Individual differences in Human-Computer Interaction: A review of empirical studies

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Abstract

In the field of Human-Computer Interaction, researchers have found evidence of performance differences which may be attributed to variation among individual users. User's traits, cognitive styles, cognitive abilities, psychomotor abilities and culture have been investigated as levels that could help explain this variability. This literature review focuses on eleven years of empirical journal publications on individual differences in HCI in the period of 2004-2014. Using different search terms and criteria, we included a total of 98 studies to be reviewed. We describe and evaluate studies' domains, methods and impact. In addition, this paper presents a number of gaps in current research, implications and thoughts on designing computer systems and several recommendations for future research.

1. Introduction

Researchers have been studying individual differences in psychology for about a century (e.g. Dawis, 1992). However, in the field of Human-Computer Interaction (HCI) individual differences were often overlooked in the early years. This broad field of research focuses on interactions between humans and computers, including studies on users, design and methods to gather user data or to improve design. In Dillon and Watson (1996) the authors argue that user analysis in HCI could benefit from the field of individual differences within psychology. They argue that this field appears to be of use in issues regarding practical design. More specifically, it is argued that work on individual differences offers the HCI community the chance to create a framework that improves user analysis and computer systems design. Early work on individual differences within HCI suggests that performance can differ by a large amount as a result of individual differences. For instance, Egan (1988) reviewed several studies obtaining completion time measures on text editing, information search and programming. He states that, for moderately small sample sizes (10 to 30 subjects), completion times of a text editing task between the maximum and minimum time ranged about 5:1. In other words, the lowest completion time was five times faster than the highest completion time on the same task. This variability is thus not due to differences in the task at hand, but due to differences between individuals. This effect was even more apparent in information search and programming tasks where the ratios between fastest and slowest completion times were about 9:1 and 22:1 respectively. This paper reviews contemporary studies on individual differences in HCI to present the reader the current status of this type of research.

One way to study individual differences in HCI is to study categories of individual difference that could predict performance and behavioural differences in computer use. In Egan (1988), mentioned categories include 'technical' aptitudes (i.e. spatial and reasoning aptitudes, mathematics and science achievements), age, experience, domain-specific knowledge and personality. Dillon and Watson (1996) emphasize the role of cognitive abilities in psychological studies and the potential this has for HCI. Besides cognitive abilities, potentially influencing factors include personality (traits), cognitive style and psychomotor ability. Furthermore, there are many studies on the influence of culture and its effects on the self and others (see Markus & Kitayama, 1991 for a review).

Regarding design, the idea that computer systems should be accessible and usable for all people, taking diversity (i.e. different user characteristics, usage contexts, tasks) into account is known as universal design or design-for-all (e.g. Stephanidis, Antona, & Savidis, 2006). Research on individual differences focuses on this diversity in the human population. The design for people with disabilities is often associated with universal design (Stephanidis et al., 2006), but universal design entails a more broad definition of user characteristics. For designing computer systems, Aykin (1991) lists three strategies. The first strategy is to design for one uniform user group, which focuses on the average user and differences between users are not taken into account. The second strategy is to design different interfaces for different user groups, which can take individual differences into account by carefully studying user groups. The third strategy is to design an adaptive interface, which is an automatic adaptation of computer interfaces to the individual user's characteristics and needs (see also Benyon, 1993; Jennings, Benyon, & Murray, 1991). A potential fourth strategy, robust design, is mentioned by Zhou, Heesom and Georgakis (2007). This type of design focuses on creating the product in such a way that the influence of external variability is minimized. Other implications of individual differences could, for instance, be that researchers choose their strategies for sampling the population more carefully, as in many cases it is likely that individual differences exist between participants.

Nowadays, with many more people using computers and the internet than 25 years ago (cf. Egan, 1988), a review of recent work on individual differences in HCI could shed light on contemporary differences. Hence, the present study reviews the literature on individual differences in HCI of the past decade (2004-2014) to see how the HCI community on individual differences has evolved after the Dillon and Watson (1996) paper. We explore how and in which domains the HCI community reports on individual differences and how strongly these individual characteristics actually influence computer performance. Lastly, we discuss the potential of these categories of individual difference to guide computer systems design. By making use of Egan's (1988) and Dillon and Watson's (1996) categories and the influence of culture, we will review the HCI literature on individual differences in the following categories: *traits, cognitive style, cognitive and psychomotor ability*, and *culture.*

2. Theoretical background

Before describing the methods we used for the literature review, we first describe the categories of individual difference, and their (potential) relation to computers. We report the most common dimensions on which people can be described for the categories and some methods for measuring the impact these dimensions may have in human-computer interaction.

2.1. Traits

Psychologists generally regard traits as internal dispositions that are relatively stable over time and remain relatively stable in different situations (McAdams, 2009). Over the years, a taxonomical structure to describe people's behaviour was developed (for a historical view, see e.g. Goldberg, 1993). This has led to the emergence of five overarching factors of personality traits (i.e. the Big Five). These factors include: Extraversion, Neuroticism, Openness to Experience, Conscientiousness and Agreeableness (John & Srivastava, 1999; McCrae & Costa, 1987). Extraversion is related, for instance, to being warm, talkative, spontaneous and sociable. Neuroticism relates to being nervous, emotional, insecure and impatient. Openness to experience is related to being creative, imaginative, curious and daring. Conscientiousness relates to being careful, reliable, well-organized, perceptive and punctual. Lastly, Agreeableness is related to being good natured, helpful, generous, forgiving and sympathetic (McCrae & Costa, 1987). The Big Five factors have been researched and validated extensively (e.g. Peabody & Goldberg, 1989) and they continue to be used in contemporary research (e.g. Specht, Egloff, & Schmukle, 2011).

