Evaluating Manipulations for Creating Perceived Human-AI Seamlessness

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Abstract

Algorithms contain biases that must be detected; therefore, deferring responsibility for basic human operations like corrective feedback to algorithms leaves the media user vulnerable to technologically-enabled threats. Recent research demonstrates that certain qualities of technology can make it more difficult to accurately monitor one's extended cognitive environment. This research is an initial attempt to create a flexible testbed for investigating the influence of technology-enabled perceptions of seamlessness on participants' ability to detect errors produced by predictive text algorithms. Specifically, we seek to determine whether perceived seamlessness with technology manifests in the combination of perceived interactivity of, perceived identification with, perceived credibility of, and perceived familiarity with a technology.

Keywords: Media psychology, seamlessness, human-computer interactions

Evaluating Manipulations for Creating Perceived Human-AI Seamlessness

Artificial intelligence (AI), which involves the simulation of human intelligence processes by machines, affords qualities that allow people to meld with technologies to form an extended self (c.f., Clark, 2011). For example, AI software that generates predictive text operates on common messaging platforms, such as WhatsApp, Facebook, and Gmail, to create a collaborative message sent by the user. These softwares utilize algorithms, machine learning, and natural language processing to operate on behalf of the user to generate a self-represented message (Hancock, Naaman, Levy, 2020). Yet, algorithms do not represent users faithfully. Algorithms can produce low-risk errors like spelling or grammar errors that misrepresent a users' intentions. Algorithms can also produce high-risk errors: search engines perpetuate racial and ethnic stereotypes (Noble, 2018; Sweeny, 2013), algorithms have wrongfully labeled women as more likely to reoffend when determining parole eligibility (Hamilton, 2019), and healthcare algorithms have been shown to prioritize White patients over Black patients (Obermeyer et al., 2019). Algorithms contain biases that must be detected; therefore, deferring responsibility for basic human operations like providing corrective feedback to algorithms leaves the media user vulnerable to technologically-enabled threats. It is critical that humans who collaborate with AI are able to detect errors and biases in machines as they arise.

Recent research demonstrates that certain qualities of technology can make it more difficult to accurately monitor one's extended cognitive environment. Ward (2013, 2021) found that feelings of familiarity with a search engine can lead people to conflate technology-enabled answers to general-information trivia questions as self-produced. If users overestimate the extent to which they contribute to technology-produced answers, users may also misunderstand when it is necessary to override the answers of the operating device. Fisher, Goddu, and Keil (2015;

Experiment 4c) demonstrated that an illusion of knowledge following internet search remains even in cases where the search query fails to provide relevant answers or even results at all. Storm, Stone, and Benjamin (2017) found that using the internet to access information inflates future use of the internet to access other information. In these empirical examples, we see a tendency for people to mindlessly rely on the outputs of a digital source to accomplish personal cognitive goals. Pereira, Kelly, Lu, & Risko (2022) demonstrated that individuals who offloaded memories to a digital store did not tend to notice when that digital store had been manipulated unless they were explicitly notified or were told that information in the store would be inaccessible in the future. When we collaborate with technology, it is easy to lose sight of our responsibility to supply feedback and correction to our devices. We take as a starting point that cues emanating from a device (or devices) play a powerful role in our ability to intervene when devices respond inappropriately.

This research is an initial attempt to create a flexible testbed for investigating manipulations of seamlessness that influence metacognition, the awareness and understanding of one's thought process. Seamlessness occurs when people feel one with a device (or devices). Seamlessness is a perception of fluency created through technology-mediated interaction. Ample evidence demonstrates a pattern that when people feel seamless with technology, they are prone to metacognitive errors. For example, AUTHOR (2023) demonstrated that when people have immediate access to answers to procedural knowledge questions, they are prone to overestimating their ability to answer new questions without the internet. Empirical evidence suggests that humans are prone to metacognitive errors when they seamlessly operate platforms like search engines (e.g., Fisher, Goddu, & Keil, 2015; Ward, 2013, 2021), digital agents (e.g., AUTHOR, 2021), or smartphones (e.g., AUTHOR, 2018). Yet, we know much less about the qualities of technologies that cue seamlessness. Past research has taken a bottom-up approach to theorize patterns that may contribute to the tendency to mindlessly offload responsibility to technology. Here, we take a top-down approach by investigating four variables that may result in a tendency to offload responsibility for detecting algorithmic errors, thereby increasing susceptibility to metacognitive errors. Specifically, we propose that perceived seamlessness with technology manifests in the combination of perceived interactivity of, perceived identification with, perceived credibility of, and perceived familiarity with a technology. We closely examine each of these components in the following sections and provide evidence of how their manifestation contributes to perceived seamlessness.

