams

Interpersonal trust is important to human teams – autonomy needs to explain and be explicable. But how much and is that enough? Should it be trusted?

CHART Human-Autonomy Teaming Research

- Complex Team Tasks
- Testbeds/Synthetic Task Environments
- Wizard of OZ
- Biometric Sensing

ASU Global Security Initiative

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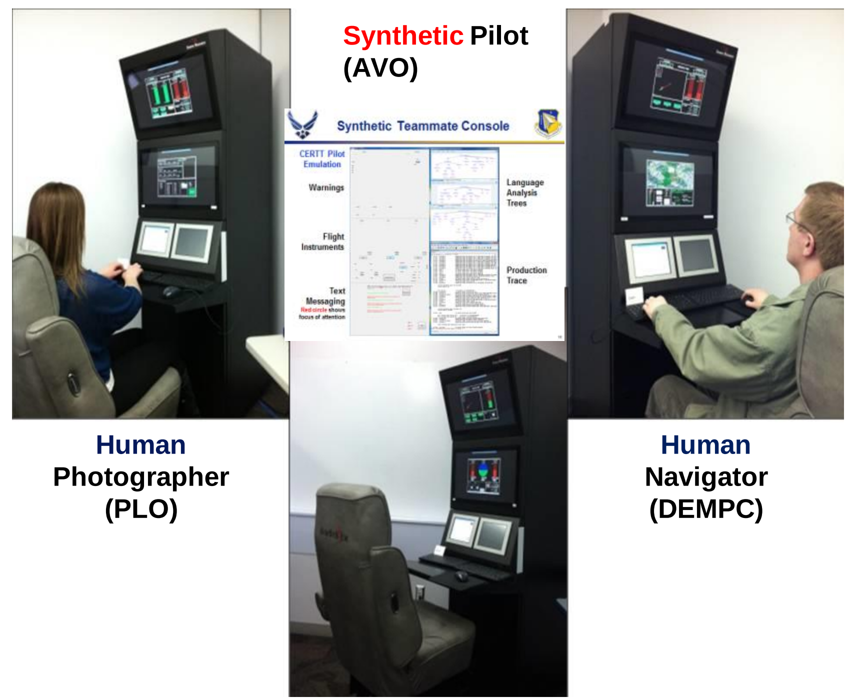
Team Cognition in Sociotechnical Systems

I study the cognitive processing of teams <u>in the context</u> of sociotechnical systems to improve team effectiveness

Action-Oriented Teams

Decision Making Teams

Human-Autonomy Teams

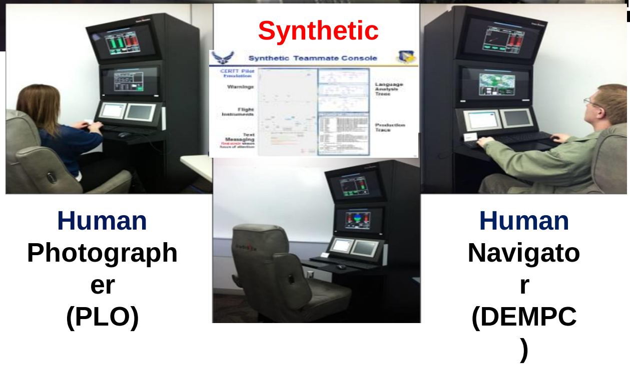


Synthetic Pilot (AVO)

Human Photographer (PLO)

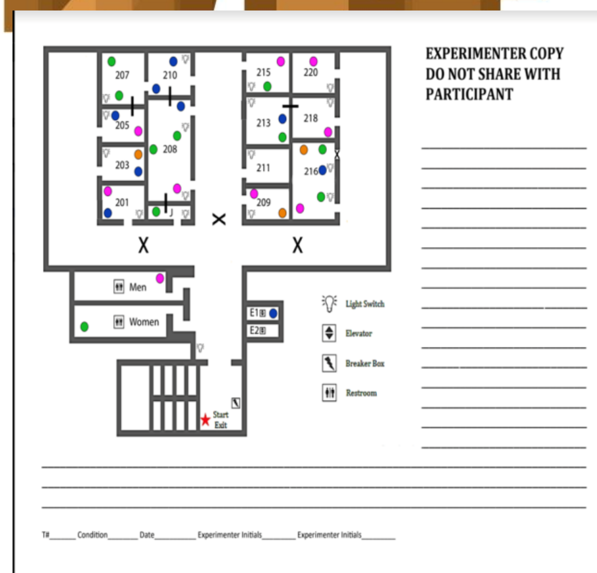
Human Navigator (DEMPC)

By Using Synthetic Task Environments, we bring the context into the lab



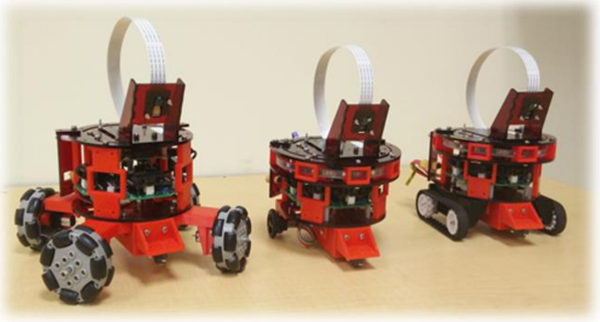
Minecraft Testbed for Human-Robot Teaming for Urban Search and Rescue

- Minecraft simulates a collapsed building
- Wizard of OZ – robot on inside searches for victims and text chats with rescuer
- Human rescuer on outside who has map
- Task is to locate victims needing immediate assistance, mark them on the map and mark structural changes
- Manipulating type of explanation – human aware or not
- Measures
    - Situation Awareness
    - Trust
    - Team Verbal Behaviors
    - Workload
    - Performance
    - Demographics



WoZ allows human-autonomy teaming concerns to drive development of autonomy

CHARTopolis: A Testbed for Studying Driver Interaction with Autonomous Vehicles

- Some vehicles will be autonomous and some remotely driven
- Human-driven cars will have to interact with the driverless cars
- Will be situated in a model urban setting

The Synthetic Teammate Project

Synthetic Teammate Kickoff Meeting
Arizona State University
December 7-8, 2017

Jerry Ball, Nancy Cooke, Mustafa Demir, Jamie Gorman, Craig Johnson, Nathan McNeese, Chris Myers, Steve Shope, Alex Wolff, Sophie He, Garrett Zabala

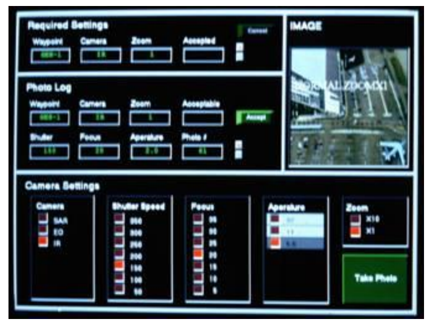
RPAS Research Testbed

RPAS-STE: Remotely Piloted Aircraft System (ground control station) Synthetic Task Environment

In our RPAS-STE three operators must coordinate over headsets or text chat to maneuver their RPA to take pictures of ground targets

Three team members with inter-dependent tasks

Payload Operator
controls camera settings, takes photos, and monitors camera systems



DEMPC
navigator, mission planner, plans route from target to target under constraints

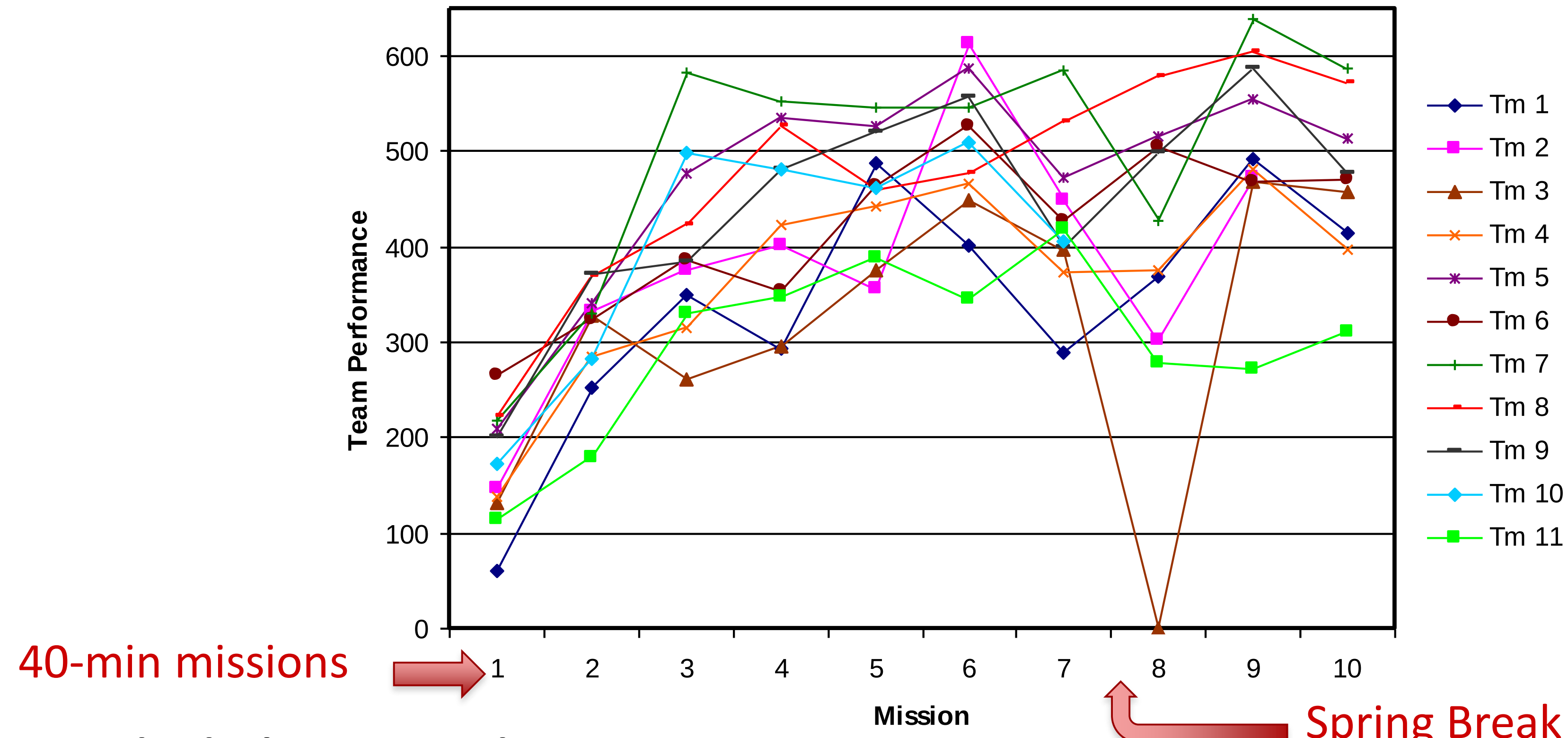
Air Vehicle Operator
controls RPA airspeed, heading, and altitude and monitors air vehicle systems

Interdependence requires interaction, communication, & coordination

Some Early Work with 3-Human Teams

Team Skill Acquisition

As teams acquire experience, performance improves, interactions improve, but not individual or collective knowledge



- **Individuals are trained to criterion prior to M1**
- **Team performance is a composite score based on how many targets they accurately process**
- **Asymptotic team performance after four 40-min missions (robust finding)**
- **Knowledge changes tend to occur in early learning (M1) and stabilize**
- **Process improves and communication becomes more standard over time**

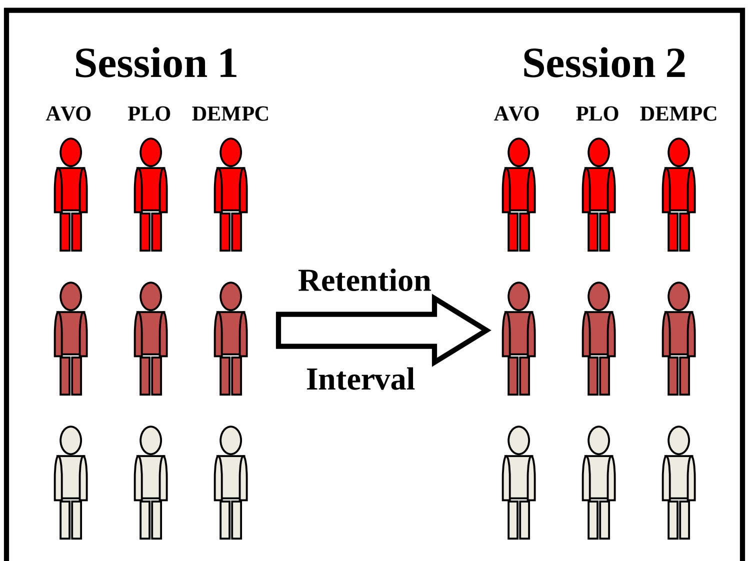
Team Retention & Composition

- 117 males(92) & females(25) divided into 39 3-person (unfamiliar) Session 2 teams
- Two between subjects conditions (retention interval and familiarity) randomly assigned with scheduling constraints
- Participants randomly assigned to one of three roles
- Session 1: 5 40-min missions
- Session 2: 3 40-min missions

