Computers in Human Behavior 83 (2018) 288–305

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Full length article

Mouse behavioral patterns and keystroke dynamics in End-User Development: What can they tell us about users' behavioral attributes?

Tzafilkou Katerina [a,*], Protogeros Nicolaos [b]

[a] University of Macedonia, Postgraduate Program in Information Systems, 156 Egnatia Street, 54006, Thessaloniki, Greece
[b] University of Macedonia, Department of Accounting and Finance, 156 Egnatia Street, 54006, Thessaloniki, Greece

ARTICLE INFO

Article history:
Received 17 July 2017
Received in revised form
5 February 2018
Accepted 13 February 2018
Available online 14 February 2018

Keywords:
End-User Development (EUD)
Mouse tracking
Mouse behavioral patterns
Keystroke dynamics
End-user behavior

ABSTRACT

Studying human behavior is of particular interest within the field of Human-Computer Interaction (HCI) as it can provide insight into human performance. Prior HCI research suggests that mouse and keyboard monitoring may provide a more complete picture of user behavior under high cognitive loads like decision making and developing tasks. In this exploratory study we investigate the potential correlation between mouse behavioral patterns or keystroke dynamics and a set of End-User Development (EUD) behavioral attributes. We conduct a field test on 30 end-users interacting with a modern web-based EUD tool for the construction of simple web forms. Our findings reveal the existence of several significant correlations between end-users' behavioral attributes and mouse pattern metrics or keystroke dynamics during the development process. Mouse pattern metrics like random and straight movements, mouse hovers, etc., can be associated with perceived ease use, perceived usefulness, self-efficacy, willingness to learn or risk-perception. Similarly, some keystroke dynamics like key press speed and down-to-down time can be associated with perceived ease of use or self-efficacy. The findings of this work show a new interesting research direction and may motivate the EUD research community to study further the end-users' mouse and keyboard behavior in today's web-based EUD systems.

1. Introduction

Modern computing advocates the idea of end-users using mobile and web applications to accomplish their daily tasks. This has given rise to the need for web-based development activities by the end-user. End-User Development (EUD) activities are considered cognitively demanding since they demand non-professional end-users to develop their own artifacts without getting trained and without knowing programming languages.

Understanding end-users' behavior under high cognitive loads, like developing and decision making activities, has become a major focus in Human Computer Interaction (HCI) research (Djamasbi, Tulu, Loiacono, & Whitefleet-Smith, 2008; Payne, Bettman, & Johnson, 1988; Svenson, 1993) as it can provide insight into user performance. One class of behavior that is of interest within HCI research is mouse and keyboard behavior and therefore, techniques for studying mouse movements and keystroke dynamics have been considered an effective means of HCI. In the area of web-user interaction mouse and keyboard monitoring is a vital part since it can implicitly and dynamically provide useful information about the users' state of mind, their perceived user experience and the system usability.

Mouse movement can be thought of as a series of moves, i.e. gestures, and each gesture is a specific and continuous physical process initiated and concluded by the user (Arapakis, Lalmas, & Valkanas, 2014). Several mouse-tracking studies suggest the existence of a typology of users based on observed cursor behavior (Leiva & Hernando, 2008; Rodden and Fu, 2007; Rodden, Fu, & Spiro, 2008). Researchers estimate that mouse features can reflect specific user behavior patterns regardless of the task and the environment, and can be used to model users' behavior (Hinbarji, Albatal, & Gurrin, 2015). Common mouse behavioral patterns,

* Corresponding author.
E-mail addresses: katerinatzaf@gmail.com (T. Katerina), proto@uom.edu.gr (P. Nicolaos).

https://doi.org/10.1016/j.chb.2018.02.012
0747-5632/

such as hesitation pattern, straight pattern, random pattern, etc. have been identified in many research works (e.g. Atterer, Wnuk, & Schmidt, 2006; Ferreira, Arroyo, Tarrago, & Blat, 2010; Lee & Chen, 2006; Mueller & Lockerd, 2001, pp. 1–2; Rodden et al., 2008) but their characterization is generally vague. Their identification remains a largely visual process and is mainly based on qualitative analysis. Mouse pattern related metrics remain undefined and hence mouse patterns have not been quantitatively measured and analyzed in some important HCI behavioral research areas like EUD-user behavior.

Recently, keystroke dynamics (i.e. the timing information describing key press and key release events), an approach from user authentication research, has also been used in HCI research to detect user cognitive and affective states, like mood and emotions (e.g. Epp, Lippold, & Mandryk, 2011; Khanna & Sasikumar, 2010). Similarly to mouse behavior, keystroke dynamics seem promising for modeling user behavior (Epp et al., 2011). However, despite their easy and useful applicability, keystroke dynamics have not been broadly studied in HCI behavioral research and particularly in EUD.

Triggered by the above-described situation this exploratory study examines whether end-users' mouse and keystroke behavior is associated with well known EUD behavioral attributes including perceived ease of use, perceived usefulness, self-efficacy, willingness to learn and risk perception. Our main objective is twofold: i) to divide each 'popular' mouse behavioral pattern in a set of measurable mouse metrics and examine the potential correlations between these 'pattern-derived' attributes and EUD-user behavioral attributes, and ii) to examine the potential association between a set of common keystroke dynamics and EUD behavioral attributes.

The central goal of our research is to identify possible connections between mouse movements and/or keystroke dynamics and a set of EUD user behavioral attributes, like self-efficacy, risk-perception, etc. and understand how mouse behavioral patterns and keystroke dynamics are related to user behavioral states during EUD task execution.

The findings of this work seem promising and may provide the EUD research community with background knowledge and a motivation to study further and understand end-user developer mouse and keyboard behavior in today's web-based EUD systems. Results also encourage the use of mouse and keyboard monitoring as implicit feedback mechanisms in user modeling implementations and self-adaptive software in web-based EUD environments. Such adaptations could assist users (by providing appropriate feedback or changing the interface attributes) to enhance their performance in their developing activities.

This paper is organized as follows. The second section presents the literature background, including an overview of the End-User Development field, the behavioral EUD-user attributes we plan to measure, the mouse behavioral patterns and keystroke dynamics as well as similar past works. The third section presents the research objectives and questions that need to be examined. The fourth section describes the research methodology which is composed of four parts: i) the prototype web EUD tool that was used for the field test, ii) the monitoring mechanism and the data extraction method, iii) the field test implementation including: the participants and procedure, the given user task, the performance measure design and the questionnaire survey and finally ix) the data analysis method. The fifth section presents the results and the sixth section discusses the main findings and explains the study's possible issues and limitations. The last section presents the main conclusions and some future research directions.

2. Theoretical framework

2.1. End-User Development

According to Lieberman, Paternò, and Wulf (2006), EUD is 'a set of methods, techniques and tools that allow users of software systems, who are acting as non-professional software developers, at some point to create, modify or extend a software artifact'. What characterizes end-user developers is that they express a need to modify on their own the computer systems they use and to gain more control over their computer applications (Lieberman et al., 2006; Repenning & Ioannidou, 2006).

EUD is inherently different from traditional software development. Burnett and Scaffidi (2011) declare that trying to support EUD by simply mimicking traditional development approaches will possibly lead to unsuccessful outcomes.

Fortunately, there are many remarkable EUD approaches, most of them presented in details in the work of Spahn, Dörner, and Wulf (2008) and Paternò (2013). Indicatively, such approaches include programming using visual attributes, programming by demonstration (PBD), programming by specification, programming with text, interface customization, natural programming, visual programming, spreadsheets, etc.

Many EUD technologies have been designed according to the abovementioned approaches. For instance, PBD-based tools are available for creating animations and are often used in combination with visual or textual languages. According to programming by specification, Liu and Lieberman (2005) implemented a system that accepts specification in natural language and generates a corresponding program written in Python. Some systems, like the Topes System of Scaffidi, Myers, and Shaw (2008) provide a forms-based visual interface, restricting the user's specifications to only those that can be handled by the tool. The CoScripter (Scaffidi et al., 2010) tool is a good example of combining visual with textual specifications, since it uses a textual language to represent a web macro, which is a script that directs a web browser to navigate the web and manipulate websites in a particular way (Burnett & Scaffidi, 2011).

While the first EUD tools were mainly focused on desktop graphical applications, in recent years a considerable amount of work has been carried out to apply the EUD approach to web environments (Paternò, 2013). According to Rode, Bhardwaj, Perez-Quinones, Rosson, and Howard (2005), web EUD tools can be categorized to three main categories: database-centric tools that are primarily intended to help end-users put databases online for viewing and editing purposes, form-centric tools that are intended to help end-users create forms for collecting data and website-centric tools whose primary purpose is assisting the user with the creation of static or dynamic websites. Some examples of database-centric EUD tools are PhpClick (Rode et al., 2005; 2006, pp. 161–182), FORWARD (Ong, 2010), Visque (Borges & Macías, 2010), XIDE (Litvinova, 2010), CRIUS (Qian, LeFevre, & Jagadish, 2010) and Simple-Talking (Protogeros & Tzafilkou, 2015). There are also some query-centered approaches for mobile systems, such as Query by Zoom (Silveira, Eloy, & Montiero, 2010) and Query- by-Object (Akiyama & Watanobe, 2012).

2.2. User behavioral attributes in End-User Development

End-users follow different approaches and reasoning strategies to modeling, performing and documenting the tasks to be carried out in a given application domain (Blackwell & Morison, 2010; Costabile, Mussio, Provenza, & Piccinno, 2008). In this context, research in Human-Computer Interaction (HCI) has put considerable effort over the past decades to build theories and models which attempt to explain end-users' perception while using computer software to customize, program and/or develop artifacts.

A series of end-user behavioral theories that shed behavioral attributes in HCI and EUD research have been developed. Some of the most dominant theories in the EUD community are: Self-Efficacy Theory (Bandura, 1977; 1986), Attention Investment Theory (Blackwell, 2002), Information gap Theory (Loewenstein, 1994) and Technology Acceptance Theory (Davis, 1989). These theories have shed light on the significance of several EUD/HCI behavioral attribute such as Self-Efficacy, Risk-Perception, Willingness to Learn, Perceived Usefulness and Perceived Ease of Use. These variables are important to be measured for the analysis of end-users' behavior since they tend most of the time to influence their performance (Tzafilkou, Protogeros, Karagiannidis, & Koumpis, 2017).

Following we briefly present each one of them.

2.2.1. Self-Efficacy

According to Self-Efficacy theory studies, self-efficacy (SE) conveys an individual's level of confidence to execute courses of action in a given situation. Self-efficacy has been studied in depth by Bandura (1977; 1986) who found that it can be influenced by environmental situations, cognitive and personal factors as well as demographic characteristics. Social cognitive theory (Bandura, 1977; 1986) posits self- efficacy as a key determinant of skill acquisition and task performance.

Computer self-efficacy is an extension of self-efficacy that is specifically related to computer usage (Compeau & Higgins, 1995). Pajares (2002) argues that self-efficacy can affect task effort, persistence, expressed interest, and the level of difficulty of goals users will strive to attain. Stated in Blackwell, Rode, and Toye (2009) point out that being a challenging task, software development renders a person with low self-efficacy may be less likely to persist when a task becomes challenging. Moreover, self-efficacy is tightly linked to positive physiological and emotional states in the aftermath of a successful execution of certain behavior (Shea & Bidjerano, 2010).

2.2.2. Risk-Perception

Analyzed in Blackwell's Attention Investment Model theory (Blackwell, 2002), Risk-Perception (RP) is considered as a factor that strongly influences the end user's behavior through their cost/benefit evaluation. According to Blackwell (2002), risk is the probability that no pay-off will result, or even that additional future costs will be incurred from the way the user has chosen to spend attention. If users decide that the costs and/or risks are too high in relation to the benefits they may choose not to follow through with the action. Perception of risk thus plays an important role in a user's decision making about whether to use particular application features (Beckwith & Burnett, 2004). The Attention Investment Model predicts that higher perception of risk can lead to differences in actual behavior. Risk-Perception can strongly influence computer related behavior (e.g. Willingness to learn, Self-Efficacy, etc.) since it determines the whole 'confidence and security' the end-user feels while interacting with the computer environment.

Low Risk-Perception has been shown to be positively related to performance during computer related tasks. High Risk-Perception renders users less likely to make use of unfamiliar features (Beckwith et al., 2005) eliminating their 'high performance' possibilities and the successful task completion. High perceived risk results in avoidance behavior (not using features that might help them in their task), then the result could be lower task performance, or a higher cost (in time) to accomplish the desired computer task (Beckwith & Burnett, 2004).

