Bias in Cognitive Engineering for Human-Machine Teaming Literature

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Abstract - Machines have a plethora of applications in spaces dangerous, hostile, or high-risk to humans. Given such applications, the fields of human-machine teaming and cognitive engineering, while nascent, are developing at a staggering rate. At the heart of these disciplines is a doctrine espousing an agent-centric concept based on common properties shared between machines and human operators. Symbiotically, the goal is to ensure machine and human mutually benefit from the teaming. Yet, the literature has been fixated on system design and machine-agent optimization for performance. Thus, the literature appears to be biased as it does not consider the cognitive requirements of the human agent. The problem then, is that recommendations from the literature focus on changing the machine to instigate less demanding human participation rather than adapting the human to induce optimal machine participation. For this reason, this work examined what characteristics of human-machine teaming literature demonstrate a statistically significant relationship with the category of focus in the same research. The characteristics-as-variables included author discipline, count of publications in the field, author affiliation, gender, and country of origin. A multinomial regression revealed a significant relationship with focus on the machine element as opposed to the human element in human-machine pairing in the cognitive engineering literature. Furthermore, author discipline, affiliation, and country of origin, demonstrated a significant bias effect towards the machine element in human-machine pairing literature.

Keywords: cognitive engineering, human-machine teaming, bias, literature characteristics, regression

I. INTRODUCTION

The human-machine teaming (HMT) paradigm implies a dynamic whereby human and machine agents work toward a common end state (Ryan, 2018). Yet historically, anthropomorphic assumptions framed HMT research. That is, machines existed in such a framework to assist humans, rather than partner with them (McDermott et al., 2017; Hancock et al., 2011; Schaefer et al., 2017). As a result, the critical lens centered on system design. However, while system design as a technical engineering discipline improves machine performance, it does not inherently address the cognitive requirements of the human participant. The problem then, is that recommendations from HMT literature focus on changing the machine to instigate less demanding human participation rather than adapting the human to induce optimal machine participation.

We suggest the problem is worse because of the lack of comprehensive HMT research in the military, where the generic human agent in human-machine teaming becomes an individual Soldier agent (Ryan, 2018). In such scenarios, non-specific domain research is an abstraction at most. Thus, this study aims to disambiguate universal HMT literature by untangling bias. Specifically, the purpose of this study was to investigate the potential relationship between characteristics of existing HMT literature that may lead to bias toward optimizing the machine over the Soldier.

II. BACKGROUND

A. Human-Machine Teaming

Fundamentally, human-machine teaming is an agent-centric concept based on symbiotic properties.

Symbiosis, by definition, is achieved when both agents mutually benefit through one or more exchanges (Schaefer et al, 2014). Thus, an optimal state occurs when both agents accomplish intended incremental objective towards a common end state. Yet, HMT research biases toward the machine; the human is present in the equation only insofar as they are a recipient of the exchange. To that end, qualitative teaming analysis has limited itself to themes related to design content and concerns only the manipulation of the machine element (McDermott et al., 2017). In other instances, quantitative research minimized the role of human-related factors altogether (Hancock et al., 2011). Further, a recent meta-analysis highlighted the limitations of historical literature. Specifically, a lack of empirical research on human-machine interaction and subfield specificity constrains efforts to leverage the work against modern applications (Schaefer et al., 2017).

Accordingly, the updated descriptive model for HMT presented by Schaefer et al. (2017) is a more exact representation of the partnering dynamic natural in human-machine teaming arrangements. Such a model echoes complementary research seeking to expand conventional frameworks and consider such elements as intelligence, cognition, and autonomy, which are critical to machine intelligence advancement (Fong et al., 2001; Yagoda, 2012; UK Ministry of Defence, 2018). Yet, while Schaefer et al. (2017) made critical contributions to distinguish between human- and machine-focused characteristics and expand the role of the human in the interaction, the model remained binary and categorical. That is, demographic traits are expressly nominal; and states, cognitive factors, and emotive factors are all ordinal variables. In short, the findings do not capture the complexity and dynamism of modern, or future, human-machine teaming.

