Typing Fast versus Typing Slow: Using Typing Dynamics to Reveal Authentic and Imposter Users

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Abstract

Real-time assessment of users' cognitive states has practical importance, allowing organizations to infer user behaviors. Realizing its importance, prior studies – specifically those using mouse cursor movements – have applied various theories to answer a similar question, i.e., how does a high cognitive load influence the users' device usage behavior? While numerous activities can increase cognitive load, we argue that the mechanisms behind how humans process information can more holistically be explained using Dual Process Theory (DPT) (i.e., when cognitive load is either low or high) and can be applied under a broad range of usage contexts. Using a within-participant experiment and a simple typing task, we demonstrate that DPT is robust to work by examining DPT and mouse cursor movements. Specifically, users' typing speed and task execution are significantly slower when engaged in the task (System 2) and significantly faster when completing the task with lower cognitive effort and engagement (System 1).

1. Introduction

Digital transformation has arrived, and the adoption of Internet technologies is growing exponentially in nearly every facet of business and society . With such transformation, there is a need for improved models for identifying and assessing factors that drive specific user behaviors in various domains, including, but not limited to, cyber security (Tuor et al. 2017), education(Hwang and Tsai 2011), and healthcare (Webster 2007). Yet, real-time assessment of user behavior is a substantial challenge as user behaviors are influenced by various cognitive processes, which are difficult to capture, infer, and act upon outside highly artificial environments (e.g., data collection using fMRI, EEG caps, eye tracking, and so on).

Rooted on various cognitive and social science theories, prior Information Systems (IS) literature in the Human-Computer Interaction (HCI) domain aims to provide objective metrics that can be used to assess multiple online users' behaviors, including habituation (Vance et al. 2018), concealing information (Jenkins. et al. 2019), and fraud(Hibbeln et al. 2014; Weinmann et al. in press). Specifically, previous literature mainly focused on specific situations where humans would experience heightened cognitive load (i.e., similar context); thus, the leveraged theories provide the support that applies to a confined set of situations. For instance, Hibbeln and colleagues (2017) drew from Attention Control Theory (Eysenck et al. 2007) to explain how negative emotions heighten cognitive load and thus influence mouse cursor movements (e.g., feeling negative emotions resulted in slower mouse cursor speeds). Weinmann and colleagues (forthcoming) leveraged Cognitive Load Theory (CLT) and the Response Activation Model (RAM) to demonstrate that more extensive fraud (i.e., more cognitively demanding) increased mouse movement deviations and decreased movement speed (Sweller 2011; Welsh and Elliott 2004).

Although these prior studies suggest that mouse movement speed slows down because increased cognitive load degrades fine motor control (i.e., controlling your hand movements), there are several limitations. First, heightened cognitive load is a temporal state that may not persist for a prolonged period. Prior literature provides little explanation of the user behaviors under a low cognitive load state. Second, the foundational theories used for these studies do not apply to various instances of system usage as they are confined within specific contexts (e.g., feeling negative emotions). For example, users may experience high cognitive load when viewing online advertisements (Bang and Wojdynski 2016) ,

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exploring an unfamiliar website (Sénécal et al. 2015), and engaging in online learning (Mayer 2019) - which prior theories have little applicability. In summary, the theories that primarily focus on cognitive loads provide little explanation of the underlying mechanisms (i.e., the interplay of low and high cognitive load states) of how humans process information during live system usage. Thus, there is a need for a more encompassing conceptual framework that can be applied to a broader range of situations (i.e., under low or high cognitive load).

This study focuses on extending the prior literature by providing a more encompassing theory that aligns with the prior studies and can be used to conceptualize situations where users experience ***both*** low and high cognitive loads. In doing so, we present methods for practitioners and researchers to assess how low and high cognitive states interplay in device usage behaviors based on the motor learning literature and Dual-Process Theory (DPT), which asserts that human cognitive processes are interactions between intuitive (Type 1 process) and deliberate (Type 2 process) thinking (Kahneman 2011). Since the initial emergence of DPT, researchers have extensively worked on introducing different extensions and variations of DPT (Bronstein et al. 2019; Cash and Maier 2021; Over 2020). This study's focus is not to pick and apply different variations and extensions of DPT. Thus, we will focus on how the foundational idea of DPT applies in the context of capturing changing in cognitive and emotional states using HCI devices.