Often regarded as a separate trait as well is people's locus of control. Rotter (1966) describes it as the extent to which a person considers events happening to be due to his own doing or characteristics (i.e. internal locus of control) or that these events occur (partly) due to chance, luck or other people (i.e. external locus of control).

In the context of HCI, we can imagine that these dispositions could for instance influence the behaviour online or influence what a user thinks about (a certain) computer, service or system.

2.2. Cognitive style

Cognitive styles can be defined as “people's characteristic and typically preferred modes of processing information” (Sternberg & Grigorenko, 1997, p. 700). Dimensions of cognitive style include, for example, the verbalizer-visualizer distinction (e.g. Mayer & Massa, 2003) and field dependency (e.g. Witkin, Moore, Goodenough, & Cox, 1977). The verbalizer-visualizer distinction is based on the apparent differences between people thinking with words or thinking with images (Mayer & Massa, 2003). Field independency reflects the degree to which perception is dominated by the surrounding field. Field independent people experience objects as more or less separate from the surrounding field, whereas field dependent people’s perception is more dominated by the surrounding field (Witkin et al., 1977).

We can relate cognitive styles to HCI by imagining that a user’s preferred processing mode could influence his or her performance on a computer. In addition, their overall preferences for certain design elements may be explained by their cognitive styles.

2.3. Cognitive and psychomotor abilities

Carroll (1993) defines cognitive tasks as “any task in which correct or appropriate processing of mental information is critical to successful performance” (p.13). A cognitive ability, then, is “any ability that concerns some class of cognitive tasks” (p.13). A broadly accepted framework for cognitive abilities is the Three-Stratum model by Carroll (1993). In this model, a hierarchical framework of cognitive abilities is described on three levels of generality. The top level (i.e. third stratum) consists of a general intelligence factor (g). The second stratum consists of broad cognitive abilities (e.g. visual perception and retrieval ability). Lastly, the first stratum contains more than 80 narrow cognitive abilities, which are specialized and more specific abilities.

The Three-Stratum model has been combined with another intelligence model (i.e. the Cattell-Horn Gf-Gc model by Horn and Noll, 1997) into the Cattell-Horn-Carroll (CHC) model of cognitive abilities (McGrew, 2009). This model resembles the Three Stratum model, but identifies several more broad categories (stratum II). For example, the broad ability of visual processing is distinguished with narrow abilities like visual memory, imagery and spatial relations. Other broad cognitive abilities include, for instance, long-term memory retrieval and storage, processing speed, fluid reasoning and reaction and decision speed.

The CHC model also includes psychomotor abilities and psychomotor speed in the second stratum. Narrow psychomotor abilities are more specific abilities such as finger or manual dexterity, aiming, control precision and multi-limb coordination. Furthermore, for narrow psychomotor speed abilities, movement time and speed of limb movement are mentioned (McGrew, 2009).

Users' cognitive and psychomotor abilities may produce variability in performance with computers as well. For instance, think about reaction speed and hand and finger dexterity in using a computer mouse or touchpad.

2.4. Culture

The term 'culture' is used widely and various definitions exist. For instance, culture is defined as "the social production and reproduction of sense, meaning and consciousness" (O'Sullivan, Hartley, Saunders, Montgomery, & Fiske, 1994, p.68). Hofstede (1994) defines culture as "the collective programming of the mind which distinguishes the members of one category of people from another" (p. 1). For example, these categories of people could be a nation, region, gender group, social class, religious group or a work organization (Hofstede, 1994). In the context of HCI, Ford (2005) defines culture as "the patterns of thinking, feeling and acting that influence the way in which people communicate amongst themselves and with computers" (p.38). It is clear that various definitions exist and that cultural differences can be researched in several categories of people, ranging from relatively small groups in a work organization to much larger groups of members of a certain religion.

In order to get a measure of culture, Hofstede (as cited in Hofstede, 1994) proposed five widely used dimensions on which cultures can be described. Power distance, which refers to the extent to which less powerful members of a certain culture accept and expect that the distribution of power is unequal. Individualism versus collectivism, representing the degree to which individuals are integrated into groups. On the side of the individualist, the ties between individuals within a certain group are loose. Collectivists on the other hand, are integrated in cohesive in-groups who protect each other in exchange for unquestioning loyalty. Masculinity versus femininity refers to the distribution of roles between sexes. It is often characterized by an assertive pole (masculine) and a modest, caring pole (feminine). Uncertainty avoidance, which deals with a society's tolerance for ambiguity and uncertainty. It is an indication of the extent to which members feel comfortable or uncomfortable in unstructured, novel and unknown situations. Lastly, long term versus short term orientation is associated with people's concerns with past, present and future and the values they attach to each of them. Long term orientation is associated with persistence and perseverance, while short term orientation is associated with respect for tradition and fulfilling social obligations.

Another well-known dimension of culture is Hall's (1976) dimension of contextuality, which distinguishes low context cultures from high context cultures. In high context cultures, communication relies on the physical context and information is not entirely contained in words, sentences and grammar. Communication is more implicit and words used should be interpreted with regard to the context (Kim, Pan, & Park, 1998). In low context cultures, information is conveyed explicitly through words and is regarded more context-independent.

2.5. Control variables - experience and domain knowledge

We can readily imagine that people with different amounts of experience with something will display different behaviour. For example, novices tend to use different (overall less effective) search strategies in information search than more experienced users (Hembrooke, Granka, Gay, & Liddy, 2005). However, experienced and less experienced users are not always performing that differently from each other. With proper design, less experienced users may perform just as well as more experienced users, as shown in Finstad (2008). Related to experience is domain knowledge, which can be described as the knowledge a person has of a certain domain. Indeed, Hambrick and Engle (2002) have shown that domain knowledge was a stronger predictor of cognitive performance on domain-relevant tasks than working memory capacity, for instance. In HCI, domain knowledge is influential in, for instance, learning in a hypermedia environment (Mitchell, Chen, & Macredie, 2005).