2.2.3. Willingness to learn

Willingness to Learn and use new features (Burnett, Fleming, & Iqbal, 2010; Grigoreanu et al., 2008) is a EUD behavioral attribute affecting the end-users' overall performance since it reveals the user's motivation power, determines the amount of effort the user makes and the perspectives of his/her future performance enhancement. It is included among the main behavioral attributes in GenderHCI studies since many times it tends to affect male and female end-users' differently while interacting with EUD tools (Beckwith & Burnett, 2004).

Willingness to learn can also be seen as a type of exploratory behavior. Exploratory behavior is directly associated to learning and has been proved to be 'used' in a different way by end-users. In particular, some end-users tend to 'explore' much more than others (Burnett et al., 2008).

According to Loewenstein's information gap theory (1994), willingness to learn is also highly associated with self-efficacy since a user needs to have a certain level of self-efficacy in order to reach a useful level of curiosity. This curiosity will leverage the levels of their exploratory behavior and hence willingness to learn, enhancing at last their performance (Burnett & Scaffidi, 2011). Willingness to Learn is an important attribute because it can 'predict' the end-user's willingness to try, persist, tinker and even search for guidance or study to learn how to use new features and EUD technologies.

2.2.4. Perceived Usefulness and Perceived Ease of Use

The original Technology Acceptance theories, developed by Davis (1989), do not necessarily focus on end-users as their primary audience, and the technologies studied are general software technologies. Nevertheless, there are strong ties to the more specific research of end-user problem solvers (Beckwith & Burnett, 2007).

The main purpose of Technology Acceptance Model (TAM) (Davis, 1989), is to explain and predict information technology (IT) acceptance and facilitate design changes before users have experience with a system. TAM is considered one of the well-known models related to technology acceptance and use since it has shown great potential in explaining and predicting user behavior of IT (Park, 2009).

According to TAM, when users are presented with a new technology, two key factors influence their decision about how and when they will use it: perceived usefulness and perceived ease of use (Davis, 1989; Venkatesh & Morris, 2000). TAM suggests that perceived ease of use and perceived usefulness are the two most important factors in explaining system use. Additionally, the End-User Computer Acceptance (EUC) theory introduces the most relevant human factors affecting the end-users' overall behavior and performance including perceived ease of use and usefulness (Chen & Corkindale, 2008; Cyr, Hassanein, Head, & Ivanov, 2007; Sun & Zhang, 2008).

Following we describe the meaning and terminology of the two above mentioned key acceptance attributes:

- Perceived ease of use is defined as the degree to which a person believes that using the system would be free of effort (Davis, 1989). Given that effort is a finite resource, an application perceived to be easier to use than another is more likely to be accepted by users (Davis, 1989). Its role is crucial in EUD tasks and it can affect users' performance, as mentioned in many researches (e.g. Beckwith, Burnett, Grigoreanu, & Wiedenbeck, 2006; Beckwith & Burnett, 2007; Beckwith et al., 2005; Burnett et al., 2008; 2010; Burnett & Scaffidi, 2011).
- Perceived usefulness is determined as the degree to which a person believes that using a particular system will enhance his/her job performance (Davis, 1989). Davis (1989) describes a

system high in Perceived Usefulness as one for which a user believes in the existence of a positive user-performance relationship. The user perceives the system to be an effective way of performing the task(s).

2.3. Mouse behavioral patterns in HCI and related work

Like most of the web tracking technology, the main goal of mouse tracking is a deeper understanding of the user behavior for inferring user intentions. In recent years, research focus has turned to whether mouse tracking could offer a scalable alternative to eye tracking for measuring usability of web pages, search relevance, user attention, cognitive processes, psychological or affective states and more. Compared to eye-tracking, mouse tracking is cheaper, simpler to implement and can be used for massive studies without the need of test monitor presence (Arroyo, Selker, & Wei, 2006; Atterer et al., 2006; Chen, Anderson, & Sohn, 2001; Cooke, 2006; Leiva & Hernando, 2008).

In the area of HCI researchers have been trying to quantify the movement of humans who perform pointing tasks on computers and other devices. Mouse cursor movement is a vital part in this field and has been used in many studies. One of the initial and main measurements used in those studies is Fitts' law for movement time (Fitts, 1954; Fitts & Peterson, 1964). This law originated from the desire to quantify the pointing behavior of humans and is currently most used to measure the efficiency of an interface's layout. The efficiency is measured in the time period that is needed to use the interface i.e. to click the buttons or to navigate within the interface. Since Fitt's law many researchers have used mouse movement analysis to deeper understand users' cognition process, psychological aspects (such as frustration), perception, level of difficulty, etc.

In 2001, Mueller and Lockerd proposed the use of cursor patterns behavior as input to deliver personalized content to users. Unfortunately, the identification of patterns has not significantly advanced since then. Mouse patterns characterization is generally vague, and their identification remains a largely visual process and qualitative analysis.

There are not many research works that clearly attempt to detect users' behavioral attributes via mouse behavior. One example of research close to the diagnosis of user behavioral state is the research of Khan, Brinkman, Fine, and Hierons (2008) who correlated mouse and keyboard usage to the outcome of personality tests. Also, Zimmermann, Guttormsen, Danuser, & Gomez (2003) examined mood through mouse and keyboard input and recorded both mouse clicks and mouse coordinates. Dijkstra (2013) investigated the diagnosis of self-efficacy levels in simple question-based e-learning environments using as mouse metrics the distance and time differences as well as the mouse pauses. Tzafilkou, Protogeros, and Yakinthos (2014) attempted to diagnose users' self-efficacy and hesitation levels in order to improve user experience in web-based activities. Navalpakkam and Churchill (2012, p. 2012) demonstrated that mouse movement patterns can predict whether the experience of a user is perceived as pleasant or not. Arapakis et al. (2014) analyzed the frequency of common mouse metrics like speed, distance, acceleration, direction, etc. to diagnose well-known user engagement items like focused attention and effect.

Although its significant usefulness to analyse user behavior in HCI tasks, mouse tracking has not been studied yet in common everyday web-based activities like web-based End User Development. Mouse behavior in EUD could be monitored and analyzed to measure user intention and engagement, diagnose perception and acceptance states, predict user performance, etc. User modeling implementations based on implicit mouse and keyboard input could also be used to personalize and adapt the EUD system developing approach or interface elements and assist end-users perform better in their developing tasks.

There are several studies that have identified some common patterns of cursor movements, such as reading patterns, direct movements, random movements, hesitation patterns, fixed and guide patterns. These patterns have been identified in different web contexts like search engine result page, interaction with web forms and web site navigation (Atterer et al., 2006; Hornbæk & Frøkjær, 2003; Magnuson, 2005; Mueller & Lockerd, 2001, pp. 1–2; McKinstry, Dale, & Spivey, 2008; Freeman, Dale, & Farmer, 2011). These works are of significant HCI contribution, since identifying mouse behavioral patterns allow us to infer the activity performed by the user, for example, usability problems and user experience (Navalpakkam et al., 2013).

Following we briefly present the most common mouse behavioral patterns suggested in the reviewed literature. We also attempt to conclude (based on previous research findings) which EUD-user behavioral attribute(s) every pattern could reflect on.

2.3.1. Straight pattern

The straight pattern (Lee & Chen, 2006) or else the 'direct mouse movements' (contradictory to the random ones) refers to the users' 'confident movements'. These are characterized by a pause before a direct movement towards a target since "once traced the desired feature users move the mouse straight to it" (Lee & Chen, 2006). According to Rodden et al. (2008), this pattern defines direct movements that occur once the user has decided which action to take and this could reveal certainty and task-oriented self-efficacy.

On presence of this pattern, researchers infer that there is an earlier decision and the user feels certain about his/her movement and hence they associate this pattern to the user's self-efficacy levels. A direct movement pattern may reveal that an activity is easy and simple, reflecting an earlier decision making.

In the context of interaction with web applications, direct movement is characterized by "a direct movement whit no big pauses" (Ferreira et al., 2010).

Hence, drawing from the related literature review, mouse trajectory (e.g. straight lines) or selected targets (i.e. clicks) after direct movements may measure the end-user's self-efficacy level or perceived ease of use when interacting with computer applications.

2.3.2. Hesitation pattern

Hesitation pattern is first explicitly defined in Cheese project (Mueller & Lockerd, 2001, pp. 1–2). According to the authors "hesitation on links or text could potentially provide information about what else interests the user on the page". This hesitation could be expressed by the cursor as a mouse hover over the under decision item (i.e. element to click).

Other studies which focused on the analysis of movements of the cursor in web forms refer to the pattern of hesitation as movements between "two or more answers while trying to decide which one to choose (Ferreira et al., 2010). Hesitation patterns have also been identified during interaction with navigation menus (Atterer et al., 2006).

Hesitation pattern may suggest doubt, difficulty and decision-making activity. Generally, via the hesitation pattern the user reflects a doubt about the option to choose. For instance, in the case of forms the greater the degree of difficulty, the more hesitation patterns are observed (Ferreira et al., 2010). In commercial applications of mouse tracking, as ClickTale (2006), the pattern of hesitation is defined as "the average time from the beginning of a mouse hover to the moment of the mouse click".

As we see, there is a clear distinction between those who believe that the hesitation may occur on a single target, as a pause before the click (ClickTale, 2006) and among those studies that consider the hesitation as a pattern of doubt among many possible targets (Ferreira et al., 2010).

Hesitation pattern could hence be used to infer users' perceived difficulty, risk-perception levels (since the user evaluates the cost benefits of choosing an action among others), or even the perceived usability from his/her interaction with the system.

2.3.3. Reading pattern

The reading pattern can be divided into two different types of behavior: the horizontal reading pattern that is characteristic but not so common among users (Rodden et al., 2008) and the vertical reading pattern where the mouse path traces a vertical line, with small or large pauses. In Ferreira et al. (2010) the horizontal reading pattern is characterized by "a smooth mouse movement that trails horizontally across paragraphs". In comparative studies with eye-tracking it is defined as a movement that follows the eye horizontally (e.g. Rodden et al., 2008).

The vertical reading pattern is defined as a movement of "following the eye vertically" (Rodden et al., 2008). This pattern is observable in vertical lists like a menu where the users "use the mouse as a marker when they are looking through a list of links" (Mueller & Lockerd, 2001, pp. 1–2).

2.3.4. Random and fixed pattern

According to Ferreira et al. (2010) the random pattern is characterized by movements "without any specific intention, just playing around and doing random movements whit short pauses or not". The authors noted that the random movements often arise when the difficulty level of the task increases (in contrary to the straight pattern movements).

Hence, on presence of a random pattern we can infer doubt, difficulty, low self-efficacy, anxiety, etc.

Described in Lee and Chen (2006), the fixed pattern refers to the areas where the users mostly used for "repose" the cursor. For Lee and Chen (2006) these areas usually are on the right-side of the page. This area is also mentioned as "White space" (Ferreira et al., 2010) and research indicates that a large number of users use whitespace to rest the mouse, thus avoiding accidentally clicking a link. Fixed pattern could be expressed via long or shorter mouse pauses on 'neutral' web-page areas. During this time users may reflect on the task, read (eye tracking could only reveal reading behavior during mouse pauses) or evaluate the costs and benefits of making particular decisions (e.g. clicks, actions). Hence, fixed pattern could measure risk-perception or usefulness levels.

2.3.5. Guide pattern

Defined in Lee and Chen (2006), the guide pattern defines a behavior of continuous movement of the cursor. According to the authors this pattern seems to reflex an "exploratory" role that suggests a relationship between mouse and eye movement" and hence this pattern may give us an idea of the user expectations. Hence, guide pattern may be associated with users' acceptance, i.e. perceived usefulness and ease of use and also willingness to learn.

However, guide pattern is very similar to the reading pattern since it can be expressed via 'smooth' (i.e. slow) cursor movements identifying horizontal or vertical reading.

2.4. Keystroke dynamics in HCI and related work

Keystroke dynamics have been typically used in biometrics and user authentication (Bergadano, Gunetti, & Picardi, 2003; Monrose & Rubin, 2000). As defined in Monrose and Rubin (2000) "keystroke dynamics is the process of analyzing the way a user types at a terminal by monitoring the keyboard inputs thousands of times per second in an attempt to identify users based on habitual typing rhythm patterns".

In a more 'HCI-friendly' and generic approach, Epp et al. (2011) describes keystroke dynamics as 'the study of the unique timing patterns in an individual's typing, and typically includes extracting keystroke timing features such as the duration of a key press and the time elapsed between key presses".

Recently, keystroke dynamics have been used in affective computing research to detect user affective states like mood and emotions (Epp et al. 2011; Khanna & Sasikumar, 2010).