B. Considering Transhumanistic Philosophy

Given the bias emphasizing the machine portion of HMT, it naturally follows that research into human engineering for HMT is limited. There are a multitude of explanations for such bias. However, we feel the philosophical framework underlying HMT and human cognitive engineering (CE) is materially different and calls for examination as a first-cause principle. Interestingly, the potential philosophical frameworks align with the operational components in HMT.

Cognitive engineering implies a deliberate manipulation of human cognitive patterns for some specific benefit. As such, this study will consider cognitive engineering transhumanistically. Transhumanism rejects the concept of finality as it relates to human development (More, 2013). Specifically, transhumanists view technology as the primary means of progressing the human species along natural and artificial world continua (Bostrom, 2005). Thus, the philosophical framework of transhumanism is tightly coupled to human cognitive engineering.

Conversely, it appears that the bias towards the machine in general HMT is more closely associated with post-humanistic thought. Where transhumanism holds the transcendence of humans through technology as a central tenet, posthumanism is a philosophical correction to such anthropocentrism. In other words, posthumanism holds non-humans as capable of cognition as humans (Wolfe, 2009). Certainly, the focus on the machine- at a minimum, even as a mediating construct- in HMT literature associates strongly with posthumanism philosophy.

Accordingly, this paper adopts Woods and Roth’s (1988) definition of cognitive engineering as a creative discipline based in applied science. That is, cognitive engineering is human behavioral design aimed at improving participation in complex systems (Woods & Roth, 1988). Consequently, the transhumanistic approach to HMT places the onus of active participation as much on the human as the machine (insofar as it is the addition of the machine that engenders the expansion of human ability). Such a concept is essential to the idea that successful human-machine teaming is not necessarily a technical re-engineering of the machine but rather a cognitive re-engineering of the human vis-à-vis technology.

C. Principles and Military Applications

The theoretical architecture of cognitive engineering describes the mechanisms that bound the application of cognitive science in a given domain. Specifically, we inferred from Woods and Roth (1988) that the machine is part of the domain world, not a tool within it. As such, “one must understand how representations of the world interact with different cognitive demands imposed by the application world in question and with characteristics of the cognitive agents, both for existing and prospective changes in the world” (p. 424). Here, the benefit of cognitive engineering in the military HMT space is in its ecology (Vicente, 2002). That is, it applies specifically to the “multidimensional, open world” inherent in military operations whereby multiple cognitive agents work in tandem (Woods and Roth, 1988, p. 418).

Moreover, CE emphasizes contextual knowledge acquisition, meaning that it accounts for the semiotic and semantic distinctions intrinsic to a given domain (Woods & Roth, 1988). For example, military terrain analysis and tactical communications act as unique delivery systems for domain-specific semiotics. Similarly, plain English code words hold one meaning to the agent, analyst, or operator while conferring a different meaning to the civilian. What makes this contribution particularly important to military HMT is that it alleviates the focus on individual objects in the space and instead focuses on "changing behavior [or] performance in that [space]" (Woods & Roth, 1988, p. 419).

By adopting Woods and Roth's (1988) framework, the main differentiate between machine-centric approaches to HMT engineering and the transhumanistic one becomes introspection. That is, the ability of the participant to understand their own active and passive participation in the world (Halff, Hollan, & Hutchins, 1986; National Research Council, 2008; Sherlin et al. 2011). Such a concept echoes the Army's recent adoption of learner-centric environments and upholds existing cognitive training doctrine (TRADOC, 2017). Thus, the goal of cognitive engineering is to achieve the mental functions and expertise outlined within the HMT world: situational recollection, holistic recognition, intuitive decision making, and absorbed awareness.

In a model where the human and machine are cohesive domain actors in the same world, the symbiotic end state is one in which humans and machines execute intuitive functions naturally, while simultaneously working cooperatively toward logical functions. To carry out such parallel and convergent task orientation, the military adopted the Boyd decision making model, known colloquially as the *OODA loop* (Clarke & Knudson, 2018). The OODA model's integration into the military organizational system rests in its alignment to military measures of effectiveness (MOE). That is, the goal of both OODA and MOE is to manipulate the predicted future world toward a specific end state, just as cognitive engineering is founded on the principle of changing behavior (Woods & Roth, 1988; Clarke & Knudson, 2018). When taken together, the resulting theoretical framework already supports CE for military applications.