2.6. Control variables - age and gender

Furthermore, the effect of age on website usability has been shown by Wagner, Hassanein and Head (2014). They found that the effect was partially mediated by spatial ability (a cognitive ability). Lastly, gender has been shown to influence human-computer interaction as well. For example, a study by Hess, Fuller and Mathew (2006) found that women report being more involved with the use of a decision support aid than men. It thus appears to be important to control for these four individual difference characteristics when examining effects of traits, cognitive styles, cognitive abilities and culture.

2.7. Impact

Recall that Egan (1988) found very large differences between people in task completion time. In order to get an impression of the impact of an effect, researchers either examine the outcome variables on a natural scale (i.e. like Egan's ratios), or they calculate effect sizes, which come in different variants. There are measures of explained variance, like η^2 (eta squared) and η_p^2 (partial eta squared) values, which indicate the proportion of the variance explained by a certain predictor on a dependent variable (in analysis of variance). For an extensive paper on differences between η^2 and η_p^2, see Levine and Hullett (2002). Another indication of the explained variance is R^2, which indicates the explained variance of an entire model on a dependent variable, instead of the explained variance per factor. Effect sizes can also be expressed in standardized group mean differences like Cohen's d, which is the difference between two means divided by their pooled standard deviation.

3. Method

To describe and explain the current knowledge which could guide professional practice is a purpose that is especially well-served by a literature review (Fink, 2010). Furthermore, an overview of the research done can reveal areas that require more thorough examination, thus guiding scientific practice. Since this paper is concerned about the individual differences in the HCI field on several levels, we formulated multiple search terms. An overview of the search terms used can be found in Table 1, along with the amount of search hits found per database. We used Scopus and Web of Science as databases, because these are multidisciplinary databases in which we expected to find a large diversity of studies. We used an approach similar to the one used in Bargas-Avila and Hornbæk (2011), which is an adaptation of the QUOROM statement (Moher et al., 1999). First, we identified potentially relevant studies by searching the databases with the search terms mentioned in Table 1. We limited our search to studies published in journals between 2004-2014. Secondly, to be included in this review, studies had to:

- Offer an empirical analysis; qualitative, quantitative and mixed studies were all candidates.
- Report on the categories of individual difference reported before in relation to a human-computer interaction related topic or task as an important purpose of the study, instead of merely mentioning the category as an afterthought.
- Be written in English.
- Be available as full texts at the digital libraries of the University of Twente.

In each of the two databases, we examined titles and abstracts of studies for every search term in order to obtain relevant studies that satisfied the above mentioned conditions. These studies were downloaded and were analyzed afterwards. Studies’ domains, samples, data collection methods, study type, effect sizes and key findings were collected from each study and recorded in a data set. Moreover, we examined whether studies measured and controlled for experience, domain knowledge, age and gender. Regarding data collection methods, we decided to report methods to assess the individual difference categories (independent variables), as well as methods for other variables (mainly dependent variables) to present the reader a complete view of the methods used in HCI research on individual differences. For each individual differences category, we classified the selected studies into subgroups based on the study's domain (e.g. social media, games). These subgroups emerged from the selected studies and were identified using a card sorting technique. More specifically, we wrote the name of each study on a card and grouped studies that were reporting on the same domain. For every study, we examined whether they fit into previously established groups. If this was not the case, a new group was created. In some studies, there was some overlap between domains. In these cases, we grouped them in the domain subgroup which fitted best with their primary research goal.

Table 1
Search terms used in Scopus and Web of Science databases

Category	Search term	Scopus hits	Web of Science hits
Traits	personality AND human-computer interaction	110	52
	personality AND computer	2074	1746
	personality AND user experience	222	342
	trait AND computer	5068	4278
Cognitive style	cognitive style AND human-computer interaction	32	10
	cognitive style AND computer	295	291
Cognitive and psychomotor ability	cognitive ability AND human-computer interaction	118	37
	cognitive ability AND computer	2070	1681
	cognitive skill AND human-computer interaction	72	17
	cognitive skill AND computer	1150	1077
	psychomotor ability AND human-computer interaction	21	2
	psychomotor ability AND computer	806	605
	psychomotor skill AND human-computer interaction	35	4
	psychomotor skill AND computer	885	684
Culture	culture AND human-computer interaction	129	47
	culture AND computer	17796	8882
	culture AND social media	3648	2884
	culture AND website	620	675

Note: We restricted the searches to a timeframe of 2004-2014 and searched for journal articles only (except for psychomotor ability and psychomotor skill).

To limit the scope of our review, we did not include studies reporting on physical and mental disabilities (e.g. individual differences due to blindness or Alzheimer's disease). We restricted ourselves to traits, cognitive style, cognitive and psychomotor ability and culture. Due to the small number of studies on psychomotor abilities we found in journals, we extended our search to include conference proceedings for just this category as well.

4. Results

Our final set of articles consist of 98 HCI studies that matched all of the selection criteria. Twenty-nine studies reporting on traits and personality were selected for inclusion, seventeen studies reporting on cognitive style, twenty-five studies on cognitive and psychomotor abilities and, lastly, twenty-seven studies were included reporting on culture.

In the following sections, we report on domains, methods, effect sizes for each of the individual difference levels. In a separate section, we describe the studies controlling for experience, domain knowledge, age and gender effects.

Table 2
Number of studies in the individual difference categories

Individual difference level	N	%
Traits	29	30
Cognitive Style	17	17
Cognitive and psychomotor abilities	25	26
Culture	27	28

Note: Percentages do not add up to 100% due to rounding

4.1. Traits

In this section, we present the domains, methods and effect sizes of the studies we selected on traits and human-computer interaction.