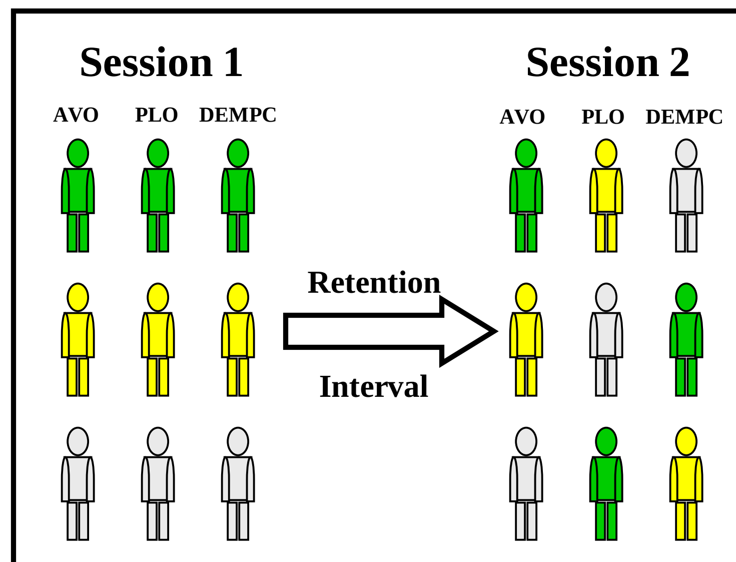
Retention Interval

Composition		3-5 weeks	10-13 weeks
	Same	10 Teams	9 Teams
	Mixed	10 Teams	10 Teams

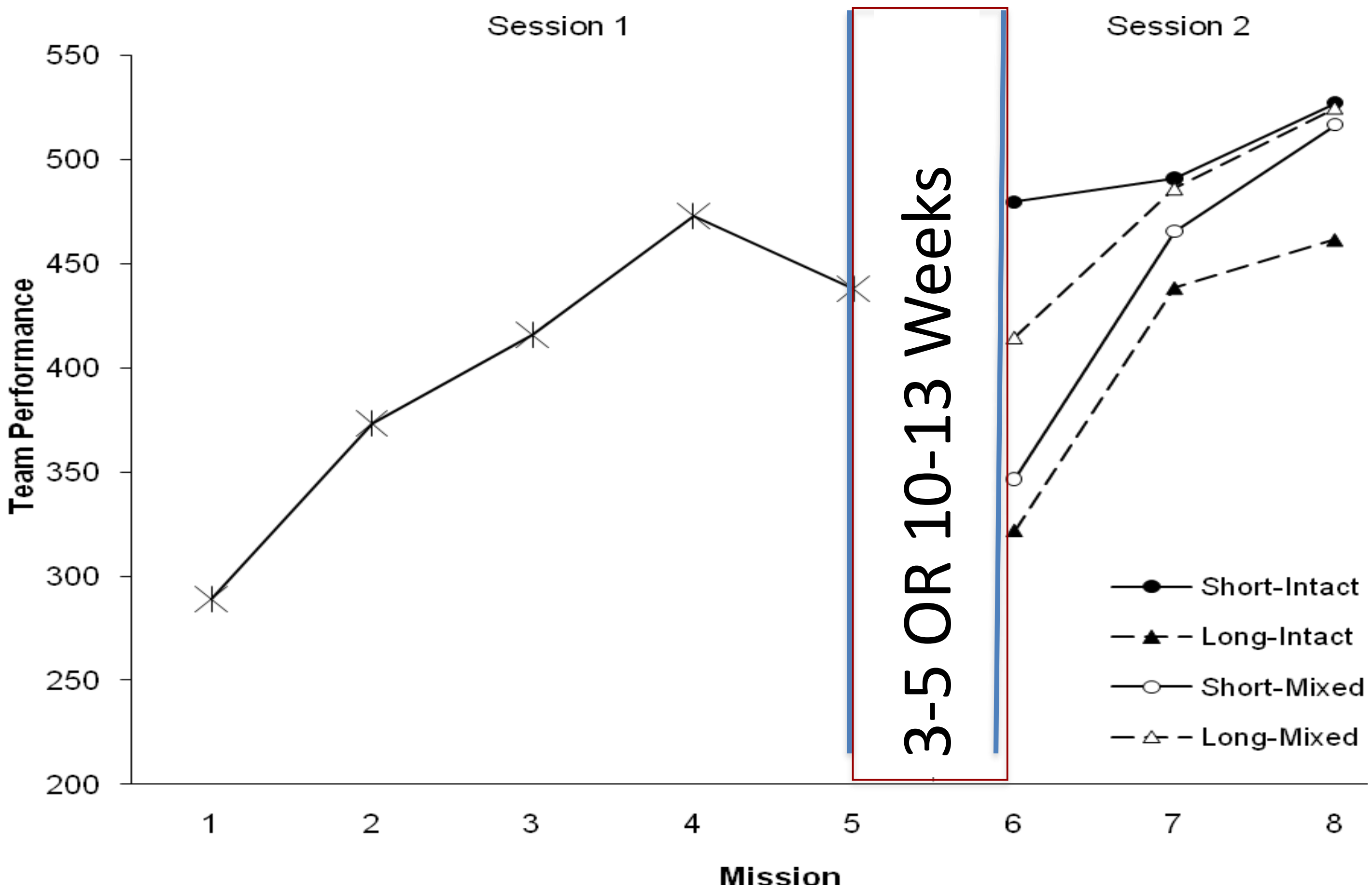
Same Condition



Mixed Condition



Team Retention and Composition

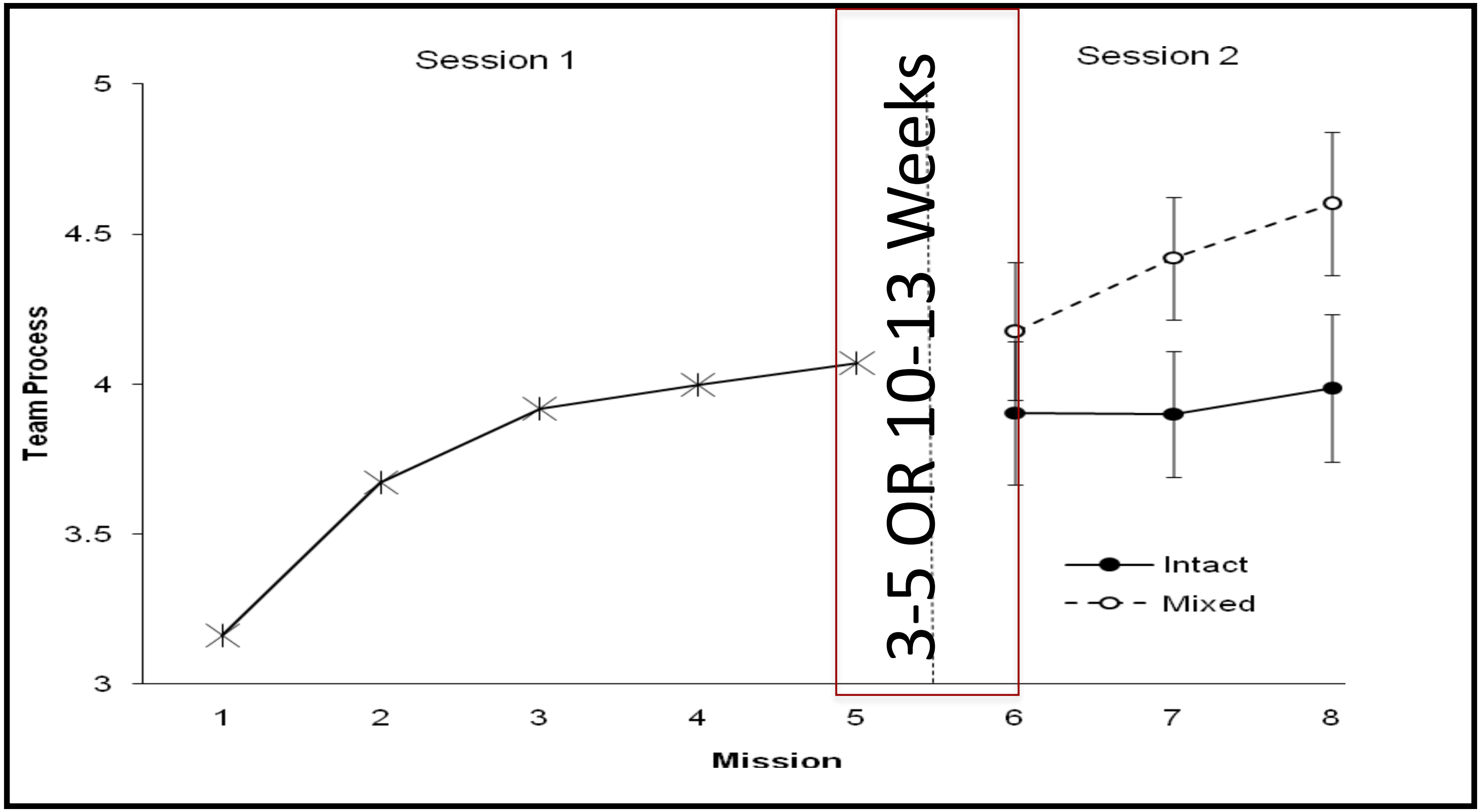


All but Short-Intact teams suffer <u>performance</u> loss after the break

But a different story for <u>Team Process</u>…

Team Process improves for mixed, but not intact teams after the break.

This is unexpected and supports Interactive Team Cogntiion



(There were no changes in knowledge after the break)

* Result also supported in mission planning testbed – change roles vs. seats

Interactive Team Cognition

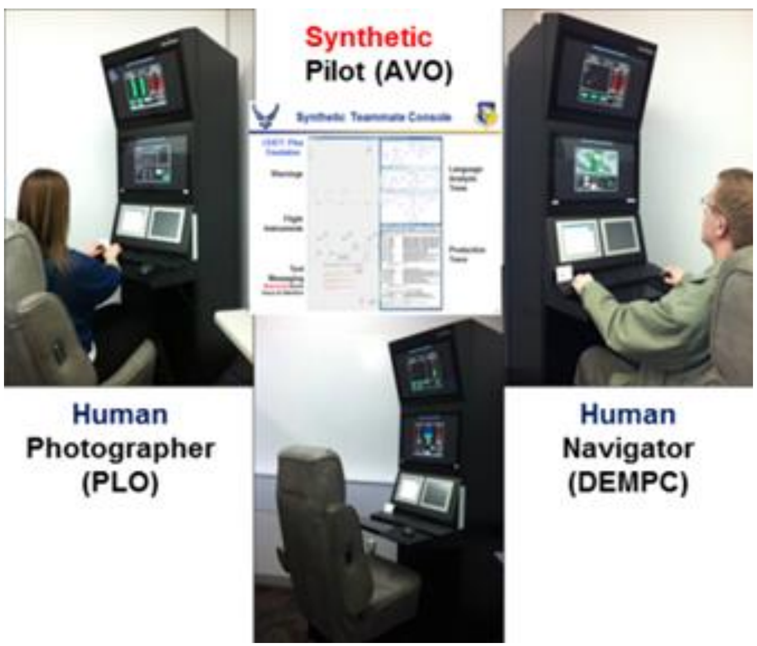
Team interactions often in the form of explicit communications are the foundation of team cognition

ASSUMPTIONS

1) Team cognition is an **activity; not a property** or product
2) Team cognition is inextricably **tied to context**
3) Team cognition is best measured and studied when the **team is the unit of analysis**

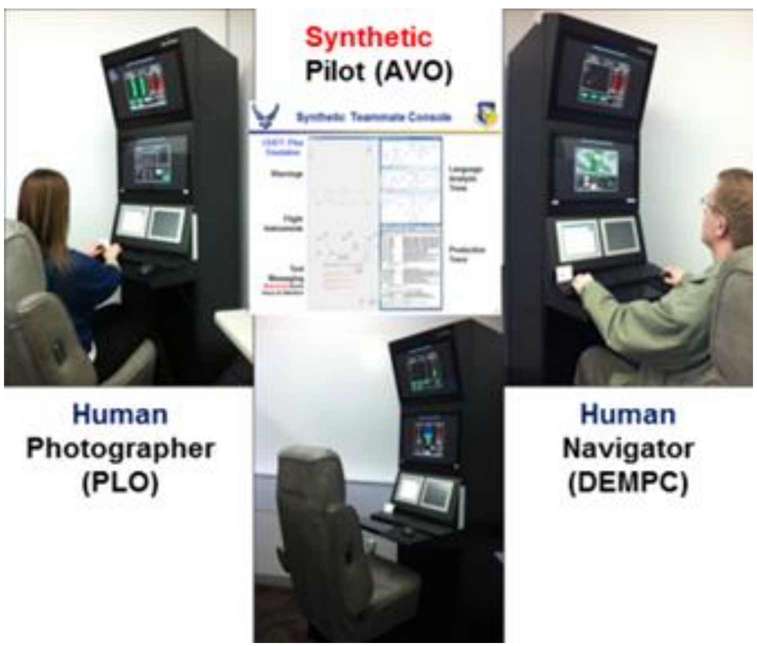
Cooke, N. J., Gorman, J. C., Myers, C. W., & Duran, J.L. (2013). Interactive Team Cognition, *Cognitive Science, 37, 255-285,* DOI: 10.1111/cogs.12009.

