REDUCING DEFAULT AND FRAMING EFFECTS IN PRIVACY DECISION-MAKING

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PREFACE

This document serves a report in partial fulfillment of the requirement with the Marshall Plan Foundation. The research carried out in this report was conducted within a period of 4 months (1 March – 1 July, 2015), at the Donald Bren School of Information and Computer Sciences of the University of California, Irvine.

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ABSTRACT

Online forms are one of the main methods for website to directly collect users' personal information. A lot of modern web browsers provide the opportunity for users to automatically fill in the fields of the form for them with previously collected data. This way they try to reduce the burden of filling out all the forms on websites repeatedly. Despite the wide adoption and the seemingly benefits they offer, these auto-completion tools also diminish users' elaborateness to disclose personal information. It creates such a convenience, that it causes over-disclosure: users do not actively assess the necessity of each field anymore, but choosing for convenience instead. This creates a major source of digital vulnerability. In the studies that are reported in this report, we developed systems that provide alternative auto-completion tools, which creates more awareness what users fill in without compromising the convenience of traditional auto-completion tools. When comparing our alternative auto-completion tools with the traditional one, we show that users indeed over-disclose when using traditional tools, but also show that with the alternative auto-completion tools, users disclose information that is more in line with the purpose of the website. Besides developing alternatives, we also looked deeper into the underlying mechanisms (i.e., subjective evaluations of the systems) in order to get a deeper and better understanding of why users behave in a certain way. Using our alternative tools, users show more elaboration, are more satisfied, easier to use, and are more motivated to use it and continue to use it in the future.

INTRODUCTION

With people increasing being continuously connected with the digital environment, exposure of personal information comes at risk. A vast proportion focusing on digital environments has been focusing on factors that affects users' disclosure decisions, including trust (Bansal & Gefen, 2010; Belanger, Hiller, & Smith, 2002; Malhotra, Kim, & Agarwal, 2004), personality or demographic differences (Lu, Tan, & Hui, 2004), privacy awareness and experiences (Nowak & Phelps, 1995; Phelps, Nowak, & Ferrell, 2000; Smith, Milberg, & Burke, 1996), and culture (Dinev & Hart, 2006). When it comes to explaining privacy decisions to disclose information, there are two prominent directions: the major stream that argues that individuals employ a "privacy calculus". That is, a deliberate decision making process in which individuals consciously weigh the anticipated benefits against the anticipated costs of disclosing personal information (Culnan & Bies, 2003; Dinev & Hart, 2006; Hui, Teo, & Lee, 2007; Xu, Teo, Tan, & Agarwal, 2009). The second stream, a relatively new one, argues that individuals' privacy related decision making cannot be full explained as a rational trade-off between the perceived benefits and risks, as suggested by the privacy calculus. This stream argues that individuals rather use heuristics, or shortcuts, to come to a decision (Acquisti & Grossklags, 2007; Acquisti, John, & Loewenstein, 2012; Lowry et al., 2012). The current literature has identified a number of issues that are caused by the heuristics individuals use in their decision making process (Acquisti, Adjerid, & Brandimarte, 2013; Acquisti & Grossklags, 2005; Adjerid, Acquisti, Brandimarte, & Loewenstein, 2013; Cho, Lee, & Chung, 2010; LaRose & Rifon, 2006; Lowry et al., 2012), there are no solutions yet that counteract the problem that heuristics are causing.

In this current report we investigate ways to counteract the problems that follows from heuristics in privacy decision making. We specifically examine the role of heuristics (i.e., the default effect) in shaping users' privacy-related decision making and disclosure behavior in the context of auto-completion tools. These tools are a common means nowadays for modern web browsers to provide users with an easy way to handle reoccurring (endless) forms to fill in (also referred as "auto-fill," or "auto form-fill"). They reduce the disclosure burden for users (Bicakci, Atalay, & Kiziloz, 2011; Trewin, 2006), and reduce time and effort the user need to spend on filling in the form. Recently, third-party tools offer comprehensive features (e.g., RoboForm,[1] LastPass,[2] Dashlane[3]) to the traditional auto-completion tools of web browsers (e.g., cross-device auto-completion). In order for these tools to work comprehensively, experts recommend web developers to build their form according to certain standards, so that the tools can correctly fill in the form fields (Garrido, Rossi, & Distante, 2010; Wroblewski, 2008). Although current auto-completion tools fill out only certain type of forms, the pace with which technological advances progress in web personalization, it is expected that this kind of technology will become more powerful in the near future.

Despite the obvious benefits that auto-completion tools offer, they also introduce a paramount vulnerability for society. Users are becoming more susceptible to the influence of default effects when making privacy-related decisions. That is, these tools typically fill out all requested information in a form by default, including optional fields (Preibusch, Krol, & Beresford, 2013). This convenience of filling in forms, increases the likelihood that users unintentionally disclose more (personal) information than they would normally desire (i.e., when the form was not automatically filled in by the tool). Having forms being auto-completed by tools, thus can make users less aware about what they are actually disclosing, and thereby making them more vulnerable to privacy threats. Given the pervasive and ubiquitous nature of auto-completion tools, focusing on these kind of tools can significantly enhance our understanding of vulnerabilities caused by these systems, and thereby opens the way to effectively created mechanisms that can counteract on the negative effects of these tools. We investigated two new auto-completion tools that counteracts on the vulnerability that the traditional auto-completion tool causes. In this study we created a “remove” auto-completion tool (i.e., opt-out with buttons: fills out all fields by default and provides a remove button adjacent to each field) and an “add” auto-completion tool (i.e., opt-in with buttons: leaves all fields blank by default and provides an add button adjacent to each field).

[1] http://www.roboform.com
[2] http://www.lastpass.com
[3] http://www.dashlane.com

In this report we describe several studies that try to understand the vulnerabilities that auto-completion tools are causing, and test whether these vulnerabilities can be counteract on with alternative auto-completion tools. With this work we try to answer several main questions: (1) Does the default effect that is intrinsic in traditional form auto-completion tools result in over-disclosure of personal information, and hence make users vulnerable to privacy risks? If so, can this vulnerability be overcome by providing users with alternative auto-completion tools that help them make more deliberate decisions about their information disclosure?, (2) What are the underlying mechanisms that influence users' heuristic versus elaborate decision making?, (3) Do users' subjective evaluations of their experience with the auto-completion tool improve when presented with the alternative tools rather than the traditional tool?

In order to address these research questions we conducted three online experiments (N_1 = 460, N_2 = 290, and N_3 = to be decided). The findings that we present here have several theoretical contributions and practical implications. The theoretical contributions extends the current understanding of the Elaboration Likelihood Model (ELM). We extend the effects of the ELM by placing the model in the context of digital data collection, by proposing alternative designs to traditional auto-completion tools in order to influence users' elaboration on disclosure decisions. We show that with alternative auto-completion tools, disclosure decisions can be influenced significantly, and more importantly, become decisions become more deliberate. In other words, our results signifies the vulnerability that auto-completion tools are causing to privacy, but risks can be mitigated by applying the right designs.

Additionally, our results contribute to the literature on the privacy calculus by adopting the notion of contextual integrity (i.e., the fit between context and requested information). We show that when there is a match between the requested information by a form and the context of the requesting website, less risk is perceived by the user, and is found to be more relevant to disclose that respective information.

Finally, with the extended auto-completion tools that were created for this study, we examined the effects of the different tool type (i.e., add and remove) on subjective measures. Such as, easy-of-use, satisfaction, attitude, overall privacy threat, and intention. One of the interesting results that we found is that although both of the alternative auto-completion tools help users become more elaborate in their privacy decision making and support to eliminate the drawbacks of the traditional tool, the add type had a clear favor in all subjective measures compared to the remove type.

The findings that we lay out in this report provides insights into the vulnerabilities of users when using traditional auto-completion tools. We offer practical and managerial insights that can be used to revamp traditional tools in commercial settings, as well as to drive public policy decisions regarding privacy defaults to mitigate their effects and improve society's welfare.

In the following sections we briefly discuss each of the studies that we conducted, and follow with the related work of each study. After that we continue discussing each of the studies deeper, and present the analyses and results. We conclude with discussions, future work and limitations, and conclusions.

THE STUDIES

Several studies were conducted were conducted to gain more insights in the vulnerabilities that traditional auto-completion tools are causing, and how to counteract on that by providing alternative solutions. In the upcoming sections, we highlight briefly the purpose of each study.

STUDY 1

In the first study that was conducted we aimed to get insights into the behavioral aspect when users are presented with different types of auto-completion tools (i.e., traditional, add, and remove). We observed whether different auto-completion tools influences how users would make privacy related decision making when filling in forms on different kind of websites.

STUDY 2

In the second study we extend the first study, by trying to understand the behavioral attitudes that underlie the influence of the different auto-completion tools. We measures several behavioral attitudes towards the different auto-completion tools: perceived efficacy, motivation, perceived ease of use, perceived privacy threat, attitude, satisfaction, and intention to continue use.

STUDY 3

Based on the results of the first two studies, we created a third study to gain more understanding about what actually is causing the effects that were found. In this study we varied the appearance of the buttons as well as how the default is presented. This allowed us to investigate to which extend the buttons and the default influences user's decision making to disclose. This part is not originally belong to the studies that have been done during the stay abroad, but we decided to continue the collaboration and perform follow-up studies together. Since this part is still ongoing, we will not discuss this extensively in the main part of this report, but will give some attention to it at the very end.

RELATED WORK

The conducted studies are based on different theoretical backgrounds, whereas Study 1 and 2 share the same theoretical background. In the upcoming section we first start with laying out the theoretical foundations for Study 1 and 2.

STUDY 1 AND 2

The different major streams in the literature provide the theoretical foundations for Study 1 and 2. There are three different streams that can provide support for these studies. The first stream conveys the literature on the privacy calculus, which explains the disclosure behaviors from a rational perspective. Secondly, there is the heuristic decision making literature, which lays down the foundation on how different auto-completion tools affect disclosure due to the default effect. Lastly, the literature on the elaboration-likelihood model (ELM) combines the first two streams into a conceptual model to explain how users may exhibit different levels of elaboration based on the auto-completion tool they use.

