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**ИНОСТРАННЫЙ ЯЗЫК
АНГЛИЙСКИЙ ЯЗЫК
AUTOMATION ENGINEERING**

Учебное пособие

**Санкт-Петербург
2022**

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Высшая школа технологии и энергетики**

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Утверждено Редакционно-издательским советом ВШТЭ СПбГУПТД

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Учебное пособие соответствует программам и учебным планам дисциплины «Иностранный язык. Английский язык» для студентов, обучающихся по направлению подготовки 15.04.04 «Автоматизация технологических процессов и производств». Разработано для изучения академического аспекта английского языка. Учебное пособие посвящено практическому овладению научной речью в сфере профессиональной коммуникации.

Пособие предназначено для подготовки магистрантов очной и заочной форм обучения.

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ПРЕДИСЛОВИЕ

Данное учебное пособие разработано для студентов магистратуры Института энергетики и автоматизации, обучающихся по направлению подготовки «Автоматизация технологических процессов и производств», для изучения академического аспекта английского языка.

Основной задачей курса «Иностранный язык. Английский язык. Automation Engineering» является обучение практическому владению научной речью в сфере профессиональной коммуникации.

Основой построения программы обучения является направление, или аспект, «Язык для специальных целей» (Language for Specific Purposes – LSP). Данный аспект предполагает развитие навыков, необходимых для освоения соответствующего регистра речи.

Целью данного курса является подготовка высококлассного специалиста международного уровня, одной из составляющих в будущей профессиональной деятельности которого станет языковая грамотность и культура речи. Задачи, стоящие перед студентом: закрепление навыков правильного английского произношения (Oxford English); знание особенностей построения научно-технических текстов из оригинальных источников и овладение техникой работы с ними; самостоятельный поиск и извлечение информации на иностранном языке и ее дальнейшее применение в профессиональной сфере; умение поддержать и вести беседу с зарубежными специалистами на темы широкого спектра с учетом различных деловых культур.

В аспекте «Язык для специальных целей» осуществляется: развитие навыков чтения специальной литературы с целью получения информации; знакомство с основами перевода литературы по специальности. Обучение языку специальности ведется на материале произведений речи на профессиональные темы.

Освоение учащимися фонетики (для правильного чтения учащимися технических терминов и аббревиатур), грамматики, синтаксиса, словообразования, сочетаемости слов, а также активное усвоение наиболее употребительной лексики и фразеологии английского языка происходит не в виде заучивания свода правил, а в процессе работы над связными, законченными в смысловом отношении текстами.

Обучение предусматривает: а) формирование фонематического слуха посредством аудирования; б) формирование практических навыков и умений чтения и перевода; в) развитие устной речи; г) отработку грамматического материала с последующим использованием в разговорной речи; д) формирование навыков самостоятельной работы.

В программу самостоятельной работы студентов входят освоение теоретического и практического материала, разобранного вместе с преподавателем на занятиях, подготовка к практическим занятиям в форме словарной работы со статьей, запоминание произношения и написания новых слов и выражений, построение и разучивание диалогов по учебной программе, формирование умений свободно выражать мысли на изучаемом языке, составлять эссе и делать презентацию по заданной теме.

ЧАСТЬ I. ФОНЕТИКА

Английский алфавит

1.	A a	[eɪ]	14	N n	[en]
2.	B b	[bi:]	15	O o	[əʊ]
3.	C c	[si:]	16	P p	[pi:]
4.	D d	[di:]	17	Q q	[kju:]
5.	E e	[i:]	18	R r	[ɑ:]
6.	F f	[ef]	19	S s	[es]
7.	G g	[dʒi:]	20	T t	[ti:]
8.	H h	[ertʃ]	21	U u	[ju:]
9.	I i	[aɪ]	22	V v	[vi:]
10.	J j	[dʒeɪ]	23	W w	['dʌbl'ju:]
11.	K k	[keɪ]	24	X x	[eks]
12.	L l	[el]	25	Y y	[waɪ]
13.	M m	[em]	26	Z z	[zed]

Чтение окончания -s (-es)

-s читается [z] после гласных и звонких согласных:

lives, mills, stands, forms, stays, tries, trees, goes, studies, cars;

[s] после глухих согласных:

likes, parents, flats, stops, asks, maps;

[ɪz] после шипящих и свистящих звуков [s, z, ʃ, tʃ, ʒ, dʒ]:

sizes, boxes, watches, bridges, colleges, washes, wishes, gases, addresses, pages, uses, branches, classes.

Примечание: помните, что окончание -s бывает у существительных и глаголов.

Не следует путать:

- у существительных окончание **-s** – признак *множественного* числа: papers (бумаги, документы), books, students, forms (формы), lights (огни);
- у существительных окончание **-s** – признак *притяжательного* падежа (отвечает на вопрос **чей?**). Сравните:

my friend	мой друг
my friends	мои друзья
my friend's work	работа моего друга
my friends' work	работа моих друзей

- у глаголов окончание **-s** – признак третьего лица *единственного* числа во времени Present Simple: he (she) reads – он (она) читает, he (she) knows – он (она) знает, he (she) goes – он (она) идет, he (she, it) lights – он (она, оно) освещает, it snows – идет снег, he (she, it) influences – он (она, оно) влияет.

Задание 1. Прочтите следующие слова:

advises, matches, prizes, sheets, thinks, works, photos, stories, shows, throws, pulps, cooks, rises, 'services, causes, forces, cities, maps, pages, judges, passes, sciences, tries, answers, presses, places, praises, stops, asks, wishes, takes, papers, fibers, chemicals, inches, roots, de'velops, 'surfaces, pro'duces, makes, wastes, 'furnaces, 'purposes, woods, 'processes, 'influences, bags, 'methods, 'differences, 'differs, 'offers, su'ggests, pro'poses, studies, reaches, runs, scientists.

Чтение окончания -ed

-ed читается [d] после звонких согласных и гласных:

formed, dried, tried, closed, played, studied, changed, functioned,
contained, used, planned, employed;

[t] после глухих согласных:

worked, watched, stopped, helped, liked, stressed, forced,
walked, cooked, pulped;

[ɪd] после согласных **t** и **d**:

waited, invited, wanted, decided, visited, de'manded, com'pleted,
su'pported, acted, di'rected, consisted, 'limited, tested, resulted.

Задание 2. Прочтите следующие слова:

washed, di'vided, de'veloped, burned, im'proved, ab'sorbed, pro'duced, helped, learned,
'regulated, mixed, 'generated, 'operated, pro'vided, liked, in'tended, turned, ex'tracted,
com'bined, suited, bleached, 'separated, 'processed, trained, con'verted, solved, missed,
di'ssolved, re'mained, in'cluded, heated, produced, po'lluted, 'influenced,
manu'factured, con'taminated, changed, looked, littered, a'ttracted, dropped, e'quipped,
printed, planted, warmed, lasted.

ЧАСТЬ II. ГРАММАТИКА

Перевод двучленных и многочленных атрибутивных словосочетаний, выраженных существительными («цепочки» существительных)

Инструкция 1. Двучленные или многочленные атрибутивные словосочетания, или «цепочки» существительных, – это словосочетания, состоящие из существительного и определений, расположенных слева от него.

В качестве левого определения могут быть *существительные* (от двух до пяти или шести). Существительным могут предшествовать: прилагательное, причастие, местоимение или числительное, а также сочетания из этих слов, соединенные дефисом.

Необходимо обратить внимание на то, что внутри такого сочетания *слова не отделены друг от друга ни артиклями, ни предлогами, ни запятыми:*

strong acid pump;

white water treatment equipment;

high consistency oxygen bleaching system.

Для перевода «цепочки» существительных важно найти в ней основное слово. Помните, что *основным словом* любой «цепочки» существительных является *последнее существительное, с которого и следует начинать анализ* такой «цепочки». Все существительные и другие части речи, стоящие слева от основного слова, являются *определениями* к нему (отвечают на вопрос «какой?», «какие?»). Справа от основного слова, указывая на то, что «цепочка» закончилась, может стоять новый артикль, предлог, местоимение, прилагательное, причастие или глагол-сказуемое с предшествующим наречием или без него.

I. Перевод двучленных словосочетаний («цепочки» состоят из двух существительных)

Инструкция 2. Перевод двучленных словосочетаний *начинаем с последнего существительного*, а существительное, стоящее слева, переводится *существительным в родительном падеже*.

Образец:	1) pulp quality	- качество целлюлозы
	2) water level	- уровень воды
	3) wood consumption	- расход древесины
	4) cooking time	- продолжительность варки

stock (волокнистая масса) preparation; stock temperature; stock production; sheet properties; sheet formation (формование).

Инструкция 3. В «цепочке», состоящей из двух существительных, первое переводится *прилагательным*.

- Образец:
- | | |
|------------------|---------------------|
| 1) wood fiber | - древесное волокно |
| 2) gas bleaching | - газовая отбелка |
| 3) cooking acid | - варочная кислота |
| 4) paper stock | - бумажная масса |

wood chips; acid digester; wood species (порода); sulphite digestion; oxygen bleaching; stock pump; laboratory tests; spruce chips; bleaching plant (отдел); hand operation; pine chips; water vapor; cooking process; bag paper.

Инструкция 4. Перевод «цепочки» существительных начинаем с последнего существительного, а первое переводим *существительным с предлогом* (в, из, на, для и др.).

- Образец:
- | | |
|----------------------|---|
| 1) hardwood pulp | – целлюлоза <i>из</i> лиственной древесины |
| 2) drying costs | – затраты <i>на</i> сушку (затраты, связанные с сушкой) |
| 3) pollution control | – борьба <i>с</i> загрязнением |

digester pressure; softwood pulp; acid (кислая среда) hydrolysis; linen (льняное тряпье) paper; board products; evaporator (испаритель) gases; hardwood sulphite pulp.

II. Перевод многочленных словосочетаний («цепочки» существительных состоят из трех и более существительных и других частей речи)

Инструкция 5. При переводе многочленных словосочетаний рекомендуем:

- 1) перевести последнее существительное «цепочки»;
- 2) разбить остальную часть словосочетания на *смысловые группы* и перевести их (внутри смысловой группы анализ проводится слева направо);
- 3) перевести все словосочетание (всю «цепочку»), следуя справа налево.

- Образец:
- | | |
|---|---|
| 1) stock mixing system | – система для смешивания массы; |
| 2) wood fiber products | – изделия из древесного волокна; |
| 3) water quality results | – результаты по качеству воды; |
| 4) stock preparation machine operation | – работа машины по приготовлению массы. |

В данных словосочетаниях – по две смысловые группы. Основное слово выделено курсивом.

Переведите, следуя инструкции 5.

- а)
chip packing (уплотнение) device;
strong acid pump;

stock preparation machine;
paper machine operation;
fiber suspension flow;
b)
paper formation (формование) time;
chlorine dioxide generation (образование);
pulp preparation operation (процесс);
steam flow rate;
headbox (напорный ящик) control (регулирование) system;
c)
chain (цепь) length distribution (распределение);
fiber length distribution;
chemicals recovery system;
heat transfer (передача) coefficient;
water conservation costs (затраты);
d)
fiber wall thickness;
cooking liquor circulation;
gas diffusion constant;
quality control method;
paperboard test (анализ) result;
e)
plant design changes;
cooking liquor pressure;
stock preparation equipment;
air pollution (загрязнение) problem;
air pollution abatement (уменьшение);
water purity level (степень).

Образец: sodium base| sulfite *pulping*
Sulfite pulping – сульфитная варка;
Sodium base – натриевое основание;
= сульфитная варка на натриевом основании.

Переведите, используя образец:
various cooking liquor composition;
high yield sulfite pulp;
constant vapor phase region;
ammonia base sulfite pulping;
caustic soda recovery (регенерация) system;
white water (оборотная вода) treating equipment;
paper mill steam supply (обеспечение);
particle size distribution determination;
calcium base cooking liquor.

Инструкция 6. Если «цепочка» существительных начинается с прилагательного, необходимо обратить внимание на то, к какому слову оно относится.

Образец: 1) high yield pulp – целлюлоза с высоким выходом;
2) new sheet structure – новая структура листа;
3) maximum cooking temperature – максимальная температура варки.

Инструкция 7. В состав «цепочки» существительных в качестве определения могут входить числительные, местоимения, причастия, существительные в притяжательном падеже и т. д. Обратите внимание, к какому слову эти определения относятся. Помните, что основное слово словосочетания – последнее существительное.

Образец: 1) this high pressure steam – этот пар высокого давления;
2) rate determining factor – фактор, определяющий скорость.

Инструкция 8. Иногда одно из слов «цепочки» существительных необходимо перевести поясняющими словами (группой слов).

Образец: 1) paperboard machine – машина для выработки картона;
2) chipping operation – предприятие, осуществляющее заготовку щепы;
3) bark products – продукты переработки коры.

Страдательный залог глаголов (The Passive Voice)

Инструкция 1. Страдательный залог глагола употребляется в том случае, если само подлежащее не действует, действие совершается над ним.

Глагол-сказуемое в страдательном залоге можно найти в предложении по вспомогательному глаголу **"to be"** в соответствующем времени, лице и числе и **Past Participle** (причастию прошедшего времени смыслового глагола).

Примечание 1

Past Participle (Participle II) образуется путем прибавления окончания **-ed** к правильным глаголам. Если глагол неправильный, употребляется его 3-я форма (built, taken, written...). Рекомендуем повторить 3 формы неправильных глаголов.

Примечание 2

Обратите внимание на то, что Past Participle правильных глаголов совпадает по форме со временем Past Simple (produced, achieved). Определить их можно только в контексте. (Подробнее о Past Participle см. в разделе, посвященном причастиям).

Таблица 1 – Страдательный (пассивный) залог. Образуется: глагол to be (в соответствующем времени) + Participle II

Правила и способы перевода	Пример	Перевод
1. Страдательный залог показывает, что действие глагола-сказуемого направлено на лицо или предмет, выраженный подлежащим. В ряде случаев подлежащее переводится прямым или косвенным дополнением и ставится, соответственно, в форме винительного или дательного падежа.	He was given a task.	Ему дали задание.
	We were informed that a new idea had been advanced recently.	Нас информировали, что новая идея была выдвинута недавно.
2. Если после глагола в пассиве есть дополнение с предлогом by или with , то оно указывает, кем или чем производится действие. Предлоги переводятся «путем», «при помощи», «посредством» либо соответствуют творительному падежу и не переводятся.	The calculation is done by computer programs.	Подсчеты делаются компьютерными программами (при помощи компьютерных программ).
	The production line is supplied with raw material.	Производственная линия снабжается сырьем.

Продолжение табл. 1

Правила и способы перевода	Пример	Перевод
3. Сочетанием глагола «быть» с кратким страдательным причастием с суффиксами -н- или -т-. Глагол «быть» в настоящем времени опускается.	The mill is built by the workers. are built was built were built has been built have been built shall/will be built will be built	Фабрика построена рабочими. построены была построена были построены была построена были построены будет построена будут построены
4. Глаголом на -ся в соответствующем времени, лице и числе.	The goods are being sold with profit. were being sold	Эти товары продаются с прибылью. продавались
5. Глаголом действительного залога в 3-м лице множественного числа, в неопределенно-личном предложении.	The company's account is checked . was checked will be checked	Отчет компании проверяют . проверили будут проверять

Правила и способы перевода	Пример	Перевод
6. Глаголы с относящимся к ним предлогом, которые переводятся также глаголами с предлогом: to depend on – зависеть от to insist on – настаивать на to look at – смотреть на to rely on – опираться на to speak of (about) – говорить о to refer to – ссылаться на, называть to deal with – иметь дело с и др. переводятся глаголами в неопределенно-личной форме, причем соответствующий русский предлог ставится перед английским подлежащим.	The new plant is much spoken about. This article was often referred to.	О новом заводе много говорят. На эту статью часто ссылались.
7. Глаголы без предлогов, которые переводятся глаголами с предлогом: to affect – влиять на to answer – отвечать на to influence – влиять на to follow – следовать за и др. переводятся глаголами в активном залоге или неопределенно-личной форме, причем соответствующий русский предлог ставится перед английским подлежащим.	The conditions of work are greatly affected by the government.	На условия работы сильно влияет правительство.

Неличные формы глагола Инфинитив (Infinitive)

Инфинитив – основная форма глагола, от которой образуются все личные формы глагола во всех группах времен в действительном и страдательном залогах. Инфинитив, или неопределенная форма глагола, сочетает в себе свойства глагола и существительного.

Признаком инфинитива является частица "to". Она иногда опускается:

- после модальных и вспомогательных глаголов; must (can) produce; do not produce; Did the mill produce? Will produce и т. д.
- после глаголов физического восприятия: see, hear, feel, watch, notice в объектных инфинитивных оборотах и некоторых других случаях.

Инструкция 1

Повторите формы инфинитива:

Время	Active Voice	Passive Voice
Indefinite – выражает действие, одновременное с действием, выраженным глаголом-сказуемым	to produce	to be produced
Perfect – выражает действие, предшествовавшее действию, выраженному глаголом-сказуемым	to have produced	to have been produced
Continuous – длительный характер действия	to be producing	—
Perfect Continuous – действие началось в прошлом и все еще продолжается	to have been producing	—

Функции инфинитива

Инструкция 2

Помните, что инфинитив в роли подлежащего всегда стоит перед сказуемым (в начале предложения).

Переводится:

- 1) существительным;
- 2) неопределенной формой глагола.

Образец: *To know English is necessary.* – Необходимо *знать* английский. *Знание* английского необходимо.

Инструкция 3

Инфинитив в роли обстоятельства цели отвечает на вопрос «для чего?», «с какой целью?». Стоит либо в начале, перед подлежащим, либо в конце предложения. Может вводиться союзами *so as (to) – с тем, чтобы, in order (to) – для того чтобы*.

Переводится:

- 1) неопределенной формой глагола с союзом «чтобы», «для того, чтобы»;
- 2) существительным с предлогом «для».

Образец: *To know English you should work hard.* – *Чтобы* *знать* английский, вы должны много работать.

Инструкция 4

Инфинитив в роли обстоятельства следствия отвечает на вопрос «для чего?» и стоит после слов *too – слишком, enough, sufficiently – достаточно, sufficient – достаточный, very – очень*. Переводится неопределенной формой глагола с союзом «(для того) чтобы». Сказуемое при переводе часто имеет оттенок возможности.

Образец: 1) *I am too tired to go to the exhibition* – Я *слишком* устал, чтобы идти на выставку (чтобы я мог пойти...)
2) *He is clever enough to understand it.* – Он *достаточно* умен, чтобы (он мог) понять это.

Примечание

В английском языке слово "enough" всегда стоит после прилагательного, но перевод следует *начинать именно с "enough"*, а потом переводить прилагательное: *strong enough – достаточно прочный; accurate enough – достаточно точный* и т. д.

Инструкция 5

Обратите внимание на *инфинитив в роли определения*. Он всегда стоит после определяемого существительного и отвечает на вопрос «какой?». Инфинитив в роли определения чаще всего имеет форму страдательного залога и переводится определительным придаточным предложением, вводимым союзным словом «который». Сказуемое русского предложения выражает *долженствование, будущее время или возможность*.

Образец: 1) The method *to be used* – метод, который нужно (можно, будут) использовать.
2) A beater roll breaks up the material *to be pulped*. – Барабан ролла измельчает сырье, которое нужно превратить в массу (которое будет превращено в массу).

Инструкция 6

Инфинитив – часть сказуемого. Инфинитив может быть частью: а) простого сказуемого; б) составного именного или в) составного модального сказуемого (=составного глагольного сказуемого) лишь в том случае, если ему предшествуют глаголы *to be, to have, модальный или вспомогательный глагол*.

Образец: 1) The purpose of the system *is to maximize* production. – Цель этой системы – максимально повысить производительность. Цель системы *состоит в том*, чтобы максимально... Целью системы *является* максимальное повышение...
2) The system *is (has) to maximize* production = The system *must (should) maximize* production. – Эта система должна максимально повысить производительность.