Autonomous agent as a collaborator on a heterogeneous team (role and nature of agent) that operates a Remotely Piloted Aircraft to take reconnaissance photos



Autonomous agent as a collaborator on a heterogeneous team (role and nature of agent) that operates a Remotely Piloted Aircraft to take reconnaissance photos

automation



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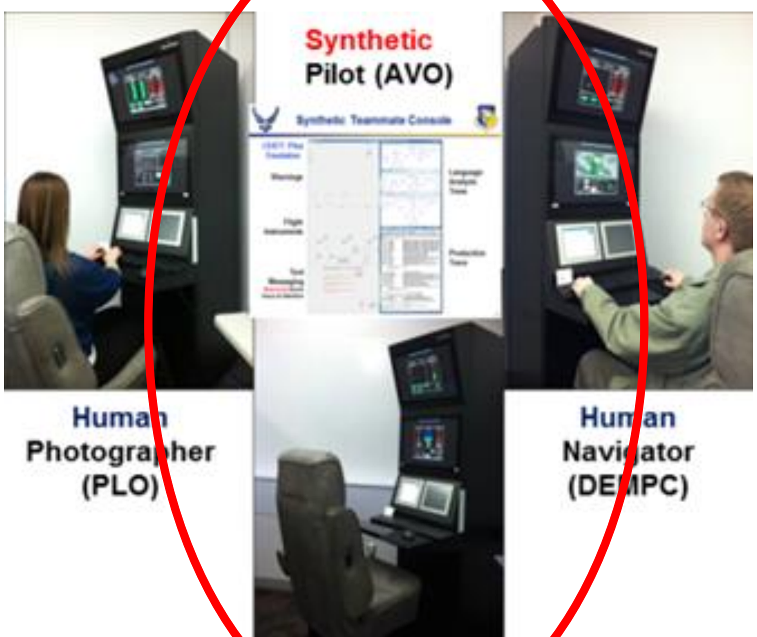
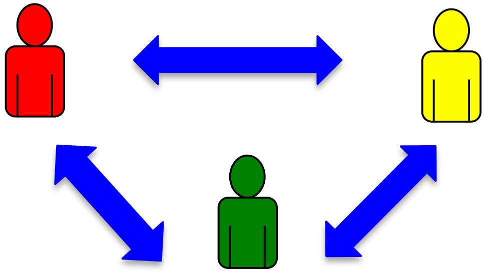


autonomy

IMPLICATIONS OF INTERACTIVE TEAM COGNITION FOR SYNTHETIC TEAMMATE



1) Interaction goes beyond language understanding and generation
2) Coordination is central to this task – timely and adaptive passing of information among team members
3) Humans display sometimes subtle coordination behaviors that may be absent in the synthetic teammate
4) Failures of synthetic teammate will highlight the requisite coordination behaviors

The Synthetic Teammate

- Cognitively plausible agents capable of performing complex tasks & interacting with human teammates in natural language
- Effective team training any time anywhere, in DoD relevant, complex, dynamic environments
- Facilitate transition to new DoD applications

Take cognitive modeling to the level of functional systems

- The largest cognitive model built in ACT-R
  - 2459 Productions
  - 57,949 Declarative Memory chunks
- Among the largest cognitive models built in any cognitive architecture
  - 5 major components
- By computer science standards, a large program

SYNTHETIC TEAMMATE DEMO SYSTEM

CERTT
Consoles:
Navigator
Photographer
Pilot

Text Messaging
Subsystem

Synthetic
Teammate
(Pilot)

WPAFB Dayton, OH

THE **SYNTHETIC TEAMMATE** COMMUNICATES WITH **HUMANS**

Sender	Sent	Message
DEMPC	517.22	the speed restriction for f-area is from 150 to 200.
PLO	530.16	good photo. go on.
PLO	572.02	go to next waypoint.
DEMPC	633.1	the next waypoint is prk. it is entry.
AVO	736.63	What is the effective radius for oak?
AVO	747.35	What is the next point after prk?
DEMPC	768.78	no effective radius for oak.
DEMPC	803.77	the next waypoint is s-ste. it is target. the altitude restriction is from 3000 to 3100.
AVO	843.41	What is the next point after s-ste?
DEMPC	924.9	the speed restriction for s-ste is from 300 to 350.
DEMPC	982.94	the next waypoint is m-ste. it is target.
DEMPC	1123.08	the next waypoint is m-ste.

SYNTHETIC TEAMMATE VALIDATION EXPERIMENT

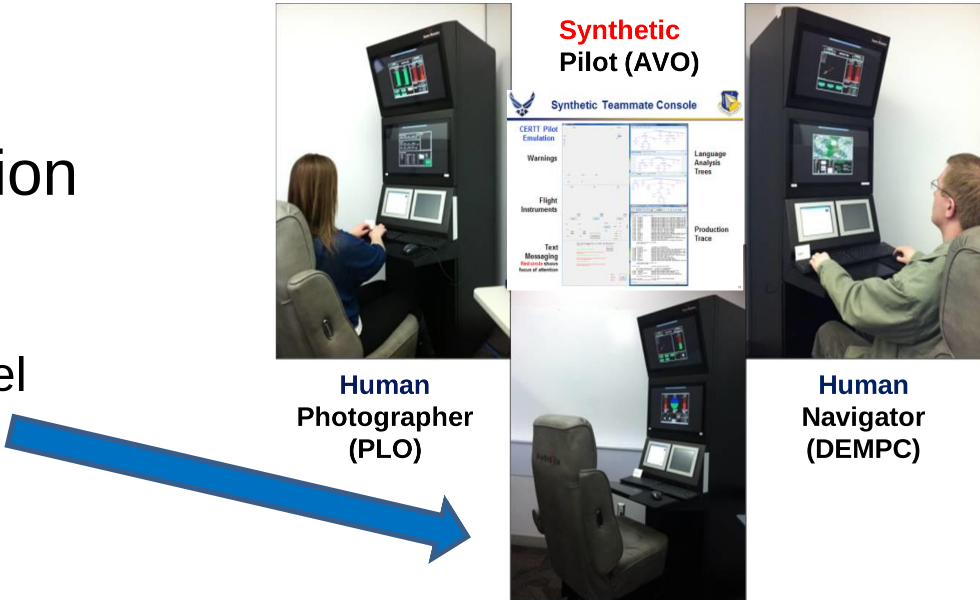
Purpose: Compare synthetic teammate teams to all-human control teams and to an all-human team with an experienced AVO (Experimenter)

Method

Participants: 30 3-agent teams,
10 team per condition

Conditions

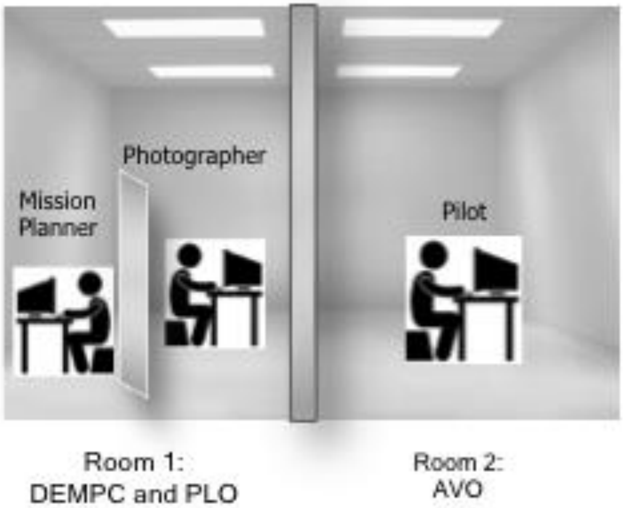
- Synthetic
  - AVO is ACT-R based cognitive model
  - Less expertise than experimenter
- Control
  - AVO is participant
- Experimenter
  - AVO is experimenter (experienced AVO)
  - Pushes and pulls information across team using a coordination script



SYNTHETIC TEAMMATE VALIDATION EXPERIMENT

Procedure

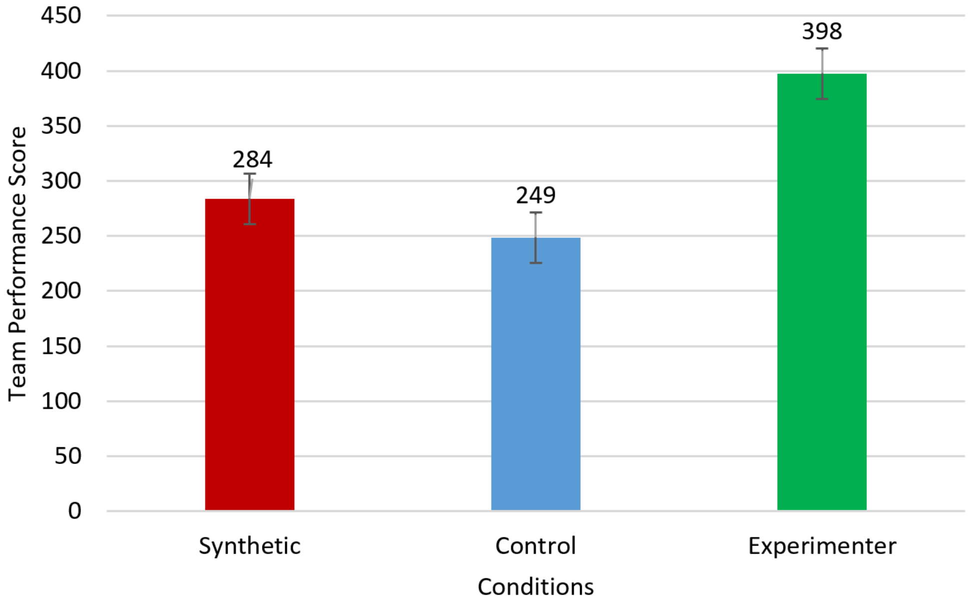
Sessions		Procedure
1	Welcoming	Consent forms.
2	Interactive Training	Interactive Training PowerPoint Slides
3	Training Mission	Hands on Training
4	Mission 1	Mission 1 is conducted
5	NASA TLX/ Knowledge Measures	Session 1: Conducting taskwork and teamwork questions, and administering the workload questions
6	Mission 2	Mission 2 is conducted
7	Mission 3	Mission 3 is conducted
8	Mission 4	Mission 4 is conducted
9	Mission 5	Mission 5 is conducted
11	NASA TLX/ Knowledge Measures	Session 2: Conducting taskwork and teamwork questions, and administering the workload questions
12	Demographics/ Debriefing	Conducting demographic questions, and giving debriefing
13	Post Checklist	



Measures

- Team performance
- Team process (process ratings, communication flow, coordination, situation awareness, verbal behavior)
- Workload, NASA TLX

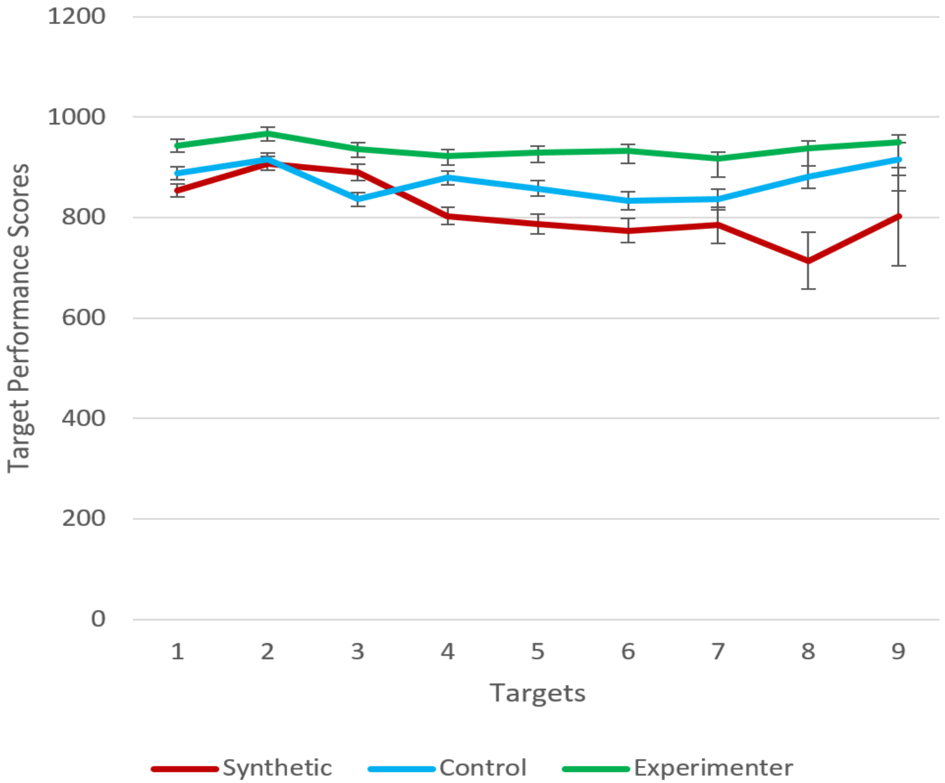
RESULTS: TEAM PERFORMANCE



Synthetic = Control < Experimenter

Experimenter teams demonstrated superior team performance compared to the <u>control and synthetic teams which were statistically equivalent</u>.