4.1.1. Domains

Table 3 presents an overview of the domains in which we categorized our selection of studies reporting on traits and human-computer interaction (n=29). Half of these studies were conducted on individual differences in social media, like Facebook (Moore & McElroy, 2012). Two studies examined the effects of personality on both Facebook and Twitter (Davenport, Bergman, Bergman, & Fearrington, 2014; Hughes, Rowe, Batey, & Lee, 2012). Note that we also included e-mail in the domain of social media; thus, a broad definition of social media was employed. Furthermore, within the ‘Other’ subdomain of social media we included studies on, for instance, the effect of personality traits on instant messaging (Wang, Ngai, & Wei, 2012), on product ratings and participation at online forums (Helm, Möller, Mauroner, & Conrad, 2012) and on dating site behavior (Kim, Kwon, & Lee, 2009). In the ‘Internet usage’ domain (14%, n=4), we categorized studies reporting on internet addiction (Chak & Leung, 2004), global internet use (Engelberg & Sjöberg, 2004) and user-generated content consumption (Moon, Kim, & Armstrong, 2014).

4.1.2. Methods

Most studies used quantitative methods (86%, n=25), while the other four (14%) used a mixed-methods design. For example, Subramanian, Wise, Davis, Bhandari, and Morris (2014) employed quantitative methods to measure explicit, self-reported, self-esteem as well as implicit self-esteem by using an Implicit Association Test designed to measure self-esteem (Greenwald & Farnham, 2000). In addition, they performed a qualitative content analysis in order to assess narcissistic Facebook use. A similar study on Facebook usage was conducted by Moore and McElroy (2012), only they examined the effect of the Big Five personality traits on Facebook usage, studied using content analysis as well. In a study by Schüssel et al. (2012), users of a multimodal system were observed in their interactions to find relations with personality traits. There were no studies using solely qualitative methods in traits research.

Table 3
Domains in traits research

Domain measured	Example	N	%
Social media		15	52
Facebook	Kuo & Tang (2014)	5	17
Facebook and Twitter	Hughes et al. (2012)	2	7
Social network site unspecified	Correa, Hinsley, & de Zúñiga (2010)	2	7
E-mail	Hair, Renaud, & Ramsay (2007)	1	3
Other	Luse, McElroy, Townsend, & DeMarie (2013)	5	17
Internet usage	Chak & Leung (2004)	4	14
Emotions in computer use	Korukonda (2007)	3	10
Games	Orr, Ross, & Orr (2012)	3	10
Adaptivity	Goren-Bar, Graziola, Pianesi, & Zancanaro (2006)	1	3
Multimodal interaction	Schüssel, Honold, & Weber (2012)	1	3
Mobile phone usage	Butt & Phillips (2008)	1	3
Virtual reality	Wallach, Safir, & Samana (2010)	1	3

Note: Percentages do not add up to 100% due to rounding

An overview of the methods used is presented in Table 4. Due to the large number of validated questionnaires (n=60), we present only those questionnaires that were used in more than one study. An exception to this rule was made for measures of the Big Five personality traits, which were all mentioned. Over half of the studies used self-developed questionnaires (59%, n=17). In most of these studies (n=7), the authors listed the items either in text, tables or in the appendix (e.g. Davenport et al. (2014) who used a self-developed questionnaire to get an impression of participants' Facebook and Twitter usage, their reasons for updates and number of friends/followers). Others only mentioned some of the items used or did not mention the items at all (n=6 and n=4, respectively). For instance, Cole & Hooley (2013) measure participants' number of months playing Massive Multiplayer Online Games, their daily time spent gaming ''and other relevant characteristics" (p. 5), without mentioning what these other characteristics were and how they were measured. Note that most of the self-developed questionnaires were used to gain measures of dependent variables, experience and domain knowledge (i.e. not for measuring personality). In order to measure personality traits, most studies used validated measures. However, in Kim et al. (2009) a measure of participants' sociability was obtained by a self-developed, unstandardized, 4-item questionnaire and in Helm et al. (2012) a self-developed questionnaire for lack of social recognition was used. In the latter study, Cronbach's Alpha is provided and exploratory and confirmatory factor analyses were performed. Of the validated measures, the Big Five NEO-FFI (Costa & McCrae, 1992) and Rosenberg's Self-Esteem Scale (Rosenberg, 1965) were used most often (18%, n=5 studies for both). Most studies (59%, n=17) used a measure of the Big Five personality traits. Some other used measures of personality included Narcissism (e.g. Krishnan & Atkin, 2014), Locus of Control (e.g. Hair et al., 2007) and Shyness (e.g. Marriott & Buchanan, 2014), all measured by questionnaires.

There was one study that also included a cognitive style measure to examine the effects of personality and cognitive style on preference for working in virtual teams (Luse et al., 2013). Furthermore, two studies included a measure of cognitive ability, namely emotional intelligence (Engelberg & Sjöberg, 2004) and math skills (Korukonda, 2007).

4.1.3. Impact

More than half of the studies mentioned effect sizes of some sort (62%, n=18). Most studies (n=16) present the reader values of R^2 (i.e. the variance explained by the tested model). There is quite some variation within these values and some models include more variables than others. For instance, for social media, Davenport et al. (2014) mention explained variance of less than 10% for narcissism, age and gender combined on social network site usage and motives. Similar effect sizes were found in Correa et al. (2010), but for extraversion, neuroticism and openness to experience on social media use. On the other hand, larger effect sizes in social media research were found in Moore and McElroy (2012). They performed their analyses in steps so that, when personality was added to their model containing experience and gender, values of 41% extra explained variance due to Big Five traits were found for number of Facebook postings about others. Recall that this study performed a content analysis of Facebook profiles. A study by Amichai-Hamburger and Vinitzky (2010) also performed a content analysis of Facebook data, but found low amounts of variance explained by Big Five personality traits (R^2 = .05 for uploading personal information and .07 for number of friends).