PRIVACY CALCULUS

The privacy calculus perspective on privacy related decision making argues that individuals engage in a process that involves consciousness decision making by weighing anticipated benefits against costs of taking action (Culnan & Bies, 2003; Dinev & Hart, 2006; Hui et al., 2007; Laufer, Proshansky, & Wolfe, 1973; Laufer & Wolfe, 1977; Xu et al., 2009). This perspective of the privacy calculus is a well-established theory (Y. Li, 2012; Pavlou, 2011; Smith, Dinev, & Xu, 2011), that is frequently being used by researchers to investigate antecedents of information disclosure (Culnan & Armstrong, 1999; Culnan & Bies, 2003; Dinev & Hart, 2006; Hann, Hui, Lee, & Png, 2007; Keith, Babb, Lowry, Furner, & Abdullat, 2013; H. Li, Sarathy, & Xu, 2010; Milne & Gordon, 1993; Petronio, 2012; Wilson & Valacich, 2012; Xu, Luo, Carroll, & Rosson, 2011; Xu et al., 2009). The privacy calculus is a domain specific instance of decision-making theories, like utility maximization or expectancy-value theory (Awad & Krishnan, 2006; Y. Li, 2012; Rust, Kannan, & Peng, 2002; Stone & Stone, 1990). The utility maximization theory argues that individuals make trade-offs between the costs and benefits of the options available in order to maximize the utility (Bettman, Luce, & Payne, 1998; Simon, 1959). The expectancy-value theory states that individuals gather various aspects about all the available options in order to assign values to each of these aspects in order to make a weighted decision (Fishbein & Ajzen, 1975). In line with these theories, the privacy calculus argues that individuals make privacy trade-offs between costs (i.e., perceived chance and severity of negative consequences) and benefits (i.e., perceived chance and magnitude of positive consequences) of disclosing information.

HEURISTIC DECISION MAKING

The perspective of heuristic decision making states that privacy decision making are made by various heuristics, which are in turn influenced by subconscious thoughts (Acquisti, 2008; Acquisti et al., 2013; Lowry et al., 2012). Important heuristics are the: social proof heuristics (Acquisti et al., 2012), foot in the door and door in the face techniques (John, Acquisti, & Loewenstein, 2011) , the affect heuristic (John et al., 2011), and default and framing effects (Adjerid et al., 2013; Angst & Agarwal, 2009; Lai & Hui, 2006). The social proof heuristics are influenced by the willingness of others to disclose personal information. The foot in the door, and door in the face techniques are influenced by the order of sensitivity in which items are asked. The affect heuristic is influenced by the overall professionalism of the user interface design, and the default and framing effects are influenced by whether the disclosure decision is framed as an opt-in or opt-out option.

These heuristics, as discussed above, create vulnerabilities for individuals of disclosing information. For example, the default effect influences the way how people choose their health and insurance plan, which may even result in a bad decision (Sunstein & Thaler, 2012; Thaler & Sunstein, 2008). This default effect is also causing the lack of organ donors who adapt an opt-in strategy. That is, people need to register (opt-in) themselves, in order to become an organ donor (Johnson, Bellman, & Lohse, 2002). In the case of information disclosure from a privacy perspective, the default effect can cause over disclosure of information (unconsciously or unintentionally) when disclosing is framed as an opt-out option. That is, when information is set by disclose by default, and users need to manually opt-out for it. (Adjerid et al., 2013; Angst & Agarwal, 2009; Lai & Hui, 2006). The default effect occurs because of the "status quo bias." By sticking to the status quo avoids stress and effort to engage in elaborate decision making processes. In other words, holding on to the default is easier (Baron & Ritov, 1994; Kahneman, Knetsch, & Thaler, 1991; Samuelson & Zeckhauser, 1988).

Elaboration Likelihood Model (ELM)

In this work, we use the ELM as the basis of how individuals engage in their privacy decision making. According to the ELM (DUANE, 1999; Petty & Cacioppo, 1986), individuals utilizes two routes to process information: central route and the peripheral route (see Figure 1). The central route represents the engagement in an elaborate effortful thought process (Zhang, 1996) in order to create and form attitudes about a choice alternative (i.e., the options that are available to choose from). Taking the central route to come to a decision involves taking most relevant information available into account. Such as, argument quality (Cacioppo, Petty, Kao, & Rodriguez, 1986), messages that highlight superiority of the choice alternatives (Petty, Cacioppo, & Schumann, 1983), or distinct features of the choice alternatives (Lord, Lee, & Sauer, 1995). When taking the peripheral route, individuals rely on easy accessible, often superficial, cues. For example, mood or general feelings, consensus heuristics (Slovic, Finucane, Peters, & MacGregor, 2004), credibility or attractiveness of the message source (Petty & Cacioppo, 1986), or famous endorsers (Petty et al., 1983). In online environments, typical cues involve: website reputation (Shamdasani, Stanaland, & Tan, 2001), and design quality (Bansal & Zahedi, 2008). In terms of the privacy calculus and heuristic decision making: the privacy calculus fits the central route, whereas the heuristic decision making the peripheral route (Andrade, Kaltcheva, & Weitz, 2002; John et al., 2011; Y. Li, 2014).

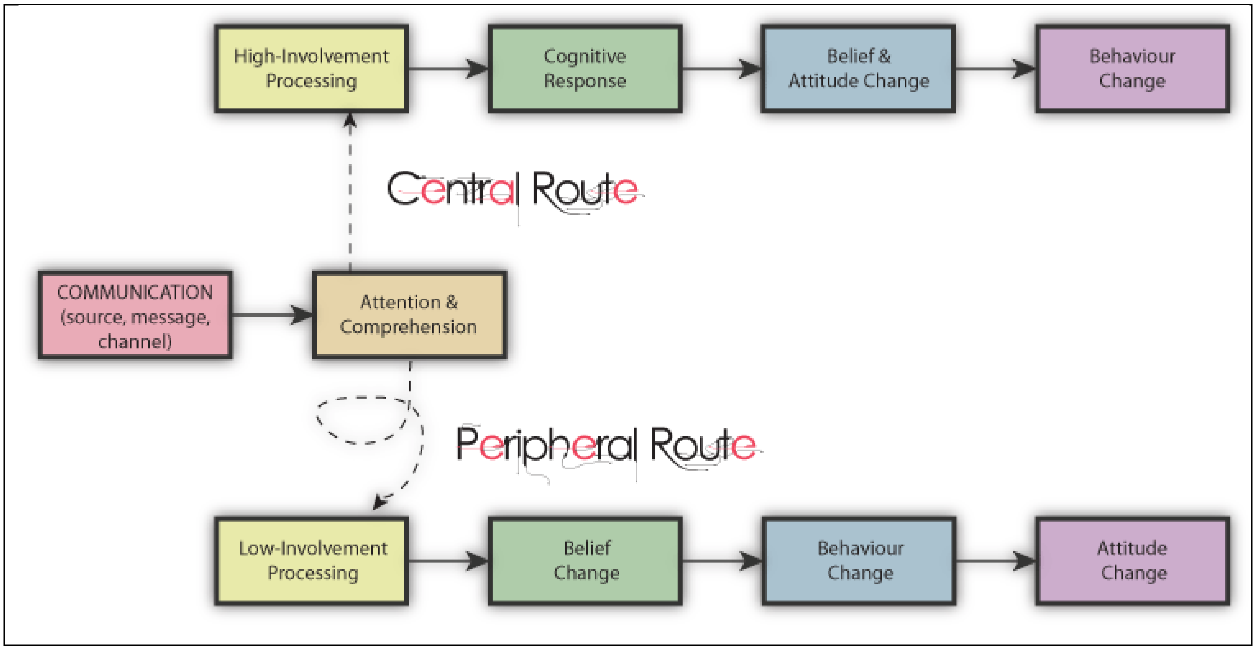

FIGURE 1 CLASSIC EXAMPLE OF THE ELM (PETTY & CACIOPPO, 1986)

Two important factors that are defined by the ELM to indicate whether an individual involves in the central or peripheral route are: motivation and ability. The motivation to engage in effortful elaboration is influenced by personal/dispositional characteristics (e.g., need for cognition), or situational characteristics (e.g., personal relevance, involvement). Similarly, the ability the process the information presented is influenced by personal characteristics (e.g., prior knowledge, expertise in the subject) or external factors (e.g., time constraints, distraction) (Cacioppo et al., 1986; Petty et al., 1983).

The ELM has been used before to investigate the foundation of privacy-related attitudes and behavioral intentions (Angst & Agarwal, 2009; Lowry et al., 2012; Yang, Hung, Sung, & Farn, 2006; Zhou, 2012). Prior results have found that engaging in the central route of the ELM can be related to several privacy-related attitudes. For example, higher levels of privacy concerns (e.g., higher motivation) and/or higher self-efficacy or low trait-anxiety (e.g., higher perceived ability) are more likely to take the central route of information processing. Not surprisingly, privacy-related decision making appear to be more influenced when engaged in the central route than when engaged in the peripheral route. For example, the effect of objective information (central route) and third-party seals (peripheral route) on privacy assurance perceptions has been investigated, and has shown that the peripheral route is more prominent among those who show high trait-anxiety and low involvement, while the inverse show for those engaging in the central route (Zhang, 1996). In the context of mobile banking (Zhou, 2012) and websites (Bansal & Zahedi, 2008), central cues, such as content-based arguments and information quality are more important for individuals with higher levels of privacy concerns and self-efficacy. More superficial information (peripheral route), such as, structural assurances, design, company information, and reputation, are more important for those with lower levels of privacy concerns and self-efficacy. In another study about users' attitudes towards electronic health records, the strength of arguments are more likely to affect individuals with high privacy concerns and involvement than those low on these factors (Angst & Agarwal, 2009).