In Khanna and Sasikumar (2010) the authors used keystroke dynamics to model three emotional classes (positive, neutral, negative). Attributes used in Khanna and Sasikumar (2010) are: typing speed, mode, standard deviation, standard variance, range, total time taken, number of backspaces used and interval between typing (if any).

Epp et al. (2011) used keyboard dynamics in emotion detection and showed the classification of 15 emotional states and could identify six emotions (confidence, hesitance, nervousness, relaxation, sadness and tiredness). They also showed promising results for anger and excitement.

Nahin, Alam, Mahmud, and Hasan (2014) have presented a method of determining user emotion by combining both keystroke dynamics and text pattern analysis.

There is not much research in analyzing keystroke dynamics and end-users behavioral states. Some related research may concern personality detection through keyboard and mouse input. For instance, in Khan et al. (2008) the authors suggest that some of the main traits and sub traits of personality can be measured from keyboard and mouse use. The keyboard attributes measured in two exploratory studies were 'key-up' and key-down'. Their findings revealed some limited significance since only recording the standard deviation of the average time between events gave some insight into a user's activity level, a sub trait of extraversion.

In Vizer, Zhou, and Sears (2009) the authors used keystroke timing features of free text in conjunction with linguistic features to identify cognitive and physical stress.

In a more related study of Dijkstra (2013) the author examined the correlation between mouse or keyboard input and self-efficacy levels. Although mouse input showed some promising results for detecting self-efficacy levels, no correlations were found between typing keyboard behavior and self-efficacy.

3. Aims and research questions

Since EUD has some important differences from other HCI areas where mouse tracking has already been studied, we should consider some constraints before formulating our research objectives.

First, a web-based EUD system does not consist of static web pages (like most mouse tracking studied environments); instead it is composed of dynamic web pages and in some cases it is a Single Page Application (SPA). Thus, we will not define any areas of interest (AOIs) in the web page and the suggested mouse metrics will be context and region-independent, ignoring the interface layout. Our approach will be suitable to be used in other similar EUD research works.

Second, we will measure the average mouse-behavior during the time needed by a user to complete a development task. This time may be different for each user and is defined as 'task duration time'. For this reason the time related mouse metrics (e.g. average pause time, average time between clicks, etc.) are divided by the task duration time for each user and this ratio is used as the main mouse metric. This gives the analogy of the measured mouse time variable to each user's EUD completion time.

Also, to quantitatively examine mouse patterns in EUD activities we have first to find a measurable manner. That is to subdivide each mouse pattern (from the ones described in the literature) in a set of measurable mouse metrics. In Churruca (2011) the author subdivided each mouse pattern in a set of mouse movements but they measured them using only visual representation via video recording. In the current research we attempt to subdivide every mouse pattern in a set of measurable mouse metrics and examine them separately to see which ones are met in end-user developers' mouse behavior and which ones of them are significantly correlated to one or more of their EUD behavioral attributes. Our main research objective is to examine the bivariate potential correlations between the pattern-related mouse attributes (direct moves, number of clicks, number of hovers, etc.) and end-users' behavioral attributes (perceived ease of use, perceived usefulness, self-efficacy, willingness to learn and risk perception).

We also plan to measure the activity level of mouse movements, i.e. the relationship between movement of the cursor and the duration time of the EUD session. We will then examine the correlation between activity level and EUD behavioral attributes.

Finally, we will examine the potential correlations between a set of main keystroke dynamics (dwell time, flight time, etc.) and the measured EUD behavioral attributes. Although web-based EUD activities do not include a lot of text typing tasks, users still have to provide some important input through the keyboard (e.g. form fields' names, options values, object's names and descriptions, etc.), and although limited, this input could still reveal a meaningful contribution.

The existence of significant correlations will undoubtedly reveal a promising research venue in the future of end-users' behavioral analysis and the usefulness of mouse and keyboard tracking methodologies as implicit feedback gathering mechanisms in web-based EUD systems.

Hence our main research questions are the following:

RQ1 *Are straight pattern attributes associated with end-users' behavioral attributes?*
RQ2 *Are hesitation pattern attributes associated with end-users' behavioral attributes?*
RQ3 *Are random pattern attributes associated with end-users' behavioral attributes?*
RQ4 *Are fixed pattern attributes associated with end-users' behavioral attributes?*
RQ5 *Are guide pattern attributes associated with end-users' behavioral attributes?*
RQ6 *Is the activity level of mouse movements associated with end-users' behavioral attributes?*
RQ7 *Are any keystroke dynamics associated with end-users' behavioral attributes?*

This is an exploratory study and we do not construct any hypotheses regarding which pattern reflects which behavioral attribute since every pattern is a composition of different mouse metrics and some metrics could reflect one behavioral state while some others could reflect another one. Also metrics of different patterns could be associated with the same behavioral states.

To examine the above-presented research questions, as explained, we have first to subdivide every behavioral mouse pattern into a set of measureable mouse attributes (mouse metrics). Following we present the mouse metrics for each one of the presented mouse patterns and argument on their selection. We exclude the reading pattern from our study since its metrics are really close to the guide pattern and there are not many reading tasks (except some instructions or wizard-based guidance text) in the EUD environments.

3.1. Straight pattern attributes

According to Lee and Chen (2006), "in straight pattern (or else direct pattern), the mouse movement starts from an initial region, while users are presumably visually browsing other regions of the page. It is surmised that once users spotted the link that they were asked to find, they moved the mouse straight to it, and usually terminated the action with a click".

Based on the above conclusion, in Churruca's (2011) visual interpretation, the straight pattern can be expressed through direct movements that may or may not include a pause and they usually move toward a target, that is, they end up in a mouse click.

Hence, the mouse metrics-attributes we plan to examine in regards to the straight pattern include the following:

- Direct movements (i.e. straight lines);
- Clicks in the end of straight lines (e.g. direct movements towards a target that was clicked);
- Average time passed between straight lines (e.g. time elapse between direct movements; this could also show how often a user makes a decision to trace a direct trajectory).

We note that it is not necessary all the attributes to exist. The existence of only some of them could represent the straight pattern in a measurable way.

The same rule concerns all the below patterns as well.

3.2. Hesitation pattern attributes

As mentioned, in ClickTale (2006) the pattern of hesitation is defined as "the average time from the beginning of a mouse hover to the moment of the mouse click".

In other research works hesitation may occur on a single target, as a pause before the click or it regards a dilemma between two or more choices and hence can be expressed through mouse hovers between at least to items in the same sequence (Guo et al., 2008).

In a more generic term we could also link hesitation as mouse hovers, pauses before clicks and average time between clicks as well.

Hence, the mouse metrics-attributes we plan to examine in regards to the hesitation pattern include the following:

- Hovers that turned into clicks;
- All hovers in general;
- Average time from mouse hover to mouse click;
- Average time of pauses before clicks;
- Average time between clicks.

3.3. Random pattern attributes

According to Ferreira et al. (2010) a movement is random when it occurs without apparent intention, that is, it is not between targets. Also it may or may not include short pauses.

Random movements may reveal user anxiety and doubt (Churruca, 2011) and hence they should be clearly different from straight pattern movements.

The random related metrics we plan to examine are:

- Curved (i.e. not direct or random) movements;
- Clicks that occurred outside direct movements;
- Total number of movements (since a large amount of mouse movements could include a large percentage of movements with no intention).

3.4. Fixed pattern attributes

In Lee and Chen (2006), the fixed pattern refers to the areas where the users mostly used for "repose" the cursor. That is that except from the area where the mouse is reposing, it stays there for a 'long' time. In our case, this can be translated into 'long pauses'.

Different studies use different time thresholds to characterize a pause as long or short. Since this is a EUD exploratory study, and because of the nature and the cognitive load of a developing task, we consider as long pauses those over 4 s. Short pauses (or else pauses) remain 200 ms as underlined in the related literature (Dijkstra, 2013).

Also, as explained, we do not plan to explore the position of cursor in the page (i.e. the area) where the mouse reposed, since the EUD interface page layout is different than search related and other web sites where previous work (e.g. Lee & Chen, 2006), was conducted.

Hence, our fixed related metrics include the following:

- Long pauses;
- Average time of long pauses;
- Average time of all pauses (including short pauses).

3.5. Guide pattern attributes

The guide pattern (Lee & Chen, 2006) defines a behavior of continuous movement of the cursor and it seems to reflex an "exploratory" role that suggests a relationship between mouse and eye movement (Leiva & Hernando, 2008). Hence, guide pattern is similar to the reading pattern since it implies that the mouse traces slow or long movements while following the eye.

In our study, long movements are considered as direct movements with distance more than 10pixels and slow (or smooth) movements are considered as movements that their time interval exceeds 3 s.

Hence, the guided related metrics we plan to examine are the following:

- Long movements;
- Slow (smooth) movements.

In Fig. 1 below we summarize the measurable mouse attributes we gathered for each mouse behavioral pattern that we plan to examine.

3.6. Keystroke attributes

Since there are not similar behavioral EUD or other related research on keystroke dynamics, we will 'borrow' some typical keystroke metrics from other HCI related studies like emotion recognition.

The main keystroke dynamics-attributes we plan to analyse are depicted in Fig. 2 and they are based on key press speed, duration (dwell time), latency (flight time) and down-to-down time as proposed in Khanna and Sasikumar (2010), Nahin et al. (2014) and in Epp et al. (2011).

In our exploratory field test we will examine the potential correlations between these typical keystroke dynamics and the measured EUD behavioral attributes of self-efficacy, risk-perception, willingness to learn, perceived usefulness and ease of use.

4. Research methodology

The research methodology follows a four-step approach to examine potential mouse/keyboard and perception/acceptance correlations in a prototype web-based EUD environment for creating simple web forms to store data for particular objects (entities).

First we present the prototype tool that was used for the experiment. Then we present the mouse and keyboard monitoring mechanism and explain its implementation as well as the data extraction method. After, we describe the field test including the sample and procedure details, the user-task, the performance calculation and the measured dependent variables and questionnaire. Finally, we present the data analysis process.

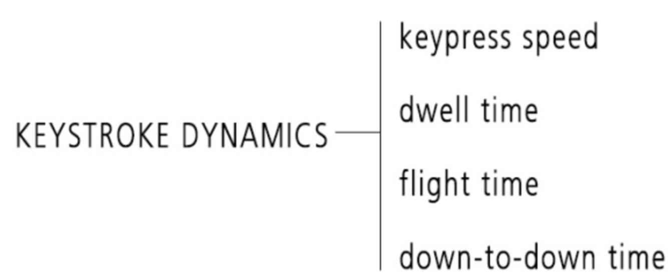


Fig. 2. Chosen measurable keystroke dynamics attributes.

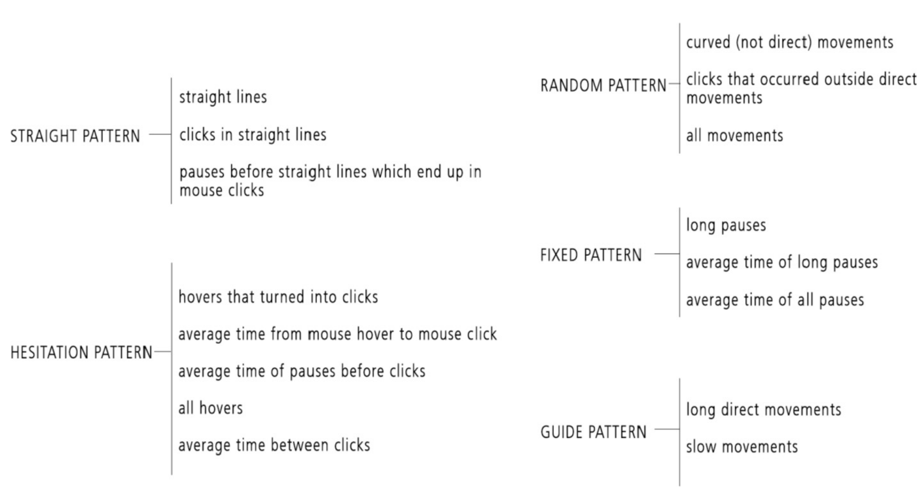


Fig. 1. Chosen measurable mouse attributes per mouse behavioral pattern.

4.1. Prototype web EUD tool

The prototype EUD tool was designed to assist end-users in creating simple web forms. The tool interface was user friendly and easy to use with many and clear 'click elements' (buttons, links, fields, etc) so that the mouse tracking implementation and later analysis would be easy and efficient.

The participants had to create a set of objects (i.e. the entities they wish to store data for) and build the corresponding web forms by constructing and editing one by one the various types of form fields (see Fig. 3). They could also edit some design elements (colors, font sizes, button styles, etc.) and preview the result.

