Gender-based behavioral analysis for end-user development and the 'RULES' attributes

Abstract This paper addresses the role of gender in End-User Development (EUD) environments and examines whether there are gender differences in performance and in correlations between performance and a set of behavioral attributes. Based on a review of the most prominent EUD-related behavioral Human Computer Interaction (HCI) theories, and the influence of gender on them, it attempts to classify all the gender related behavioral attributes influencing the end-users' performance. Then, it theoretically selects a subset of these attributes, namely Risk-Perception, Usefulness-Perception, Learning Willingness, Ease-ofUse-Perception, and Self-Efficacy, presents an example application and conducts a basic evaluation testing. The proposed attributes (their initials form the word RULES) can form the basis for the design of EUD-oriented user modeling techniques for gender-neutral self-adaptive software EUD environments.

Keywords GenderHCI ; End-user development (EUD); Human factors in EUD ; Behavioral user modeling; behavioral user profiles

1 Introduction

End-User Development (EUD) is usually defined as 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 artefact (Lieberman et al. 2006). In other words, people who are not professional developers can use EUD tools to create or modify software artifacts and complex data objects without significant knowledge of a programminglanguage.ThroughEUD,end userscan tunesoftware to fittheirrequirements more closely than would be possible without EUD. Moreover, because end-users significantly outnumber professional software developers (Scaffidi et al. 2008), EUD 'scales out' software development activities by enabling a much larger pool of people to participate.

According to Wikipedia, there are two basic reasons why EUD has become popular: one is because organizations are facing delays on projects and using EUD can effectively cut the time of completion on a project; the second reason is that software tools are more powerful and easier to use. Lessons learned from EUD solutions can significantly influence the software life cycles for commercial software products, in house intranet/extranet developments and enterprise application deployments.

While first EUD tools mainly focused on desktop graphical and spreadsheet applications, in recent years a considerable amount of work has been carried out to apply the EUD approach to web environments (Paternò 2013). There are several examples of EUD approaches for web applications (e.g. Ghiani et al. 2011, 2016, Lin et al. 2010; Macías and Paternò 2008; Miller et al. 2010; Nestler et al. 2011; Nichols and Lau 2008; Protogeros and Tzafilkou 2015; Soriano et al. 2007, etc.) and some for mobile applications (e.g. Cuccurullo et al. 2011; Danado et al. 2010; Danado and Paternò 2012a, 2012b; Seifert et al. 2011; Zbick et al. 2014, etc.). These web EUD tools attempt to meet interactive design and user-centered principles to enhance user experience and positively affect user perception (Kim and Ritter 2015; Sundar et al. 2014).

Many studies have emphasized the existence of different mental models between programmers and non-programmers, as well as of different priorities and motivations: they follow different approaches and reasoning strategies to modeling, performing and documenting the tasks to be carried out in a given application domain (Costabile et al. 2008; Blackwell and Morrison 2010). 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′ behavior while using computer software to customize, program and/or develop artefacts, since we can build better End-User Development tools if we know how end-users think (Rode et al. 2005).

Most of the resulting theories assume that end-user behavior is influenced and many times determined by a set of attributes/user characteristics, such as gender, age, location, level of education, interests, habits, goals, mood, personality traits, learning style, experience/expertise, etc. (McLeod and MacDonell 2011; Osvalder and Ulfvengren 2009; Rode et al. 2005; Rode and Rosson 2003). It should be clarified that the end-user population does not form one single mental category since various human factors tend to shape different end-user ′behavioral groups′.

HCI and EUD behavioural studies have concluded that gender plays a significant role in the end-users′ computer interaction behaviour, perception, acceptance and hence their overall user experience. Various research has shown that gender is a determinant factor to the end-users′ developing performance (Beckwith et al. 2005, 2006; Beckwith and Burnett 2004, 2007) and can determine their choices, debugging strategies, motivations and effort (Burnett et al. 2011; Grigoreanu et al. 2008; Kulenza et al. 2009). Gender-based behavioral consideration is important in recent (and mainly webbased) End-User Development since web environment renders a different type interaction between the software and the end-user and hence, a number of studies of women and EUD have also been conducted, focusing on how the design of web applications could be planned (Harshbarger and Rosson 2012; Rosson et al. 2007, 2010).

However, recent EUD research field has not comprehensively ′exploited′ the behavioral end-user theories to build appropriate user models and develop adaptive EUD software environments (in contrast to other HCI fields such as Learning Management Systems) to assist end-user developers build ′better′ software. This ′lack′ motivated our interest to gather all the gender-based behavioral attributes that affect EUD performance an select a subset of those which could be used to construct a behavioral user modeling approach. Later, this approach could be used as base line for the future implementation of self-adaptive and web-based EUD software systems. Our study is also a first attempt to gather and classify the gender-based behavioral attributes that tend to influence the end-user developers′ performance when working in EUD environments.

Aggregating though all the behavioral attributes referred in the distinct HCI literature works would be ′exhausting′ and probably inappropriate and misleading for the particular population of end-user developers, since we consider them be a special subgroup of the generic end-user population. Such a generalized approach would also lead to a user model structure composed of too many parameters, impractical to be implemented in the EUD modeling mechanisms. Hence, we had to restrict our research to the behavioral factors (and the attributes deduced by them) that are closely related to the end-user developers′ performance and can be identified in their behavior while interacting with EUD environments. In a combined research study of the most dominant EUD-HCI behavioral theories and the study field of GenderHCI (which is mainly focused on the end-user programmers/developers behavior) we could not but notice that gender is one EUD behavioral factor of particular importance: recent research has shown that gender is a very strong and determinant factor to the end-users′ overall development performance (Beckwith et al. 2005, 2006; Beckwith and Burnett 2004, 2007). Moreover, many times it determines the end-users choices, debugging strategies, motivations and even the users′ effort and generic perception while their computer interaction (Burnett et al. 2011; Kulenza et al. 2009). Literature research shows that gender also influences many (if not most) of the behavioral attributes (e.g. self-efficacy, ease-of-use perception, etc.) that are contributing to the end-users′ final performance.

Be social, psychological, biological or other, we do not aim to analyze the reasons that render male and female end users think or work differently, but we do step on these differences and consider gender as a de-facto strong factor influencing the end-users′ computer-personality^ and hence their developing-task behavior. All these gender differences have been already confirmed to exist by the underlying literature works, but what misses is a comprehensive behavioral model to analyze the end-user developers′ behavior and its relation to performance. In this context, this paper aggregates all the gender-influenced behavioral attributes existing in the end-user developers population and ′uses′ them (as main parameters) to build the structure of EUD behavioral user models. Our suggested subset of attributes (RULES) can be regarded as the very first step to create end-user developers′ behavioral profiles, so as EUD self-adaptive tools take them under consideration and assist the end-users in their developing activities.

Hence, the purpose of this paper is two-fold: to review the main gender-HCI theory foundations in order to aggregate the most dominant EUD gender-behavioral attributes and also to suggest the composition of a EUD behavioral user profile (or else model). This model can be implemented in adaptive software EUD systems to assist end-users enhance their developing performance.

The remaining of the paper is organized as follows. The next section presents some basic concepts of the Gender-EUD related literature stressing the most basic gender based behavioral differences existing among the end-users. What follows is a presentation of the theoretical foundations that dominate behavioral research in the HCI area. Gender related literature is outlined to result in the aggregation of the main gender differences that have been found to influence end-user developers. Afterwards, we present a basic literature review on user modeling principles and previous works. Then, we propose the RULES approach as a subset of the literature underlined behavioral attributes, namely Risk-Perception, Usefulness-Perception, Learning-Willingness, Ease-of-Use-Perception, and Self-Efficacy and providing theoretical assessment for their 'selection' to form our model's parameters. In order to provide with a deeper explanation and possible application of our approach we present an example application based on a use case scenario. Then, we conduct a field test, in a Greek university, using a modern web-based EUD prototype tool to evaluate the generic usefulness of such an approach. We present the experimental method, the research hypotheses and describe the procedure. Afterwards we present the results, discuss about their coherence and explain the reasons for the validity and usefulness of our suggested approaches. Finally, we conclude with a discussion on the application of the proposed approach and the wider implications of our work for the development of future EUD environments.

2 Theoretical foundation

In the past decades numerous studies reported on marked gender differences interacting with computers, such as different conception of computers, different motives for using computers, different preferences, different styles (Saadé et al. 2012) and even different cognitive styles (Hubona and Shirah 2004).

Behavioral studies also accept and explain the existing grounded differences in the way male and female end users process information and generally behave during their interaction with computer systems (Beckwith et al. 2006; Saadé et al. 2012; Subrahmaniyan et al. 2008). Gender has also been singled out as an important variable in the design of user interfaces and visualization techniques. It is also considered as an important user diversity issue for achieving Buniversal usability of web-based and other computer services (Hubona and Shirah 2004).

Researchers have been long reporting theory and empirical data pointing to gender differences in the use of end-user programming environments. Evidence of these differences has accumulated, indicating gender differences in programming environment appeal, playful tinkering with features, usage and attitudes toward end-user programming features, as well as end-user debugging strategies (Beckwith and Burnett 2004, 2007; Beckwith 2003; Beckwith et al. 2005, 2006, 2007; Burnett 2009; Burnett et al. 2008, 2010, 2011; Kissinger et al. 2006; Grigoreanu et al. 2006). In these studies, the two genders have been shown to both use different features and to use same features in a different way. One of the most important conclusions of these studies is that the features most conducive to females' success are different from the features most conducive to males′ success (Beckwith and Burnett 2004).

Moreover, according to Beckwith and Burnett (2004), ignoring the gender issue, while designing end-user programming environments, would miss the opportunity of enhancing the effectiveness of end-user programmers. As they explain, such a solution could be achieved by incorporating appropriate mechanisms to support gender associated differences in decision making, learning, and problem solving.

In their extended both qualitative and quantitative research, Beckwith et al. (2007), have aggregated a series of potential gender differences in end-user problem-solving environments, specifically regarding how each gender interacts with the environment, and to specific problem solving features within the environment. Their experimental results showed that gender differences do exist among end users in self-efficacy, motivations, problem-solving styles, learning styles, and information processing styles.

However, most of the previous-mentioned EUD and HCI behavioural studies have conducted their experiments on traditional EUD desktop spreadsheet environments (such as Excel sheets). As already mentioned, in recent years a considerable amount of work has been carried out to apply the EUD approach to web environments (Paternò 2013).