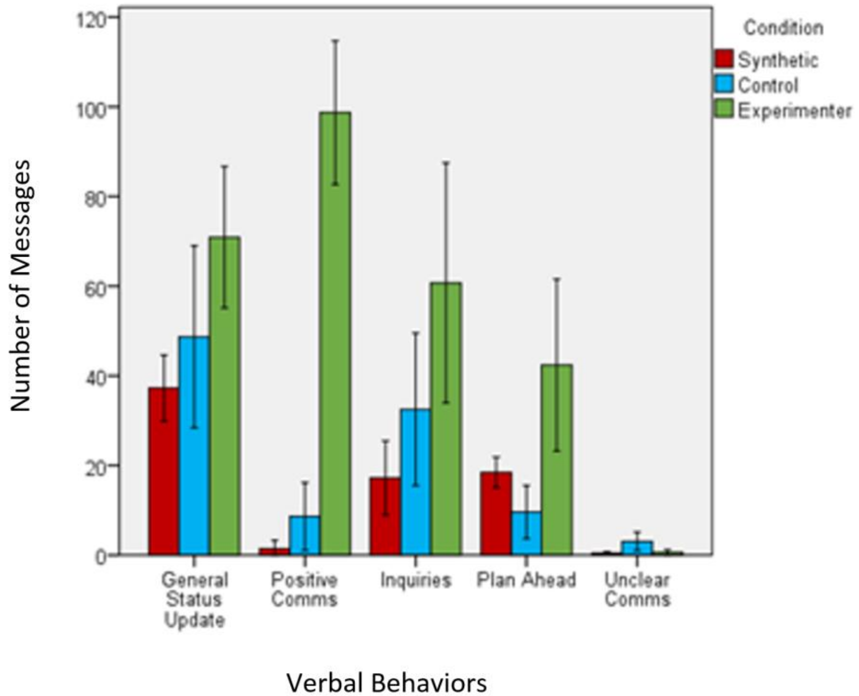
RESULTS: TARGET PROCESSING EFFICIENCY



Synthetic < Control < Experimenter

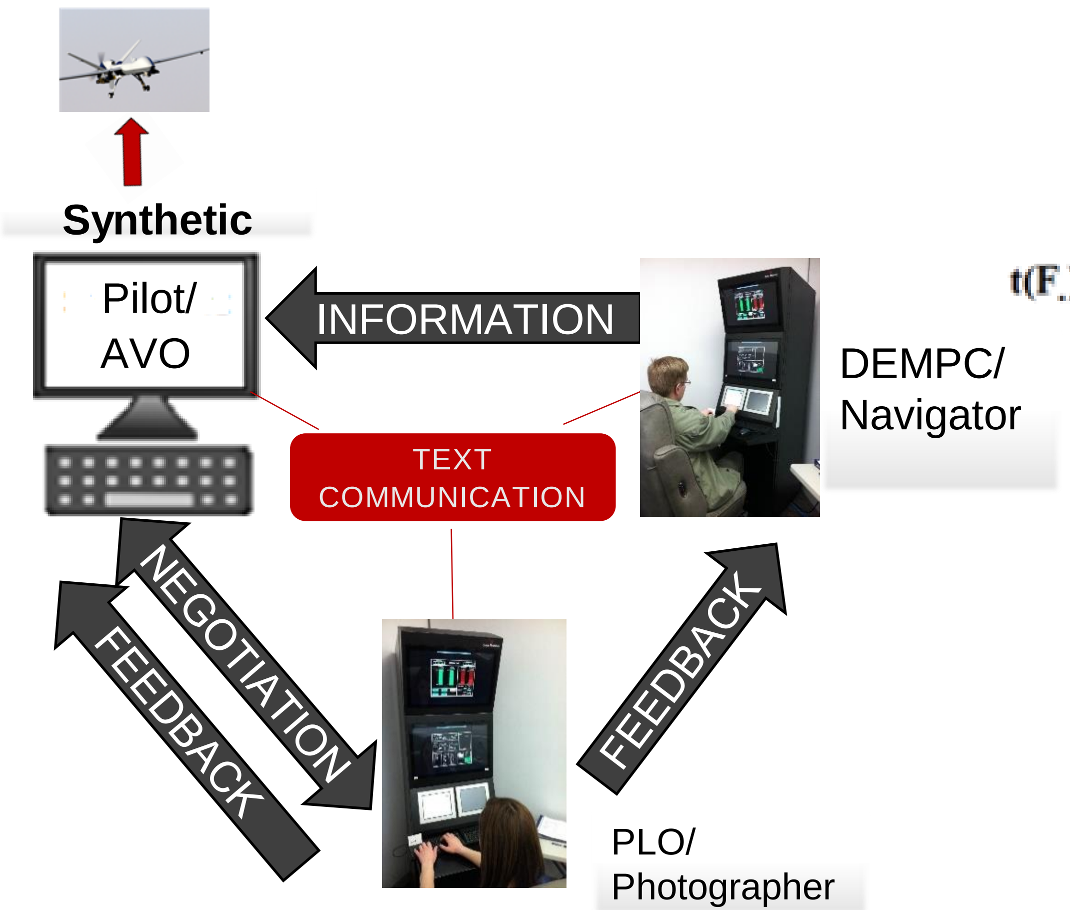
Target processing efficiency was poorer for Synthetic teams than Control teams which was poorer than the Experimenter teams; and the Synthetic teams' processing efficiency declined over time.

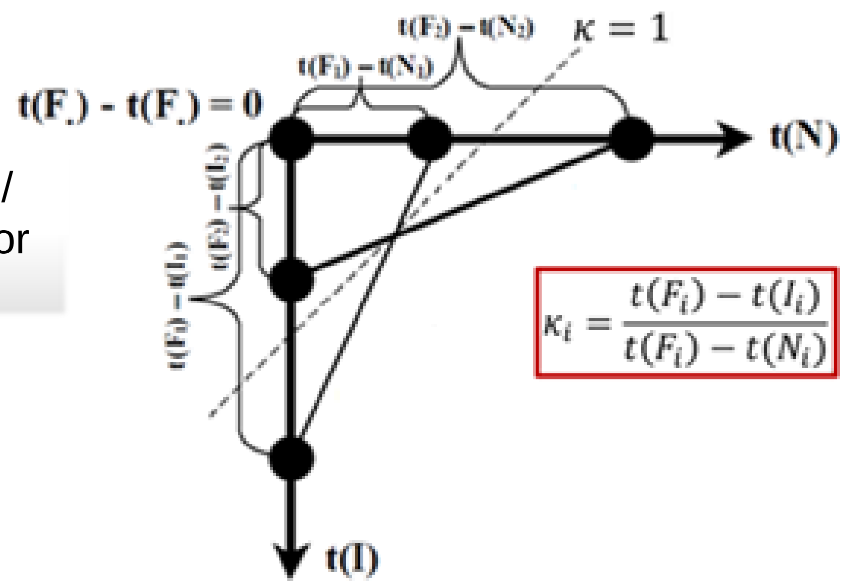
RESULTS: VERBAL BEHAVIORS OF SYNTHETIC VS. HUMAN PILOTS



The Synthetic pilot demonstrates different verbal behaviors compared to Control and Experimenter pilots (fewer status updates, positive communications, inquiries). Also Synthetic teams had fewer general status updates and more repeated requests for information. More pulling than pushing of information.

RESULTS: COORDINATION





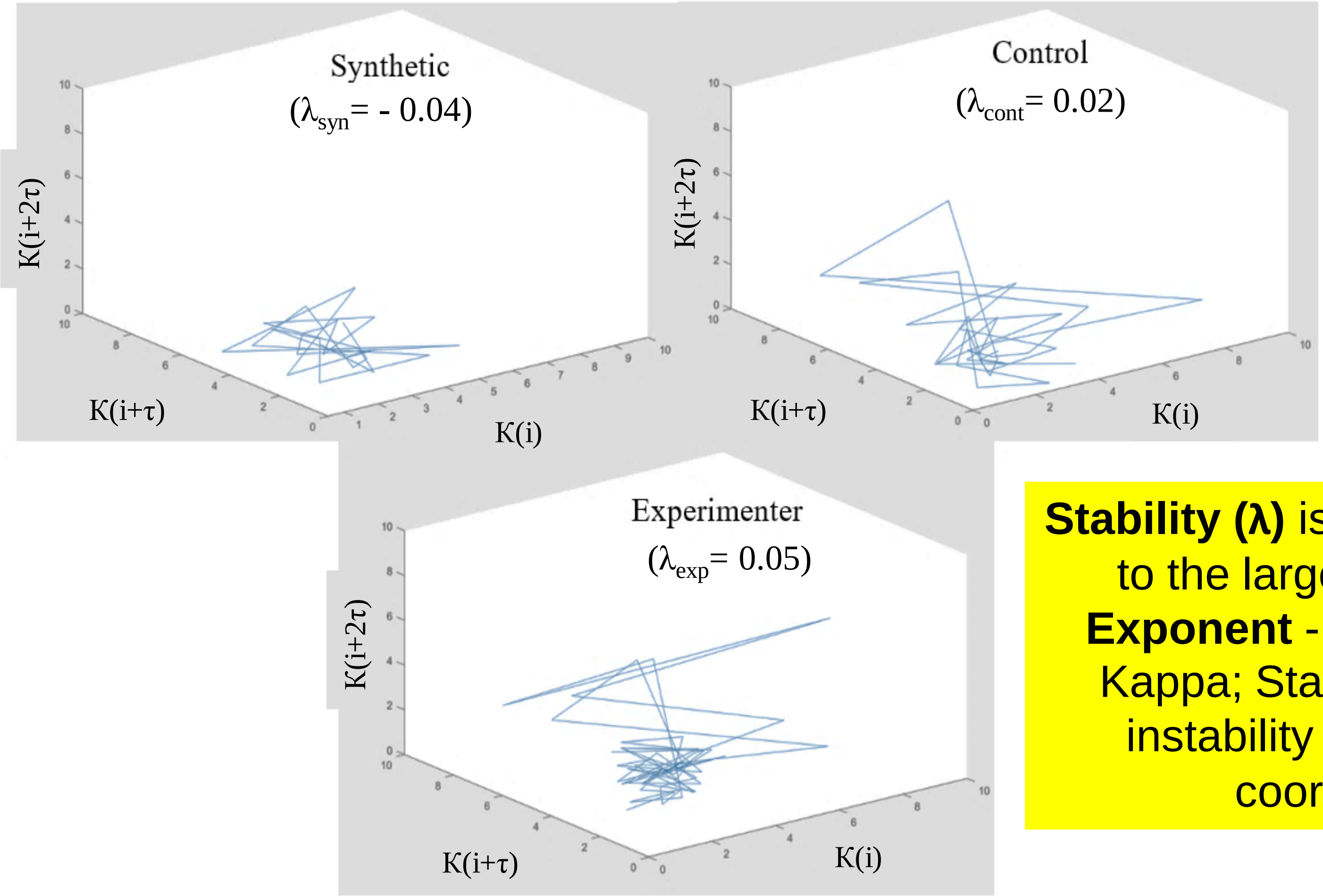
Team coordination: three key communication events at each target waypoint, Information-Negotiation-Feedback (INF), is captured by a Kappa Score (κ) (Gorman, Amazeen, & Cooke, 2010)

RESULTS: ATTRACTOR RECONSTRUCTION

- Attractor reconstruction was used to visualize team coordination dynamics
- Recover a system's dynamical structure from a one-dimensional Kappa time series and time-delayed versions of the Kappa.

