Creative Artificial Intelligence –

Algorithms vs. humans in an incentivized writing competition

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**Funding**: This project has received funding from the European Research Council (ERC) under the European Union’s Horizon 2020 research and innovation programme (grant agreements: ERC-StG-637915; ERC-AdG 295707) from Research Priority Area Behavioral Economics (University of Amsterdam, proposal number 201906250406).

**Conflict of Interest**: The authors declare that they do not have any conflict of interests.
Abstract

The release of openly available, robust text generation algorithms has spurred much public attention and debate, due to algorithm’s purported ability to generate human-like text across various domains. Yet, empirical evidence using incentivized tasks to assess human behavioral reactions to such algorithms is lacking. We conducted two experiments assessing behavioral reactions to the state-of-the-art Natural Language Generation algorithm GPT-2 ($N_{total} = 830$). Using the identical starting lines of human poems, GPT-2 produced samples of multiple algorithmically-generated poems. From these samples, either a random poem was chosen (Human-out-of-the-loop) or the best one was selected (Human-in-the-loop) and in turn matched with a human written poem. Taking part in a new incentivized version of the Turing Test, participants failed to reliably detect the algorithmically-generated poems in the Human-in-the-loop treatment, yet succeeded in the Human-out-of-the-loop treatment. Further, the results reveal a general aversion towards algorithmic poetry, independent on whether participants were informed about the algorithmic origin of the poem (Transparency) or not (Opacity). We discuss what these results convey about the performance of NLG algorithms to produce human-like text and propose methodologies to study such learning algorithms in experimental settings.

Keywords: Natural Language Generation; Computational Creativity; Turing Test; Creativity; Machine Behavior
Creative Artificial Intelligence – Algorithms vs. humans in an incentivized writing competition

Artificial intelligence (AI), “the development of machines capable of sophisticated (intelligent) information processing” (Dafoe, 2018, p. 5) is rapidly advancing and has begun to take over tasks previously solely performed by humans (Rahwan et al., 2019). Algorithms have also begun to assist humans in writing text, such as autocompleting sentences in emails and even helping creative fiction writers to write novels (Streitfeld, 2018). Besides supporting humans, such Natural Language Generation (NLG) algorithms can also autonomously create different types of texts. Already in use in the field of digital journalism, algorithms can generate news pieces based on standardized input data such as sports scores or stock market values (van Dalen, 2012). However, autonomous creative text generation presents a bigger challenge as it requires the generation of original content that is deemed appealing and useful (Bakhshi, Frey, & Osborne, 2015). Hence, creative writing has long been considered a task impregnable for algorithms (Keith, 2012; Penrose, 1990).

Yet, more recent developments in machine learning have expanded the scope and capacities of NLG (Jozefowicz, Vinyals, Schuster, Shazeer, & Wu, 2016). A notable case is the open-source algorithm called Generative Pre-Training 2 (GPT-2; Radford et al., 2019). At close to zero marginal cost, it produces text across a wide variety of domains, ranging from non-fiction, like news pieces, to fiction, such as novels. The text outputs adhere to grammatical and semantical rules, and allegedly generally reaches human levels. Due to such claims about the unprecedented abilities and the potential ethical challenges it raises, for example as a tool for disinformation (Kreps & McCain, 2019), much controversy accompanied the algorithm’s release (The Guardian, 2019). However, systematic empirical examination of these claims is largely lacking – especially from an experimental social science perspective. In particular, it remains
unknown whether humans are able to reliably distinguish creative text that is generated by an algorithm from one written by a human, when they are incentivized to do so. Do people actually prefer creative text written by fellow humans over those generated by algorithms? Also, does the information about the respective origin – being a human or an algorithm – sway this preference for the creative text output? And does it make a difference whether humans are involved or not in the selection of the text output generated by the algorithm? To address these questions, we use incentivized paradigms to extend previous research into computational creativity by emphasizing the human behavioral reactions to NLG. While much research has been focused on the machinery – how algorithms can be programmed to write creative text (Boden, 2009; Gonçalo Oliveira, 2018; Oliveira, 2009) – research on humans’ behavioral reactions to such algorithms is much less pronounced.

**Distinguishing between Artificial and Human**

To gain empirical insights into people’s ability to discern artificial from real content, we draw on the famous Turing Test (Saygin, Chaminade, Ishiguro, Driver, & Frith, 2012; Turing, 1950). Based on a thought experiment, Turing proposed it as a way to find out whether machines can think. The basic set-up entails three agents: One judge and two participants. The judge seeks to find out which of the other two participants is a machine and which one is a human. In the classical version, the judge has five minutes to ask multiple questions and receives answers from the participants after which the judge indicates which of the two is a human and which one is a machine.

Since its introduction, various algorithms have attempted to pass the test in multiple tournaments and competitions (see for an overview, Warwick & Shah, 2016). In 2014, a chat bot, called Eugene Goostman, was claimed to have passed the Turing Test, by tricking 33% of
human judges into believing that they were communicating with a 13 year old Ukrainian boy (Marcus, Rossi, & Veloso, 2016; Walsh, 2017; Warwick & Shah, 2016). Hence, a deceptive strategy of pretending to have rudimentary English proficiency paid off. Therefore, many scholars have criticized the standard Turing Test for rather identifying deceptive ability than intelligence (see for example, Riedl, 2014; Walsh, 2017). In pursuit for better measures of machine intelligence many extensions, modifications, and alternative tests have been proposed (see for an overview the special issue on the subject in AI magazine, Marcus et al., 2016).

However, according to the results of a systematic literature review (see for more details SOM), no version of the Turing Test has contained financial incentives for judges’ accuracy. That is, judges typically do not receive any financial reward for successfully detecting the human among the competitors. Hence, it remains somewhat unknown whether people are unable, or might simply not be motivated, to differentiate human from machine counterparts. Filling this gap, we introduce a new version of the Turing Test that entails incentives for judges’ accuracy. In both studies, we tested the prediction that humans’ accuracy in correctly identifying whether the text is human-written or algorithmically generated does not exceed random guessing.

**Overconfidence about algorithmic detection**

Besides examining people’s actual ability to detect human from algorithmically generated text, it plays an important role to understand whether people have accurate beliefs about their own ability in that domain. Multiple studies have revealed overconfidence, hence the systematic overestimation of one’s own capabilities (Kruger & Dunning, 1999). While causing personal and social harm (Malmendier & Tate, 2008; Moore & Healy, 2008), overconfidence in the domain of algorithm detection poses the threat of making people especially vulnerable to deception. That is, when people overestimate their own abilities to detect algorithmic behavior,
and in fact fail to reliably do so, they can fall prey to being influenced by algorithms without noticing it. To examine whether the commonly observed phenomenon of overconfidence also exists for algorithmic detection, we tested the hypothesis that people’s perceived ability to detect algorithms systematically exceeds their actual accuracy levels.

**Aversion and appreciation of artificial creativity**

Classically, machines have been seen as static rule-based systems. Since creativity requires the generation of original and useful ideas (Amabile, 1983), it was historically considered unfathomable that machines could be creative. In fact, creativity still provides a big obstacle for machines that merely rely on automation (Bakhshi et al., 2015). Yet, recent advances in machine learning (ML) have increasingly enabled computers to “‘learn’ and change their behaviour through search, optimisation, analysis or interaction, allowing them to discover new knowledge or create artefacts which exceed that of their human designers in specific contexts” (McCormack & D’Inverno, 2014; p. 2). Hence, algorithms become increasingly able to adapt, learn and create original, unpredictable outputs.

ML has also changed the field of computational creativity (Boden, 2009; Loller-Andersen & Gambäck, 2018; Majid al-Rifaie, Cropley, Cropley, & Bishop, 2016; Oliveira, 2009; Sloman, 2012). Multiple algorithms have been developed to serve single creative purposes such as generating story narratives (Bringsjord & Ferrucci, 1999), craft jokes (Ritchie et al., 2007) or write poetry (see for an overview, Oliveira, 2009). While these algorithms have been programmed with single purposes – e.g. creating poetry – recent developments in ML have rendered algorithms capable of text generation across various domains. The algorithm GPT-2, released in 2019 by OpenAI, is one of the most famous examples of such a robust text generating algorithm. In short, using ML technology, GPT-2 is a transformer-based language model, trained
on an unprecedentedly large data set, to predict the next word for a given textual input (see for more details on the algorithm, Radford et al., 2019). Due to these extensive training data sets, the algorithm has a more thorough ability to reproduce syntax and thus autonomously generate text, including new creative content.

Yet, do human readers actually find such algorithmically-generated text equally (or more) appealing than human written creative text? And, do people’s preferences differ when they are aware (Transparency) vs. unaware (Opacity) about the algorithmic origin of the text? We thus experimentally examine how information about the algorithm shapes humans behavioral reactions – reflecting current directions in AI-safety research that deal with algorithmic transparency (Craglia et al., 2018; Garfinkel, Matthews, Shapiro, & Smith, 2017; Marcinkowski, Kieslich, Starke, & Lünich, 2020; Shin & Park, 2019). While transparency can refer to different types of disclosures around algorithmic decisions, here we focus on algorithmic presence, hence the disclosure about whether an algorithm is involved in the decision at all (Diakopoulos, 2016). It pertains to the current policy debate of whether people have a right to know when they deal with an algorithmic counterpart. For example, a proposed “Turing’s red flag law” (Walsh, 2016) states that “An autonomous system should be designed so that it is unlikely to be mistaken for anything besides an autonomous system, and should identify itself at the start of any interaction with another agent” (Walsh, 2016, p. 35). Requests for such transparent information regimes have become increasingly voiced in light of the recently published hyper-realistic phone call assistant GoogleDuplex (Leviathan & Matias, 2018), and robust text generation algorithms such as GPT-2 (The Guardian, 2019).