Perceived Interactivity

Perceived interactivity depicts the psychological state experienced by a user when interacting with a technology that manifests in users' perceptions of active control, two-way communication, synchronicity, and other factors (McMillian & Hwang, 2002; Wu, 2005). Perceived interactivity plays an important role in creating seamless perceptions because it empowers both parties to communicate the information produced, the experience, and feedback (Sundar et al., 2016). In consumer research, perceived interactivity has been shown to positively influence consumers' initial online trust in an e-vendor (Wu, Hu, & Wu, 2010), attitudes toward the website and memory of products (Chung & Zhao, 2004), and perceived efficiency and effectiveness of the website that ultimately contribute to consumers' e-loyalty (Cyr, Head, & Ivanov, 2009).

In AI-mediated environments, technology may not always afford high levels of interactive elements in the way it is purported to users, but instead employ designs that manifest higher perceptions of interactivity. For example, AUTHOR (2020) found that individuals favor recommendations by digital agents that make them feel as if the digital agent selects products the user is mostly likely to endorse. The self-endorsement manipulation is partly achieved by creating perceived interactivity with the self-endorsing agent. Bandura (2001) explains that personal agency gains in magnitude when individuals influence others in desirable and self-fulfilling ways. It is no surprise that feelings of feedback between the user and digital agent can play a strong role in instilling psychological empowerment (Stavrositu & Sundar, 2012). Predictive algorithms allow users to decide whether they accept or reject a typing suggestion and provide feedback to the algorithms, activating cues of active control and two-way communication. Such a sense of empowerment may reinforce users' misbelief that the technology is attuning to their cognition and thus reflects their true thoughts, but at the same time, leaves them incapable of detecting biases generated by the algorithms.

Perceived Identification

Perceived identification allows users to infer self-relevance from technology, and tempts users to see themselves in technology (Fox & Beilenson, 2009; AUTHOR, 2020). Perceived identification is often a manifestation of users' psychological ownership with technology (Shu & Peck, 2011). In a virtual reality setting, Fox and Bailenson (2009) found that a virtual representation of the self can sufficiently boost exercising activities, explained by high perceived identification, compared to a representation of the other. Similarly, AUTHOR (2020) showed that personalized digital agents promote a more positive attitude and stronger purchase intention toward a product than a control agent when they believed that the self-agent represented their personal characteristics. These findings suggest a psychological connection with technology is essential to build the perception of seamlessness.

In AI-mediated environments, the ability for technology to create and customize using users' personal information may signal a seamless psychological connection between users and their digital devices that can leave the device's actions unchecked. Technology that allows users to customize and thereby provide "proxy" agency to users is becoming increasingly capable of exerting its own agency (Sundar, 2020). In this regard, personalized algorithms that strategically promote psychological bonding and ownership with users may indirectly put users in jeopardy; for instance users may unconsciously integrate errors suggested by algorithms into their own outputs (e.g., messages, profiles).

Perceived credibility

Credibility perceptions signal the competence of technology to assist and even substitute users in the process of accomplishing a task, thus facilitating uncertainty reduction and trust-building with technology (Liu, 2021). In AI-mediated environments, establishing a sense of trust with the technology can help guide users' reliance and navigate their decision-making, especially when confronting complexity and uncertainty (Lee & See, 2004). Machine heuristics are mental shortcuts based on the belief that machines are objective, trustworthy, unbiased, and may contribute to higher perceptions of credibility and trustworthiness of the technology, regardless of actual levels of credibility (Sundar, 2008). Prior research has pointed out a tendency for people to grant more power and trust to suggestions from machines as a replacement for information seeking and processing—a phenomenon known as automation bias (Mosier et al., 1998). Sundar and Kim (2019) found that, in the context of online transactions that involve disclosing personal information, participants showed higher trust to machine agents than human agents, suggesting the use of machine heuristics yet possible negative outcomes of automation bias. Once technological attributes trigger cognitive heuristics that inform credibility perceptions of the source, users may engage in a less careful examination of the credibility of the messages.