Since web-based EUD is mostly a recent trend (Paternò2013), there is limited gender or other user behavioral human-oriented research on recent, web-based EUD environments. There are various research works analyzing gender differences in website production, web interface and task preferences and interaction with web in general (e.g. Moss and Gunn 2009) but only a few research has been conducted to study users′ behavior while interacting with web-based developing-oriented (EUD) applications.

Given all the previous evidence, it can be said that gender differences are potentially critical to our understanding of how end users make their decisions about adopting and using new computer software to develop their own artifacts.

3 Theory foundations

This section outlines some of the most predominant end user behavioral theories that shed light on gender factors in HCI and EUD behavioral research, namely: (i) Attention Investment Theory, (ii) Technology Acceptance Theory, (iii) the Self-Efficacy Theory, (iv) the Information Gap Theory, and (v) Personality Traits Theory. Finally, we include in our theories the recently emerged (vi) Gender HCI research field which focuses on current behavioral issues in EUD area.

The above theories were selected mainly due to their impact on EUD, as this is demonstrated in the related literature. The proposed model′s constructs have been derived by these theories. These constructs need to be short in number because range of the adaptation responses that can be provided to the user according to their model is not very large (EUD adaptation approaches and interface design approaches, such as elements of intelligent interfaces, are limited).

3.1 The attention investment theory

The Attention Investment theory (Blackwell 2002) proposes a model of how end-users make decisions (to use particular environment features, for example) when engaged in problem solving. As described in Blackwell and Hague (2001), the Attention Investment model is a Bdecision-theoretic account of programming behavior^.

Simply explained by Burnett et al. (2011), Attention Investment is an analytical model of user problem-solving behavior that allows a designer to account for the costs, benefits and risks that users need to consider in deciding how to complete a task. That is, end-users, in deciding to take any action, first weigh the perceived costs, pay-offs, risks and benefits of taking that action. Perception of risk thus plays an important role in a user′s decision making about whether to use end-user programming features. Risk Perception is actually a subpart of the more generic Problem Solving attribute. As explained in Blackwell′s Attention Investment Model theory (Blackwell 2002; Blackwell et al. 2009) Risk Perception strongly influences the end users′ behavior through their cost/benefit evaluation. According to Blackwell (2002) terminology, 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. Blackwell′s Attention Investment model provides a cognitive model of these insights, describing individuals′ allocations of attention as cognitive Binvestments. According to the model, a user weighs four factors (not necessarily explicitly) before taking an action: (Bandura 1977) perceived benefits, (Bandura 1986) expected pay-off, (Batrinca et al. 2012) perceived cost, and (Beckwith and Burnett 2004) perceived risks. If they 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 and Burnett 2004). The Attention Investment model is related to other descriptions of end-user strategy such as Carroll and Rosson′s Paradox of the Active User (1987) which describes the way that users are reluctant to suspend productive use of already learned (but perhaps inefficient) methods, and tend not to engage in learning further skills, even though this might bring longer-term benefits.

According to the definition of Bauer (1960) Risk Perception is the combination of uncertainty plus seriousness of outcome^. Researchers have discovered that if an individual feels uncertain, uncomfortable and/or anxious toward a new service then the greatest influence on the adoption decision is the individual′s risk perception (Featherman and Fuller 2003). Similarly, Beckwith et al. (2011) suggest that such behavior can also apply to end-users deciding to use new features in problem-solving and other computing environments.

Gender comes into play because it influences the perception of cost, benefit, and risk. There is evidence that women perceive higher risk in everyday choices and behaviors than men do (Finucane et al. 2000). Just as the Attention Investment Model predicts, higher perception of risk can lead to differences in actual behavior, and such differences have been many times tied to gender. For example, due to the self-efficacy differences a female's perception of the cost of learning a new feature may be higher than a male's perceived cost to learn the same feature. Moreover, detected differences in motivations to use technology also suggest gender differences in perceived benefits (Burnett et al. 2011).

3.2 The technology acceptance theory

The original Technology Acceptance theories (i.e. those 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 and Burnett 2007).

In particular, the recently emerged End-User Computer Acceptance (EUC) theory introduces the most relevant human factors affecting the end-users' overall behavior and performance as follows (Chen and Corkindale 2008; Cyr et al. 2007; Sun and Zhang 2008).

- Computer Self-Efficacy: A person's perception of their ability to use computers to complete a task.
- Computer Enjoyment: A person's reception of joy from using software.
- Perceived Ease of Use: The degree to which a person believes that using specific software will be easy and effortless.
- Perceived Usefulness: The degree to which a person believes that using specific software is useful for his/her job performance.
- Subjective Norm: The degree to which a person believes that other people that believe that that he/she is capable of accomplishing a particular task.
- Internal Computing Support and Training: Training and technical support provided inside the company.
- Task-Technology Fit: The degree to which an organization's application meets the information needs of the task.
- External Computing Support and Training: Management support or external training provided from outside the company.

According to TAM, user acceptance, and ultimately technology use, is determined by two key factors (among the above mentioned): perceived usefulness and perceived ease of use (Venkatesh and Morris 2000). The relative importance of each differs by gender (Venkatesh and Morris 2000). Gender related empirical findings in TAM show that female and male users differ in beliefs, intention and usage. Venkatesh and Morris (2000) found that women are more influenced by perceived ease of use in adapting new technology whereas men are more strongly influenced by perceived usefulness. The same is concluded in Terzis and Economides (2011) where the authors, based on TAM constructs, examined gender differences in users′ behavioral intention to use a computer based assessment (CBA). Their findings also indicate gender differences in perceived ease of use, behavioral intention and social influence.

According to Teo et al. (2015) the limited empirical findings in this area suggest that gender differences or lack thereof, related to perceived usefulness of technology may depend on the context in which the relevant technology will be used.

Technology acceptance gender issues are crucial in the interaction between users and EUD systems since perceived ease of use and perceived usefulness are strong variables that can determine the end-users′ perceived experience and their developing task performance (Beckwith et al. 2006, 2007; Beckwith et al. 2005; Burnett 2009, Burnett et al. 2008, 2010, 2011; Lee 2008). Hence, technology acceptance should be integrated in the behavioral analyses of EUD researches.

3.3 The self-efficacy theory

Bandura′s (1977, 1986) self-efficacy theory defines self-efficacy as a person′s belief in his/her ability to do a specific task. Presuming ability to complete a task, self-efficacy distinguishes how individuals will approach and perform the task.

Self-efficacy actually predicts reaction and behavior in challenging situations (Bandura 1986). According to Bandura′s (1977) social-cognitive theory, people with low self-efficacy for a task tend to expend less effort on the task, use simpler cognitive strategies, show less persistence when encountering difficulties, and reveal lower performance rate than people with high self-efficacy. Not only does self-efficacy predict end-user task behavior, but it ultimately affects performance outcomes, influencing whether or not an individual succeeds at the task. Individuals with high self-efficacy for a specific task have several characteristics that aid their success in these tasks, characteristics that ′self-doubters′ lack (Bandura 1986). Hence, research has linked self-efficacy much closely to performance accomplishments, level of effort, and the persistence a person is willing to expend on a task.

As Blackwell et al. (2009) point out, being a challenging task, software development renders a person with low self-efficacy may be less likely to persist when a task becomes challenging or may calculate attention investment trade-offs differently.

In software applications, studies have found gender differences in self-efficacy. Females generally have lower computer self-efficacy than males, and this has been tied to feature usage (Hartzel 2003) and many times to debugging features.

Being a specialized subset of self-efficacy, ′computer self-efficacy′ is defined as a person′s judgment of his/her capabilities to use computers in a variety of situations (Compeau and Higgins 1995).

Researchers have reported gender differences in computer self-efficacy across nationalities and across levels of computer expertise (e.g. Beckwith et al. 2007; Beyer et al. 2003; Colley and Comber 2003; Margolis and Fisher 2003). And low computer self-efficacy among females is a prevalent research result in the literature. Females' low self-efficacy is further complicated by their tendency to attribute failure at a task to their own lack of capability, whereas the males attribute this to the difficulty of the task (Stipek and Gralinski 1991).

3.4 The information gap theory

Loewenstein's (1994) information-gap theory draws several earlier theories on curiosity in to one theory. According to Loewenstein, curiosity arises when one's informational reference points in a particular domain become elevated above one's current level of knowledge^, where the informational reference point^ is what one wants to know.

The information-gap theory was the backbone in the development of the surprise-explain-reward strategy (Robertshon et al. 2004; Ruthruff et al. 2004; Wilson et al. 2003) an approach, aimed at changing end-user programmers' perceptions of risk and reward. The development and success of the surprise-explain-reward strategy relies on raising a user's curiosity to an ideal level, such that he/she becomes aware of missing knowledge, but perceives it as attainable. For this reason, understanding the underlying theory of the information-gap theory is important for the design of problem-solving environments that depend on it.

Research into curiosity indicates that surprising a user to arise his/her curiosity can render him/her search for an explanation. Hence, the Bsurprise^ component is intended to distract users from bias toward a habitual strategy (arising their curiosity), the Bexplain^ provides enoughinformationfortheusertoreassesstheattentioninvestmentfactors,andtheBreward ^ makes clear to the user what the payback has been for that investment choice, in a way that will influence future choices of strategy. Scaffidi et al. (2010) implement a Surprise-ExplainReward Model to 'manipulate' end-users testing and debugging behavior in spreadsheet environments. In particular, they use colored borders to surprise the user and attract user's attention to areas that need testing, also providing him/her with a potential reward.

As regarding to gender, it can significantly impact the effectiveness of using a Bsurprise^ component to arise the user's curiosity. In particular, the differences in end-users' self-efficacy can determine the level a user's curiosity could reach at, and hence predict the 'surprise' effectiveness to the particular user.

3.5 The personality traits theory

Traits are lasting aspects of individuality that differentiate one person from another. All persons share the same basic set of traits, but people are different in how much the trait applies to them (McCrae and Costa 1999). Much research suggests that individual personality traits can be classified into five basic dispositional traits which are typically called the Big Five or OCEAN: Openness, Conscientiousness, Extraversion, Agreeableness, and Emotional Stability (sometimes denoted as the opposite, Neuroticism) (Costa and McCrae 1992; Costa et al. 2001).