When people are informed about algorithmic presence, extensive research reveals that people are generally averse towards algorithmic decision makers. This reluctance of “human
decision makers to use superior but imperfect algorithms” (Burton, Stein, & Jensen, 2019; p.1) has been referred to as algorithm aversion (Dietvorst, Simmons, & Massey, 2015). In part driven by the belief that human errors are random, while algorithmic errors are systematic (Highhouse, 2008), people have shown resistance towards algorithms in various domains (see for a systematic literature review, Burton et al., 2019). For example, people dislike, machines making moral decisions (Bigman & Gray, 2018), especially when they appear eerily human (Laakasu, Palomäki, & Köbis, 2019), devalue purely algorithmic political choices (Starke & Lünich, 2019), trust algorithms less than other humans (Dietvorst et al., 2015), and are even averse to relying on superior algorithmic recommendations about which jokes others would find funny (Yeomans, Shah, Mullainathan, & Kleinberg, 2019).

When it comes to aversion towards algorithmically generated text, research within digital journalism has assessed people’s perceptions of news generated by algorithms (Carlson, 2015; Diakopoulos & Koliska, 2017). For example, companies like Automated Insights produce articles for the Associated Press in domains where information exists in standardized formats, such as finance, sports or weather. Experiments have compared people’s evaluations of such algorithmically generated news pieces with those written by journalist (Clerwall, 2014; Graefe, Haim, Haarmann, & Brosius, 2018; Sundar & Nass, 2001). In one study, participants judged, among other facets, the overall quality, credibility, and objectivity of the text. The results reveal that the algorithmically-generated content is rated as more descriptive and boring, while at the same time viewed as objective and not necessarily distinguishable from content written by journalists (Clerwall, 2014). Another online experiment assessing people’s perception of news pieces, systematically manipulated the articles’ actual and declared authors (Graefe et al., 2018). Assessing credibility, readability, and journalistic expertise of the stimuli revealed that
participants consistently favored the human-written articles. People thus reveal aversion towards algorithmically generated newspaper articles, i.e. non-fiction text.

Yet, do they equally dislike algorithmically generated fiction, creative text? And does the information disclosure actually influence revealed preferences? Gaining answers to these questions bears relevance for understanding the advances in artificial creativity and gauging the potential impact algorithms might have for creative industries (Bakhshi et al., 2015). Understanding whether people like or dislike creative text written by an algorithm also provides insights into whether NLG algorithms could be used to deceive others into believing that the creative text stems from a human. That is, if people find the current output of algorithms like GPT-2 entirely unappealing the potential for ethical harm is less imminent. If, however, people find human and AI-written creative text comparably appealing this would open the door for AI being used to craft text on humans’ behalf.

To find out whether people are averse to algorithmically generated creative texts, we assessed people’s revealed preference for algorithmically-generated creative text. From pairs of poems – each time one originated from an algorithm and the other from a human – participants picked one they liked more. Between subjects, we either disclosed the respective origin of the poem (Transparency) vs. not (Opacity). We differed the degree of proficiency on the side of the human writers: untrained novices in Study 1 and experts in Study 2 and compared their performance with the state of the art algorithm GPT-2. We tested the prediction that humans would prefer the human written poem, in particular when they were informed about the origin of the poem. Moreover, in Study 2 we additionally assessed stated preferences of algorithm aversion, by asking people how they generally perceive algorithms that write creative text. Here, we tested our prediction that stated and revealed preferences correlate positively.
Human selection in and out of the loop

Moreover, the combination of understanding people’s detection accuracy of and preference for algorithmically generated text, enables new insights into the deceptive potential of NLG algorithms. That is, if people cannot tell the text apart, and do not systematically prefer humans over algorithms as authors of the creative text, then GPT-2 and other algorithms might indeed be used as a new form of plagiarism. One key feature to understand the deceptive potential of such algorithms is the degree of autonomy the algorithms have. Someone using the algorithm to craft text on one’s behalf can scan through the outputs – algorithms like GPT-2 are capable of creating multiple samples of text in mere seconds – and pick the one most suitable for a particular task. This reflects a selection process with *humans-in-the-loop* (Goldenfein, 2019). On the other end of the spectrum are unfiltered algorithmic outputs, such as many chatbots, tweetbots and other automated text-generating algorithms. These algorithms act autonomously. The selection process occurs with *humans-out-of-the-loop*.

Previous research suggests that human involvement in algorithmic decision-making crucially shapes perceptions of identical outcomes (Starke & Lünich, 2019) and the degree of a machine’s autonomy drives moral evaluations of machines (Bigman, Waytz, Alterovitz, & Gray, 2019). Yet, the behavioral reactions to these different regulation regimes remains largely unknown, in particular in relation to the NLG algorithms. To gauge the creative abilities of such algorithms, it makes a big difference whether a human is in or out of the selection processes of the algorithm’s output. Therefore, we introduce a *human-in-the-loop* (HITL) and a *human-out-of-the-loop* (HOTL) treatment. We tested the predictions that when it comes to algorithmic poetry people’s detection accuracy and revealed algorithm aversion drop when they read poems that
were preselected by humans (HITL) compared to when reading poems that were randomly picked from the outputs generated by GPT-2 (HOTL).

**General Method**

In two studies we incorporate established tournament designs from behavioral economics to computational creativity research by creating a competition between two agents and have an independent third party function as a judge (see for similar set-ups, Gneezy, Saccardo, & van Veldhuizen, 2019). Extending previous behavioral research, in which two humans have competed with each other (see for an overview, Camerer, 2011), in our experimental set-up humans directly compete with an AI-agent, in this case the text generating algorithm GPT-2.

Both studies contain four parts (see for an overview Table, 1). Part 1 consists of creating pairs of human-AI poems. On the human side, in Study 1, poems were written by participants who took part in an incentivized real-effort creative writing task, while in Study 2, we used existing, professional poems. On the algorithm’s side, the poems stem from a state-of-the-art NLG algorithm GPT-2. In Study 1, we, the authors, selected from the text outputs that the algorithm generated. In Study 2, we introduced a between subjects manipulation of selection procedure, namely whether the poems entering the competition were again selected by the authors, hence *Human-in-the-loop (HITL)* versus randomly sampled from the text outputs that GPT-2 produced, hence *Human-out-of-the-loop (HOTL)*.

Part 2 entails a judgement task. In it, a separate sample of participants act as third-party judges and indicate their preference for the creative texts. In both studies, we manipulated between subjects whether participants received information about the origin of the text, i.e. which of the two poems was written by a human. Comparing the *Transparency* treatment, in
which participants were informed about the origin with the *Opacity* treatment, in which they were oblivious, enables us to gain causal insights how the information about algorithmic presence shapes revealed preferences. In Study 2, the selection manipulation of *HITL* vs. *HOTL* treatment additionally allows testing how human involvement in the selection procedure of the outputs of GPT-2 shape these preferences.

Part 3 consists of an incentivized version of the classical Turing Test (Saygin et al., 2012; Turing, 1950) to assess people’s accuracy in identifying algorithmically-generated creative text. Judges naïve to the origin of the poems faced the task to correctly distinguish human-written from algorithmically-generated text. In contrast to the standard version, however, judges could not directly interact with the two participants by asking questions, but merely received the text output. As a second refinement, we introduced incentives for accuracy. That is, judges could earn €0.50 if they correctly identified the origin of the text. In Study 1, participants in the *Opacity* treatment engage in this version of the Turing test, while for Study 2 we recruited a separate sample of participants. Study 2 further contained the selection treatment to assess how human involvement in the selection procedure shapes people’s ability to differentiate human from algorithmically-generated creative text.

As part 4, accompanying the accuracy assessment, participants indicated their confidence in their detection accuracy. In Study 1, this measurement was unincentivized, while in Study 2, we attached financial incentives for correctly estimating the performance. Namely, participants received a reward of €0.50 if they correctly indicated the number of rounds in which they identified the correct origin of the poem. This modification allows us to gauge how people’s estimated performance compares with their actual performance, and how incentives influence a potential gap between the two.
Pre-registration statement

All studies reported in this manuscript are pre-registered on the Open Science Framework\(^1\), where we provide an overview of all hypotheses, pre-analysis plans, material, data and R analysis scripts for the analyses reported in the manuscript as well as additional tests. We further provide several accompanying documents that provide background information and technical details on the use of the NLG algorithm, the procedure employed to gather and select the poems for the competitions.

\(^1\) Pre-registration Study 1: https://osf.io/znjex
Pre-registrations for both parts of Study 2: https://osf.io/z6fhr & https://osf.io/uvmjx
Table 1. Overview of two studies that each contain four parts.

| Part 1 – Selection of poems as stimulus material | Study 1 | Study 2 |
|-----------------------------------------------|---------|---------|
| Poems written by untrained writers ($N=30$)   | vs.     | Poems written by untrained writers ($N=30$)   |
| GPT-2 Medium (final poems selected with HITL)  | vs.     | GPT-2 Medium (final poems selected with HITL)  |
| Professional poems (e.g. Maya Angelou)        |         | GPT-2 Medium (between subjects treatment of final poems selected either with HITL or HOTL) |

| Part 2 – Preference | Study 1 | Study 2 |
|---------------------|---------|---------|
| Participants ($N=200$) reveal preference for human vs AI poems (either while knowing the origin of the poem Transparency or not Opacity) | Participants ($N=400$) reveal preference for human vs AI poems (either while knowing the origin of the poem Transparency or not Opacity) |

| Part 3 – Detection Accuracy | Study 1 | Study 2 |
|-----------------------------|---------|---------|
| Incentivized version of Turing Test among participants in Opacity ($N=100$), reward = €0.50 | Incentivized version of Turing Test with separate sample ($N=200$), reward = €0.50 |

| Part 4 – Confidence | Study 1 | Study 2 |
|---------------------|---------|---------|
| Unincentivized assessment of Confidence in detection ability | Incentivized assessment of Confidence of detection ability |
Study 1

Method

Participants and Procedure. Thirty participants ($M_{Age} = 29.40, \ SD_{Age} = 8.75; \ female = 56.67\%$) completed the task to write a poem and answering a few exit questions, which in total took on average around eleven minutes. To obtain high quality online data, we recruited the participants via the online research platform Prolific Academic (see for a discussion of different online research platforms, Peer, Brandimarte, Samat, & Acquisti, 2017), paid participants an average of €15,- per hour, and restricted the sample to be proficient in English. After providing informed consent, participants were informed about the incentivized competition that they would enter (see for full instructions SOM). Namely, they could win a prize of €2, when their text was chosen as the winner in the competition, which led to a total amount of bonuses paid out of €40.