D. Military Cognition

Thus, imperative to the practical application of CE for HMT are (a) viewing both the machine and human as domain agents of the same world; (b) acknowledging HMT as a continuous endeavor toward a given end state; and (c) recognizing end state relevancy as the sum of its parts. In fact, existing literature draws direct links between CE and successful military training (Halff, Hollan, & Hutchins, 1986; Noble, 1989; Blacker et al., 2018). Further still, cognitive science is regularly applied to training domains outside the scope of military intervention (Simons et al. 2016; Strobach & Karbach 2016). Notwithstanding, Blacker et al. (2018) differentiate military CE from other domains, noting, "outcomes for multifaceted skills [are especially important], as military operations inevitably require coordination of multiple cognitive abilities. For example, there is not one specific laboratory-based task that encompasses all components of room clearing, piloting a military aircraft, or navigating a ship" (p. 3). Thus, the cognitive requirements in a military population are innately distinguishable from other populations (Blacker et al., 2018). Accordingly, military cognitive engineering must account for the unique demands of service members.

III. Method

We sought to answer a single research question: what characteristics of HMT literature (e.g., author, scientific discipline, etc.) demonstrate a statistically significant relationship with the type of HMT research (e.g., machine-focused). To that end, we operationalized six characteristics of HMT literature as variables. Moreover, we grounded the characteristics by adopting those illustrated by Elamrani and Yampolskiy (2019) and used by Norris (1997) to relate those characteristics to bias. Such characteristics include author discipline, count of publications in the field, author affiliation, gender, and country of origin. Where one or more characteristics are unknown, it is indicated.

A. Coding

Author discipline was coded by the author's self-identified area of research in available profiling, including either within the publication or available on their public page. *Count of publications in the field* was calculated by counting all publications associated with the author's name, regardless of author position. *Author affiliation* was determined first by the affiliation listed on the publication; when no affiliation was listed on the publication or by the publishing authority, affiliation was determined by the author's current professional or academic position or role. *Gender* was coded as binary and represented only male or female. *Country of origin* was based on the origin of the author's affiliation.

Furthermore, we identified three types of research: *Machine-focused*, *Human-focused*, and *Hybrid*. To identify these types, we measured the frequency of related keywords in each piece of literature. We interpreted a frequency of greater than 51% to indicate majority and thus type. A frequency in which machine and human keywords were evenly split was a hybrid type. For example, keywords were associated with each code (machine-focused, human-focused, and hybrid), such that *machine*, *computer*, *system*, *robot* represented machine-focused terminology while human encompassed terms such as *human, person, people, Soldier*.

B. Population and Sample

The initial sample of relevant HMT literature consisted of the entire online archive of EBSCO studies specific to eight search queries ("human machine teaming", "human robot teaming", "human machine systems", "human machine trust", "human automation trust", "human machine cognitive engineering", "human machine design", and "human robot interaction and behavior"). We selected only those studies which were published in an academic journal and had relevant search engine ranking. When search engine ranking was taken into account, the population size decreased from 1,051 to 201. In addition to the ESCBO search, the review also included the entire online archive of Google Scholar results as of January 1, 2014 (6,300) specific to the search query "human machine teaming". The results were further refined by search engine ranking. As such, our analysis was restricted to 118 studies or 47% of the relevant population. We excluded foreign language literature as language translation would have been outside the scope of this study and, without such, we would not have been able to properly code for "type of research".

C. Analysis

Once the studies were coded, we generated descriptive statistics and followed with a multinomial logistic regression (Gayle, Lambert, & Davies, 2009) as a predictive analysis technique to determine what characteristics of HMT literature (e.g., author, scientific discipline, etc.) demonstrated a statistically significant relationship with the type of HMT research (e.g., machine-focused). Such a technique was most appropriate given the type of dependent variable in the study. Additionally, the use of multinomial logistic regression supported the complex, psychological nature of the research question.