As Shneiderman (1980) has stated in his famous book Software Psychology: Personality variables play a critical role in determining interaction among programmers andintheworkstyleofindividualprogrammers^.Manyresearchershavenotedthepersonal characteristics of individuals who appear intrinsically motivated to notice and explore new technology options (e.g. Rosson et al. 2004; Zang and Rosson 2010). Researchers generally agree that personality is more important than intelligence in programming tasks. Being such a crucial factor for programmers one could easily deduce that personality plays a key role for end-user programmers as well. And indeed many recent studies suggest that the user′s personality in HCI plays an important role for the overall success of the interaction (Batrinca et al. 2012; Bickmore and Picard 2005; Nass and Brave 2005).

Many researchers have also associated personality traits to technology acceptance and computer use in general. For instance, the results in Terzis et al. (2012) indicate that the five personality factors affect Computer Based Assessment (CBA) acceptance. Devaraj et al. (2008) and Özbek et al. (2014) showed that user personality has effects on perceived usefulness and subjective norms toward the acceptance and useof technology. Papamitsiou and Economides (2014) showed that personality factors are significant predictors in the temporal estimation of students′ performance in computer based testing.

Moreover, many scientists from different research areas as Psychology, Neurology, Philosophy and Affective Computing agree that human reasoning and decision making use human psychological aspects (Thagard 2006; Trappl et al. 2003). Therefore, when humans try to personalize services to other humans, psychological aspects like Personality Traits, should be taken into account.

Research evidence suggests that the two genders differ with respect to personality traits (Costa and McCrae 2001; Mastor 2003; Srivastava et al. 2003). The literature also suggests a potential link between personality traits, gender, and computer self-efficacy. As already mentioned, computer self-efficacy (that is strongly gender defined) is important in user acceptance of information technology and end-user performance. Recent research results (Saleem et al. 2011) indicate that four of the five stable personality traits, as measured by the Big-five factors of personality, contribute to explain computer self-efficacy. Taking gender into account, results show that the traits of neuroticism, extraversion, and agreeableness are significantly related to computer self-efficacy for women but not for men. In this light, we strongly believe personality traits to be coexisting determinant factors for the perceived gender differences in EUD, as presented in the next sections.

3.6 The gender HCI research field

According to the Encyclopedia of Gender and Information Technology (Trauth 2006a), field studies have been conducted in different countries to further develop and evaluate the Theory of Individual Differences as it relates to IT and gender (Trauth 2002, 2006b, 2006c, 2013; Trauth et al. 2004, 2009).

In the field of Human Computer Interaction (HCI) and its sub-field of End-User Development (EUD), many research works (e.g. Beckwith et al. 2005, 2006, 2007; Beckwith and Burnett 2004, 2007; Burnett 2009; Burnett et al. 2010; Burnett et al. 2008, 2010, 2011; Saadé et al. 2012; Subrahmaniyan et al. 2008) have found that endusers tend to be ʻproneʼ to the influence of human factors such as gender, while interacting with computer environments.

Gender HCI examines ways in which software features can interact with gender differences. While HCI concerns itself with the design and evaluation of interactive systems for human beings, such as user interface design, Gender HCI focuses on the differences in how males and females relate to these interactive systems and their respective designs.

Gender HCI (Beckwith and Burnett 2004) explores the different way male and female end-users behave when interacting with computer systems, especially with desktop-based end-user programming environments. The authorsʼ research was a continuation of investigating visual programming for managing spreadsheets. Gender HCI has proved that men and women tend to have different perceptions and preferences with respect to the use and satisfaction with different features of these computer systems. The main aspects of Gender HCI include self-efficacy and confidence issues as related to problem solving tasks on a given interface design, willingness to try out new and different features, performance of tasks, tinkering/exploratory behavior, motivations for system usage, general attitudes towards interface designs, etc.

In particular, Gender HCI research regards the following aspects:

- Confidence as related to problem solving tasks on a given interface design. (In this point we have to note that when refer to Gender HCI, confidence reflects to selfefficacy, i.e. a personʼs belief in his ability to perform a specific task (Bandura 1977) and it should not be confused with self-confidence, which has a more general meaning including the value one is giving to himself.).
- General attitudes towards interface designs, web apps, and how and why to use them. & Willingness to try out new and different features on an extant and familiar interface design.
- Performance of tasks on large vs. small user interface displays.
- Graphic design reactions.
- Testing and debugging strategies.
- Tinkering/ Exploratory behavior.
- Motivations for systemsʼ usage.

Gender HCI example research works regarding EUD issues are the ones of Burnett (2009); Burnett et al. (2008, 2010, 2011); Beckwith and Burnett (2004, 2007) and Beckwith et al. (2005, 2006, 2007) in which the researchers study the users′ gender based differences while developing debugging strategies and/or using features while working on spreadsheet environments. They have designed and implemented features for spreadsheet prototypes that take the gender differences into account (Burnett et al. 2011). According to Beckwith and Burnett (2004), ignoring the gender issue while designing end-user programming environments would miss the opportunity of enhancing the effectiveness of end-user programmers. As they explain, such a solution could be achieved by incorporating appropriate mechanisms to support gender associated differences in decision making, learning, and problem solving.

Kulenza et al. (2009) present an innovative machine learning approach to determine arisen debugging issues, both in general and also separately for male and female end-users. Other recent studies focus on the usability provided by different interface designs as related to gender (Saadé et al. 2012) and in differences between men and women regarding their perceptions and effects on the relationships among the constructs that affect the behavioral intention to use computer based assessment systems (Terzis and Economides 2011).

A number of studies of women and EUD have also been conducted, focusing on how the design of web applications could be planned (Harshbarger and Rosson 2012; Rosson et al. 2007; 2010).

Stressing this need to address gender-differences in computer interaction, a recent research work of Burnett et al. (2016) designed and suggested a new methodology, named GenderMag, to find gender-inclusiveness issues in software, so that software developers or user experience designers can design and produce problem-solving software that is more usable by the end-users. GenderMag can be used to analyse usability based on a set of gender-oriented attributes such as self-efficacy, risk-perception, tinkering, motivation and information processing style.

3.7 List of gender attributes in EUD behavior

To organize the relevant literature into a coherent form, we have theoretically devised a list-taxonomy of this work (see Table 1). Each element of the list is a particular issue that has emerged as a recurring theme from the literature we survey here. These are recognized to influence the end-users′ behavior as well as their computer performance, especially in EUD activities.

Many of the listed issues have interdependencies with one another but each issue was selected due to having received attention as a gender-influenced attribute for the end-users in multiple literature works.

Attempting to strictly focus on EUD research, our list does not include HCI broad gender-differentiated attributes that are being indicated in some HCI literature works, such as those of Problem Solving, Learning Style and Information Processing, because of being generic and this would increase complexity in our user model 'construction'.

These attributes' values (eg. linear/nonlinear Problem Solving, holistic/elaborative Information Processing, abstract/concrete Learning Style) can significantly increase the end-users' overall behavior and performance (e.g. nonlinear Problem solving could reveal Correlation among unrelated concepts/lack of objective/attention deficit/lose control/higher risk of failure, etc.; elaborative Information Processing could reveal Higher cognitive effort/information overload for simple tasks, and abstract Learning Style could reveal Difficulty in: concentrating at one thing at a time).

Although excluding them (because of their generic aspect), many of the reviewed theoretical foundations (e.g. Information Gap Theory − Loewenstein 1994; Attention Investment Theory, −Blackwell 2002; etc.) have developed to reveal all the aforementioned specific behavioral attributes.

Hence, instead of using these generic attributes, we include in our model some basic sub-parts of them. For instance, Risk-Perception can be considered as a sub-part of the generic problem-solving attitude (Blackwell 2002), Curiosity is reflected in the generic information processing attitude (Loewenstein 1994) and Tinkering can be reflected in the Learning style; for example tinkering behavior can reveal an experiential related learning style (e.g. Davies et al. 2012; Marin 2014).

Moreover, related literature indicates some additional gender-determined factors as influencing the end-users' behavior, such as Facilitating Conditions and Social Influence (Terzis and Economides 2011), but we do not consider them as end-user developers' behavioral attributes, since they depend on 'external' sources.

In this point we should make clear that we do not aim to provide analytic statistical results showing that end-user developers do differentiate their behavior depending on the following attributes, since their examination can be found in the corresponding research works. Our distinct contribution is to concentrate and clearly taxonomy all the gender-based behavioral attributes that main EUD-related HCI researches found to influence the end-users' developing performance. This papers scope is the attributes' concentration and not the confirmation of the gender differences reflected on them. All these gender differences have been already confirmed to exist by the underlying literature works, but as we have already mentioned what misses is a comprehensive behavioral model to analyze the end-user developers' behavior.

Table 1 List of gender-based EUD behavioral attributes

Behavioral attribute	Theory foundation	Support evidence
Self-efficacy (or computer self-efficacy)	Self-efficacy theory; Technology acceptance theory; Personality traits theory; Gender HCI	Beckwith et al. 2005, 2006, 2007; Hartzel 2003; Burnett et al. 2010, 2011; Beckwith and Burnett 2004; Grigoreanu et al. 2008; McIlroy et al. 2001; Shea and Bidjerano 2010; Terzis and Economides 2011
Overconfidence	Gender HCI	Burnett et al. 2003; Beckwith and Burnett 2004
Curiosity	Information gap theory	Hartzel 2003; Grigoreanu et al. 2008
Tinkering (or exploring-behavior)	Gender HCI; Technology acceptance theory	Beckwith et al. 2005, 2006, 2007; Burnett et al. 2010, 2011; Grigoreanu et al. 2008; Martinson 2005; Rode 2008
Willingness to learn (new tech, or to use new features), or else learning willingness	Attention investment theory; Gender HCI	Beckwith et al. 2005; Broos 2005; Burnett et al. 2010; Grigoreanu et al. 2008
Risk-perception	Attention investment theory; Gender HCI	Beckwith and Burnett 2004; Finucane et al. 2000; Byrnes et al. 1999
Usefulness-perception	Technology acceptance theory	Chen and Corkindale 2008; Cyr et al. 2007; McLeod and MacDonell 2011; Featherman and Fuller 2003; Saadé et al. 2012; Sun and Zhang 2008
Ease-of-use-perception	Technology acceptance theory	Beckwith and Burnett 2004; Featherman and Fuller 2003; Saadé et al. 2012
Perceived-playfulness (or playful-behavior)	Technology acceptance theory	Grigoreanu et al. 2008;Terzis and Economides 2011

As will be showed in the results' section, these attributes tend to differently affect male and female end-users developing performance. Table 1 shows all the reviewed Gender-based EUD behavioral attributes and Fig. 1 summarizes their relevant theories foundations.