In the remainder of this paper, we first briefly review the DPT and its' relation to cognitive load and motor movement. Next, we review the existing IS literature that examines the impact of users' various cognitive states on fine motor control and explains how these prior studies (e.g., mouse movement literature) align with DPT. Lastly, we extend the prior literature that examined DPT using mouse cursor movements and demonstrate that the users' typing dynamics (i.e., multi-device) slow down as the user is more likely to rely on Type 2 process types of thinking. We draw from the DPT, framed within the typing behavior, to predict that the individuals will have a faster transition between the keys and more rapid progression throughout the fields when entering familiar information (i.e., their personal identity information) on a form.

To test our hypotheses, we conducted a study where the participants entered a set of personal identity information and unfamiliar identity information, which is hypothesized to be more cognitively demanding:

1. We looked into the behavioral differences observed between the two-information entry event to replicate the studies from prior literature that examined the impact of heightened cognitive load on device usage behaviors.
2. To examine the robustness of DPT, we further observed whether the participants had executed the task in an intuitive (i.e., Type 1 process) or deliberate (i.e., Type 2 process) manner. Specifically, we observed whether the participants had paid attention to the survey instructions to correctly execute the task (i.e., the participants carefully read and followed task instructions).
3. We subsequently compared the information entry behaviors of the participants who had entered the personal information on both forms (i.e., likely to be answering intuitively) vs. participants who had followed the instructions and provided both personal and synthetic identity information (i.e., reading the instruction and answering deliberately).

Our results show that the typing speed and task execution speed are significantly slower for the users who followed the instruction (i.e., entering synthetically generated identity information) – demonstrating that putting more reliance on the Type 2 process manifests as deliberation in answering behaviors (i.e., typing).

We contribute to the literature in various ways. First, we provide an overarching theory of existing theories within this research area (i.e., a metatheory) that relies on different theoretical mechanisms to help explain all prior results from mouse movement literature. Specifically, we extend the prior literature by providing examples of how the main findings of the prior studies can be aligned under DPT. Second, we extend a prior study that examined how Type 1 and Type 2 thinking manifests in mouse cursor movement (Kim et al. 2022) and demonstrate that DPT is robust on other HCI devices (i.e., computer keyboards). Lastly, our methods can be practically applied in any instance where users type information onto a form field.

2. Background

2.1. Prior Literature: Linkage Between Cognitive Processes and Hand Movements

Prior literature has demonstrated that cognitive and neurological monitoring devices such as EEG, fMRI machines, and high-definition cameras that capture face and eye movements can be leveraged to infer users' cognitive states (Vance et al. 2018). However, since users do not use these devices regularly, they cannot be used to understand user behaviors in a more natural setting. Thus, to overcome the limitations and ecological validity concerns of such devices, an emerging stream of IS research has been leveraging non-invasive, highly scalable HCI devices such as computer mice, keyboards, and mobile (touch) devices to examine various cognitive and emotional phenomena (Epp et al. 2011; Hibbeln et al. 2017; Jenkins. et al. 2019; Valacich et al. 2020).

While exploring user behaviors in a more natural setting is valuable, this introduces a lack of control as users can multitask and be distracted. Thus, the past literature conducted various studies under specific scenarios where the user would experience heightened cognitive load and exhibit different device usage patterns (Hibbeln et al. 2017; Jenkins. et al. 2019; Jenkins et al. forthcoming; Weinmann et al. forthcoming). For instance, as referenced previously, Hibbeln and colleagues (2017) drew from Attention Control Theory (ACT) (Eysenck et al. 2007) – that negative emotions act to impair attentional control – to explain how such feelings resulted in less accurate and slower mouse cursor speeds. Alternatively, Jenkins et al. (2019) used the Response Activation Model (RAM) and Cognitive Load Theory (CLT) to explain why an orienting response will change people's mouse movements when providing a predetermined response—participants were told beforehand how to respond to a particular question. According to the RAM, competing cognitions and reevaluation of response details can influence fine motor control (Welsh and Elliott 2004). The RAM proposes that hand movements respond to all thoughts that have even minor potential (i.e., actionable potential) to result in movement changes. According to CLT, short-term or working memory is limited and can only handle so much information effectively simultaneously. Using this framing, Jenkins et al. (2019) show that mouse movements predictably differ between guilty (higher cognitive load) and innocent people in sanctioned deception scenarios.

