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Published Online: June 2, 2020

Software Program, Bot, or Artificial Intelligence? Affective Sentiments across General Technology Labels

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ABSTRACT

People may refer to technologies by a range of general descriptions, which may differ not only in definition but also by affective sentiment– evaluation, potency, and activity. We measured the affective sentiments, agency, and frequency of use for 25 common technology terms. We find that respondent's familiarity with technologies relates to perceiving them as increasingly good, while they perceive advanced technologies as less good. Additionally, respondents perceive physical technologies as more powerful and active than digital ones. These data extend affect control theory, allowing for social interaction simulations with computer agents in addition to humans.

INTRODUCTION

In recent decades, technology widely differs in what it looks like, how it functions, and the purpose it serves. This rapid development has caused society to generate a glut of new labels to identify different groupings or functions of technologies – what we refer to as general technology labels. The terms *bot*, *computer program*, and *artificial intelligence* might be used to label different technologies with different purposes and functions, for example based on their autonomy, physicality, or sophistication. Yet all three labels are also commonly used for the exact same technology (e.g., *a chat bot, a chat software program, a chat AI*), suggesting that the selection of one term over another might be due more to its affective meaning than any specific functionality. Perhaps *a bot* signals more agency and activity compared to *a computer program* while *an artificial intelligence* may signal more power. Our purpose herein is to consider how traditional versus advanced (i.e., autonomous or intelligent) technology labels and digital versus physical technology labels systematically relate to their affective meaning. This contributes to classifying types of technology by affective perceptions and to affect control theory's capacity to model interactions between humans and technological actors.

AFFECTIVE SENTIMENTS

As humans socially interact with other humans, their cumulative experiences enable them to develop sentiments – general affective responses – towards the labels and identities of others. Three well-established sentiment dimensions are evaluation, potency, and activity (Scholl 2013). Evaluation encapsulates moral goodness, warmth, and pleasantness, potency refers to social power and physical strength, and activity relates to energy level, liveliness, and intensity (Heise 2010, Osgood, Suci and Tannenbaum 1957). These measures are stable and universal constructs across cultures, despite variance between cultures on specific terms (Osgood, May and Miron 1975). They are important in understanding how people socially interact, including how people pick up on verbal and non-verbal cues, understand emotions, and interpret behaviors (Scholl 2013).

Prior research collects quantitative measures of sentiments using individual surveys asking subjects about their feelings towards human identities, behaviors, emotions, and potentially objects such as technology (Heise 2010, Osgood, May and Miron 1975).The present study utilizes this method in which participants rate a term on scales of evaluation, potency, and activity ranging from -4.00 to 4.00. Anchors are used to express the scales with *bad and awful* to *good and nice* for evaluation, *powerless and weak* to *powerful and strong* for potency, and *slow, quiet, and inactive* to *fast, noisy, and active* for activity. Each scale is further divided using nine equidistant adverb markers labeled *neutral* (0), *slight* (±1), *quite* (±2), *extremely* (±3), and *infinitely* (±4). Collected scores from each dimension are then averaged, generating a final score that depicts the general sentiments of the sample population for each term (Heise 1970, Heise 2010).

Affect control theory – a mathematically-grounded symbolic interactionist theory of social interaction and perceptions – uses these sentiments to predict how people will socially interact based on their affective impressions. Affective sentiments are based on a culture's perceptions of labeled identities, while affective impressions are based on a specific person in the context of an unfolding social interaction. However, affect control theory is modeled for and traditionally applies to humans engaged in a social interaction, so most data collection of sentiments of labels involve human identities, behaviors, traits, emotions, and settings. Collecting data on technological labels opens up the possibility of integrating technological actors with affect control theory (Shank 2010, Shank and Lulham 2016).