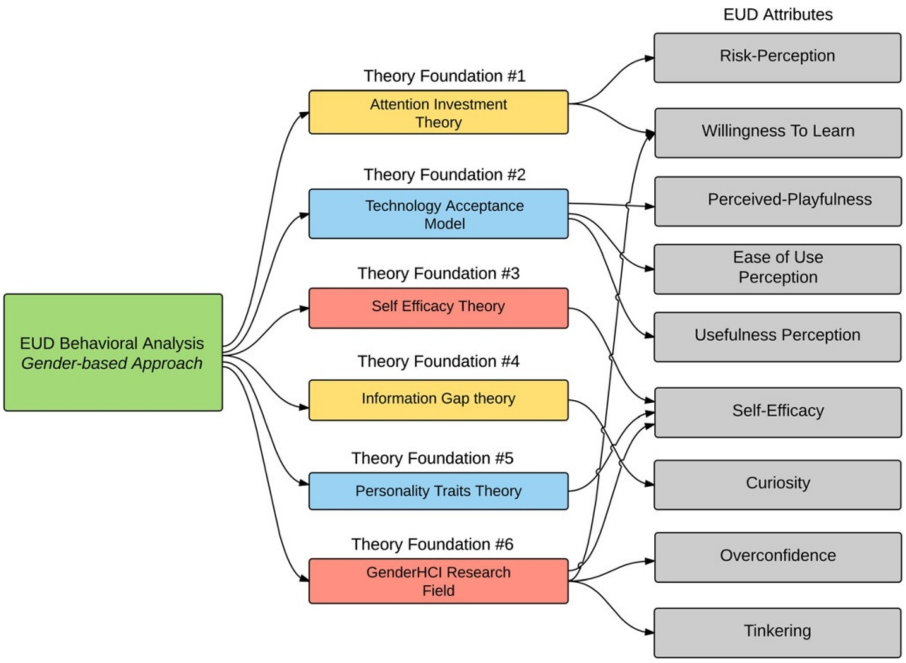

Fig. 1 EUD gender-behavioral attributes and relevant theories

4 Behavioral user modeling and related work

In this section we describe the main philosophy of user modeling for adaptive systems and we present some previous works closely related to our suggested EUD modeling approach (which is presented in the next section).

4.1 User modeling for adaptive systems

One of the goals of software adaptation is to assist users in performing their task in the most efficient way. That implies, if possible, an adaptive system should not interfere with the main task of the user and should not demand from him/her extra efforts to maintain the effective adaptation (Sosnovsky and Dicheva 2010). User modeling methodologies are concerned to provide a foundational solution to the aforementioned 'problem' area.

User modeling has inspired the development of numerous application systems in various areas, subsequently developed to collect different kinds of information about the current user, and to adapt to him/her in different ways (Kobsa 2001). Models are created of user interaction using artificial intelligence and statistical methods. They are constructed using a variety of learning techniques including the vector space model, genetic algorithms, or clustering. The acquired model can then be used for analyzing and predicting the future user behavior (Zhang et al. 2007).

There are several types of user models being the most used:

& Static user model: Information about the user is gathered and stored. The system doesn′t monitor or learns the changes in the user′s way of interacting with the system (Johnson and Niels 2005).
& Dynamic user model: The system observes the way the user interacts with it and the model is updated, resulting in an updated model of the user (Hothi and Hall 1998).
& User models by Stereotype: Based on statistical information of a targeted user demographic (Rich 1998).

Usually researchers used a mixture of the aforementioned models when developing a user model based system (Mejía et al. 2012).

Some adaptive systems store individual information only for a single characteristic while others model users along multiple dimensions. It is worth to mention that among all kinds of user-adaptive systems, it is the adaptive educational systems (AES) that have the longest history of research (Sosnovsky and Dicheva 2010). A worth to mention example is the case of AHES′ student model implementation (Martins et al. 2008) which includes aspects such as:

- initial user knowledge;
- objective and plans;
- cognitive capacities;
- learning styles;
- preferences;
- academic profile (technological studies versus economic studies and management, knowledge of literature, artistic capacities, etc.);
- age and type of student;
- cognitive style (affective, impulsive, etc.);
- personality aspects (introverted, extroverted, etc.).

What the AHES finally produces is an adaptive navigation support, an adaptive content selection and an adaptive presentation.

Another interesting approach adapting user modeling methodologies which is relative to ours, is the one used by some recommender systems. In general recommender systems are able to act on behalf of the user by gaining knowledge of the user′s value system and decision policy, something similar to our goal if we consider the EUD environment as a system that ′recommends′ to the user specific developing features based on his/her preferences and observed behavior. Lakiotaki et al. (2011) have developed in their work a recommender system framework which creates user-profile groups and uses collaborative filtering with multi criteria decision analysis techniques to provide a comprehensive user modeling methodology. In their inspiring work they face the recommendation process as a decision problem, offering the prospect to exploit techniques from Decision Theory to build a model representing the user′s preferences. Such a perspective seems to be useful for our particular EUD oriented approach. Complementary, Nunes et al. (2008) suggest the creation of psychological user profiles to support the decision making process in recommendation systems. Their research proves that user personality traits stored in user profiles and processed by recommender systems can provide optimal recommendations.

Relative seem also to be some works within the area of intelligent user interfaces. An interesting approach is the Dynamic Bayesian Network (DBN) developed by Hui and Boutilier (2006) aimed to observe the user′s behavior and generate a general user model based on specific user′s attitudes and personality traits. After the observations made, the DBN has to decide whether to suggest help to the user. Such an approach has derived from Microsoft Research on the Lumiére Project (Horvitz et al. 1998) which suggested a Bayesian Network model to take into account the user′s needs and goals and showed that it is possible to identify user goals and needs. Moreover it determined that the users′ necessity of assistance depends on their expertise level and the difficulty of the task. Finally, it was proved that the users′ needs influence their behavior such as the menu surfing and pausing after an activity.

The urgent need for human centered modeling techniques is recently emphasized by Mejía et al. (2012) who confirm that there is not a model that integrates aspects such as psychological, cognitive, and physical. Thus they suggest a user model integrating all the user′s characteristics (psychological, cognitive, demographic, education, etc), aimed at achieving an adaptive software interface improving the overall usability of any system. Their proposal seems to be complementary to ours since it contributes to the state of the art of human oriented modeling implementations for adaptive systems.

As we can see, all the afore mentioned approaches either implement user modeling techniques in specific HCI fields or simply suggest a general more human-centered adaptation. However, there is not an approach to comprehensively implement behavioral user modeling targeted at the development of adaptive EUD system environments programmed to take into account the specific needs and preferences of the particular end-user developer population. Thus, in the current study we attempt to accomplish such a behavior-oriented user modeling approach, aiming at the enhancement of the end-user performance while his/her interaction with adequately adaptive EUD system environments.

4.2 The proposed ′RULES′ attributes

Based on the analysis of section 3, we propose RULES as a subset of behavioral attributes that could be used in behavioral modeling implementations for the EUD users. More particular, our suggested approach uses a subset of the attributes presented in Table 1 in an attempt to define the structure of behavioral end-user profiles, suitable to be used during user modeling implementations in EUD environments.

Hence, we propose a user profile formation approach consisting of five behavioral attributes. As it is explained below, these five attributes can collectively reveal the users′ ′developing task personality′, shedding light on their strong and weak points concerning their overall EUD task performance. Based on the users′

gender and behavioral profile (i.e. the five attributes-based user model), the system can implement a decision making mechanism to provide the appropriate adaptation.

Instead of using all of the afore-presented attributes (in Table 1) for our model formation, we attempt to exclude some of them based on the correlations they have with each other (according to the studied literature) and the quantity of information they provide. Doing this, we create a clear and simple user profile (or else user model), composed of particular attributes (functioning as the model′s parameters) that can be easily defined and detected by the EUD system behavior observation (or monitoring) mechanisms.

The first attribute we exclude is Curiosity. According to Loewenstein, Bcuriosity arises when one′s informational reference points in a particular domain become elevated above one′s current level of knowledge^, where the Binformational reference point^ is what one wants to know. Curiosity as a behavioral attribute was the backbone in the development of the surprise-explain-reward strategy (Robertshon et al. 2004; Ruthruff et al. 2004; Wilson et al. 2003) an approach, aimed at changing end-user developers′ perceptions of risk and reward. The development and success of the surprise-explain-reward strategy relies on raising a user′s curiosity to an ideal level, such that he/she becomes aware of missing knowledge, but perceives it as attainable. Research into curiosity indicates that surprising a user to arise his/her curiosity can render him/her search for an explanation, but curiosity needs self-efficacy in order to be expressed by the user. Moreover, according to Loewenstein′s information gap theory, 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 (tinkering) and willingness to learn, enhancing at last their performance (Burnett et al. 2011). Hence, we decided to exclude Curiosity mainly because it is tightly associated to Tinkering and Self-Efficacy (Beckwith et al. 2006; Grigoreanu et al. 2008) and Tinkering is much easier to be detected in a user′s behavior, a user for instance that chooses new features, searches through the menu items and moves backwards after completing new actions, suggest Curiosity be totally substituted by Tinkering. Self-Efficacy is also easy to be measured through the user mouse movements (e.g. straight patterns, movement inclination towards items, time between clicks, pausing times, etc.) (Lee and Chen 2007; Ferreira et al. 2010). Moreover, curiosity could be hidden behind Learning Willingness actions and Learning-Willingness can be easily detected in the user′s behavior (e.g. through instructions reading, video- tutorials viewing, searching on the web, using new features etc.). Learning-Willingness is an important EUD behavioral attribute thataffectstheend-users′overallperformancesinceitrevealstheuser′smotivationpower, determines the amount of effort the user makes and the perspectives of his/her future performance enhancement. Willingness-To-Learn is important because it can ′predict′ the end-user′s willingness to try, persist, tinker and even study to learn how to use new features and EUD technologies (Burnett et al. 2010; Grigoreanu et al. 2008).

Perceived-Playfulness could be associated to Tinkering (exploratory behavior), hence we also exclude it. In fact, what ′Perceived-Playfulness′ or ′Enjoyness′ means in other theories such as the Technology Acceptance Model, can be totally replaced by the term of Tinkering in the area of EUD.