Table 4
Data collection methods in personality traits research

Methods	N	%
Questionnaires	29	100
Self-developed (all items listed)	7	24
Self-developed (items unknown)	4	14
Rosenberg's Self-Esteem Scale (Rosenberg, 1965)	5	17
Self-developed (items partly known)	6	21
Eysenck Personality Questionnaire Extraversion/Neuroticism (Eysenck, Eysenck, & Barrett, 1985)	2	7
Narcissistic Personality Inventory (NPI-40; Raskin & Terry, 1988)	2	7
Locus of Control Questionnaire (LoCQ; Rotter, 1966)	2	7
Big Five questionnaires	17	59
Big Five NEO-FFI (Costa and McCrae, 1992)	5	17
Big Five NEO PI-R (Costa and McCrae, 1992)	2	7
Big Five Inventory (John, Donahue, & Kentle, 1991)	2	7
Big Five 10-item Personality Inventory (Gosling, Rentfrow, & Swann, 2003)	2	7
41-item Five Factor Inventory (Buchanan, Johnson, & Goldberg, 2005)	1	3
Big Five NEO PI (Costa & McCrae, 1985)	1	3
Big Five Mini-IPIP (Donnellan, Oswald, Baird, & Lucas, 2006)	1	3
Big Five IPIP (Goldberg et al., 2006)	1	3
44-item Big Five Inventory (John & Srivastava, 1999)	1	3
Big Five Markers Scale (Italian version; (Perugini & Di Blas, 2002)	1	3
Big Five Inventory (Wiggins & Trapnell, 1997)	1	3
Tests	1	3
Implicit Association Test Self-Esteem (Greenwald & Farnham, 2000)	1	3
Content analysis	3	10
User observation	1	3

Note: n=17 studies; percentages do not add up to 100% because several studies used more than one data collection tool.

Studies in other domains report R^2 values of 23.6% explained variance by Big Five traits and self-esteem in time spent writing and receiving SMS messages (Butt & Phillips, 2008), 26% explained variance by empathy, immersive tendencies and locus of control on presence scores in a virtual environment (Wallach et al., 2010) and 35.5% explained variance by social phobia and trait anxiety on problematic internet behaviour in games (Cole & Hooley, 2013). Some studies (e,g, Wang et al., 2012) reported variance explained by other predictors, but not for personality.

Other effect sizes measures include semi-partial correlations squared (sr^2; Worth & Book, 2014) and partial eta squared (η_p^2; Schwark, Dolgov, Hor, & Graves, 2013). The former study found, for instance, that openness to experience explained 11.4% of the variance for engaging in immersive game play of Massive Multiplayer Online games. The latter study found high values of explained variance (η_p^2 = .56) of neuroticism for the degree of affect change due to a hedonic computing paradigm, but only for women.

4.2. Cognitive style

In the following section we present the domains, methods and effect sizes of selected studies reporting on cognitive style and human-computer interaction

4.2.1. Domains

Table 5 shows the domains in which we categorized the studies reporting on cognitive styles as an individual difference level in human-computer interaction (n=17). Most of the studies (approximately 47%) were in the domain of E-Learning. For instance, Angeli (2013) examined the effects of Field Dependence on problem solving performance and interaction with a computer modelling tool. Furthermore, Workman (2004) studied the effects of cognitive styles in computer-based education as well as computer-aided education. In the domain of 'Generic computer usage' studies report on cognitive style in relation to internet usage (McElroy, Hendrickson, & Townsend, 2007), attitudes toward computers (Altun & Cakan, 2006) and information seeking performance and behaviour (Yuan, Zhang, Chen, & Avery, 2011). Among the least occurring domains were virtual reality and multimedia preferences. In addition, we chose to include a study by Lee (2010) on anthropomorphic interfaces. We acknowledge that Human-Computer Interaction has overlap with Human-Robot Interaction on this domain. However, a line has to be drawn and we considered this domain to belong in HCI.

Table 5
Domains in cognitive style research.

Domain measured	Example	N	%
E-Learning	Höffler and Schwartz (2011)	8	47
Generic computer usage	Yuan, Zhang, Chen and Avery (2011)	3	18
Website design preferences	Chen, Magoulas and Dimakopoulos (2005)	3	18
Virtual reality	Hecht and Reiner (2007)	1	6
Multimedia preferences	Ghinea and Chen (2008)	1	6
Anthropomorphic interfaces	Lee (2010)	1	6

Note: Percentages do not add up to 100% due to rounding.

4.2.2. Methods

Most studies used quantitative methods (82%, n=14) and others used a mixed-methods design (18%, n=3). For example, Triantafillou, Pomportsis, Demetriadis and Georgiadou (2004) used a questionnaire and a debriefing interview to collect qualitative data along with their quantitative questionnaire in order to measure participants' cognitive styles, performance and attitudes towards an adaptive educational system. There were no studies using solely qualitative measures. Other qualitative measures include user observation (Angeli, 2013) and an open-ended questionnaire (Chen et al., 2005). Most quantitative data, by contrast, was obtained by questionnaires. Chen (2010) also examined log-files of the interaction with a web-based learning program to obtain measures of participants' navigational behaviour within the program.

An overview of the data collection methods is presented in Table 6. About half of the studies on cognitive style made use of self-developed questionnaires for dependent variables, experience and domain knowledge (59%, n=10). In three of these studies, the items of the questionnaire were not mentioned by the authors (e.g. Chen et al. (2005), in which "thirty closed questions were applied to identify the participants' perceptions toward the features of interface design" (p.74), without mentioning exactly what these items were). Five other studies mentioned some of the items in text or in tables. Lastly, only two studies using self-developed questionnaires listed all items either in text, tables or in the appendix (e.g. Lee and Koubek (2011) which mentioned all items on a questionnaire that measured perceived usability, perceived aesthetics and user preference before actual use of simulated systems). Note that, for the measurement of cognitive styles, every study used a validated questionnaire and/or test. Most self-developed questionnaires were created to obtain data on participants' previous experience with a computer or system or participants' domain knowledge. Another study used a self-developed questionnaire to measure attitudes towards computers as well (Triantafillou et al., 2004).