Таблица 2 – Причастие

Вид причастия	Функция в предложении и перевод		
	часть сказуемого	определение	обстоятельство
1. Participle I Active voice selling writing	He is selling his goods. Он продает свои товары. (Для образования времен группы Continuous. Самостоятельно не переводится).	The merchant selling his goods pays a profits tax. Торговец, продающий свои товары, платит налог с прибыли. The seller examined the letter containing an interesting offer. Продавец изучил письмо, содержавшее интересное предложение. (Причастие на -щий, -вший).	(When, while) selling his goods, the merchant pays a profits tax. Продавая свои товары, торговец платит налог с прибыли. (Деепричастие на -а, -я).
2. Participle I Passive voice being sold being written	The goods are being sold . Товары продаются . (Для образования группы времен Continuous пассивного залога. Самостоятельно не переводится).	The goods being sold were foreign made. Продаваемые товары были произведены за границей. (Причастие на -емый, -имый).	(While) being moved the goods are insured against all risks. Когда их перевозят (во время перевозки) товары страхуются против всех рисков. (Придаточное обстоятельственное предложение; существительное с предлогом).

Вид причастия	Функция в предложении и перевод		
	часть сказуемого	определение	обстоятельство
3. Participle II Passive voice sold written	1) He has sold his goods. Он продал свои товары. (Для образования времен Perfect. Самостоятельно не переводится). 2) The goods are sold . Товары проданы. (Для образования пассивного залога. Самостоятельно не переводится).	The goods sold gave substantial profit. Проданные товары принесли существенную прибыль. The problem discussed yesterday is very important. Проблема, обсуждавшаяся вчера, очень важна. (Причастие на -щийся, -мый, -ный, -тый, -вшийся).	If sold , the goods will give substantial profit. Если их продать , товары принесут существенную прибыль. (Обстоятельственное придаточное предложение).
4. Perfect Participle active voice having sold having written	—	—	Having sold his goods he got substantial profits. Продав свои товары, он получил существенную прибыль. (Деепричастие на -ив, -ав).
5. Perfect Participle Passive voice having been sold having been written	—	—	Having been sold , the goods gave substantial profit. После того как товары были проданы , они принесли существенную прибыль. (Придаточное обстоятельственное предложение).

Таблица 3 – Герундий

Функция в предложении	Примеры	Перевод
1. Подлежащее	Chartering of ships is very important for shipments of goods.	Фрахтование кораблей (фрахтовать корабли) очень важно для перевозки товаров. (Инфинитив, существительное).
2. Часть сказуемого	The main task is keeping customer's accounts.	Главная задача – хранение счетов клиентов (хранить счета клиентов). (Существительное, инфинитив).
3. Прямое дополнение	The situation requires controlling the supply.	Ситуация требует управлять (управления) поставками. (Инфинитив, существительное).
4. Определение (обычно с предлогом of, for после существительного)	The ability of influencing the commerce is studied attentively.	Способность влиять (влияния) на торговлю изучается внимательно. (Существительное, инфинитив).
5. обстоятельство (обычно с предлогами: in – при, в то время как, on (upon) – по, после, after – после, before – перед, by – творит. падеж, instead of – вместо того чтобы, for – для и т. д.	He is able to discuss the terms of an order without receiving our special authorization.	Он может обсуждать условия заказа без получения (не получая) нашего специального разрешения на это. (Существительное с предлогом, деепричастие с отрицанием).

ЧАСТЬ III. ЧТЕНИЕ НАУЧНЫХ СТАТЕЙ

Article 1

Task 1. Read the text below.

Near-perfect automation: investigating performance, trust, and visual attention allocation

(Cyrus K. Forugi, Shannon Devlin, Richard Pack, Noel L. Brown, Ciara Sibley, Joseph T. Coyne)

Abstract

Over the past decade, the number of deployed automated technologies has sharply increased. We are quickly moving to a new phase of human-automation interaction where humans may be monitoring near-perfect automated systems. In many cases, these systems will be 99.9 % reliable or higher (e. g., United States Department of Defense, 2017). However, humans are still likely to be tasked to intervene when it does fail, and those failures are projected to be costlier than before (Onnasch et al., 2014). Although there is an immediate, real-world need to understand how humans interact with these near-perfect automated systems, there is a dearth of research. Here, our goal was to holistically assess performance, trust, and visual attention during the monitoring of a near-perfect automated system that fails 1 % of the time.

1. Human performance and automation

Introducing automation to offset a human's limitations in attention and reduce manpower hours seems primarily advantageous. However, research has clearly shown that trade-offs exist when introducing automation such as the loss of situation awareness (Endsley & Kiris, 1995), manual skill (Bainbridge, 1983), and overall system trust (Hoff & Bashir, 2015). Researchers have used many terms to describe these trade-offs: for example, "automation conundrum" (Endsley, 2017) and "irony of automation" (Bainbridge, 1983). Endsley (2017) describes the problem well: "The more automation is added to a system, and the more reliable and robust that automation is, the less likely that human operators overseeing the automation will be aware of critical information and able to take over manual control when needed."

Automated systems of the future will likely have near-perfect reliability (e. g., 99.9 %), and it is unlikely that humans will be able to reliably detect these rare-event failures and, even less likely, be able to then step in to correct said failures. Very little research has evaluated how well humans can detect rare-event automation failures in these near-perfect automated systems. A bulk of the previous research has evaluated how well humans detect failures with automation ranging from 60 % to 90 % reliability (e. g., Chancey et al., 2017; Dixon & Wickens, 2006; Dixon et al., 2007; Foroughi et al., 2019; Rovira et al., 2007). Some researchers have found human performance increases as automation reliability increases (e. g., Chancey et al., 2017), while others have found that human performance improves when interacting with a varied reliability

automated system as opposed to a consistently reliable system (Parasuraman et al., 1993). Recently, our group showed that although the combined human–automation accuracy increased as automation reliability increased, the contribution from the human’s detecting of automation failures (specifically, when it missed a target) remained relatively stable as the automation reliability increased. That is, the contribution from the human remained mostly consistent as the reliability of the automated system increased (Foroughi et al., 2019).

We do not expect humans to perform well in a task where automation failures are extremely rare (e. g., vigilance task; see Parasuraman, 1986; Warm et al., 2008). However, establishing a specific point estimate that can be considered “poor” performance at the onset of the experiment is challenging. In realistic terms, unless humans are able to detect these rare-event failures at a high rate, their role as an automation monitor may not be worthwhile. With that being said, including additional measures such as subjective trust ratings and attention allocation as a function of whether someone detected the automation failures helps in holistically understanding the human’s role when monitoring these systems. Including these analyses could inform how to achieve a more effective human–automation interaction and subsequently improve technology design or training practices. For example, studying a human’s trust calibration process of automation has led to an increased understanding of human–automation interactions as they happen in real time.

2. Trust in Automation

Trust is a human’s attitude that another entity (e. g., human, machine, system) will help achieve one’s goals in the face of uncertainty and vulnerability (Lee & See, 2004). A human’s behavior with a system can be dramatically affected by their level of trust (Muir, 1994; Muir & Moray, 1996). For example, very high trust in an automated system can lead to a person over-relying (not enough monitoring) or over-complying (blind acceptance), even if it is unreliable, a state known as complacency (Parasuraman & Riley, 1997). On the other hand, under-trust leads to humans shunning automation and suffering the negative effects of manual performance in intensive situations (e.g., experiencing mental overload or catastrophic performance outcomes). This relationship between reliability and trust is sometimes referred to as “trust calibration” (Lewandowsky et al., 2000; Parasuraman & Riley, 1997). Calibration is a continuous process as it updates and evolves with the present situation.

Because of the important role that trust plays in human–automation performance (Lee & Moray, 1994), a great deal of research has sought to examine what affects trust and how it affects performance (Hoff & Bashir, 2015; Lee & See, 2004). One of the most well studied factors is the reliability, or perceived reliability of the system. In an early investigation of how trust is influenced by system characteristics, Lee and Moray (1994) found that human trust in a system could simply be predicted by, among other things, the level of reliability of the system itself. However, research has found that trust is lost faster than it is regained (Wiegmann et al., 2001). Additionally, humans have been found to narrow their attentional resources on the area of automation where it did fail, leading to decreased surveillance of the rest of the system (Dixon & Wickens, 2006; Thomas & Wickens, 2004). While the coupling of human However, with regard to near-perfect automation, there are two related remaining questions regarding

performance and the dynamics of trust. First, consistent with prior research, we expect humans to have high levels of trust with exposure to more reliable systems. Does this high level of trust result in complacent behaviors, such as marked, quantitative decrease in attentional narrowing, and contribute to reduced performance in detecting extremely rare failures? The second question is in regard to the dynamics of trust: how is trust affected by extremely rare failures? It could be argued that extremely rare failures are more memorable and could result in more extreme trust dynamics than with moderate reliability automation. However, trust may be able to be adequately rebuilt due to the system's overwhelming reliability the majority of the time, which has been a challenge with moderately reliable systems. These questions can be accessed via measuring trust levels over several different time points, and can be especially informative when they come after a rare-event automation failure. However, another potential way to quantify and further understand the impact that these extremely rare failures have on the operator is by studying their real-time attention allocation.

3. Attention allocation and automation

Previous research studying human–automation interaction has relied on a variety of different eye-tracking metrics (Bagheri & Jamieson, 2004; Dehais et al., 2015; Sarter et al., 2007; Thomas & Wickens, 2004). Recently, research has specifically investigated how eye tracking can be used as an objective measure of operator's trust of an automated system (Glaholt, 2014; Hergeth et al., 2016; Parasuraman & Manzey, 2010; Victor et al., 2018). Research generally supports monitoring frequency to be inversely related to human trust—meaning the more the human trusts the automation, the less frequently it will be monitored (Bagheri & Jamieson, 2004; Brown & Noy, 2004; Hergeth et al., 2016; Moray & Inagaki, 1999). Hergeth et al. (2016) found this to be evident, but investigated if it was primarily due to a decrease in monitoring in general. They compared the total amount of time monitoring the automated tasks to the total amount of time monitoring all the other non-automated tasks. This ratio measure was positively correlated, meaning changes in monitoring the automation was not solely due to changes in monitoring in general. Hergeth et al. (2016) suggest future research should continue to study monitoring ratios when humans have more “decisional freedom,” for example, when they are not explicitly instructed on how to attend to tasks and to investigate if other eye-tracking metrics can be sensitive and reliable measures of trust. When research expands to additional eye-tracking metrics, it usually captures the static and aggregate patterns of visual attention, and sometimes only in reference to a specific area of interest (AOI). For example, Victor et al. (2018) found that in a simulated autonomous vehicle environment, the percentage of glances on the road was not able to predict a human's ability to intervene in a timely that the overarching goal of the present work was to observe any differences in visual attention allocation patterns between participants who did and did not detect each automation failure, both types of metrics and analyses were included. Finally, eye-tracking metrics that are found to be consistently different between performance groups will be analyzed in the same method as the trust ratings (i. e., by detection rate and over time) in order to make comparisons between the two results.

4. Current study motivation and goals

The current study was motivated by the immediate need to understand how humans interact with near-perfect automated systems by assessing three information streams essential to successfully monitoring and detecting rare- event automation failures: performance, trust, and visual attention allocation. To do this, we deployed the Supervisory Control Operations User Testbed (SCOUT), an automated supervisory control environment (Fig. 1) that was designed to simulate the current and future demands of unmanned aerial vehicle (UAV) pilots (Sibley et al., 2016).

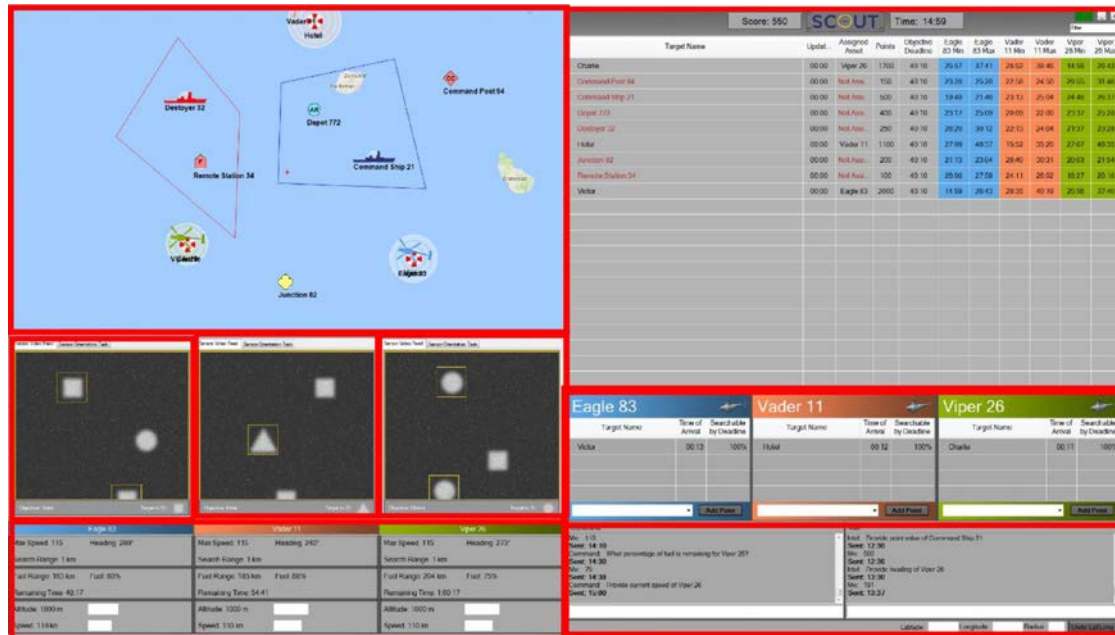


Figure 1. The supervisory control user testbed (SCOUT)

The reliability of this environment was 99.9 %, meaning participants encountered only two automation failures while completing the experiment. Subjective trust questions were asked throughout the experiment, and eye-tracking data were collected as a real-time index of visual attention allocation. Our goals were to (1) determine how well participants could detect the rare-event automation failures, (2) determine how subjective trust changes as a function of detection rates, and (3) determine the relation between visual attention allocation and detection type.

5. Method

This research complied with the American Psychological Association Code of Ethics and was approved by the Institutional Review Boards at both the U.S. Naval Research Laboratory and George Mason University. Informed consent was obtained from each participant.

5.1. Participants

Seventy-three students with normal or corrected-to-normal vision (M age = 20.5 years, SD age = 4.2 years, 51 females) from George Mason University participated in this research for course credit.

5.2. Tasks

The Supervisory Control Operations User Testbed (SCOUT) is a simulated supervisory control environment (Fig. 1) designed by scientists at the U.S. Naval Research Laboratory (Sibley et al., 2016) to simulate the current and future demands of UAV pilots. This testbed requires individuals to plan a search mission using three UAVs, then monitor those UAVs while completing secondary tasks. Some of these tasks include responding to chat updates from command (e. g., confirming flight status or relaying intelligence) and updating UAV information (e. g., updating flight speed or altitude). SCOUT includes many self-report probes including trust, fatigue, and workload.

Importantly, when a UAV reaches its target, the sensor search feed for that UAV becomes active, and the user must monitor the search feed to identify possible targets. The search feed is automated such that the system will help the user identify targets by highlighting possible targets with a gold box (Fig. 2). This automation is immediately displayed with no delay. Each sensor search feed had a different target shape—either a triangle, circle, or square (see Target ID in Fig. 2), meaning all other shapes for that feed were defined as distractors. All objects would enter at the top of the feed and then vertically scroll down it for 14 s. In that time, the automation was tasked to highlight each target with a gold box. For example, if a sensor search feed’s target was a triangle, the participant would need to ensure that all of the triangles (i. e., potential targets) that scrolled across the screen were highlighted, and none of the circles or squares (i. e., distractor targets) were not highlighted. The state of any object (i. e., highlighted or not highlighted) could be changed by clicking on that object. Each search feed had a different target resulting in participants searching for triangles in one feed, circles in another feed, and squares in the third feed.

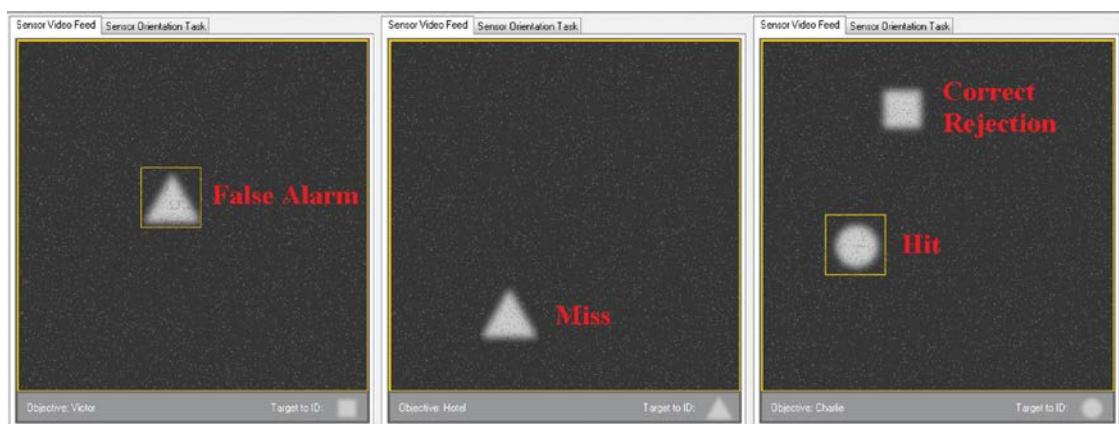


Figure 2. An example of the sensor search feeds from SCOUT

There is an icon below each sensor search feed indicating the target of interest: square, triangle, and circle from left to right respectively, as noted by the red arrows. The automated system automatically highlights targets by placing a gold box around them. Participants were tasked to ensure that the automated system accurately identifies

the correct targets. If the automated system misses a correct target (miss) or incorrectly highlights the wrong target (false alarm), participants must click on the object to fix the error. In this specific example, we have shown all four possible outcomes of what the automated system could do. The red labels are added for this figure and are not in the experiment. To correct the automation failure (i.e., miss or false alarm), participants would need to click on the shape to either select or deselect it appropriately.

5.3. Equipment

A 24-inch Dell P2415Q monitor set at 2560×1440 resolution was used for this experiment. The participants used a standard mouse and QWERTY keyboard to complete the task. For the eye-tracking data collection, a Gazepoint GP3 eye tracker with a sampling rate of 60 Hz and 0.5–1 degree of visual accuracy was used and placed right below the monitor. Participants sat approximately 65 cm (25.6 in) from the monitor. The eye tracker was calibrated for each participant using a 9-point calibration program built by Gazepoint. The GP3 provides left and right eye point of gaze in pixels and assigns a binary quality measure to each point to indicate whether the system believes the data is valid or not. Based on these three values, each data point was marked as either valid or invalid for analysis. A valid data point was one where its quality measure was maximized and both the left and right point of gaze was a positive coordinate value. Only valid data points were used for eye-tracking metric calculations.

5.4. Procedure

After signing an informed consent form, participants were instructed to be comfortably seated in the desk chair where the experiment would take place. First, the participant calibrated to the eye tracker using the Gazepoint GP3 software. Next, participants completed a fixation test as an additional calibration tool. Participants then completed a luminance change task and the shortened automated operation span. These tasks were not analyzed for this manuscript, as both are part of a larger individual differences project that is not yet complete.

Participants then completed a SCOUT training session to learn how to properly complete the task. During training, participants were informed that the automation may not be perfect and that they would need to ensure that all targets were correctly identified. After completion, participants were given a short comprehension test about SCOUT to ensure that they understood all of the features of the task. Participants were shown a static screenshot of SCOUT and asked to answer questions about features within the task (e.g., Can you tell me the current speed of Vader 11? How many targets are in Vader 11's sensor feed?). Participants were required to answer every question correctly to continue. All participants answered all the comprehension questions correctly on their first attempt.

Participants then completed a 40-min experimental scenario within SCOUT. For this experiment, all three UAVs had preset targets and no participants deviated the UAVs from their targets. All three search feeds activated within 1 s of each other ensuring near equal display time. Participants had 14 s to decide if any object was incorrectly highlighted or not highlighted, and to correct the object accordingly. Objects appeared at a rate of 1 every 5s, on average for each sensor search feed. Objects could be on multiple search feeds at once. Chat queries (e. g., What percentage of fuel is remaining for Eagle 83?) occurred every 60 s on the lower right side of SCOUT.

These events did not coincide with the manually injected automation errors (mentioned below) to avoid split attention.

For this experiment, with the exception of the two manually injected automation failures, the automation reliability was set to 100 %. These manually injected automation failures (namely, one automation miss and one automation false alarm) occurred at approximately 19:05 and 39:05 in the center sensor feed (for concerns about the impact of center-bias, see Supplemental Material). Participants were not given specifics on which sensor feed an automation failure could occur. The types of failures (i.e., miss and false alarm) were counterbalanced. These two automation failures made the overall automation reliability of the system 99.9 % across the entire experiment. Additionally, participants were prompted with a trust question at four time points: approximately 10:15, 19:25, 30:15, and 39:25. They were specifically asked “To what extent do you trust (i. e., believe in the accuracy of) the automation aid in this scenario?” and were able to respond using a sliding scale from “Not at all” to “Completely.” After completing the SCOUT scenario, participants completed a short demographics survey.