Further, Jenkins et al. (forthcoming) studied how user noncompliance resulted in slower and less accurate mouse cursor movements, also framed under the RAM along with CLT, but now including Cognitive Dissonance Theory (CDT). CDT posits that in situations where individuals have conflicting attitudes, beliefs, or behaviors, they will have feelings of mental discomfort (i.e., due to increased cognitive load and negative emotions), leading to an alteration in one of the attitudes, beliefs, or behaviors to reduce the discomfort and restore balance. Thus, CDT is tightly linked to CLT; as dissonance increases, so do cognitive load and negative emotions. When people knowingly provide misleading information online, they are likely to doublecheck, reconsider, hesitate, or question actions. When these cognitive events occur, the mind automatically and subconsciously programs a movement response to fulfill that intention. Thus, these studies show a tight linkage between cognitive and emotional changes and changes in mouse cursor movements.

More broadly, in a review of early mouse tracking studies from the cognitive and neuroscience literature, Freeman et al. (2011) stated that the "movements of the hand…offer continuous streams of output that can reveal ongoing dynamics of [cognitive] processing, potentially capturing the mind in motion with fine-grained temporal sensitivity" (p. 1). Thus, it has been unequivocally demonstrated that emotional and cognitive changes influence fine motor control. Modern HCI devices have fine-grained sensors for capturing this information.

One limitation of such studies is that, although these studies essentially examine how cognitive or emotional changes manifest as changes in device usage patterns, the source of cognitive and emotional changes proposed by the literature varies significantly. As a result, although the prior studies examine the state of heightened cognitive loads, they leverage multiple theories and concepts for motivating and interpreting research results. Each of these perspectives, we believe, is not only related but can be captured under a larger conceptual framework, Dual-Process Theory (DPT). Here, we extend the prior literature by introducing an overarching metatheory, DPT, to conceptualize our current study and reconcile the theories used in the prior related studies.

2.2 Dual-Process Theory

DPT, a widely accepted model in psychology, explains how the interplay of Type 1 process and Type 2 process types of thinking manifests in human decision-making.

2.2.1. Type 1 process – Intuitive System. Type 1 process comprises a set of sub-systems that operate with autonomy (Evans and Stanovich 2013). When given a task, the user generates autonomous, non-reflective responses that help complete the task (Over 2020). Generating these responses does not require extensive cognitive resources (i.e., it is effortless to know your age) and often entails behavioral outputs that are instinctive, immediate, effortless, and fast.

2.2.2. Type 2 process – Analytic System. Type 2 process types of thinking are used when individuals confront tasks requiring reasoning and assessments (Evans and Stanovich 2013). For instance, when given a problem the individuals cannot easily comprehend or answer (e.g., performing a very complex computation), they will activate the Type 2 process to evaluate the problem-solving steps and the answers continuously. Naturally, such processes are cognitively demanding and require extensive cognitive resources. When the Type 2 process is active, individuals will be more careful, slower, and effortful when executing the task.

2.3 Dual-Process Theory and Motor Movements

Motor learning, which refers to a set of processes aimed at learning and refining new skills through continuous practice, explains how humans become proficient in executing various motor movements, including typing on a keyboard (Filippi et al. 2018; Nieuwboer et al. 2009). Such skill acquisition process becomes less deliberate and effortful over time as they become more automatized (Shiffrin and Schneider 1977). Skilled actions acquired by motor learning typically unfold automatically (e.g., executing strokes in swimming), while conscious processing can mediate this automatic processing (i.e.., paying attention to the action during execution) (Beilock and Carr 2001).