Perceived Familiarity

Perceived familiarity with technology manifests users' prior psychological experience with technology that often serves as a fast-acting, relatively-automatic heuristic cue, and arises at the early stage of exposure to technology (Rosburg, Mecklinger, & Frings, 2011; Schwikert & Curran, 2014). While familiarity with technology is operationalized by factual knowledge of technology and digital literacy (e.g., Li & Chen, 2021), perceived familiarity manifests in people’s self-assessment and is largely driven by prior experience (Wojcieszak et al., 2021), self-efficacy (Hargittai, 2008), personal attitudes, and emotions (Park et al., 1988) that can affect their subsequent psychological responses.

Sundar (2020) suggests that prior experience can shape perceptions about an AI-driven medium and determine the degree to which users activate heuristics when collaborating with AI technology. Perceived familiarity can make a process feel more natural. For instance, Ward (2013) found that individuals who used Google to search for answers to trivia questions were more confident in their ability to think about, remember, and locate information than individuals who did not use Google to complete the trivia quiz. The effect was attenuated when participants used an equally useful, but unequally used, search engine (i.e., Lycos; Experiment 1). Accomplishing cognitive or communicative goals through a familiar access point like Google (Ward, 2013) or a personally-owned device (Hamilton & Yao, 2018) can create a feeling of seamlessness that may make it more difficult to monitor the digital source.

Present Investigation

The purpose of this research is to evaluate peoples' ability to detect errors created by two algorithms that have been programmed with varying levels of imagined affordances (c.f., Norman, 1988) that we suspect are related to seamlessness. We are primarily interested in whether perceptions of seamlessness influence participants' ability to detect errors produced by predictive text algorithms. However, our ability to detect this effect is dependent on our ability to manipulate perceptions of seamlessness. Therefore, this initial test is concerned with determining whether our manipulations of seamlessness are detectable to participants.

We designed an open-source smart compose simulator called EMail Predictive Text Imitator (EMPTI) for conducting experimental research to detect individuals' sensitivity to errors produced by algorithms on the basis of their psychological responses to imagined technological affordances. EMPTI allows us to manipulate the interface design, algorithmic suggestions, and collect rich behavioral data to study effects of perceived seamlessness on users' ability to detect errors produced by a predictive text imitator. In this experiment, we created four manipulations of seamlessness, each related to one of the four components of seamlessness described above. We predicted the following:

H1: Participants will perceive higher interactivity with the predictive text algorithm in the high seamlessness condition than the predictive text algorithm in the low seamlessness condition.

H2: Participants will perceive higher identification with the predictive text algorithm in the high seamlessness condition than the predictive text algorithm in the low seamlessness condition.

H3: Participants will perceive higher credibility for the predictive text algorithm in the high seamlessness condition than the predictive text algorithm in the low seamlessness condition.

H4: Participants will perceive higher familiarity with the predictive text algorithm in the high seamlessness condition than the predictive text algorithm in the low seamlessness condition.

If there are differences in the perceived interactivity of, perceived identification with, perceived credibility of, and perceived familiarity with the predictive text algorithms on the basis of our conceptual manipulations, then we can determine whether these differences mediate a person's propensity to detect errors produced by the predictive text algorithm. If we fail to detect differences between the two conditions, then we will have a clearer understanding of the contexts that do not produce perceptual differences in seamlessness.

If we observe differences in manipulations of seamlessness, we make the following prediction:

H5: The effect of perceived synergy on users' ability to detect algorithmic errors will be mediated by (a) perceived credibility of, (b) perceived familiarity with, (c) perceived interactivity of, and (d) perceived identification with a predictive algorithm.

Method

We chose to adopt a Bayesian approach to evaluate our data to allow for continuous refinement of our manipulations. Bayesian inference is based on the assessment of the strength of evidence for or against a hypothesis on a continuous scale, whereas frequentist hypothesis tests provide binary decisions to reject or fail to reject the null hypothesis. A Bayes factor represents the ratio of evidence favoring either hypothesis. All Bayes factors herein are reported in terms of evidence favoring the null – any values over 1 reflect support for the null and under 1 reflect support for the alternative hypothesis.