From Demir dissertation 4/2017

RESULTS: SYNTHETIC TEAMS MORE STABLE THAN OTHERS

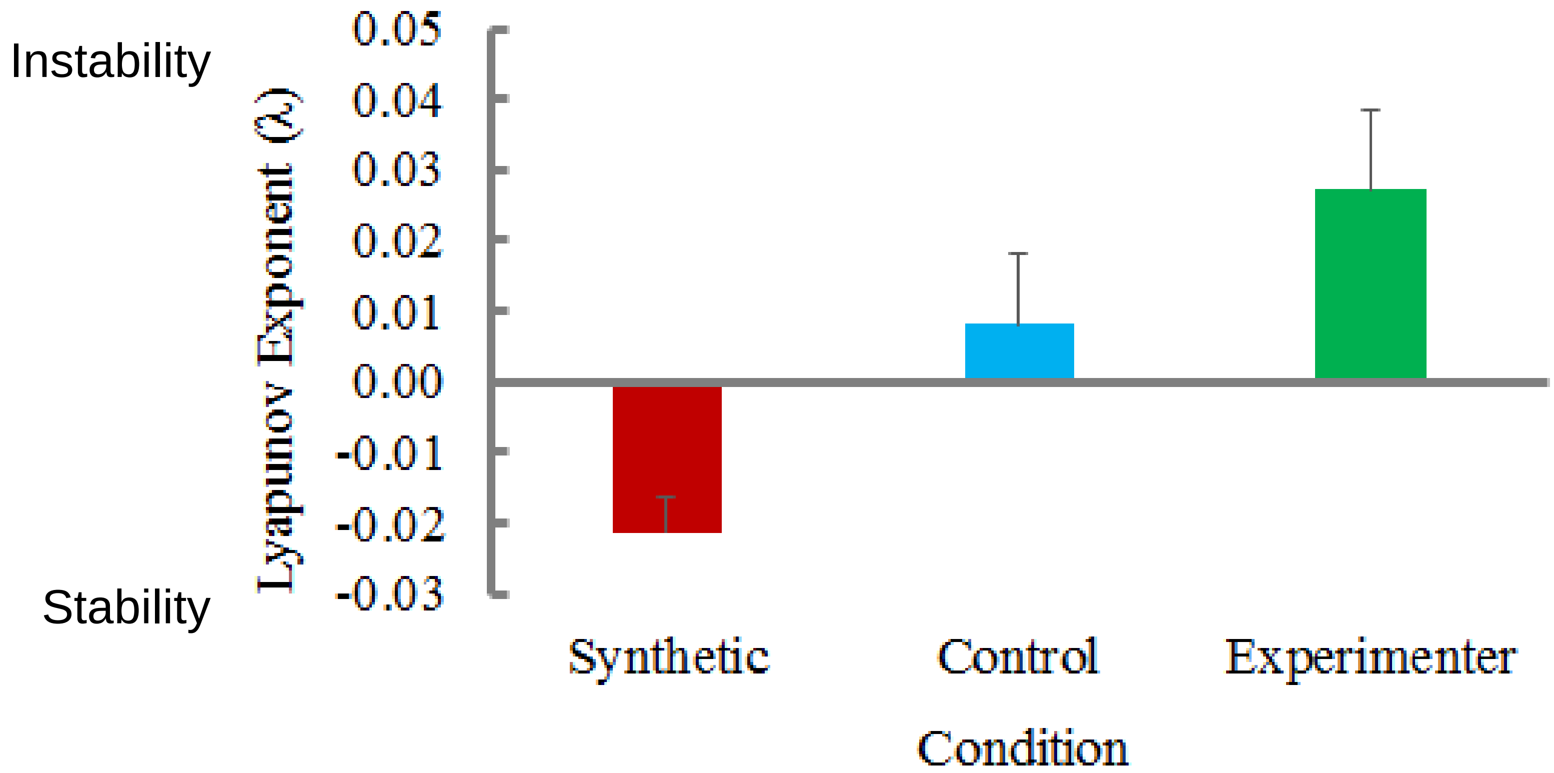


Stability (λ) is inversely related to the largest **Lyapunov Exponent** - estimated from Kappa; Stability ($\lambda<0$) and instability ($\lambda>0$) of team coordination

Sample Reconstructed attractors from three teams: a three-dimensional phase space as coordinates for the three-dimensional space [$\kappa(i)$, κ(i+τ), κ(i+2τ)]

From Demir dissertation 4/2017

RESULTS: SYNTHETIC TEAMS MORE STABLE THAN OTHERS



Mean largest Lyapunov exponents = **Stability** across the conditions (vertical lines indicate SE) **synthetic < control = experimenter**
From Demir dissertation 4/2017

RESULTS: JOINT RECURRENCE QUANTIFICATION ANALYSIS (JRQA)

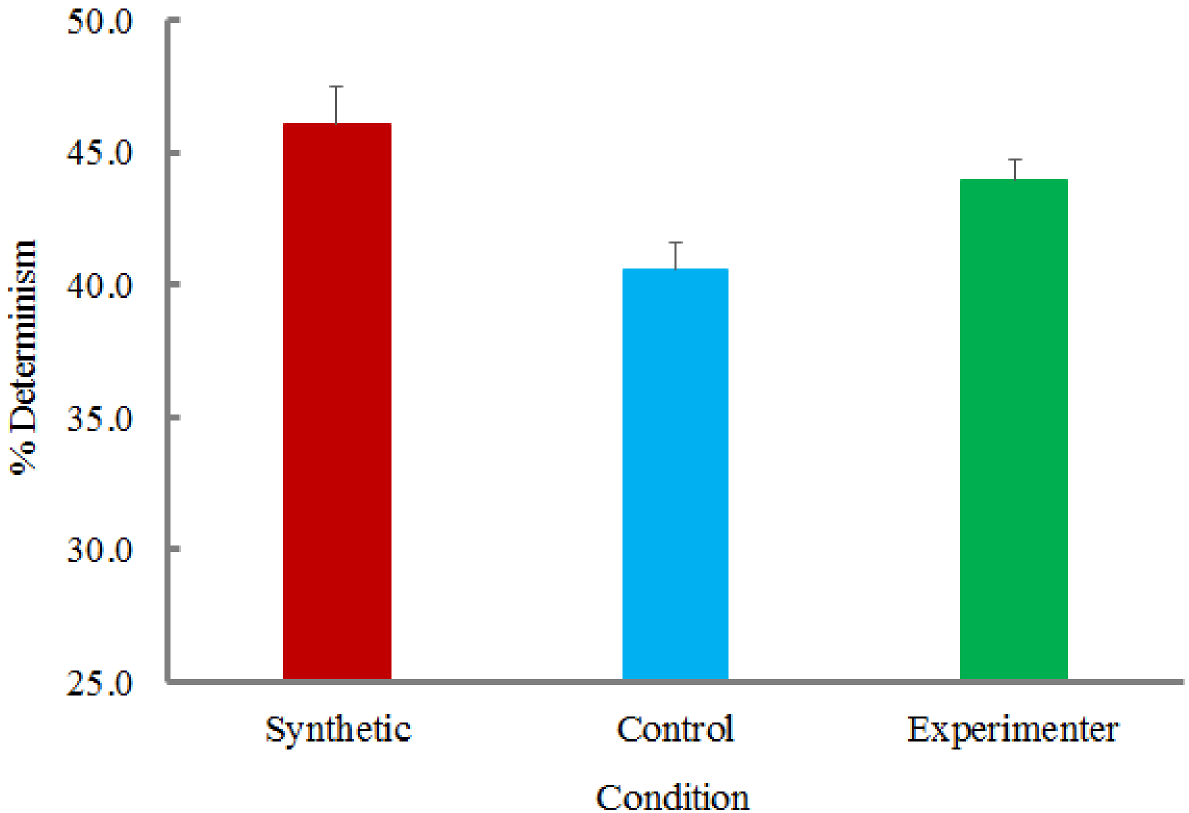
JRQA was used to assess joint influence of one team member on the other

- JRQA was applied on communication flow data (i.e., sent time stamp from each UAV mission)
- % Determinism (DET): measure of system's predictability was extracted from JRQA

From Demir dissertation 4/2017

RESULTS: SYNTHETIC TEAMS MOST STABLE/PREDICTABLE AND CONTROL LEAST

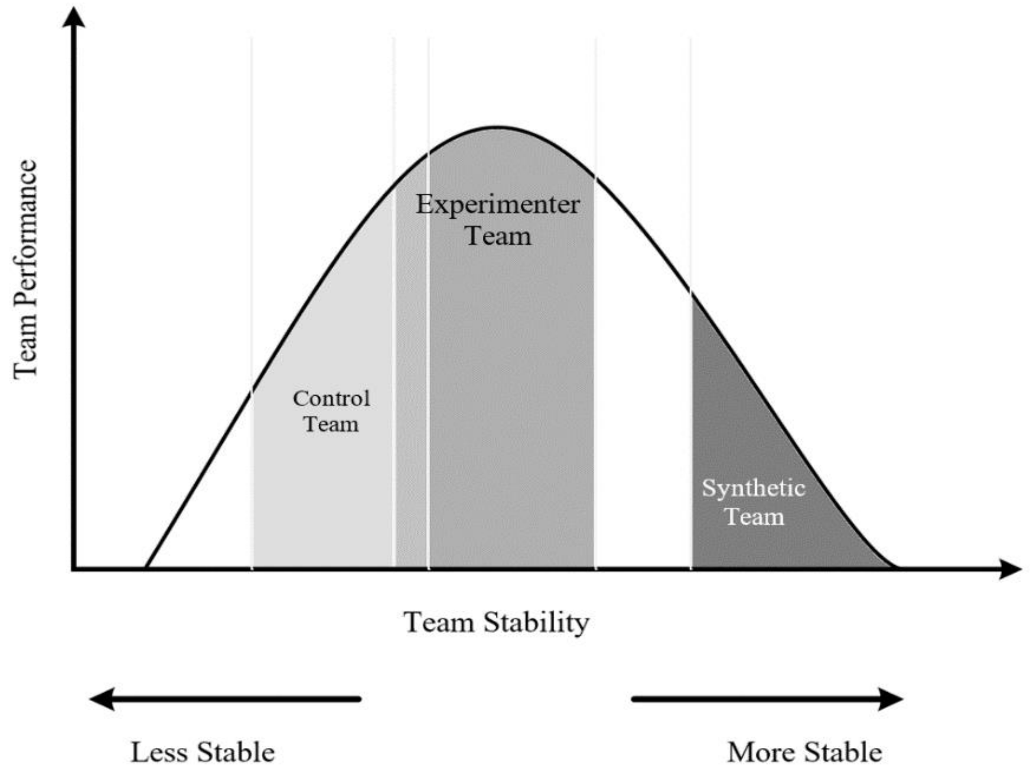
More Predictable



Less Predictable

Mean % DET = **Predictability** across the conditions
(vertical lines indicate SE) **synthetic > control < experimenter**
From Demir dissertation 4/2017

RELATION BETWEEN TEAM PERFORMANCE AND COORDINATION

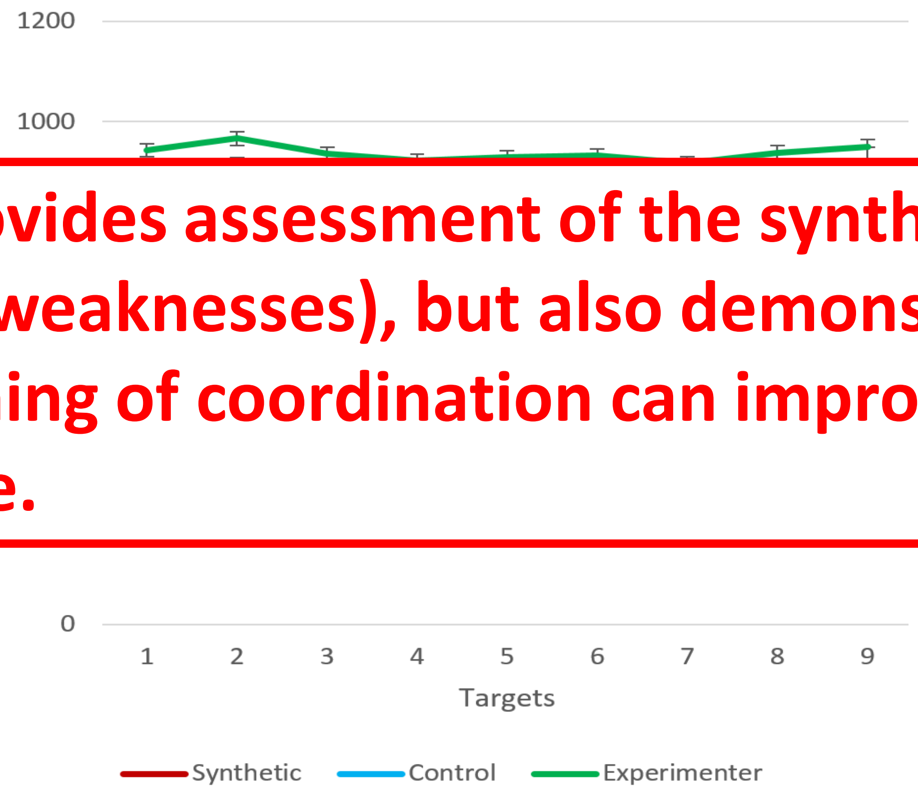


From Demir dissertation 4/2017; Coordination stability "sweet spot" discovered

SYNTHETIC TEAMMATE VALIDATION RESULTS

- The synthetic teams performed as well as control teams, but had difficulties coordinating and processing targets efficiently – failure to anticipate
- A synthetic teammate can impact team coordination and performance - entrainment
- Experimenter condition demonstrates how a teammate who excels at coordination can elevate coordination of the whole team
- Conditions were nominal. Coordination especially important in off-nominal conditions.

Results: Target Processing Efficiency



Not only provides assessment of the synthetic teammate (along with weaknesses), but also demonstrates how subtle coaching of coordination can improve team performance.