Prior literature that studied motor learning and execution made significant progress in explaining how automatic processing influences motor movements. Yet, there was limited progress in formulating a construct that can be leveraged to perform a more fine-grained analysis (Toner and Moran 2021). Thus, researchers studying motor movements have begun adapting DPT – suggesting that motor movements consist of cognitive and automatic processes - to assess the relationship between controlled thoughts (i.e., Type 2 process) influence motor movements (Furley and Memmert 2015; Masters and Maxwell 2008; Mylopoulos and Pacherie 2017).

Executing highly practiced motor skills can be influenced by external factors such as task difficulty, emotional pressure, and external stimuli (e.g., crowds at a sporting event). As a response to the external factors, a person executing the motor skills would leverage both automated (i.e., Type 1 process) and controlled processes (i.e., Type 2 process) rather than using them independently (Carr 2015).

Motor movement and learning are closely related to device usage behaviors requiring hand inputs. In a typing context, these behaviors include but are not limited to transitioning from one key to another, pressing and holding down on a key while typing another character, and progressing from one typing task to another.

2.4 How Dual-Process Theory and Motor Learning Applies to Prior HCI Studies

Recall that Hibbeln et al. (2017) proposed that cognitive load would be heightened as a person's attention is distributed to broader spaces as they feel negative emotions, resulting in slower and less accurate movements. From a DPT perspective, the user is now using both the Type 1 process and Type 2 process to execute their practiced motor skills (e.g., click, dragging, and moving the mouse cursor) while reacting to the stimuli (i.e., working memory is consumed on non-task related factors). Thus, DPT suggests that the mouse cursor movement will be slower as the users leverage both the Type 1 process and Type 2 process to complete the research tasks after being exposed to the stimuli (the accuracy of the movement is outside of the Dual Process context).

Similarly, Jenkins et al. (2019) proposed that cognitive resources are constrained when concealing information versus when telling the truth, resulting in a slower mouse movement for people concealing information. From a DPT perspective, when people are concealing information, their limited working memory is more likely consumed, requiring individuals to rely on the Type 2 process, resulting in slower mouse movements.

In Jenkins et al. (forthcoming), slower and less accurate mouse cursor movements were exhibited for individuals having conflicting attitudes, beliefs, or behaviors due to increased cognitive load and negative emotions. From a DPT perspective, when individuals are experiencing cognitive dissonance, their limited working memory is consumed, and they will be more likely to rely on the Type 2 process, resulting in slower mouse movements.

As a final example, Weinmann et al. (forthcoming) proposed that providing false information increased cognitive load and reduced working memory when committing fraud. Further, they found that giving fraudulent responses when completing an online form resulted in slower mouse cursor movements. Again, in line with the explanation provided by Jenkins et al. (2019), generating false information is more likely to require Type 2 process thinking, resulting in slower mouse cursor movements.

Thus, we believe that Dual-Process Theory provides a higher-level conceptual framework, a metatheory, for understanding how cognitive and emotional changes will manifest in how individuals use computer mice, touch screens, keyboards, and other types of HCI devices. We posit that the findings from prior literature that establish the linkage between DPT and motor movement can be applied in the HCI context, especially for the devices accessible via users' hands (e.g., computer mice and keyboards). Motor learning (also called motor memory) is a process of embedding a specific motor task into memory through repetition. When a given movement, such as typing your name on a keyboard, is repeated over time, motor learning occurs, which results in faster and smoother typing (i.e., less variability). Also, as motor learning happens over time, typing well-practiced words can be performed with less conscious effort. Thus, over time, a person forms a habitual typing behavior that is unique and consistent, whether on a traditional keyboard or a mobile touch keyboard. Because typing is a task where people increase their fluency (i.e., typing speed and accuracy) through practice, motor memory increases as a person repetitively type the exact words over time. This results in less variability when typing those words than for words not typed as frequently. Thus, as motor memory increases, the variability of typing dynamics decreases.