Participants

Sample size determination in Bayesian analysis is typically based on practical considerations, such as the feasibility of collecting data, rather than on the need to achieve a certain level of statistical power. Bayesian statistics permits the sample size to be adjusted during the study to make the best use of available resources. Our strategy was to first recruit a sample of 100 participants, or further (+50 participants) until a Bayes Factor of over 3 (or under 0.33) is achieved. According to Jeffreys (1961), Bayes Factors under 3 (and above 0.33) do not constitute much evidence for one hypothesis over another. We recruited 218 participants to our study using mTurk. We excluded participants who sped through the tasks, did not complete the study, and failed the manipulation check (n=132), resulting in a total number of 86 participants in the final dataset. 43% of the sample identified themselves as women (n = 37), 55% as men (n = 47), and 2% didn't specify their gender (n = 2). Participants' ages ranged from 19-70, with an average age of 35.38 (SD = 10.13). 15% identified as Asian (n = 13), 7% as Black/African American (n = 6), 2% as Latino (n = 2), 71% as White (n = 61), and 3% either mixed race or other (n = 3). Three participants (3%) did not specify their race.

Stimuli

EMPTI (EMail Predictive Text Imitator; https://github.com/austinmacmath/EMPTI/wiki) is a web application which simulates an email client augmented with a predictive text algorithm. The algorithm predicts text by learning text patterns from a given input, in our case an email prompt, and by reading a text frequency dictionary. The predictive text algorithm was implemented with Predictionary (Klaus, 2020), an open source JavaScript word prediction library that learns text prediction patterns by reading a word frequency corpus. In our context, EMPTI reads experimental stimuli given to the user and keeps track of users' behaviors (i.e., accept or reject) to increase the relevancy of text suggestions. A new prediction is generated each time a character is typed.

We operationalized “errors” as misspelled words generated by the predictive algorithms. To experimentally manipulate errors produced by the predictive text algorithm, we created two repositories that were incorporated into our predictive algorithms: one with a total of 25,000 correctly spelled words (no errors) and one with 513 commonly misspelled words in substitution for their correct versions (errors). Participants in the error conditions received typing suggestions from an algorithm that was trained based on the misspelled word repository.

Design & Procedure

This study featured a web-based experiment with a 2 (perceived seamlessness: high vs. low) by 2 (algorithmic typing suggestions: no errors vs. errors) within-subject design.

We recruited participants to a study designed to test the usability of two different predictive algorithms that provide typing suggestions while participants completed the email task: Smart Predictor (high seamlessness; Figure 1) and CS Predictor (low seamlessness; Figure 2). All participants completed this online experiment on a desktop or laptop device at a location of their choice, providing a natural environment to engage with the stimuli. Before using either predictive algorithm, participants filled out a writing habits questionnaire adapted from existing writing skills questionnaires (Grammarly, 2021; National Center for Education Statistics, 1997) as part of our manipulation. The writing habits questionnaire was purported for Smart Predictor (high seamlessness condition) to build a hyper-personalized algorithm and generate typing suggestions unique to their personal writing style for later email response tasks. The next page displayed a sentence that said “please give us a few seconds for Smart Predictor to learn your writing habits and provide you with the most personalized writing suggestions later in the experiment”, with a blue circle rotating for ten seconds. In reality, the predictive algorithms associated with Smart Predictor and CS Predictor were identical.

After completing the writing habits questionnaire, we randomly assigned participants to either start with Smart Predictor (high perceived seamlessness) or CS Predictor (low perceived seamlessness) as they wrote responses to the first four randomly distributed emails, and then switched to the other condition for the last four emails. See Figure 3 for instructions. We selected eight email prompts through pre-testing using a small undergraduate sample to ensure email prompts were easy to answer, related to our participants, and generalizable to the real-world population. Before starting the email writing task, participants completed an interactive tutorial that outlined the features (i.e., our experimental manipulation) of each predictive algorithm as well as the instructions of the tasks. In line with our theoretical conceptualization, we manipulated participants’ perceptions of interactivity, identification, credibility, and familiarity with the predictive algorithm to create experimental conditions with high and low perceived seamlessness. We operationalize each manipulation as follows.

