Effects of Personality Type on Trust in Autocorrect and Preferences

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ABSTRACT

User acceptance of a given feature depends upon its perceived trustworthiness. Despite imperfections, trust seems to be evenly split for autocorrect. In this study, we use the Big Five personality test and text entry tasks to investigate the effect of users' personality type on their trust in autocorrect when encountering autocorrect errors. Results indicate that individuals ranking higher in neuroticism distrust autocorrect more. Our qualitative observations showed frustrated behaviors for autocorrect errors during the text entry tasks. Half of our participants reporting distrust in autocorrect still had the feature on. The results lend insights into connections between personality type and preferred text-based communication methods, which needs to be investigated further in future work.

CCS CONCEPTS

• **Human-centered computing → Keyboards**.

KEYWORDS

Big Five personality test, autocorrect, error behaviors, mobile device text entry

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1 INTRODUCTION

We all make mistakes. Luckily, we can sometimes rely on technology to step in and correct some of them. Autocorrect replaces implausible typed words with likelier alternatives. Yet, its errors can in the worst case severely affect a users' relationships, or, at best, be a source of humor. Autocorrect leaves some users frustrated, while others appreciate the immediate corrections and roll the autocorrect dice, despite its imperfections. Yet more than half use autocorrect [5], which poses the question: why do so many still have it on? And why do they continue to use it, even if it occasionally fails spectacularly?

Opting into engaging with a feature requires trust. One would not continue to use a device or software if one is truly distrustful of its accuracy or performance. But can a device gain trust simply by being statistically reliable? While a user's priority when considering adopting a feature varies – it might be efficiency gained or the accuracy of said feature – trustworthiness is a defining factor if features are relied upon and users feel good about using them. For web systems, important aspects for fostering trust include allowing users choice and some level of control, as well as prior knowledge of the risks involved when interacting with the system [13]. In automated driving, anxiety, as well as self-esteem and self-efficacy, have significant effects on trust level, such that high-anxiety users displayed low levels of trust and vice versa, supporting the notion that trust is affected by individual behavior patterns and self-evaluations [12].

Autocorrect's inconclusive adoption [5] (and merits) led us to question whether personality type determines one's acceptance of this feature. Here, we investigated individual personality types and level of trust in autocorrect to narrow down which aspects of behavior could potentially determine one's tendency to trust or distrust autocorrect. Taking individual differences into account, our findings could then be applied to improve next generation text entry interfaces.

2 RELATED WORK

The human factor is difficult to quantify under any circumstances, especially when it concerns aspects of human personality. So, which personality aspects are crucial to inter-individual differences in user-technology interaction?

Attig et al. [2] found that broad personality-based categories often overlapped conceptually when applied. The Big Five personality test measures extraversion, stress-based personality traits, such as neuroticism, patience-related measures, such as agreeableness, and uncertainty avoidance measures, like openness to experience [4, 7, 11, 16]. In human-computer interaction (HCI), Aykin et al. [3] used Jungian personality types and other dimensions and found mainly that introverts preferred theoretical explanations when using computer interfaces, whereas extroverts preferred examples. Pocius [15] reviewed HCI work investigating effects of personality and identified a correlation between extraversion and other aspects of HCI, such as attrition rate and speed of completion. Such previous work indicates that the way participants perceive technological interactions might also play a role in how users interact with text entry systems, yet without identifying specific behavior patterns or personality traits. As previous studies show correlations between HCI and uncertainty avoidance, patience, and levels of extraversion, we chose the Big Five test for this work.

Looking across research in various fields [2–4, 6–8, 15, 17, 18] trust has shown wide-reaching effects across a broad scope of behaviors, many of which are represented in the Big Five test. Yet,

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most existing evaluations of trust relate directly to automation, measurable economic principles, and reward-based behaviors. What remains unclear is whether various personality types are prone to trust autocorrect features during mobile text entry.

Mobile text entry errors have been studied in the past, with substitution errors being the most salient type [10, 14]. Autocorrections make up a small portion of mobile text entry, e.g., only 0.6% of all events in an "in the wild" study [5]. Though this is a low value, a negative impact of autocorrection on mental and physical demand, as well as on effort and frustration has been identified [1], with potentially lasting effects on relationships.

Palin et al. investigated the effects of autocorrection and autocompletion on mobile text entry rates in 37,370 volunteers [14] and found a positive correlation between autocorrect usage and text entry rates, but a negative one between autocomplete usage and text entry rates. While autocorrect may speed up the typing process, this did not account for uncorrected errors: 2.3% of errors were left uncorrected. Thus, we decided to investigate how various personality types trust autocorrect features for mobile text entry through a quantitative analysis of self-reported trust.