AFFECTIVE SENTIMENTS OF TECHNOLOGICAL ACTORS

Present day technology grants us with increasingly anthropomorphic, multifaceted designs from the voice responsive personal assistant Alexa to seemingly autonomous advertising bots. When a technology includes anthropomorphic cues like a voice, face, or body, this tends to increase social interaction and trust (Gong 2008, Waytz, Heafner and Epley 2014). Yet evidence from over 25 years of research shows people often behave toward technology socially even when it possesses no anthropomorphic cues (Nass and Moon 2000, Reeves and Nass 1996). People do not have to believe a technology is sentient, attribute it mind, or anthropomorphize it to respond in social-psychological ways to it, including forming affective sentiments and impressions of it (Shank 2010, Shank 2014).

Originally, datasets of affective sentiments included many non-human, non-technology terms such as *free will*, *pencil*, and *sin* (Osgood, May and Miron 1975) although most affect control theorists collect human identities, social behaviors, and human modifiers. However, collections of affective sentiments can be conducted on specific domains such including technology. Affective sentiments have been collected for online identities, behaviors, and settings (e.g., *chatroom, newbie, surf the web;* King 2001), for terms of human-computer interaction (e.g., *computer, run analysis;* Troyer 2004), and for common technological actors and behaviors (e.g., *DVD player, smart phone, Mustang, to cyber attack;* Shank 2010, Shank and Lulham 2017).

Cultures have some consensus on technological concepts, yet the level of agreement is not as strong as human concepts given the ever changing nature of technology (Shank 2010). The affective sentiments of technology share both similarities and differences from those of human concepts. One similarity is that the sentiments of technology can modify the impression of human identities (e.g., *a salesclerk with a Mustang*) via a similar process as emotion and trait modifiers (Shank and Lulham 2017). One difference is weaker affective attributions: that autonomous computer agents are perceived as less potent than autonomous humans, and restricted computer agents are perceived as less impotent than restricted humans (Shank 2014).

What has yet to be explored is the affective differences within technology based on its general technology label. We suggest that (**H1**) advanced technology may be less familiar thereby leading to lower ratings of evaluation (Shank 2010, Zajonc 1968). However, (**H2**) advanced technology should also be perceived as more agentic (Gray and Wegner 2012, Shank and DeSanti 2018) leading to greater potency and activity (Shank and Burns 2018). (**H3**) Physical technology, in contrast to digital, should be perceived as more agentic (Gray and Wegner 2012, Shinozawa et al. 2005), again leading to greater potency and activity (Shank and Burns 2018). Finally, while not a hypothesis, we will explore whether the affective sentiments of general technology labels are similar to those of general human identities.

METHODS

After creating a list preliminary list of 53 promising general technology labels, we eliminated any term that was neither listed at techterms.com, techopedia.com, nor generated a million+ hits on a Google search. We also eliminated terms that were too domain specific (e.g. *a cellular phone*) and selected one among pairs that were extremely similar (e.g., *software program* vs *computer program*). The final 25 terms differed by whether they are clearly digital or physical (or either/both) and if they are an autonomous and/or intelligent technology versus neither, which we refer to advanced versus traditional (Table 1).

Table 1: Categories of the general technology labels.

	Digital	Digital and/or Physical	Physical
Traditional	*website, app, software application, software program, software app*	*computer interface, digital interface*	*computer, laptop, device, machine, computer system, hardware system*
Advanced	*sim, software agent,*	*bot, artificial*	*smart device,*

	intelligent agent	*intelligence, automated system, autonomous system*	*android, robot, humanoid robot, autonomous robot*

Paid Amazon Mechanical Turk participants took a Qualtrics survey where they rated each term on evaluation, potency, and activity on the scales detailed above. Additionally, they rated them on autonomy (*How often does __ act on its own?*), intentionality (*How often does __ appear to act intentionally?*) and familiarity (*How often do you hear the term "__"?*), all on 5-point scales from *Never* (0) to *All the time* (4) or *Unsure* (excluded). Autonomy and intentionality ($r=0.96$, $p<0.001$) were averaged to form agency.