Moreover, we exclude the attributes of Overconfidence and Tinkering since they can both be determined by Risk-Perception. For instance, high Risk Perception can lead to low Tinkering and vice versa (Kim 2010; Saadé et al. 2012; Terzis and Economides 2011). Moreover, as already explained, tinkering is based on curiosity (Burnett et al. 2011; Scaffidi et al. 2010) which needs high levels of self-efficacy to be triggered (Loewenstein 1994). Hence Tinkering cannot exist without self-efficacy. As regards to Overconfidence, based on the studied literature, Overconfidence leads to errors and low performance but high Risk Perception can lead to control mood and double checking of the user actions, avoiding speed and other confidence related errors. Since high levels of Risk Perception could possibly eliminate the errors made by Overconfidence, we decide to keep in our model only one of these two attributes. Additionally, while implementing tracking methodologies to monitor user behavior (e.g. ClickTale 2010; Ferreira et al. 2010), overconfidence can many times be confused with high self-efficacy. Although self-efficacy regards the user′s confidence on their own skills not revealing ′superficiality′, overconfidence related attitude can many times be reflected in extremely high levels of self-efficacy. For all these reasons we decided to exclude Overconfidence and Tinkering and to ′keep′ Risk-Perception and Self-Efficacy.

In the following table (see Table 2) we summarize the inclusion and exclusion of the above discussed variables (i.e. the behavioral attributes) in our model. Additionally, for the excluded attributes we present their linkage to other variables, as well as a brief justification for their exclusion based on the reviewed literature foundations.

Hence, the main attributes (basic variables) left to compose our Model are: Learning Willingness, Ease-of-Use-Perception, Usefulness-Perception, SelfEfficacy and Risk-Perception (see Fig. 2).

Learning Willingness, Self-Efficacy and Risk Perception are determinant attributes for the end-users′ performance and are prominent in the very specific field of EUD. The attributes of Ease-of-Use and Usefulness Perception, which are included in the RULES model, are prominent in the whole HCI area and every usability and user experience related study. Ease-of-Use and Usefulness Perception are very important for the EUD user modeling since ease of use and usefulness are key elements in user-centered design and they can provide a range of adaptation elements that could be ′offered′ to the users in order to assist them enhance their developing performance.

The remaining attributes are being excluded due to strong association to the basic ones as explained in Table 2, since most of them tend to function as extraneous or mediating variables. Contrary, the basic attributes that form our model/profile, tend to directly influence the end-user performance.

Table 2 Behavioral attributes′ inclusion and exclusion

Behavioral attribute	Included	Closely related to	Brief justification
Self-efficacy (or computer self-efficacy)	Yes	-	-
Overconfidence	No	Risk-perception	Overconfidence can be associated to perceived risk levels, i.e. too low risk perception could lead to high overconfidence. Risk perception values can be estimated (in one dimension) based on overconfidence levels (among others). Overconfidence can many times be confused to high self-efficacy.
Curiosity	No	Tinkering, Selfefficacy	Curiosity can many times be expressed through tinkering behavior, and curiosity needs high levels of self-efficacy to be expressed.
Tinkering (or exploring behavior)	No	Risk-perception	Tinkering behavior is rationally associated to perceived risk level, i.e. high tinkering reveals low risk perception (contrary to overconfidence). Levels of risk perception can be detected in the user′s tinkering actions (among others). Tinkering needs curiosity to be expressed and curiosity needs self-efficacy. Hence tinkering is highly dependent to self-efficacy.
Learning willingness	Yes	-	-
Risk-perception	Yes	-	-
Usefulness-perception	Yes	-	-
Ease of use-perception	Yes	-	-
Perceived-playfulness (or playful-behavior)	No	Tinkering	Perceived-playfulness can be regarded as playful-behavior that can be reflected in tinkering behavior. Productive tinkering can express enjoyness and interest that can positively affect the users′ performance.

Our suggested user profile/model (UM) composition can be depicted as following:

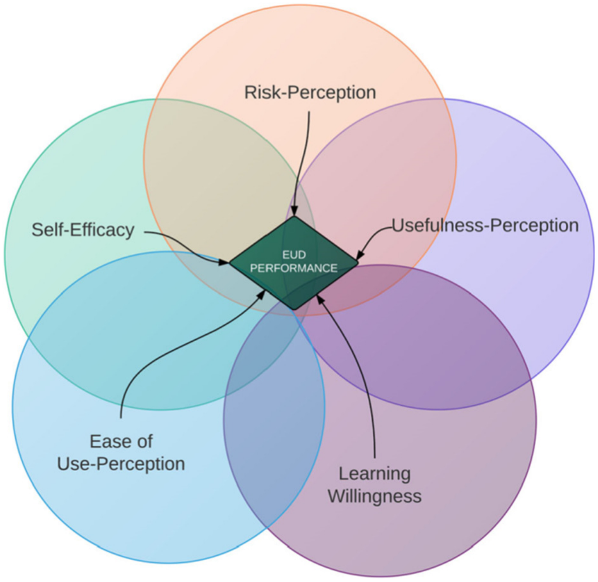

Fig. 2 The RULES model composition (of five EUD gender-behavioral attributes)

RULES is the acronym of the five attributes of the previous vector (Risk Perception, Usefulness Perception, Learning Willingness, Ease of Use Perception, and Self-Efficacy).

At this point we should remind and clarify that by user 'model' is actually a subset of behavioral attributes that were collected via a literature review work and could be implemented in future EUD user modeling mechanisms. The remaining attributes (in Table 1) should not necessarily be omitted but that could play a secondary role in the formation of basic behavioral user profiles in EUD environments.

4.3 Example application

Following we present a sample user scenario in order to better explain the usefulness of the suggested behavioral user modeling approach.

Let's assume that a EUD system aims to provide personalized services for each user. To this end, the system needs to create a user model (UM) for each individual user so as to adapt accordingly. If the system is based on the proposed model, then the user model will be a vector including the five main attributes as follows: The system needs to assign specific values for each of these attributes in the user model of each individual user. This can be done through a number of ways, either automatically (i.e. the system is monitoring usage and extracts this information) or manually (e.g. through a questionnaire that is presented to the user the first that that she/he uses the system). We do not analyses further this issue since it is beyond the scope of this paper, and since adaptive systems literature includes numerous solutions for this issue since it is central to every system that aims to support adaptations.

These values could be used by the systems decision making components to decide on the adequate adaptation responses. In particular, the system can provide different adaptation states based on the user′s gender and the values assigned to their model′s behavioral attributes. That means that female and male end-users may have the same attributes values but the system adaptation responses will not always be provided in a universal manner: many times different adaptation approaches are suitable for male and female users even if they reveal same behavior (i.e. same attribute value).

Low risk-perception means that the user ′dares′ to try new features and tinker a lot, but could also mean low task consciousness leading to an error prone behavior (usual to male users). Knowing that user′s Risk-Perception is low, the system by combining this information to the user′s high Tinkering (which is a lot influenced by Risk-Perception) it should find ways to elevate the user′s Risk-Perception if his/her Tinkering is negative and to keep it stable if Tinkering is positive. Elevation of Risk-Perception could be achieved by the system by providing ′what if′ tools that could highlight the negative effects that some choices could have, rendering the user more careful and conscious. On the other hand, high Risk-Perception renders users less likely to make use of unfamiliar features. Risk-based adaptations have been proposed by Beckwith et al. (2005) such as the ′advice′ component that by balancing the quality and quantity of provided explanations, it tends to decrease the users perceptions of risk.

High usefulness-perception reveals that the user believes that specific software is useful for his/her job performance. This leverages the user′s interest and makes him/her try harder and leverage his/her performance. Knowing that Usefulness Perception assists user to perform well, the system should find ways to keep its ′usefulness′ in the same level throughout the whole lifecycle of the user′s task. It could for example provide the user with system use cases and example implementations so that the user could read them and associate his/her work to the one of the given examples. It could also provide the user a sandbox version where the user could test his/her artifacts under real conditions to better perceive the system′s usefulness. Moreover, since usefulness-perception tends to affect more male users (Ong and Lai 2006; Venkatesh and Morris 2000), the system could provide with ′stronger′ adaptations (such as many control elements so that user can view their ′progress′ and realize the system′s usefulness to achieve their goals) in cases of male and-users.

Low learning willingness reveals the user′s unwillingness to use any new features and spend time on learning how to use them. Hence, the system is well aware of the fact that the user will neither read any tutorial nor any long instruction that the system offers for his/her assistance. Thus, the system should be adapted in a way that the user will not be 'faced' with many new features at once, but he/she could learn to use them progressively (gentle slope) if for example be provided with very short but comprehensive explanations. Moreover, the Surprise-Explain-Reward strategy could be implemented also in the case of low Willingness-to-Learn in order to increase the user's curiosity on specific features and motivate him/her to use them. This could be accomplished with the usage of animation or different colors that highlight the 'new' features.

High ease-of-use-perception could imply that the user is familiar with this environment style, has some significant experience or that the system is 'perfectly' designed in user-centered way. Knowing that Ease-Of-Use-Perception assists user to perform well, the system should find ways to keep its 'friendliness' in the same level throughout the whole lifecycle of the user's task. That is, the system should try not to change the user interface while the adaptation since the user seems to find it convenient. In the opposite case, the system should adopt a more novice-friendly 'design', to help the user perceive the whole environment as 'easier'. For example more wizard-like entities could be used, since novice users (or user behave as novices) and especially female users tend to reveal strong wizard preference (Beckwith et al. 2005; Burnett et al. 2010). Indeed, the minimalist learning theory (Carroll 1998) suggests that new system features be introduced by engaging users in activity and providing scaffolding to help them gradually increase their skills. Other adaptations for novice and expert users can be found in many recent works (such as in Jason et al. 2010; Eachus and Cassidy 2006). Moreover, based on previous research works (e.g. Kim 2010; Ong and Lai 2006; Venkatesh et al. 2003) perceived ease of use is more important for female users since men are more familiar than women towards computer use. So, the system's adaptation responses should be more 'rigorous' and 'strong' for the female end-users.

High self-efficacy is also the desirable user behavior concerning the particular attribute. However, in case of low Self-Efficacy the system should find ways to assist the user in his/her task performance, since low Self-Efficacy is strongly tied to bad performance. Many research works (e.g. Beckwith et al. 2005, 2006, 2007; Blackwell and Morrison 2010; Ko et al. 2011) have proposed ways to SelfEfficacy related adaptations, such as use of WYSIWYT (What you Use Is What You Test) editors and even supporting videos that tend to have positive selfefficacy results for the female end-users. For male users the system could provide with debugging and explanatory elements, e.g. similar to the 'Whyline' (Ko and Myers 2004) approach, so that users could always realize their mistakes and their outcomes.