Part 1 – Selection of poems

Human Competitor. To enter the competition, participants had to write a short piece of poetry for which they received the first two lines. Participants could freely decide on how to continue the poem, which had to be at least 8 lines long and be written in English. Instructions further explained to participants that they should abstain from (a) writing gibberish (e.g. kajsdkjasdkjaskjd), (b) address the judge directly (e.g. “choose me as the winner”), and (c) plagiarize other people's work as this would result in exclusion from the competition. Three independent blind coders screened the entries according to whether the written texts adhere to these criteria. We randomly picked 20 poems that fulfilled the pre-specified criteria. The instructions explained this procedure to the participants, who under the assumption that all
participants fulfilled the inclusion criteria, had a chance of 67 percent to enter the writing competition.

**AI competitor.** The randomly picked poems written by participants entered a competition with poems written by GPT-2. Namely, for Study 1 we used the 345M model of GPT-2, which is the second model that OpenAI released (see for the code https://github.com/openai/gpt-2). Being trained to generate poems that abide by the above mentioned rules, GPT-2 received the same two starting lines. We trained GPT-2 for this specific writing task on a self-compiled data set consisting of works from various professional poets including Jane Campion, Roald Dahl, Robert Frost and William Blake. Adhering to recent suggestions to increase reproducibility in AI-research (Gibney, 2020), the full list is available on OSF, including a 1.1 MB text file containing a list of their collected works (retrieved from www.poemhunter.com). To imitate poetry, text written by GPT-2 further had to adhere to one of the pre-specified criteria to enter the writing competition. Namely, the poem had to use lines and verses, rhyme (end or begin rhyme, assonance), alliteration (words beginning with the same letter), onomatopoeia (phonetically imitating the sound of its meaning), rhythm, repetition, symbolism, or contradictions. The training data set as well as all samples (including those that did not enter the competition) are available on OSF. Among the GPT-2 written poems that qualified 10 poems were chosen for the competition and randomly matched with a human written poem.

**Part 2-4 – Preference, Detection Accuracy and Confidence**

**Participants.** Applying the same pre-selection criteria as in Stage 1, we recruited 200 participants, again via the online research platform Prolific Academic. Participants completed the task on average within 17 minutes, yielding a mean payoff of €11.67 per hour. Applying the pre-registered attention check, we excluded eight participants. All results reported in this
manuscript remain qualitatively unaffected by the exclusions. The final sample consisted of 192 participants ($M_{Age} = 29.06$, $SD_{Age} = 10.61$; female = 39.1%, other/prefer not to indicate = 1%).

**Preference.** Participants received instructions for the judgment task in which they took the role of the judge (see full instructions in SOM). As judges, they received ten pairs of poems all beginning with the same two opening lines. For each pair they had to indicate a winner according to which poem they personally liked better. They were informed that this choice had financial consequences as one of the ten comparisons would be paid out and the chosen winner would receive a prize of €2. Judges also received the information that in each pair, one poem stemmed from a human writer and the other poem stemmed from the algorithm GPT-2. To avoid efficiency concerns of judges seeking to reward the human writer, randomly chosen token players received the prize when the GPT-2-written poem won the competition. Namely, it was common knowledge to all participants that if GPT-2 won the pay-off relevant round, another randomly writer received the reward.

**Information Treatment.** Participants were randomly assigned to one of two treatments: Transparency and Opacity. In the Transparency treatment, judges received information about the origin of the poems. Hence, for each pair they knew which poem was written by a human and which one was generated by GPT-2, prior to their decision to award a winner. In the Opacity treatment, judges did not receive this information about the respective origin. Although knowing that the pair of poems stemmed from a human writer and GPT-2, judges did not know which one is which.

**Detection Accuracy.** Participants in the Opacity treatment, who were thus naïve to the origin, additionally engaged in an incentivized version of the Turing Test (Saygin et al., 2012; Turing, 1950). Akin to the original version proposed by Turing, judges faced the task to correctly
distinguish human from machine written text. In contrast to the standard version, however, judges could not directly interact with the two participants by asking questions, but merely received the text output. As a second refinement, we introduced incentives for accuracy. That is, judges could earn €0.50 if they correctly identified the origin of the poem. They received ten pairs of poems from which we randomly selected one for payment. After judging the ten pairs, participants in this treatment received the same poems and were asked to identify the true author. One of these competitions was randomly selected one for payment.

**Confidence.** Judges also estimated their level of confidence in correctly identifying the human poem on a 100-point scale (0 = “not at all confident”; 100 = “very confident”). These subjective ratings of participant’s confidence were compared to the actual level of accuracy in determining the origin of the text.

**Results**

**Part 1 – Selection of poems**

Human-written and GPT2-generated poems did not significantly differ in length as a sign-rank test on the number of words reveals ($p = .824$). Participants wrote a median of 37 words ($SD = 14.36$) using eight lines (7.55), while GPT-2 generated a median of 40 words ($SD = 12.94$), also using eight lines (7.75) on average. Thus, the poems were of similar length and could also not be distinguished visually or by other aesthetic rules. As outlined in the pre-registration, we collected additional exploratory variables assessing the authors level of confidence in winning the competition and creativity ratings of the poems (see OSF). We report the results for these measures on OSF.
Part 2 – Preference

Overall, human-written poems won 1091 out of 1915 competitions corresponding to a win share of 56.97 percent which significantly differs from a win-share of 50% ($\chi^2 = 37.23, p = <.001$). Mixed effect probit regressions with random effects to account for dependencies of responses of individuals and per poem equally consistently reveal significant preferences for human-written vs. algorithmically-generated poems shown by a significant intercept in Models 0-3 (see Table 2). Hence, overall judges showed a preference for human-written over algorithmically-generated poems.
Table 2. Mixed effect probit regressions predicting preference for the human written poem in each round.

|                | Model 0    | Model 1    | Model 2    | Model 3    |
|----------------|------------|------------|------------|------------|
| DV: Preference for human-written poetry |            |            |            |            |
| (Intercept)    | 0.18**     | 0.20**     | 0.22**     | 0.35*      |
|                | (0.03)     | (0.04)     | (0.05)     | (0.16)     |
| Treatment      | -0.06      | -0.06      | 0.07       |            |
|                | (0.06)     | (0.06)     | (0.06)     |            |
| Age            |            |            |            |            |
| Gender         |            |            |            |            |
| Education      |            |            |            |            |
| Primary School | -0.34      |            |            |            |
|                | (0.30)     |            |            |            |
| High School    |            | 0.04       |            |            |
|                |            | (0.07)     |            |            |
| Master         |            | 0.12       |            |            |
|                |            | (0.08)     |            |            |
| PhD            |            | 0.09       |            |            |
|                |            | (0.16)     |            |            |
| English Proficiency |      |            |            |            |
| None           | 0.04       |            |            |            |
|                | (0.29)     |            |            |            |
| Limited Working| -0.15      |            |            |            |
|                | (0.18)     |            |            |            |
| Professional Working |   | -0.17      |            |            |
|                | (0.16)     |            |            |            |
| Full Professional | -0.15      |            |            |            |
|                | (0.17)     |            |            |            |
| Native or bilingual | -0.19      |            |            |            |
|                | (0.17)     |            |            |            |

Note. Random effects included for the participants ID and the pair of poems. Standard errors are reported in parentheses. DV = Preference, binary variable across ten rounds coded as: 0 = preference for algorithmically-generated poem; 1 = preference for human-written poem. Independent variables: Age (continuous, standardized), Gender (dummy, reference category = male), Education (dummy, reference category = Bachelor), Language: The Interagency Language Roundtable scale is used to determine the participants’ level of English with the reference category being elementary proficiency. Significance coding: * p < .05, ** p < .01, *** p < .001.
As a first test of our hypothesis that people would be more averse to algorithmically-generated poetry in the transparency treatment, we conducted a two-sample t-test with equal variances on the total number of rounds the human written poem was chosen. The analysis indicates no significant difference between the number of wins for the human agents in the Opacity ($M = 5.59$, $SD = 1.49$) versus in the Transparency ($M = 5.82$, $SD = 1.69$) treatment ($t(189) = 1.05, p = .29$, see also Figure 1). As the assumption of normality of the aggregated wins was violated (Shapiro-Wilk: $W = 0.96, p < .001$), we additionally conducted a Wilcoxon signed-rank test which similarly indicate no significant differences in preferences across treatments ($mdn_{Opacity} = mdn_{Transparency} = 6, W = 4285, p = .39$). Further, Bayesian independent samples t-tests analysis reveals a Bayes factor of $BF_{0+} = 7.40$, hence providing moderate support that the $H_0$ of no differences between the treatments is more likely than the $H_1$ of stronger preferences towards human-written poetry in the transparency treatment. Finally, we conducted mixed effect probit regressions predicting the binary outcome of preference in each round with random effects for the participant ID and poem pair. The results reveal no significant treatment differences, also when controlling for demographics and education levels (see Models 1-3, in Table 2). Taken together, these results suggest that, contrary to our hypothesis, judges did not prefer the human-written poetry more strongly when they were informed about the origin.

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2 Conservative sensitivity analysis with $\alpha = .05$, power of $1-\beta = .8$ and 100 participants per treatment suggests that our analysis was able to detect a small effect (Cohen’s $d = 0.39$).
Figure 1. Violin plots of revealed preference for human-written poetry across information treatments.