Of the 66 initial participants who lived in the US for more than half their lives and completed at least 60% of the items on the survey, seven were removed for a polarity of affective ratings of less than .6, meaning all their ratings were near 0 (Shank and Burns 2018).

RESULTS

Affective Sentiments, Agency, and Familiarity

Technology's agency was negatively correlated with both evaluation ($r=-0.55$, $p<0.01$) and familiarity ($r=-0.47$, $p<.05$). As expected, evaluation and familiarity were positively correlated ($r=0.52$, $p<0.01$) and potency was positively correlated with both activity ($r=0.79$, $p<0.001$) and approached significance for agency ($r=0.37$, $p<0.1$). The correlation of agency to potency is quite high in other research (Shank and Burns 2018), but here diverges based on the differences in traditional and advanced concepts (analysis below).

The mean ratings across terms were slightly-to-moderately positive for evaluation (1.29), potency (1.05), and activity (0.52; Table 2). The lowest ratings were just barely negative on all three dimensions (-0.376, -0.071, -0.254, respectively) whereas the highest were near +2 (2.107, 1.768, 1.737, respectively). Only *a bot* was negative in evaluation (-0.376; see Appendix), only *a sim* was negative in potency (-0.071), and only *an app, a digital interface,* and *a website* were negative in activity (-0.254, -0.030, -0.053). Yet all of these technology labels were only slightly negative in absolute terms.

Table 2: Means, standard deviations, minimum, and maximum across all concepts for all measures.

	Mean	SD	Minimum	Maximum
Evaluation	1.291	0.526	-0.376 a bot	2.107 a laptop
Potency	1.051	0.477	-0.071 a sim	1.768 a computer
Activity	0.519	0.497	-0.254 an app	1.737 a machine
Agency	1.848	0.522	1.129 a laptop	2.796 an autonomous robot
Familiarity	2.579	0.611	1.476 a software agent	3.458 an app

Average agency was below its midpoint (1.848; Table 2) while average familiarity was above it (2.579). Even the lowest familiarity rating for *a software agent* was nearer the midpoint rather than the end of the scale (1.476) whereas *an app*, with the highest rating, was closer to the top of the scale (3.458). Agency ratings were less extreme and were all in the middle quartiles of the scale.

Affective Sentiments across General Technology Labels Categories

We conducted T-tests for each measure comparing the categories of physical versus digital and traditional versus advanced (Table 1). Supporting H1, respondents rated traditional technologies as higher in evaluation (1.595) than advanced technologies (0.961; $t(23)=3.734$, $p< 0.01$; Table 3) and they were also more familiar with them (Traditional: 2.891, Advanced: 2.240; $t(23)=3.102$, $p<0.01$). Respondents were highly familiar with traditional technologies terms (2.053 to 3.458) and felt they were slightly-to-quite good (1.230 to 2.107). Yet, they were only moderately familiar with advanced technology terms (1.476 to 2.948, except *a smart device* at 3.190) and felt they were neutral to slightly good (-0.376 to 1.274, except *a smart device* at 1.878).

Table 3: Means per category for all measures and select T-test comparisons.

	Means				
Category	Evaluation	Potency	Activity	Agency	Familiarity
All	1.291	1.051	0.519	1.848	2.579
Digital	1.284	0.634	0.121	1.686	2.571
Digital and/or Physical	0.957	1.043	0.393	2.166	2.291
Physical	1.441	1.388	0.911	1.816	2.692
Traditional	1.595	0.974	0.441	1.436	2.891
Advanced	0.961	1.134	0.604	2.295	2.240
	T-tests				
Comparison	Evaluation	Potency	Activity	Agency	Familiarity
Digital v. Physical	-0.767	-4.453***	-4.820***	-0.635	-0.390
Traditional v. Advanced	3.734**	-0.831	-0.816	-7.418***	3.102**

***p≤.001, **p≤.01, *p≤.05, †p≤.1

As predicted in H2, advanced technologies were perceived as more agentic (2.295, range 1.712 to 2.847; Table 3) than traditional technologies (1.436, range 1.129 to 1.656, $t(23)=-7.418$, $p<0.001$). Even removing the three advanced terms that mention autonomy in their names (i.e., *an automated system, an autonomous system, an autonomous robot*), the advanced category remains more agentic than the traditional (Advanced: 2.151, $t(20)=-6.962$, $p<.001$) suggesting this is not just a response to that word. Yet traditional versus advanced technologies did not differ in potency or activity, so H2 is only partially supported.