As we can see our approach could predict some basic parts of user's behavior based on the behavioral model he/she belongs to and hence to offer him/her some basic adaptation services. While the actual user-system interaction it is expected that the user's behavior may change (e.g. because of gaining system familiarity, or working on different task etc.). Thus, we suggest that within the initial personalized environment the appropriate system mechanism should dynamically observe the user's behavior and readapt its behavior in a continuous loop in order to completely adjust to the user's current behavior. However the presentation of this mechanism is out of the scope of this paper.

5 Evaluation methodology

5.1 Field test description

Based on our survey of the literature review, we conducted an experiment on a population of 35 end-users to better understand and further reinforce the validity of the RULES model that was explained in the previous section in the example application.

Five users were excluded (see 5.3) since they could not be regarded as representing the generic population of end-user developers (i.e. not representative sample) due to their too low or too high computer and web development background. The statistical analysis was based on the data of 30 participants (sample). In our study we measured all the behavioral attributes that affect the users' performance (presented in Table 1) along with the users' performance values, in order to confirm the validity of the proposed model.

We conducted the study in the context of a web-based EUD tool environment, which includes a number of features assisting the end-users to build their own web databasedriven application. Then, we conducted a questionnaire-based survey to collect the users' perceived behavioral attitude during the EUD tool and user interaction. After the end of the EUD task, each participant had to answer the online survey which consisted of 30 questions-items.

The end-users' actions were monitored and stored in a database. Their resulting applications were compared to the correct prototype application and their performance was measured in a scale from one to five. After measuring the users' performance and their behavioral attributes (based on the questionnaire) we used descriptive statistics to present the basic performance and behavioral results to the reader. Moreover, to prove the usability of our modeling approach we conducted a T-Test Analysis for the two gender groups (Males, Females) to compare the means of their performance values. That is, we used gender as the independent variable and performance as the dependent one. Doing so, we could show that differences in end-users' performance can many times be caused by gender.

Additionally, we ran a Pearson correlation analysis for every behavioral attribute (in the RULES model) in correlation to performance for each one of the gender groups. Doing so, we could show which attributes affect performance more than others for every gender group and explain once again the reasons we chose the particular five RULES attributes for the model composition.

We should mention that we did not conduct any T-Test analysis for the distinct behavioral attributes on male-female user groups separately since we did not plan to confirm nor behavioral gender differences nor similarities between the end-users. Also we did not conduct any T-Test analysis between performance and each one of the behavioral attributes, since this correlation is based on the extended literature review and we re-evaluated for our test the generic correlation between gender and performance. What we aim is to examine gender differences in the relationships and not in the mean values, between the behavioral attributes and performance. Doing this we believe to contribute in the design of gender-neutral systems that take under consideration the gender-related differences and assists both male and female users adapting to their particular needs and behaviors.

5.2 Research hypotheses

All the previous researches works (mentioned in the theoretical foundation) were focused either on the behavioral differences between the two genders or on the relationship between some behavioral attributes and performance for the whole user sample and not separately for each gender group. Moreover, there was not a EUD behavioral model composed before that would consider the relationship between behavior and performance for every gender. Since performance is a very crucial variable in the area of EUD we need to extend the previous research by examining gender differences in the relationships between the behavioral attributes and performance.

To reveal these differences and evaluate our suggested modeling approach, we conducted our experiment on a group of end-users consisted of male and female end-users. First of all it is interesting to examine whether their gender affected their performance. If so, we expect our RULES model to be ʻvalidʼ and the five suggested attributes to affect users′ performance differently for every gender group.

Based on the reviewed theory foundations (e.g. Beckwith and Burnett 2004; Beckwith et al. 2006; Burnett 2009; Burnett et al. 2008, 2010, 2011; Kulenza et al. 2009; Saadé et al. 2012) when interacting with computer environments female and male end-users not only have different feature preferences but even when selecting to use the same features, they do it in different ways and even perceive the futures′ usage/outcome differently. In general, men and women have been shown to have different perceptions and preferences with respect to the use and satisfaction with different features of EUD systems. According Osvalder and Ulfvengren (2009) when users interact with computer systems, gender (among other factors) can influence their overall performance. And as Burnett et al. (2011) state Bthe features most conducive to females′ success are different from the features most conducive to males′ success, and are the features least supported in end-user programming environments^. Hence, to begin with, we have to examine whether end-users′ EUD performance is indeed different between male and female users. Our first hypothesis (H1) is as follows:

H1: Gender will significantly affect performance.

The next hypotheses regard the evaluation of the model′s approach. We do not plan to test whether there are significant gender differences for every behavioral attribute, or to measure the degree that each attribute affects performance, since we already have a basic ides by the reviewed literature and the cited works have already examined this issue. What we plan to show is that there are differences in the mode (i.e. strength and directory) these behavioral attributes affect performance for every gender group. This is important to argument the usefulness of EUD gender-behavioral models.

For instance, one attribute could affect female end users more than male end users, and or an attribute could affect females′ performance in a different direction than it would affect males′ performance. Hence, all we have to do is to measure the correlation degree between every attribute and performance cross the two gender groups, to define the relationship′s directions and sort them by strength. Previous research works might have shown the correlation between one attribute and another (e.g. the impact of perceived usefulness to ease of use) for each gender (e.g. Ong and Lai 2006; Venkatesh and Morris 2000) but there are no studies on the correlation between one attribute and performance for male and female end users separately. For this reason we do not have previously existing hypotheses to step on, rather we compose a generic hypothesis reflecting the gender differences in behavior and performance correlations.

Since our model is the same (i.e. it is composed of the same attributes) for the two genders, we have to test whether the five attributes composing the RULES models do indeed affect the end-users′ performance differently regarding their gender. Hence our second hypothesis is:

H2: The attributes that compose our model (Risk-Perception, Usefulness-Perception, Learning-Willingness, Ease -of -Use -Perception, and Self-Efficacy) will affect performance differently for every gender group.

Confirmation of hypothesis H2 will reinforce the meaning and validity of the RULES model, since it will show that regardless the existing gender differences in behavior and the generic (i.e. not gender-based) correlation between behavior and performance (that have been already showed in the studied literature), there is also another important side to be taken under consideration: the existence of different correlations between behavior and performance for male and female end-users.

5.3 Participants and procedure

The sample size of the field test was 30 end-user participants (the population was 35), 13 male and 17 female undergraduates in a Greek university, all of whom were familiar with EUD web applications (since they had been taught some web tools in the context of the ‘e-commerce e-business′ course). All the participants were finance and accounting students with poor ICT background.

The prototype EUD tool that was used for the experiment was the one used in a recent research work of Protogeros and Tzafilkou (2015), where the authors designed a natural language approach (‘simple talking′) to assist endusers creating database-driven mobile applications. The authors also developed a prototype wizard-based web EUD tool to integrate and evaluate their EUD approach. The end-users′ high performance results indicated the validity of the EUD approach and the efficiency and usefulness of the tool. A detailed presentation of the particular EUD approach for database-driven web applications can be found in Protogeros and Tzafilkou (2015).

To explain the end-user development process and present the interface environment of the prototype web EUD tool, we provide the following descriptions and interface screenshots:

- Participants (end-users), need to follow a step-by-step wizard process (see Fig. 3) to create their own database-driven (based on an abstracted relational schema) application in order to manage their business. In every step they can create a basic database item, such as a table or a relationship and define the attributes′ (fields) data types, the integrity constraints, the relationship′s type (e.g. one-to-many, many-tomany, one-to-one), etc.
- In the end, they can select the generation of their application. A generated link is provided to each user, and they can view their application via their mobile device or a mobile emulator (see Fig. 4).
- Via their mobile device they can access all the constructed items and insert, edit, delete and search their records (see Fig. 4).

Prior to the EUD task, the participants had to answer a short online questionnaire (integrated in the registration page of the EUD prototype tool) regarding their experience level on database concepts, programming, World Wide Web and overall computer use. The experience level was measured in a scale from 1 to 5. As already mentioned, five users where excluded because their experience level was less than 2 in familiarity with web and general familiarity with computer use, and equal or more than 4 in database and programming familiarity.

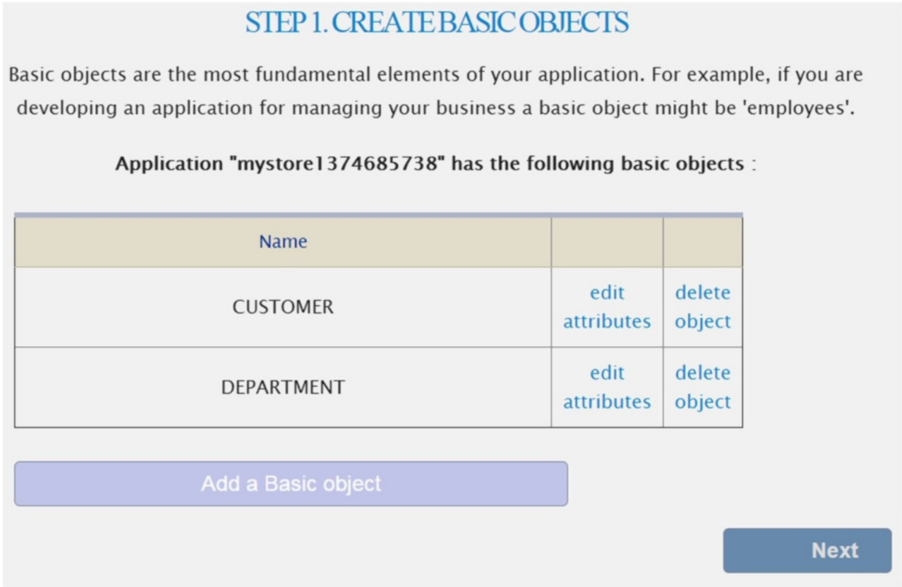

Fig. 3 EUD web interface (example of step 1)


Fig. 4 Mobile interface of the generated application

The measured mean value of the participants' (sample) database familiarity was 1.04 (STD = 1.08), revealing that they could be 'safely' considered as non-professional/ non expert end-users in database-development tasks. Additionally, their programming experience was 1.12 (STD = 1.19), their familiarity with web was 2.87 (STD = 1.29) and their general familiarity with computer use was 2.70 (STD = 1.42). These mean values satisfy our target group (end-users) 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. That is, the sample allows the collected results to be generalized to a larger population of end-users.