Of the validated cognitive style measures, the Cognitive Styles Analysis by Riding (1991) was used most often (29%, n=5), followed by the Group Embedded Figures Test (Witkin, Oltman, Raskin, & Karp, 1971) and Mayer and Massa's (2003) Verbal-Visual Learning Style Rating (n=3 and n=2, respectively). Most validated measures were only mentioned in a single study. These include the Myers-Briggs Type Indicator Form M (Myers & Myers, 1998) and the Rational-Experiential Inventory short version (Pacini & Epstein, 1999).

Beside cognitive styles, some studies measured other individual difference levels as well. For instance, cognitive ability measures were also obtained in a study on hypermedia navigation (Calcaterra, Antonietti, & Underwood, 2005) and in a study on multimedia instructions (Massa & Mayer, 2006). One study included a measure of personality (McElroy et al., 2007).

4.2.3. Impact

Only six of the studies (35%) reported effect sizes of some sort. Massa and Mayer (2006) and Angeli (2013) both mention η^2 values. These values differ substantially between the two studies; whereas 20% of the variance in overall computer interaction and 16% of the variance in problem-solving performance with a computer modelling tool was explained by Field Dependency (Angeli, 2013), the study by Massa and Mayer (2006) found a maximum of 5% explained variance for a verbalizer-visualizer distinction on an electronic learning test score. One study used partial eta-squared (η_p^2), but found many low proportions of explained variance (5% and less) for cognitive styles and social responses to anthropomorphic interfaces (Lee, 2010). McElroy et al. (2007) present values of R^2 of 10% and 11% explained variance in internet use and e-selling respectively, albeit not for cognitive style but for personality. These values were obtained after adding personality to the existing model of control variables like computer anxiety, self-efficacy and gender.

Table 6
Data collection methods in cognitive style research

Methods	N	%
Questionnaires	17	100
Self-developed (items partly known)	5	29
Self-developed (items unknown)	3	18
Self-developed (all items listed)	2	12
Verbal-Visual Learning Style Rating (VVLSR; Mayer & Massa, 2003)	2	12
Myers-Briggs Type Indicator Form M (Myers & Myers, 1998)	1	6
Other (e.g. Thinking Style Inventory, Rational-Experiential Inventory)	6	35
Tests	11	65
Cognitive styles analysis (CSA; Riding, 1991)	5	29
Group Embedded Figures Test (Witkin et al., 1971)	3	18
Gregorc Style Delineator (GSD; Gregorc, 1982)	1	6
Extended Cognitive Style Analysis Wholistic/Analytic Test (Peterson & Deary, 2006)	1	6
Hidden Figures Test (HFT; French, Ekstrom, & Price, 1963)	1	6
User observation	2	12
Log file analysis	2	12
Interview (type (e.g. semi-structured) not mentioned)	1	6

Note: n=17 studies; percentages do not add up to 100% because several studies used more than one data collection tool.

The only study that reported Cohen's d values was Lee and Koubek (2011). For instance, they found that visualizers (high and low; d = 0.432) responded more sensitively to aesthetic features than verbalizers (high and low; d = 0.081). It is noteworthy that this study reported d values of non-significant findings as well. Lastly, Miller (2005) mentions differences in the amount of material learned from a computer-based instruction system between participants with different cognitive styles. For example, the author states that Concrete Random participants learned 22% more than Concrete Sequential participants. Furthermore, Abstract Random participants learned 14% more than Concrete Sequential participants. This way of reporting the impact of cognitive styles is similar to the way Egan (1988) reported his findings. Differences are expressed in percentages, but no standard deviations are mentioned anywhere in the paper. Hence, Cohen's d cannot be calculated and it will be harder to compare this study's results with other studies.

4.3. Cognitive and psychomotor ability

In this section, we present the domains, methods and effect sizes of selected studies on cognitive and psychomotor ability and human-computer interaction.

4.3.1. Domains

An overview of the domains in which we categorized HCI studies reporting on cognitive and psychomotor ability as a level of individual differences is presented in Table 7. In total, we selected 25 studies that met the criteria. Most studies on psychomotor ability were conducted within the domain of input device usage (20%, n=5). In the input device usage domain only studies of psychomotor ability were mentioned. For instance, in an early study by Cheong, Pham, Phan and Shehab (2005), the authors found that precision control ability was related to movement time in a computer mouse task. In a later study, Cheong, Shehab and Ling (2013) analyzed the effects of age and psychomotor ability (e.g. arm-hand steadiness, wrist-finger speed and manual dexterity) on computer mouse aiming movement. The authors found that manual dexterity was related to most measures of mouse movement (e.g. peak velocity and the time needed until peak velocity was reached). In the E-learning domain, Ownby, Czaja, Loewenstein and Rubert (2008) found that psychomotor speed and cognitive ability were associated with older participants' performance on a computer-based training program. A commonality in all these studies is that they argue that age itself may not directly affect performance, but that other characteristics like psychomotor ability mediate the influence of age. In addition, Sutter, Oehl and Armbrüster (2011) mention domain-specific motor skills with using an input device like a touchpad or a mini-joystick as influencing factors of usage of these devices. Experts and novices of touchpads and mini-joysticks were compared and it was found that experts performed at a novice level on the non-congruent device (i.e. expert users of touchpads performed at a novice level on mini-joysticks and vice versa). Novices were even able to outperform experts in mouse movement time when training was received. The authors claim that domain-specific motor skills are essential for expert performance in these devices. In other words, they argue that experience is associated with increased motor skills, which in turn is associated with better performance.