The physicality of the technology did not change the perception of agency, in contrast to the first part of H3, but it did alter potency and activity. Labels for physical technology were more potent (1.388) than those for digital technologies (0.634, $t(17)=-4.453$, $p<0.001$; Table 3) with those classified as "digital and/or physical" having an intermediate rating (1.043). The digital technologies ranged in potency from -0.071 to 1.034, where aside from the outlier of *a device* (0.395), physical technologies ranged from 1.290 to 1.768. Likewise, physical technologies were more active (0.911) than digital technologies (0.121, $t(17)=-4.820$, $p<0.001$) with those "digital and/or physical” technologies at an intermediate rating (0.393). Digital technologies ranged from -0.254 to 0.490 in activity, whereas the physical technologies ranged from 0.273 to 1.737. Therefore, H3 is partially supported.

Are General Human Identities Similar to General Technology Labels?

Using shortest Euclidean distance we matched the technology’s affective sentiments to their nearest human identity from the 2015 USA affect control theory dictionary (Smith-Lovin et al. 2016). This showed that 13 of the 25 were general identities that may be enacted across situations (Appendix Table: last column). These include general personal identities (*person, myself as I really am),* general work and education identities (*colleague, student)* and specific relational identities that can be master statuses (*boyfriend, single parent*). Like these human identities that can easily cut across situational contexts, our general technology labels were selected for their applicability across domains. It may be general labels, both human and technological, tend to be rated as slightly-to-quite good, powerful, and active, but not negative or extremely positivity in any dimension.

APPLICATIONS AND CONCLUSION

While the partially supported hypotheses warrant additional investigation, there are clear applications from our findings. First, they provide a baseline for examining more domain-specific technology terms: *a chat bot, a chat software program,* or *a chat artificial intelligence* each include a general technology label which differ significantly in affective sentiments. Second, affect control theory can be applied to technological actors that are interacting socially with humans. Like human role-identities, which can vary from specific to diffuse, we conceptualize technologies as those that may be specifically named and identifiable versus those that are more diffuse with more general labels. Therefore, these general technology labels with the affective sentiments collected here can be used in theoretical simulations and predictions according to affect control theory.

Technology terms have become a vital integration to modern day life with many different labels and categories by which these technologies exist. Interacting with technology is an almost inevitable part of many people’s day including technologies in social roles. One reason the labels given to technology are critical is that people hold different feelings about differently labeled technologies. The difference in these sentiments has implications for human-technology interaction as well as conversations, media reports, legal definitions, and our general understanding of these technologies.

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Appendix A: Mean values for all measures for all terms, and closest human match (in Euclidian distances in affective space) from the affect control theory USA 2015 dictionary.