We address two important research gaps by proposing a meta-theory that can explain the prior studies. First, we provide theoretical explanations for the differences in users' typing behaviors. Second, we extend the findings from the motor learning literature that leverage DPT and examine how the results could be generalized in an IS context, specifically in device usage behavior. Based on the identified gaps, we draw the following research question:

1. Could the DPT be used to identify valid and reliable relationships between the users' underlying cognitive processes and device usage behaviors (e.g., typing)?

We address both research questions using simple typing tasks involving high and low motor memory levels (i.e., entering identity information on a form). For example, users would have higher motor memory when typing their identity information versus someone elses' identity information. We utilize a repeated-measures experimental design (i.e., use the same typing forms for baseline and experimental conditions) to mitigate the risks associated with potential confounding effects of the differences in individuals' cognitive capacity while ensuring the generalizability of the study. Precisely, we define:

1. High motor memory task (i.e., Type 1 process) – entering their own identity – on a form

2. Low motor memory task (i.e., Type 2 process) – entering an unfamiliar identity (e.g., synthetically generated first name, last name, date of birth) – on a form.

The external factors at a sporting event differ vastly from the potential factors influencing the users' device usage. However, the concept of motor learning and DPT still applies to instances where the user uses a device that requires any motor movements. Thus, we hypothesize that:

H1: Users will exhibit slower key transition times on motor execution tasks, likely relying more on the Type 2 process.

H2: Users will exhibit slower field transition times on motor execution tasks, likely relying more on the Type 2 process.

While H1 and H2 are useful, factors such as differences in individuals' cognitive capacity can introduce potential confounding effects. To mitigate these risks, we first categorize the instances where the users' are executing the tasks based on intuition versus the cases in which users' are performing tasks in a controlled manner:

1. Intuitive Responding (Type 1 process): entering the same information on both conditions (i.e., not following the instructions)

2. Controlled Responding (Type 2 process): entering different information on both conditions (i.e., carefully following the instructions)

Users who are intuitively responding are likely to rely more on the Type 1 process, as the responses are effortless, automatic, and often independent of cognitive ability (Neys 2006; Raoelison et al. 2021). In other words, intuitively responding users are likely to pay less attention and spend less cognitive resources on task-specific factors while executing the tasks promptly. Thus, we hypothesize that:

H3: Users executing the tasks by providing intuitive responses will likely utilize the Type 1 process and have faster key transition times.

H4: Users executing the tasks by providing intuitive responses will likely utilize the Type 1 process and have faster field transition times.

3. Methodology

3.1. Procedure and Manipulation

During the experiment, participants were asked to enter their personal information, including first name, last name, date of birth, and zip code. This serves as the baseline condition for our analysis. They were also asked to fill in information for a fictional character (imposter) and provide his personal information on a form. This serves as the imposter condition. We randomized the order in which form was presented first to the participants to negate the impact of the ordering effect.

3.1.1. Baseline Condition. All participants entered their permanent information in a form. The first two fields are character fields where the participants entered their first and last names. Subsequent fields were the date of birth and zip code fields (See Figure 1).


Enter your permanent information in the fields below.
First Name:
Last Name:
Date of Birth (MM/DD/YYYY):
Zip code (Permanent Address):

Figure 1. Example of identity information form provided to the participants

3.1.2. Imposter condition. Participants were instructed to navigate to an external link to find the imposter information (See Figure 2). Subsequently, participants were asked to complete the form that requested the same information as the baseline condition. Similarly, unexpected questions were created upon form submission.

Please use the following information to complete the form:

Identity 1		
First Name:	John	
Last Name:	Foster	
Date of Birth:	03/08/1968	
Zip code (Permanent Address):	43731	

Figure 2. Imposter identity information (distributed using an external link)

3.2. Participants

We recruited 202 participants from a large public university in the United States. As we recruited participants from a university, most participants were young adults between 18-24 years old (94%). The male-to-female ratio was about 57 to 43. Participants were awarded extra credit points for completing the study.