6. Results

All analyses were screened for outliers and violations in normality. Outliers were considered to be anything beyond 1.5x of the interquartile range (IQR). If outliers were detected, they were removed from the dataset and if normality was not met, corresponding nonparametric tests (e. g., Mann–Whitney) were used. The selected significance level was $\alpha = .05$. For omnibus tests, partial eta squared (η_p^2) is reported for effect size, where the values of .01, .06, .14 are interpreted as small, medium, and large effect size, respectively (Cohen, 1988). For tests of means, effect size is reported by using Cohen’s *d* and values of 0.2, 0.5, 0.8, which indicate a small, medium, and large effect size, respectively (Cohen, 1988).

6.1. Performance

Overall, 34 % (25 of 73) of the participants correctly identified the automation miss and 67 % (49 of 73) correctly identified the automation false alarms. As for the distribution of participants detecting failures in general, 18 did not detect any failure, 36 detected one failure (i. e., the first *or* second failure), and 19 detected both failures. To summarize how automation failure type and timing impacted performance, when the first failure was an automation miss (37 of 73 participants), 15 participants detected no failure across the entire experiment, nine participants detected both failures, four participants detected only the first failure (miss), and nine participants detected only the second failure (false alarm). When the first failure was an automation false alarm (36 of 73 participants), three participants detected no failure across the entire experiment, ten participants detected both failures, 21 participants detected only the first failure (false alarm), and two participants detected only the second failure (miss). To summarize, the data show that the main driver of performance was the type of automation failure (i.e., miss or false alarm) as opposed to the timing of the failure.

6.2. Trust

Fig. 3 presents the changes of subjective trust ratings as a function of time and detection performance. Using the lme4 package within R (Bates et al., 2014), we ran a mixed-effects model with time and detection rate as predictors (fixed effects), and subjective trust rating as the outcome variable. Time is a within-subject factor with four levels: Time 1 (before a failure occurred), Time 2 (after one failure occurred), Time 3 (10 min after the first failure occurred), and Time 4 (after the second failure occurred). Detection rate is a between-subject factor with four levels: None (did not detect either failure), First (detected the first failure only), Second (detected the second failure only), and Both (detected both failures). We found a significant main effect of time ($F(3,69) = 8.5$, $p < .001$), a significant main effect of detection ($F(3,207) = 4.1$, $p = .007$), and a significant interaction ($F(9,207) = 18.6$, $p < .001$). We were interested in determining whether subjective trust ratings changed following the detection of a failure. This resulted in running different analyses by detection group. Consistent with the first failure effect (Wickens & Xu, 2002), for the group that detected the first failure, a paired contrast between T1 and T2 revealed a significant decrease between subjective trust scores ($\text{MDIFF} = -6.72$, $\text{SE} = 2.01$, $p = .001$, $d = .50$). For the group that detected the second failure, a paired contrast between T3 and T4 revealed a significant decrease between subjective trust scores ($\text{MDIFF} = -11.64$, $\text{SE} = 3.04$, $p < .001$, $d = 2.19$). To further explore the simple main effect of time, we ran a one-way repeated-measures ANOVA for the group that did not detect any failure and one for the group that detected both failures. For the group that detected no failures, a one-way repeated measures ANOVA revealed an effect of Time ($F(3,51) = 12.41$, $p < .001$, $\eta^2 = .422$) such that subjective trust rating increased over time. For the group that detected both failures, a one-way repeated-measures ANOVA revealed an effect of Time ($F(3,54) = 14.46$, $p < .001$, $\eta^2 = .446$) such that subjective trust rating decreased over time.

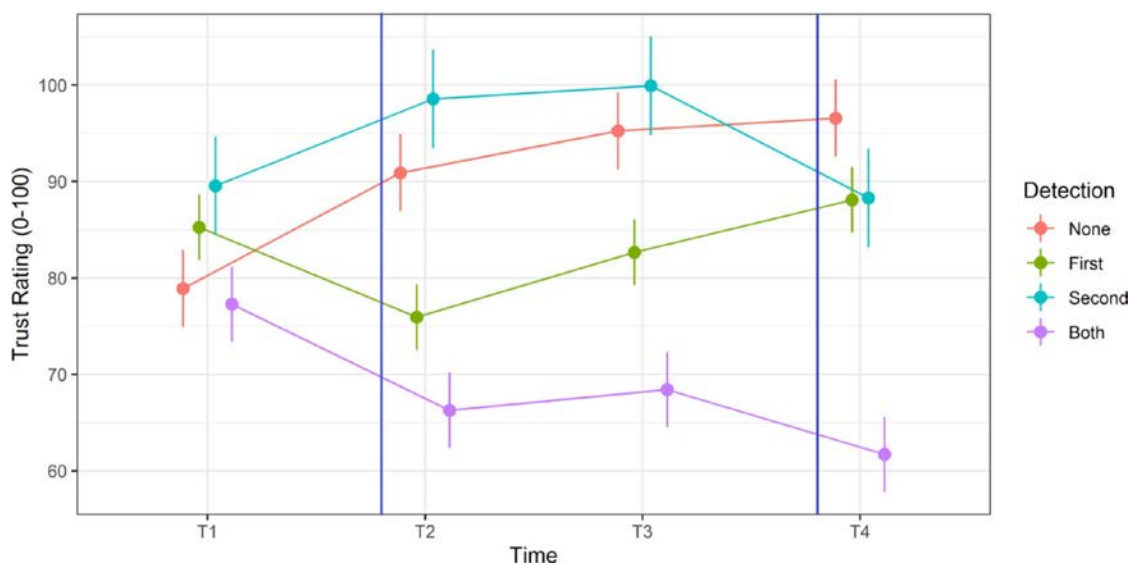


Figure 3. Mean subjective trust ratings ($\pm\text{SE}$) as a function of time and detection

The vertical blue lines provide an approximate visual representation of when the automation failures occurred. Time is a within-subject factor with four levels: T1 (before a failure occurred), T2 (after one failure occurred), T3 (10 min after the first failure occurred), and T4 (after the second failure occurred). Detection is a between-subject factor with four levels: None (did not detect either failure), First (detected the first failure only), Second (detected the second failure only), and Both (detected both failures).

6.3. Eye Tracking

6.3.1. Overall eye-tracking analysis

Mean time between fixations (MTBF) was not significantly different for those who did or did not detect the miss or for those who did and did not detect the false alarm (all $p > .05$). This result suggests the speed of visual attention allocation was not significantly different between performance groups. Normalized gaze transition (GTE) and stationary gaze entropy (SGE) were not significantly different between those who did and did not detect the miss or between those who did and did not detect the false alarm (all $p > .05$).

The local metrics, that is, the ones focused on the center sensor feed as that was the specific AOI associated with the automation failure, were then calculated. For total dwell ratio of the center sensor feed, those who detected the miss had significantly higher total dwell ratio ($M = .31$, $SD = .09$) than those who missed the miss ($M = .19$, $SD = .08$; $t(33.027) = -4.3532$, $p < .001$, $d = 1.442$). Those who detected the false alarm ($M = .263$, $SD = .09$) had a significantly higher total dwell ratio than those who missed the false alarm ($M = .183$, $SD = .09$; $t(15.371) = -2.3698$, $p = .031$, $d = .8965$). This suggests that those who detected the miss and false alarm had a significantly higher proportion of time in the center sensor feed than those who did not detect the miss and false alarm. For the number of transitions to the center sensor feed, those who detected the miss had significantly more transitions, to this feed ($M = 2185$, $SD = 722.3$) than those who did not detect the miss ($M = 1413.8$, $SD = 629.1$; $t(35.719) = -3.548$, $p = .001$, $d = 1.141$). Similarly, those who detected the false alarm had significantly more transitions to the center sensor feed, ($M = 1938.8$, $SD = 738.2$) than those who did not detect the false alarm ($M = 1356.4$, $SD = 739.83$; $t(15.647) = -2.148$, $p = .047$, $d = .7881$). This suggests that those who detected the miss and false alarm transitioned to the center sensor feed more frequently than those who did not detect the miss and false alarm.

6.3.2. Two-minute window centered around each automation failure

For MTBF, there was no significant difference between those who did and did not detect the miss or false alarm ($p > .05$). There was no significant difference in normalized GTE for those who did and did not detect the miss ($p > .05$). However, there was a significant difference between those who did ($M = .41$, $SD = .064$) and did not detect the false alarm ($M = .35$, $SD = .049$; $t(13.634) = -2.366$, $p = .0334$, $d = .9815$), suggesting the 2-min scan sequence of those who detected the false alarm was more complex than those who did not detect the false alarm. There was no significant difference in normalized SGE for those who did and did not detect the miss or false alarm ($p > .05$).

As for metrics focused specifically on the center sensor feed, that is, the one experiencing the automation failure, those who detected the miss had significantly higher total dwell ratio ($M = .37$, $SD = .09$) than those who missed the miss ($M = .21$, $SD = .07$; $U = 10$, $p < .001$, $d = 1.906$). Those who detected the false alarm ($M = .38$, $SD = .15$) also had a significantly higher total dwell ratio than those who did not detect the false alarm ($M = .14$, $SD = .07$, $t(18.247) = -5.2144$, $p < .001$, $d = 2.096$). So for the minute before and after the automation failure, those who detected the miss and false alarm spent a significantly higher proportion of time in the center sensor feed (relative to all other AOIs), than those who did not detect the miss and false alarm. For the number of transitions to the center sensor feed it was found, again, that those who detected the miss had significantly more transitions, to the center sensor feed ($M = 114.9$, $SD = 31.1$) than those who did not detect the miss ($M = 67.33$, $SD = 23.7$, $U = 17$, $p < .001$, $d = 1.733$). Similarly, those who detected the false alarm had significantly more transitions to the center sensor feed, ($M = 107.9$, $SD = 42.1$) than those who did not detect the false alarm ($M = 43.8$, $SD = 4.65$, $t(20.67) = -6.647$, $p < .001$, $d = 2.741$). This suggests that for the minute before and after the automation failure, those who detected the miss and false alarm transitioned to the center sensor feed significantly more frequently than those who missed the miss and false alarm.

6.3.3. Over time analysis for the local eye-tracking metrics as a function of detection

In an attempt to robustly address our third research goal (i. e., examine the relation between visual attention allocation and detection type), we also analyzed the local eye-tracking metrics in the same format as the trust ratings (as a function of detection rate and over time). We limited this analysis to the local eye-tracking metrics only given the consistent significant differences found with these metrics between those who do and do not detect each type of automation failure. A two-way mixed ANOVA where the between-subject effect was the four performance groups (no detection, only first failure detected, only second failure detected, detected both failures) and within-subject effect was time period (i.e., the durations of T1–T4) was used for both local eye-tracking metrics. For dwell ratio, there was a main effect of performance group ($F(3,35) = 6.87$, $p < .001$) but not time ($F(3,105) = 2.355$, $p = .076$) nor their interaction ($F(9,105) = 1.889$, $p = .061$). For number of transitions, there was a main effect of performance group ($F(3,33) = 4.708$, $p = .08$) and time ($F(3,99) = 225.904$, $p < .001$) but no significant interaction ($F(9,99) = 1.810$, $p = .076$). Therefore, individuals may not update their visual attention strategies even when they detect errors in near-perfect automation which is in stark contrast to the trends found with the trust ratings.

7. Discussion

The goal for this research was to improve our understanding of how humans interact with near-perfect automated systems by assessing three important human-automation interaction features: performance, trust, and attention allocation. Overall, 34 % of the participants correctly identified the automation miss, and 67 % correctly identified the automation false alarm. Consistent with prior research (e. g., Bliss, 2003; Chancey et al., 2015), participants detected significantly more false alarms than

misses. Unfortunately, misses are often costlier than false alarms (e.g., bomb detection), and although false alarms are often considered annoying and can lead to “cry wolf” syndrome (Parasuraman & Riley, 1997), some evidence suggests that domain experts are more accepting of false alarms than misses (Masalonis & Parasuraman, 1999). Regardless, in general, the results found that the number of participants who detected both automation failures and the number who detected neither was practically equal, whereas the number of participants that detected one of the failures was approximately twice as many as either group. In summary, the performance results from this research show that humans are only marginally reliable (34 % and 67 %) at intervening to correct rare-event automation failures. One could argue that any intervening detection from a human could be worthwhile, even if the improvement is marginal. The key assumption to this argument is that the additional cost of that improvement is minimal. It is possible that training or expertise could improve these detection trends, but previous research in supervisory control suggests it is unlikely training alone will lead to acceptable performance levels (e. g., Victor et al., 2018) and training would come at some cost (e. g., money, time, etc.). In summary, if near-perfect automation systems are going to include human monitoring as a layer of overall system reliability, research needs to study the human’s monitoring process in these environments and design for them accordingly. Part of this process is the person’s trust calibration process.

The trust ratings from participants trended as expected: trust decreased when participants detected the automation failure(s) and increased when they did not. However, the rate at which trust was lost and rebuilt was unexpected. One interesting finding from this analysis is that those who detected the first automation failure, but not the second, reported that their trust levels recovered to a level that was similar to the first trust reading, (i. e., the first 10 min of the simulation where no automation failures occurred) and similar to those who detected no automation failures. However, trust decreased rapidly from start to end for those who detected both automation failures. For context, the automation was 99.9 % reliable, even with the two failures, but trust dropped to ~60 % for those who detected both failures. This further supports that the trust calibration process is not directly proportional to automation reliability and is highly variable as the human detects failures. Future studies should precisely examine the relationship between the number of automation failures and the dynamics of trust recovery. The eye-tracking analysis helps to clarify the discrepancy between automation reliability and trust.

There were no significant differences between the two performance groups (those who did and did not detect the automation failures) when comparing global visual attention patterns over the entire experimental session, which is inconsistent with some previous work (Bagheri & Jamieson, 2004). This may be due to the length of the scenario being 40 min and possibly “washing out” any general visual attention allocation trends. Given that operators in the field may be tasked to this role for much longer amounts of time, this emphasizes the need for eye-tracking analyses to be analyzed on a more “real-time” basis in order to accurately capture the current state of the operator. This is somewhat supported in the present work, given that gaze transition entropy was significantly different between those who did and did not detect the false

alarm for the 2-min analysis only, meaning the more complex scan patterns for those who detected the false alarm was only evident during the 2 min centered around the automation failure. This finding suggests global eye-tracking metrics should be analyzed on a more granular basis if they are to be informative of performance differences with near-perfect automation. Future research should further corroborate these findings with the exploration of different types of metrics and time intervals.

Alternatively, the local eye-tracking metrics (i. e., the ones associated with the specific sensor search feed where the automation failures happened) were significantly different between performance groups (i. e., those who did and did not detect each type of automation failure) and for all analyses (i. e., the entire experimental session, the 2 min centered around the automation failure, and overall detection rates). Overall, participants who detected the automation failures spent the most time monitoring the center sensor feed for an average of 21 %–24 % of all monitoring time. They also visited this feed 1.2–1.8 times more than any other search feed (i.e., the left and right sensor feeds) and 1.3–9.2 times more than any other AOI. These results directly quantify how participants narrow their attention when near-perfect automation failed, which is consistent to previous work (Dixon & Wickens, 2006; Thomas & Wickens, 2004). These results also begin to make direct comparisons on how visual attention patterns differ between the trust levels of those who detected none and both automation failures. Interestingly, the trust ratings changed dramatically over time depending on detection rates, but the local eye-tracking metrics did not. There are two potential explanations for this: the first being a characteristic of the system and the second being a characteristic of the human. The first potential explanation of these diverging trends is due to a positive feedback loop (Smith & Smith, 1987): if you detect automation failures, you believe you are sufficiently monitoring the automation, so you do not change your monitoring approach. If you do not detect errors, you are unaware that automation needs to be monitored at all, so you do not change your monitoring approach. Second is the monitoring rates of automation are trait and not state based, that is, monitoring rates are more dependent on the characteristics of the person than the characteristics of the environment. Future studies could directly address these competing theories, but regardless, both will need to eventually inform how to provide active, real-time assistance to the operator. This is clearly warranted because regardless of some operators monitoring the automation “sufficiently” (whatever is defined as sufficient for the environment/automation at hand) and some not, the current evidence suggests those monitoring rates are relatively stagnant over time even as failures are detected, suggesting that failure detection is not sufficient feedback to impact changes in visual attention allocation patterns. Furthermore, the analysis of the local eye-tracking metrics highlights that the level of sufficiency may come at a high and unrealistic visual attention cost to the operator (e. g., spending ~21 % of time monitoring one sensor feed of the whole display). Even more concerning is this cost may not lead to a reciprocal benefit of substantially improved system reliability as participants were not overwhelmingly reliable in correcting automation failures. As a sanity check, all eye-tracking data were screened to ensure participants were not attending to a secondary task when the automation failed. Given that no participants were attending to a secondary task, this suggests that participants either (1) missed the

failure even when their point of gaze was in the center sensor feed that is, inattentional blindness or (2) they were allocating their attention elsewhere without being prompted to do so. To investigate if there were instances of inattentional blindness, the eye-tracking data were used to determine if at least one fixation was present in the center sensor feed at some point during an automation failure (i. e., the 14 s it was in the center sensor feed) yet it was still not detected. Of the 59 instances where an automation failure was not detected (across both automation failure types), 42 had at least one fixation in the center sensor feed during the automation failure (i. e., 71.2 % of all instances). This alarming percentage of inattentional blindness seems to further indicate that the current cost of humans monitoring near-perfect systems outweighs any benefit. In total, the eye-tracking analysis shows the need to study eye-tracking metrics in more granular units of time to detect potential performance decrements, to include local eye-tracking metrics (i.e., ones that contextually relate to the task's goals) and to determine optimal visual attention allocation patterns. Future work should thoroughly validate all of these aspects before delivering final design guidance for near-perfect automated systems.

This work is not without limitations. The generalizability of the work needs to be limited as this was a lab-based experiment. This experiment was only 40-min long, and it is likely that real-world operators will be interacting with near-perfect automated systems for much longer periods of time. However, this could suggest that our performance findings are understating the negative effects (e. g., vigilance decrement). Relatedly, the participants may not be representative of the person who would be tasked to this kind of monitoring, making it even more important to tease out state- and trait-based effects in monitoring. Finally, the monitoring task itself was (purposefully) simple, in order to have participants reach task proficiency in a relatively short amount of time. Realistically, monitoring tasks will be more contextually relevant to a specific aspect in a given field and will most likely be done by an expert, which may make the task more engaging and better prioritized. Future research should incorporate these elements, as well as the suggestions made above, when investigating human performance, trust, and visual attention allocation in near-perfect automated environments.

8. Conclusion

Taken together, the performance, trust, and eye-tracking data show that humans are not well suited for monitoring near-perfect automated systems. Performance is inadequate and calls into question whether humans should ever be in these roles. Additionally, inadequate performance is problematic as it dictates the trust calibration process, coming at a large cost to the human's attentional resources. From a human factors standpoint, improving the human-computer interface design of the system may be an appropriate first step. For example, uncertainty communication has been found to increase automation transparency and assist in correcting operator's mental models of the automation, which informs the trust calibration process (Beller et al., 2013; Endsley, 2017; Victor et al., 2018). Incorporating eye-tracking to aid the operator's overt visual attention allocation may improve performance, but as evidenced by data from this experiment, it is not a certainty (i. e., 71.2 % of inattentional blindness instances). More generally, trying to understand the traits and current state of the

operator may be more informative on their ability to successfully complete these tasks. Eye tracking may be able to aid in that understanding (e. g., apply the method used in Mracek et al., 2014 to parse out the trait and state levels of eye-tracking metrics that have found to differ on both of these levels, for example, de Haas et al., 2019; Tsukahara et al., 2016), but more work in this domain is needed. In conclusion, this research shows that humans are not well suited in the monitoring of near-perfect automated systems. Should humans be pushed into these roles, far more research is needed to understand how to best design for them.