Development of the Theoretical Model

We use the previously discussed theories and model, to form the theoretical model of Study 1 and 2 to explain personal information disclosure with auto-completion tools. Based on the heuristic decision making literature, we suggest that disclosure behavior is directly influenced by the type of auto-completion tool (traditional, add, remove; see Figure 2 for the proposed model). Because of the default effect, we suggest that those who use the traditional auto-completion tool, will disclose significantly more than those who make use of the alternative auto-completion tools. We build on theories of the ELM and the privacy calculus, and posit that the tool type influences the effect of the privacy calculus on users' disclosure behavior, and lead users to make deliberate decisions on their disclosure behavior. The definitions of the constructs that we used can be found in Table 1.

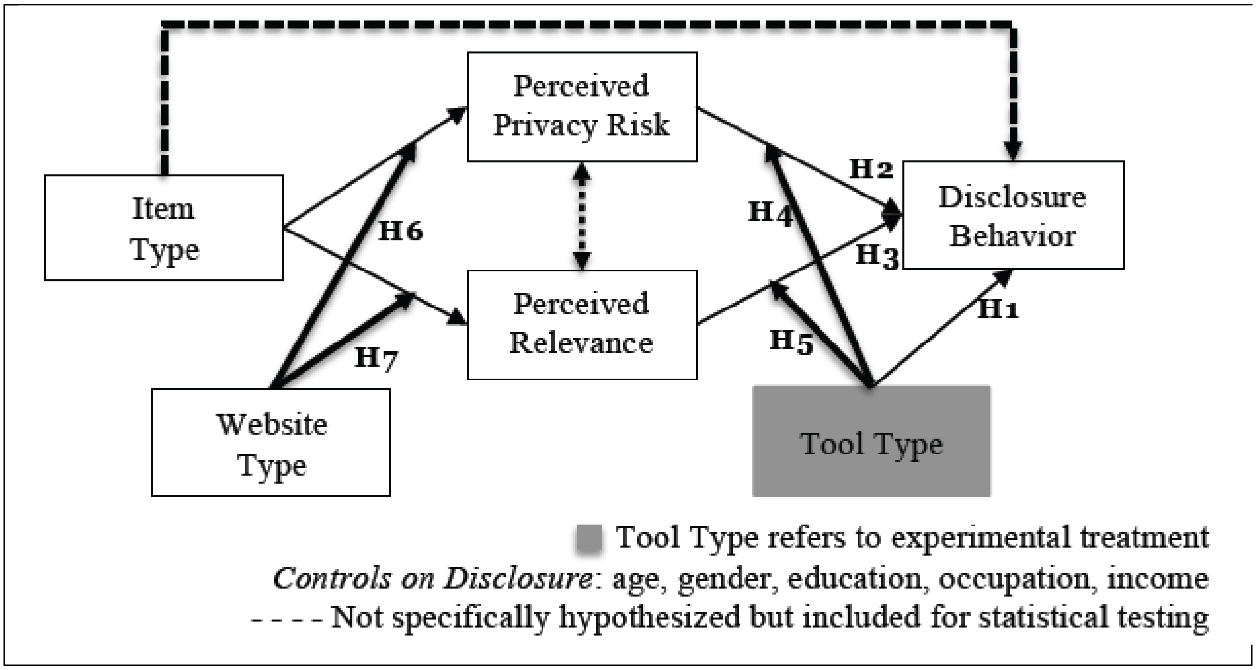

FIGURE 2 THE PROPOSED BEHAVIORAL MODEL

Construct	**Definition**	**Source**
Tool type	The type of form auto-completion form	Experimental treatment
Disclosure behavior	The degree to which the requested personal information are disclosed to the third-party website	Perception
Perceived privacy risk	An individual's judgment of information privacy related-risks involved for disclosing each of the requested item to the requesting third-party website	Perception
Perceived relevance	An individual's judgment of whether the requested item serves to the purpose of the third-party website	Perception
Item type	The type of personal information requested by the website	Contextual control
Website type	The type of website which request the personal information	Contextual control

TABLE 1 DEFINITIONS AND SOURCES OF CONSTRUCTS

According to the theories about the default effect, users will keep the setting of the auto-completion tool. For the traditional auto-completion tool (i.e., where all the fields are automatically filled in), users need to manually remove any information that they do not wish to disclose. As a consequence, users are more likely to not change anything about the automatically filled in fields, which causes information to be disclosed that they would not to otherwise. To overcome the default effect, we created two alternatives to the traditional auto-completion tool, which increase the convenience of adding or removing the personal information from each individual form of the form by clicking a button placed adjacent to the corresponding field. The first alternative is the remove type of the auto-completion tool. It fills out all field of the form by default, and displays a remove button next to each field, which can be used to empty the information of a specific field (i.e., opt-out tool with buttons). The second alternative that we propose, is an alternative auto-completion tool that instead of a remove button, consist of an add button next to each field. In this case the default of the form is that the fields are empty, and the button can be used to fill in pre-collected information into the desired fields of the form (opt-in tool with buttons). Examples of the traditional auto-completion tool and its alternatives can be find in Figure 3b-d.

RESEARCH SETTING AND METHOD

To investigate the effects of the alternative auto-completion tools, we conducted two empirical studies. The first study we conducted, investigates the behavioral model as seen in Figure 2 by means of an online experiment. For this first study we used 460 participants. In the second

FIGURE 3 THE DIFFERENT EXTERNAL WEBSITES THAT ARE USED FOR THIS STUDY:

A: FORMFILLER: INITIAL INFORMATION ELICITATION FORM.

B: BLOGHEROES: REPRESENT THE TRADITIONAL AUTO-COMPLETION TOOL

C: IWORK: REPRESENTS THE REMOVE TYPE AUTO-COMPLETION TOOL

D: CODACARE: REPRESENTS THE ADD TYPE AUTO-COMPLETION TOOL

study, we tested the effect of tool type (i.e., add and remove) on users' subjective evaluations of their experience with the alternative auto-completion tools by conducting an online experiment with 290 participants. In the following sections we discuss the details of both studies.

STUDY ONE: TESTING THE PROPOSED MODEL

To investigate the proposed behavioral model (see Figure 1) we developed the proposed auto-completion tools (i.e., add, remove, and traditional). Functionality was tested on a small group of participants. In the main part of the experiment, participants were asked for their consent to participate in the study. After consent was provided they were randomly assigned to one of the experimental conditions, sequentially instructed about the experimental procedures, and given a description of the assigned auto-completion tool. To test participant's comprehension of the instructions, a quiz was presented that could only be passed once the right answer was given.

After participants passed all the requirements, they were redirected to the main part of the experiment. Participants were asked to disclose a wide range of personal information (see the "item type" construct in Table 2) by filling out the information elicitation form (see Figure 3a). We ensured participants that all the information they filled in here, would only be stored locally and temporarily (only for the current purpose of the study). Once participants filled in the complete elicitation form, they were redirected to one of the mockup websites that were developed specifically for this study (see the "website type" construct in Table 2). On each of these mockup website, participants were going to experience one of the versions of the auto-completion tools that they were randomly assigned to. In order to hide that the websites are just mockups, we purchased domain names for website and created distinct designs to make them look legitimate and real (see Figure 3b-d). Additionally, we build in a small delay when participants were redirected from the information elicitation form to one of the websites, by including a 3-second "loading" screen. On each of the mockup websites, participants were welcomed with a brief description of the personalized service of the auto-completion tool, with subsequently presented with the task they were expected to fulfill (i.e., filling in the registration form of the mockup website that they were assigned to, with help of one of the auto-completion tools). Once participants were about to fill in the form that consisted on each of the mockup website, the assigned auto-completion tool popped up, indicating that it had detected a form requesting previously collected information, and took the liberty to act upon it. What kind of action the auto-completion tool performed was depended on the type of tool the participants were assigned to: the traditional auto-completion tool would fill in the whole form with the previously collected information, the remove type would fill in the form and included a "remove" button to each of the fields (in order for participants to easily remove the filled in content), and the add type would leave the whole form blank but included an "add" button to each of the fields in the form (this allowed participants to easily fill in a blank field when desired). Each tool reminded the participants that they are totally allowed to clear, fill, or change any field, at any time before submitting. That is, all fields were optional to be filled in or left blank. After form submission, participants were told that personalized services would not be provided in order to avoid conflicts with the remaining part of the experiment. Participants were redirected back to the "experiment" website, where they first started off to conclude the experiment with a post-study questionnaire. In this last part of the experiment, participants were asked about their perceived privacy risk and relevance for the actions that they performed during the study (i.e., depicting the 20 personal information items that were requested during the study on the mockup websites), as well as an additional number of control questions.

Construct	**Source**	**Operationalization**
Disclosure behavior	Actual behavior	Refers to the extent to which participants disclose personal information. The variable was created by examining the rate of disclosure for each of the requested item. It is measured as a dichotomous variable (0= disclosure, 1=no disclosure)
Tool type	Experimental treatment (between-subject)	The following auto-completion tools were developed: 1) Traditional auto-completion tool: an "opt-out tool without buttons." This version automatically fills out all the fields of a form and allows users to delete any of these fields manually. 2) Add type auto-completion tool: an "opt-in tool with buttons." This version allows users to fill out fields of a form with pre-collected information using an "add" button. 3) Remove type auto-completion tool: an "opt-out tool with buttons." This version automatically fills out all

		the fields of a form and allows users to delete any of these fields using a remove button.
Privacy risk	Perception	The extent to which participants perceive privacy risks in disclosing an item to the requesting website. The question was asked for each of the requested items and rated on a 7-point scale: providing [item] to [website] is: “very safe for my privacy” – “very risky for my privacy”
Relevance	Perception	The extent to which participants perceive an item to be relevant to disclose the requesting website. The question was asked for each of the requested items and rated on a 7-point scale: the fact that [website] asked for [item] was: “very inappropriate” – “very appropriate”
Item type	Contextual control (within-subject)	The following items and item categories were used. 1) Contact information: first and last name, gender, age, address, city, state, zip, e-mail address 2) Personal interest: favorite movie, favorite band/artist, favorite food, favorite weekend past time, political views 3) Job skills: current/previous job title and sector, employment status, work experience, income level, highest completed degree. 4) Health record: overall health, dietary restrictions, weight, birth control usage, medical conditions
Website type	Contextual control (between-subject)	The following external websites were developed. 1) Blog heroes: an online blogging network that uses the users’ personal information to categorize them into “guilds” of bloggers that have similar interests. 2) I <3 WRK: a job search website that uses the users’ personal information to find jobs. 3) Codacare: a health insurance company that uses the users’ personal information to tailor their health care to their personal needs and perferences

Purpose specificity of disclosure	(item type * website type match	The following websites and item categories were matched: 1) Blog heroes – personal interest 2) I <3 WRK – job skills 3) Codacare – health record

TABLE 2 SOURCES AND OPERATIONALIZATIONS OF CONSTRUCTS

EXPERIMENTAL TREATMENTS AND OPERATIONALIZATION OF CONSTRUTS

The study was set up to be a repeated measures 3x3x4 mixed factors experiment, which represent 3x3 between-subject conditions (tool type and website type) and 4 within-subjects conditions item type that are repeated 5 times per participants (i.e., five items per item type). The description of the sources and the operationalizations of the constructs as well as the details of the experimental treatments can be found in Table 2.