4. Results

We evaluate hypotheses H1, H2, H3, and H4 using Welch's t-tests. First, we conduct field-to-field analysis (e.g., first name – baseline condition vs. first name – imposter condition) to examine whether the users have entered information differently on specific fields. As each field entails a different level of task complexity (e.g., typing numbers vs. alphabetic characters are inherently different), the typing behaviors across each field can vary. Second, we conduct a form-to-form comparison to examine the overall behavioral differences across the form. While the field-to-field analysis is useful, a limitation of the field-to-field analysis is that the total number of key entries on a field is often too small to extract meaningful insights (e.g., five numbers for a US Zip code). Thus, by aggregating the key entry instances at a form level, we alleviate the concerns associated with the number of text entries. Lastly, we examine H3 and H4 by dividing the participants into Type 1 dependent and Type 2 dependent groups and evaluating how they completed the personal identity entry task.

4.1. Testing Hypothesis 1

H1 stated that when users engage in tasks that are likely to put more reliance on the Type 2 process, their Key Transition times will be higher (i.e., slower transition). The Key Transition measure was compared at a field and a form level using Welch's t-tests to examine the differences across the task (see Table 1, and 2).

The results from the field-to-field analysis suggest that, except for the last name field on the main form and state field on the follow-up questions, the average transition time was faster for all the other fields. Further, the t-test results (Table 2) of the Key Transition measure for form-to-form analysis demonstrate that the average Key Transition time is faster for personal identity. Thus, we conclude that H1 was supported.

Table 1. Field-to-field key transition (Welch's t-tests)

Field	P-value	Significance	Direction
First Name	0.03274	*	Faster for Personal Identity
Last Name	0.1983	N/S	Faster for Personal Identity
Date of Birth	< 2.2e-16	***	Faster for Personal Identity
Zipcode	9.995e-05	***	Faster for Personal Identity
Key: N/S = p > 0.10 ; . = p < 0.10 * = p < 0.05; ** = p < 0.01; *** = p < 0.001			

Table 2. Form-to-form key transition (Welch's t-tests)

Measure	P-value	Significance	Direction
Key Transition	5.503e-15	***	Faster for Personal Identity
Field Transition	8.288e-15	***	Faster for Personal Identity
Key: . = p < 0.10 * = p < 0.05; ** = p < 0.01; *** = p < 0.001			

4.2. Testing Hypothesis 2

H2 stated that when users engage in tasks that are likely to rely more on the Type 2 process, their Field Transition times will be higher. Similar to how we examined hypothesis H1, the Field Transition measure was compared at a field and a form level using Welch's t-tests (See Table 2, 3).

The results suggest that the participants had a higher average field transition time when entering imposter identity in all cases. The results were consistent for both field-to-field and form-to-form analysis. Thus, we conclude that H2 was supported.

Table 3. Field transition

Transition	P-value	Significance	Direction
First Name to Last Name	< 2.2 e-16	***	Faster for Personal Identity
Last Name to Date of Birth	0.0002	***	Faster for Personal Identity
Date of Birth to Zipcode	< 2.2 e-16	**	Faster for Personal Identity
Key: . = p < 0.10 * = p < 0.05; ** = p < 0.01; *** = p < 0.001			

4.3. Testing Hypothesis 3 and Hypothesis 4

H3 and H4 stated that users who provide intuitive responses would likely rely more on the Type 1 process and have faster key and field-to-field transition times. To examine H3 and H4, we coded whether participants followed instructions and correctly entered both their own identity information and that of the imposter identity in the requested order (Type 2 dependent) versus those that failed to follow instructions and incorrectly entered their own identity information when imposter identity information was requested (Type 1 dependent).

Because the Type 1 dependent and Type 2 dependent participants executed the tasks in the imposter condition differently (i.e., entering familiar when imposter information was requested), the inclusion of these erroneous data points from the imposter condition biases our results. Thus, they were excluded when testing H3 and H4. Note that participants who failed to follow task instructions were removed when testing H1 and H2. The results suggest that when entering the same types of information on an identical form, participants classified as Type 1 dependent had faster key transition times and field transition times – suggesting that Type 2 dependent progressed slowly when entering personal identity information (See Table 4). Thus, we conclude that H3 and H4 were supported.