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Words and word combinations:

- automation [ɔ:tə'meɪʃ(ə)n] – автоматизация;
- performance [pə'fɔ:m(ə)ns] – производительность;
- trust [trʌst] – доверять;
- visual attention ['vɪʒ(j)ʊəl ə'tenʃ(ə)n] – зрительное внимание;
- manpower hours ['mænpəʊə 'aʊəz] – рабочее время;
- behaviour [bɪ'heɪvjə] – поведение;
- near-perfect [nɪə 'pɜ:fɪkt] – почти идеальный;
- bottleneck ['bɒt(ə)lnek] – узкое место;
- eye tracking [aɪ 'trækɪŋ] – технология отслеживания положения глаз;
- measure ['meʒə] – мера;
- scrolled across [skrəʊld ə'krɒs] – прокручивать;
- altitude ['æltɪtju:d] – высота;
- confirm [kən'fɜ:mɪŋ] – подтверждать, утверждать;
- highlight ['haɪlaɪt] – основной момент;
- triangle ['træɪæŋg(ə)l] – треугольник;
- approximately [ə'prɒksɪmətli] – приблизительно;
- correctly [kə'rek(t)li] – правильно, верно;
- attempt [ə'tem(p)t] – попытка;
- below [bi'ləʊ] – ниже, внизу.

Task 2. Summarize all the ideas of the article and write an essay.

Task 3. Make a presentation based on the article.

Article 2

Task 1. Read the text below.

Progress and prospects for accelerating materials science with automated and autonomous workflows (by Helge S. Stein, John M. Gregoire)

Abstract

Accelerating materials research by integrating automation with artificial intelligence is increasingly recognized as a grand scientific challenge to discover and develop materials for emerging and future technologies. While the solid state materials science community has demonstrated a broad range of high throughput methods and effectively leveraged computational techniques to accelerate individual research tasks, revolutionary acceleration of materials discovery has yet to be fully realized. This perspective review presents a framework and ontology to outline a materials experiment lifecycle and visualize materials discovery workflows, providing a context for mapping the realized levels of automation and the next generation of autonomous loops in terms of scientific and automation complexity. Expanding autonomous loops to encompass larger portions of complex workflows will require integration of a range of experimental techniques as well as automation of expert decisions, including subtle reasoning about data quality, responses to unexpected data, and model design. Recent demonstrations of workflows that integrate multiple techniques and include autonomous loops, combined with emerging advancements in artificial intelligence and high throughput experimentation, signal the imminence of a revolution in materials discovery.

1. Introduction

Grand missions, such as combating climate change through proliferation of renewable energy technologies, necessitate technological advancements for which discovery of functional materials is often a prerequisite. Historically, transformative materials discoveries have been the result of serendipity from experimenting in a related area and/or decades of systematic materials development. Early examples of automated synthesis and screening techniques were implemented to accelerate both processes, for example in the identification of a hysteresis-free shape memory alloy. Continued automation of materials experiments is motivated by potential benefits including lowering per-experiment costs and eliminating human error, and to enable active learning-driven experiments that identify and explore the most promising regions of materials parameter space. In solid state materials science, advancements in automation have largely been driven by the combinatorial materials science community, where comprehensive exploration of a high dimensional materials parameter space requires a substantial number of synthesis and screening experiments. While these efforts have provided automation of individual research tasks for a wide variety of materials and functional properties, manual execution of several experiment steps, as well as manual design of experiments and data interpretation, result in

partially-automated workflows. The emerging vision of autonomous materials discovery requires a higher level of automation. Establishment of an autonomous workflow is referred to as “closing the loop” since complete task-to-task integration is required to allow computer-controlled iteration. Initial and ongoing progress towards realizing such closed-loop systems can be tracked by the level of process automation and integration in a workflow.

Sanchez-Lengeling and Aspuru-Guzik recently described the advent of closed-loop experimentation as a paradigm shift in materials and molecular discovery. The illustration of Fig. 1 provides the high level template of a closed-loop workflow, and in the present work we critically review the progress towards this vision in solid materials experiments. The integration of sequential automated processes is challenging due to the need for mutually compatible parameters and planning, with requirements spanning from a commensurate sample format, to a protocol for decision-making based on results from the prior experiment, and to the identification of measurement failure. To facilitate the analysis of where process integration has been successfully implemented as well as the remaining challenges, we present a framework and ontology for the automation of the materials experiment lifecycle.

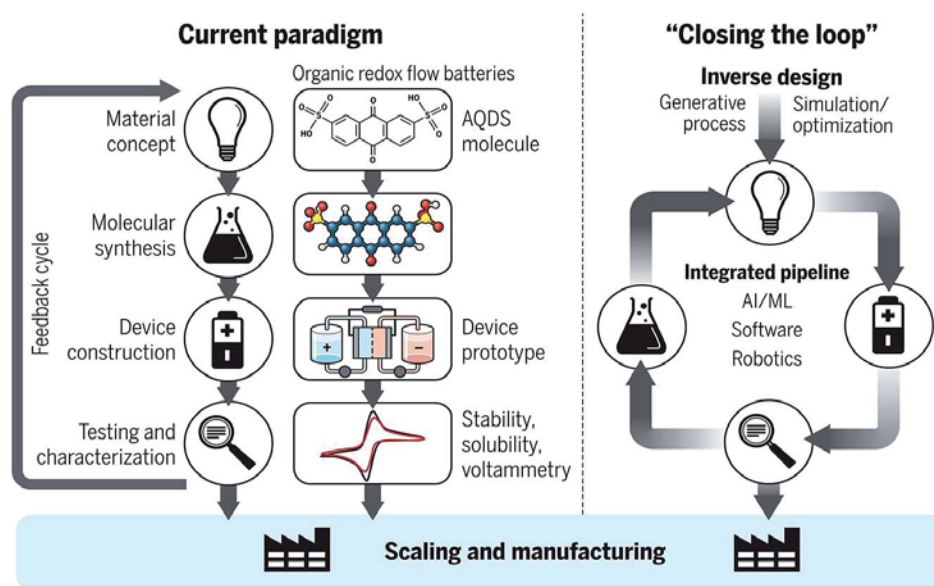


Figure 1. High level comparison of paradigms for materials/molecular sciences. Left: current paradigm exemplified with redox flow batteries. Right: closed-loop discovery utilizing inverse design and a tightly integrated workflow to enable faster identification, scale-up and manufacturing. Figure reproduced from Science, 361, 6400, 360–365 with permission from The American Association for the Advancement of Science

The exploration of vast materials spaces (i. e. composition, structure, processing, morphology) *via* combinatorial materials science has yielded a wide variety of discoveries and advancements in fundamental knowledge and has additionally

produced experiment databases with unprecedented breadth of materials and measured properties, as exemplified by the recent publication of the High Throughput Experimental Materials database (HTEM) based on photovoltaics materials and the Materials Experiments and Analysis Database (MEAD) based on solar fuels materials. These compilations of raw and analyzed data from individual combinatorial materials science laboratories complement the suite of computational materials databases as well as a rapidly growing number of materials data repositories including the Citrination platform, the Materials Data Facility (MDF), and text mining of the literature. For the purposes of the present analysis of automating materials science workflows, these databases serve as successful examples of experiment automation and as resources that can be used to accelerate experiment planning, for example by training machine learning models to identify promising materials. In such planning, it is important to note complementary search goals of optimizing a given material property and establishing relationships that represent fundamental materials knowledge. Mapping composition–structure–processing–function relationships is a tenet of combinatorial materials research, which contrasts with direct implementation of active learning to optimize one or a few properties without requiring acquisition of data to elucidate the underpinnings of the materials optimization. Indeed the experiment workflow and its operation must be designed to meet the specific research goals, although workflow automation is important for accelerating many different modes of discovery.

We discuss the lifecycle of materials science experiments and the three primary stages of workflow acceleration, (i) the integration of new techniques into traditional research tasks to accelerate process throughput, (ii) the integration of research tasks into a cohesive workflow to mitigate bottlenecks, and (iii) integration of tasks with automated analysis and decisions to close experiment loops and enable autonomous iteration thereof. We find that the solid state materials science community has demonstrated tremendous progress in the first stage, substantial progress in the second stage including high throughput workflows, and seminal demonstrations in the third stage with relatively simple workflows, making concurrent advancement of both the level of autonomy and extent of the workflow a priority research direction.

2. The experimental materials science research lifecycle

At a high level, the experiment lifecycle† for functional materials discovery consists of a set of core research tasks: synthesis, processing, characterization and performance evaluation. This set transcends the specific techniques used to perform each task, and their generality is evident in their consistent discussion in reviews, laboratory workflow descriptions, and database designs for high throughput materials science. Often unmentioned, though virtually always performed, are the additional core research tasks of planning, data management, data interpretation, and quality control. Individual and sequences of experiments require these tasks, with the extent and style varying with research strategy. In a traditional materials experiment, the 4 experiment tasks are performed manually, as are the complementary 4 tasks, for example planning via a stated hypothesis and data management via lab notebooks. The corresponding workflow can be represented as shown in Fig. 2a and represents the foundation on which more advanced and accelerated workflows are built. As noted above, the first stage of workflow acceleration involves implementation of techniques we refer to as

“accelerators” into one or more of the workflow tasks. Classifying all possible accelerators is more subjective than the above classification of workflow tasks, and for the present work we find the 6 accelerators noted in Fig. 2b enable effective annotation of experimental workflows from the literature. Some accelerator-task combinations are readily achievable, for example parallelization of processing by annealing multiple materials in a furnace. Other combinations may not be meaningful, such as active learning of data management. Of the many combinations that are both meaningful and impactful, some have been effectively realized while others are opportunities for further experiment acceleration, as summarized below for each accelerator.

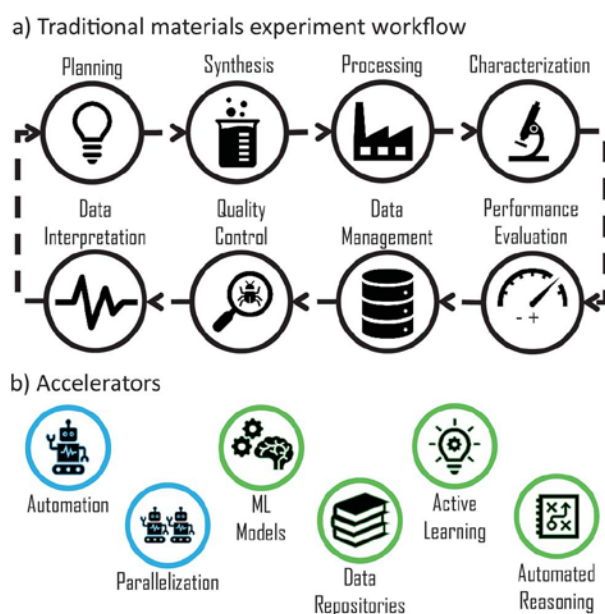


Figure 2. (a) Overview of core research tasks with arrows indicating the cyclic execution of a traditional materials science experimental workflow. (b) Acceleration of each task in a workflow can be obtained by incorporating acceleration technique(s), as represented by these 6 types of accelerators

3. Automation and parallelization

Automated execution of a serial experiment typically involves incorporation of robotics into a traditional experiment. Parallelization typically involves development of custom instrumentation to perform many experiments simultaneously. Both approaches are commonly used in combinatorial materials science where accelerated synthesis techniques include co-sputtering, co-evaporation, ink-jet printing, combinatorial ball-milling, high-throughput hydrothermal synthesis, and bulk ceramic hot-pressing. Similarly, the acceleration of the characterization of materials properties and evaluation of performance for a target functionality have been the focus of extensive methods development in the past two decades, with notable demonstrations including electrochemical testing, X-ray diffraction, processing, optical spectroscopy, electric properties, shape memory, and phase dynamics. These advancements in experiment automation have undoubtedly led to discoveries that

would not have been made in the same time frame using traditional techniques. Automation and parallelization-based removal of synthesis and characterization bottlenecks introduces new challenges for further acceleration of materials discovery, which are generally being addressed with data and data science-related accelerators.

4. Data repositories

As noted above, the emergence of experiment databases from high throughput experimentation offer opportunities for data-based accelerations. The established uses of data repositories for accelerating research tasks include the data interpretation for crystallography by matching X-ray diffraction patterns to those from a database, planning synthesis based on phase diagrams, and planning catalyst performance evaluation using computational databases of Pourbaix stability. Data-driven discoveries are typically enabled by a data repository produced via careful data management. While guidelines such as FAIR exist, these general guidelines focus on data dissemination and do not express the data management requirements for establishing autonomous loops, which require fully automated data ingestion and seamless communication between experimental tasks.

5. Machine learning

Acceleration by Machine Learning (ML) models encompasses a broad range of applications of computer science algorithms to perform regression, classification or embedding tasks. The recent literature abounds with discussions of the existing and potential impact of ML in materials research. Given recent reviews covering this topic, the present discussion focuses on its role in experiment workflows. ML-based acceleration of research tasks typically involves either research planning or data interpretation through evaluation of ML models trained on prior data. Representative examples include selection of composition spaces for exploring metallic glasses based on ML predictions of glass forming ability and identification of ultra-incompressible materials. ML methods have also been developed to accelerate data interpretation in areas including phase mapping from XRD patterns, microscopy data, signal identification in spectroscopy data, annotation of microstructure images, and visualization of complex compositions. ML methods can also be developed into active learning and reasoning techniques, although due to their different roles with respect to experiments, those techniques are discussed separately, as detailed below.

6. Active learning

Active learning involves the choice of the next experiment based on an acquisition function that typically requires a prediction for a figure of merit and the uncertainty thereof. ML models are used for the prediction and uncertainty estimation, with a distinguishing feature of active learning being the need to update the model in real time during execution of the experimental workflow. Active learning is a key component of closed-loop workflows that can ultimately yield self-driving laboratories. Algorithms such as Phoenix have been specifically developed for chemistry experiments and integrated into workflow management software such as ChemOS. The carbon nanotube (CNT) autonomous research system (ARES) project, which is discussed further below, is an example of a closed-loop system of a workflow where tasks such as data interpretation are readily automated. There have been additional implementations of active learning in materials science to accelerate

individual tasks, for example by acquiring only the necessary X-ray diffraction patterns for phase diagram characterization. Sophisticated examples of active learning in related fields including functional genomics, separations optimization, and multi objective molecular optimization for small molecule drug discovery. While many optimization-oriented searches are amenable to acceleration via active learning, its utility for materials discovery has yet to be sufficiently explored and demonstrated, making the above examples a springboard for assessing the ability of active learning to accelerate complex experimental workflows and the generation of fundamental understanding in materials science.

7. Automated reasoning

For complex measurement workflows where competing interpretations of the data need to be considered or a model needs to be reinterpreted given the most recent measurements, the data interpretation, quality control, and planning tasks are not readily automated with existing algorithms, motivating the development of automated reasoning to accelerate these tasks with AI methods that mimic and/or supersede human execution of these tasks (i. e. “superhuman performance”). Examples of automated incorporation of physics and chemistry-based models into such tasks include tuning the morphology of a thin film based on a structure zone diagram and fine-tuning the composition to obtain a desired doping type in semiconducting metal oxides based on spinel doping rules. The opportunity for AI development in this area is the topic of a recent perspective, and among the promising research directions is the establishment of generative models that expand the purview of active learning to design materials based on desired properties. While inverse design has been successfully demonstrated for discovery of functional materials, integration into automated workflows remains a challenge for solid state materials research. The corresponding high level challenge for closed-loop experimentation of solid state materials is that the scope of a given automated synthesis tool is often quite limited compared to the scope of materials that may be predicted by an active learning or inverse design algorithm. In organic synthesis, for example, there has been more success in developing workflows that encompass the entirety of the synthesis scope of interest, enabling deeper integration of automated reasoning.

8. Integration of tasks into a workflow

The most common type of accelerated discovery workflow consists of an automation-accelerated synthesis and an automation-accelerated characterization or performance evaluation, followed by extensive manual analysis, interpretation, and planning of both additional characterization experiments and future iterations of the workflow. Most commonly the highly automated instruments require manual interfacing (e.g. alignment, measurement parameter setup, supervision for quality control), where an increased human involvement corresponds to a lower degree of integration. To simplify the present discussion, we consider two classes of task integration with the distinguishing feature being whether expert involvement is required, which designates the integration as “expert mediated” and indicates the integration is incomplete. This level of integration is prone to creating bottlenecks due

to the scarcity of experts. Technique integration by robotics is not distinguished from integration by trained technicians in the present work because the resulting impact on workflow throughput requires more in-depth evaluation of the specific workflow.

To further illustrate how accelerated materials experiments have been integrated, we inspect four reported projects and construct the corresponding workflows in Fig. 3. Each workflow exhibits unique aspects that collectively frame the state of the art in accelerated materials discovery and illustrate the intricacies of workflow acceleration. The scope of each workflow schematic is the sequence of tasks described in the respective publications, and the largest demonstrated equivalent of traditional experimentation is provided for each workflow. The primary example of closed-loop discovery in solid state materials science is the ARES project for carbon nanotube synthesis. Nikolaev et al.¹⁴ demonstrated optimization of carbon nanotube growth with a workflow that mitigates expert-mediated integration and features acceleration by automation and active learning. Automated control of growth temperature, pressure, and atmospheric conditions enables a unique growth condition in each experiment, with a series of experiments performed by spatially addressing an array of seeds on a substrate. Processing and characterization are intertwined as laser illumination provides both heating and excitation for Raman spectroscopy, producing spectrograms that are analyzed to determine the nanotube growth rate.^{14,65} With this materials characterization also providing the figure of merit, the workflow contains no further performance evaluation. The automated data management and interpretation enables closed-loop operation for up to approximately 100 growth experiments planned by active learning-based selection of growth conditions. Expert intervention in this closed loop occurs occasionally (estimated to be 1–3 %) to assess the quality of the active learning and adjust the objective as necessary. Upon exhaustion of the array of CNT growth seeds, manual intervention is required to change samples and restart the workflow.

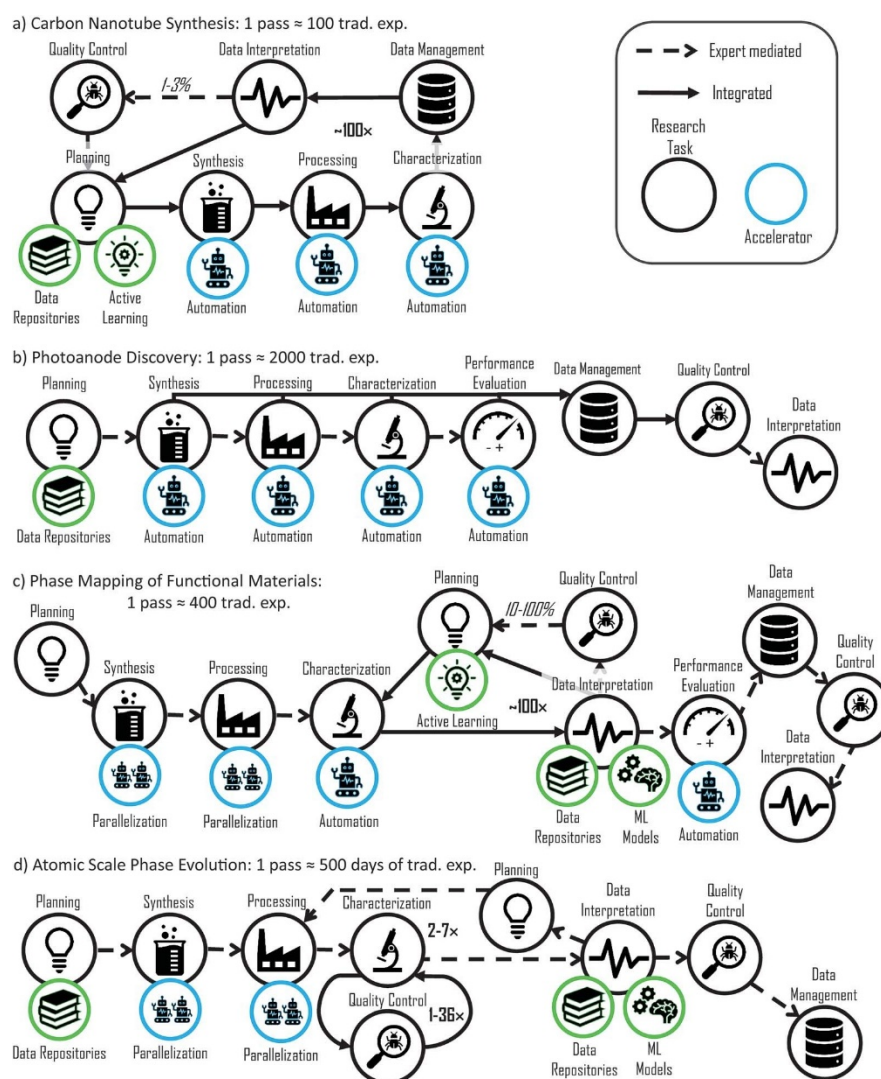


Figure 3. Workflow diagrams of accelerated materials experimentation spanning a range of techniques, strategies and research goals. Based on (a) Nikolaev et al.,¹⁴ (b) Yan et al.,²⁰ (c) Kusne et al.,⁶⁶ and (d) Li et al.,²⁹ each workflow involves accelerated tasks with various levels of automation and task-to-task integration. The productivity for a single pass through the workflow is noted, corresponding to the number of equivalent traditional experiments for (a)–(c) and duration of traditional experiments for (d). Feedback loops are each labelled with the approximate number of iterations per workflow execution (bold), and in (a) and (c) the percentage of iterations involving expert mediation is also approximated (italics)

The photo anode discovery pipeline in Fig. 2b represents the tiered screening by Yan et al. that includes both theory and experiment-based down-selection of candidate metal oxides. With respect to the experiments, the computational screening is an accelerant and represented as such in the planning task. The Materials Project database serves as the primary repository, with additional calculations specific to photo anode screening, and while these calculations are critical to the success of the work, they are not fully integrated into the experimental workflow. Synthesis, processing, characterization, and performance evaluation are accelerated using automation, with

tens to thousands of materials being synthesized or measured automatically. While this sequence of tasks is in principle amenable to more autonomous operation, setup and selection on meaningful experimental conditions are chosen by an expert, resulting in expert mediated linkages in the workflow. The heavy use of parallelization and automation is supported by automatic data management and quality control, with data interpretation requiring expert mediation. A key attribute of this workflow is the establishment of automated techniques for a large breadth of experimental tasks, from synthesis to performance evaluation that can operate on libraries with up to ca. 2000 unique materials. The research strategy involves collection of combinatorial materials datasets that facilitate data interpretation and scientific discovery, as well as evaluation of every prediction from the computational screening to assess its efficacy. These aspects of the research limit the value of further task-to-task integration and application of active learning, with the broader message being that the impact of the closed-loop concept varies with research strategy and goals.