The dependent variable of interest in this experiment is the users' information disclosure behavior. This refers to how much personal information eventually is willing to be disclosed on the mockup websites. The level of disclosure is reflected in a repeated dichotomous variable (0 = not disclose, 1 = disclose) for each of the requested items (i.e., for each of the 20 items). For more details of the asked items see the "item type" in Table 2. Items that were only partially disclosed (e.g., first name, but not the last name), were counted as not being disclosed. Also, information disclosed to the fields on the mockup websites were checked for bogus information (i.e., information was changed to false information compared to what participants filled in during the form elicitation phase), and coded as not being disclosed when it was the case. When bogus information was already present during the form elicitation phase, and therefore the auto-completion tool also filled in bogus, entries were coded as missing values.

For the auto-completion tools, there were three different version: 1) the traditional auto-completion tool, 2) add type auto-completion tool, and 3) remove type auto-completion tool. The traditional auto-completion tool was designed to match commonly found auto-completion tools in modern browsers. That is, when users start typing their information into the first field, a popup field appears with suggestions for the complete form. For the sake of experimental control, we left this step out where users need to intervene, and chose for an approach where all the fields are automatically filled in. The add/remove types represent our proposed alternatives to the traditional tool.

Perceived relevance and privacy risks questions were asked in the post-study questionnaire. Here, participants were asked to rate each disclosure item on the mockup websites, whether they perceived the disclosed information to be relevant or risky (on a 7-point scale).

In the information elicitation phase, participants were requested 24 information items that belong to four major items: general contact, personal interests, job skills, and health record information. To further improve realism of the experiment and create contrast between the information elicitation websites, and the mockup websites, item order and form field wording were varied. The contact information items were always requested first by the external website, followed by the remaining items in a random order. The item order was additionally used as a control variable in the analysis. For further realism of the study, one item of each category was not requested by the mockup website (this was the same for each participant). So, although participants filled in 24 items in the form elicitation phase, they were only asked to fill in 20 items on the mockup websites.

Each mockup website was carefully designed in such a way that they offered a valuable personalized experience to the participants. In order to achieve this level of personalization, the websites requested 20 of the 24 personal information items that participants disclosed during the information elicitation phase. Each mockup website served as a contextual control. This means that each of them corresponded to a particular category of personal information that was requested by the auto-completion tool. For example, “Blog Heroes” represents a blogging community, and was designed as such to put emphasis on items matching the personal interest category. Whereas, “I <3 Work” was designed as a job search website, and therefore designed to match the items requested in the job skills category. Finally, “Codacare” was made as a health insurer website, and as such was requesting information to match the health record category. Each mockup website consisted of matching information (relevant information to the website, e.g., requesting work experience by the job search website), but also non-matching information

(information that is not relevant for the functionality of a specific website, e.g., doctor visits by the blogging community). The combination of the within-subjects (i.e., item type) manipulation, and the between subjects (i.e., website type) manipulation, allowed us to measure purpose specific information disclosure of participants when using each of the three auto-completion tools.

STUDY PARTICIPANTS

Participants were recruited through Amazon Mechanical Turk (AMT). AMT is a popular recruitment tool that is often used to conduct user experiments (Kittur, Chi, & Suh, 2008). Participation was restricted to participants (also called "workers" on AMT) located in the U.S. and who had a high "reputation" on AMT. Worker's reputation is an indicator of the number of tasks (experiments) they completed as well as how well they performed within the tasks (accuracy). Only workers with at least 50 tasks completed and with an accuracy of at least 96% were allowed to participate. As a compensation, participants were rewarded with $2 after completion of the experiment. The study was approved by the Institutional Review Board of the sponsoring university (UC Irvine, CA).

In total 543 participants completed the study. Of them 66 participants were eventually removed, because they did not pass the manipulation check (i.e., they indicated that they noticed that the mockup websites were fake, hence possibly not participated in a representative way). Furthermore, we excluded an additional 17 participants, because of failing the data quality checks. This could be due to one of the following problems: providing inconsistent and/or bogus answers to attentions questions, manipulation check questions, or reverse-coded questions. In total 83 participants were removed from the initial dataset. This left us with 460 completed and valid responses to further analyze. Further inspection of the demographics show that the remaining 460 participants reflect the U.S. Internet population in the following, adequate, way: income (median personal income: $25K-$50K), level of employment (68% employed, 12% students, 8% looking for work, 2% unable to work or retired), and education (16% high school, 31% some college, 40% undergraduate degree, 13% post-graduate degree). We found a slight overrepresentation of younger (median age: 31) and female (254) participants.

STUDY TWO: MEASURING USERS' SUBJECTIVE EVALUATIONS OF AUTO-COMPLETION TOOLS

We adopted the same experimental design and procedures for Study two, as used for Study one. In addition participants were presented with subjective evaluation questions at the end of the study to evaluate their experiences with the tool. Users were again randomly assigned to one of the three version of the auto-completion tools, but in this study, they were all redirected to the same website (i.e., BlogHeroes). This to ensure consistency among the participants and in order to isolate the effect of the different tool types on participants' subjective evaluations of their experiences with the tool. All constructs were measures relatively through multiple self-report measures on a 7-point scale. These additional subjective evaluations of experiences are measured by different constructs as presented in Table 3. The different questions asked can be found in **Error! Reference source not found.**

Construct	**Source**	**#Items**
Perceived self-efficacy (PSE)	Developed for this study	6
Motivation (MOT)	Developed for this study	5
Perceived ease of use (PUE)	Developed for this study	5
Perceived privacy threat (PPT)	(Bulgurcu, 2012)	6
Attitude (ATT)	(Ajzen, 1991)	5
Satisfaction (SAT)	(Crites, Fabrigar, & Petty, 1994; Doll & Torkzadeh, 1988)	5
Intention to continue use (INT)	(Ajzen, 1991; Titah & Barki, 2009)	3

TABLE 3 SOURCES OF MEASUREMENT ITEMS

Two rounds of pilot testing was done to assess the psychometric properties of the measurement scales and to confirm their measurements quality with over 500 participants. During the pilot testing, participants were asked to comment on the wording of the items and to share other concerns about the constructs. The initial measurement were modified based on the feedback received from participants. Further improvement of the item quality was accomplished through a card-sorting exercise with seven participants. Adequate scores of validity and reliability were obtained during the second round of pilot testing, hence used in the final questionnaire.

In study two, a total of 330 participants participated, of which 290 were eventually included for the analyses by using the same cleaning requirements as used in Study one. No deviations were found in geographical location, gender (46% female), income (median personal income: $25K - $50K), level of employment (74% employed, 7% students, 9% looking for work, 7% not looking for work, 3% unable to work or retired), and education (15% high school, 25% some college, 46% undergraduate degree, 13% post-graduate degree). A slight overrepresentation of younger participants was observed here as well as in Study one (median age: 31).

DATA ANALYSIS AND RESULTS

Several manipulation checks were conducted to ensure the data quality prior to the running of the data analyses of Study one. We used the presentation of the item categories on the mockup websites as a control variable in the analysis. Exploring whether the order of presentation had any effects, did not turn out significant, and therefore, excluded from further analysis.

We performed a confirmatory factor analysis (CFA) on the item categories and corresponding personal information in order to confirm their explanatory factors. The CFA with the four item categories as factors showed a good model fit (*CFI = .993, TLI = .992, RMSEA = .040, 90% CI: [.032, .047]*). A good model has a χ^2 that is not statistically different from a saturated model ($p > .05$). However, it has been argued that this statistic is too sensitive, and therefore other fit indices are proposed (Bentler & Bonett, 1980). Cut-off points for these indices are proposed to be: *CFI > .96, TLI > .95,* and *RMSEA < .05* (with the upper bound of its 90% CI falling below .10).

To evaluate the psychometric properties of the subjective evaluations that were asked in Study 2, we conducted another CFA. To ensure individual reliability and convergent validity of the constructs, squared loadings (variance extracted) were examined of each of the items, and the average variance extracted (AVE) of each construct. The items showed to share at least 50% of their variance with their designated construct (Chin, 1998), also see **Error! Reference source not ound.** for the statistics. Also the AVEs were thus all higher than the recommended value of 0.50 (see Table 4), indicating adequate convergent validity. Discriminant validity was tested as well, by taking the square root of the AVE of each construct (diagonal values of Table 4). These indicate that they are higher than the correlations of the constructs with other constructs (off-diagonal values of Table 4). We also calculated correlations of all items with the saved factor scores (see Table 12). They show that all items were correlated at least *r = .78* with their own factor, and at least .10 less with the other factors, as recommended (Gefen & Straub, 2005). Lastly, to confirm the scale reliability, Cronbach's alpha was calculated for each factor. All alpha scores were higher than .91 (see Table 11) meaning that the scale consist of an excellent reliability (Gefen & Straub, 2005; Nunnally, Bernstein, & Berge, 1967).