Note. The plot depicts the distribution of aggregated rounds in which the participants chose the human written poem across in the Transparency treatment (left pane) and Opacity treatment (right pane). Inside the violin plot mean and 95% confidence intervals are plotted, indicating a significant preference for human-written poems in both treatments, yet no differences across treatments.
Part 3 – Detection Accuracy

Overall, judges identified the correct origin with an average accuracy of 50.21 percent (95% CI [46.4; 53.9]). To test our pre-registered conjecture, that judges’ accuracy levels in detecting the algorithmically-generated poem would not exceed random guessing, we conducted a Wilcoxon signed-rank test comparing judges’ performance with chance (= 50%)\(^3\). The results reveal that judges’ accuracy does not significantly differ from chance ($V = 1479, p = .935$). This result is further supported by Bayesian binomial test, yielding a Bayes Factor of $BF_{01} = 24.91$, and hence providing strong support that the $H_0$ of judges’ accuracy not exceeding chance is more likely than the $H_1$. We also conducted mixed effect probit regressions with random effects for the participant ID and the pair of poem, predicting the judges’ accuracy in each round. The results reveal no significant deviation from chance at detecting the correct poem, also when controlling for standard demographics of age, gender and education (see Table 3). Taken together, the results indicate that people are not reliably able to identify human versus algorithmic creative content.

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\(^3\) Conservative sensitivity analysis with $\alpha = .05$, power of $1-\beta = .8$ and 100 participants and a normal parent distribution suggests that our analysis was able to detect a small effect (Cohen’s $d = 0.28$).
Table 3. Mixed effect probit regressions predicting accuracy of detecting the correct poem in each round.

|                      | Model 0   | Model 1   | Model 2   |
|----------------------|-----------|-----------|-----------|
| **DV: Detection Accuracy** |           |           |           |
| (Intercept)          | 0.01      | 0.01      | -0.35     |
|                      | (0.05)    | (0.14)    | (0.27)    |
| **Age**              |           |           |           |
|                      | 0.02      | 0.05      |           |
|                      | (0.05)    | (0.06)    |           |
| **Gender**           |           |           |           |
|                      | -0.13     | -0.19     |           |
|                      | (0.10)    | (0.10)    |           |
| **Education**        |           |           |           |
| High School          |           |           | -0.04     |
|                      |           |           | (0.11)    |
| Master               |           |           | -0.01     |
|                      |           |           | (0.15)    |
| PhD                  |           |           | -0.22     |
|                      |           |           | (0.21)    |
| **English Proficiency** |         |           |           |
| None                 |           |           | *1.72     |
|                      |           |           | (0.65)    |
| Limited              |           |           | 0.45      |
|                      |           |           | (0.31)    |
| Professional Working |           |           | *0.62     |
|                      |           |           | (0.29)    |
| Full professional    |           |           | 0.33      |
|                      |           |           | (0.28)    |
| Native or bilingual  |           |           | 0.47      |
|                      |           |           | (0.28)    |
| N                    | 733       | 733       | 733       |

Note. Random effects included for the participants ID and the pair of poems. Standard errors are reported in parentheses. DV = Detection Accuracy, binary variable across ten rounds coded as: 0 = incorrect guess; 1 = accurate guess. Independent variables: Age (continuous, standardized), Gender(dummy, reference category = male), Education (dummy, reference category = Bachelor), Language: The Interagency
Language Roundtable scale is used to determine the participants’ level of English with the reference category being elementary proficiency. Significance coding: * $p < .05$, ** $p < .01$, *** $p < .001$.

**Part 4 – Confidence**

As non-pre-registered exploratory analyses, we examined judge’s level of confidence in detecting the correct origin, prior to having read any samples. On a scale from 0 to 100, the average confidence level of the judges was $M = 62.27$ ($SD = 22.27$), with the distribution being moderately left skewed ($skewness = -0.496, SE = 0.09$; see Figure 2, left pane). Hence, on aggregate people rate their confidence level higher than chance. Regression analysis between peoples’ confidence in differentiating human from GPT-2 written poems and their actual performance reveals no significant relationship ($b < .01; \beta = .017, t(74) = 0.143, p = .887$). Hence, self-rated confidence did not predict their actual performance. Moreover, we find that a significant proportion of participants (69.33%) reveals overconfidence, defined as confidence levels exceeding participants’ actual accuracy in their performance (see also Figure 2, right pane). Overall, these results provide a first tentative indication that people are not able to accurately predict, instead overestimate, how well they will perform in the incentivized Turing Test.
Figure 2. Density distribution of the judges’ confidence score ranging from 0 to 100% (left pane). Scatterplot illustrating the relationship between confidence and their actual standardized performance across all rounds of the incentivized version of the Turing Test (right pane).
Discussion

Study 1 examined the behavioral responses to algorithmically generated creative text. The results reveal that judges slightly preferred human-written over algorithmically-generated poems, independent on whether they were cognizant (Transparency) or oblivious (Opacity) about the origin of the poem. This effect occurred even though their decisions had financial consequences for the authors. Moreover, in line with our expectations, judges were unable to reliably distinguish human from artificial poetry. In light of the financial rewards for accuracy in our version of the Turing Test, these results are among the first to indicate that detecting artificial text is not a matter of incentives but ability. At the same time, most judges’ confidence levels exceeded their actual performance in recognizing artificial poetry – a first sign of overconfidence in algorithm detection.

Study 2

One potential criticism of Study 1 states that the comparison favored the algorithm. Namely, poems created by novices competed with the output of a state-of-the-art algorithm trained on the works of prolific poets. Indeed, the recruited participants did not have any prior training in poetry writing and were put on the spot to write a poem within a short time frame. While algorithmically-generated poetry was able to pass as human, and people’s preferences did not change whether they were informed about the origin of the poem, it remains unknown what happens when trained, or even professional poets compete against an NLG algorithm. To address these questions, we drew on existing poems written by renowned professional poets such as Maya Angelou or Hermann Hesse (for a full list of poems see OSF), and let them enter the competition on the human side.
On the algorithm’s side we fed the full model of GPT-2 the first two lines of these professional poems to generate samples of poems. In the selection of the generated poems to enter into the competition, we introduced a new treatment, differing in the degree to which humans are involved. Ample AI-research points out that whether humans are involved in the decision chain has a crucial impact on the performance of the algorithm and on people’s evaluation of these outcomes (Rahwan, 2018; Schirner, Erdogmus, Chowdhury, & Padir, 2013; Starke & Lünich, 2019; Wang, Harper, & Zhu, 2020; Zhu, Yu, Halfaker, & Terveen, 2018). Yet behavioral reactions to these different regulation regimes remain largely unknown. Studying machine and human behavior means dealing with autonomous, unpredictable outcomes on the sides of the human and the machine (Rahwan et al., 2019). In our case the NLG algorithm GPT-2 produces samples of different outcomes each time it is run. For the purpose of the current study this raises the important question: how to determine which of the various outputs, i.e. poems, that GPT-2 produces in a single run to use for the competition?

Two main strategies can be applied. The first is human selection where humans pre-screen and select the poem they deem most suitable, hence humans-in-the-loop (HITL). This reflects the situation in which someone uses GPT-2 as a writing aid and selects the output deemed most useful. The second is random selection, in the which the algorithmic output is randomly sampled and hence, enters the competition unfiltered, with humans-out-of-the-loop (HOTL). This selection procedure reflects unfiltered use of NLG algorithms such as for most tweet- or chat-bots. Using HITL vs. HOTL in the selection of poems this way, Study 2 provides some of the first answers whether and how much these different strategies for the selection of the algorithmically generated content affect people’s behavioral reactions. We thus again examined
people’s preferences, their accuracy of detecting algorithmically-generated text and their confidence levels of doing so.

**Method**

**Part 1 - Selection of poems**

*Human and AI competitor.* We again created pairs of human vs. AI poems. As outlined in more detail in the documentation of the stimulus material (see helper file on OSF), the human-written poems stem from a collection of poems written by professional poets, while the AI-generated poems were generated using the full model of the open source NLG algorithm GPT-2. Akin to Study 1, GPT-2 received the same two starting lines of the existing poem and generated alternative endings to it.

*Selection treatment.* As a new treatment we manipulated the way in which the algorithmically generated poem was selected. When letting GPT-2 XL generate text outputs it produces samples of multiple poems at once. As a between subjects manipulation, we manipulated how we determined which poem to choose from this sample (see more details on the selection procedure on OSF). In brief, in *HITL* treatment, the authors (NCK & LDM) selected the best poem by consensus voting from a collection of outputs generated by GPT-2. In the *HOTL* treatment, the poem to be entered in the competition was randomly chosen from the same output.

**Part 2 – Preference**

*Participants and Procedure.* For the poetry judgement task, we recruited a sample of 400 participants, again via Prolific, in which we paid €1.98 for a study that took on average 16
minutes (= €8.40/hr). After applying the pre-registered exclusion criteria, we excluded participants who failed the attention check, leading to a final sample of 371 participants ($M_{age} = 31.38$, $SD_{age} = 11.92$, female = 47.14%, other/prefer not to say = 0.54%). After giving informed consent, participants received ten human-vs.AI poem pairs and, for each pair, picked the poem that they liked more.

**Information Treatment.** Identical to Study 1, we again manipulated whether participants were informed about the origin of each poem. Hence in the *Transparency* treatment they received the information which poem was written by a human and which one was generated by an algorithm, while in the *Opacity* treatment they did not receive that information.

**Algorithm Aversion Scale.** To assess stated algorithm aversion, we included a new item to an existing scale to measure algorithm aversion (Castelo, Bos, & Lehmann, 2019). The scale consists of multiple items each describing different tasks (e.g. “driving a car”), for which participants have to indicate who they trust more to execute that task. Answers are given on a 100-point slider scale ranging from 0 (=a qualified human) to 100 (=an algorithm). To the list of existing items we included a new item that stated “Writing poetry”.

**Part 3 & 4 – Detection Accuracy & Confidence**

**Participants and Procedure.** To assess detection accuracy and confidence of detecting algorithmically-generated text, we recruited a separate sample of 200 participants via Prolific for a study that took on average 13.92 minutes and paid €2.26 (= €10.93/hr). After applying the pre-registered exclusion criteria, the sample consisted of a total of 185 participants ($M_{Age} = 27.66$; $SD_{Age} = 9.47$, female = 47.02%).
Detection accuracy. Identical to Study 1, we used the incentivized version of the Turing Test in which people can receive a financial reward of €0.50 for correctly identifying whether a poem is human-written vs. AI-generated.