The workflow of Fig. 3c describes a different implementation of combinatorial materials science for studying functional materials where synthesis, processing and performance evaluation are accelerated by parallelization and automation with expert-mediated integration similar to that of Fig. 3b. The unique aspect of this work is the use of an active learning loop in the middle of the workflow to accelerate the mapping of phase boundaries in a composition library, demonstrating the use of active learning in a sub-workflow to accelerate a bottleneck experiment (and save valuable beamline time). The synchrotron X-ray diffraction (XRD) characterization described by Kusne et al. includes on-the-fly data interpretation and automated selection of the next composition for XRD measurements, with occasional expert supervision of the clustering-based identification of pure-phase patterns.

The atomic-scale phase evolution workflow by Li et al. illustrated in Fig. 3d uses a specialized nanometer sized reactor to assess phase stability with ca. 1 hour of experiment time yielding the same data as over 500 days of annealing in traditional bulk experiments. Using data repositories of phase diagrams and stability ranges of multicomponent complex metal alloys to plan synthesis, an array of 36 reactors is deposited, for example with equiatomic mixtures of the Cantor alloy Cr–Mn–Fe–Co–Ni. The loop in this workflow is based on the step-wise annealing of the reactor array with subsequent atom probe tomography (APT) characterization after each processing step. Each APT characterization involves destruction of one of the reactors, and the number of reactors is made to be several times larger than the number of processing steps due to routine failure of the APT measurement. The critical advancement enabled by a small autonomous loop is the real-time monitoring of APT data acquisition with well-integrated quality control. Data interpretation is performed by comparison to external data and visualization is done through a machine learning model. The richness of the APT data coupled with significant annealing time reduction yields high throughput knowledge generation even though the workflow contains mostly expert-mediated integration of tasks. Increased autonomy in the workflow would only be warranted after substantial advances in automated data interpretation.

For each of these workflows, the nominal time to execute the entire workflow is on the order of 1 day. The equivalent number of passes through a traditional workflow,

or the number of days of traditional experimentation to produce the equivalent data, provides the nominal acceleration factor of the workflow, which is only equal to the acceleration factor of knowledge discovery if the selection of experiments and quality of the resulting data is equivalent to those of traditional experiments. Assessment of such data value is beyond the scope of the present discussion but remains a critical consideration for quantifying workflow acceleration, particularly in settings where the research goals involve understanding the underlying materials science as opposed to performance optimization.

9. Conclusions and outlook

The urgent need for better materials demands faster turnaround cycles from basic research, such that better, more efficient, eco-friendlier, and more economically viable materials can enter the market sooner than the traditionally observed 40 years. Accelerated materials experiment workflows have been demonstrated to increase throughput by up to a few orders of magnitude compared to traditional methods. Surveying the reported workflows reveals two primary areas for workflow sophistication, the integration of sequential tasks without requiring expert involvement and the expansion of feedback loops to incorporate a larger fraction of the workflow tasks. The ARES workflow achieves both of these goals with a relatively small workflow compared to the functional materials discovery research where the variety of characterization and performance evaluation experiments increases the number of workflow tasks as well as the demands on data management, data interpretation, and quality control.

To visualize progress to date and the expected advances from ongoing research, Fig. 4 illustrates the continuum of materials workflows in terms of the scientific complexity and workflow automation complexity. To elucidate our intended meaning of scientific complexity, representative tasks spanning minimal complexity to very complex are listed. Arguably the most important aspect of a successful science program is the ability to identify interesting problems and ask the important questions that guide research activities. These tasks are beyond the purview of present autonomous research and will be for the foreseeable future. Advances in natural language processing for materials science may automate aspects of scientific communication, but critical analysis of the literature and communication of the insights provided by a given experiment will continue to rely on human intellect for the foreseeable future.

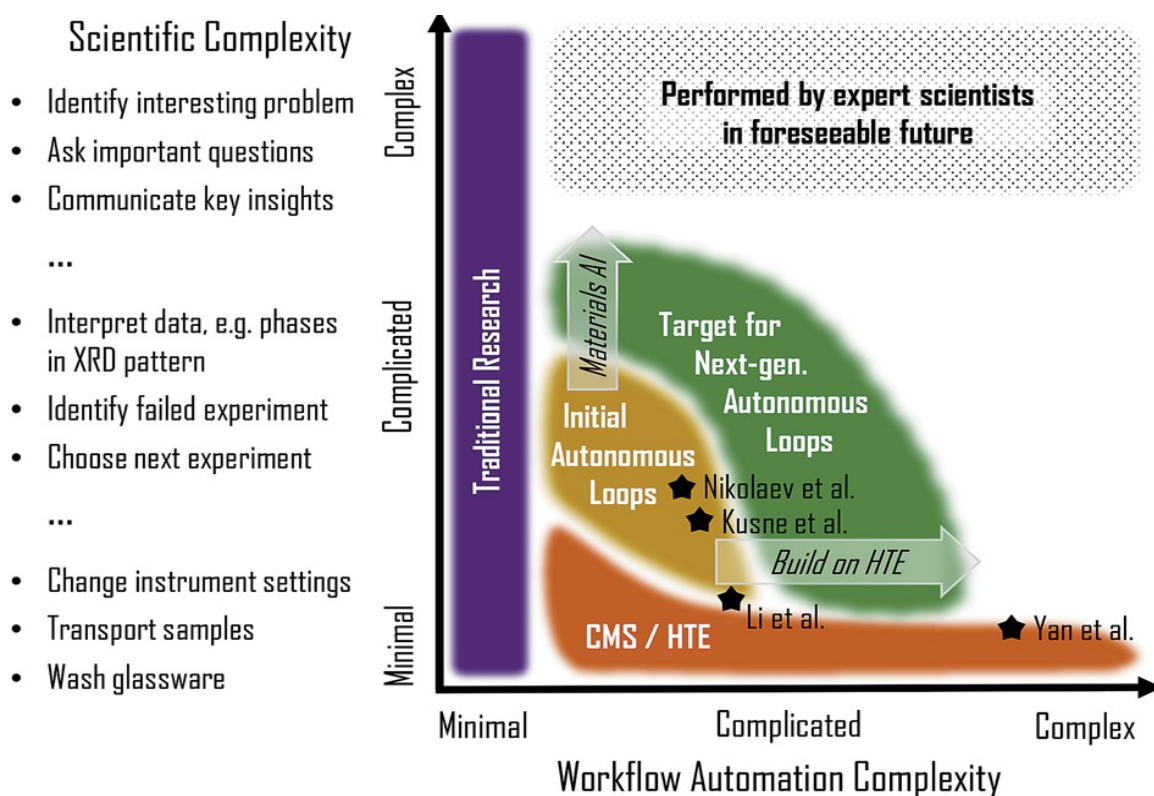


Figure 4. Visualization of the landscape of materials experiment workflow in terms of the scientific complexity of automated tasks and the workflow automation complexity, which is based on the number, variety, speed, and difficulty of experimental steps in the workflow

The advancements in combinatorial materials science and high throughput experimentation have been largely along this latter axis, and initial demonstrations of autonomous loops have made progress on the former axis with automation of more intellectually challenging research tasks. The nominal location of the 4 workflows from Fig. 3 are noted by stars. While research will push the frontier of automated experiments along both axes the most complex scientific tasks will remain the responsibility of human experts for the foreseeable future.

Determining the most effective advancements in a materials experiment workflow requires critical evaluation of bottlenecks for progress against the research goals. Even when expert mediation is required between tasks, workflow throughput is often limited by the manual steps at the front and back ends of automated experiments. These peripheral activities, which fall under the intermediate “complicated” level of scientific complexity in Fig. 4, can be difficult (or currently impossible) to fully automate due to the routine use of expert knowledge, for example in judgement of data quality based on extensive previous experience with related data. Advances in artificial intelligence (AI) for materials encompasses a wide variety of strategies for addressing these challenges, which will be critical for expanding the scope of autonomous loops. This approach to pushing the frontier of materials workflows is illustrated by the “Materials AI” arrow in Fig. 4 and will ideally accompany the expansion of autonomous loops to include more complex and a larger variety of experimental tasks. This complementary approach to pushing the frontier of materials workflows is illustrated by the “Build on HTE” arrow due to the demonstrated successes in experiment automation from the high throughput experimentation community. The

ability to leverage this existing work makes autonomous workflows more readily extendable into complex automation as compared to the extremes of complex scientific reasoning.

An outstanding question with regard to the next generation of experimental workflows is how to best combat human biases that can severely limit innovation. Advanced autonomous experimentation may remove biases within a given search space through computationally designed experiments. However, the scope of the search space is limited by both instrument capabilities and active learning strategy, whose designs originate with human identification of the materials space of interest. To the extent that human biases disseminate from the “complex” scientific tasks of Fig. 4, bias removal within an autonomous workflow must be complemented by sociological solutions for removing bias in decisions beyond the experiment workflow.

We are aware of several research groups that are building autonomous experiments in the “next generation” regime of Fig. 4, including emerging reports from perovskite synthesis and molecular materials for organic photovoltaics and organic hole transport materials. Continuation of these concerted efforts to increase automation and develop tailored AI algorithms will enable the materials science community to realize a paradigm shift in scientific discovery where expert scientists can dedicate a substantially larger fraction of their time to performing the critical tasks of identifying important problems and communicating critical insights.

(Joint Center for Artificial Photosynthesis, California Institute of Technology, Pasadena, CA 91125, USA, Division of Engineering and Applied Science, California Institute of Technology, Pasadena, CA 91125, USA, First published 20 Sep 2019). URL: <https://pubs.rsc.org/en/content/articlelanding/2019/SC/C9SC03766G>

Words and word combinations:

- encompass [ɪnˈkʌmpəs] – заключать в себе;
- accelerate [əkˈseləreɪt] – ускорять;
- workflow [ˈwɜːkfləʊ] – трудовой процесс;
- proliferation [prəˈlɪfəˈreɪʃn] – распространение;
- renewable [rɪˈnjuːəbəl] – возобновляемый;
- necessitate [nɪˈsesɪteɪt] – сделать необходимым;
- serendipity [ˌser(ə)nˈdɪpɪtɪ] – интуиция;
- eliminating [ɪˈlɪmɪneɪtɪŋ] – ликвидация;
- unprecedented [ʌnˈpresɪdɪntɪd] – беспрецедентный;
- throughput [ˈθruːpʊt] – пропускная способность;
- life cycle [laɪf ˈsaɪk(ə)l] – жизненный цикл;
- database [ˈdeɪtəbeɪs] – база данных;
- technique [tekˈniːks] – метод;
- implementation [ɪmˈplɪmənˈteɪʃ(ə)n] – реализация;
- anneal [əˈniːl] – отжигать;
- characterization [kærəktəraɪˈzeɪʃ(ə)n] – характеристика;
- parallel [ˈpærəlel] – параллельный;
- spectroscopy [spekˈtrɒskəpi] – спектроскопия;
- establish [ɪˈstæblɪʃn] – устанавливать, оставлять;
- ingestion [ɪnˈdʒestʃ(ə)n] – прием данных.

Task 2. Summarize all the ideas of the article and write an essay.

Task 3. Make a presentation based on the article.

Article 3

Task 1. Read the text below.

Towards a model of automation adoption

**(by Ian McCandliss, Kevin Zish, J. Malcolm McCurry, J. Gregory Trafton
George Mason University, Peraton Inc., U.S. Naval Research Labs)**

Abstract

This study examines the impact of prior experience on the adoption of automation in a supervisory control task. Automation is typically implemented as a means of reducing a person's effort or involvement in a task. When automation is first introduced in a new product, the experience on the yet-to-be automated task is variable. Some users have experience with the task prior to the automation while others have little to no prior experience. Automation adoption between levels of experience was investigated in a mixed design study. One group was trained to use a manual version of a task before learning of an automated version. A second group was only trained to use the automated version of the task. The results of this study indicate that both training and experience are needed before users can make robust predictions about future automation adoption.

1. Background

Automation can be considered the reduction of human intervention through the use of automatic control systems. Through the implementation of automation, human oversight may be shifted or removed entirely as a part of a system (Parasuraman, Sheridan & Wickens, 2000). By shifting attention away from previously necessary tasks, cognitive and material resources become freed to be put to new use. Consider telephone operation which previously required many humans to manually connect and disconnect lines but which has now been supplanted by an almost completely autonomous process. Or consider how the seed-drill automated the process of digging out a hole, planting a seed and packing soil into place, allowed farmers to plant crops faster and over a much larger acreage (Sayre, 2010).

While these automated systems have been widely adopted, not all attempts at automation succeed, at least not immediately. For example, most new cars sold in the United States are automatic transmissions, with manual transmissions being in sharp decline (Duffer, 2018). In spite of the clear ease of use with which automatic transmissions provide (Schoner, 2004), there yet remain people who prefer the more reliable "old" way of doing things, as this is primarily what they have grown accustomed to using (Akple, Turkson, Biscoff, Borlu & Apreko, 2013).

When an automated system is introduced, there are some who will gravitate towards it and view it as providing additional utility and perceiving it as easier to use (Zhang, Zhu & Liu, 2012). Conversely there are others who will view the old way of doing things as more reliable (Akple et al., 2013) and refuse to adopt the new automation. However, as the automation becomes more widespread and even accepted

there will also be people who have had no prior experience with the older technology or the way things used to be done.

Is it possible to then model automation adoption? One way to examine the use and adoption of automation may be the Technology Acceptance Model (TAM) (Venkatish & Davis, 2000). This model is helpful in many ways as it ascribes the actual use of the technology onto several latent variables which can be measured via surveys. These latent variables vary from study to study but most often include the Perceived Ease of Use (PEOU) and the Perceived Usefulness (PU) of the technology by the user. These measures of the user's perception of the product are then loaded onto the users reported Behavioral Intention (BI) to use the product. That is, it is a prospective measure of how much, or to what extent, the user will utilize the given technology. While there are a number of other versions and successors to the TAM, almost all of them contain at least some elements of the initial model (Sanchez & Hueros, 2010).

While previous studies have assumed a strong relationship between Behavioral Intention and Actual Use (AU) of the product, this relationship may be overstated (Lee, Kozar & Larsen, 2003). Many studies assume that the relationship is so strong that they do not even examine it, halting their examination after obtaining information about the BI (Battacherjee & Premkumar, 2004; Helia, Asri, Kusri, & Miranda, 2018; Leong, Ibrahim, Dalvi-Esfahani, Shabazi & Nilashi, 2018; Razmak & Belanger, 2018). A potential reason for this disconnect is that measuring actual use is time-consuming and difficult and that such findings may be considered settled (Turner, Kitchenham, Brereton, Charters & Budgen, 2010). However, there is a danger in following this assumption, as the relationship may be altered from previous studies if AU is measured using objective or subjective measures (Turner et al., 2010). Given that a core principle of automation is to free the user from a task, obtaining measures of actual use of the automated technology may be more difficult to acquire than traditional technology. Furthermore, the TAM in its most basic form does not account for the impact of prior exposure to a technology, or the way a person was first introduced to it.

This issue could potentially be addressed by utilizing a more complex model dubbed the TAM-2 (Venkatish & Davies, 2000) as it does include factors which represent experience. However, in this model experience is noted as only acting as a moderating variable for perceived social pressure to utilize a new technology. While the validity of this conclusion is not in dispute, it does not necessarily capture the way automated technology is introduced both to those who have had years of experience without it, and those who have always had it as the norm. It also does not differentiate this from exposure to the technology over time. Furthermore, it still has the same vulnerability as the TAM as BI still fully mediates the relationship between all other latent variables and actual use. Consider the impact that simply presenting a new tool or object has on a person, especially in an experimental setting. The person may incorrectly assume that because it was presented this way that they should provide it with a positive rating to align with the experimenters assumed expectations (Lee, Kozar & Larsen, 2003; Mummalo & Peterson, 2018). While this could have a strong impact on their Perceived Usefulness of an object (as is the case described in the TAM2) it may not necessarily have an impact on their actual use of the tool. This in turn would require

an examination of the tools actual use, which as stated previously may be difficult given that a major part of automation is disengaging the user.

Given that variables which may be of crucial interest for modeling automation are either unexamined or under examined in present TAM literature, it may be more prudent to develop a new model which is specifically intended to handle automated technologies. In order to develop this model, we start with the most basic variables of the TAM, Behavioral Intention to Use and Actual Use of the automation. In order to measure these key variables, a task must be developed that meets certain criteria. First it must allow the researcher to examine both the participants' stated Behavioral Intention, as well as an objective measure of how frequently or to what degree they utilized it.

Secondly, as the model is intended to measure the adoption of automation and automation is meant to supplant a previously manual operation, it follows that the task must have both manual and automated functionality. By providing both of these systems to participants, they will be able to utilize or abandon automated and manual controls as they consider appropriate for the task.

Thirdly, as the user population lacks uniformity in their experience with either automated or manual controls, the task must be controlled to simulate these user groups. The task must allow some participants to utilize only manual options at first and later provide access to automated options (as a person who has worked in a task for a long time would encounter), while allowing other participants full access to all of the tools from the beginning (as a neophyte to a task would encounter).

Lastly, while the latent variables of the TAM may only load onto the participants Intention to Use, it would be foolhardy to discount them outright. As such the core variables of Perceived Usefulness and Perceived Ease of Use should also be considered in the model.

Formally stated, the goal of this study is to develop a model of Automation Adoption and to examine the impact of exposure to automation on actual use of an automated system.

2. Method

2.1. Participants

A total of 68 participants (23 males) with ages ranging from 18 to 37 all enrolled in undergraduate psychology courses at George Mason University. Thirty two were in the full automation condition while thirty one were in the partial automation condition. Five participants were excluded from analysis due to technical failures which resulted in their data being lost. All participants received course credit for their participation. Previous research has indicated that student samples may serve as stand-ins for more expert populations, but not for general populations (King and He, 2006). This was desirable in this study given the high skill-floor of the task utilized to develop the model.

2.2. Materials

A computer loaded with the Research Environment for Supervisory Control of Heterogeneous Unmanned Vehicles (RESCHU) was used.