	Alpha	AVE	PSE	MOT	PEU	PPT	ATT	SAT	INT
Perceived self-efficacy	.94	.786	.886	.753	.342	-.618	.644	.645	.579
Motivation	.95	.835	.763	.914	.182	-.450	.425	.431	.394
Perceived ease of use	.93	.828	.342	.182	.910	-.297	.600	.539	.508
Perceived privacy threat	.97	.914	-.618	-.450	-.297	.956	-.584	-.598	-.615
Attitude	.93	.844	.644	.425	.600	-.584	.919	.874	.837
Satisfaction	.93	.810	.645	.431	.539	-.598	.874	.900	.834
Intention to continue use	.98	.957	.579	.394	.508	-.615	.837	.834	-.978

TABLE 4 SCALE VALIDITY SCORES AND LATENT VARIABLE CORRELATIONS

RESULTS OF STUDY 1

We used MPlus to test the proposed repeated measures path model (see Figure 4) using a weighted least squares estimator. Standard demographical information was initial included in the analysis, but did not return significant, hence not further included. The estimation of the final model resulted in an excellent fit (*CFI = 1.00, TLI = 1.00, RMSEA <.001, 90% CI: [.000, .011]*).

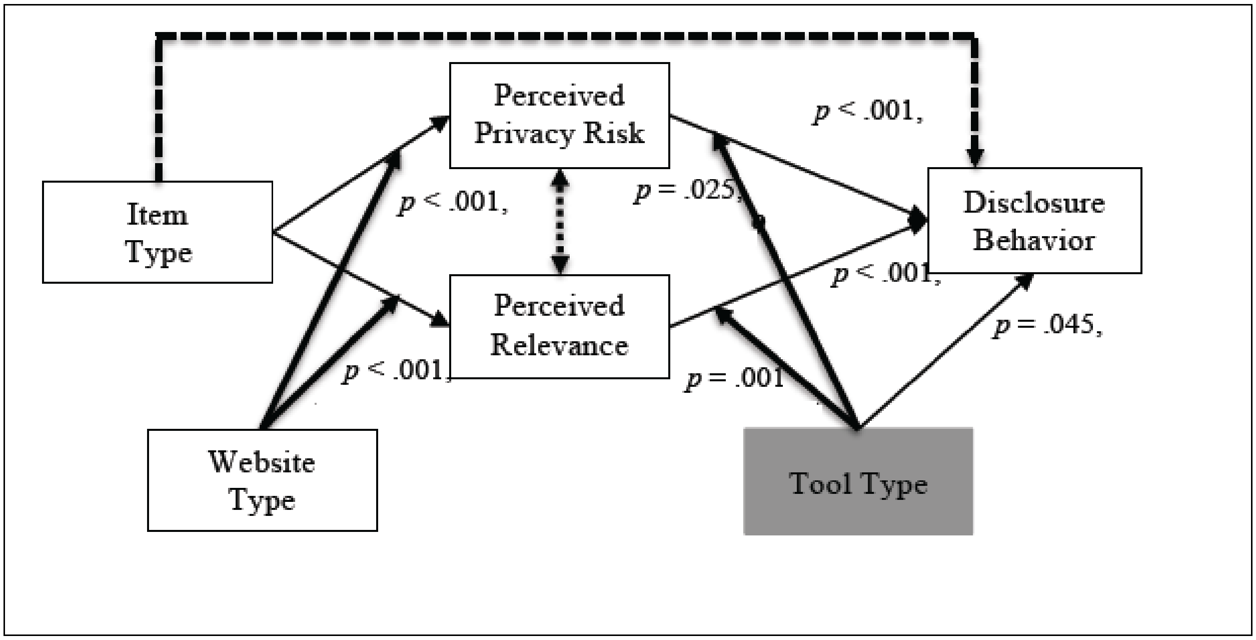

FIGURE 4 TESTED PATH MODEL WITH THE RESULTS

We firstly investigated the model without the moderating effects of tool type. After that, we estimated the moderating effect of tool type with help of separate path-models. This allowed us to first investigate the main effect, and sequentially the interaction effects. A simplified overview of the found results can be seen in Figure 4.

We firstly investigated the relationship between the tool type (i.e., traditional, add, or remove) against users' disclosure behavior. Results show that the contrast between the traditional auto-completion tool and the alternative auto-completion tools (i.e., add or remove) are significantly different ($\chi^2(1) = 4.037$, $p = .045$). When controlling for perceived privacy risk, perceived relevance, and item type, the odds of disclosure was significantly lower when participants were presented with the alternative tools compared to the traditional auto-completion tool. This gives the impression that participants using the alternative tools were showing more considerate behavior. We found a 24% lower ($d = .165$, $p = .047$) disclosure behavior for the remove tool, and 18.9% lower for the add tool ($d = .107$, $p = .130$). Although we found a difference between the add and remove tool in disclosure behavior, this was not statistically significant.

In the next step, we looked at the effects of perceived privacy risks and relevance on users' disclosure behavior. We controlled for item type, tool type, and perceived relevance, and found that a one point increase in perceived privacy risk results in a 19.2% decrease in odds of disclosure ($p < .001$, $r = .245$). When controlling for item type, tool type, and perceived privacy risk, a one point increase was found in perceived relevance resulted in a 7.9% increase in the odds of disclosure ($p < .001$, $r = .125$). Lastly, we investigated the direct main effect of item type on disclosure, while controlling for the other main effects (i.e., tool type, perceived relevance, and perceived privacy risks). We found that disclosure of personal interest and health record items was higher than disclosure of general contact information and job skills. The results here are summarized in Table 5.

IV	Disclosure odds ratio	95% CI	P-value	Effect size
Intercept	4.225	3.287 – 4.225		
Perceived privacy risk	0.818	0.782 – 0.856	<.001	.245
Perceived relevance	1.079	1.042 – 1.118	<.001	.125
Tool: traditional	1.0			
Tool: remove	0.760	0.580 – 0.996	.047	.165
Tool: add	0.811	0.619 – 1.063	.130	.107
Item: contact	1.0			
Item: personal	1.292	1.023 – 1.631	.031	
Item: job	0.946	0.795 – 1.127	.536	
Item: health	1.320	1.096 – 1.591	.004	

TABLE 5 MEASUREMENT OF THE PATH MODEL FOR DISCLOSURE

After investigating the main effects of the path model, we continued by looking for moderating effects of tool type on the perceived privacy risk and relevance on users' disclosure behavior. Because the correlation between perceived privacy risk and relevance appeared to be very high, we explored the moderating effects on each of them separately.

In order to be able to test for moderating effects of tool type (i.e., traditional, add, and remove), we created a multiple group model. This allowed us to compare the add and remove auto-completion tools against the traditional auto-completion tool, where at the same time all the other parameters are fixed except for the intercepts and the effects of perceived privacy risk set to zero. This results in a model with an excellent fit (*CFI = .990, TLI = .988, RMSEA = .007, 90% CI: [.000, .013]*). The results show a significant difference between the contrasts of the traditional auto-completion tool and the alternatives ($\chi^2(1) = 5.017$, $p = .025$). When we controlled for perceived relevance and item type, we found that a one point increase in perceived risk resulted in a 13.7% decreased in the odds of disclosure for participants that interacted with the traditional auto-completion tool. A one point in perceived risk resulted in a 24.6% decrease in the odds of disclosure for participants that interacted with the remove auto-completion tool, showing a significantly stronger decrease in odds compared with the traditional tool ($p = .025$). Also, a one point increase in perceived risk resulted in an 18.9% decrease in the odds of disclosure for participants interacting with the add tool. However, this effect did not appear to be significantly stronger compared to the traditional tool ($p = .179$). A summary of the results can be found in Table 6.

IV	Disclosure odds ratio	95% CI	P	Effect
Intercept: traditional	3.773	2.570 – 5.541		
Intercept: remove	2.804	1.978 – 3.974		
Intercept: add	3.740	2.876 – 4.863		
Perceived privacy risk: traditional	0.863	0.816 – 0.914	<.001	.361
Perceived privacy risk: remove	0.754	0.682 – 0.833	<.001	.371
Perceived privacy risk: add	0.811	0.761 – 0.866	<.001	.330
Perceived relevance	1.073	1.037 – 1.109	<.001	.115
Item: contact	1.0			
Item: personal	1.225	0.966 – 1.553	.093	
Item: job	0.937	0.790 – 1.111	.452	
Item: health	1.346	1.142 – 1.587	<.001	

TABLE 6 REGRESSION ON DISCLOSURE (TOOL TYPE * PERCEIVED RISK → DISCLOSURE)

We tested for moderating effects of tool type on the effect of perceived relevance on disclosure in a separate model. For this, we followed the same procedure as for testing moderating effects on the effect of perceived risk on disclosure behavior. Again, we created a multiple group model, and compared the add and remove auto-completion tools against the traditional tool, while fixing all parameters except for the intercept and set the effect of perceived relevance to zero. Also, this model showed an excellent fit (*CFI = .993, TLI = .992, RMSEA = .006, 90% CI: [.000, .012]*). When controlling for perceived privacy risk and item type, we found a one point increase in perceived relevance causing a 1.1% decrease in the odds of disclosure for participations that were in the traditional auto-completion tool group. However, this effect was not significant (p = .736). Furthermore, a one point increase in perceived relevance resulted in a 13.3% increase in the odds of disclosure for those in the remove auto-completion tool group, which is significantly stronger compared to the traditional tool (p = .003). Also, a one point increase in perceived relevance resulted in an 11.4% increase in the odds of disclosure for participants interacting with the add tools. This effect is significantly stronger compared to the traditional tool as well (p = .006). A summary of the findings can be found in Table 7.