3 MOTIVATION AND HYPOTHESES

Based on the above, we predict that externally focused traits, such as extraversion, anxiety-related traits, such as neuroticism, or uncertainty avoidance-related measures, such as openness to experience, are tied to trust in autocorrect. As extroverts prefer examples [3], we predict that they would be interested in autocorrect's replacement feature. As neuroticism measures is linked to stress response and tendency to experience negative thoughts or emotions [4, 7, 11, 16], we expect to see users high in neuroticism to experience negative or increased feelings of distrust towards autocorrect. We also expect those ranking high in openness to experience, which measures an individuals' tendency to embrace new situations [4, 7, 11, 16], to find autocorrect trustworthy due to its potential benefits. Although our predictions are evaluated in part through self-reported trust levels in our survey, individual differences in users' personality type and disposition in interaction tasks also matter [2, 3]. Thus, we observed participant's text entry behaviors while they completed three text entry tasks.

4 METHOD

We explore our hypotheses through a mixed-methods, within-subject study which included a survey and three text-entry tasks. We investigated self-reported trust towards autocorrect relative to Big Five scores, and observed behaviors when encountering autocorrect errors during mobile device communication.

To avoid potential effects due to language barriers, we administered all surveys and tasks in the participant's native language. 22 participants (half male, half female) aged 15-66 years took part. After informed consent, they filled out an online Big Five test [9]. Subsequently, participants were asked whether they had autocorrect on or off, whether they preferred handwritten or typed notes, and how much they trusted autocorrect, on five-point Likert scales.

Then, we administered three text-entry tasks. The first was a description task in their preferred notes app, to observe their free-typing behavior. The second description task asked them to use the communication tool and method of their choice, to identify preferences. The third one was a transcription task with short phrases [11], to observe behaviors to text-entry errors with pre-defined content, when using their own mobile device, so that all settings and features were familiar and would be used naturally. We video-recorded the session to identify other behaviors, such as gestures.

We then iteratively coded the videos by reviewing them for noticeable reactions to any error they made in the three text entry tasks. We grouped conceptually overlapping behaviours that appeared throughout our participant pool. Participants' reactions, within the bounds of the coded categories, were then cross-referenced with their personality scores to determine whether a particular pattern of responses was the same within a certain personality type.

5 RESULTS

Out of our 22 participants, 18 (81.8%) had autocorrect on, of which eight (44.4%) reported to trust autocorrect (strongly agree, agree), seven (38.8%) did not trust autocorrect (disagree, strongly disagree), while three (16.6%) were neutral.

We compared Big Five personality scores to participant's trust in Autocorrect through a logistic fit. For simplicity, we grouped trust levels into three categories: trust, neutral, and distrust. There was a significant effect of neuroticism on trust in autocorrect, such that users who ranked higher in neuroticism distrust autocorrect more ($R2 = 0.18$; $p = 0.01$). All other dimensions did not show significant correlations, see Figure 1.

From the coded videos we identified which mobile device text entry method participants chose and any response that stemmed from an autocorrect encounter. Responses included vocalizations, hand movements, and correcting a word after an autocorrect error. We observed the following 7 behaviors and reactions: When given a choice, 80% of participants resorted to touch-based text entry over speech-based methods (B1). While a few chose audio-only voice messages, no participant used speech-to-text (B2). Interestingly, and although 40% percent looked at maps for help with the description task, only one participant chose imagery (a map) to communicate during the "participant's choice" task (B3), which was surprising given how efficient screenshotting can be for a map-based task. A vocalization of frustration (B4) was also frequently observed (35%), with one participant getting louder and louder in the only accumulation of errors we observed in this study. By far the most frequently exhibited behavior when encountering an autocorrect error (70%) was multi-backspace deletion (B5). One participant uniquely used swiping for the initial text entry, and then corrected only with tap-to-edit (B6). This participant ranked low in neuroticism and reported to trust autocorrect. They did not encounter autocorrections, but still had to correct errors. 20% of participants were slow and deliberate (B7), rarely encountered autocorrects and corrected them when they occurred with one or two backspaces [1].