Since this study posits that there is underlying bias in the literature, logistic analysis appropriately disambiguates the relationship between the dependent variable (bias) and its associated indicator variables (author discipline, count of publications in the field, author affiliation, gender, and country of origin). Further, because we identified five potential indicators, a multinomial logistic regression specifically fit our data analysis needs. Coded data were imported into IBM SPSS and the appropriate function executed. Then, the bias prediction results were assessed to be significant only when $p \leq 0.05$ (bias exists or does not exist) for both the overall model and for individual indicator contribution to the model.

IV. Results

The general question we sought to answer was whether author discipline, publication count, institutional affiliation, gender, and country of origin might be predictors for the apparent bias of published cognitive engineering literature focusing on the as opposed to the human element in human-machine pairing. Ultimately, we found our overall model fit our conjectured outcome wherein three of the five individual factors demonstrated statistical significance. The following sections present the descriptive and quantitative findings.

A. Description of Literature and Factors

The literature we collected focused on topics that related human cognitive engineering and machines. That is, the research examined only those publications that sought to explore the relationship between organic and artificial agents. Once the sample was selected, factors were extracted from the literature and processed per our research protocol. The results are as follows.

1) Author Discipline

We found a total of 73 author disciplines in the sample of literature. The percentage of authors associated with these fields ranged from 0.2 percent (one author) to 17% (73 authors). There were 31 disciplines showing a 0.2 percent representation whereas there were 21 disciplines with one percent or greater representation.

2) Publication Count

Next, we observed author *publication count* (Table 1) as being diverse (M = 70.4, SD = 121.67) with the minimum number of publications being one and the maximum being 1,190. Further, the majority of authors had publication counts in the one to one-hundred range (80%) out of 421 total authors. The median was 25 and the mode was one.

TABLE I. NUMBER OF AUTHORS WITH PUBLICATION COUNTS CATEGORIZED BY HUNDREDS

	1-100	**101-200**	**201-300**	**301-400**	**401-500**	**501+**
Machine	164	24	7	4	5	2
Human	100	8	4	2	2	1
Hybrid	73	10	6	4	4	1
Totals	337	42	17	10	11	4

3) Affiliation

Following publication count, we examined the *authors' affiliation*. The distribution of this variable favored University affiliations. That is, the majority of authors were publishing for a University or as representatives of a University (%). This was followed by U.S. military agents (%) and Industry (%). Industry reflects any commercial or private, non-research-based entity.

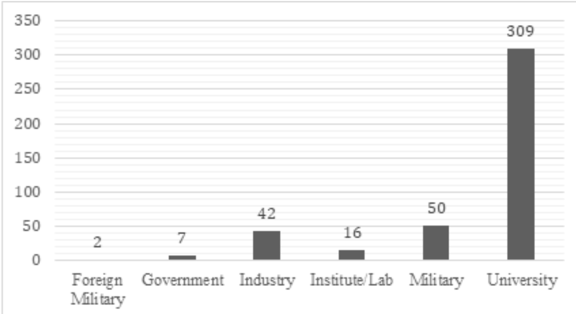


Fig. 1. The distribution of author affiliation by professional category

4) Gender

Gender is represented as a binary categorical variable. Of known author gender, there were 223 males and 115 females. As such, men represented 66% of authors in this space. While both men and women favored machine-centric research, the distribution within each gender for human- and hybrid-focused research differed. Specifically, the male variance between human- and hybrid-focused research was negligible (56 compared to 57, respectively). Comparatively, women were more likely to publish human-focused literature (38 authors compared to 27).

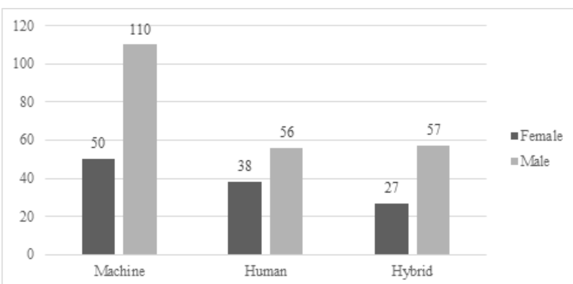


Fig. 2. The distribution of author gender categorized by bias coding

5) Country

Country of origin was based on the origin of the author's affiliation. That is, the country factor is representative of the strength of the author's professional or academic ties (i.e. affiliation), rather than their birth place. The decision to code country based on this methodology was to prevent the disclosure of PII related to an author's birth record. The decision also mitigated validity risks since birthplace identification is not a readily publicized or available piece of information.