3. Procedure

This study involved the use of RESCHU, a complex task created as part of a Naval Research Labs project (Boussemart & Cummings, 2008). The task is a computerized simulation in which participants must control multiple unmanned aerial vehicles (UAV's) in a dynamic environment to both avoid hazards and send planes to designated targets. In this version of RESCHU two UAV's were required to travel to each target. The RESCHU task contains an automation feature that provides additional utility over manual controls methods which the participants may also utilize. This automated feature is an easy to manipulate component in establishing the conditions for this automated feature is an easy to manipulate component in establishing the conditions for this study. The layout for the task is displayed below in Fig 1. The first UAV to arrive scanned the target for danger; the second UAV to arrive took a photograph of the target. There were four control mechanisms for guiding the planes to different targets, two manual methods and two that utilized automation. Regardless of the control mechanism used, once a plane was assigned to a target a visible straight-line would appear between the UAV and the target, denoting its flight path. The plane would then fly along the flight-path until it reached the target, unless the participant right clicked on a plane while in flight, selected the "add waypoint" button and clicked somewhere on the map. In this case planes would begin flying to the waypoint prior to heading to the target. This allowed the planes to maneuver around the hazards, denoted in yellow circles which would appear and disappear in different portions of the map throughout the experiment.

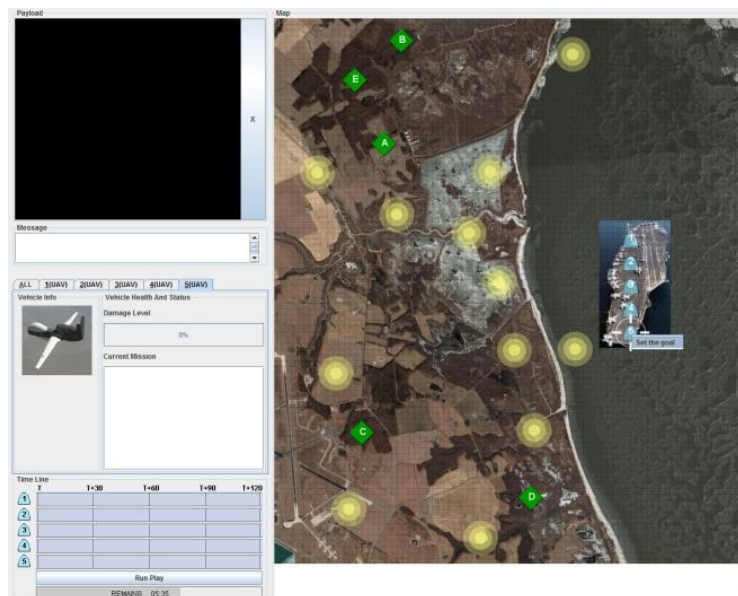


Figure 1. This displays a view of the overall task arrangement. Planes are numbered one through five in blue and are set on the aircraft carrier on the left side of the screen. The targets are green diamonds labeled A through E. The yellow circles are Hazards which must be avoided

The first of the manual controls consisted of right clicking a plane on its starting position, clicking the subsequent button that popped up and then clicking on a target. The second of the manual controls consisted of clicking and dragging the dot at the end of a planes flightpath while it was enroute to a target. The first of the automated controls was accessed by right clicking and interfacing with the target. Upon doing so, the two nearest planes which were not already enroute to a target would begin flying to that target. The second of the controls which used automation was the “Run Play” button, displayed in the bottom left corner of the screen. Whenever this button was clicked, the nearest unassigned plane would begin flying to the nearest available target.

Regardless of which control mechanism was used, when the first plane arrived at a target, the target would change from green to yellow and the plane would automatically begin flying back to the spot it initially took off from. Participants were informed that they should avoid having their planes return to the take-off position and should instead redirect them in flight. When using the manual controls, the second UAV would stop at the target and begin flashing red. Participants would then need to right click on the plane and select the pop-up button, which would allow them to begin the visual search task as described below. No such visual search task was required if the plane was sent via automated controls.

The visual search task consisted of a photographic image displayed in the upper left corner of the screen with a target located somewhere within it. A written description for this target was given in a small box immediately below the picture taking area. Participants were informed that they would need to read the text in order to identify the target in the visual search. Participants were provided with immediate feedback on whether or not they were successful in the visual search task via the textbox where they received the targets descriptor.

Participants were informed that they should attempt to score as many points as they could within the time allotted. Points could only be scored using the manual controls if the user successfully completed the visual search task. In addition to a simplified control mechanism, the automated tools also removed the requirement of a visual search task on the part of the participant. This allowed them to score points with fewer steps.

4. Design

Two conditions were used for this experiment. The continuous automation condition received access to the automation at the beginning of the experiment. A graphical display of the order of events for each condition is shown in Fig. 2. The partial automation condition received access to the automated tools only after completing a full session with only access to manual controls. While both conditions were given an overview of the task, the partial automation condition were not instructed in and unable to use the automated tools until later in the experiment.

After the initial overview, the partial automation condition engaged in a training exercise using only the manual control mechanisms. The partial automation group then engaged in an experimental trial with only the manual controls. Following this, the partial automation group was given a secondary overview and training, now including

the automatic controls. This was then followed by two experimental trials in which they had full access to all of the tools.

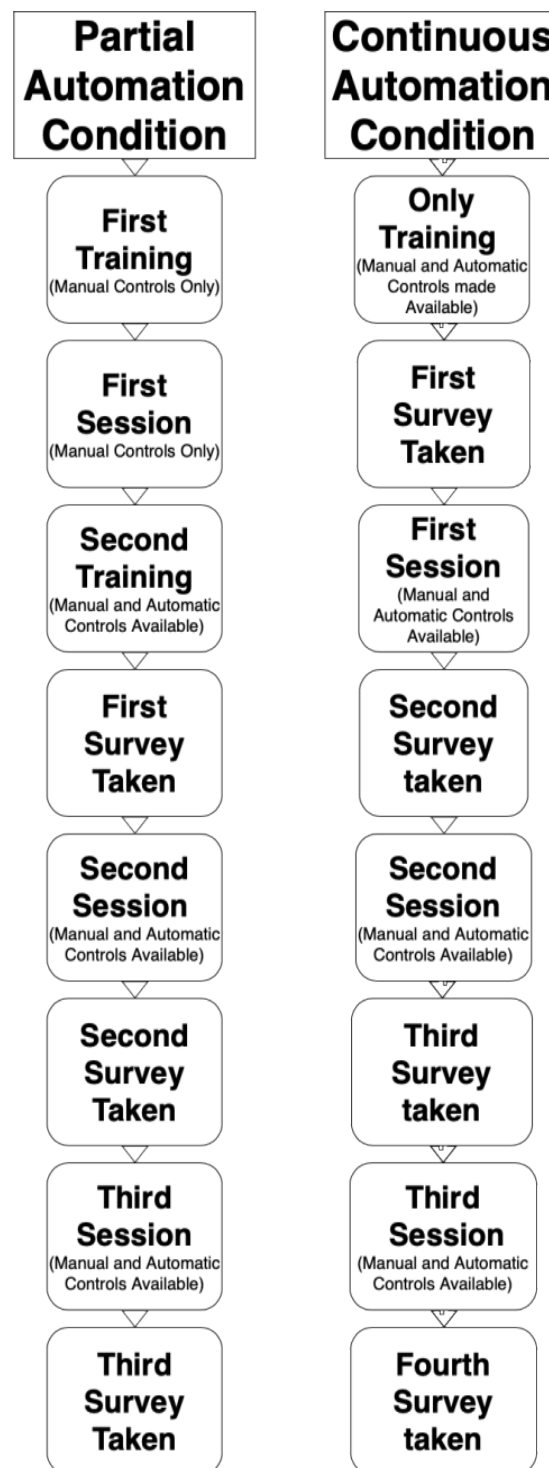


Figure 2. A display of the order of tasks participants engaged in for each condition

During the initial overview, the continuous automation group was fully informed of all the tools available to them and underwent a training session with all tools

available. After this, the participants engaged in three other sessions with all tools available.

After the participants were introduced to the automated controls, they were given a survey meant to measure their intention to use the automated controls. This survey was also intended to assess both the users perceived utility and perceived ease of use of the automated controls. Subsequent surveys were given out after each session so as to assess how these variables changed with experience. At the end of all treatments, participants were asked an open ended question about what they thought of the automation and their responses recorded by the experimenter.

5. Results and discussion

We first examined how frequently participants used automation: If a majority of participants eschewed automation (or, conversely, used it exclusively), a model of automation usage would be useless, since there would be nothing to predict.

As Fig. 3 suggests, however, participants varied widely in their automation usage.

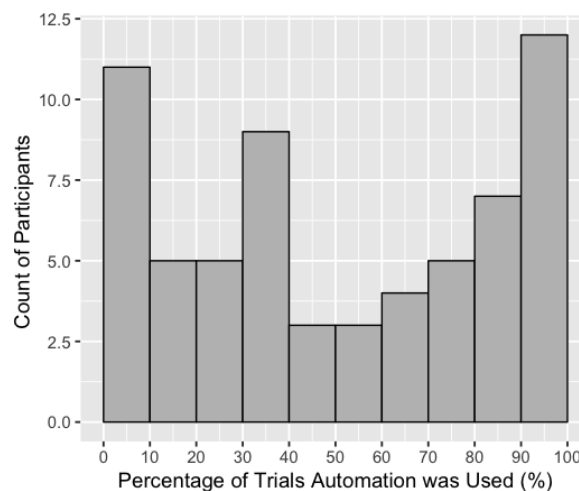


Figure 3. The figure shows the frequency of people who utilized the automation when automation was available. The extreme ranges represent people who did not use automation at all, and those who utilized only automation respectively. The intervening columns represent those who utilized some combination of manual and automated controls

To demonstrate the relationship between Behavioral Intention to Use and Actual Use, only surveys that preceded a session were analyzed. Multiple regressions were used to determine the impact of Perceived Usefulness and Perceived Ease of Use on Intention to use for each condition and survey. For the First survey of the Partial Automation Condition ($F(2,28) = 25.01, p < .01, R^2 = .61$) both Perceived Usefulness ($\beta = .43, p < .01$) and Perceived Ease of Use ($\beta = .52, p < .01$) were statistically significant. Similar results were found for the Second survey ($F(2,28) = , p < .01, R^2 = .68$) as both Perceived Usefulness ($\beta = .42, p < .05$) and Perceived Ease of use ($\beta = .47, p < .01$) were both significant.

While the first survey of the continuous automation condition ($F(2,28) = 8.81$, $p < .01$, $R^2 = .34$,) did show a significant impact of Perceived Usefulness on intention to use ($\beta = .51$, $p < .01$) Perceived Ease of Use did not demonstrate a significant impact ($\beta = .24$, $p > .05$). The second survey of the continuous automation condition ($F(2,29) = 32.4$, $p < .01$, $R^2 = .67$) also showed significance for both Perceived Usefulness ($\beta = .51$, $p < .01$) and Perceived Ease of Use ($\beta = .30$, $p < .05$). The third survey of the Continuous Automation condition ($F(2,29) = 45.15$, $p < .01$, $R^2 = .74$) was similar to the Continuous Automation condition as it also showed a significant impact of Perceived Usefulness ($\beta = .79$, $p < .01$) but did not demonstrate a significant impact of Perceived Ease of Use ($\beta = .09$, $p > .05$).

Multiple regression analysis was also used to determine the impact of the participants Behavioral Intention to Use on Actual Use of the automatic tool. The partial automation condition's first survey showed a significant impact of intention to use on the actual use of the automated tool ($F(1,29) = 8.28$, $p < .05$, $R^2 = 0.20$). The partial automation condition's second survey also showed a significant impact of Behavioral Intention to Use on Actual Use ($F(1,29) = 14.26$, $p < .05$, $R^2 = .31$). These results indicate that for the partial automation condition Behavioral Intention was always a consistent predictor of actual use.

In contrast, the continuous automation condition's first survey did not demonstrate a significant impact of Behavioral Intention to Use on Actual Use. However, the continuous automation condition's second survey did show a significant impact of Behavioral Intention to Use on Actual Use ($F(1,30) = 7.75$, $p < .05$, $R^2 = .18$). The continuous automation condition's third survey also showed a continuation of this relationship ($F(1,30) = 20.75$, $p < .05$, $R^2 = .39$). The continuous automation condition's relationship between Behavioral Intention to Use and Actual Use, was initially not predictive of actual use, but became predictive as the participants gained greater exposure to the task. A graphical depiction of the relationship between the latent variables (Perceived Usefulness, Perceived Ease of use and Intention to Use) and their impact on the participants Actual use is displayed below in Fig. 4.

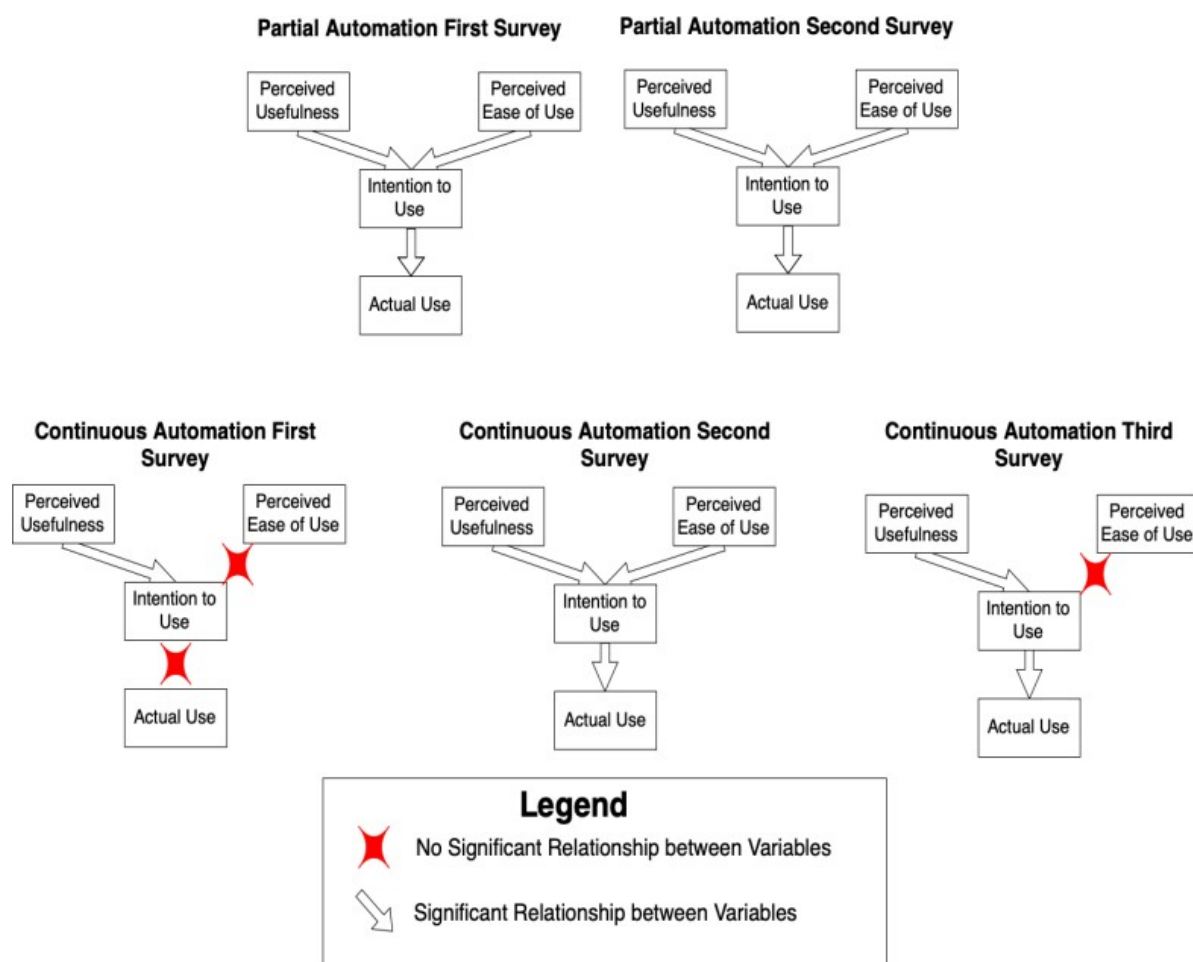


Figure 4. The relationship of the latent variables Perceived Usefulness and Perceived ease of Use on Intention to Use by Survey and Condition. It also shows the Impact of Intention to use on Actual Use, though this was part of a separate analysis

Initial findings support the idea that the treatment of either continuous exposure automation or partial automation lead to the key differences in initial behavioral outcomes. Participants who were exposed to only automatic controls were initially unable to make an accurate prospective judgement on how they would actually use the tools. Conversely, those who were exposed first to the manual controls and only later had exposure to the automatic controls, were able to make accurate judgements from the first time they took the survey.

However, it is unlikely that the order of introduction of the tools was the full reason for this effect, though this may be explored further in future studies. While both conditions had exposure to a guided training period prior to taking the first survey, the partial automation condition still had more exposure to the task due to the experimental design. As the partial automation condition had exposure to nearly a full experimental session than the continuous automation condition prior to the first survey, their greater experience allowed them to make a more accurate judgement on their behaviors than the continuous automation condition did. However, as time went on and the continuous

automation condition gained experience equivalent to the partial automation condition, their assessment accuracy rose to match that of the other treatment.

It may then be possible to attribute the earlier overly inflated assessment of intention to use to experimenter effects. Given the situation, and the way the questions were phrased, participants inflated their estimates of how much they would use the automation initially as a means of satisfying what they believed were the experimenters' expectations. However, after gaining experience with the task in a more realistic way, participants in the continuous automation condition were able to provide an accurate description of how much they would use automation (Behavioral Intentions).

This finding has broad reaching effects especially for future automation. Generally, the results indicate that if a person has training, but no tangible understanding of the environment they will be working in, then their intention to use automation does not predict their actual use of it. However, if a person has prior experience with the environment, even if they only have a small amount of training with the automation, then their BI may in fact be a very strong indicator of how they will utilize the automation.

This provides valuable insight when constructing future studies when model building for Automation Adoption. In order to create appropriate comparisons, future studies will need to establish a certain level of baseline experience before a full analysis can be undertaken. In the meantime, it does provide us with insight about being able to predict the actual usage of automation from people who are already familiar with their task. How long it takes to reach this state is a matter that future studies may look at.

Qualitative data was also collected at the end of the experiment with the experimenter asking open ended questions about what they thought of the automation. While this data requires further analysis, there were consistent patterns of participants who chose not to use it or the automation taking them out of the loop. Some acknowledged that using the automation would be easier, but that doing so would result in them losing control. One of the participants in the partial automation condition stated that while using the automation did make things easier, it was also more boring. These statements suggest how the model may be refined in the future. The level of controllability of the automation could be examined as well as whether or not the participants consider the lack of interaction a value adding or value subtracting experience.

In conclusion, these results provide support to the idea that if a person has experience in a domain that they can make accurate statement about how they would choose to use or disuse a corresponding automated system. This may be helpful when an organization seeks to introduce an optional automated tool to a previously non-automated task and they wish to determine if experienced operators will utilize it or not. Future studies may examine how much exposure to a given domain is required before this judgement may be accurately made.

(George Mason University , Peraton Inc.² , US Naval Research Laboratories, First Published November 20, 2019).

URL: <https://journals.sagepub.com/doi/abs/10.1177/1071181319631254>

Words and word combinations:

- prior ['praɪə] – прежний;
- adoption [ə'dɒpʃ(ə)n] – принятие;
- intervention [ɪntə'venʃ(ə)n] – вмешательство;
- adopt [ə'dɒpt] – принимать;
- widespread ['waɪdspred] – широко распространенный;
- examine [ɪg'zæmɪn] – исследовать;
- utilize ['ju:tɪlaɪz] – использовать;
- assume [ə'sju:m] – предполагать;
- especially [ɪ'speʃ(ə)li] – особенно;
- supplant [sə'plɑ:nt] – вытеснять;
- relationship [rɪ'leɪʃ(ə)nʃɪp] – взаимосвязь, взаимоотношения;
- significant [sɪg'nɪfɪk(ə)nt] – значительный, существенный;
- initial [ɪ'nɪʃ(ə)l] – начальный;
- be engaged [ɪn'geɪdʒd] – заниматься;
- exercise ['eksəsaɪz] – упражнение, осуществление;
- including [ɪn'klu:dɪŋ] – включая, в том числе;
- access ['ækses] – доступ, проход;
- trial ['traɪəlz] – испытание;
- participant [pɑ:'tɪsɪpənts] – участник;
- suggest [sə'dʒests] – предполагать;
- available [ə'veɪləb(ə)l] – доступный.

Task 2. Summarize all the ideas of the article and write an essay.