Confidence. After participants completed the accuracy assessment, participants were asked to estimate in how many of the rounds they correctly identified the origin of the poem. We incentivized this elicitation of confidence by rewarding correct estimation of the number of rounds with a financial bonus of €0.50. We assessed the estimated performance after and not before participants completed the incentivized Turing Test to avoid hedging, i.e. participants changing their performance in the task to match their estimation.

Knowledge of Poetry. After completing Parts 2-4, we assessed participants prior poetry knowledge. We presented the poems used in the study and asked two questions. First as a stated poetry knowledge assessment we asked the participants whether they had read the poem prior to participating in this study (Y/N). Second, as a measure of revealed knowledge, we asked them to impute the respective poet’s name.

Demographics. Using the same questions as in Study 1, we again assessed standard demographic information of age, gender, education, as well as their experience with computer science, and their views on the development of general artificial intelligence at the end of the study.
Results

Part 2 – Preference

As a first test of the hypothesis, predicting that people would overall prefer the human written poem, we conducted a $\chi^2$ tests to compare the expected win share of 50% differs from the observed win-share of human-written poems (64.90%), which suggested significant deviation from chance ($\chi^2(1) = 340.82, p < .001$). Similarly, a t-test with the expected value of 5 across all rounds which reveals that the observed number of rounds in which the AI-written poem is chosen ($M = 3.51, SD = 1.64$) is significantly lower than the expected 5, ($t(383) = -17.73, p < .001$). We further conducted mixed effect probit regression models with random effects for the participant ID and the poem pair. The results reveal significant intercept in all models (see Table 4) indicating a significant preference for human written poems which further corroborate this finding. Taken together, the results replicate results obtained in Study 1 and confirm our hypothesis that people overall reveal a preference for human-written poems over algorithmically-generated poems.

To test the pre-registered hypothesis that people reveal a stronger preference for human-written poems in the Transparency treatment compared to the Opacity treatment, we conducted a two-sample t-test. A comparison of the mean of algorithmically chosen poems in the opaque ($M = 6.41, SD = 1.82$) vs. transparent condition ($M = 6.58, SD = 1.42$) suggests no significant differences ($t(362) = 0.65, p = .52$). Since a Shapiro-Wilk test of normality suggests that the assumption of normality is violated ($W = 0.96, p < .0001$), we additionally conducted a Wilcoxon signed-rank sum test which also indicates that median number of rounds in which AI is chosen in the transparent condition ($mdn = 6$) does not exceed the median number of rounds in which
the AI poem is chosen in the opaque treatment ($mdn = 7$, $W = 17961$, $p = 0.44$). We further conducted mixed effect probit regressions predicting the binary preference measure in each round with random effects for the participant ID and the poem pair. The results reveal no significant differences for the information treatment dummy (see Models 1,3 & 4 in Table 4). Hence, contrary to our hypothesis, people did not reveal stronger preferences for human-written poems in the Transparency treatment compared to the Opacity treatment.

As a first test of the hypothesis predicting that people reveal a stronger preference for human-written poems compared to AI-generated poems in the HITL treatment compared to the HOTL treatment we conducted a t-test. A comparison of the mean of AI chosen poems in the HOTL ($M = 6.71$, $SD = 1.71$) vs. HITL condition ($M = 6.24$, $SD = 1.54$) suggests significant differences ($t(366) = -2.82$, $p = .005$). A Wilcoxon signed-rank sum test also indicates that median number of rounds in which AI is chosen in the HITL treatment ($mdn = 6$) significantly exceeds the median number of rounds in which the AI poem is chosen in the HOTL treatment ($mdn = 7$; $W = 14288$, $p = .006$). These findings are corroborated by mixed effects probit regressions consistently revealing significant treatment differences of stronger preference for the human written poems in the HITL treatment compared to the HOTL treatment (see Selection treatment dummy in Models 2-4, Table 4).
Table 4. Mixed effect probit regressions predicting preference for the human written poem in each round.

|                        | Model 0  | Model 1  | Model 2  | Model 3  | Model 4  |
|------------------------|----------|----------|----------|----------|----------|
| DV: Preference for human-written poetry |           |          |          |          |          |
| (Intercept)            | 0.66***  | 0.69***  | 0.51***  | 0.35***  | 0.35***  |
|                        | (0.15)   | (0.16)   | (0.06)   | (0.10)   | (0.10)   |
| Information Treatment  | -0.05    | -0.03    | -0.02    | 0.21***  | **0.14   |
|                        | (0.08)   | (0.05)   | (0.05)   | (0.08)   | (0.05)   |
| Selection Treatment    |          |          |          |          |          |
| Revealed Poetry Knowledge |        |          |          |          |          |
|                        | -0.14    | -0.12    |          |          |          |
|                        | (0.14)   | (0.14)   |          |          |          |
| Age                    |          |          |          |          |          |
| Gender                 |          |          |          |          |          |
| Male                   | -0.01    |          |          |          |          |
|                        | (0.05)   |          |          |          |          |
| Other                  |          |          |          |          |          |
|                        | 0.59     |          |          |          |          |
|                        | (0.36)   |          |          |          |          |
| N                      | 3840     | 3710     | 3710     | 3710     | 3710     |

Note. Random effects included for the participants ID and the pair of poems. Standard errors are reported in parentheses. DV = Preference, binary variable across ten rounds coded as: 0 = preference for algorithmically-generated poem; 1 = preference for human-written poem. Independent variables: Information treatment (dummy, reference category = Opacity), Selection treatment (dummy, reference category = HITL), Revealed Poetry Knowledge (continuous), Age (continuous, standardized), Gender (dummy, reference category = female). Significance coding: * p < .05, ** p < .01, *** p < .001.
Besides revealed preference for human written poetry, we additionally assessed stated algorithm aversion. The mean value of the algorithm aversion item assessing whether people prefer humans over algorithms to write poetry ($M = 19.50$, $SD = 20.73$), significantly deviates from the mid-point of the scale ($t(383) = -28.83$, $p < .001$), indicating a stated algorithm aversion to algorithmically generated poetry. As a first test of our hypothesis, predicting a positive correlation between the algorithm aversion towards AI writing poetry and the number of rounds the human-written poem was chosen, we conducted a point-biserial t-test. The results reveal a significant positive correlation, ($t(382) = 2.55$, $r = 0.11$, $p = .01$). Mixed effect probit regressions similarly reveal a positive association between algorithm aversion and preferences for human-written poems ($b = 0.06$, $SE = 0.03$, $Z = 1.93$, $p = .05$). The marginal effect is $b = 0.06$, $SE = 0.02$, $Z = -2.55$, $p = .01$), which remains significant when controlling for both treatments, knowledge of the poets and demographic information of gender and age (all $bs > 0.5$, $ps < .03$).

Taken together we find evidence for a weak but significant link between stated algorithm aversion and revealed algorithm aversion in the domain of algorithmic poetry.

**Part 3 – Detection Accuracy**

As a first test of the hypothesis, stating that people’s accuracy in detecting the correct poem does not exceed chance levels, we conducted a one-sample t-test. We compare aggregated accuracy across all rounds to the expected value of 5 if people’s accuracy was at chance level of 50%. Results of the t-test suggest that the average number of correct trials ($M = 5.94$, $SD = 2.01$) significantly exceeds the chance level of 5 ($t(184) = 6.33$, $d = 0.47$, $p < .001$). Since the assumption of normality is violated (Shapiro-Wilk: $W = 0.967$, $p < .001$), we additionally conducted a Wilcoxon signed-rank test which similarly indicates that the overall observed accuracy ($mdn = 6$) exceeds chance levels ($V = 8406$, $r = 1.25$, $p < .001$). We also conducted
mixed effect probit regressions with random effects for the participant ID and the poem pair predicting the accurate detection in each round. Results reveal a significant intercept when not including control variables (see Model 0, in Table 4). In sum, this finding suggests that overall participants are able to detect the correct origin at better than chance level.

Table 5. Mixed effect probit regression predicting the accurate identification of the origin of the poem per round

|                      | Model 0   | Model 1   | Model 2   | Model 3   |
|----------------------|-----------|-----------|-----------|-----------|
| DV: Detection Accuracy|           |           |           |           |
| (Intercept)          | 0.26***   | 0.10      | 0.09      | 0.20      |
|                      | (0.09)    | (0.09)    | (0.09)    | (0.10)    |
| Selection Treatment  | 0.34***   | 0.33***   | 0.32***   |           |
|                      | (0.08)    | (0.08)    | (0.08)    |           |
| Revealed Poetry Knowledge | 0.62**   | 0.67**    |           |           |
|                      | (0.25)    | (0.25)    |           |           |
| Age                  | 0.00      |           |           |           |
| Gender               | -0.19*    |           |           |           |
|                      | (0.04)    |           |           |           |
| N                    | 1850      | 1850      | 1850      | 1850      |

Note. Random effects included for the participants ID and the pair of poems. Standard errors are reported in parentheses. DV = Detection Accuracy, binary variable across ten rounds coded as: 0 = incorrect guess; 1 = accurate guess. Independent variables: Selection treatment (dummy, reference category = HITL), Revealed poetry knowledge (continuous) Age (continuous, standardized), Gender(dummy, reference category = female). Significance coding: * p < .05, ** p < .01, *** p < .001.

As a first test of the hypothesis predicting higher accuracy levels in the HOTL treatment compared to the HITL treatment, we conducted a two-sample t-test, comparing the aggregate accuracy levels across all ten rounds. The results reveal that the mean accuracy levels in the HITL treatment are significantly lower ($M = 5.37$, $SD = 1.95$), than accuracy levels in the HOTL treatment ($M = 6.55$, $SD = 1.90$) ($t(183) = -4.19$, $d = -0.62$, $p < .001$). Due to violation of normality for both treatments ($Ws > 0.958$, $ps < .002$), we also conducted a Mann-Whitney test. The results indicate that the median number of correct rounds in the HITL treatment ($mdn = 7$)
exceeds the median correct rounds in the HOTL treatment (\(mdn = 5; U = 2872.5, r = -0.33; \ p < .001\)). This finding is corroborated by mixed effect probit regressions which reveal significant treatment differences (see Models 1-3 in Table 5). Taken together, the results provide support for the predicted effect that people are better at detecting the author of the poem for randomly chosen poems generated by GPT-2 (HOTL) compared to human selected poems (HITL).