Synthetic < Control < Experimenter

Target processing efficiency was poorer for Synthetic teams than Control teams which was poorer than the Experimenter teams; and the Synthetic teams' processing efficiency declined over time.

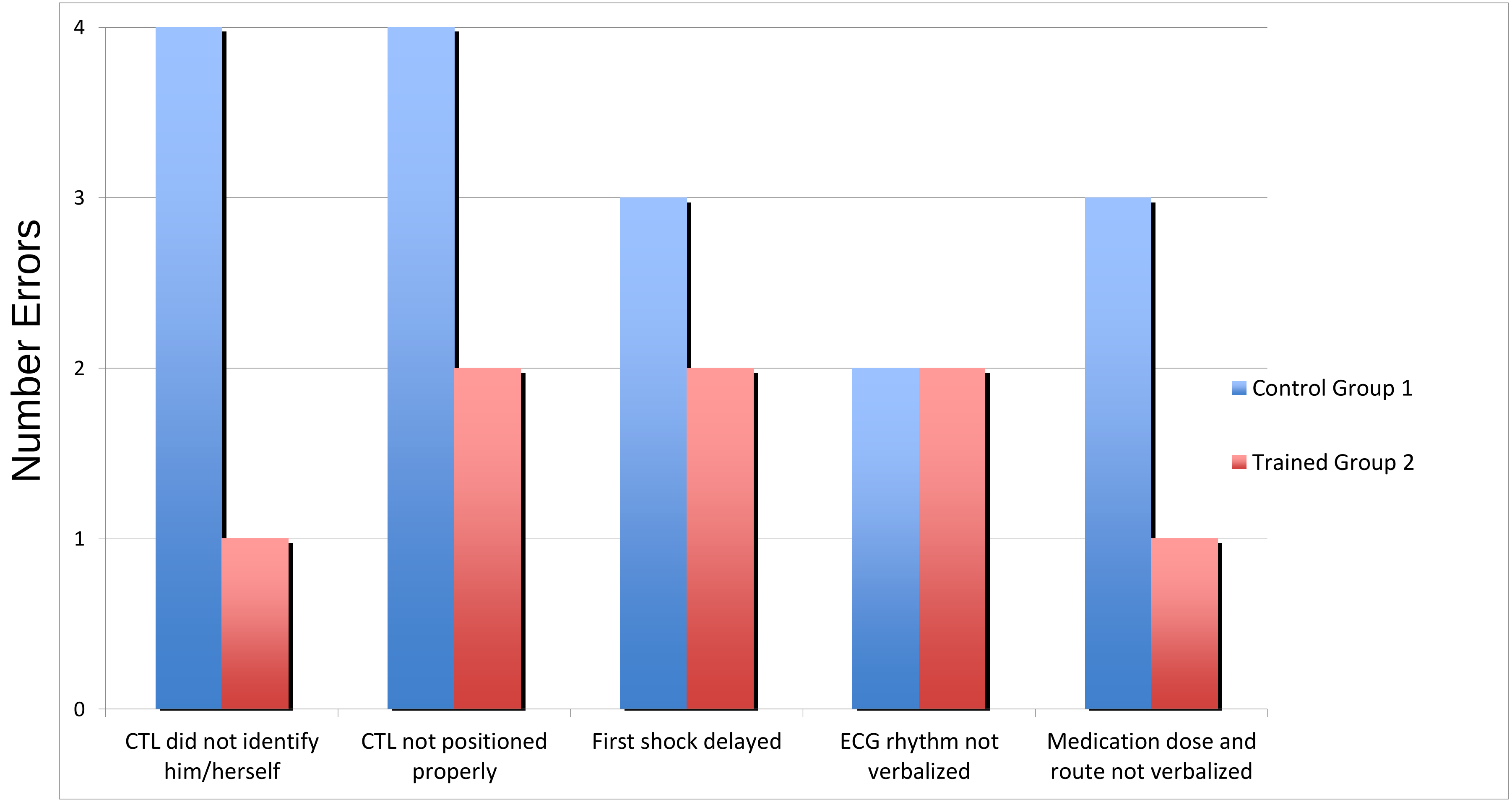
Applying Coordination Coaching to Code Blue Resuscitation

Sandra Hinski (2017) dissertation, ASU

Intensivist code leaders studied communication model for 5-10 min. prior to mock code

Arrival to code	Introduces self as code team leader
Contingency	IF: Code RN does not immediately give the CTL a brief history, code status, and confirm advanced monitoring is established THEN: CTL must directly ask the Code RN for the information
Within 30 seconds of arrival to code	Asks about ABCs IF: No one person is performing CPR or performing bag mask ventilating upon arrival of CTL THEN: CTL must direct code team member to immediately perform CPR and the RT to bag the patient
Once monitoring is established	Asks for ACLS therapies as indicated IF: Medication or shock delivery is delayed more than 10 seconds after identification of rhythm THEN: CTL must directly as pharmacist or RN do deliver the meds and/or shock
constant feedback	Asks if there are any problems, so CTL can troubleshoot or delegate task to another person, keeps team on task, should be in SBAR format
Contingency	IF: Code team does not clarifies ROSC/stabilization of ABCs OR clinical worsening THEN: CTL must clarify disposition (i.e. transfer to ICU, need for more advanced therapies, discontinuation of efforts, etc.)

Code Team Errors



Human-Autonomy Teaming
Under Degraded Conditions

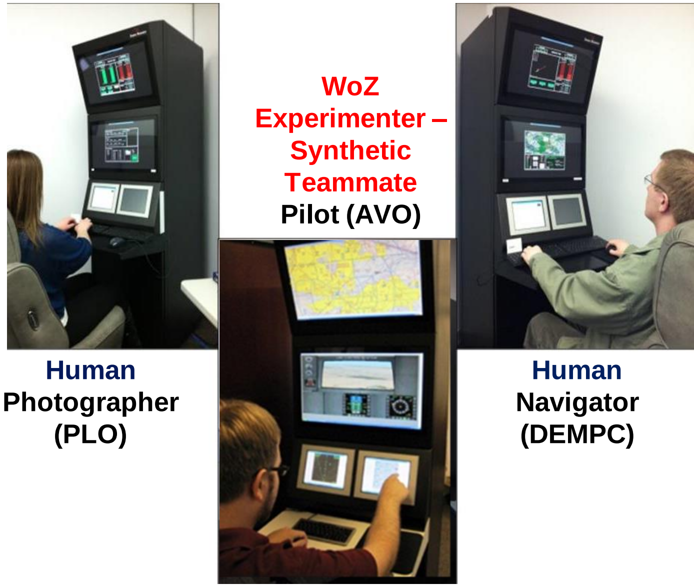
Purpose: Identify challenges of human-autonomy teaming under degraded conditions and strategies of high performing teams to address them.

Method

Wizard of Oz Paradigm: synthetic pilot was mimicked by an experienced (remote) experimenter who failed in specific ways at specific times

Participants: 21 3-agent teams

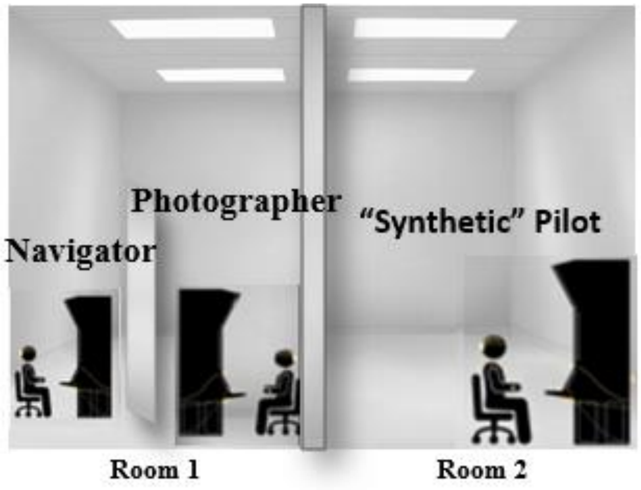
10 Missions (with multiple targets) across two sessions



Human-Autonomy Teaming Under Degraded Conditions

Procedure (Two Sessions separated by 1-2 week interval)

SESSION-I (with breaks Total: 6 hours)	SESSION-II (with breaks Total: 7 hours)
1) Consent forms (15 min)	**1)** Mission 5 (40 min),
2) PowerPoint (30 min) and hands on training (30 min)	**2)** NASA TLX I (15 min)
3) Mission1 (40 min)	**3)** Mission 6 (40 min),
4) NASA TLX I (15 min)	**4)** Mission 7 (40 min),
5) Missions 2 (40 min)	**5)** Mission 8 (40 min),
6) Mission 3 (40 min),	**6)** Mission 9 (40 min),
7) Mission 4 (40 min),	**7)** Mission 10 (40 min),
8) NASA TLX-II, Trust & Anthropomorphism (30 min)	**8)** NASA TLX-II, Trust, Anthropomorphism, Demographics, and Debriefing (30 min)
	9) Post-Check Procedure (15 min)



Measures

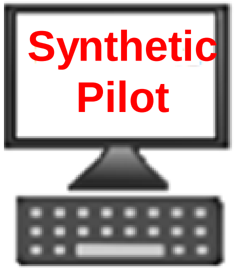
- Team performance (mission and target levels)
- Team process (process ratings, communication flow, coordination, situation awareness, verbal behavior)
- Team trust & resilience
- Workload (NASA TLX)
- Anthropomorphism
- Heart Rate (ECG), Electrical Activity of the Brain (EEG), & Facial Expression

Human-Autonomy Teaming Under Degraded Conditions

- **Automation Failures –** display fails

- **Autonomy Failures –** synthetic teammate comprehension failure

- **Malicious Attacks on Autonomy** provides appropriate feedback as it enters wrong area



Human-Autonomy Teaming Under Degraded Conditions

Experimental Sessions and Application of Failures during specific targets for each mission

		Target/ Automation	Target/ Autonomy	Target/ Malicious
Session I	Training	No Failure	No Failure	No Failure
	Mission 1	No Failure	No Failure	No Failure
	Mission 2	2nd/ Type I	4th/ Type I	No Failure
	Mission 3	4th/ Type II	2nd/ Type II	No Failure
	Mission 4	1st/ Type III	3rd/ Type III	No Failure
Session II	Mission 5	2nd/Type III	4th/ Type II	No Failure
	Mission 6	4th/ Type I	2nd/ Type I	No Failure
	Mission 7	1st/ Type II	3rd/ Type II	No Failure
	Mission 8	3rd/Type III	1st/ Type III	No Failure
	Mission 9	3rd/Type II	5th/ Type II	No Failure
	Mission 10	2nd/Type III	4th/ Type III	Last 10 min

RESULTS: OVERCOMING FAILURES AND ATTACKS

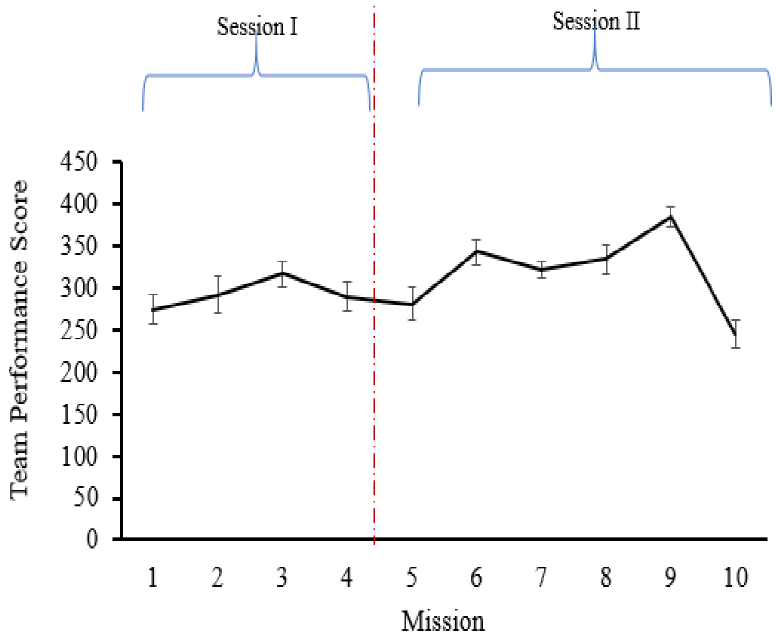
Automation & Autonomy Failures, and Malicious Attacks

- Proportion of 22 teams that overcame failures was approximately equal for both types: automation (65%) and autonomy (64%), and malicious attacks (41%)

- Performance of overcoming *automation failures* increased across the missions, but decreased for *autonomy failures*

RESULTS: TEAM PERFOMANCE

Team Performance (Mission Level)



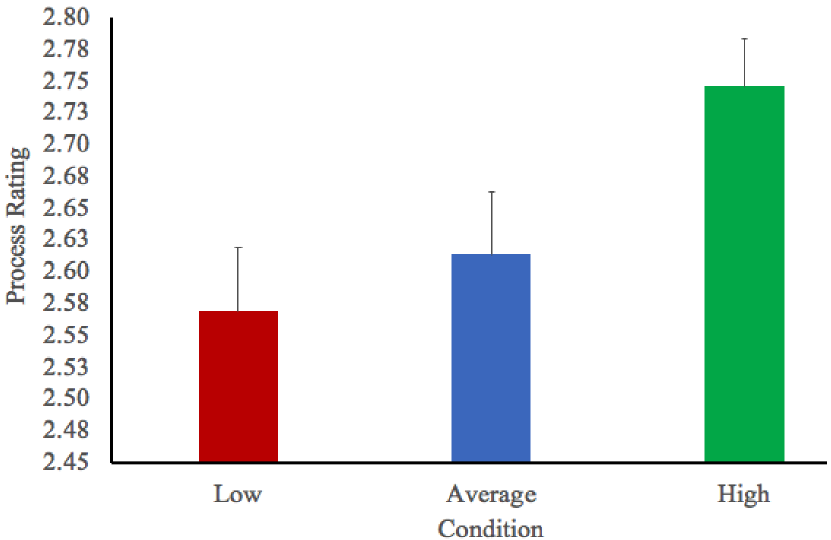
Team performance increased across the missions.