Perceived interactivity manipulation. Our interactivity manipulation featured three floating dots at the bottom left of the typing area that simultaneously swung as participants typed to manifest high perceived interactivity in the high seamlessness condition. In the low seamlessness condition, there were no floating dots.

Perceived identification manipulation. Participants were led to believe that Smart Predictor is a highly personalized algorithm that learns from their typing patterns over time and provides suggestions that are tailored towards their own writing styles (based on responses to the writing habits questionnaire). We explained that CS Predictor can only provide typing suggestions that a majority of users would have typed based on the probability model. In reality, there was no difference between the two algorithms, and neither was able to make any personalized suggestions.

Perceived credibility manipulation. Communicating sources that cue credibility heuristics (e.g., reputation heuristic) facilitate a less effortful credibility assessment, especially when encountering difficulty forming evaluations (Sundar, 2008). Therefore, we manipulated credibility perception by telling participants that Smart Predictor is designed by the Computer Science Department at our university in collaboration with Google's Smart Compose Team, while CS Predictor is developed by a group of Computer Science junior students at our university as a final project in their AI Programming course.

Perceived familiarity manipulation. Our perceived familiarity manipulation was accomplished by two different designs for the email pages. The high seamlessness design simulates the layout of Gmail and adopts its logo and fonts, while the low seamlessness design appears to be generic and outdated.

After completing the tutorial, participants responded to four emails using a predictive algorithm that provided suggestions with spelling errors for two emails and error-free suggestions for the other two in random order. On the top of the page, there was a dialogue box that outlined instructions for the session, including who designed the specific algorithm they were using, whether the writing habit questionnaire would be used in their session, and how to interact with the algorithm, to reinforce our credibility and identification manipulation. Participants were required to respond to each email in at least a hundred words for us to collect enough behavioral data. When typing, predictive suggestions appeared as a gray text after the cursor, and participants had the option to either press the TAB key on their keyboard to accept and autocomplete the suggestion, or reject it by simply ignoring it and continuing typing.

At the end of each condition, participants filled out a questionnaire that featured the studied variables. After they completed both conditions, they filled out another questionnaire that featured control variables and demographics.

Measures

Perceived Interactivity. Previous research suggests that while actual interactivity is operationalized based on the levels of potential for an interaction empowered by an embedded stimuli (e.g., the presence and the number of interactive components), perceived interactivity can be measured using an itemized scale (Wu, 2005). Users' perceptions may vary depending on the degree to which the interactive elements are realized, regardless of the actual level of interactivity (Lee, Lee, Kim, & Stout, 2004). We adapted a 14-item perceived website interactivity scale to measure perceptions of active control, two-way communication, and synchronicity. A sample question is: "While working with Smart Predictor, I had absolutely no control over what I could do with it." Responses were recorded on a 7-point scale.

Perceived Identification. We adapted a seven-item self-brand connection scale to measure the extent to which participants could identify with the predictive algorithms assigned to them (e.g., "I could use Smart Predictor to communicate who I am to other people") (Escalas, 2004). Responses were recorded on a 7-point Likert scale.

Perceived Credibility. Following suggestions of previous research on core dimensions of AI credibility (e.g., Shin, 2020; Bedue & Fritzsche, 2021), we adapted a 7-point semantic differential scale to measure participants' credibility perception of a predictive algorithm on dimensions including competence, expertise, trustworthiness, transparency, fairness, benevolence, credibility, and bias (Garrett & Poulsen, 2019; Kotcher et al., 2017). .

Perceived Familiarity. Perceived familiarity was measured by an adapted version of a self-reported AI-MC literacy scale (Goldenthal et al., 2021; Hargittai, 2008). We assessed participants' perceived familiarity with a predictive algorithm by asking their perceptions of familiarity and understanding (e.g., "How well do you feel you understand predictive algorithms like Smart Predictor"), comfort (e.g., "How comfortable do you feel using predictive algorithms like Smart Predictor"), and confidence (e.g., "When using predictive algorithms like Smart Predictor, how confident are you that you can accomplish what you're trying to achieve"), on a 7-point Likert scale.