Table 7
Domains in cognitive and psychomotor ability research

Domain measured	Example	N	%
Information seeking	Westerman, Collins and Cribbin (2005)	5	20
Input device usage	Cheong, Pham, Phan and Shehab, 2005)	5	20
Virtual reality	Richardson, Powers and Bousquet (2011)	4	16
E-Learning	Kollöffel (2012)	4	16
Games	McDermott et al. (2014)	3	12
Voice response systems	Pak, Czaja, Sharit, Rogers and Fisk (2008)	2	8
Social media – E-mail	Gwizdka and Chignell (2004)	1	4
PDA usage	Arning and Ziefle (2009)	1	4

Most studies on cognitive ability were conducted within the domain of information seeking (20%, n=5). For example, Dommes, Chevalier and Lia (2011) examined the influence of cognitive flexibility and vocabulary abilities of older and younger users on finding information using Google. Another example in the information seeking domain is the study by Downing, Moore and Brown (2005). The authors examined the effects of spatial visualization ability and domain knowledge on information search using an electronic archive tool. In the domain of virtual reality (VR), studies report on, for instance, the effects of spatial ability in VR versus non-VR (Lee & Wong, 2014), spatial ability and experienced presence in a public speaking virtual environment (Ling, Nefs, Brinkman, Qu, & Heynderickx, 2013) and visual attention ability on navigation in a virtual environment and manipulation of an object in a virtual environment (Tyndiuk, Lespinet-Najib, Thomas, & Schlick, 2007). Furthermore, three studies on individual difference in cognitive ability were conducted in the domain of games (16%). These studies report on differences in visual short-term memory between action game players and non-gamers (McDermott et al., 2014), on differences between expert gamers and non-gamers in object tracking performance, visual short-term memory, mental rotation and task switching (Boot, Kramer, Simons, Fabiani, & Gratton, 2008) and differences in mathematical skill, logical skill and school performance between Massive Multiplayer Online Role Playing Game players and non-gamers (Campello De Souza, De Lima E Silva, & Roazzi, 2010). Studies in the E-Learning domain (16%, n=3) were mostly focused on spatial ability in relation to performance on animated versus static computer-based learning material (Falvo & Suits, 2009; Lee & Shin, 2011). In Kollöffel (2012), the relation between performance on a spatial visualization test and a computer-based mathematical learning task was explored. Among the less researched domains was voice response systems (e.g. Pak et al. (2008) report on the mediating effects of spatial ability, working memory and attention in age-related performance decline on an auditory voice response task).

4.3.2. Methods

Most studies in our selection used solely quantitative measures (92%, n=23), whereas a study by Sharit et al. (2008) also conducted a structured interview to measure participants' domain knowledge of the internet and search engines besides quantitative measures (e.g. the Paper Folding test; Ekstrom, French, Harman, & Dermen, 1976) and a study by Agudo et al. (2010) observed children interacting with a computer mouse and recorded how many errors were made. In the quantitative studies on psychomotor ability, mouse usage was mostly measured by log files of the interaction. Data such as initiation speed, peak velocity and peak acceleration were obtained this way (e.g. Cheong et al., 2013). Quantitative measures on cognitive ability were mostly in the form of tests and questionnaires. There were five studies (20%) that analyzed log files of their participants' interaction with the computer, obtaining measures like navigation behaviour.

A total of 55 validated tests and 8 validated questionnaires were used. Of these measures, 50 tests measured cognitive ability and there were no questionnaires measuring cognitive ability (the 8 validated questionnaires mainly measured personality traits). Only three of the six psychomotor ability studies measured psychomotor abilities. For example, Cheong et al. (2013) measured participants' psychomotor ability with several standard apparatus (see Cheong et al., 2013). In Cheong et al. (2005), one of these apparatus (i.e. a photoelectric rotary pursuit unit) was used to measure precision control ability. The other psychomotor ability studies did not provide any measures of these abilities, but nevertheless made inferences about them.

Two cognitive ability tests were self-developed, without providing any attempts to validate them. These include the Knowledge Test and Psychometric Test in Campello De Souza et al. (2010). Due to the large number of validated questionnaires and tests, we decided to present only those measures that were used in more than one study in Table 8. Regarding questionnaires for measures other than cognitive and psychomotor ability, what stands out is the amount of self-developed questionnaires with unknown items (60%, n=15). We found that many studies do not report the items used to measure individual differences in mainly experience and domain knowledge. For example, Lee and Wong (2014) gave their participants a pretest (to measure prior domain knowledge) and a posttest but do not provide the reader with the items used. Similarly, Falvo and Suits (2009) do not report the items used on their pretest for domain knowledge and do not report items used to measure participants' experience in science either. On the other hand, two studies reported the items used partly (e.g. Dommes et al. (2011), who present slightly more information about the items) and two studies listed all used items (e.g. Arning & Ziefle (2009), who present all items used for gathering information about participants' duration of computer usage, ease of computer usage and frequency of computer usage).

Table 8
Data collection methods in cognitive and psychomotor ability research

Methods	N	%
Questionnaires	18	72
Own (items unknown)	15	60
Own (all items listed)	2	8
Own (items partly known)	2	8
Tests	21	84
Paper Folding Test (Ekstrom et al., 1976)	7	28
Cube Comparison test (Ekstrom et al., 1976)	3	12
Building Memory Test (Ekstrom et al., 1976)	2	8
Log file analysis	9	36
Structured interview	1	4
User observation	1	4

Note: n=19 studies; percentages do not add up to 100% because several studies used more than one data collection tool.

In order to measure cognitive abilities, the Paper Folding test (Ekstrom et al., 1976) was used most often (37% of the studies, n=7). Indeed, two more cognitive ability tests by Ekstrom and her colleagues (1976), the Cube Comparison test (16%, n=3) and the Building Memory test (11%, n=2), were used in more than 1 study. Among the other tests which were used by only a single study, and thus not incorporated in Table 8, were cognitive tests like the WAIS-IV (Wechsler, 2008).