IV	Disclosure odds ratio	95% CI	P	Effect
Intercept: traditional	3.773	2.557 – 5.579		
Intercept: remove	2.732	1.916 – 3.895		
Intercept: add	3.800	2.905 – 4.970		
Perceived risk	0.816	0.786 – 0.847	<.001	.266
Perceived relevance: traditional	0.989	0.927 – 1.055	.736	.026
Perceived relevance: remove	1.133	1.064 – 1.206	<.001	.285
Perceived relevance: add	1.114	1.057 – 1.175	<.001	.208
Item: contact	1.0			
Item: personal	1.260	0.998 – 1.591	.051	
Item: job	0.959	0.809 – 1.137	.629	
Item: health	1.409	1.188 – 1.671	<.001	

TABLE 7 REGRESSION ON DISCLOSURE (TOOL TYPE * PERCEIVED RELEVANCE → DISCLOSURE)

Furthermore, we tested whether the website type (i.e., BlogHeroes, I <3 Work, or Codacare) moderates the item type (information asked to be filled in) by the website on perceived privacy risk and perceived relevance. In other words, we wanted to see whether perceived risk would be lower and perceived relevance would be higher when the requested information matches the purpose of the website than when the requested information does not match the website's purpose. The moderating effect of website type on the relationship between type of requested information and perceived risk was significant ($\chi^2(6) = 246.41$, $p < .0001$). Table 8 shows significantly lower levels of perceived risk for the disclosed information that matches the website's purpose. For a visual overview see Figure 5.

	BlogHeroes	I <3 Work	Codacare
Contact info	-0.692	-1.019	-1.268
Interest	**-1.683**	-1.293	-1.065
Job skills	-0.752	**-1.512**	-0.930
Health record	-0.519	-0.044	**-1.585**

TABLE 8 MEAN PERCEIVED RISK (-3 - +3) PER WEBSITE TYPE AND ITEM CATEGORY

Also, the moderating effect of website type on the relationship between personal information type and perceived relevance showed significant ($\chi^2(6) = 913.47$, $p < .0001$). Also here (see Table 9) significantly higher levels of relevance for personal information disclosure of questions that matches the purpose of the designated websites. For a visual overview see Figure 5.

	BlogHeroes	I <3 Work	Codacare
Contact info	0.994	1.346	1.819
Interest	**0.76**	-1.180	-1.394
Job skills	0.091	**1.820**	0.516
Health record	-1.158	-1.724	**1.906**

TABLE 9 MEAN PERCEIVED RELEVANCE (-3 - +3) PER WEBSITE TYPE AND ITEM CATEGORY

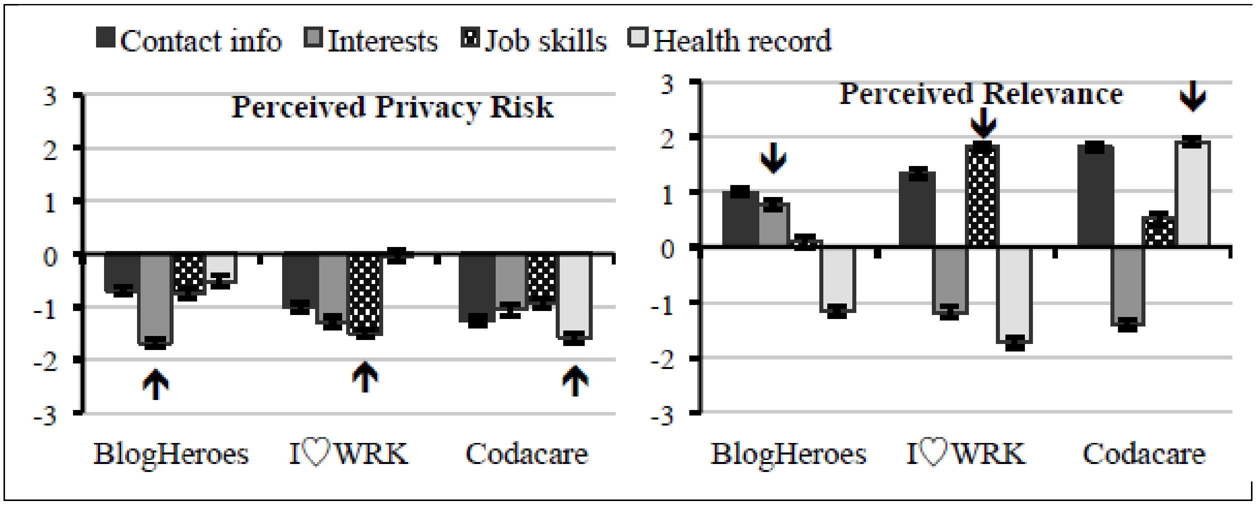

FIGURE 5 PERCEIVED RISK AND PERCEIVED RELEVANCE PER WEBSITE TYPE AND CATEGORY. ARROWS POINTS TO THE MATCHING ITEM TYPES, AND ERROR BARS ARE +/- 1 STANDARD ERROR.

To summarize the findings of the model that we proposed and investigated, as presented in Figure 6, the alternative auto-completion tools (i.e., add and remove) make people more considerate of the website's purpose to request specific information. Whereas, when it comes to the traditional auto-completion tool, what information users eventually disclose is less in line with the specifics of the website. Meaning that users may disclose more than they need, which may not even be relevant to the functionality of the website. This in turn affects users by disclosing information that is not necessary, but also the system that end up with information that is not directly important to provide users a personalized experience.

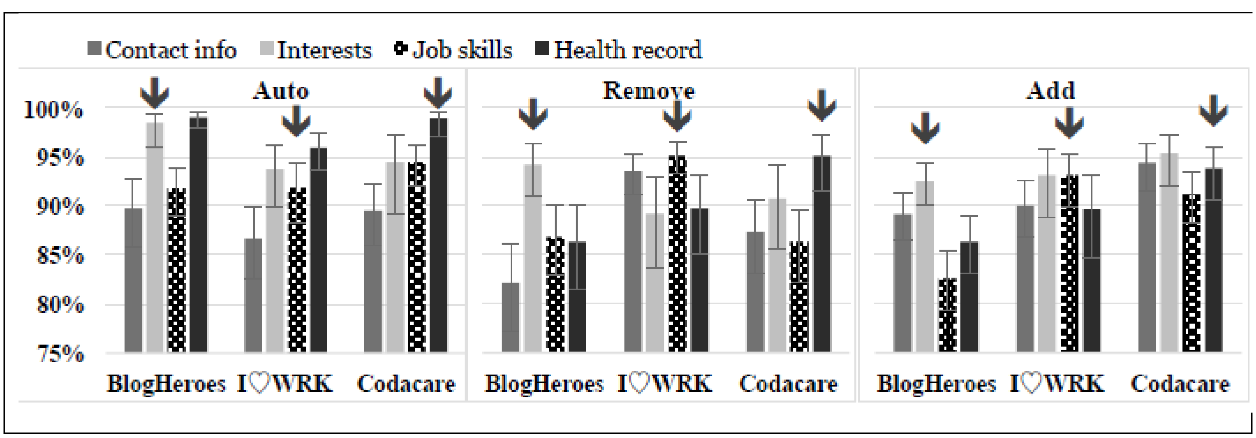

FIGURE 6 DISCLOSURE RATES FOR EACH WEBSITE, TOOL TYPE, AND ITEM TYPE. ARROWS POINTS TO THE MATCHING ITEM TYPES, AND ERROR BARS ARE +/- 1 STANDARD ERROR.

RESULTS OF STUDY 2

In Study 2 we extended our results with additional subjective evaluations of users about the different auto-completion tools. This allows us to get a deeper and more thorough understanding of why users engage in certain disclosure behaviors, and how to anticipate on that behavior.

Firstly, we looked at the relationship between tool type and users' perceived self-efficacy and motivation in disclosing information that fits the purpose of the website. The difference between the tools in perceived self-efficacy appeared to be significant ($\chi^2(2) = 13.819$, $p = .001$). Results show that those interacting with the remove auto-completion tool ($\beta = .433$, $p = .005$) or the add auto-completion tool ($\beta = .500$, $p = .001$) perceived a higher self-efficacy that those interacting with the traditional auto-completion tool. However, no significant difference was found between the two alternative tools ($\chi^2(2) = 2.922$, $p = .232$). Although not statistically significant there were indications that those presented with the remove auto-completion tool ($\beta = .234$, $p = .132$) or the add auto-completion tool ($\beta = .203$, $p = .159$) perceived a higher level of motivation that those interaction with the traditional auto-completion tool.

In Study 2 we looked at subjective evaluations of users about the different auto-completion tools. We looked at the relationship between tool type and users' perceived ease of use, perceived privacy threat, attitude, satisfaction, and intention to continue use. Compared to participants with the traditional auto-completion tool, those who used the add auto-completion tool perceived a higher ease of use ($p = .011$), lower privacy threat ($p < .001$), more positive attitudes ($p < .001$), higher satisfaction ($p < .001$), and a higher intention to continue using this kind of auto-completion tool ($p < .001$). On the other hand, user of the remove tool also perceived a lower privacy threat ($p = .059$), more positive attitudes ($p = .026$), higher satisfaction ($p < .042$), and a higher intention to continue use with the remove auto-completion tool ($p < .060$). However, the effects found are weaker for the remove tool than the add auto-completion tool. Additionally, the differences found between the add and remove tool are all statistically significant. A summary of the just discussed results can be found in Table 10 and a visualization in Figure 7.