After the end of the EUD task, each student had to answer the survey which consisted of 23 questions (items) which measure the nine variables of Table 1, including the five of the RULES model (see Appendix Table 8). A five point Likert-type scale with 1 = Bstrongly disagree^ to 5 = Bstrongly agree^ or 1 = Bnever^ to 5 = Bmany times^ was used to measure the items. Our questionnaire structure was based on previous research behavioral computer related questionnaires (e.g. Compeau and Higgins 1995; Davis 1989; Moon and Kim 2001; Venkatesh et al. 2003; Thompson et al. 1991; Wang et al. 2009) but we adjusted and extended the questions in order to cover all the under survey attributes. The original questionnaire was in a Linker scale form consisted of a prompt, Bduring the usage of the EUD tool I felt that . . . I was totally confused, or I was bored, or I was confident^ etc. The questionnaire included also generic computer related items so as to examine the generic user attitude towards computer usage and not only the specific EUD task oriented attitude.

At the end of the procedure we compared the user performance levels to their behavioral states in order to evaluate our modeling approach.

5.4 Data analysis and experimental results

5.4.1 Sample characteristics

Since the sample size of 30 participants is quite small, we conducted a normality distribution testing to test whether the values of every measured dependent variable were approximately normally distributed for the sample size.

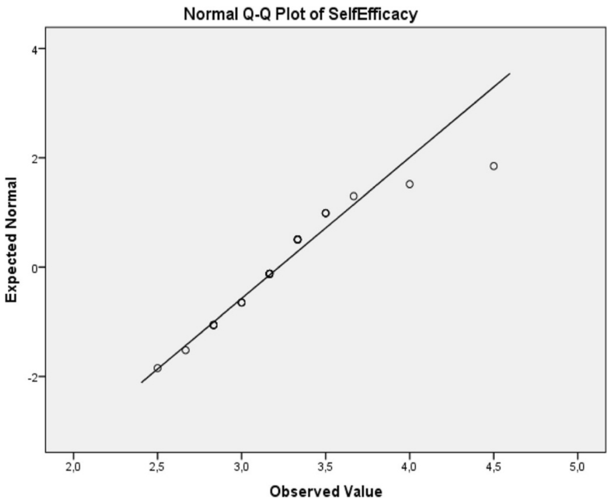

Fig. 5 Normal Q-Q plot of self-efficacy

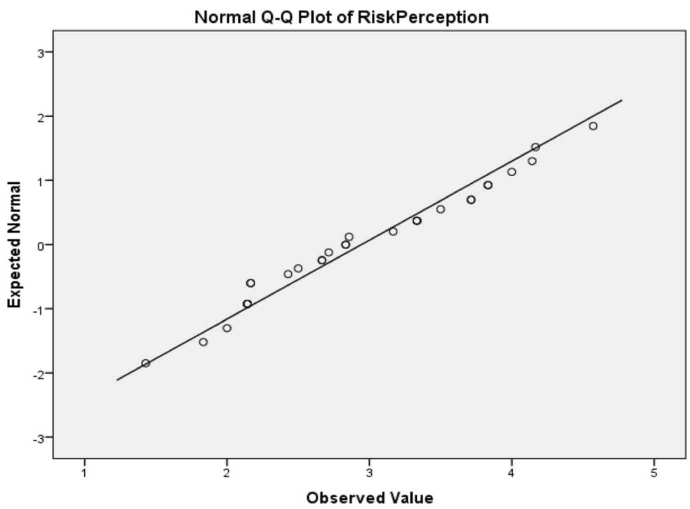

Fig. 6 Normal Q-Q plot of risk-perception

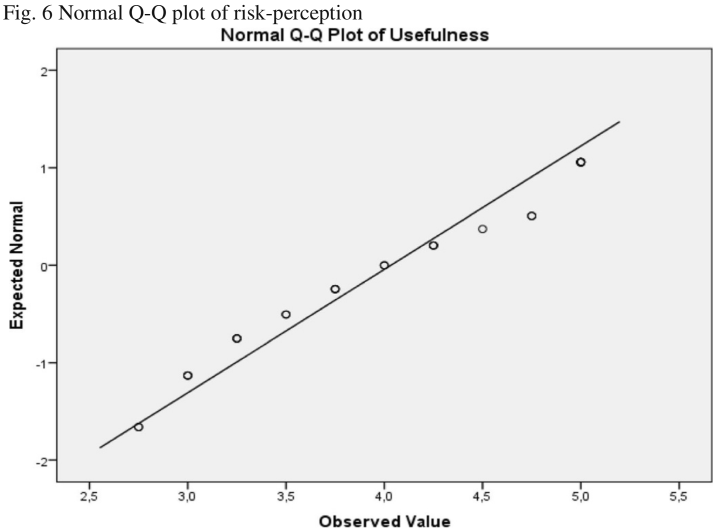

Fig. 7 Normal Q-Q plot of usefulness-perception

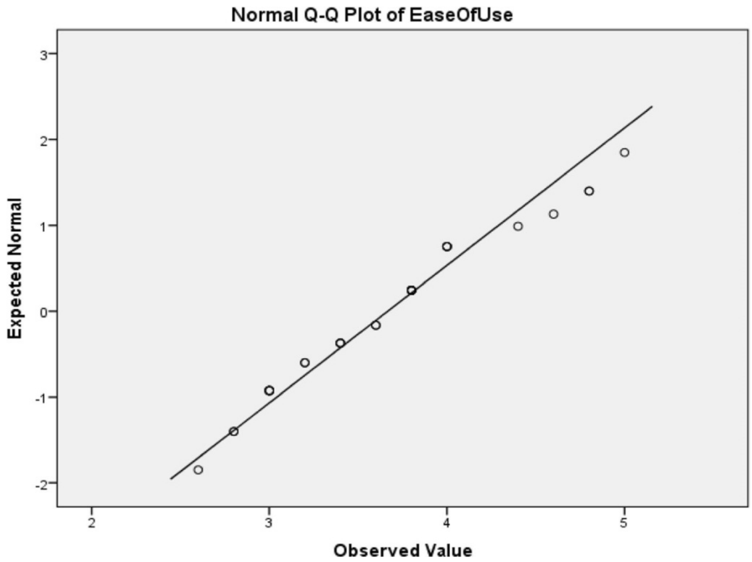

Fig. 8 Normal Q-Q plot of ease of use-perception

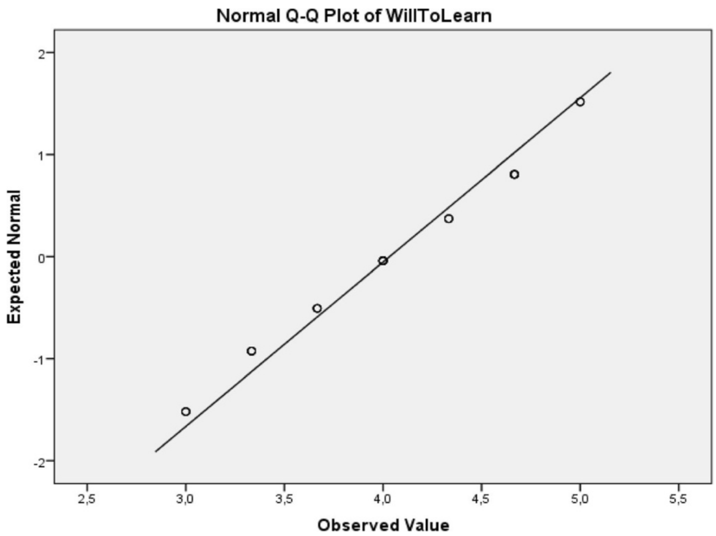

Fig. 9 Normal Q-Q plot of ease of willingness to learn

A Shapiro-Wilk′s test ($p > 0.05$), which is ideal for small sample sizes, and a visual inspection of their histograms and normal Q-Q plots (see Appendix Table 9, Figs. 5, 6, 7, 8 and 9) showed that the values of Self-Efficacy, Risk Perception, Perceived Usefulness, Perceived Ease of Use and Willingness to Learn were approximately normally distributed for the end-user participants.

5.4.2 Internal validity

Construct validity and reliability have been tested to ensure that the results are reliable and consistent. Calculating Cronbach's alpha coefficient tested the construct reliability. This measures the internal consistency by indicating how a set of items are closely related as a group (Moolla and Bisschoff 2012). Nunnally (1967) suggests that a Cronbach alpha value of 0.7 is acceptable, with a slightly lower value might sometimes be acceptable.

In Appendix Table 8, Cronbach's alpha values 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.

5.4.3 Descriptive statics

Following we present the descriptive statistics results for all the measured variables both for the entire sample and for the two gender groups separately (Tables 3 and 4). The variables are all measured in a scale 1–5. As already explained, performance was measured from the users' database stored application data (by their developing task)

Table 3 Descriptive statistics for the measured items for the entire sample

Variable	Mean (0–5)	Variance	Standard error	Mean square deviation
Performance	4,43	0,24	0,10	0,49
Usefulness -perception	3,97	0,95	0,20	0,98
Ease-of-use-perception	4,03	0,36	0,10	0,6
Self-efficacy	3,24	0,27	0,10	0,5
Perceived-playfulness	3,22	0,20	0,10	0,45
Learning-willingness	4,13	0,50	0,10	0,70
Risk-perception	2,90	0,60	0,16	0,77

and the rest of the items was measured based on the questionnaire feedback (see Appendix Table 8).

5.4.4 T-test analysis (gender/performance)

We conducted a T-Test between the variables of gender and performance to show the existence of performance differences due to gender. This would validate our suggested model presented in section 4since it would reveal its usefulness. The alpha significance level is set to α = 0,05.

Table 5 shows the T-Test analysis for the users′ performance in relation to their gender. As the results reveal there is a significance difference between male and female users′ performance since probability value (p = 0,05) is equal to alpha value (α = 0,05). 5.4.5 Correlation matrix (five attributes/performance/gender group)

Table 6 shows the correlation coefficients between the behavioral attributes of our model and performance for every gender group. As the results show there are some basic differences across the two groups regarding the correlations′ strength and direction. The results have been sorted from largest to smallest according to their absolute values.
Table 7 summarizes the main results that derive from the above-presented statistical tables. In particular Table 7 shows the correlation strength value between each one of the measured attributes and performance for the two gender groups (the closer

the distance in Table 6 the stronger the relationship) and a logic comparison between the mean values of male and female users′ behavioral attributes.