Sensitivity (d') to predictive text errors. We adopted a signal detection theory (SDT) approach to study people's psychological sensitivity to successfully detect signals among noises. SDT provides us a plausible way to understand people's perceptual responses to different stimuli afforded in their technologically mediated environment, and allows us to probe how people make decisions among noise. Following this framework, we recorded a *hit* when users accept an error-free suggestion, a *false alarm* when users accept an error, a *miss* when users reject an error-free suggestion, and a *correct rejection* when users reject an error. After categorizing the responses, we calculated the likelihood ratio of each category. That is, the hit rate (H) is the proportion of unbiased suggestions to which participants actually accepted; the false alarm rate (FA) is the proportion of biased suggestions to which participants actually accepted. Sensitivity (d') describes how easily users are able to distinguish and thus accept error-free suggestions from errors. It is measured as: $d' = z(H) - z(FA)$. Thus, participants who have a higher d' value are likely to discriminate against error-prone algorithmic suggestions, compared to those who have a lower d' value.

Results

H1. Effect of seamlessness on perceived interactivity

We used a Bayesian paired sample t-test to analyze the difference in perceived interactivity between the low and high seamlessness conditions. The results of the analysis provide strong evidence of no difference in perceived interactivity between the predictive algorithms programmed with low (M = 4.10, SD = 1.35) and high (M = 4.01, SD = 1.23) perceived seamlessness (BF_{01} = 9.34).

H2. Effect of seamlessness on perceived identification

We used a Bayesian paired sample t-test to analyze the difference in perceived identification between the low and high seamlessness conditions. The results of the analysis provide strong evidence of no difference in perceived identification between the predictive algorithms programmed with low (M = 3.00, SD = 1.78) and high (M = 2.94, SD = 1.73) perceived seamlessness (BF_{01} = 10.17).

H3. Effect of seamlessness on perceived credibility

We used a Bayesian paired sample t-test to analyze the difference in perceived interactivity between the low and high seamlessness conditions. The results of the analysis provide strong evidence of no difference in perceived interactivity between the predictive algorithms programmed with low (M = 4.75, SD = 1.18) and high (M = 4.73, SD = 1.21) perceived seamlessness (BF_{01} = 11.10).

H4. Effect of seamlessness on perceived familiarity

We used a Bayesian paired sample t-test to analyze the difference in perceived interactivity between the low and high seamlessness conditions. The results of the analysis provide strong evidence of no difference in perceived interactivity between the predictive algorithms programmed with low (*M* = 4.10, *SD* = 1.51) and high (*M* = 3.99, *SD* = 1.55) perceived seamlessness (BF_{01} = 7.45).

H5. Mediating effect of perceived synergy on users' ability to detect algorithmic errors

Because we observed no significant differences between the high and low seamlessness conditions, we decided to not proceed with the mediation analyses, as suggested by Baron and Kenny (1986).

General Discussion

Our experiment endeavored to take a top-down approach for creating perceived seamlessness. Based on our evaluation of prior research, we identified four components that have been successfully employed to create feelings of seamlessness. To test our claims, we designed EMPTI, an open-source smart compose simulator for conducting experimental research to detect individuals' sensitivity to biased algorithms based on psychological responses to imagined technological affordances (Norman, 1988), such as interactivity, credibility, familiarity, and identification. The simulator consists of three parts: 1) an email interface with within-subjects manipulations of technological features, 2) a natural language processing algorithm that incorporates a within-subjects manipulation of bias into an emailing task, and 3) a relational database that calculates algorithmic bias sensitivity (with d').

The results of our Bayesian tests suggest that users did not perceive a difference between the two predictive text algorithms manipulated to cue seamlessness. Our Bayesian analyses provide strong evidence that participants could not perceive any difference between the perceived interactivity of, perceived identification with, perceived credibility of, and perceived familiarity with the two distinct predictive text algorithms programmed with low or high seamlessness. Therefore, we could not test H5, the prediction about whether differences in perceived seamlessness influence the detection of spelling errors in our predictive algorithms.