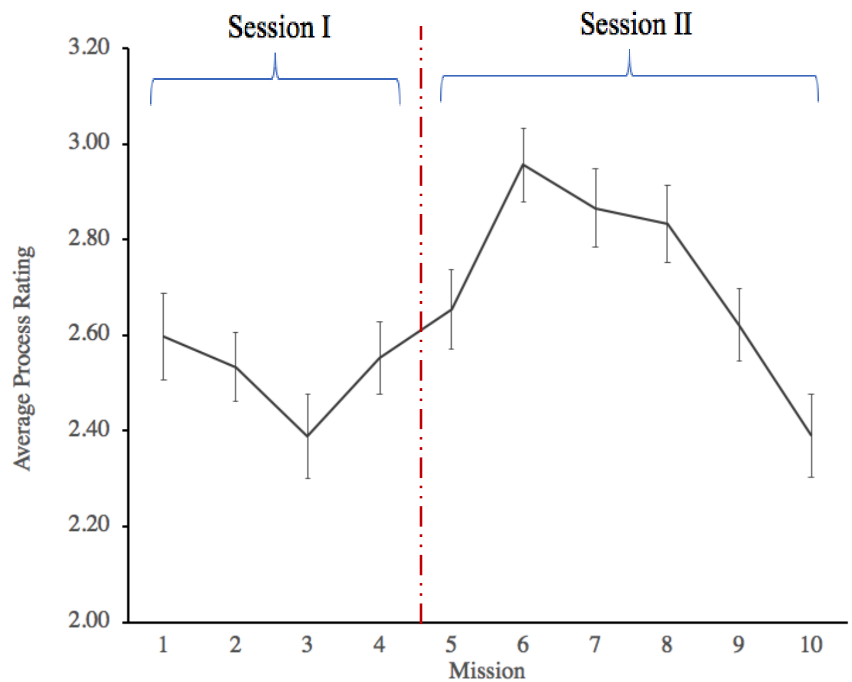
Clusters Based on Performance

- Identify high vs. low performing teams
- Team clusters via K-Means Cluster analysis
- Data
  - Mission performance score
  - Target performance score
  - Number of failures overcome
- Resulted in 3 groups of teams

Metrics\ Conditions	High-Performed	Average	Low-Performed
Number of Teams	6	8	6

RESULTS: TARGET PROCESS RATING

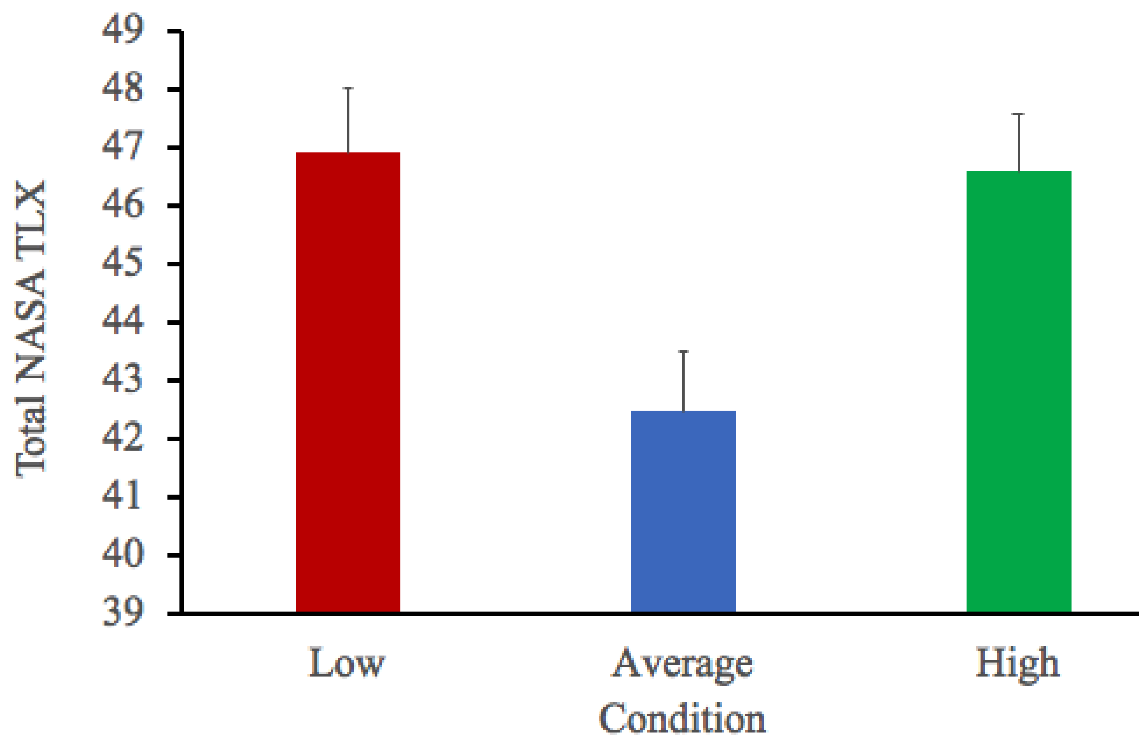




Low = Average < High Performed Teams

High-performing teams demonstrated superior team process compared to the <u>average and low teams which were statistically equivalent</u>.

RESULTS: NASA TLX WORKLOAD



High-performed = Low > Average-performed teams

The average teams had lower workload than the low- and high-performing teams; and the photographer had lower workload than the navigator.

RESULTS: TRUST

1) lower levels of trust in the autonomous agent in low performing teams than both medium and high performing teams

2) there is a loss of trust in the autonomous agent across low, medium, and high performing teams over time

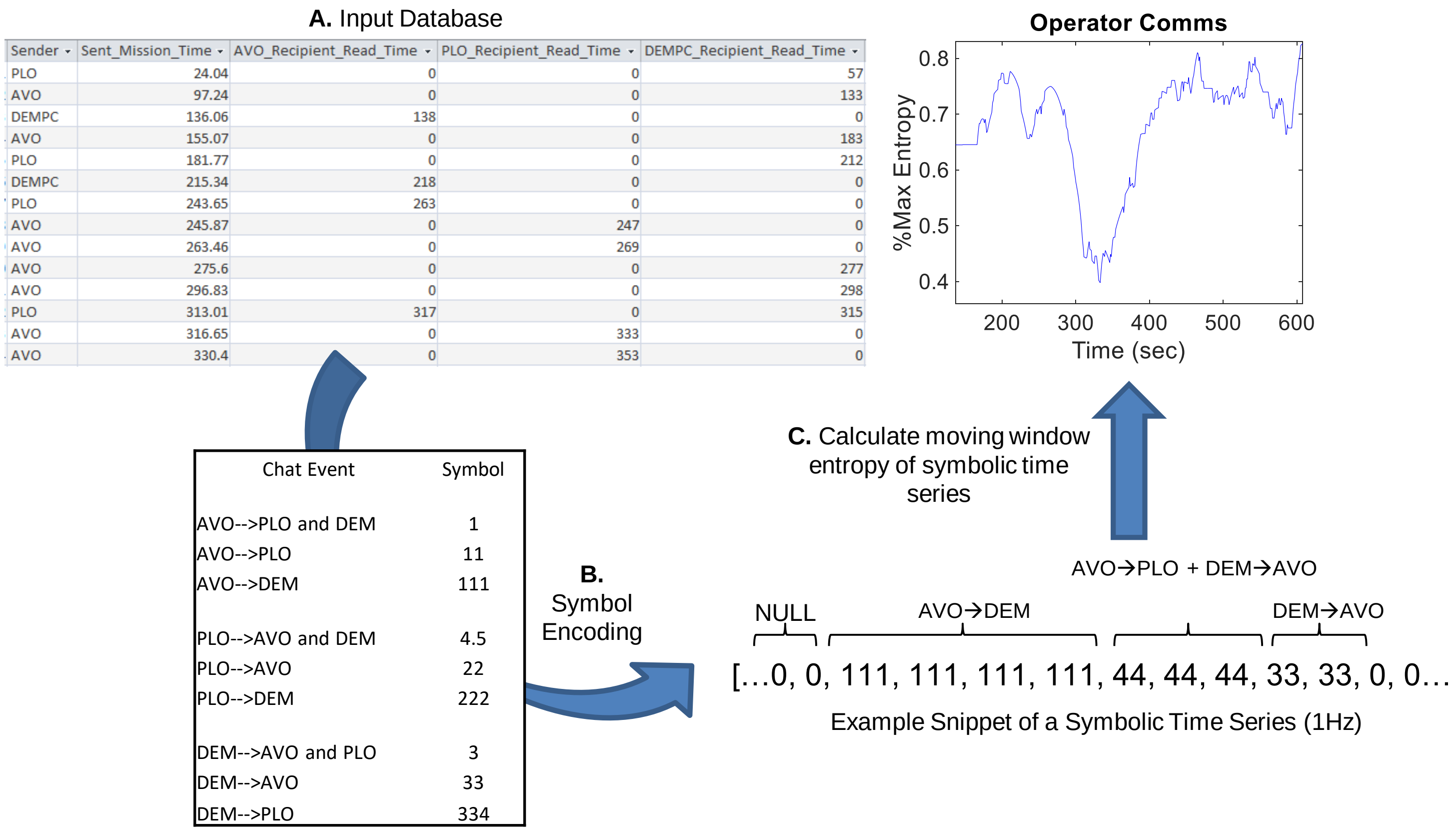
3) both low and medium performing teams also indicated lower levels of trust in their human team members

Coordination Dynamics Under Degraded Conditions

- These analyses utilize database files that contain timestamped information of vehicle, controls, and communication state throughout a mission
  - *Layered dynamics* – visualizing and tracking changes in how the system (RPAS) is organized over time
  - *Deep dive* – content analysis of mission chat transcripts to understand how the humans and autonomy dealt with automation failures and how the humans dealt with autonomy failures

Sender	Sent_Mission_Time	AVO_Recipient_Read_Time	PLO_Recipient_Read_Time	DEMPC_Recipient_Read_Time
PLO	24.04	0	0	57
AVO	97.24	0	0	133
DEMPC	136.06	138	0	0
AVO	155.07	0	0	183
PLO	181.77	0	0	212
DEMPC	215.34	218	0	0
PLO	243.65	263	0	0
AVO	245.87	0	247	0
AVO	263.46	0	269	0
AVO	275.6	0	0	277
AVO	296.83	0	0	298
PLO	313.01	317	0	315
AVO	316.65	0	333	0
AVO	330.4	0	353	0

Layered dynamics



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AVO	296.83	0	0	298
PLO	313.01	317	0	315
AVO	316.65	0	333	0
AVO	330.4	0	353	0

Chat Event	Symbol
AVO-->PLO and DEM	1
AVO-->PLO	11
AVO-->DEM	111
PLO-->AVO and DEM	4.5
PLO-->AVO	22
PLO-->DEM	222
DEM-->AVO and PLO	3
DEM-->AVO	33
DEM-->PLO	334

- *Windowed entropy measures the number of arrangements a system occupies over a fixed amount of time.*
- *Entropy is one operational definition of system reorganization (others are %DET and %REC).*

Layered dynamics

Different layers for visualizing and tracking where failures are addressed in the system

Vehicle

Fuel
Battery
Film
Temperature
Left Turn
Right Turn
Warning/Alarm
Altitude
Airspeed
Climbing
Descending
Accelerating
Decelerating
Flaps Position
Gear Position
X Location
Y Location