6 DISCUSSION

Our results support our corresponding hypothesis for neuroticism, confirming previous work in social psychology [15], and we demonstrate the same effect with autocorrect during mobile text entry, i.e., in an interactive system. Beyond the link with neuroticism, we

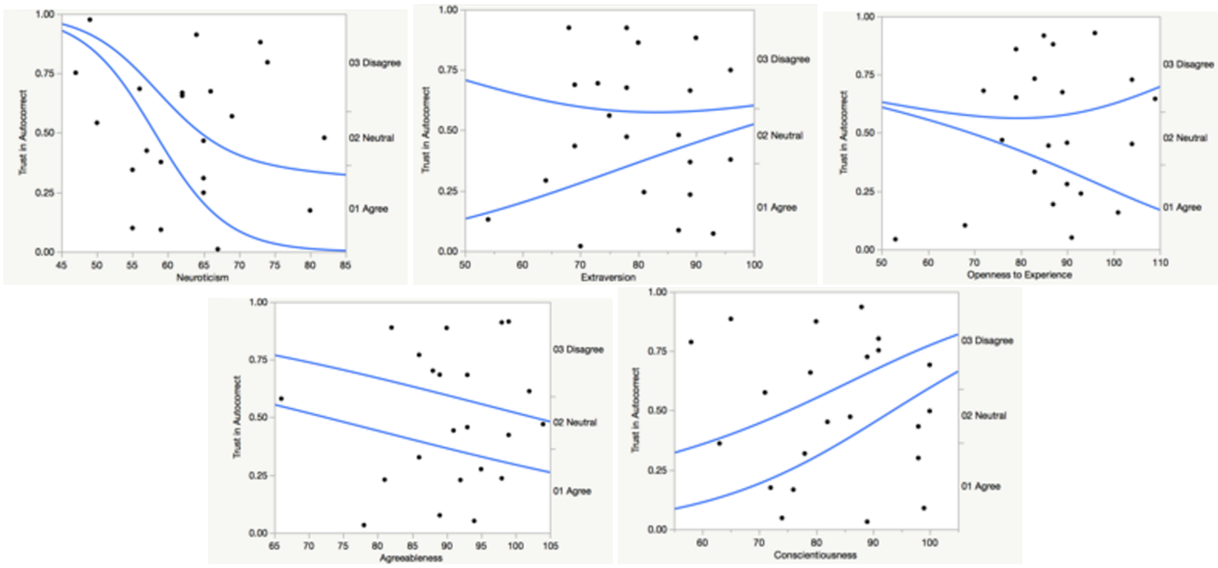

Figure 1: Logistic fit of Neuroticism, Extraversion, Openness to Experience, Agreeableness, and Conscientiousness scores compared to Trust in Autocorrect

found no other correlations, such as with extraversion and openness to experience. While half our users distrust autocorrect, they still had it on. Informal follow-up suggests that disinterest in typing efficiency, lack of awareness of autocorrect being optional, or trouble finding the setting might be to blame, effectively overriding the occasional autocorrect frustration. Or autocorrect does not occur frequently enough to motivate a change.

Instead of tapping the word directly to edit it (15%), we observed many instances of aggressively hitting backspace to delete an erroneously corrected word (70%). This phenomenon, the action of taking multiple steps to achieve a result that a few well-directed taps could more efficiently accomplish, might come from a false sense of productivity.

Most of the slow and deliberate texters had turned off autocorrect in the past and seem very aware of autocorrect. Others expect autocorrect's automatic adjustments and type with "reckless abandon", hoping that autocorrect does its job accurately. While we focused on behaviors in response to autocorrect events, the overall amount of autocorrection events was small. Given the well-known frustration with autocorrect [1], it is worthwhile to investigate such events, as the frustration is much larger than the frequency might imply. Yet, especially when time is of the essence, erroneous autocorrections can pose only a nuisance, e.g., if the accurate word can be deduced from the context or if the inaccurate version is funny. Then the effort to correct may not be worth expending. Yet, participants in our study always corrected their errors, potentially due to the presence of an experimenter and the office setting.

There are a variety of options for applying our results to interface design for text entry, depending on specific user habits and preferences. For example, if certain users have a low patience threshold, they may want to have access to an easily and quickly available option to turn autocorrect off, at least temporarily. Or, if a user wants to rely heavily on autocorrect, additional autocorrected choices could be offered to increase the possibility of an accurate correction.

7 CONCLUSION

Overall, participants ranking higher in neuroticism are more likely to distrust autocorrect. Other Big Five personality traits showed no significant effect on trust in autocorrect. Our observations identified a variety of solutions for dealing with autocorrect and general mobile device text-entry issues, including venting frustration, different deletion methods, and slowing down to avoid autocorrect altogether. For this last group, it would be interesting to investigate whether careful texting stems from an aversion to autocorrect, or simply a lack of incentive to find the autocorrect settings (to turn it off). A pain-versus-gain threshold analysis could reveal how many autocorrect errors participants can endure before they switch it off. This could also lend insight as to why users who claim to distrust autocorrect still have it on.

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