Task 3. Make a presentation based on the article.

Article 4

Task 1. Read the text below.

The effects of automation and role allocation on team performance (by Murat Dikmen, Yeti Li, Philip Farrell, Geoffrey Ho, Shi Cao, Catherine Burns)

Abstract

An experiment was conducted to investigate the effects of automation and role allocation on performance in a simulated picture compilation task with fourteen two-person student teams. In the absence of automation support, the system integrated sensor information. In the presence of automation support, the system both integrated sensor information and identified contacts. Roles were assigned either based on warfare domain or geographical sectors. Results showed that human-automation system performance was similar in two automation conditions, but participants were slower in classifying tracks and overall classified fewer tracks when the automation was present. We conclude that working with automation may lead to degraded team performance due to complacency and additional task complexity.

1. Introduction

The effect of automation on individual performance has been relatively well studied. However, there is little research on automation in teams, especially in the maritime domain (Qin et al., 2019). Compared to a single operator working with the automation, a team of multiple operators working with the automation creates new challenges that need to be addressed, such as determining appropriate crew size in the human automation teams and how crews need to modify task strategies in order to adapt to the increased automation capabilities (e.g. allocating tasks between crew members and the automation). On behalf of the Royal Canadian Navy, Defence Research and Development Canada is exploring how multisensor data fusion (MSDF) for constructing the battlespace picture impacts crewing and human-automation ‘team’ performance. This work presents an investigation into the effects of increased automation capability on team performance in a simulated naval environment

1.1. Background

The operations (OPS) room onboard a warship typically is in charge of integrating all of the ship’s sensor information. One of the main tasks involves a team of operators responsible for building the tactical picture of the ship’s operating environment which includes a comprehensive understanding of all the sea surface and air traffic in the area. This task is called picture compilation. Picture compilation typically involves detecting contacts (i. e. a ship or a plane) with sensors, tracking the contacts, evaluating them, and gathering all relevant identification data for the contacts (Canadian Forces Naval Operations School, 2007). To do this, operators must integrate signals from various sensors such as radars, electronic warfare sensors, and passive sensors to build a track that represents the path of a ship or a plane. Tracks must also

be classified and identified. For example, a ship might be classified as friendly, neutral or hostile. This task is performed by the operators using a variety of information sources to assess the contact's identity such as receiving information from transponders, intelligence, and also information from the contacts such as its movement, vehicle type, and other key identifiers. Over time, ideally the tracks and their identities form an accurate and coherent tactical picture for commanders. Automation can support operators performing the picture compilation task. For example, data fusion automation could merge the data from various sensors, leaving the operators to focus on identifying and assessing the contact. In the future, automation can also support human operators in classifying and identifying contacts, which is explored in this study. From a human factors perspective, it is important to understand how allocating tasks to automation affects crew performance and whether any changes to crew size can be realized as a result. While automation can support contact classification, the OPS room operators would still be responsible for validating the automation. Previous work on the impact of automation on team performance showed that automation can lead to reduced mental workload (Jentsch & Bowers, 1996), however not in all cases (Van Dijk, 2010). Moreover, team performance is only improved if the automation is highly reliable (Hillesheim & Rusnock, 2016; Wright & Kaber, 2005). At the same time, interaction with higher intelligent agents will likely produce some residual error in the agents' goal achievement (Farrell, 2003), which can lead to degraded human-automation team performance. Previous studies have investigated teamwork and automation failures (Mosier et al., 1998), adding automation as a team member, (Miescher, Spitz, Anastosi, & Lind, 2001), and crew composition (Chow, Lamb, Charest, & Labbé, 2016). However, there is little research on role allocation in human-automation teams. Traditionally, naval operators separate the picture compilation task by warfare domains (i.e., air, surface, and subsurface) such that one person is primarily responsible for one warfare domain. However, with automation supporting contact classification, it might be more advantageous to separate the picture compilation task using other strategies to divide the task load. One such method is to split up roles by geographical sectors. This allows for a better distribution of task load since operators could divide up the work depending on the density of traffic in various sectors to distribute the workload.

1.2. Overview of the Study

In the present study, we investigated the impact of automation for track classification and operator role allocation on team performance. Two-person teams were presented with a picture compilation task in a simulated navy environment. We varied the automation capability, as well as the role allocation.

2. Method

2.1. Design

The experiment was a 2×2 repeated measures design. Independent variables were automation capability and role allocation. Automation capability had two levels: (1) system without classification automation support (without classification condition) and (2) system with classification automation support (with classification condition). These levels were considered as lower and higher level of automation in this study, respectively. Role allocation had two levels: (1) role allocation based on geographical

division (i. e. west, east) and (2) role allocation based on warfare domain (i. e. surface, air).

2.2. Participants

Fourteen teams of two university students participated in the study. Team members were familiar with each other and had completed at least one course project together. The mean age was 21.4, and there were both same-gender and mix gender teams in the study.

2.3. Apparatus

ISR360 – a multi-sensor multi-tracking software suite by Trackgen Solutions – was modified to create a simulated environment for the study that retained realistic data fusion and target identification capabilities. The two-person team shared a map that displayed their own ship, other ships and aircraft (Fig. 1). Tracks in the own ship's operating environment were produced by simulated sensors (radar and automated identification system, AIS). Each track was represented by a symbol which indicated that it was a plane or a ship. The color of the symbol indicated whether the identity was unknown (yellow), friendly (blue), neutral (green) or hostile (red). The actions of one team member were visible on the other member's screen.

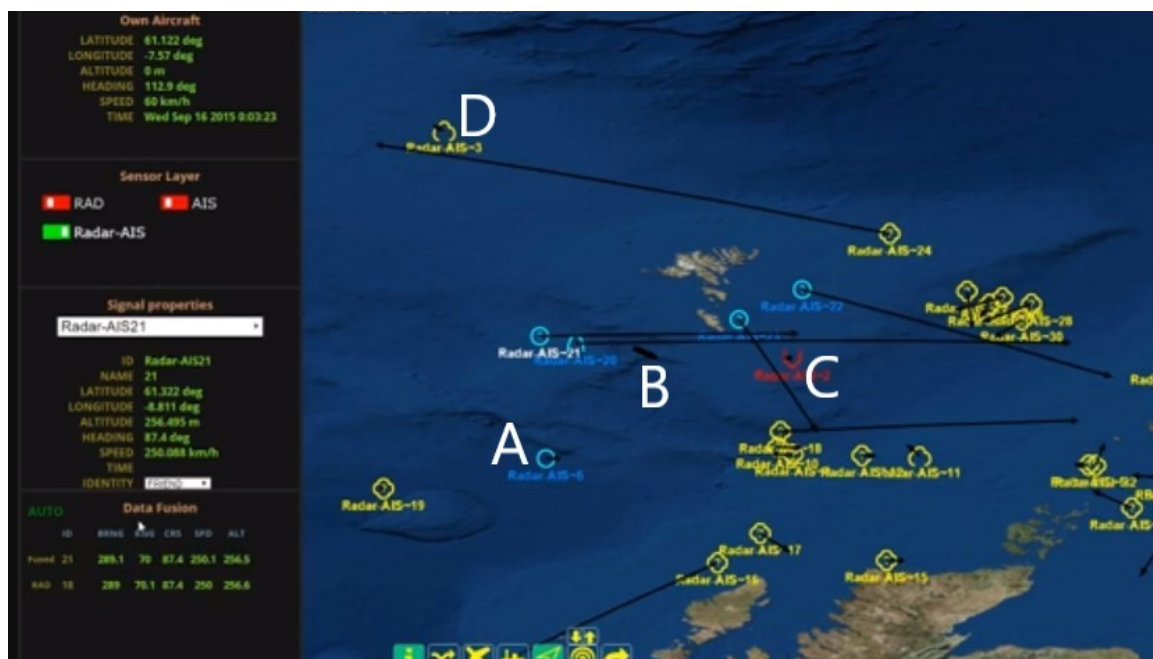


Figure 1. Simulator screen. A: Friendly contact (blue). B: Ownship (black). C: Hostile contact (red). D: Unknown contact (yellow)

Team members could click on tracks to see its attributes such as speed and heading and could classify them using a contextual menu. When a track was classified, its symbol changed accordingly to friendly, neutral, or hostile. The simulator also had controls to de-clutter the display by turning on or off the shipping lane / flight routes.

2.4. Task

Participants performed a picture compilation task where each team member had the shared map on their own workstation. The experiment was divided into four scenarios, each corresponding to one condition. In each scenario, participants had to classify tracks based on criteria such as speed and heading of the target, altitude (for air tracks), and whether the target follows commercial routes. Each property could be an indication of a friendly or hostile characteristic. For example, heading towards the participants' own ship was as a hostile characteristic whereas heading away from the ship was a friendly characteristic. There were five such characteristics for ships and four for planes. Participants had to classify tracks as friendly if it did not have any hostile characteristics, neutral if it had some, and hostile if it had more than three hostile characteristics. Additionally, participants had to consider any suspicious behavior such as sudden turns. These rules were provided during the training.

In conditions without classification automation, tracks appeared on the screen and were classified as unknown tracks. In conditions with classification automation, all tracks were pre-classified by automation. The classification automation labeled the tracks only as neutral or hostile and it was not able to integrate all criteria for classification, and this resulted in an average automation accuracy of 63 %. When the classification automation was present, participants had to "verify" the automation's decision by reclassifying the tracks. This was considered overriding the automation's decision, in which case the automation did not further classify that track.

In geographic sector-based role allocation conditions, one team member was responsible for classifying tracks to the west of their own ship, and the other team member to the east. In warfare domain-based role allocation conditions, one team member was responsible for classifying ships and the other team member planes. In each scenario, whether a track was an air or surface target was known as their symbols were different.

2.5. Procedure

The experiment consisted of a training session, followed by four main scenarios. The order of the scenarios was randomized. During the training, participants familiarized themselves with the task by completing several training missions. Before each scenario, participants were briefed on the automation capability and role allocation. Each scenario started with most of the targets appearing on the screen in the first few seconds. Participants had to work as a team (but also within their responsibility area) to classify as many tracks as possible. Each scenario was 10-minutes long. At the end of each scenario, participants completed a NASA-TLX (Hart and Staveland, 1988) questionnaire.

2.6. Measures

All performance measures were collected at the team level. Subjective mental workload (NASA-TLX) was collected for each individual using the weighting method described in Hart and Staveland (1988), then averaged to create a team mental workload score.

Human-automation system accuracy was the same as operator accuracy when the classification automation was absent (without classification automation conditions). When the classification automation was present (with classification

automation conditions), human-automation system accuracy consisted of both operator accuracy and automation accuracy.

2.7. Results

Data from one group was not recorded by the simulator, therefore we conducted the analysis with data from 13 teams. For data analysis, 2x2 repeated measures ANOVAs were used.

2.8. Classification Ratio

Fig. 2 shows the percentage of tracks classified by participants in each condition. Overall, participants classified almost all targets when the automation was absent and missing about 30 % when the automation was present. This difference was significant, $F(1, 12) = 27.72, p < .001, \eta^2 = .48$. There were no other differences, all p 's $> .05$.

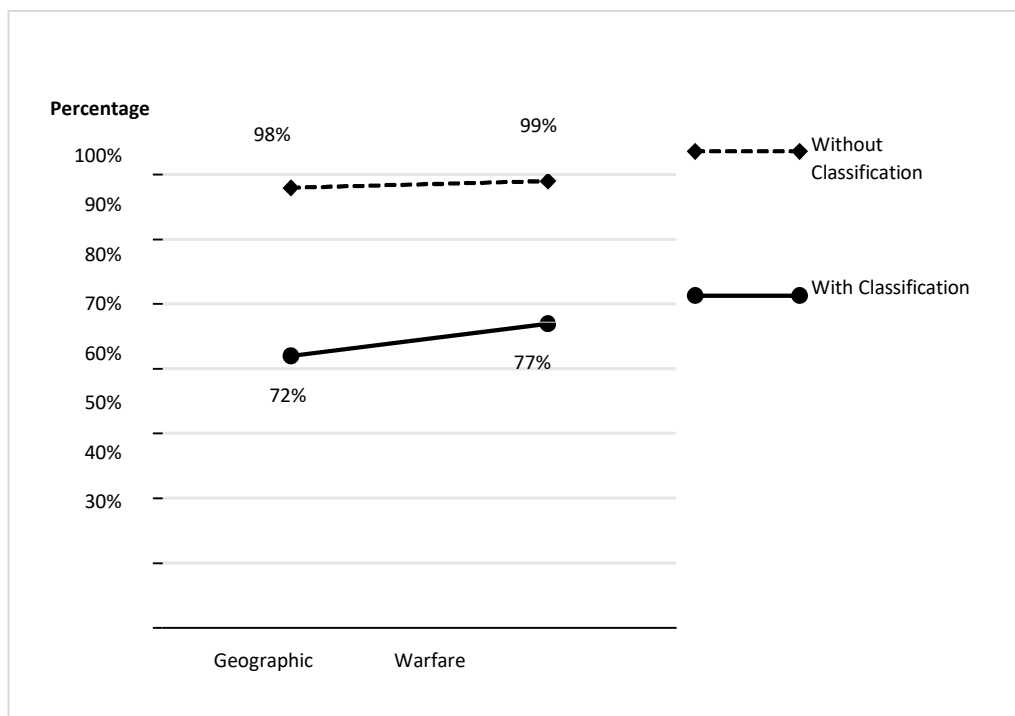


Figure 2. Percentage of tracks classified by participants

2.9. Operator Accuracy

As shown in Fig. 3, operator accuracy was higher without classification automation than with classification automation, $F(1, 12) = 14.28, p = .003, \eta^2 = .26$. No other effects were significant, all p 's $> .05$. Note that the reduced accuracy with classification automation condition takes into account the reduced percentage of tracks classified by participants.

2.10. Operator Accuracy for Classified Tracks

For tracks that were classified by participants, there was no significant difference in accuracy between conditions, all p 's $> .05$. In other words, when participants classified or verified, they performed similarly. The accuracies were 71 %, 70 %, 73 %, and 70 % for conditions 1, 2, 3, and 4, respectively (see Table 1 for the conditions).

2.11. Human-Automation System Accuracy

Fig. 4 shows the human-automation system accuracy results. For reference, the dotted line represents baseline accuracy of automation (i.e. if automation classifies all targets, it would be accurate 63 % of the time). Statistical tests showed no significant difference between conditions, all p 's > .05.

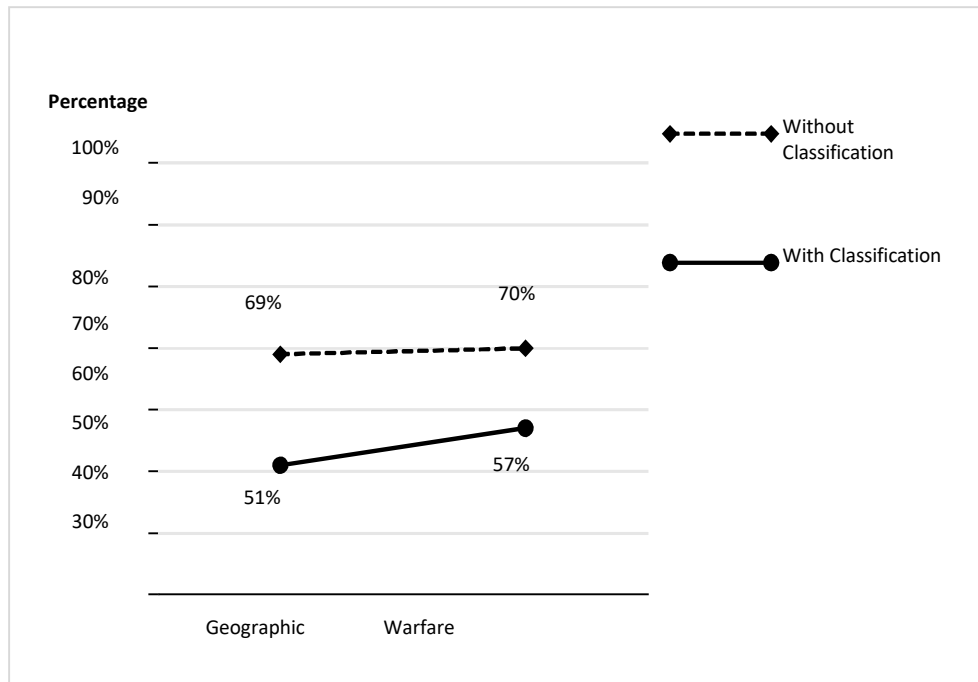


Figure 3. Operator accuracy

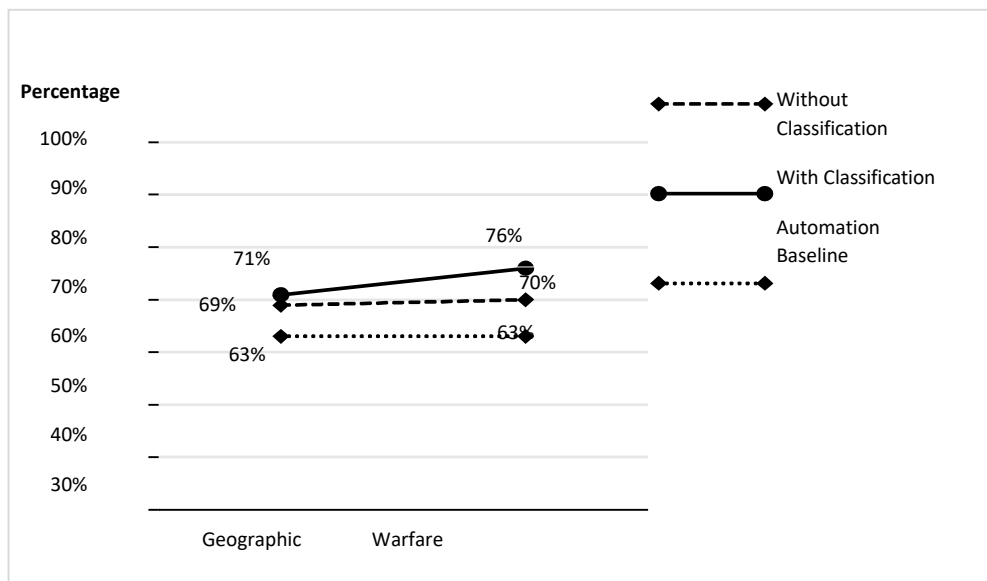


Figure 4. Percentage of tracks correctly classified by the human-automation system

Additional one-sample t-tests were conducted to compare all four conditions to baseline automation accuracy.

2.12. Average Time to Correctly Classify a Track

Participants were slower to correctly classify tracks with classification automation compared to without classification automation, $F(1, 12) = 13.83$, $p = .003$, $\eta^2 = .16$. There was also a significant interaction effect, $F(1, 12) = 4.92$, $p = .046$, $\eta^2 = .07$. As shown in Fig. 5, participants were faster in warfare-based role allocation with classification automation, however opposite effects were observed without classification automation.

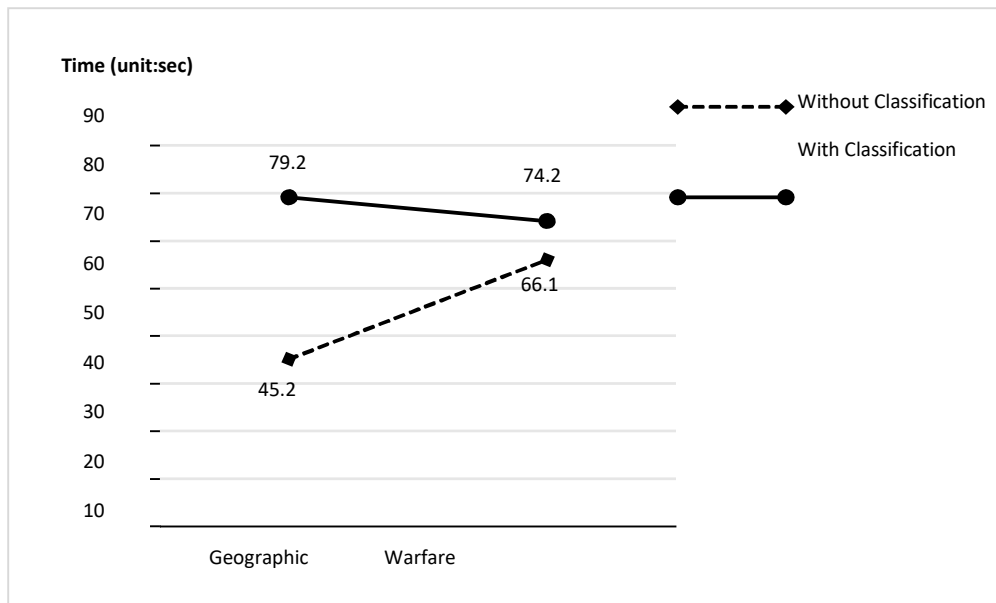


Figure 5. Average time participants spent to correctly classify tracks

2.13 Mental Workload

There were no significant differences between conditions. Mean NASA-TLX scores were 49.8 (SD = 21.4), 52.6 (SD = 20.7), 53.4 (SD = 19.5), and 51.9 (SD = 20.1), for conditions 1, 2, 3 and 4, respectively. Average NASA-TLX score was 52 across conditions, indicating a medium level of mental workload.