Controls

Set Shutter Speed
Set Focus
Set Camera Type
Set Aperture
Set Zoom

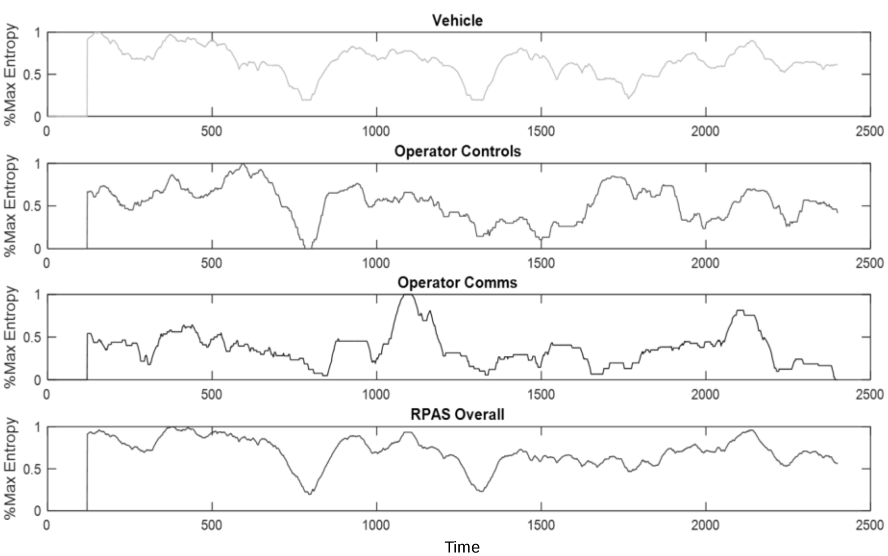
Check Required Settings
Charge Battery
Reset Lens
Reset Temperature
Take Photo
Accept Photo
Change Current Route
Send Route Plan
Request Flight Plan
New Queued Waypoint
New To Waypoint
Set Center of Gravity
Set Airspeed
Set Altitude
Refuel

Communications

AVO-->PLO and DEM
AVO-->PLO
AVO-->DEM

PLO-->AVO and DEM
PLO-->AVO
PLO-->DEM

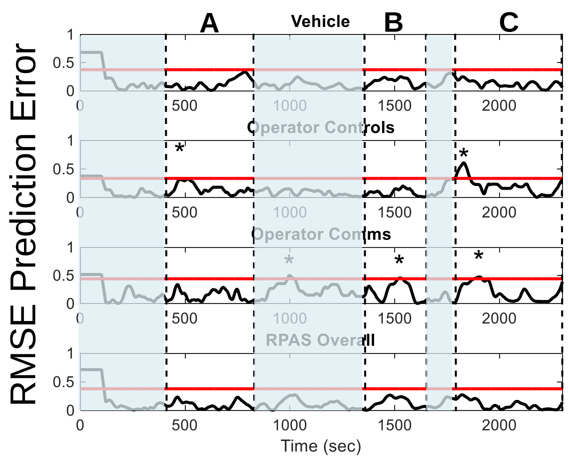
DEM-->AVO and PLO
DEM-->AVO
DEM-->PLO

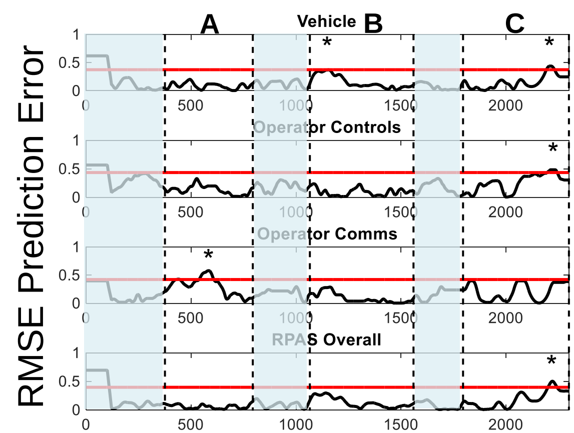


Layered Dynamics

<u>Reorganization time</u> – time from failure onset to peak significant system reorganization

A – automation failure B – autonomy failure C – malicious attack on autonomy





Effective = successfully overcoming failures

<u>*Effective teams tend to:*</u>

- Autonomy failures
  - Short reorganization time in the Controls/Vehicle layers ($p < .05$)
- Automation failures
  - Long reorganization time in the Communication layer ($p < .05$)

Summary: What we Have Found from the Dynamics Thus Far

For building resilient teams, intervention(s) may be developed around the core concepts of locus of resilience and loci of reorganization

Resilience to Failures

More Dynamic — More Static

Dimensions	Automation Failures	Autonomy Failures
Locus of Resilience	Interaction-based	Role-related
Behavioral Qualities	Adaptivity	Consistency/Persistence
Theoretical Underpinning	Interactive Team Cognition	I/O, Social Psychology
Measures	CAST	Trust, Anthrop., Demo’s
Mechanism(s)	Communication/Interaction	Traits, Dispositions, Attitudes

Human-Autonomy Teaming Under Degraded Conditions

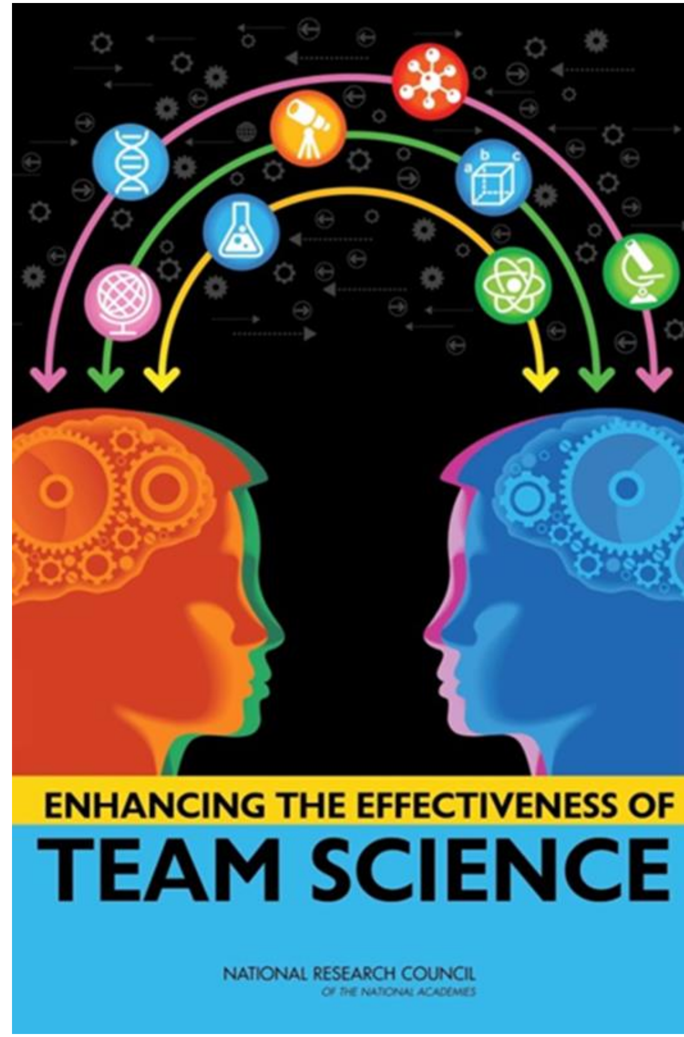
- High performing teams exhibit superior process behaviors, and also higher workload
- Trust in autonomous agent declines over time with increasing failures and is especially low for low performing teams
- Response to failures in automation requires team coordination
- Response to failures in autonomy may be more linked to attitude and trust
- Next study will test an intervention to improve response to failures

Next Steps: Taking Team Performance Measurement Out of the Lab

- Outcome can be measured in the lab because we know ground truth
- Outside of the lab, there is often no ground truth (cyber, intelligence, RPAS, USAR)

- Often team performance is measured as outcome
  - In the lab effective teams have positive outcomes
  - Outside the lab there is no obvious outcome (science teams) or outcome ≠ effectiveness (Code Blue Resuscitation, sports)

Outcome vs. Effectiveness

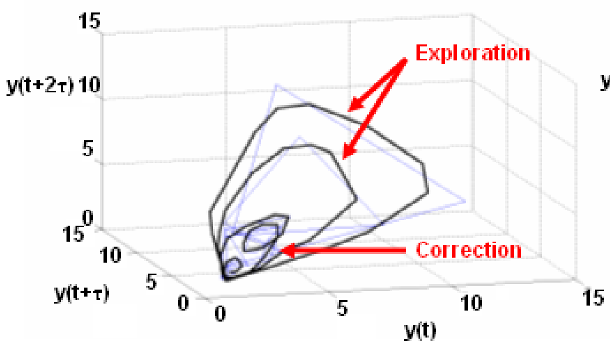


Measuring Team Effectiveness

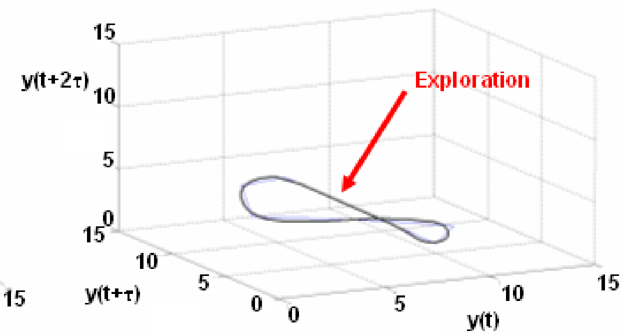
What is team effectiveness?

- Adaptivity: Teams respond quickly to a perturbation
- Resilience: Teams bounce back quickly from a perturbation

Measure Team effectiveness through performance dynamics



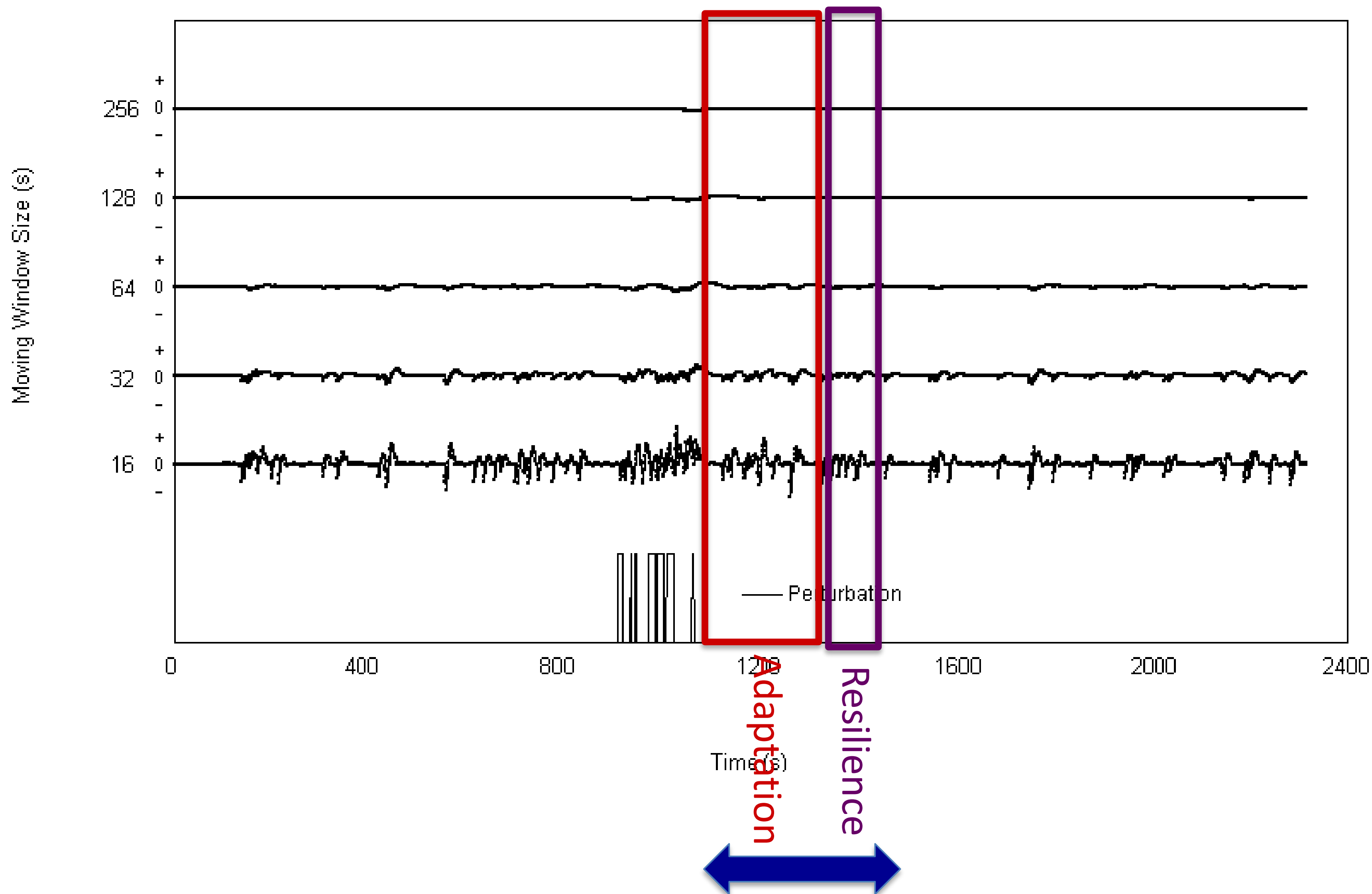
SAME



MIXED

Effective teams are adaptive and stable

Dynamics and Team Effectiveness



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Thank You to Our Collaborators!

Thanks to My Collaborators

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