Although the results of our experiment leave several questions unanswered about what constitutes perceived seamlessness and how perceptions of seamlessness influence tendencies to monitor the accuracy of predictive text suggestions, we believe we have created a flexible testbed that may be useful to future experimenters. Intelligent systems like predictive text algorithms make biased decisions because they are trained on biased data (Arnold, Chauncey, & Gajos, 2018). Our relational database leverages signal detection theory (SDT) to provide a plausible picture of how information in a person's environment is combined to make a decision. In the context of email responses, EMPTI allows us to collect rich data, based on SDT, to gain insight into users' psychological responses to accept or reject content suggested by algorithms. Such a tool allows myriad opportunities to investigate generalizable communication phenomena mediated by a predictive algorithm.

Ultimately, we have much to learn about the qualities of technology that influence perceptions of agentic control. As technology is programmed with software that utilizes algorithms, machine learning, and natural language processing to operate on behalf of the user, media users must learn to adapt to the temptation to defer critical responsibilities of the human operator to a device. Nonetheless, we will not be able to teach users how to anticipate contexts that create perceived seamlessness until we can learn how to systematically measure these related concepts that contribute to a seamless interaction.

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Figure 1

High Seamlessness Condition (Smart Predictor)

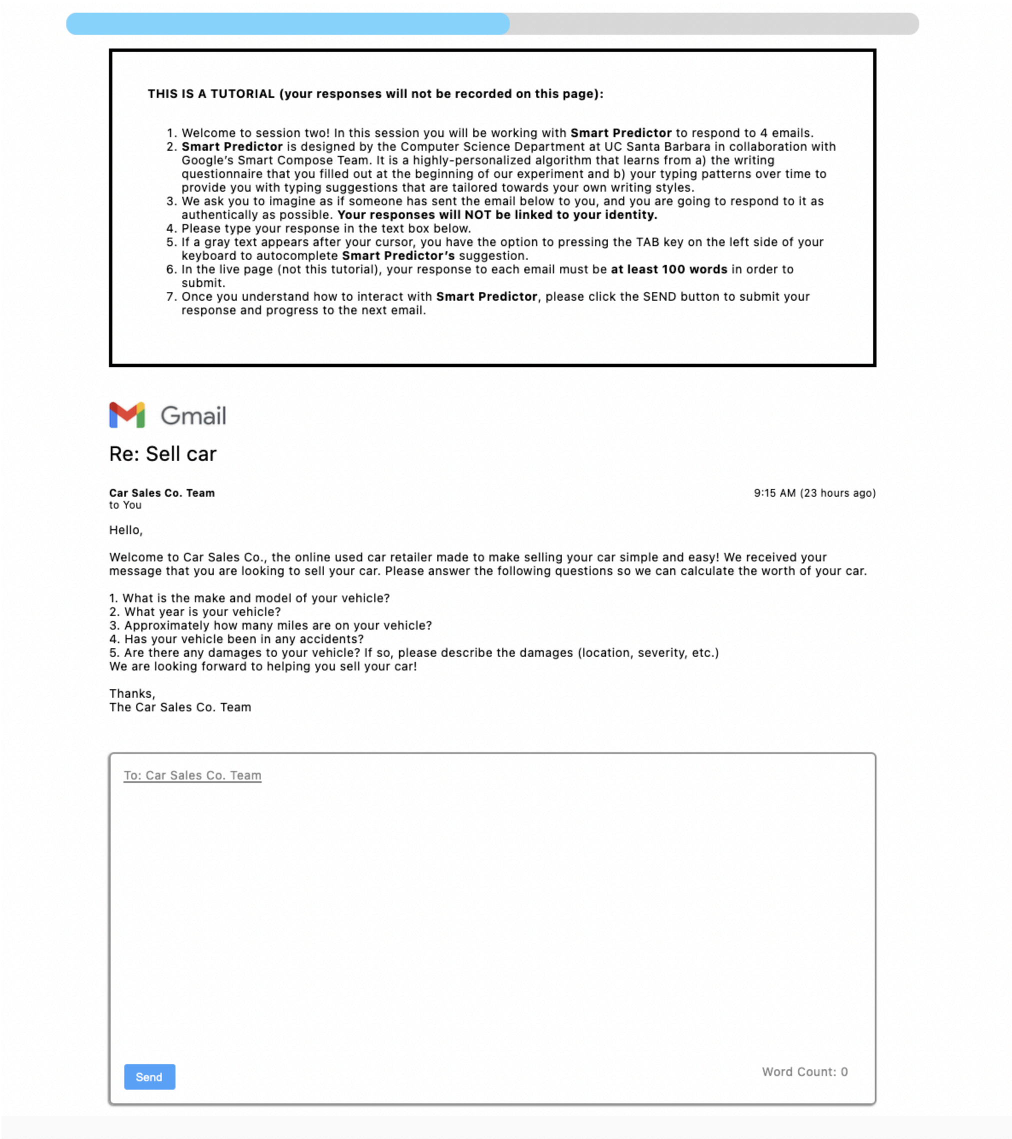

Figure 2

Low Seamlessness Condition (CS Predictor)

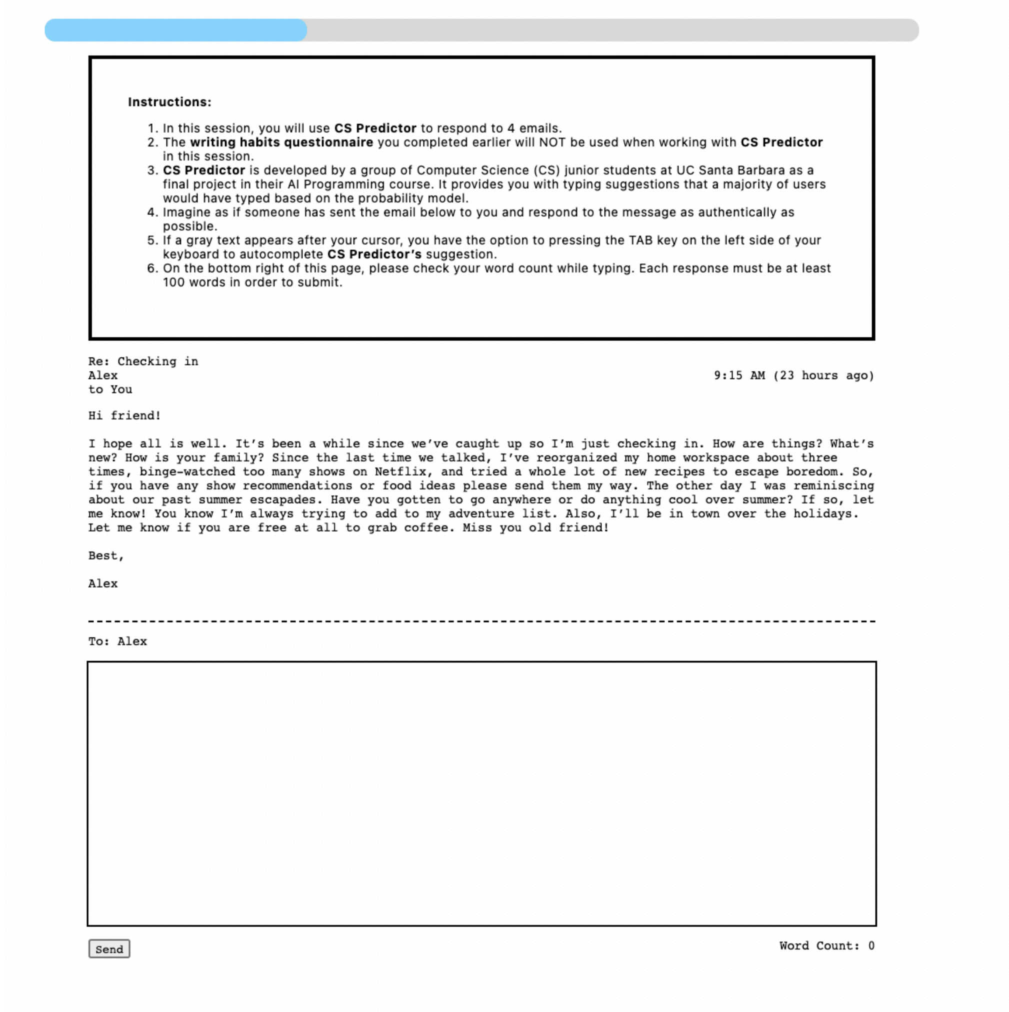

Figure 3

General Instructions for Email Task