Table 4. Differences in typing dynamics between Type 1 and 2 processing (Welch's t-tests)

Measure	P-value	Significance	Direction
Key Transition	0.01626	*	Faster for Type 1 dependent
Field Transition	0.00669	***	Faster for Type 1 dependent
Key: . = p < 0.10 * = p < 0.05; ** = p < 0.01; *** = p < 0.001			

5. Discussion

The overall results suggest that users had significantly slower key transition and field transition times when entering imposter identity on a form. Thus, H1 and H2 were supported. Further, H3 and H4 suggest significant behavioral differences exist between intuitively and deliberately responding participants typing familiar and unfamiliar information. Most importantly, our results suggest that behavioral differences based on Type 1 and Type 2 thinking can be captured using users' typing dynamics.

5.1. Implications for Research

We contribute to the literature by (1) explaining how the prior mouse movement literature's findings align in the context of DPT and (2) demonstrating that DPT is robust across different devices. Specifically, by explaining how the prior mouse movement literature can be explained under the theoretical lens of DPT, we provide an overarching explanation of how the interplay of Type 1 process and Type 2 process types of thinking influence fine motor control that can be captured using mouse cursor movements and other HCI devices. In a controlled experiment, we empirically validated that DPT is robust on any HCI devices that the user will interact with their hands (i.e., computer keyboard)

In summary, we not only present a metatheory that could explain all prior HCI literature that examined the impact of heightened cognitive load on HCI device usage, but also present a new method that can be applied to social science research that collects data from an online platform.

5.2. Implications for Practice

There are several practical implications for using computer keyboards to measure an individual's reliance on Type 2 process types of thinking.

First, the real-time assessment of user behavior is a substantial challenge as user behaviors are influenced by various cognitive processes, which are difficult to capture, infer, and act upon outside highly artificial environments (e.g., data collection using fMRI, EEG caps, eye tracking, and so on). When the same techniques are used in a more natural environment, the constructed model can generate strange insights that may lead to poor management decisions. As computer keyboards are widely adapted, they are adequate for capturing user behaviors (i.e., typing) in a more natural setting.

Second, entering information on a form is a typical online task executed regularly. Some examples include, but are not limited to, instances where users sign up for a website, apply for a loan application, and fill out the identity information for public institutions. By looking into the typing dynamics, practitioners can identify different points within the form where the user may be having difficulties (i.e., putting more reliance on the Type 2 process) while filling out a form online. Third, our results examining H3 and H4 suggest that when users are more engaged in the Type 2 process, their device usage behaviors are likely to be slower. Practitioners can apply our results to identify various points where the users can potentially be using Type 2 processes (e.g., paying attention to an online advertisement) to identify improvement areas.

5.3. Limitations

There are several limitations of our study. First, although we have demonstrated the robustness of DPT using typing dynamics, we still do not know how the results would generalize to other commonly used devices (e.g., mobile phones). Second, the users may multi-task while being on the internet. The measures such as field transitions may be influenced by such behavior and potentially generate biased results. Third, though our methods could virtually be implemented in any instances where the user enters information on a form, the results may not generalize well to typing instances where the information is not as structured (e.g., academic writing). Lastly, given the limited experimental material (e.g., only using one form and examining DPT using a single device), further research should be conducted to examine whether our results are robust concerning design-specific factors (e.g., form designs). Future research should examine how DPT may apply to a broader range of contexts (i.e., device types, users' browsing behaviors, and task complexity) to alleviate these concerns.

6. Conclusion

By leveraging DPT, we contribute to the literature by explaining how providing intuitively and deliberately responding manifests as faster and slower typing behaviors. Specifically, we present a metatheory that could explain prior mouse movement literature that examined the impact of heightened cognitive load on mouse cursor movements. We further believe that the methodology of measuring cognitive load in the DPT context could be applied in various other disciplines and HCI devices.

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