The participants' high performance results (4,6 out of 5) and their high levels of perceived ease of use (4,09 out of 5,00) as depicted in Table 4 indicated the efficiency of the tool as well as a positive user experience.

4.2. Monitoring mechanism and mouse/keyboard data extraction

For the purpose of the mouse and keyboard tracking work we designed a JavaScript-based prototype monitoring tool that, based on the reviewed mouse patterns, captures user mouse and keyboard behavior and stores every event in a MySQL database.

The server-side part of the tool is based on Node. js while the client side is based on JavaScript and makes use of the socket. io library. The transmitted data relates to mouse movements and user keyboard clicks that are captured on the controlled web pages. Socket. io is fast enough to cope with near real time data transmission and allows no information to be lost.

JavaScript allows easy logging of keyboard and mouse events when navigating a web page. The programmer can monitor the press and release of a keyboard key and press and release of a mouse button. In particular, JavaScript allows us to monitor and track the following events:

- keydown (fires when the user depresses a key. It repeats while the user keeps the key depressed);
- keypress (fires when an actual character is being inserted in, for instance, a text input. It repeats while the user keeps the key depressed);
- keyup (fires when the user releases a key, after the default action of that key has been performed);
- mousedown (fires when the user depresses the mouse button);
- mouseup (fires when the user releases the mouse button);

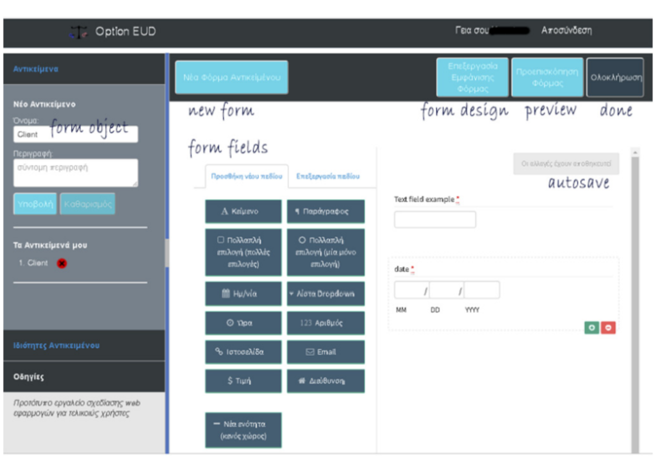


Fig. 3. EUD tool interface (some translation in English is provided in hand-written fonts).

- click (fires when a mousedown and mouseup event occur on the same element);
- dblclick (fires when two mouse click events occur on the same element within a reasonable time).

The keydown and keypress scheme outlined above is originally a Microsoft invention (Microsoft, 2017).

An important feature of the prototype tool is that the tool displays graphs and statistics in real-time at any website connected via JavaScript file in the central server (see Fig. C1 in Annex C).

Hence, we connected the monitoring tool to the EUD prototype tool to implicitly monitor the end-users' mouse and keyboard behavior while working on their developing task.

To link the questionnaire answers to each user's mouse and keyboard behavior we generated a unique client id for every user and we stored it in every database table and in a questionnaire's answer field.

We stored all the recorded mouse and keyboard data in the following five relational MySQL database tables:

- mouse clicks;
- mouse moves;
- mouse hovers;
- key press;
- key release.

The raw mouse data consisted of mouse clicks, moves and hover events, their coordinates (x,y), their time intervals (in μs) and a timestamp (in μs) of when every mouse event occurred.

The raw keystroke data consisted of key press and release events, unique codes for each key, their time intervals (in ms), and a timestamp (in ms) of when the key event occurred.

For example, as the code fragments in Fig. C2 Parts A and B (see Annex C) depict, the table of mouse clicks (ms_clicks) consists of the following fields: coordinate x, coordinate y, time since last mouse click, time the mouse click occurred, click element, element's content and client's id. The recorded time is very accurate since it is the client time in microseconds when the event has occurred. This time along with the coordinates and other event information is put in a message and queued with the help of the socket. io library, before being sent to the server and stored in the database. Thus, any delay in the transmission and storage process will not affect the actual data of the event and the reliability of the database.

Similar is the approach to creating the other tables and recording the time. As shown in the code snippets in Fig. C2, there is an SQL query that initially creates the database table, and then a series of other queries that store mouse data generated by users (and logged by JavaScript events) as records in this table. Any event that represents a single user action of some sort (e.g. a mouse button click) is stored in the mouse event table as a new record, whereas events such as mouse movement can result in the storage of multiple records containing the information for the mouse path pixels. The data is stored through the server side functions in a central database. A representative example of the inserted data management is shown in Fig. C2 Part C (see Annex C).

To extract the mouse and keyboard metrics (see Table 1 and Table 2) we used a set of PHP algorithms and SQL queries. Thus, we could retrieve from the database the desired mouse and keyboard behavior for every user.

To build the data extracting algorithms (which are later discussed), we needed first to set some size and time thresholds necessary to decide whether a click relates to a particular application element or not. The thresholds were optimized after much experimentation. Finally, the max width of the clickable elements

Table 1
Extracted mouse attributes.

Feature	Type	Meaning
num-mv	Count (units)	Number of mouse movements in a session.
num-crv	Count (units)	Number of non-direct (curved) movements in a session (slope >0.01 and distance between two points >3.5px).
num-outlineClks	Count (units)	Number of clicks outside direct movements (lines) in a session (slope >0.01 and distance between two points >3.5px).
num-inlineClks	Count (units)	Number of clicks in the end of direct movements (lines) in a session (slope<0.01).
num-longPauses	Count (units)	Number of mouse long pauses (time elapsed since last movement ≤ 4sec) in a session.
avg-longPauses	Time (ms)	Ratio of average time of long pauses (time elapsed since last movement >5sec) to the task duration time.
num-dirMv	Count (units)	Number of direct movements in a session (slope <0.01).
avg-timeBtwDir	Time (ms)	Ratio of the average pauses time between direct movements to the task duration time.
num-hvrToClk	Count (units)	Number of mouse hovers that turned into mouse clicks (time interval from mouse hover to mouse click ≤ 4sec) in a session.
avg-hvrToClk	Time (ms)	Average time from mouse hover to mouse click on the same element (time interval from mouse hover to mouse click ≤ 4sec).
avg-btwClk	Time (ms)	Ratio of average time between clicks to the task duration time.
avg-pause	Time (ms)	Ratio of average time of pauses (>200 ms) to the task duration time.
avg-pauseBfrClk	Time (ms)	Ratio of average time of pauses (>200 ms and <10sec) before clicks to the task duration time.
num-longDirMv	Count (units)	Number of long (>10px) direct movements in a session.
num-slowMv	Count (units)	Number of slow (>2sec) movements in a session.
num-hvr	Count (units)	Number of all mouse hovers in a session.
task-dur	Time (ms)	The EUD task total duration (completion) time (which is different for every user).
acl-mv	Time (%)	Activity level for mouse movements (i.e. time of movements in a session/task-dur).

Table 2
Extracted keyboard attributes.

Feature	Type	Meaning
speed-char	Count (units)	Number of characters pressed every 4 s.
dwell-time	Time (ms)	Time elapsed between key press and key release (time interval was set to 100 ms).
flight-time	Time (ms)	Time elapsed between a key release and the next key press (time interval was set to 1 s).
d2d-time	Time (ms)	Time elapsed between the characters pressed every 4 s.

was set to 220px and the max height to 96px. The time thresholds are all depicted in the following tables (Tables 1 and 2) next to the relevant measures.

Table 1 below describes the mouse attributes (as they presented in Section 3) that we extract.

As already explained, the time mouse features (avg-longPauses, avg-hvrToClk, avg-btwClk, avg-pauseBfrClk, avg-pauses BtwDirand avg-pause) are taken into account along with the EUD task duration (task-dur) time which is different for every user. That is, where 'avg-shortPause' is the ratio avg-shortPause/task-dur, and so on.

Table 2 below describes these keystroke attributes we plan to extract. As already mentioned, the main keystroke attributes we extracted were based on key press (character) speed, dwell, flight and down-to-down time as proposed in Khanna and Sasikumar (2010), Nahin et al. (2014) and in Epp et al. (2011).

Regarding speed-char (key press speed) we used a threshold of 4 s instead of 5 s proposed in the reviewed literature (e.g. Nahin et al., 2014), since as explained web-based EUD is not a typing task hence we need shorter time thresholds to measure users' keyboard activity.

To show the logic of the data retrieval algorithm described above, some representative PHP and SQL code fragments are presented in Appendix C. In particular, in Fig. C3 a PHP code fragment is presented that extracts the average time from mouse hover to mouse click on the same element (avg-hvrToClk). In this function the maximum width of clickable elements was set to 220px and the maximum height to 96px. Also, the maximum elapsed time from mouse hover to mouse click should be less than (or equal to) 4 s (<= 4000 ms). Of course these constraints can be changed to match the tool user interface and the EUD context.

In addition, Fig. C4 shows PHP and SQL code fragments used to extract keystroke dynamics data. The particular example shows the extraction of the flight-time (see Table 2). In this function the maximum time interval from keyboard press (kb_pr.Time) to keyboard release (kb_rl.Time) was set to one second.

Similar approaches to all other PHP algorithms and SQL queries used, to extract the desired mouse and keystroke data.

4.3. Field test

4.3.1. Participants and procedure

The experiment was conducted in an introductory e-commerce course, in the Department of Accounting and Finance in a Greek University. The participants' initial population was 42 volunteers and the final sample consists of 30 end-users, 18 male and 12 female. The sample size was reduced to 30 individuals because seven volunteers did not complete the EUD task and five did not submit the questionnaire form. Hence their data could not be used in the analysis process. There were no significant age and expertise differences among the participants. To confirm the sample EUD representation, i.e. the participants' similar level of computer and developing experience, an expertise pre-test was conducted (see Fig. 4).

The participants were given a EUD task to solve, in the form of an exercise demanding the construction of a simple web form. The use of the prototype tool was simple and the interface text was in Greek. Instructors made a basic presentation of the EUD tool at the beginning of the field test and did not give any other special instructions, apart from the exercise (i.e. the requested development task). Few students who were not very comfortable with the use of the system and asked help received some further information and instructions. In the end, participants could be informed about their performance and discuss their experience and difficulties or ask any further questions.

The conducted field test did not take into account the students' large population but the EUD generic population which according to Costabile, Fogli, Letondal, Mussio, Piccinno (2003), Costabile, Fogli, Fresta, Mussio, & Piccinnov, (2003). 'it is not a uniform population, but divided in no mutually exclusive communities characterized by different goals, tasks and activities. The EUD

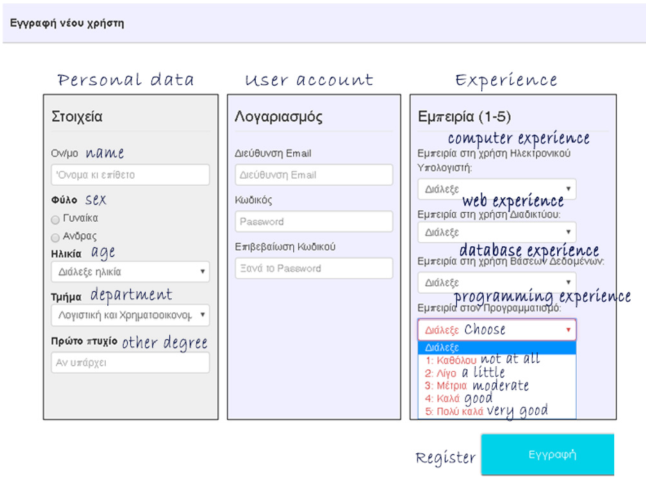


Fig. 4. Web questionnaire prior to EUD task, regarding the user personal info and computer experience (translation in English is provided in hand-written fonts).

population can be different according to cultural, educational, training, and employment background, experience in computer use, age (the very young and the elderly), types of (dis)abilities, etc.' (Costabile, Fogli, Fresta et al., (2003)). Based on the EUD terminology given by Lieberman et al. (2006), that end-users act as are non-professional developers to build or modify applications, we require from our participants to belong to the generic end-user developer population. That is, they should be familiar enough with web and computer software's and concepts but they should not to be experts and of course not programmers.

Drawing from all these, the targeted EUD group population is young (age 18–25) users from a European country (Greece), with no disabilities, having the regular computer skills and experience (e.g. computer use and web surfing) but they are not professional developers, meaning that they do not have any programming or web development skills.

To confirm these criteria, some personal information (sex, age, educational background) was collected and as mentioned, prior to the EUD task the participants were also asked to answer a short questionnaire regarding their experience level on database concepts, programming, World Wide Web and overall computer use. Their experience level was measured in a scale from 1 to 5, as depicted in Fig. 4.