There were 427 counts of Country. The United States was represented in a plurality of the literature, with 203 associations (48%). This was followed by China (11%), Italy (6%), Japan (6%), Australia (4%), the United Kingdom (4%), and Germany (3%). The remaining countries accounted for less than 10 codes each.

6) Factors and Relationships

We identified five potential factors which we operationalized as predictor variables: author discipline, publication count (in the field), institutional affiliation, gender, and country of origin. None of the variables were transformed during the logistic regression process. Procedurally, we first analyzed the overall model and then proceeded to examine individual variables. The results are detailed in the following subsections.

7) Overall model evaluation

The overall model appeared to fit our conjecture, based on the research methodology and analysis protocol (Table 2). That is, the identified predictors fit within the stated model more positively compared to the null model. Granted, the ultimate validity of the model was limited by the sample size; however, the results exhibit a foundation for inference insofar as there is a measured effect at work given the selected variables. Determining which specific variables were involved constituted the next step.

TABLE II. MULTINOMIAL LOGISTIC REGRESSION FOR OVERALL MODEL

Model	-2 Log Likelihood	Chi-square	df	Sig.
Intercept Only	841.110			
Final	137.240	703.870	482	.000

8) Predictor variables

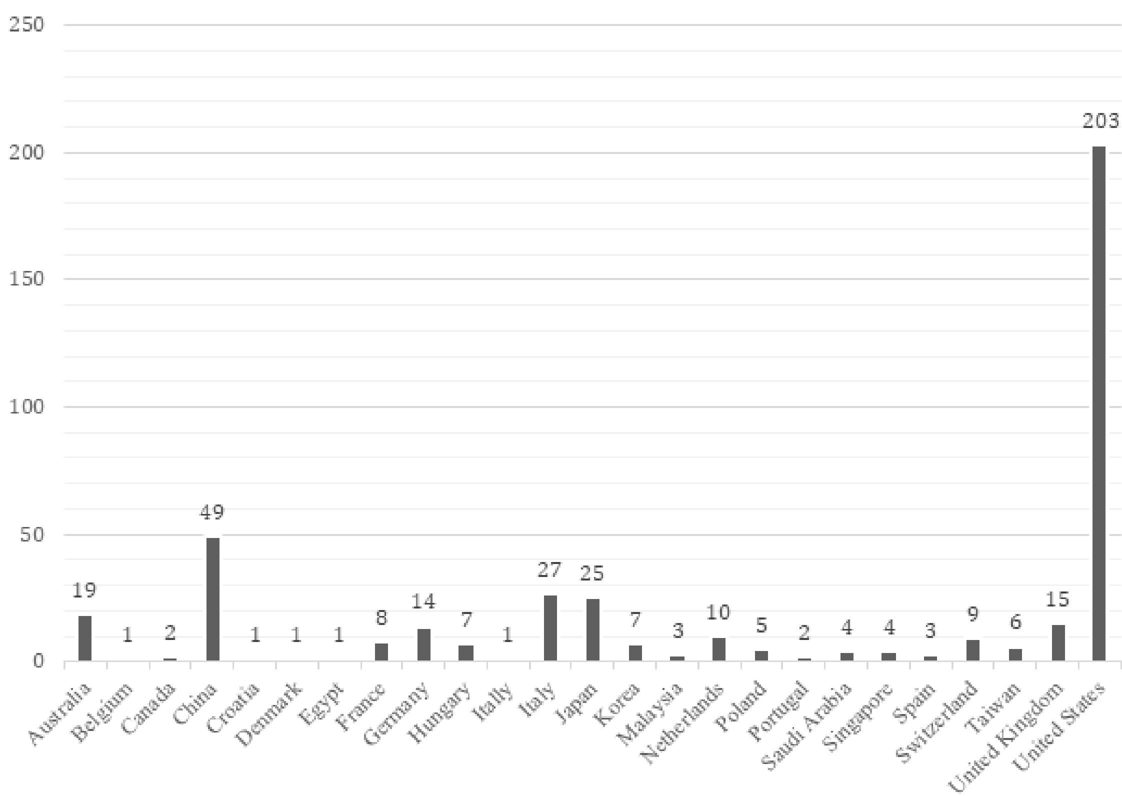
The multinomial logistic regression of the variables (Table 3) revealed three of the five with a significance less than 0.05. More specifically, the discipline, affiliation, and country of origin associated with authors demonstrated significant effect on the outcome of the analysis. Within the context of this work, the results point at a positive bias towards the machine element in human-machine pairing literature.