	Mean (Standard Deviation)					Human
Label	Evaluation	Potency	Activity	Autonomy	Familiarity	Match (Euclidian distance)
a sim	0.918 (1.607)	-0.071 (2.018)	0.067 (1.999)	1.712 (1.35)	2.118 (1.052)	telephone installer (0.049)
a bot	-0.376 (2.029)	1.096 (1.789)	0.08 (2.025)	2.35 (1.205)	2.843 (1.027)	bureaucrat (0.247)
a software application	1.584 (1.397)	1.034 (1.844)	0.205 (1.913)	1.539 (1.129)	2.719 (0.959)	colleague (0.163)
a software program	1.463 (1.458)	0.756 (1.834)	0.183 (1.838)	1.494 (1.051)	2.776 (1.044)	colleague (0.178)
a software app	1.376 (1.546)	0.802 (1.753)	0.105 (1.774)	1.539 (1.099)	2.877 (0.867)	computer support specialist (0.135)
a computer system	1.845 (1.39)	1.671 (1.611)	0.847 (1.76)	1.656 (1.141)	2.828 (1.062)	boyfriend (0.047)
an automated system	1.384 (1.381)	1.098 (1.695)	0.823 (1.729)	2.545 (1.184)	2.316 (1.003)	client (0.093)
a software agent	0.681 (1.724)	0.671 (1.713)	0.227 (1.802)	1.874 (1.179)	1.476 (1.087)	insurance agent (0.162)
an autonomous system	1.048 (1.643)	1.162 (1.707)	0.621 (1.83)	2.847 (1.145)	1.923 (0.926)	single parent (0.056)
a hardware system	1.477 (1.4)	1.346 (1.786)	1.062 (1.925)	1.46 (1.298)	2.421 (1.101)	music director (0.226)
a machine	1.372 (1.795)	1.57 (1.97)	1.737 (1.639)	1.536 (1.245)	3.105 (1.047)	restaurant operator (0.203)
a humanoid robot	0.565 (1.693)	1.478 (1.609)	0.742 (1.606)	2.187 (1.013)	1.58 (0.992)	bailsman (0.213)
an autonomous robot	0.991 (1.518)	1.425 (1.688)	1.185 (1.526)	2.796 (1.065)	1.778 (0.925)	building contractor (0.161)

a device	1.236 (1.364)	0.395 (1.635)	0.273 (1.775)	1.325 (1.144)	2.964 (1.17)	Chinese (0.158)
a smart device	1.878 (1.528)	1.34 (1.812)	0.314 (1.823)	1.753 (1.068)	3.19 (0.805)	aide (0.176)
a computer interface	1.725 (1.541)	0.596 (2.045)	0.021 (2.085)	1.248 (1.188)	2.053 (0.971)	student (0.156)
a digital interface	1.23 (1.646)	0.572 (1.74)	-0.03 (2.027)	1.189 (1.162)	2.2 (1.069)	fellow (0.131)
a website	1.637 (1.495)	0.298 (2.084)	-0.053 (2.163)	1.368 (1.289)	3.458 (0.988)	plumber (0.167)
an app	1.622 (1.388)	0.566 (1.837)	-0.254 (2.096)	1.598 (1.164)	3.458 (0.988)	plumber (0.256)
an artificial intelligence	1.126 (1.553)	1.409 (2.05)	0.481 (1.976)	2.563 (0.947)	2.948 (0.907)	white collar worker (0.174)
an intelligent agent	0.99 (1.624)	1.018 (1.741)	0.49 (1.78)	2.366 (1.117)	1.683 (1.171)	person (0.167)
a laptop	2.107 (1.562)	1.29 (1.927)	0.591 (2.18)	1.129 (1.18)	3.397 (0.793)	myself as I really am (0.168)
a computer	2.061 (1.758)	1.768 (1.802)	1.047 (1.693)	1.581 (1.161)	3.328 (1.015)	bride (0.168)
an android	1.052 (1.738)	1.502 (1.929)	1.066 (1.949)	2.46 (1.171)	2.237 (1.04)	building contractor (0.115)
a robot	1.274 (1.438)	1.481 (1.675)	1.157 (1.69)	2.091 (1.074)	2.789 (0.995)	manager of branch store (0.120)
Average	1.291 (1.569)	1.051 (1.812)	0.519 (1.864)	1.848 (1.151)	2.579 (1.000)	– (0.155)

AUTHORS' NOTE

This research was partially supported by Leonard Wood Institute in cooperation with the U.S. Army Research Laboratory and was accomplished under Cooperative Agreement Number W911NF-14-2-0034 and under grant the Army Research Office under Grant Number W911NF-19-1-0246. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the Leonard Wood Institute, Army Research Office, or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation herein.

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