The measured mean value of the participants' database familiarity was 1,45, revealing that they could be 'safely' considered as non-professional/non-expert end-users in database-development tasks. Additionally, their programming experience was 1,30, their familiarity with web was 2,97 and their general familiarity with computer use was 2,78 (see Table 3 and Fig. 5). These mean values satisfy our target group (end-user developers) requirements, i.e. users that are non-experienced programmers, with no or limited knowledge on database concepts but with efficient familiarity with web interaction and computer use in general. This information could allow us to generalize the results from a small sample and make broad claims about web-based EUD behavior of similar EUD populations.

Table 3
Descriptive statistics of participants' experience level.

Measured Item	Mean (0–5)	St. Deviation	St. Error
Computer Experience	2,78	0,81	0,11
Web Experience	2,97	0,80	0,11
Database Experience	1,45	0,75	0,32
Programming Experience	1,30	0,69	0,10

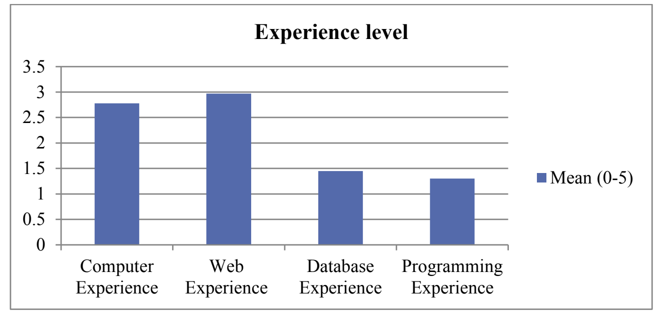


Fig. 5. Diagram of participants' experience level (N = 30).

4.3.2. User task and performance measure

The exercise (user task) needed to be small enough to be solved in a limited time by the participants, and as comprehensive as possible in order to capture a logic amount of mouse movements and keystroke events. The example of a web form is simple and comprehensive, since forms and fields are familiar to most end-users and its construction encompasses a set of items such as field types (text, number, list, etc), choice options, length and design elements (fonts, colors, button styles, etc.) as well. So, the exercise given to the participants was to create a simple web form to store a set of customer data.

First, the end-users had to create an object named 'customer' and give it a description. Then, for this object they had to create a form and construct the following form fields:

- a text type field to store the customer name and last name;
- a dropdown type field with two options to store the customer age;
- an email type field to store the customer email address.

The participants could also set the fields as required or not, define their length and some other form aspects.

To calculate user performance for every participant we used a score scale from 1 to 5 and assigned a relative weight of importance to each constructed item as the following equation (1) shows:

$$P = o*1.0 + f*1.0 + t*0.5 + d*0.25 - e*0.25 \quad (1)$$

Where, P=Performance, o = Object, f = Field name, t = Field type, d = Dropdown list option (in the dropdown type field) and e = Extra (i.e. unnecessary) field. The relative weights reflect the importance of each item of the above equation.

After completing the above-described user task, each participant had to answer a self-report questionnaire-based survey consisted of 22 items measuring a set of EUD behavioral variables (see Annex A). The questionnaire was provided to the users as an online survey form, embedded in the last page of the EUD application.

4.3.3. Dependent variables and questionnaire

The following list contains the set of user-oriented (EUD behavioral) variables measured for each user from the post-task questionnaire survey.

EUD behavioral (dependent) variables:

- Self Efficacy (SE)
- Risk Perception (RP)
- Willingness To Learn (WL)

- Perceived Usefulness (PU)
- Perceived Ease of Use (PEOU)

Performance was excluded from the list of the dependent variables since the paper focuses on the variables of EUD behavioral attributes, and performance was calculated only to reinforce the tool's efficiency and the research validity.

The questionnaire survey was consisted of 22 questions (items) which measure the five independent above-listed variables. A five point Likert-type scale with 1 = "strongly disagree" to 5 = "strongly agree" or 1 = "never" to 5 = "many times" was used to measure the items. Our questionnaire structure was based on previous research of computer perception and acceptance related questionnaires (e.g. Compeau & Higgins, 1995; Davis, 1989; Moon & Kim, 2001; Venkatesh, Morris, Davis, & Davis, 2003; Thompson, Higgins, & Howell, 1991; Wang, Wu, & Wang, 2009) but we adjusted and extended the questions in order to cover all the under survey attributes. The original questionnaire was in a Likert scale form consisted of a prompt, "during the usage of the EUD tool I felt that I was totally confused, or I was confident" etc.

As presented in Annex A, five items were used to measure Self-Efficacy, Risk-Perception and Perceived Ease of Use, three were used to measure Willingness to Learn and four items were used to measure Perceived Usefulness. The internal validity of the questionnaire is presented in Table A1 in Annex A.

4.3.4. Data analysis

4.3.4.1. Sample characteristics. A normality distribution test was conducted to test whether the values of every measured dependent variable were approximately normally distributed for the whole sample.

A Shapiro-Wilk's test ($p > 0.05$) (Shapiro & Wilk, 1965) and a visual inspection of box plots (see Table B1 and Fig. B1 in Annex B) showed that the values of Perceived-Usefulness, Perceived-Ease of Use, Willingness to Learn, Self-Efficacy and Risk-Perception come from a normal distribution.

The fact that the sample size is normally distributed reinforces the validity of the statistical results.

4.3.4.2. Data analysis method. Since our data is approximately normally distributed we can use a parametric analysis method. Hence, in order to measure the bivariate correlations between the measured variables we used the Pearson correlation analysis since it is an appropriate method to define the strength of the association among a set of continuous variables.

To present the general results concerning every measured variable we used descriptive statistics.

To evaluate the questionnaire internal consistency we calculated the value of Cronbach alpha (α).

Later, in the Discussion section we highlight our main findings and discuss a number of potential limitations of the current experimental design.

5. Results

Construct validity has been tested to ensure that the results are reliable and consistent. By calculating Cronbach's alpha coefficient we tested the construct reliability. This measures the internal consistency by indicating how a set of items are closely related and forming a group (Moolla & Bisschoff, 2012). Nunnally (1967) suggests that a Cronbach's alpha (α) value of 0,70 is acceptable, were a slightly lower value might sometimes be acceptable as well.

In Table A1 in Annex A Cronbach's αvalues for all factors are above 0,70, indicating that all measures employed in this study demonstrate a satisfactory internal consistency and the measurement model is supported.

Table 4 below presents the descriptive statistics for the EUD behavioral measured items for the whole sample. Performance statistics are also included since performance calculation was used to reinforce the EUD prototype tool's efficiency.

Diagrams in Fig. 6 below show the mean values of the recorded mouse and keystroke attributes. Mouse time related metrics (average pauses, etc.) are not depicted.

Table 5 below shows the Pearson correlations (r) between every extracted mouse metric and EUD behavioral attribute. As depicted, several significant correlations have been revealed. Last row depicts the Pearson correlation between activity level of mouse movements and behavioral variables.

Table 6 below shows the Pearson correlations (r) between every extracted keystroke metric and EUD behavioral attributes. As depicted, some significant correlations have been found.

6. Discussion

The field test results are encouraging for the future of mouse and keyboard monitoring for EUD behavioral analyses. Initial exploratory findings have given us key insights since various correlations have been revealed between mouse/keyboard behavior and EUD behavioral attributes.

Most of our research questions have been answered in a contributing way since the findings reinforced the usefulness of mouse and keyboard behavioral analysis in web-based EUD activities.

Following we summarize the main findings that came up for every research question formed in Section 3.

RQ1 *Are straight pattern attributes associated with end-users' behavioral attributes?*

Results in Table 5 show that one of the straight pattern's metrics (the number of direct movements) is significantly associated with perceived ease of use and perceived usefulness, and one metric (the metric of average time between direct movements) is significantly associated with willingness to learn. A possible reason for this latter correlation could be the fact that willingness to learn can be better 'expressed' via time related metrics. As we see in the rest patterns correlations, willingness to learn is mainly correlated to time-based metrics such as average time between clicks, average pause time before click and average time from mouse hover to click.

We also notice that number of clicks inside direct movements showed no correlation to EUD behavioral attributes. One would also expect, based on the reviewed literature, the existence of some significant correlations between straight pattern attributes and self-efficacy since straight pattern implies user confidence. The absence of a self-efficacy correlation could mean that self-efficacy and straight pattern related mouse metrics should be studied more in the field of EUD and a deeper behavioral analysis is needed

Table 4
Descriptive statistics of user questionnaire measured items and performance (N = 30).

Measured item	N	Mean (1–5)	Std. Deviation
Perceived Usefulness	30	3,78	0,60
Perceived Ease Of Use	30	4,09	0,70
Self-Efficacy	30	3,96	0,78
Risk-Perception	30	2,42	0,75
Willingness To Learn	30	3,70	0,82
Performance	30	4,60	0,66
Valid N (listwise)	30		

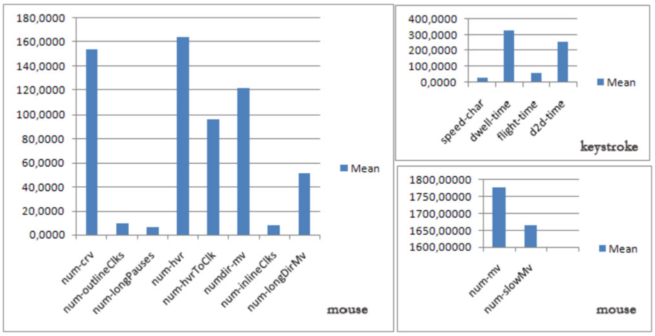


Fig. 6. Diagrams of participants' mouse and keyboard actions' values (N = 30).

to understand which mouse behavior (if any) can clearly reveal EUD self-efficacy levels. Also, we see no correlation between straight pattern metrics and risk-perception. Risk-perception shows some correlation only with hesitation and fixed pattern. This could possibly be explained by the fact that risk-perception is a more 'time-prone' attribute since in the literature review is clearly stated that it is related to time-demanding cognitive tasks where the end-users attempt to evaluate the costs and benefit of their next actions. Based on this, risk-perception might be more affected by mouse pattern metrics, most of which are time based, e.g. average pause time etc.

RQ2 *Are hesitation pattern attributes associated with end-users' behavioral attributes?*

Results in Table 5 show that hesitation pattern related metrics are significantly associated with all the measured behavioral attributes, i.e. perceived ease of use, perceived usefulness, willingness to learn, self-efficacy and risk-perception. We notice that no correlation appears between hesitation pattern metrics and self-efficacy. As seen in Table 5, self-efficacy is only correlated with fixed and random patterns. As mentioned earlier, self-efficacy and mouse correlation may need to be studied deeper in the EUD field to provide a richer literature background.

In particular, hesitation pattern metrics revealed the following EUD correlations:

- Number of hovers that turned into clicks is significantly correlated to perceived ease of use;
- Average time from mouse hover to click is significantly correlated to willingness to learn and self-efficacy;
- Average time between clicks is significantly correlated to willingness to learn and risk-perception;
- Average pause time before clicks is significantly correlated to perceived usefulness and willingness to learn;
- Number of hovers is significantly correlated to perceived usefulness.

RQ3 *Are random pattern attributes associated with end-users' behavioral attributes?*

Results in Table 5 show that random pattern related metrics are significantly associated with perceived ease of use, perceived usefulness and self-efficacy. We notice that no correlations are shown between random pattern metrics and willingness to learn and risk-perception.

In particular, random pattern metrics revealed the following EUD correlations:

- Number of movements is significantly correlated to perceived ease of use, perceived usefulness and self-efficacy;
- Number of curves (not direct movements) is significantly correlated to perceived ease of use and perceived usefulness;
- Number of clicks outside direct movements (straight lines) is significantly correlated to perceived ease of use.

RQ4 *Are fixed pattern attributes associated with end-users' behavioral attributes?*

Results in Table 5 show that fixed pattern related metrics are significantly associated with perceived usefulness, self-efficacy, willingness to learn and risk-perception. We notice that no

Table 6
Correlation analysis between keystroke attributes and user behavioral attributes (N = 30).

Keystroke Attribute	PU (r)	PEOU (r)	SE (r)	WL (r)	RP (r)
speed-char	−0,17	**−0,35**[a]	**−0,34**[a]	−0,14	0,23
dwell-time	0,19	0,24	0,22	0,23	−0,40
flight-time	0,13	0,01	0,08	0,28	−0,06
d2d-time	−0,23	−0,29	**−0,37**[a]	−0,20	0,17

[a] Correlation is significant at the 0.05 level.

Table 5
Correlation analysis between mouse metrics and user behavioral attributes (N = 30).