Further, subgroup analyses reveal that while the accuracy rates in the HOTL treatment deviate significantly from chance (Student: \(t(88) = 7.72, p < .001\); WSR: \(Z = 2304, p < .001\)), in the HITL treatment accuracy levels do not (Student: \(t(95) = 1.83, p = .07\), WSR: \(Z = 1820.5, p = .1\), see also Figure 3). To further corroborate these subgroup effects, we conducted non pre-registered Bayesian analysis. The results reveal extreme evidence that in the HOTL treatment people’s accuracy significantly deviates from chance (\(BF_{10} = 5.095e+8\)). Contrarily, in the HITL treatment, the results reveal anecdotal evidence in support of the null hypothesis that people are not better than chance to detect the correct origin (\(BF_{01} = 1.79\)). In line with that, subgroup analysis using mixed effect probit regressions suggest that people are better than chance at detecting the HOTL selected poems (\(b = 0.44, SE = 0.10, Z = 4.53, p < .001\)), while not deviating significantly from chance in the HITL treatment (\(b = 0.10, SE = 0.09, Z = 1.06, p = .26\)). These patterns remain robust when introducing control variables of demographics and knowledge of the respective poem (see Models 2 & 3, Table 5). Taken together, these findings support the prediction that people’s ability to detect the correct origin of the poem depends on the way the poem is selected. While people can tell apart professional poems from algorithmically-generated poems that are randomly chosen with a human-out-of-the-loop, they cannot reliably do so when these poems are selected by a human-in-the-loop.
Figure 3. Violin plots depicting the distribution of accurate rounds across the selection treatment.

Note. The plot depicts the distribution of aggregated rounds in which the participants correctly identified the origin of the poem across in the Human-in-the-loop treatment (left pane) and Human-out-of-the-loop treatment (right pane). Inside the violin plot mean and 95% confidence intervals are plotted, indicating a significant ability of people to identify the correct origin only in the HOTL treatment preference for human-written poems in both treatments.
Part 4 – Confidence

As a first exploration of overconfidence we again examined the distribution of confidence. On the scale of 0 to 10 the average confidence level of the judges was $M = 5.99$ ($SD = 1.77$), with the distribution slightly left skewed ($skewness = 0.26, SE = 0.18$ see Figure 4, left pane). Akin to Study 1, we assessed the percentage of people who overestimate their performance, calculating the difference score between confidence and accuracy and classifying those with a positive score as overconfident. This time we find that 38.91 percent of the participants are classified as overconfident. We ran a linear regression of confidence predicting accuracy levels to assess whether actual and believed performance correlated. The results indicate a significant positive relationship ($b = 0.93, SE = 0.03, t(185) = 34.92, p < .0001$, see Figure 4, right pane).

To test the hypothesis, that participants’ estimated accuracy levels significantly exceeds their actual accuracy levels we conducted a one-sample t-test. Comparing the actual to the estimated performance ($M = 5.60, SD = 1.77$) reveals no significant differences ($t(184) = -0.35, p = .64$). Due to violation of normality (Shapiro-Wilk: $W = 0.97, p <.001$), we also conducted Wilcoxon signed-rank test which equally suggests no overall differences in observed and estimated performance ($W = 17045, p = .95$). Mixed effect linear regressions predicting overconfidence (i.e. confidence - accuracy), reveal no significant intercept, also when controlling for demographics and stated as well as revealed poetry knowledge ($bs < 0.06, ps > .18$). In concert, these results suggest that people overall do not show overconfidence and rather accurately estimate their ability to detect algorithmically generated poems.
Study 2 replicated two main findings observed in Study 1, and provides novel insights indicating that humans being in vs. out of the loop in the selection process of the poems crucially shapes both preferences and detection accuracy. First, the findings again reveal that people prefer human-written over algorithmically-generated poems, which is unswayed by the information about algorithmic presence, hence whether the origin of the poem was transparently communicated or opaquely revealed. As a second replication, people were again unable to reliably distinguish human from artificial poetry, while being incentivized to do so. However, this inability only occurred when humans were involved in the selection process (i.e. in the HITL treatment). When poems were randomly selected (i.e. in the HOTL treatment), people could detect the algorithmically-generated poem with higher than chance levels. Lending further credence to the importance of the selection procedure involved, the results, equally show significantly higher preference for algorithmically-generated poems when humans were involved.

**Figure 4.** Density distribution of the judges’ confidence score ranging from 0 to 10 (left pane). Scatterplot illustrating the relationship between people’s estimated (x-axis) and actual (y-axis) detection accuracy (right pane). The graphs plots linear regression slope as well as a slope with binomial smoothened estimates.

**Discussion**

Study 2 replicated two main findings observed in Study 1, and provides novel insights indicating that humans being in vs. out of the loop in the selection process of the poems crucially shapes both preferences and detection accuracy. First, the findings again reveal that people prefer human-written over algorithmically-generated poems, which is unswayed by the information about algorithmic presence, hence whether the origin of the poem was transparently communicated or opaquely revealed. As a second replication, people were again unable to reliably distinguish human from artificial poetry, while being incentivized to do so. However, this inability only occurred when humans were involved in the selection process (i.e. in the HITL treatment). When poems were randomly selected (i.e. in the HOTL treatment), people could detect the algorithmically-generated poem with higher than chance levels. Lending further credence to the importance of the selection procedure involved, the results, equally show significantly higher preference for algorithmically-generated poems when humans were involved.
in the selection process. As some of the first insights into the behavioral responses to different levels of human involvement in the selection process of AI-generated content, the results show that humans being involved or not in the selection process strongly impacts the abilities of the algorithm.

The results provide nuance to the link between estimated and actual algorithm detection accuracy. While in Study 1 participants’ unincentivized estimated performance significantly exceeded their actual performance, Study 2 elicited these estimations in an incentivized way. Contrary to the results of Study 1 and the hypothesis, the estimated performance did not significantly exceed actual performance and a positive link between detection accuracy and confidence therein existed.

**General Discussion**

Algorithms increasingly influence humans’ daily lives. Due to their growing learning abilities, autonomy and unpredictability in outcomes, it becomes pertinent to understand such machine behavior, and how it affects human behavior (Rahwan et al., 2019). The current set of studies contributes to this research by examining behavioral responses to the state-of-the-art NLG algorithm, GPT-2. Our results provide four main insights. First, while people reveal and state algorithm-aversion against artificial poetry, this aversive tendency does not increase when they are informed about the algorithmic origin of the text. These results bear special relevance when considering the second main insight: people reveal an apparent inability to reliability detect poetry that is generated by algorithms, although they are incentivized to do so and even when the algorithm competes with esteemed poets. Third, while overconfidence in the algorithm detection abilities exist when assessed in an unincentivized way (Study 1), no sign of systematic overconfidence exists when measured in an incentivized way (Study 2). Finally, the results of
Study 2 points towards the important role that humans play in the implementation of algorithmic outputs: humans involved in the process of selecting poems reduce revealed algorithm aversion and detection accuracy. In fact, when people are not involved in the selection process, accuracy does exceed chance levels. We discuss the implications of each of these insights in turn.

**Algorithm aversion and appreciation of algorithmic creativity**

Although first algorithms reach, and even surpass, human capacities in many narrow tasks, humans often show a general aversion towards adopting algorithms (Burton et al., 2019; Castelo et al., 2019; Dietvorst et al., 2015; Starke & Lünich, 2019). Contributing to current policy debates about transparency of algorithmic presence (Diakopoulos, 2016), our studies provide insights into the interplay of information and preferences for artificial vs. human text outputs. Contrary to our expectations, people reveal no stronger algorithm aversion when they are informed about the algorithmic origin of the text. Moreover, results of Study 2 allow linking such revealed behavioral preferences with stated preferences. Here, we find that people’s views on algorithms crafting poetry are strongly aversive. These views correlate consistently, but weakly with their behavior in choosing human poems over algorithmic poems.

Our findings thus contribute to ongoing research seeking to disentangle when people are aversive and when they are appreciative of algorithmic decision making. By now, multiple studies have examined people’s attitudes towards algorithmic decision making across various domains (Castelo et al., 2019; Lee, 2018; Pew Research Center, 2018). One key finding arising from that emerging literature is that people dislike algorithms to execute emotional (vs. mechanical) tasks. Hence, one interpretation of our results documenting aversion towards algorithmic poetry could stem from people viewing poetry as an emotionally charged task. We derive first support for that notion from our data collected using the existing algorithm aversion items. One of the original
items asked participants about their views about algorithms writing newspaper articles. Comparing the views on the items in which algorithms perform a language generation task – poetry and newspaper articles – reveals that people are significantly more approving of algorithms in the role of journalists rather than as poets (see full analysis in OSF).

**Distinguishing between Artificial and Human**

The question we brought to the online lab – are people actually able to distinguish artificial from human poetry – has attracted academic (Oliveira, 2009; Riedl, 2014) and public attention (Schwartz, 2015). For example, in a TED talk with more than 850k views, Oscar Schwartz compares poems by poets with generative poetry and based on his results claims that computers can indeed write poetry (Schwartz, 2015). Here, we extend such previous approaches in two fundamental ways. First, instead of using generative poetry algorithms that are specifically developed to merely write poetry, we use GPT-2, an algorithm more robust to different environments. The fact that although the algorithm is not specifically tailored to generate poetry, yet still manages to pass as a human writer, underlines the purported abilities of the algorithm in creating human-like texts (Radford et al., 2019).