DV	Wald omnibus	Remove – traditional	Add – traditional
Self-efficacy	$\chi^2(2) = 13.819$, $p = .001$	$\beta = .433$, $p = .005$	$\beta = .500$, $p = .001$
Motivation	$\chi^2(2) = 2.922$, $p = .232$	$\beta = .234$, $p = .132$	$\beta = .203$, $p = .159$
Ease of use	$\chi^2(2) = 9.641$, $p = .008$	$\beta = -.053$, $p = .749$	$\beta = .465$, $p = .011$
Privacy threat	$\chi^2(2) = 19.731$, $p < .001$	$\beta = -.281$, $p = .059$	$\beta = -.650$, $p < .001$
Attitude	$\chi^2(2) = 24.359$, $p < .001$	$\beta = .332$, $p = .026$	$\beta = .786$, $p < .001$
Satisfaction	$\chi^2(2) = 15.619$, $p < .001$	$\beta = .288$, $p = .042$	$\beta = .590$, $p < .001$
Intention to continue use	$\chi^2(2) = 28.474$, $p < .001$	$\beta = .310$, $p = .060$	$\beta = .809$, $p < .001$

TABLE 10 STATISTICAL TESTING RESULTS

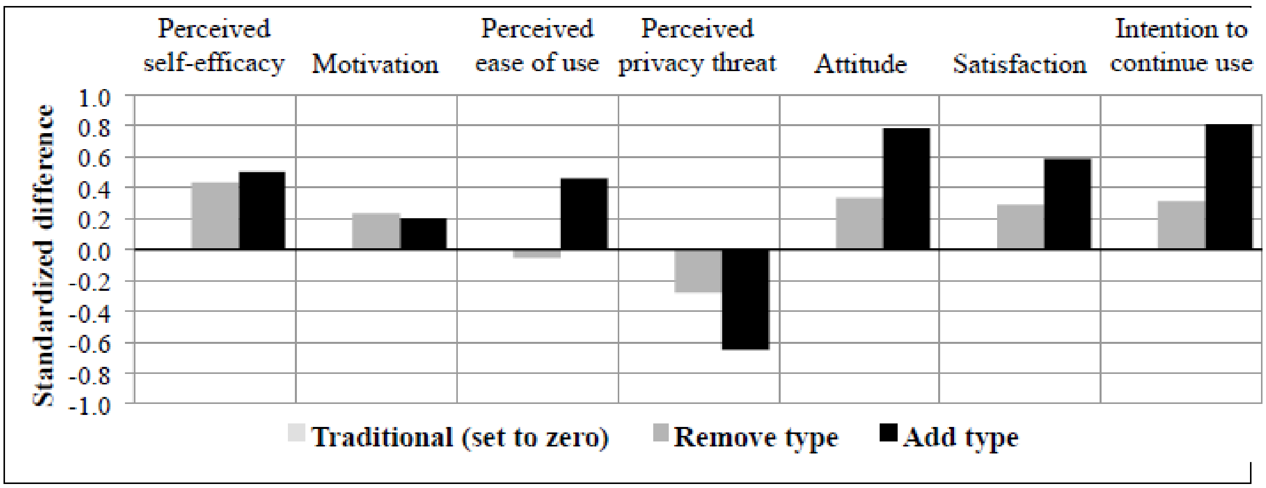

FIGURE 7 STANDARDIZED EFFECTS OF TOOL TYPE ON THE DEPENDENT VARIABLES

DISCUSSION

In these studies we showed that the type of auto-completion tool has a direct influence on users' heuristically motivated disclosure behavior. The tendency with which users disclose information was significantly influenced: those interaction with the traditional auto-completion tool disclosed more than those interaction with the alternatives that are proposed in this work.

Our findings have theoretical and practical implications. On a theoretical side, we showed that technological design can serve to influence users' likelihood to elaboration on privacy related decision making, and additionally the vulnerability to a default effect would be one of the consequences of heuristics rather than deliberate decision making. We furthermore extend the knowledge of the applicability of psychological theory usage (in especially on the ELM). We showed that the theory on ELM can be extended to technological design, instead of limiting to personal or situational characteristics, as a main tool of elaboration. This has consequences and opening possibilities for future design implication of technologies. Subtle design elements can be applied to graphical user interfaces that entice users to engage in a more central route of information processing and decision making, rather than choosing for a peripheral route. Letting users make use of their central route follows that better and more deliberate decision are able to be made.

From a practical perspective, we showed that traditional auto-completion tools can cause overexposure of personal information. It can cause that users unintentional disclose more than they intended to, or information that is not directly relevant to the purpose of the website. Due to this overexposure, users are exposed to a major source of vulnerability. Additionally, we developed alternatives to the auto-completion tools that mitigate the vulnerability that are caused by traditional tools.

We showed with our alternative auto-completion tool, that the consequences of the default effect that is introduced by the traditional auto-completion tool, can be act upon. Drawing upon theory, we showed that our alternative auto-completion tools increased elaboration, and thereby may have counteracted on the default effect of the traditional tool. For the add auto-completion tool, the add button may have enticed participants to think about the potential positive consequences of disclosing certain information, while the remove button may have enticed participants to think more about the potential negative consequences.

With our results we also show that there is a kind of contextual integrity (i.e., context-information fit). We show that the disclosure of information in certain context depends on the interaction between the type of information and the type of website, which in turn is mediated by perceived risk and relevance. Users perceive disclosing information as more relevant and less risky, when the type of information matches the purpose of the website. Hence, more likely to behave as such in terms of disclosing the information. This is especially the case for the alternative auto-completion tools, where participants showed to be more deliberate about their decisions. This contributes to overcome the vulnerability of traditional auto-completion tools.

CONCLUSIONS AND FUTURE WORK

We investigated the effect of form auto-completion tools on the privacy calculus of users and the influence on purpose-specific information disclosure. With our results we showed that users interacting with a traditional auto-completion tool fall prey to the default effect. This causes that they may disclose more information than they would do otherwise. Our alternative auto-completion tools that we developed, counteracts on this, and results in that users are more deliberate about their actions and elaborate what they eventually disclose, by putting users into the central route of information processing. This overcomes the vulnerability caused by the default effect, which is inherent to the traditional auto-completion tool.

It is furthermore important to highlight some limitations of our approach. We used a controlled experiment where we developed mockup websites. Even though we excluded participants that reported that the notice that everything was part of a controlled experiment, an actual field study with the proposed alternative auto-completion would be necessary to conclude the findings that we present here.

A SHORT INTRODUCTION OF STUDY 3

After the conducted studies that are reported in this report, we decided to continue our collaboration and extend the findings that we have reported here.

In Study 1 and 2 we investigated the effects of different auto-completion tools on disclosure and subjective evaluations of the used systems. Aside from a traditional auto-completion tool, two alternatives were developed, each resembling the traditional tool, but adapted to make it easier for users to switch between disclosing (including an add button) to withholding (including a remove button) the information.

The add and remove alternatives of the auto-completion tool lead to disclosure rates that were not significantly different. Due to the default effect, the remove condition should have had a higher disclosure rate, as seen as with the traditional auto-completion tool, as the field was already filled in upfront. However, this was not the case. When experience a default, people are more likely to choose the default option than to act and change the default. People generally fear negative consequences of action more than negative consequences of inaction.

Does this mean that there was no default effect, or that some other effect countered the default effect? The difference between the auto-completion tool study and typical studies of the default effect is that the alternative auto-completion tools had a button to undo the default with a single click. This button may have had its own, opposite effect on users' disclosure rates. Specifically, the presence of a button might encourage people to click it, thereby counteracting the default effect.

In sum, the following questions are going to be addressed (Figure 8 a visualization of the conditions):

- Did the default effect play a role at all? If the default effect did not play a role, it makes sense that the conditions ended up with the same disclosure rates. In our experiment we will test this by comparing the two defaults against a version of system that has no default (see Manipulations; compare conditions 3 and 4 with condition 5).
- Alternatively, is there a button effect that counters the default effect? If the button effect is present, it counteracts the default effect, which is an alternative explanation for the fact that the conditions ended up with the same disclosure rates. In our experiment we will test this by comparing the "fill" and "clear" conditions to new versions of these conditions that have the same default but *both* buttons (see Manipulations; compare conditions 1 and 2 with conditions 3 and 4). These conditions present both options (disclose and withhold) to the user, and are thus arguably less likely to encourage people to change the default.

Alternatively, we try to manipulate the button effect by various means (conditions 6 through 13).

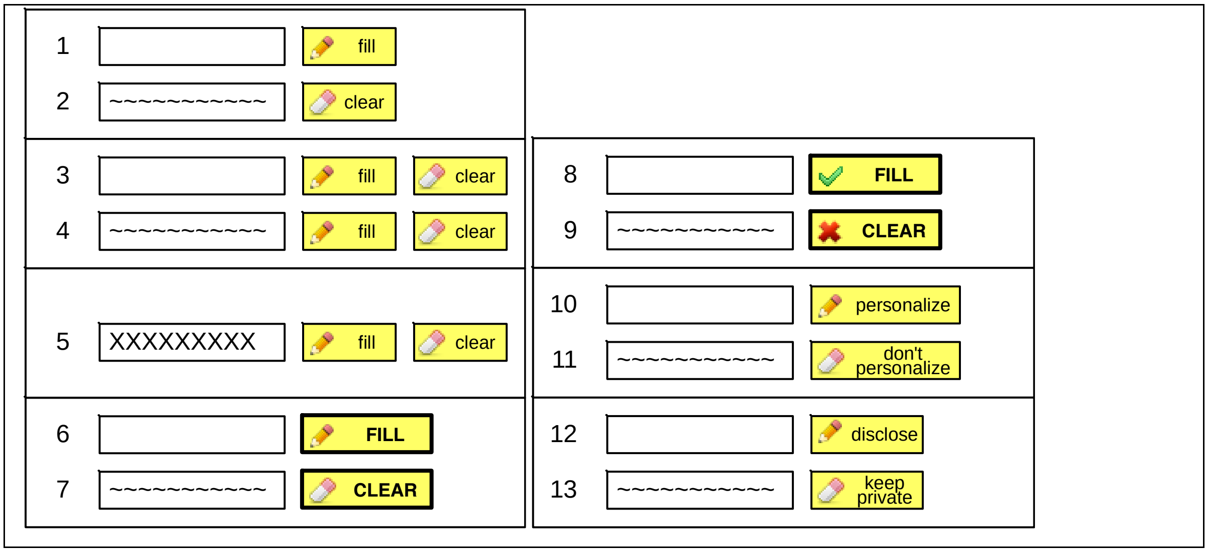

FIGURE 8 EXPERIMENTAL CONDITIONS

The conditions

1. Original condition. The form is empty by default, but fields can be filled by clicking the "fill" button.
2. Original condition. The form is filled by default, but fields can be cleared by clicking the "clear" button.
3. No button effect. The form is empty by default, but fields can be filled by clicking the "fill" button. A "clear" button is also displayed to reduce the button effect that arguably occurs when only the "fill" button is present.
4. No button effect. The form is filled by default, but fields can be cleared by clicking the "clear" button. A "fill" button is also displayed to reduce the button effect that arguably occurs when only the "clear" button is present.
5. No button, no default. All fields are filled with "xxxx" by default. For each field the user will need to click either the "fill" or the "clear" button. The user has to make this decision for each field before they can submit the form. This is the most neutral condition.