Pattern category	Mouse attribute	PU (r)	PEOU (r)	SE (r)	WL (r)	RP (r)
Random	num-mv	**−0,43**[b]	**−0,41**[b]	**−0,31**[b]	−0,20	0,18
	num-crv	**−0,36**[b]	**−0,38**[b]	−0,29	−0,28	0,16
	num-outlineClks	−0,22	**−0.38**[b]	−0,304	−0,18	0,16
Fixed	num-longPauses	−0,21	−0,32	**−0,43**[b]	−0,44	0,27
	avg-longPauses	0,32	0,34	**0,44**[b]	0,27	−0,87
	avg-pause	**0,39**[b]	0,24	0,21	**0,32**[b]	**−0,31**[b]
Straight	numdir-mv	**−0,36**[b]	**−0,37**[b]	−0,24	−0,28	0,14
	avg-timeBtwDir	−0,25	−0,06	−0,12	**0,31**[b]	−0,29
	num-inlineClks	−0,15	−0,28	−0,27	−0,28	−0,37
Hesitation	num-hvrToClk	−0,26	**−0,44**[b]	−0,28	−0,16	0,15
	avg-hvrToClk	0,25	0,28	0,29	**0,50**[a]	−0,17
	avg-btwClk	0,61	0,25	0,22	**0,35**[b]	**−0,31**[b]
	avg-pauseBfrClk	**0,38**[b]	0,21	0,18	**0,33**[b]	−0,27
	num-hvr	**−0,31**[b]	−0,28	−0,16	−0,23	0,11
Guide	num-longDirMv	**−0,31**[b]	**−0,34**[b]	−0,19	−0,24	0,12
	num-slowMv	**−0,36**[b]	**−0,36**[b]	−0,25	−0,28	0,15
–	acl-mv	**−0,38**[b]	−0,24	−0,20	-,0,30	−0,30

[a] Correlation is significant at the 0.01 level.
[b] Correlation is significant at the 0.05 level.

correlations are shown between fixed pattern metrics and perceived ease of use.

In particular, random pattern metrics revealed the following EUD correlations:

- Number of long pauses (>5sec) is significantly correlated to perceived ease of use, perceived usefulness and self-efficacy;
- Average time of long pauses (>5sec) is significantly correlated to self-efficacy;
- Average time of all pauses (both long and shorter >200 ms) is significantly correlated to perceived usefulness, willingness to learn and ease of use.

RQ5 *Are guide pattern attributes associated with end-users' behavioral attributes?*

Results in Table 5 show that the guide pattern related metrics are significantly associated only with the two acceptance attributes, i.e. perceived usefulness and perceived ease of use. We notice that no correlations are shown between guide pattern metrics and self-efficacy, willingness to learn and risk-perception.

In particular, random pattern metrics revealed the following EUD correlations:

- Number of long direct movements (>10px) is significantly correlated to perceived ease of use and perceived usefulness;
- Number of slow (smooth) movements (>2sec) is significantly correlated to perceived ease of use and perceived usefulness.

RQ6 *Is the activity level of mouse movements associated with end-users' behavioral attributes?*

As results in Table 5 show, activity level for mouse movements is associated only with perceived usefulness in web-based EUD activities.

RQ7 *Are any keystroke dynamics associated with end-users' behavioral attributes?*

As results in Table 6 show, only two out of four keystroke dynamics (key press speed and down-to-down time), revealed some significant correlations to EUD behavioral attributes. In particular, keystroke dynamics attributes revealed the following EUD correlations:

- Key press speed (threshold = 4sec) is significantly correlated to perceived ease of use and self-efficacy;
- Down-to-down time (threshold = 4sec) is significantly correlated to self-efficacy.

Table 7 summarizes the results of Tables 5 and 6, presenting a clearer image of the bivariate correlations between the measured mouse/keyboard metrics and EUD behavioral attributes. As we see, every mouse behavioral pattern can be correlated to many user behavioral attributes since every mouse metric reveal its distinct particularities regardless the pattern it 'belongs to'. Thus, we notice that many mouse pattern metrics are correlated to more than one EUD behavioral attributes. This was the main reason we could not construct any particular hypotheses on the correlations between mouse patterns and particular behavioral attributes. However, we can notice some clear common behavioral correlations of patterns. For instance, we observe that fixed pattern is mainly associated to self-efficacy, whereas guide and random patterns are mainly oriented to perceived usefulness and ease of use. Straight pattern shows no correlation to willingness to learn and risk-perception, as we discussed these two attributes reveal a more 'time-prone' correlation and straight pattern is not mainly composed of time-based metrics. Hesitation pattern expresses a multi-item orientation since hesitation mouse metrics are more in number plus not so close (in terms of mouse action) one to another.

Regarding keystroke dynamics correlations, we notice that both key press speed and down-to-down time are correlated to self-efficacy, revealing a strong relationship between user's self-efficacy and keystroke dynamics in EUD tasks. Key press speed also reveals a relationship with perceived usefulness. Dwell and flight time did not show any meaningful contribution in the current web-based EUD behavioral research.

As a conclusion we could say that we cannot detect particular behavioral attributes from one single mouse behavioral pattern. Mouse pattern 'translation' and division in measurable mouse metrics is necessary before conducting a EUD-related correlation analysis. Additionally, different research works could enrich or differentiate these metrics resulting in some different or more/less correlations.

But now the question is *how to take up these (or similar) findings of correlations and put them to practical use to actually change the interaction for EUD in positive ways*.

Based on the behavioral correlations found, mouse and keyboard tracking can be useful as implicit feedback gathering mechanisms in user profiling and modeling mechanisms. Implicit monitoring allows indirect and real time data collection without interrupting the end-users' cognitive process during ongoing development tasks. Mouse tracking allows the continuous observation of user behavior during user-system interaction. Data collected through mouse tracking can be considered more 'sincere' since they do not depend on the perceived user experience and provide clear indication of user behavior during the user-system interaction. Compared to questionnaire surveys, user interviews or focus groups, implicit feedback collection has multiple benefits in EUD, mainly due to the real time nature and 'validity' of the collected data (e.g. a user can forget that he/she has clicked on a particular element at a certain time but the system will not). Also, implicit feedback ensures sufficient data collection since end-users are not always willing to provide explicit feedback, making the system's adapting agents unable to adapt the system to their particular needs and preferences.

The collection of implicit feedback is important for the dynamic provision of personalized services and the adaptation of the system environment to the peculiarities of the user. That is, self-adaptation and personalization agents could adapt the EUD systems' content logic and interface elements in an assistive way for the end-user developer to enhance their user experience and developing performance.

For instance, based on Tzafilkou et al. (2017) we could define a EUD behavioral user model as a set of values from low to high for every measured behavioral attribute (Risk-Perception, Usefulness, Ease of Use, Willingness to Learn, Self-Efficacy). Gathering mouse and keyboard feedback we could define these values and adequately provide the necessary feedback to the user to support them better in their developing activity. However, this research direction is out of the current paper's scope and should be deeper analyzed as a separate EUD research work.

As already mentioned, mouse behavioral patterns have not yet matured in the HCI behavioral research and their mouse metrics remain vague. However, steps like the current study are contributing to the evolution of mouse behavioral patterns and their broader application in user-oriented HCI and EUD research.

Table 7
Summary of significant correlations between EUD behavioral attributes and mouse/keyboard metrics.

Mouse/Keystroke Attribute	Mouse Behavioral Pattern	User Behavioral Attribute
Mouse metrics		
num-mv	Random	PU, PEOU,SE
num-crv	Random	PU, PEOU
num-outlineClks	Random	PEOU
num-longPauses	Fixed	SE
avg-longPauses	Fixed	SE
avg-pause	Fixed	PU, SE, WL, RP
num-dirMv	Straight	PU, PEOU
avg-pausesBtwDir	Straight	WL
num-inlineClks	Straight	–
num-hvrToClk	Hesitation	PEOU
avg-hvrToClk	Hesitation	SE, WT
avg-btwClk	Hesitation	WL, RP,
avg-pauseBfrClk	Hesitation	PU, WL
num-hvr	Hesitation	PU
num-longDirMv	Guide	PU, PEOU
num-slowMv	Guide	PU, PEOU
al-mv	–	PU
Keystroke metrics		
speed-char		PEOU, SE
dwell-time		–
flight-time		–
d2d-time		SE

6.1. *Possible issues and limitations*

Since this research is the first in the area of mouse tracking in EUD environments it comes with certain limitations.

First, the approach involves a limited number of behavioral variables, mouse and keyboard metrics and there are a number of other important end-user behavioral attributes (e.g. curiosity, pleasure, willingness to learn, exploratory behavior, etc.) and mouse metrics (e.g. distance travel, speed of movement, etc.) or even keyboard events that could be added in future studies.

A second possible limitation is the generalizability issue. The current field test is conducted on a generally small sample size and this can possibly affect the ability to generalize the findings. The current study does not take into account the generic users' or students' population but a EUD subset and based on this, it evaluates the sample representation. As mentioned, we refer to a EUD subpopulation since according to Costabile, Fogli, Fresta et al. (2003) EUD population is not uniform and is divided in a set of communities characterized by different goals, tasks and activities. EUD population can be different according to cultural, educational, training, and employment background, experience in computer use, age, types of (dis)abilities, etc.

Also, since this study has a limited number of participants, it can be considered a preliminary study and future studies with larger sample sizes should be conducted.

Finally, there may be another possible limitation involved by the SPA (single page application) design of the prototype EUD tool. Other design paradigms such as the wizard-logic have been proved to be preferred by female users (Beckwith et al., 2005; Burnett et al., 2010) and it can positively affect their perception, acceptance or performance. Also, this can possibly lead to differentiated results in future web-EUD research that will be conducted on multipage or wizard like interface designs.

7. Conclusions and future work

In this exploratory study we examined the correlation between a set of EUD behavioral attributes and mouse behavioral patterns and keystroke dynamics. Our aim was to find out whether end-users' behavioral attributes can be reflected on their mouse and keyboard behavior during web-based EUD activities.

The measured EUD behavioral attributes were self-efficacy, risk perception, willingness to learn, perceived ease of use and perceived usefulness. The mouse behavioral patterns we examined were the straight pattern, the hesitation pattern, the fixed pattern, the random pattern and the guide pattern. Reading pattern was excluded due to the dynamic nature of EUD activities and their limited 'content to read'. The measured keystroke dynamics that were chosen were the four main ones, as derived from the reviewed literature, including key press speed, dwell time, flight time and down-to-down time.

A set of research questions were formed to structure the research objectives and distinguish the measured variables. Except mouse pattern-related variables we also measured mouse activity level of movements and included it in our correlation research.

To explore our research questions we conducted a field test using a prototype web-based EUD tool to assist end-users in creating simple web forms, and we monitored their mouse behavior via a prototype mouse tracking mechanism. Mouse and keyboard monitoring data from 30 participants (from an initial population of 42 end-users) was analyzed.

The conducted filed test showed that there are several significant correlations between mouse measurable attributes and EUD behavioral states. Keystroke dynamics also revealed some significant correlations to perceived usefulness and self-efficacy. Summary conclusions in Table 7 show that mouse and keyboard monitoring is a useful mean of gathering real time implicit feedback in EUD activities.

The main contribution of this work is to provide HCI and EUD research community with a basic research background and a motivation to study further and to understand the end-user behavior in web-based EUD environments, as well as the correlation between mouse and keystroke actions and end-users 'behavioral items while interacting with these systems' environments. This study can be perceived as a preliminary work towards the design of user modeling methodologies in EUD environments. The findings of this work show interesting correlations among mouse and keyboard actions and end-user behavioral attributes like self-efficacy, risk-perception, etc. Furthermore, this study contributes in the practical evaluation of the so far collected mouse metrics, showing which ones are or can be useful for the EUD community.

We believe that mouse behavioral patterns should be 'back in action' and studied further in web environments to analyse end-users' behavior. As already mentioned, there are a number of other important end-user behavioral attributes (e.g. curiosity, pleasure, willingness to learn, exploratory behavior, etc.) and mouse metrics or keyboard stroke attributes that could be added in future studies.

Another interesting future research direction could also be to examine the end-users' behavior by combining mouse/keyboard monitoring and eye tracking methodologies. In our future works we plan to conduct new web-EUD exploratory studies monitoring both eye and mouse movements to detect possible new perceptional and behavioral correlations and use them as implicit feedback in self-adaptive EUD systems. In particular, combined mouse and eye tracking data can help EUD researchers deeper understand what happened in between clicks and reveal more about the users' cognitive process.

Also, as already mentioned in the Discussion section, by capturing the users' development behavior, user-modeling techniques could be developed to adapt/personalize the EUD environments, aiming to enhance the end-user performance and experience.