Second, we deviate from previous approaches by introducing financial incentives to a version of the Turing Test. This methodological feature of financially incentivizing choices is common in behavioral research using economic games and aims to reduce the measurement error by increasing people’s accuracy (Ariely & Norton, 2007). The results of both studies substantiate the view that differentiating between human-written and algorithm-generated poetry is not a matter of effort, but ability. Moreover, as we return to below, gaining a definite answer whether a computer can write poetry that passes as human depends on whether and how humans are involved in the process of selecting the output.
Confidence in algorithmic detection abilities

Incentives also play a role for the question whether people systematically overestimate their own ability in detecting algorithmic poetry. While results of Study 1 using unincentivized confidence levels reveal that most of the participants overestimate their own abilities, results of Study 2 using incentivized measures of confidence paint a different picture: no evidence for systematic overconfidence and instead a positive relationship between ability and confidence. One way to interpret these differences is that in Study 1 participants “talked cheaply” and boasted their own perceived performance. Overconfidence is particularly pronounced in public settings where people can impress others (Ronay, Oostrom, Lehmann-Willenbrock, & Van Vugt, 2017). Since we assessed confidence in a private setting it is conceivable that participants in Study 1 overestimated their own performance to feel better about themselves and thus self-deceive (van der Weele & Schwardmann, 2019).

In Study 2, when incentives were attached to detecting the algorithmically-generated creative content people seemed to calibrate their responses, as their estimated and actual performance overall match well. This lack of overconfidence is remarkable in light of participants’ inexperience with the task. They were thus not able to draw on prior knowledge of their ability to detect algorithmic poetry, yet still able to provide informative estimates when reflecting on their own performance. Taken together, the results suggest that overconfidence in algorithm detection can be curbed by providing financial rewards so that people strive to accurately estimate their own performance.
Human selection in and out of the loop

Our results suggest that computers can write poems that pass as human and that the poems are considerably appealing to readers, even when competing with the original work of professional writers. However, the results of Study 2 suggest that humans play an integral role in the process – only poems selected by humans successfully passed as human and lowered algorithm aversion. Hence, whether humans are in or out of the selection loop shaped people’s reactions to the algorithm’s performance.

Thereby our experimental findings provide some of the first behavioral insights into people’s reactions to different human-in-the-loop systems, and complement a rich (technical) literature in AI research (Schirner et al., 2013). Seeking to mitigate the limitations of algorithms, such as racial or socio-economic biases (Crawford & Calo, 2016), human-in-the-loop systems have been proposed to increase algorithmic accountability (Wang et al., 2020; Zhu et al., 2018) as keeping humans in the loop helps to monitor and adjust the system and its outcomes (Rahwan, 2018). Here, we show that humans in the loop also allow to harness the potential of recent developments in NLG, and crucially shape which conclusions about the machine’s behaviour are drawn.

Implications and future research

The results of the studies bear (ethical) implications. Language generation algorithms are entering daily lives. Using transfer learning, GPT-2 can be fine-tuned to craft text in other domains than poetry, such as online reviews, patent claims (Lee & Hsiang, 2019), or fake tweets (Ressmeyer, Masling, & Liao, 2019). Yet NLG can also be harnessed for good, such as providing useful feedback for customers (Budzianowski & Vulić, 2019) or even contribute to
curbing corruption, for example the Brazilian crowdsourced anti-corruption efforts *Operação Serenata do Amor* that uses a tweetbot to create public accountability (see [https://serenata.ai/en/](https://serenata.ai/en/)). NLG algorithms thus have potential but also perils. To contribute to a responsible use, future experimental studies examining how people react to algorithmically generated text in different domains will help to gain valuable empirical insights.

Our framework contributes to the methodological toolkit to systematically study the impact of NLG algorithms on human behavior. To gain insights into the question whether people are even aware that they are consuming algorithmically generated text we propose an incentivized version of the Turing Test. Future studies could examine NLG’s abilities in other domains, such as automated news generation (Carlson, 2015; Diakopoulos & Koliska, 2017) or longer creative texts – providing insights whether algorithmically generated texts similarly passes as human in these domains. Studies seeking to study existing NLG algorithms face the challenge of dealing with unpredictable and changing text outputs. This leads to less experimental control when it comes to the machine’s behavior (Rahwan et al., 2019), yet provides new researchers degrees of freedom in stimulus selection. Our treatment comparing *HITL* and *HOTL* shows that this methodological choice can influence the results. Standardized selection protocols and open science practices (Srivastava, 2018) play an important role to gain reliable and reproducible findings on the nexus of human and machine behavior.

Taking a step back and examining the overall pattern of results, we emphasize that the results do not indicate that machines are “creative”. In fact, one of the main functions of creativity in general and poetry in particular is the expression of (deep) emotions, a feat that machines lack (so far). The results are rather testament for the increasing abilities of NLG algorithms to create text that mimics human creative text and that people do find appealing. It is
widely assumed that algorithms such as GPT-2 have a long way to go before they can autonomously write truly creative text, especially in longer forms than poems. However, projects in which humans and algorithms form hybrid writing teams and collaboratively craft fiction text present one way in which such algorithms could enter our daily life. It however remains unclear whether such forms of hybrid collaborations between human and machines should be considered plagiarism or conversely to what extend the (developer of the) algorithm deserves (financial) credit for textual outputs. Related to the set-up used in the current studies, would an entry to an actual poetry competition by a contestant who uses GPT-2 input be counted as fraud? If so, how could it be detected? And if not, (how) should the prize money be split?

**Conclusion**

Algorithms that generate text that resembles human language become ever more widely accessible. By now, not only novelists with a writer’s block can make use of freely available algorithms like GPT-2. Understanding humans’ behavioral reactions to such algorithms helps to shape policies that ensure that artificial intelligence remains beneficial and ethical (Crawford & Calo, 2016). As a step in that direction, the present set of studies adopts a behavioral social science approach to examine creative artificial intelligence. We hope that more studies follow suit to inform policies of disclosure of algorithmic presence and provide new behavioral insights into human versus (creative) artificial intelligence.
References

Amabile, T. M. (1983). The social psychology of creativity: A componential conceptualization.  
*Journal of Personality and Social Psychology, 45*(2), 357–376. http://doi.org/10.1037/0022-3514.45.2.357

Ariely, D., & Norton, M. I. (2007). Psychology and Experimental Economics: A Gap in Abstraction. *Current Directions in Psychological Science, 16*(6), 336–339.  
http://doi.org/10.1111/j.1467-8721.2007.00531.x

Bakhshi, H., Frey, C. B., & Osborne, M. (2015). Creativity vs. Robots - The creative economy and the future of employment. *Nesta*, (April), 1–40.

Bigman, Y. E., & Gray, K. (2018). People Are Averse to Machines Making Moral Decisions.  
*Cognition, 1*(viikko 37), 399–405.

Bigman, Y. E., Waytz, A., Alterovitz, R., & Gray, K. (2019). Holding Robots Responsible: The Elements of Machine Morality. *Trends in Cognitive Sciences*.  
http://doi.org/10.1016/j.tics.2019.02.008

Boden, M. A. (2009). Computer models of creativity. *AI Magazine, 30*(3), 23.

Bringsjord, S., & Ferrucci, D. (1999). *Artificial intelligence and literary creativity: Inside the mind of brutus, a storytelling machine*. Mahwah, NJ: Lawrence Erlbaum.

Budzianowski, P., & Vulić, I. (2019). Hello, It’s GPT-2 - How Can I Help You? Towards the Use of Pretrained Language Models for Task-Oriented Dialogue Systems. In *Conference Proceedings Association for Computational Linguistics (ACL)*. (pp. 15–22). Conference Proceedings Association for Computational Linguistics (ACL).
Burton, J. W., Stein, M. K., & Jensen, T. B. (2019). A systematic review of algorithm aversion in augmented decision making. *Journal of Behavioral Decision Making*, bdm.2155.

http://doi.org/10.1002/bdm.2155

Camerer, C. F. (2011). *Behavioral game theory: Experiments in strategic interaction*. Behavioral Game Theory: Experiments in Strategic Interaction. Princeton University Press.

http://doi.org/10.1016/j.socec.2003.10.009

Carlson, M. (2015). The Robotic Reporter: Automated journalism and the redefinition of labor, compositional forms, and journalistic authority. *Digital Journalism, 3*(3), 416–431.

http://doi.org/10.1080/21670811.2014.976412

Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-Dependent Algorithm Aversion. *Journal of Marketing Research*, 56(5), 809–825. http://doi.org/10.1177/0022243719851788

Clerwall, C. (2014). Enter the Robot Journalist. *Journalism Practice, 8*(5), 519–531.

http://doi.org/10.1080/17512786.2014.883116

Craglia, M., Annoni, A., Benczur, P., Bertoldi, P., Delipetrev, P., De Prato, G., … Vesnic, A. L. (2018). *Artificial Intelligence: A European Perspective*. European Union.

http://doi.org/10.2760/11251

Crawford, K., & Calo, R. (2016). There is a blind spot in AI research. *Nature*, 538(7625), 311–313. http://doi.org/10.1038/538311a

Dafoe, A. (2018). *AI Governance: A Research Agenda. Governance of AI Program*. Oxford, UK: Oxford University. http://doi.org/10.1176/ajp.134.8.aj1348938
Diakopoulos, N. (2016). Accountability in Algorithmic Decision Making. In Communications of the ACM (Vol. 59, pp. 56–62). http://doi.org/10.1145/2844110

Diakopoulos, N., & Koliska, M. (2017). Algorithmic Transparency in the News Media. Digital Journalism, 5(7), 809–828. http://doi.org/10.1080/21670811.2016.1208053

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. Journal of Experimental Psychology: General, 144(1), 114–126. http://doi.org/10.1037/xge0000033

Garfinkel, S., Matthews, J., Shapiro, S. S., & Smith, J. M. (2017). Toward algorithmic transparency and accountability. In Communications of the ACM (Vol. 60, p. 5). http://doi.org/10.1145/3125780

Gibney, E. (2020). This AI researcher is trying to ward off a reproducibility crisis. Nature, 577(7788), 14–14. http://doi.org/10.1038/d41586-019-03895-5

Gneezy, U., Saccardo, S., & van Veldhuizen, R. (2019). Bribery: Behavioral Drivers of Distorted Decisions. Journal of the European Economic Association, 17(3), 917–946. http://doi.org/10.1093/jeea/jvy043

Goldenfein, J. (2019). Algorithmic Transparency and Decision-Making Accountability: Thoughts for Buying Machine Learning Algorithms. In Closer to the Machine: Technical, Social, and Legal aspects of AI (pp. 41–145).

http://doi.org/https://ssrn.com/abstract=3445873

Gonçalo Oliveira, H. (2018). A Survey on Intelligent Poetry Generation: Languages, Features, Techniques, Reutilisation and Evaluation. In Proceedings of the 10th International
Conference on Natural Language Generation. (pp. 11–20). http://doi.org/10.18653/v1/w17-3502

Graefe, A., Haim, M., Haarmann, B., & Brosius, H. B. (2018). Readers’ perception of computer-generated news: Credibility, expertise, and readability. Journalism, 19(5), 595–610. http://doi.org/10.1177/1464884916641269

Highhouse, S. (2008). Stubborn Reliance on Intuition and Subjectivity in Employee Selection. Industrial and Organizational Psychology, 1(3), 333–342. http://doi.org/10.1111/j.1754-9434.2008.00058.x

Jozefowicz, R., Vinyals, O., Schuster, M., Shazeer, N., & Wu, Y. (2016). Exploring the Limits of Language Modeling. Retrieved from http://arxiv.org/abs/1602.02410

Keith, R. (2012). Explaining Creativity—the Science of Human Innovation. Oxford, UK: Oxford University Press.