3. Discussion

Participants in this experiment performed a picture compilation task as teams of two with two levels of automation and in two team configurations. Results showed that participants classified fewer tracks with classification automation. However, overall human-automation system accuracy (human + automation) was similar across conditions. When participants were engaged with a track, they performed similarly regardless of the automation capability or role allocation.

3.1 Effects of Role Allocation

Overall participants were faster in correctly classifying tracks in warfare domain-based role allocation with classification automation, and opposite effects were observed without classification automation. While these results suggest that alternative

team configurations might be worth further investigation, the lack of differences in primary performance metrics suggests that role allocation had only minimal effect on team performance in this experiment and no effect on subjective mental workload.

3.2 Effects of Automation Level

Participants classified fewer tracks when automation support was present. It is possible that teams working with classification automation may have become complacent, as the tracks were already classified by the automation. Although participants were explicitly told to verify the automation, they may have been reluctant to reclassify the tracks.

Another explanation is that perhaps reclassifying automatically classified tracks requires more cognitive effort than classifying tracks in the absence of automation's suggestion. The differences in time to correctly classify tracks supports this notion. It is also possible that participants were looking for obvious anomalies or automation failures, therefore wasting time and overall classifying fewer tracks. Moreover, the automation in this experiment had low reliability and this likely negatively impacted team performance as team performance increases only if the automation has sufficiently high reliability (Hillesheim & Rusnock, 2016). Finally, the simulator did not have an action history functionality and participants had to remember which tracks need to be verified which might have contributed to the observed results. However, we should note that the participants had to monitor the contacts regularly after verifying the automation's decision. Therefore, a user interface element that draws attention to unverified contacts might have forced participants to ignore the contacts that were verified.

These findings require further research, as classifying fewer tracks would be a concern in a real-world situation, and the software used in this study was a representative industry product. One of the most important jobs of operators in an OPS room environment is to have a "clean" picture as fast as possible for a successful mission. Therefore, classifying fewer tracks, even though the accuracy is acceptable, is a concern. These findings indicate that automation should be carefully designed to avoid complacency effects such as the one observed in this study.

Finally, participants reported similar levels of mental workload across conditions. Working with automation did not reduce the mental workload, as is typically shown in the literature (e. g. Kaber & Endsley, 2004). We should note that verifying the automation's classification decisions required as much mental effort as classifying a track in the absence of a suggestion, if not more. Therefore, in this context, no change in mental workload means that reviewing automation's decisions did not result in extra mental effort.

Overall, these results are similar to the results observed in single human – automation studies. This work showed that teams are similarly at risk when a higher level of automation is introduced.

4. Conclusion

In this work, we explored how automation and role allocation affected performance of two-person teams in a simulated navy environment. Results revealed that role assignments did make minor differences in speed. Although the presence or absence of automation resulted in similar human-automation system performance,

human performance was worse in the presence of automation. This work supports the notion that adoption of automated decision support systems may not always result in better human performance, and further research is needed before introducing more capable automation into safety-critical environments.

(University of Waterloo Defense Research and Development Canada, First Published November 20, 2019).

URL: <https://journals.sagepub.com/doi/abs/10.1177/1071181319631501>

Words and word combinations:

- track [træk] – трек, дорожка;
- classification [ˌklæsɪfɪˈkeɪʃ(ə)n] – классификация;
- performance [prəˈfɔ:m(ə)ns] – производительность;
- allocation [æləˈkeɪʃ(ə)n] – распределение;
- condition [kənˈdɪʃənz] – условие, обстоятельство;
- picture [ˈpɪktʃə] – изображение;
- each [i:tʃ] – каждый, всякий;
- mental [ˈment(ə)l] – психический, умственный;
- such [sʌtʃ] – такой, таковой;
- workload [ˈwɜ:kləʊd] – рабочая нагрузка;
- experiment [ɪkˈspɛrɪmənt] – эксперимент, опыт;
- friendly [ˈfren(d)li] – дружественный;
- warfare [ˈwɜ:feə] – столкновение, борьба;
- significant [sɪɡˈnɪfɪk(ə)nt] – значительный;
- overall [ˌəʊvərˈɔ:l] – общий, полный;
- scenario [sɪˈnɑ:riəʊ] – сценарий;
- capability [keɪpəˈbɪlɪti] – возможность, способность;
- observe [əbˈzɜ:vɪd] – наблюдать;
- neutral [ˈnju:tr(ə)l] – нейтральный

Task 2. Summarize all the ideas of the article and write an essay.

Task 3. Make a presentation based on the article.

ЧАСТЬ IV. БЕСЕДА ПО СПЕЦИАЛЬНОСТИ

Summary

Task 1. Read the following instructions offered by Virginia Kearney, a university expert in writing essays (<https://owlcation.com/academia/How-to-Write-a-Summary-Analysis-and-Response-Essay>, 05.2019).

A summary is telling the main ideas of the article in your own words.

Steps in Writing

These are the steps to writing a great summary:

1. Read the article, one paragraph at a time.
2. For each paragraph, underline the main idea sentence (topic sentence). If you can't underline the book, write that sentence on your computer or a piece of paper.
3. When you finish the article, read all the underlined sentences.
4. In your own words, write down one sentence that conveys the main idea. Start the sentence using the name of the author and title of the article (see format below).
5. Continue writing your summary by writing the other underlined sentences in your own words. Remember that you need to change both the words of the sentence and the word order.
6. Don't forget to use transition words to link your sentences together. See my list of transition words below to help you write your summary more effectively and make it more interesting to read.
7. Make sure you include the name of the author and article and use “author tags” (see list below) to let the reader know you are talking about what the author said and not your own ideas.
8. Re-read your piece. Does it flow well? Are there too many details? Not enough? Your summary should be as short and concise as possible.

Sample Format

Author Tag: You need to start your summary by telling the name of the article and the author. Here are three examples of how to do that (pay close attention to the punctuation):

1. *In “How the Civil War Began,” historian John Jones explains...*
2. *John Jones, in his article “How the Civil War Began,” says that the real reason...*
3. *“How the Civil War Began,” by historian John Jones, describes....*

First Sentence: Along with including the article's title and author's name, the first sentence should be the main point of the article. It should answer the question: What is this essay about? (thesis).

Example:

In “How the Civil War Began” by John Jones, the author argues that the real reason for the start of the Civil War was not slavery, as many believe, but was instead the clash of cultures and greed for cash.

Rest of Summary: The rest of your essay is going to give the reasons and evidence for that main statement. In other words, what is the main point the writer is trying to make and what are the supporting ideas he or she uses to prove it? Does the author bring up any opposing ideas, and if so, what does he or she do to refute them?

Here is a sample sort of sentence:

_____ is the issue addressed in “(article's title)” by (author's name). The thesis of this essay is _____. The author's main claim is _____ and his/her sub claim is _____. The author argues _____. Other people argue _____. The author refutes these ideas by saying _____. His/her conclusion is _____.

Author Tag List

Author's Name	Article	Words "Said" for	Adverbs to Use With "Said"
James Garcia	“whole title”	argues	carefully
Garcia	“first couple of words”	explains	clearly
the author	the article (book etc.)	describes	insightfully
the writer	Garcia's article	elucidates	respectfully
the historian (or other profession)	the essay	complains	stingingly
essayist	the report	contends	shrewdly

Transition Words List

Contrast	Adding Ideas	Emphasis
Although	In addition	Especially
However	Furthermore	Usually
In contrast	Moreover	For the most part
Nevertheless	In fact	Most importantly
On the contrary	Consequently	Unquestionably
Still	Again	Obviously

Response

Response answers: What do you think? Does this article persuade you?

How to Write

Generally, your response will be the end of your essay, but you may include your response throughout the paper as you select what to summarize and analyze. Your response will also be evident to the reader by the tone that you use and the words you select to talk about the article and writer. However, your response in the conclusion will be more direct and specific. It will use the information you have already provided

in your summary and analysis to explain how you feel about this article. Most of the time, your response will fall into one of the following categories:

- You will agree with the author and back your agreement up with logic or personal experience.
 - You will disagree with the author because of your experience or knowledge (although you may have sympathy with the author's position).
 - You will agree with part of the author's points and disagree with others.
 - You will agree or disagree with the author but feel that there is a more important or different point which needs to be discussed in addition to what is in the article.
- How will this article fit into your own paper? How will you be able to use it?

Here are some questions you can answer to help you think about your response:

1. What is your personal reaction to the essay?
2. What common ground do you have with the author? How are your experiences the same or different from the author's and how has your experience influenced your view?
3. What in the essay is new to you? Do you know of any information the article left out that is relevant to the topic?
4. What in this essay made you re-think your own view?
5. What does this essay make you think about? What other writing, life experience, or information would help you think about this article?
6. What do you like or dislike about the essay and/or the ideas in the essay?
7. How much of your response is related to your personal experience? How much is related to your own worldview? How is this feeling related to the information you know?
8. How will this information be useful for you in writing your own essay? What position does this essay support? Or where might you use this article in your essay?

Sample Format

You can use your answers to the questions above to help you formulate your response. Here is a sample of how you can put this together into your own essay:

Before reading this article, my understanding of this topic was _____. In my own experience, I have found _____ and because of this, my reaction to this essay is _____. Interestingly, I have _____ as common ground with the author/audience. What was new to me is _____. This essay makes me think _____. I like/dislike _____ in the essay. I will use this article in my research essay for _____.

Vocabulary

article – статья;

summary – краткое изложение, конспект;

rendering – реферирование;

uncommon – редкий;

finding – находка, открытие, полученные данные;

to pay attention – уделять/обращать внимание;

conclusion – умозаключение, вывод;
to highlight – выделять;
to comprehend – понимать, осмысливать;
rough draft – эскиз, набросок;
firm grasp – четкое понимание;
assignment – предписание, инструкция, задание;
to explain – объяснять;
in plain language – простым языком;
referring to – ссылаясь на;
meaning – значение, смысл;
to convey – выражать, передавать (идею, смысл);
appropriate – подходящий, соответствующий;
to feature in – принимать участие;
concisely – кратко, сжато, лаконично, выразительно;
cut and paste – «вырезать и вставлять» (объемно цитировать без ссылки на источник, компилировать);
jumble – куча; беспорядочно сваленные в кучу вещи;
border on – граничить grade – оценка, отметка;
option – вариант, альтернатива; опция.

Task 2. Read and translate the text. Use its main ideas for rendering scientific articles:

How to write a Summary of a scientific article

Summarizing or rendering of a scientific article demonstrates your understanding of the material and presents this information to an audience that may not have a science background. It is not uncommon for a scientific article to describe an experiment and discuss its findings. To write an effective summary, you must be able to focus on the main ideas of the article. This also helps to understand scientific research better.

Instructions:

1. Read the entire article. Pay attention to the experiment methods and the conclusions presented. Read the article more than once, if necessary.
2. Look up any words or methods you do not understand.
3. Go through the article, and highlight its main ideas. Make sure you understand the main points in each paragraph. Take notes so you have a starting point for your summary.
4. Test your understanding of the article by asking yourself questions about it. Try explaining the concept of the article to a friend or family member in non-scientific language. Determine if you can clearly explain the article in a way that is easy to comprehend.
5. Start a rough draft of your summary, using the notes you've written. Review the article to ensure you have a firm grasp of the conclusion. Summarize the article's conclusion. Offer your own interpretation of the conclusion along with your opinion of the article's content.

Task 3. Look through the “George Mason University Recommendations” on the writing of a summary of a scientific article. Be ready to answer the questions:

This assignment is generally intended to help you learn to synthesize scientific materials and communicate the main points effectively, using plain language.

Start by making sure you understand the central points of what you read. Explain the article in plain language to someone else and answer questions without referring back to the article, to make sure you have grasped the essence of what you read. Dr. James Lawrey in the Biology Department uses this assignment to teach students to pick out the meaning of an article and convey the main points. The appropriate writing style for a summary of a scientific article is to use simple sentences that express one or two ideas. An example might be a story featured in the mainstream media that explains a recent scientific finding, bringing out the important aspects concisely and without too much scientific jargon. Do not “cut and paste” from the article. When students do not really understand what they read, their writing is a jumble of statements nearly straight from the article, with no interpretation or synthesis of the article's findings. This strategy is common among students who wait until the last minute to complete assignments. Besides the fact that this practice borders on or actually is plagiarism, it shows that students do not understand what they are writing about, and their grades reflect this.

Task 4. Answer the questions:

1. Who is James Lawrey? 2. What should you do at first while writing a summary? 3. Does the author limit the number of times his students should read the scientific article they are to summarize? 4. When do students use “cut and paste” function while writing a summary? 5. How do you understand the term “plagiarism”?

Task 5. Retell the Instructions on writing a Summary of a scientific article.

Task 6. Read the definition of summarizing/rendering in Russian. Try to remember as many set phrases as possible. Use them in the rendering of scientific articles.

Реферирование научных статей на английском языке – важный навык, необходимый любому современному инженеру. Суть реферирования можно свести к анализу прочитанной англоязычной работы с выделением ее главной идеи, описанием перечисленных автором фактов и доводов и подведением итогов. С этой целью можно использовать ряд вводных языковых конструкций.

1. Название статьи, автор, стиль. The article I’m going to give a review of is taken from... – Статья, которую я сейчас хочу проанализировать из... The headline of the article is – Заголовок статьи... The author of the article is... – Автор статьи... It is written by – Она написана (кем)... The headline foreshadows... – Заголовок приоткрывает...

2. Тема. Логические части. The topic of the article is... – Тема статьи это... The key issue of the article is... – Ключевым вопросом в статье является... The article under discussion is devoted to the problem... – Обсуждаемая статья посвящена проблеме... The author in the article touches upon the problem of... – В статье автор затрагивает проблему... I'd like to make some remarks concerning... – Я бы хотел(а) сделать несколько замечаний по поводу... I'd like to mention briefly that... – Хотелось бы кратко отметить, что... I'd like to comment on the problem of... – Я бы хотел(а) прокомментировать проблему... The article under discussion may be divided into several logically connected parts which are... – Статья может быть разделена на несколько логически взаимосвязанных частей, таких как...

3. Краткое содержание. At the beginning of the article its author... – В начале статьи автор... ...describes – описывает ...depicts – изображает ...touches upon – затрагивает ...explains – объясняет ...introduces – знакомит ...mentions – упоминает ...makes a few critical remarks on – делает несколько критических замечаний о The article begins (opens) with a (the)... – Статья начинается... ...description of – описанием ...statement – заявлением ...introduction of – представлением ...the mention of – упоминанием ...the analysis of / a summary of – кратким анализом ...the characterization of – характеристикой ...(author's) opinion of – мнением автора ...the enumeration of – перечнем In conclusion the author – в заключение автор ...dwells on – останавливается на ...points out – указывает на то ...generalizes – обобщает ...reveals – показывает ...exposes – показывает ...accuses / blames – обвиняет ...gives a summary of – дает обзор...

4. Отношение автора к отдельным моментам. The author gives full coverage to... – Автор полностью охватывает... The author outlines... – Автор описывает... The article contains the following facts.../ describes in details... – Статья содержит следующие факты / подробно описывает... The author starts with the statement of the problem and then logically passes over to its possible solutions. – Автор начинает с постановки задачи, а затем логически переходит к ее возможным решениям. The author asserts that... – Автор утверждает, что ... The author resorts to ... to underline... – Автор прибегает к ..., чтобы подчеркнуть... Let me give an example... – Позвольте мне привести пример...

5. Вывод автора. In conclusion the author says / makes it clear that.../ gives a warning that... – В заключение автор говорит / проясняет, что... / предупреждает, что... At the end of the article author sums it all up by saying ... – В конце статьи автор подводит итог всего этого, говоря... The author concludes by

saying that... / draws a conclusion that... / comes to the conclusion that... – В заключение автор говорит, что... / делает вывод, что... / приходит к выводу, что...

6. Выразительные средства, используемые в статье. To emphasize ... the author uses... – Чтобы акцентировать внимание ... автор использует... To underline ... the author uses... – Чтобы подчеркнуть ... автор использует To stress... – Чтобы усилить/подчеркнуть... Balancing... – Балансируя...

7. Ваш вывод. Taking into consideration the fact that – Принимая во внимание тот факт, что The message of the article is that... /The main idea of the article is... – Основная идея статьи (послание автора)... In addition... / Furthermore... – Кроме того...

On the one hand..., but on the other hand... – С одной стороны ..., но с другой стороны... Back to our main topic... – Возвращаясь к нашей основной теме... To come back to what I was saying... – Чтобы вернуться к тому, что я говорил(а)... In conclusion I'd like to... – В заключение я хотел(а) бы... From my point of view... – С моей точки зрения... As far as I am able to judge... – Насколько я могу судить... My own attitude to this article is... – Мое личное отношение к этой статье... I fully agree with... / I don't agree with... – Я полностью согласен / не согласен с... It is hard to predict the course of events in future, but there is some evidence of the improvement of this situation. – Трудно предсказать ход событий в будущем, но есть некоторые свидетельства улучшения ситуации. I have found the article dull / important / interesting /of great value – Я нахожу статью скучной / важной / интересной / имеющей большое значение (ценность).

Task 7. Retelling

Read text of the article several times. Work in pairs or groups. Divide text into parts, so that each group will have at least several sentences. Select the key words in the texts, type them in Word it Out (<https://worditout.com/>) and generate a cloud. Retell the story with the help of the generated word clouds. If two words need to be together, imagine “suffer from”, you only need to insert _ between the two words and they'll be kept together in the cloud.

Пример рассказа о научных интересах магистранта:

1. What is your name? – My name is Ivan Ivanovich Ivanov.
2. What educational institution did you graduate from? When? – I graduated from ...in 20...

3. What is your speciality? – My speciality is .../ My profession is ...

4. Why did you decide to take a post-graduate course? – I decided to take a post graduate-course because I had been interested in science since my 3-d year at the University / because scientific approach is very important in my profession.

5. What is the subject of your future scientific research? – The subject of my scientific research is ... – My future scientific research is devoted to the problem of ... – My future scientific research deals with the problem of ...

6. Who is your scientific supervisor? – My scientific supervisor is Ivan Petrovich Petrov, Professor, Doctor of technical/ economic sciences, Head of the Chair of ... / Head of the Department of ... – He has got a lot of publications devoted to the problem of ...

7. Have you ever participated in any scientific conferences? – Yes, I've participated in many conferences devoted to the most actual problems of economy/physics/geodesy/hydrology etc. – Not yet, but I hope, together with my supervisor, I'll prepare some reports for scientific conferences / I'll take part in several conferences in the near future.

8. Do you have any publications? – Yes, I've got some publications connected with my research. – Not yet, but I hope, together with my supervisor, I'll prepare some publications, they will be devoted to my research.

9. What methods are you going to use in your investigation? – Together with my supervisor we are going to apply such methods as theoretical, experimental, practical and computational methods because they will help me to complete my research.

10. What will your scientific research give the world? In what way can your investigation/research be useful to ... science?

– I think / I hope / I dare say that the problem of our scientific research is very urgent and our scientific research will be very useful for ... / it will help people in the field of ...

СПИСОК СОКРАЩЕНИЙ

сокращение	читается/означает	перевод
%	percent (per cent) [pə'sent]	процент
° C	degrees Centigrade	градус (Цельсия)
° F	degrees Fahrenheit	градус (Фаренгейта)
etc.	[et'set(ə)rə]	и так далее
e. g.	for example	например
i. e.	that is	то есть

Температура читается:

25° C – twenty-five degrees Centigrade ['sentigreɪd] (по шкале Цельсия);
34° F – thirty-four degrees Fahrenheit ['færənhaɪt] (по шкале Фаренгейта).

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