Finally, as mentioned, this can be considered a preliminary work and similar studies on larger sample sizes should be conducted, to address generalizability issues and represent broader EUD populations (such as the student population).

Hopefully our research will shed light on the necessity of similar human-oriented behavioral analyses in the EUD evolution and encourage relative future work.

Annex A. Questionnaire

Table A1
Questionnaire survey and results for validity of the measurement model

Construct Item		Cronbach α (>=0.70)
Self-Efficacy		0,89
SE1	I felt confident while I was using the system	
SE2	I believed that I could perform well	
SE3	I felt I had the control of the task	
SE4	I felt that everyone else knew what to do but me	
SE5	I felt confused while using the system	
Risk Perception		0,70
RP1	It was taking me time to decide how to move while using the system	
RP2	I felt nervous every time I took an action (e.g. pressed a button)	
RP3	I checked well my actions before moving to the next steps	
RP4	I had no hesitation to take an action	
RP5	I had no difficulty to try which feature (among other) to use	
Willingness to Learn		0,81
WL1	I wanted to learn how to use the system while I was using it	
WL2	I d like to learn more how to use the system	
WL3	I d like to learn how to use other similar systems too	
Perceived Ease of Use		0,76
PEOU1	The system is easy to use	
PEOU2	I do not need to try too hard to use the system effectively	
PEOU3	I can use the system without written instructions	
PEOU4	I can learn how to use the system easily and fast	
PEOU5	I can easily correct my mistakes while I use the system	
Perceived Usefulness		0,71
PU1	The system is useful	
PU2	The system makes me more productive	
PU3	The system makes me save time	
PU4	The system satisfies my needs and requirements	99">

Annex B. Normal Distribution Test Results

Table B1
Test of Normality (N = 30)

	Shapiro-Wilk		
	Statistic	df	Sig.
Perceived Usefulness	0,956	30	0,248
Perceived Ease Of Use	0,934	30	0,065
Self-Efficacy	0,933	30	0,057
Willingness to Learn	0,959	30	0,289
Risk-Perception	0,967	30	0,453

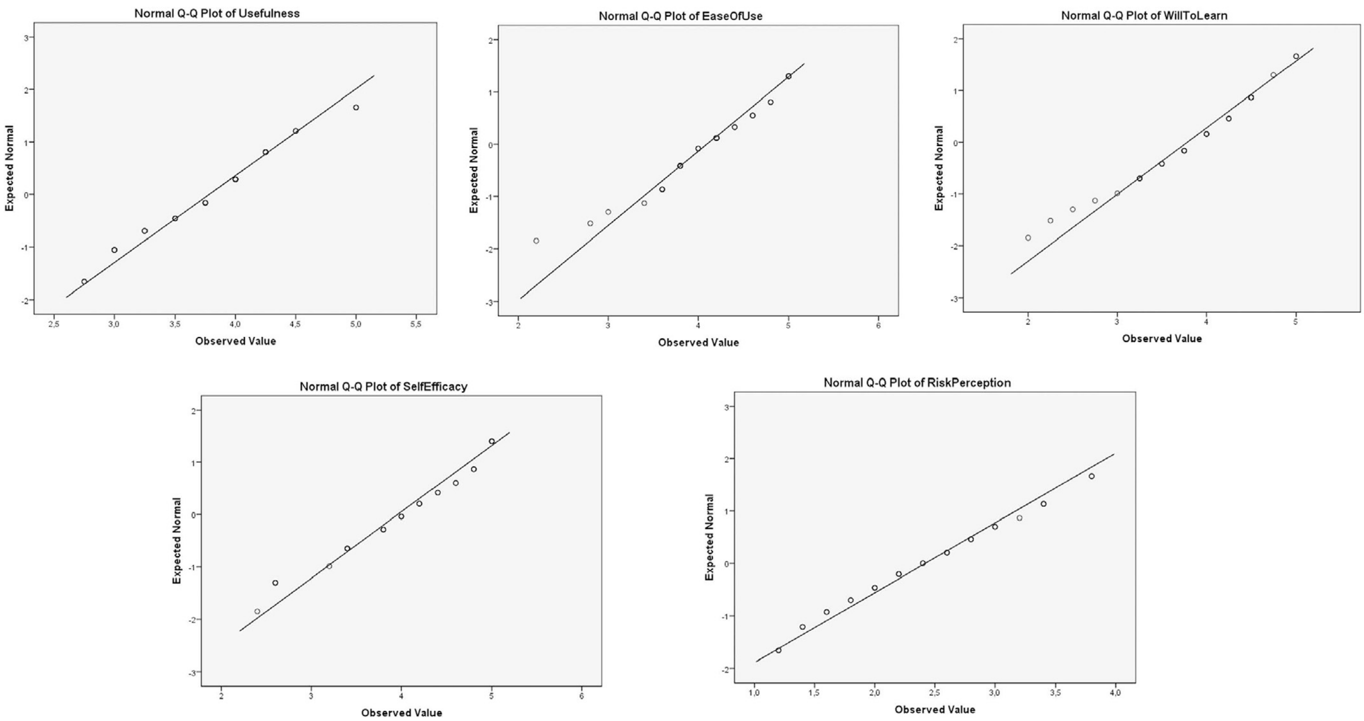
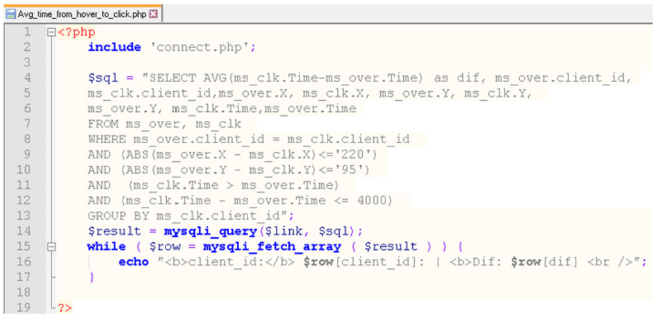


Fig. B1. Normal Q-Q Plots for the whole sample.

Annex C. Data Storage and Extraction Technology

Fig. C1. Admin panel of the mouse tracker.

Fig. C2. Code excerpts (JavaScript and SQL) for database tables' creation (A), data insert (B) and message exchange (C).

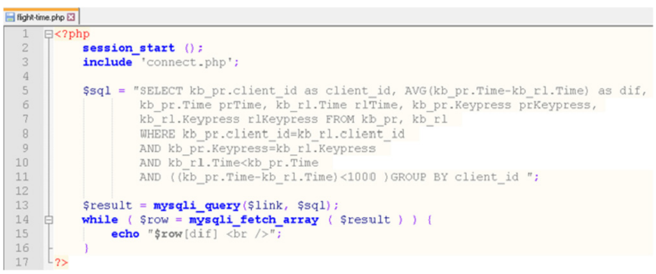



```php
<?php
    include 'connect.php';

    $sql = "SELECT AVG(ms_clk.Time-ms_over.Time) as dif, ms_over.client_id,
    ms_clk.client_id,ms_over.X, ms_clk.X, ms_over.Y, ms_clk.Y,
    ms_over.Y, ms_clk.Time,ms_over.Time
    FROM ms_over, ms_clk
    WHERE ms_over.client_id = ms_clk.client_id
    AND (ABS(ms_over.X - ms_clk.X)<='220')
    AND (ABS(ms_over.Y - ms_clk.Y)<='95')
    AND  (ms_clk.Time > ms_over.Time)
    AND (ms_clk.Time - ms_over.Time <= 4000)
    GROUP BY ms_clk.client_id";
    $result = mysqli_query($link, $sql);
    while ( $row = mysqli_fetch_array ( $result ) ) {
        echo "<b>client_id:</b> $row[client_id]: | <b>Dif: $row[dif] <br />";
    }

?>
```

Fig. C3. Code excerpt (PHP and SQL) for mouse data extraction (average time from mouse hover to mouse click).




```php
<?php
    session_start ();
    include 'connect.php';

    $sql = "SELECT kb_pr.client_id as client_id, AVG(kb_pr.Time-kb_rl.Time) as dif,
            kb_pr.Time prTime, kb_rl.Time rlTime, kb_pr.Keypress prKeypress,
            kb_rl.Keypress rlKeypress FROM kb_pr, kb_rl
            WHERE kb_pr.client_id=kb_rl.client_id
            AND kb_pr.Keypress=kb_rl.Keypress
            AND kb_rl.Time<kb_pr.Time
            AND ((kb_pr.Time-kb_rl.Time)<1000 )GROUP BY client_id ";

    $result = mysqli_query($link, $sql);
    while ( $row = mysqli_fetch_array ( $result ) ) {
        echo "$row[dif] <br />";
    }
?>
```

Fig. C4. Code excerpt (PHP and SQL) for keyboard data extraction (flight-time).

References

Akiyama, T., & Watanobe, Y. (2012). An advanced search interface for mobile devices. In *Proceedings of the 2012 joint international conference on human-centered computer environments (HCCE '12)* (pp. 230–235). New York, NY, USA: ACM.

Arapakis, I., Lalmas, M., & Valkanas, G. (2014). Understanding within-content engagement through pattern analysis of mouse gestures. In *Proceedings of the 23rd ACM international conference on conference on information and knowledge management (CIKM '14)* (pp. 1439–1448). New York, NY, USA: ACM.

Arroyo, E., Selker, T., & Wei, W. (2006). Usability tool for analysis of web designs using mouse tracks. In *CHI 2006 work-in-progress* (pp. 22–27).

Atterer, R., Wnuk, M., & Schmidt, A. (2006). *Knowing the User's every move – user activity tracking for website usability evaluation and implicit interaction*. Edinburgh, UK).

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioural change. *Psychological Review, 8*(2), 191–215.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, N.J: Prentice-Hall.

Beckwith, L., & Burnett, M. (2004). Gender: An important factor in end-user programming environments?. In *2004 IEEE symposium on visual languages - human centric computing* (pp. 107–114).

Beckwith, L., & Burnett, M. (2007). Gender HCI issues in end-user software engineering environments. In *End user software engineering*.

Beckwith, L., Burnett, M., Grigoreanu, M., & Wiedenbeck, S. (2006). Gender HCI: What about the software?. In *Computer, Nov. 2006* (pp. 83–87).

Beckwith, L., Sorte, S., Burnett, M., Wiedenbeck, S., Chintakovid, T., & Cook, C. (2005). Designing features for both genders in end-user programming environments. In *Proceedings of the 2005 IEEE symposium on visual languages and human-centric computing (VLHCC '05)* (pp. 153–160). Washington, DC, USA: IEEE Computer Society.

Bergadano, F., Gunetti, D., & Picardi, C. (2003). Identity verification through dynamic keystroke analysis. *Intelligent Data Analysis, 7*(5), 469–496.

Blackwell, A. (2002). First steps in programming: A rationale for attention investment models. In *Proc. IEEE human-centric computing languages and environments* (pp. 2–10).

Blackwell, A. F., & Morrison, C. (2010). A logical mind, not a programming mind: Psychology of a professional end-user. In *Proceedings of the 22nd annual workshop of the psychology of programming interest group (PPIG 2010). September 19-22, 2010*. Leganès, Spain: Universidad Carlos III de Madrid. Published by Maria Paloma Díaz Pérez and Mary Beth Rosson.

Blackwell, A. F., Rode, J. A., & Toye, E. F. (2009). How do we program the home? Gender, attention investment, and the psychology of programming at home. *International Journal of Human-Computer Studies, 67*, 324–341.

Borges, C. R., & Macías, J. A. (2010). Feasible database querying using a visual end-user approach. In *Proceedings of the 2nd ACM SIGCHI symposium on Engineering interactive computing systems (EICS '10)* (pp. 187–192). New York, NY, USA: ACM.

Burnett, M., Fleming, S., & Iqbal, S. (2010). Gender differences and programming environments: Across programming populations. In *Proceedings of the 2010 ACM-IEEE international symposium on empirical software engineering and measurement*.

Burnett, M., & Scaffidi, C. (2011). End-user development. In M. Soegaard, & R. F. Dam (Eds.), *Encyclopedia of human-computer interaction*. Aarhus, Denmark: The Interaction-Design.org Foundation.

Burnett, M., Wiedenbeck, S., Grigoreanu, V., Subrahmaniyan, N., Beckwith, L., & Kissinger, C. (2008). Gender in end-user software engineering. In *Proceedings of the 4th international workshop on End-user software engineering (WEUSE '08)* (pp. 21–24). New York, NY, USA: ACM.

Chen, Y. H., & Corkindale, D. (2008). Towards an understanding of the behavioral intention to use online news services: An exploratory study. *Internet Research, 18*(3), 286–312.