Kreps, S., & McCain, M. (2019). Not Your Father’s Bots. Foreign Affairs. Retrieved from https://www.foreignaffairs.com/articles/2019-08-02/not-your-fathers-bots

Kruger, J., & Dunning, D. (1999). Unskilled and unaware of it. Journal of Personality and Social Psychology, 77(6), 1121–1134. http://doi.org/10.1109/MMM.2011.2173980

Laakasuo, M., Palomäki, J., & Köbis, N. C. (2019). Moral Uncanny Valley - Robot’s Appearance Moderates How its Decisions are Judged (Working Paper). Helsinki, Finland.

Lee, J.-S., & Hsiang, J. (2019). Patent Claim Generation by Fine-Tuning OpenAI GPT-2. Retrieved from http://arxiv.org/abs/1907.02052

Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and
emotion in response to algorithmic management. *Big Data and Society, 5*(1), 1–16.
http://doi.org/10.1177/2053951718756684

Leviathan, Y., & Matias, Y. (2018). Google Duplex: an AI system for accomplishing real-world tasks over the phone. http://doi.org/https://ai.googleblog.com/2018/05/duplex-ai-system-for-natural-conversation.html

Loller-Andersen, M., & Gambäck, B. (2018). Deep Learning-based Poetry Generation Given Visual Input. In *Proceedings of the Ninth International Conference on Computational Creativity (ICCC’18)* (pp. 240–247).

Majid al-Rifaie, M., Cropley, A. J., Cropley, D. H., & Bishop, M. (2016). On evil and computational creativity. *Connection Science, 28*(2), 171–193.
http://doi.org/10.1080/09540091.2016.1151862

Malmendier, U., & Tate, G. (2008). Who makes acquisitions? CEO overconfidence and the market’s reaction. *Journal of Financial Economics, 89*(1), 20–43.
http://doi.org/10.1016/j.jfineco.2007.07.002

Marcinkowski, F., Kieslich, K., Starke, C., & Lünich, M. (2020). Implications of AI (Un-)Fairness in Higher Education Admissions: The Effects of Perceived AI (Un-)Fairness on Exit, Voice and Organizational Reputation. In *Conference on Fairness, Accountability, and Transparency*. Association for Computing Machinery.

Marcus, G., Rossi, F., & Veloso, M. (2016). Beyond the turing test. *AI Magazine, 37*(1), 3–4.
http://doi.org/10.1609/aimag.v37i1.2650

McCormack, J., & D’Inverno, M. (2014). On the future of computers and creativity. In *AISB*
Moore, D. A., & Healy, P. J. (2008). The Trouble With Overconfidence. *Psychological Review, 115*(2), 502–517. http://doi.org/10.1037/0033-295X.115.2.502

Oliveira, H. G. (2009). Automatic generation of poetry: An overview. In *1st Seminar of Art, Music, Creativity and Artificial Intelligence* (pp. 1–6).

Peer, E., Brandimarte, L., Samat, S., & Acquisti, A. (2017). Beyond the Turk: Alternative platforms for crowdsourcing behavioral research. *Journal of Experimental Social Psychology, 70*, 153–163. http://doi.org/10.1016/j.jesp.2017.01.006

Penrose, R. (1990). *The Emperor’s New Mind: Concerning Computers, Minds, and the Laws of Physics*. Oxford, UK: Oxford University Press. http://doi.org/10.1119/1.16207

Pew Research Center. (2018). *Public attitudes toward computer algorithms*. Retrieved from http://www.pewinternet.org/2018/11/16/algorithms-in-action-the-content-people-see-on-social-media/

Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). Language Models are Unsupervised Multitask Learners. *OpenAI Blog, 1*(8), 1–24.

Rahwan, I. (2018). Society-in-the-loop: programming the algorithmic social contract. *Ethics and Information Technology, 20*(1), 5–14. http://doi.org/10.1007/s10676-017-9430-8

Rahwan, I., Cebrian, M., Obradovich, N., Bongard, J., Bonnefon, J.-F., Breazeal, C., … Wellman, M. (2019). Machine behaviour. *Nature, 568*(7753), 477–486. http://doi.org/10.1038/s41586-019-1138-y

Ressmeyer, R., Masling, S., & Liao, M. (2019). “*Deep Faking*” Political Twitter using Transfer
learning and GPT-2 (Preprint). Stanford, CA, USA.

Riedl, M. O. (2014). The Lovelace 2.0 Test of Artificial Creativity and Intelligence, 2–4.
Retrieved from http://arxiv.org/abs/1410.6142

Ritchie, G., Manurung, R., Pain, H., Waller, A., Black, R., & O’Mara, D. (2007). A practical application of computational humour. In Proceedings of the 4th International Joint Workshop on Computational Creativity (pp. 91–98).

Ronay, R., Oostrom, J. K., Lehmann-Willenbrock, N., & Van Vugt, M. (2017). Pride before the fall: (Over)confidence predicts escalation of public commitment. Journal of Experimental Social Psychology, 69, 13–22. http://doi.org/10.1016/j.jesp.2016.10.005

Saygin, A. P., Chaminade, T., Ishiguro, H., Driver, J., & Frith, C. (2012). The thing that should not be: Predictive coding and the uncanny valley in perceiving human and humanoid robot actions. Social Cognitive and Affective Neuroscience, 7(4), 413–422.
http://doi.org/10.1093/scan/nsr025

Schirner, G., Erdogmus, D., Chowdhury, K., & Padir, T. (2013). The Future of Human-in-the-Loop Cyber-Physical Systems.

Schwartz, O. (2015). Can a computer write poetry. Retrieved from https://www.ted.com/talks/oscar_schwartz_can_a_computer_write_poetry?utm_campaign=tedspread&utm_medium=referral&utm_source=tedcomshare

Shin, D., & Park, Y. J. (2019). Role of fairness, accountability, and transparency in algorithmic affordance. Computers in Human Behavior, 98(March), 277–284.
http://doi.org/10.1016/j.chb.2019.04.019
Sloman, A. (2012). Meta-morphogenesis and the Creativity of Evolution. *Computational Creativity, Concept Invention, and General Intelligence, 1*, 51–58.

Srivastava, S. (2018). Sound inference in complicated research, (1). http://doi.org/.1037//0033-2909.126.1.78

Starke, C., & Lünich, M. (2019). *Artificial Intelligence for Decision-Making in the European Union: Effects on Citizens’ Perceptions of Input, Throughput and Output Legitimacy* (Pre-Print). Retrieved from https://arxiv.org/abs/2003.11320

Streitfeld, D. (2018). Computer Stories: A.I. Is Beginning to Assist Novelists. *New York Times*, pp. 1–13. http://doi.org/10.1017/CBO9781107415324.004

Sundar, S. S., & Nass, C. (2001). Conceptualizing sources in online news. *Journal of Communication, 51*(1), 52–72. http://doi.org/10.1111/j.1460-2466.2001.tb02872.x

The Guardian. (2019, February 14). New AI fake text generator may be too dangerous to release, say creators. http://doi.org/https://www.theguardian.com/technology/2019/feb/14/elon-musk-backed-ai-writes-convincing-news-fiction

Turing, A. M. (1950). Computing Machinery and Intelligence. *Mind - A Quarterly Review of Psychology and Philosophy, 236*(Oct), 433–460.

van Dalen, A. (2012). The algorithms behind the headlines: How machine-written news redefines the core skills of human journalists. *Journalism Practice, 6*(5–6), 648–658. http://doi.org/10.1080/17512786.2012.667268

van der Weele, J., & Schwardmann, P. (2019). Deception and Self-Deception. *Nature Human Behaviour, 3*(10), 1055–1061.
Walsh, T. (2016). Turing’s red flag. In *Communications of the ACM* (Vol. 59, pp. 34–37).
http://doi.org/10.1145/2838729

Walsh, T. (2017). The meta turing test. In *AAAI Workshop - Technical Report* (Vol. WS-17-01-,
pp. 132–137).

Wang, R., Harper, F. M., & Zhu, H. (2020). Factors Influencing Perceived Fairness in
Algorithmic Decision-Making: Algorithm Outcomes, Development Procedures, and
Individual Differences, 1–14. Retrieved from http://arxiv.org/abs/2001.09604

Warwick, K., & Shah, H. (2016). Can machines think? A report on Turing test experiments at
the Royal Society. *Journal of Experimental and Theoretical Artificial Intelligence, 28*(6),
989–1007. http://doi.org/10.1080/0952813X.2015.1055826

Yeomans, M., Shah, A., Mullainathan, S., & Kleinberg, J. (2019). Making sense of
recommendations. *Journal of Behavioral Decision Making, 32*(4), 403–414.
http://doi.org/10.1002/bdm.2118

Zhu, H., Yu, B., Halfaker, A., & Terveen, L. (2018). Value-sensitive algorithm design: Method,
case study, and lessons. *Proceedings of the ACM on Human-Computer Interaction,*
2(CSCW). http://doi.org/10.1145/3274463