6. Stronger button effect. The form is empty by default, but fields can be filled by clicking the “fill” button. Compared to condition 1, more attention is drawn to this button by making the button text bold and all caps.
7. Stronger button effect. The form is filled by default, but fields can be cleared by clicking the “clear” button. Compared to condition 2, more attention is drawn to this button by making the button text bold and all caps.
8. Even stronger button effect. The form is empty by default, but fields can be filled by clicking the “fill” button. Compared to condition 1 and 6, more attention is drawn to the button by not only having the button text be bold and all caps, but also by making the entire button blue.
9. Even stronger button effect. The form is filled by default, but fields can be cleared by clicking the “clear” button. Compared to condition 2 and 8, more attention is drawn to the button by not only having the button text be bold and all caps, but also by making the entire button blue.
10. Focus on benefit. The form is empty by default, but fields can be filled by clicking the “personalize” button. By changing the button text, benefits of disclosure are emphasized.
11. Focus on benefit. The form is filled by default, but fields can be cleared by clicking the “don’t personalize” button. By changing the button text, the benefits that the user will forfeit by not-disclosing are emphasized.
12. Focus on risk. The form is empty by default, but fields can be filled by clicking the “divulge” button. By changing the button text, risks of disclosure are emphasized.
13. Focus on risk. The form is filled by default, but fields can be cleared by clicking the “keep private” button. By changing the button text, risks that are avoided by non-disclosure are emphasized.

How can the button effect be manipulated?

We will test two possible causes of the button effect. First of all, the button effect might be caused by the button simply attracting attention. If this is true, then making the button stand out more should increase the button effect (conditions 6 through 9).

Another explanation is that the presence of the button might signal a social norm. The "clear" button signals the norm of non-disclosure, countering the default to disclose; the "fill" button signals the norm of disclosure, countering the default is to not disclose. If this is true, then explicitly formulating the button in a normative way that promotes disclosure (i.e. by signaling the potential benefits of disclosure; conditions 10 and 11) or inhibits disclosure (i.e. by signaling the potential risks of disclosure; conditions 12 and 13) should change the button effect in the direction of the presented norm.

Investigating the cognitive mechanism causing the default and button effects: query theory

One could argue that at the cognitive level, the default and button effects "compete for the users' attention" in their decision to disclose or not disclose each item. Query theory formalizes this cognitive mechanism, and also provides a way to measure this internal cognitive process.

Specifically, query theory suggests that arguments in favor of one's decision come to mind sooner and also come to mind in greater numbers than arguments against the choice one is making. Dinner et al. argue that the default can provide a reference point for the query theory: the default determines what arguments people see as "in favor" or "against" (Dinner, Johnson, Goldstein, & Liu, 2011). Indeed, their study results show that people's queries (their lists of arguments) can be influenced by the default option selected: Participants listed more reasons for the default and these reasons also came to mind before users thought of reasons to select the alternative option. In their research, Dinner et al. have also shown that users' decision can be predicted based on their queries (i.e. people's queries *mediate* the effect of defaults on disclosure).

We hypothesize that when a single button is present, the button effect makes people formulate the decision in line with the action presented by the button, i.e. in the *opposite* direction of the default. Moreover, when two antagonistic buttons are present, people's arguments will become a mix of the two directions, and the relative strength of each effect will determine which type of queries becomes more prominent.

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APPENDIX

Construct	Item	Mean	STD	Loading
Perceived self-efficacy (PSE)	*Using FormFiller provides me with*			
	the skills to submit the information that I really wanted to submit.	5.315	1.394	0.858
	the ability to carefully deliberate which fields to fill in and which to leave blank.	5.182	1.525	0.900
	the competency to decide the amount of information to share on an online form.	5.224	1.464	0.936
	the knowledge to control the amount and type of information that I disclose on a website.	5.185	1.536	0.887
	the ability to control the information I submit on an online form.	5.642	1.269	0.849
	the efficacy to disclose at the level I wanted to disclose.	5.455	1.321	0.887
Motivation (MOT)	*Using FormFiller*			
	makes me feel that it is worthwhile to put in the effort to decide which fields to fill in and which to leave blank, in line with the purpose of the requesting website.	5.176	1.510	0.904
	makes me think that it is important to contemplate what information best fits the purpose of the requesting website.	5.248	1.503	0.886
	motivates me to carefully consider what type and amount of information is appropriate to disclose to the requesting website.	5.164	1.624	0.931
	makes me aspire to make a considerable effort to release the information that is aligned with the objectives of the requesting website.	4.861	1.613	0.903
	motivates me to think about disclosing the right information that is useful for the requesting website.	5.073	1.579	0.943
Perceived ease of use (PEU)	*Based on what I have seen, FormFiller makes it ______ to*			
	fill out online forms.			
	easy - - neutral - - difficult	6.542	0.783	0.944
	simple - - neutral - - complicated	6.521	0.796	0.938
	convenient - - neutral - - inconvenient	6.536	0.840	0.944
	effortless - - neutral - - daunting	6.327	0.975	0.839
	straightforward - - neutral - - burdensome	6.397	0.914	0.880
Perceived privacy	*Overall, I believe that using FormFiller would ____.*			
	be harmful to my privacy.	3.494	1.821	0.979

threat (PPT)	impact my privacy negatively.	3.494	1.845	0.977
	be a threat to my privacy.	3.470	1.871	0.949
	result in a loss of control over my personal information.	3.421	1.758	0.941
	bring some uncertainty about future use of my personal information.	3.748	1.868	0.948
	make it difficult for me to predict how my information will be accessed and used in the future.	3.848	1.910	0.940
Attitude (ATT)	*Using FormFiller is ______.*			
	terrible - - neutral - - wonderful	5.424	1.226	0.925
	frustrating - - neutral - - satisfying	5.715	1.129	0.913
	disappointing - - neutral - - fulfilling	5.348	1.282	0.913
	troublesome - - neutral - - gratifying	5.382	1.257	0.926
	pleasant - - neutral - - annoying	5.545	1.433	0.914
Satisfaction (SAT)	How satisfied are you with your FormFiller experience?	5.452	1.325	0.920
	In most ways FormFiller is close to ideal.	5.100	1.520	0.763
	I would not change anything about FormFiller.	5.679	1.156	0.928
	I got the important things I wanted from FormFiller.	5.485	1.355	0.943
	FormFiller provides the precise functionality I need.	5.276	1.469	0.934
Intention to continue use (INT)	*If I were given the chance, I would intend to continue using FormFiller to*			
	fill out information in my browser.	5.330	1.549	0.968
	disclose information to web pages.	5.148	1.577	0.992
	exchange information with web pages.	5.130	1.612	0.975

TABLE 11 MEASUREMENT ITEMS AND ITEM LOADINGS FOR STUDY 2

	PSE	MOT	PEU	PPT	ATT	SAT	INT
PSE1	0.796	0.541	0.439	–0.479	0.630	0.619	0.548
PSE2	0.899	0.681	0.288	–0.500	0.513	0.524	0.442
PSE3	0.914	0.677	0.362	–0.503	0.593	0.587	0.522
PSE4	0.892	0.694	0.315	–0.503	0.515	0.518	0.483
PSE5	0.812	0.593	0.382	–0.485	0.526	0.510	0.446
PSE6	0.856	0.631	0.362	–0.537	0.523	0.528	0.497
MOT1	0.664	0.857	0.179	–0.378	0.401	0.429	0.369
MOT2	0.607	0.853	0.139	–0.310	0.327	0.328	0.281
MOT3	0.710	0.914	0.147	–0.347	0.339	0.332	0.302
MOT4	0.625	0.875	0.156	–0.324	0.338	0.331	0.248
MOT5	0.670	0.924	0.196	–0.364	0.367	0.361	0.319
PEU1	0.261	0.199	0.788	–0.178	0.426	0.409	0.347
PEU2	0.249	0.146	0.795	–0.192	0.449	0.411	0.378
PEU3	0.280	0.179	0.767	–0.223	0.458	0.421	0.410
PEU4	0.225	0.076	0.803	–0.167	0.441	0.408	0.388
PEU5	0.294	0.133	0.776	–0.243	0.439	0.440	0.417
PPT1	–0.569	–0.380	–0.288	0.960	–0.500	–0.513	–0.548
PPT2	–0.579	–0.396	–0.280	0.964	–0.511	–0.521	–0.525
PPT3	–0.550	–0.378	–0.317	0.949	–0.532	–0.540	–0.557
PPT4	–0.557	–0.387	–0.352	0.925	–0.541	–0.515	–0.546
PPT5	–0.558	–0.368	–0.314	0.909	–0.521	–0.527	–0.555
PPT6	–0.511	–0.341	–0.319	0.906	–0.508	–0.511	–0.534
ATT1	0.584	0.376	0.590	–0.473	0.902	0.788	0.743
ATT2	0.542	0.346	0.614	–0.427	0.904	0.773	0.720
ATT3	0.573	0.371	0.582	–0.474	0.896	0.770	0.716
ATT4	0.603	0.372	0.617	–0.537	0.911	0.766	0.764
ATT5	0.539	0.336	0.636	–0.497	0.890	0.779	0.773
SAT1	0.592	0.370	0.591	–0.520	0.782	0.860	0.722
SAT2	0.538	0.310	0.482	–0.391	0.639	0.748	0.536
SAT3	0.567	0.363	0.563	–0.466	0.787	0.877	0.760
SAT4	0.570	0.393	0.556	–0.504	0.767	0.907	0.750
SAT5	0.534	0.339	0.557	–0.492	0.764	0.909	0.754
INT1	0.555	0.353	0.550	–0.571	0.804	0.793	0.918
INT2	0.525	0.317	0.563	–0.551	0.783	0.785	0.968
INT3	0.522	0.334	0.566	–0.520	0.780	0.786	0.956

TABLE 12 CROSS LOADINGS