Chen, M., Anderson, J. R., & Sohn, M. (2001). *What can a mouse cursor tell us more? Correlation of eye/mouse movements on web browsing*. Ext. Abstracts CHI2001 (p. 3). ACM Press.

Churruca, S. L. (2011). *Comparative study of cursor movement patterns between a touchpad and a mouse devices*. Master Thesis. Department of information and communications Technologies, UPF.

ClickTale.(2006). http://www.clicktale.com.

Compeau, D., & Higgins, C. (1995). Application of social cognitive theory to training for computer skills. *Information Systems Research, 6*(2), 118–143. Computers in Human Behaviour, 17, 21–33.

Cooke, L. (2006). Is the mouse a "poor Man's eye tracker?. In *Usability and information design magazine*.

Costabile, M. F., Fogli, D., Fresta, G., Mussio, P., & Piccinnov, A. (2003). Building environments for end-user development and tailoring, human centric computing languages and environments, 2003. In *Proceedings. 2003 IEEE symposium on, 2003* (pp. 31–38).

Costabile, M. F., Fogli, D., Letondal, C., Mussio, P., & Piccinno, A. (2003). Domain-expert users and their needs of software development. In *Proc. Special session on EUD, UAHCI conference, Crete, Greece* (pp. 532–536).

Costabile, M. F., Mussio, P., Provenza, L. P., & Piccinno, A. (2008). End users as unwitting software developers. In *Proceedings of the 4th international workshop on End-user software engineering (WEUSE '08)* (pp. 6–10). New York, NY, USA: ACM.

Cyr, D., Hassanein, H., Head, M., & Ivanov, A. (2007). The role of social presence in establishing loyalty in eservice environments. *Interacting with Computers, 19*(1), 43–56.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*, 319–340.

Dijkstra, M. (2013). *The diagnosis of self-efficacy using mouse and keyboard input*. Master thesis. Utrecht University.

Djamasbi, S., Tulu, B., Loiacono, E., & Whitefleet-Smith, J. A. (2008). Can a reasonable time limit improve the effective usage of a computerized decision aid? *Communications of the Association for Information Systems, 23*(22), 393–408.

Epp, C., Lippold, M., & Mandryk, R. L. (2011). Identifying emotional states using keystroke dynamics. In *CHI conference on human factors in computing systems, 7–12 May, Vancouver, BC, Canada* (pp. 715–724).

Ferreira, S., Arroyo, E., Tarrago, R., & Blat, J. (2010). *Applying mouse tracking to investigate patterns of mouse movements in web forms*. Universitat Pompeu Fabra.

Fitts, P. M. (1954). The information capacity of the human motor system in controlling the amplitude of movement. *Journal of Experimental Psychology, 47*(6), 381–391.

Fitts, P. M., & Peterson, J. R. (1964). Information capacity of discrete motor responses. *Journal of Experimental Psychology, 67*(2), 103–112.

Freeman, J., Dale, R., & Farmer, T. (2011). Hand in motion reveals mind in motion. *Frontiers in Psychology*, 2.

Grigoreanu, V., Cao, J., Kulesza, T., Bogart, C., Rector, K., Burnett, M., et al. (2008). Can feature design reduce the gender gap in end-user software development environments?. In *Proceedings of the 2008 IEEE symposium on visual languages and human-centric computing (VLHCC '08)* (pp. 149–156). Washington, DC, USA: IEEE Computer Society.

Guo, Q., & Agichtein, E. (2008). Exploring mouse movements for inferring query intent. In *Annual ACM conference on research and development in information SIGIR'08, july 20-24, 2008, Singapore*. ACM 978-1-60558-164-4/08/07.

Hinbarji, Z., Albatal, R., & Gurrin, C. (2015). Dynamic user authentication based on mouse movements curves. In *MultiMedia modeling: 21st international conference, MMM 2015, Sydney, NSW, Australia, January 5-7, 2015, Proceedings, Part II* (pp. 111–122). Springer International Publishing.

Hornbæk, K., & Frøkjær, E. (2003). Reading patterns and usability in visualizations of electronic documents. *ACM Transactions on Computer-human Interaction, 10*(2), 119–149.

Khan, I. A., Brinkman, W.-P., Fine, N., & Hierons, R. M. (2008). Measuring personality from keyboard and mouse use. In J. Abascal, I. Fajardo, & I. Oakley (Eds.), *Proceedings of the 15th European conference on cognitive ergonomics: The ergonomics of cool interaction (ECCE '08)* (p. 8). New York, NY, USA: ACM. Article 38.

Khanna, P., & Sasikumar, M. (2010). Recognising emotions from keyboard stroke pattern. *International Journal of Computer Applications, 11*(9), 1–5.

Lee, G., & Chen, Z. (2006). Investigating the differences in web browsing behaviour of Chinese and European user using mouse tracking. In N. Aykin (Ed.), *Usability and internationalization, Part I, HCII 2007, LNCS 4559* (pp. 502–512). Springer-Verlag Berlin Heidelberg, 2007.

Leiva, A. L., & Hernando, V. R. (2008). A gesture Inference Methodology for user evaluation based on mouse activity tracking. In *Proceedings of the IADIS international conference on interfaces and HCI*. ISBN (Book): 978-972-8924-59-1.

Lieberman, H., Paternò, F., & Wulf, V. (2006). *End user Development: An emerging paradigm. Ser. Human-computer interaction series* (Vol. 9, pp. 1–8). Germany: Springer.

Litvinova, E. (2010). *XIDE - a visual prototype application for end user development of web applications*. Master's Thesis. Joensuu: University of Eastern Finland.

Liu, H., & Lieberman, H. (2005). Programmatic semantics for natural language interfaces. In *Proceedings of the ACM conference on human factors in computing* (pp. 1597–1600).

Loewenstein, G. (1994). The psychology of curiosity: A review and reinterpretation. *Psychology Bulletin, 116*(1), 75–98.

Magnuson, J. (2005). Moving hand reveals dynamics of thought. *Proceedings of the National Academy of Sciences of the United States of America, 102*(29), 9995.

McKinstry, C., Dale, R., & Spivey, M. (2008). Action dynamics reveal parallel competition in decision making. *Psychological Science, 19*(1), 22.

Monrose, F., & Rubin, A. D. (2000). Keystroke dynamics as a biometric for authentication. *Future Generation Computer Systems, 16*(4), 351–359. ISSN 0167-739X.

Moolla, A., & Bisschoff, C. (2012). Validating a model to measure the brand loyalty of fast moving consumer goods. *Journal of Social Sciences, 31*(2), 101–115.

Moon, J., & Kim, Y. (2001). Extending the TAM for a world-wide-web context. *Information and Management, 38*(4), 217–230.

Mueller, F., & Lockerd, A. (2001). *Cheese: Tracking mouse movement activity on websites, a tool for user modeling*. Seattle, Washington, USA: Ext. Abstracts CHI.

Nahin, A. F. M. NazmulHaque, Alam, J. M., Mahmud, H., & Hasan, K. (2014). Identifying emotion by keystroke dynamics and text pattern analysis. *Behaviour & Information Technology, 33*(9), 987–996.

Navalpakkam, V., & Churchill, E. (2012). *Mouse tracking: Measuring and predicting users' experience of web-based content*. SIGCHI.

Navalpakkam, V., Jentzsch, L., Sayres, R., Ravi, S., Ahmed, A., & Smola, A. J. (2013). *Measurement and modeling of eye-mouse behavior in the presence of nonlinear page layouts*. WWW.

Nunnally, J. (1967). *Psychometric theory*. New York: McGraw.

Ong, K. W. (2010). *Web application creation made easy: A Sql-Driven rapid development framework and a do-it-yourself platform*. Ph.D. Dissertation. La Jolla, CA, USA. Advisor(s) Alin Deutsch: University of California at San Diego.

Pajares, F. (2002). *Gender and perceived self-efficacy in self regulated learning, Theory into Practice*. The Ohio State University, on behalf of its College of Education, 41, 2.

Park, S. (2009). An Analysis of the Technology Acceptance Model in Understanding University Students' Behavioral Intention to Use e-Learning. *Education Technology & Society, 12*(3), 150–162.

Paternò, F. (2013). End user Development: Survey of an emerging field for empowering people. In *ISRN software engineering* (Vol. 2013, p. 11). Article ID 532659.

Payne, J. W., Bettman, J. R., & Johnson, E. J. (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 14*(3), 534–552.

Protogeros, N., & Tzafilkou, K. (2015). Simple-talking database development: Let the end-user design a relational schema by using simple words. *Computers in Human Behavior, 48*, 273–289.

Qian, L., LeFevre, K., & Jagadish, H. V. (2010). Crius: User-friendly database design. *Proc. VLDB Endow, 4*(2), 81–92.

Repenning, A., & Ioannidou, A. (2006). What makes end-user development Tick? 13 design guidelines. In H. Lieberman, F. Paternò, & V. Wulf (Eds.), *End-User Development: Empowering people to flexibly employ advanced information and communication technology*. Dordrecht: Kluwer.

Rodden, K. X., Fu, A. A., & Spiro, I. (2008). Eye-mouse coordination patterns on web search results pages. In *CHI '08 extended abstracts on human factors in computing systems, CHI EA '08* (pp. 2997–3002). New York, NY, USA: ACM.

Rode, J., Bhardwaj, Y., Perez-Quinones, M. A., Rosson, M. B., & Howard, J. (2005). As easy as "Click": End-user web engineering. In *Proceedings of the international conference on web engineering* (pp. 478–488).

Rode, J., Rosson, M. B., & Pérez-Quiñones, J. (2006). End user development of web applications. End user development. In *Human-computer interaction series* (Vol. 9, pp. 161–182).

Rodden, K., & Fu, X. (2007). Exploring how mouse movements relate to eye movements on web search results pages. In *WISI workshop*.

Scaffidi, C., Bogart, C., Burnett, M. M., Cypher, A., Myers, B., & Shaw, M. (2010). Using traits of web macro scripts to predict reuse. *Journal of Visual Languages & Computing, 21*(5), 277–291, 12/2010.

Scaffidi, C., Myers, B. A., & Shaw, M. (2008). Topes: Reusable abstractions for validating data. In *Proceedings of the international conference on software engineering* (pp. 1–10).

Shapiro, S. S., & Wilk, M. B. (1965). An analysis of variance test for normality (complete samples). *Biometrika, 52*(3–4), 591–611.

Shea, P., & Bidjerano, T. (2010). Learning presence: Towards a theory of self-efficacy, self-regulation, and the development of a communities of inquiry in online and blended learning environments. *Computers & Education, 55*(4), 1721–1731.

Silveira, C., Eloy, L., & Montiero, J. M. (2010). A query language for data access in ubiquitous environments. *Proceedings CILEI electronic journal, 13*(No. 3), 2010.

Spahn, M., Dörner, C., & Wulf, V. (2008). End user Development: Approaches towards a flexible software design questions to answer. In *16th European Conference on Information Systems (ECIS 2008)* (pp. 303–314). CISC(2008).

Sun, H., & Zhang, P. (2008). An exploration of affect factors and their role in user technology acceptance: Mediation and causality. *Journal of the American Society for Information Science and Technology, 59*(8), 1–12.

Svenson, O. (1993). *Time pressure and stress in human judgment and decision making*. New York, USA: Springer, Pletinum Press.

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. *MIS Quarterly, 15*(1), 124–143.

Tzafilkou, K., Protogeros, N., Karagiannidis, C., & Koumpis, A. (2017). Gender-based behavioral analysis for end-user development and the 'RULES' attributes. *Education and Information Technologies, 22*, 1853.

Tzafilkou, K., Protogeros, N., & Yakinthos, C. (2014). Mouse tracking for web Marketing: Enhancing user experience in web application software by measuring self-efficacy and hesitation levels. *International Journal of strategic and Innovative Marketing, 1*, 4.

Venkatesh, V., & Morris, M. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Quarterly, 24*(1), 115–139.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

Vizer, L. M., Zhou, L., & Sears, A. (2009). Automated stress detection using keystroke and linguistic features: An exploratory study. *International Journal of Human-Computer Studies, 67*(10), 870–886.

Wang, Y.-S., Wu, M.-C., & Wang, H.-Y. (2009). Investigating the determinants and age and gender differences in the acceptance of mobile learning. *British Journal of Educational Technology, 40*(1), 92–118.

Web Sources Microsoft (2017). https://docs.microsoft.com/en-us/windows/uwp/design/input/keyboard-events (Accessed 3 February 2018).

Zimmermann, P., Guttormsen, S., Danuser, B., & Gomez, P. (2003). Affective computing–a rationale for measuring mood with mouse and keyboard. *International Journal of Occupational Safety and Ergonomics, 9*(4), 539–551.