Table 4 Descriptive statistics results for gender groups

Variable	Male users (N = 13)			Female users (N = 17)		
	Mean (0–5)	St. Deviation	St. Error	Mean (0–5)	St. Deviation	St. Error
Performance	4,17	0,46	0,15	4,59	0,13	0,13
Usefulness -perception	3,75	0,49	0,40	4,09	0,24	0,24
Ease-of-use-perception	4,01	0,47	0,15	4,01	0,19	0,19
Self-efficacy	3,24	0,62	0,20	3,19	0,12	0,12
Perceived-playfulness	3,08	0,57	0,19	3,26	0,09	0,09

Table 5 Gender to performance

Gender groups – performance	Mean	Variance	t	P value
Performance male end-users	4,17	0,21	−2,08	0,05
Performance female end-users	4,59	0,22		

Table 6 RULES behavioral attributes to performance

Group: Male end users		Group: Female end users	
Attribute	Performance	Attribute	Performance
Usefulness-perception	0,50	Self-efficacy	0,51
Self-efficacy	0,46	Usefulness-perception	0,43
Learning-willingness	0,45	Ease-of-use perception	0,39
Ease-of-use perception	0,20	Learning-willingness	0,18
Risk-perception	0,12	Risk-perception	0,04

5.5 Discussion

Drawing from the experimental results, gender was proved to influence end-user performance in their developing activities while interacting with the prototype EUD environment. Results in Table 5 show that there is a statistically significant difference between male and female users′ performance (p value = 0,05 = α = 0,05). Hence hypothesis H1 is confirmed. This means that our model has a ′meaning and potential′ and gender-based behavioral user modeling is valid and important to be adopted by modern EUD systems so as to enhance end-users′ performance.

This fact has revealed the need for gender-based behavioral user models. After this we tested whether the attributes, that compose our model, do indeed reflect differences in the ′mode′ (i.e. strength) they affect performance for every gender group. Results in Table 6 validate our approach and confirm hypothesis H2, since BThe attributes that compose our model (Risk-Perception, Usefulness-Perception, Learning-Willingness, Ease-of-Use-Perception, and Self-Efficacy) do affect performance differently for every gender group^.

As results in Table 6 reveal, Self-Efficacy and Usefulness-Perception are at the top of the list (great strength) both for male and female end-users. However, Self-Efficacy seems to affect more females′ than males′ performance and Usefulness-Perception seems to affect more males′ than females′ performance. Learning-Willingness and Ease-of-Use-Perception is the second in order pair for the two groups, but LearningWillingness seems to affect more males′ than females′ performance while Ease-of-UsePerception seems to affect more females′ than males′ performance. Last in order (revealing lower strength) comes the attribute of Risk-Perception for both groups.

Table 7 Summary chart of gender results

Behavioral attribute	Correlation to performance (strength comparison)
Risk-perception	Stronger for males (0,12 > 0,04)
Usefulness-perception	Stronger for males (0,50 > 0,43)
Learning-willingness	Stronger for males (0,45 > 0,18)
Ease-of-use perception	Stronger for females (0,39 > 0,20)
Self-efficacy	Stronger for females (0,51 > 0,46)

As we see in the tables′ results in subsection 5.2, we only provide and compare the absolute values of the correlations coefficients since do not aim to prove whether the five suggested attributes should compose or not the RULES model, since this argumentation is provided in subsection 4.2. For this reason we did not examine possible significant correlations between performance and each one of the behavioral attributes. After all, these five attributes are among others in Table 1 gathering all the gender-behavioral attributes detected so far in the EUD research to affect performance. Our current paper's scope was not to revalidate these findings, but to show the reasons (in example application) a behavioral user model could be useful in EUD systems. The statistical analysis only extends the arguments presented example application to express in numbers the main gender differences between performance and the RULES attributes.

5.5.1 Possible issues and limitations

Despite its EUD research contribution this study suffers from some limitations.

A possible limitation is the wizard like design of the prototype tool. Wizard-logic has been proved to be preferred by female users (Beckwith et al. 2005; Burnett et al. 2010) and it can positively affect their performance and perception. Also, this can possibly lead to differentiated results in future web-EUD gender research that will be conducted on non-wizard like interface designs.

In general, probably due to software design options some gender differences were not obvious enough. However, this did not prevent us from showing differences in the EUD population: usually there are significant performance differences affected by gender, and there are main gender differences in the way behavior can affect performance.

Another possible limitation is the self-efficacy evaluation method. Many self-efficacy studies conduct both a pre-test and a post-test self-efficacy questionnaire, to track changes over time in participants' perceived levels of self-efficacy. In this study we used a post-test for all the measured items, including self-efficacy, since our sample was of approximately the same experience in programming, database, web and general computer usage. According to the theory of self-efficacy (Bandura 1997), prior experience is the strongest influential factor to self-efficacy. For this reason we did not include a self-efficacy pre-test in our survey. However, this could have led to biased results.

Location, culture and socio-demographic factors could be considered a number of possible limitations as well. Although field studies have been conducted in different countries to further develop and evaluate the Theory of Individual Differences as it relates to IT and gender (Trauth 2002; 2006b; 2006c; 2013; Trauth et al. 2004; 2009), most of the gender-oriented research in the EUD area have been conducted in United States' universities (e.g. the GenderHCI research works such as Beckwith et al. 2005; Beckwith et al. 2006; Beckwith et al. 2007; Beckwith and Burnett 2004, 2007; Burnett 2009; Burnett et al. 2010; Burnett et al. 2008, 2010, 2011). However, the current field test was conducted in a Greek university (in Europe). Since gender differences can evolve not only by time but also by space, a replication of the study in a different country with a different culture and female representation in ICT could possibly lead in different results. Thus, future works could compare their results to ours (among others) to conduct comparative gender-oriented research in EUD cross different countries.

6 Conclusions and future work

This paper presents a first approach taken for a behavioral model construction, based on a subset of gender-influenced behavioral attributes existing among the end users who attempt to develop their own applications, i.e. end-users working in EUD environments (also refereed as end-user developers). The main objective is to gather all the EUD gender-oriented behavioral attributes studied so far and to examine possible gender differences in performance and in the correlations between performance and behavioral attributes. The suggested approach composes only the very first step of a user modeling implementation, by presenting and analyzing a subset of user attributes that could compose enduser profiles. Such an approach aims to contribute in the development of selfadaptive EUD tools that measuring these behavioral attributes will be able to implement relative user modeling techniques assisting the users in the developing task.

Our study contribution could be regarded as twofold, meaning that it is both review and proposal work, since it steps on the combined HCI and EUD review research to aggregate all the parameters needed to propose a EUD oriented behavioral user model structure. According to our approach:

- Past established behavioral HCI theories have contributed to the recently emerged behavioral research in the EUD area, shedding light on the factor of gender and stressing its importance.
- Gender behavioral attributes can be used as a stepping stone for the analysis of end-user behavior and the suggestion of particular end-user behavioral models.
- A subset of behavioral attributes can be proposed based on the literature review analysis of their associations and dependencies in influencing EUD performance.
- The suggested RULES attributes can compose a user model/profile and constitute an initial approach in the design of specific EUD-centered User Modeling techniques and their latter implementation in self-adaptive EUD system environments.

Our study is actually a first attempt to gather and classify the behavioral attributes (been studied in the HCI and EUD behavioral literature) influencing the end-user developers′ performance when working in EUD environments. Then, stepping on these attributes, we propose the main structure of an end-user developer's behavioral user profile.

Our work also provides experimental evaluation and assessment of the proposed argument. Except analyzing the linkage between the HCI theories foundations and our EUD oriented modeling approach we also conducted a real-world behavioral EUD experiment on a sample of end-users.

Unfortunately behavioral EUD analysis is rare in the HCI research community works, and our initial review research is limited on current resources (mainly the GenderHCI field and the HCI theories presented in section 3) which may not be sufficient for a complete and totally objective end-user developers' behavioral 'image'. Thus, we shall not forget that for the optimal evaluation of our work further behavioral research need to be conducted regarding the EUD area. For instance, it would be useful future works to examine the correlations between EUD performance and gender-based attributes. Due to the web nature of the contemporary EUD systems, some correlations might have changed or there could be difference correlations between performance and gender-attributes in different cultures and countries. This way, newly derived gender differences and similarities could be taken under consideration in the design of future web EUD systems.

Another interesting future research work is to examine gender differences also in actual behavior, i.e. while users interact with the EUD tool. We intend to expand our research by examining the users' behavior (in term of actions) via real time mouse monitoring and eye tracking methodologies, to contribute even deeper in the field of EUD user behavior and EUD gender differences.

The scientific adaptation of the RULES or other behavioral profiling approaches in the EUD design mechanisms will possibly contribute to the EUD gender-gap elimination and assist end-users perform equally well in their developing activities. Our study strongly encourages such scientific efforts.

Appendix

As Table 8 presents, there is internal validity of the rules constructs since all values of cronbach's alpha are greater than 0,7 revealing high level of internal consistency

Table 8 Validity of the measurement model

Constructs	Items		Cronbach's a (>0,7)
Usefulness -perception			0,95
	U1	The system is useful	

	U2	The system makes me more productive	
	U3	The system makes me save time	
	U4	The system satisfies my needs and requirements	
Ease of use-perception			0,76
	E1	The system is easy to use	
	E2	I do not need to try too hard to use the system effectively	
	E3	I can use the system without written instructions	
	E4	I can learn how to use the system easily and fast	
	E5	I can easily correct my mistakes while I use the system	
Self-efficacy			0,80
	S1	I felt confident while I was using the system	
	S2	I believed that I could perform well	
	S3	I felt I had the control of the task	
	S4	I felt that everyone else knew what to do but me	
	S5	I felt confused while using the system	
Learning willingness			0,80
	L1	I wanted to learn how to use the system while I was using it	
	L2	I'd like to learn more how to use the system	
	L3	I'd like to learn how to use other similar systems too	
	L4	In general I enjoy learning new ICT related things	
Risk-perception			0,76
	R1	It was taking me time to decide how to move while using the system	
	R2	I felt nervous every time I took an action (e.g. pressed a button)	

R3	I checked well my actions before moving to the next steps
R4	I had no hesitation to take an action
R5	I had no difficulty to try which feature (among other) to use

Table 9 Test of normality

	Shapiro-wilk		
	Statistic	df	Sig.
Selfefficacy	0,902	30	0,009
Riskperception	0,962	30	0,357
Usefulness	0,896	30	0,007
Easeofuse	0,950	30	0,169
Willtolearn	0,935	30	0,069

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