TABLE III. MULTINOMIAL LOGISTIC REGRESSION OF PREDICTORS VARIABLES

Effect	-2 Log Likelihood	Chi-square	df	Sig.
Intercept	137.240	.000		
Discipline	351.879	214.639	132	.000
Pub Count	368.754	231.514	268	.948
Affiliation	163.794	36.553	16	.047
Gender	139.268	2.027	4	.731
Country	204.970	67.730	40	.004

V. CONCLUSIONS

The Human Machine Teaming domain is researched and applied through an anthropomorphic lens that emphasizes system design over cognitive engineering (McDermott et al., 2017; Hancock et al., 2011; Schaefer et al., 2017). The subsequent focus on using machines as a *tool* to help humans, without the requisite reengineering of the human cognitive space



to effectively partner with machines, is further exacerbated in the military space. When examining various agent actors, such as Soldiers, the specificity of the environment must be considered.

To that end, the importance of human-machine teaming and cognitive engineering should not be underestimated. Ensuring machine and human agents mutually benefit from teaming is not just a hope but a necessity for the nascent disciplines to solidify the

Fig. 3. The frequency of authors country of origin based on the author's affiliation.

underlying doctrines. However, the literature has fixated on system design and machine-agent optimization for performance in lieu of maintaining a holistic perspective.

As a means to bolster such a perspective, we sought to answer a single research question: *what characteristics of HMT literature (e.g., author, scientific discipline, etc.) demonstrate a statistically significant relationship with the type of HMT research (e.g., machine-focused*. To that end, we operationalized six characteristics of HMT literature as variables: author discipline, count of publications in the field, author affiliation, gender, and country of origin. We then identified three types of research: *machine-focused, human-focused*, and *hybrid*. Once our research methodology and protocol were established, we conducted a multinomial logistic regression. The model was then formulated with the identified dependent and indicator variables and fit using maximum likelihood estimation within IBM SPSS. Results show that discipline, affiliation, and country of origin associated with authors demonstrated significant effect on the outcome of the analysis. Within the context of this work, the results point at a positive bias towards the machine element in human-machine pairing literature.

As such, we posited that the machine is part of the domain world, not a tool within it (Woods & Roth, 1988). Therefore, research bias inconsistent with this position is detrimental to the effective advancement and execution of HMT. Yet, our model demonstrates that bias does exist in the HMT literature. What is not clear in these findings is what the potential effects of such bias may be to ongoing research and field applications.

Certainly, bias toward machine-centric research, at the expense of efforts to augment human cognition, limits the possibility of meaningful advancement in HMT. Specifically, the current paradigm places undue emphasis on machine engineering or human engineering. Consequently, the transactional framing of machines solely as a tool for humans creates a ceiling whereby machine-human trust is constrained by the limits of human anthropocentricism. Rejecting such posthumanistic views will bring human-centric HMT research into parity. The resulting shift will empower developers to move beyond system design and machine-agent optimization to unlock beyond the horizon advancements in the field.

Looking beyond, approaching parity in the human versus machine research point of view may empower additional but related research pathways. For example, machine learning has long been haunted by a black box decision making problem. That is, existing machine learning systems are unable to express why a decision is made within the set of plausible decisions. Whereas common techniques are geared towards having machines explain internal decisions, perhaps more success might be had if a teamed human were able to directly query the machine.

On a similar note, because of the possible existential risks posed by advanced machine intelligence, containment or boxing is a crucial topic. Understandably machine intelligence is central to this research at the cost of exploring how humans interface with the containment. However, containment by its nature limits or prevents interactions between machine and human. In addressing the bias towards machine-centric cognitive engineering, some answers for how humans and machine intelligence interact across containment may become clearer.

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