There were some studies that measured more than one level of individual difference. Two studies also included a measure of participants' cognitive style (Kollöffel, 2012; Sharit et al., 2008), one study included several traits measures, like empathy and locus of control (Ling et al., 2013) and one study included a psychomotor speed measure (Pak, Rogers, & Fisk, 2006).

4.3.3. Impact

About half of the studies reported effect sizes of some sort (52%, n=13). Most of these studies presented a measure of effect size in the form of R^2 (i.e. the variance explained by the tested model). For example, in Sharit et al. (2008) reasoning ability was the most important predictor of performance on a simple information seeking task and accounted for 21.4% of the variance over and above domain knowledge. In more complex information seeking tasks, working memory seemed to be a more important predictor, accounting for 12.2% of the variance in performance again over and above total knowledge (Sharit et al., 2008). Interestingly, adding age to the model in a subsequent step did not increase R^2 any further for simple nor complex tasks. This implies that after controlling for knowledge and cognitive ability, the effect of age on information seeking performance was absent. Pak, Rogers and Fisk (2006) also report on information search performance but mainly for spatial ability. In their study, spatial orientation (i.e. a subfactor of spatial ability) accounted for 7.7% of the variance (ΔR^2) in the more navigationally demanding condition. This effect was found after measures of perceptual and psychomotor speed, working memory, crystallized intelligence and attention were already in the model a step before spatial orientation was added. For specific tasks, cognitive abilities accounted for higher amounts of variance (as expressed by R^2) in several studies. For instance, in Dommes et al. (2011), cognitive flexibility and age together accounted for 72% of the variance in total number of requests made by the participant (age accounted for 36% of the variance in cognitive flexibility; η_p^2 = .36). Moreover, spatial ability and age accounted for 73.2% of the variance in number of tasks solved on a PDA and accounted for 74.4% variance on the time spent on these tasks (Arning & Ziefle, 2009).

Four studies mention effect sizes in η_p^2 (21%, n=4). In Gwizdka and Chignell (2004), visual memory explained 33.3% of the variance in performance time; participants with lower scores on visual memory were overall slower than their higher visual memory counterparts. Another study found an interaction between set size of a visual short-term memory task and group (action video game players vs. non-gamers), accounting for 10.2% of the variance; action video game players performed better at higher set sizes for the visual memory task than non-gamers (McDermott et al., 2014).

Two studies reported semi-partial correlations (11%). For example, Kollöffel (2012) found that verbal ability accounted for 8.9% of the variance in situational knowledge scores and spatial visualization accounted for 10.6% of the variance in situational knowledge scores. One of the findings in Miller, Gagnon, Talbot and Messier (2013) was that working memory scores predicted 16% of the variance in the number of interactive voice response tasks completed.

Lastly, one study reported Cohen's d values for some of their effects. Falvo and Suits (2009) found that high spatial ability people performed better on a post-test for knowledge than low spatial ability (d=0.60). The authors, however, did not specifically state that Cohen's d was used and merely called it 'effect size'.

The only study presenting relevant effect sizes for psychomotor abilities was Cheong et al. (2013). The authors provide effect sizes in the form of η^2 for age on computer mouse usage. They found, for instance, that age accounted for 27.7% of the variance in time from peak velocity until end of movement, 20.1% of the variance in the time until peak velocity was reached and 19.8% of the variance for time until peak acceleration was reached. They then examined how much variance was shared between age and psychomotor ability (mainly manual dexterity). For time until peak velocity, 87.7% of the variance was shared; for time until peak acceleration, 90.6% of the variance was shared. In fact, age and psychomotor ability shared more than 80% of variance for all dependent variables, except for time from peak velocity until end of movement (which the authors term the 'homing phase'). On this variable, age and psychomotor ability shared 48.9% of the variance. The authors concluded that direct age influence was minimal in the first mouse movements and that psychomotor ability mediated this effect. However, for the homing phase, the same cannot be said and other variables may be involved.

4.4. Culture

In this section, we present the domains, methods and effect sizes of selected studies on culture and human-computer interaction.

4.4.1. Domains

Table 9 presents an overview of the domains in which we categorized studies reporting the effect of culture in human-computer interaction (n=27). We found that most studies report on the cultural influences in the domain of E-commerce (41%, n=11). For instance, Lee and Choi (2006) examined the effects of horizontal and vertical individualism and collectivism on participants' attitudes towards web advertising. Most studies in the E-commerce domain were focused on websites. However, Choi, Lee and Kim (2006) explored the effects of individualism/collectivism, uncertainty avoidance and contextuality in mobile data services. Research was also focused on cultural effects in the social media domain (37%, n=10). During the process of categorization, we decided to group studies in several subdomains. Most subdomains were only researched in a single study. In the subdomain of e-mail, however, two studies were conducted. The first, Lee and Lee (2009), examined the differences between US and Korean employees in e-mail usage. In the second study, Tan, Sutanto, Phang and Gasimov (2014), the effect of contextuality on people's preferences for commercial communications via e-mail or via SMS was studied. In the 'Other' subdomain of social media, we categorized a study reporting on the effect of culture and communication medium on the degree of social conformity in a line judgment task (Cinnirella & Green, 2007).

4.4.2. Methods

Most studies used solely quantitative measures (70%, n=19), two studies used solely qualitative measures (7%) and six studies reported measures of both quantitative and qualitative measures (22%). All quantitative data was obtained through questionnaires, while qualitative data was obtained through, for instance, interviews (e.g. Choi et al., 2006), content analyses (e.g. Pflug, 2011) and focus groups (Tan et al., 2014).

Table 9
Domains in culture research

Domain measured	Example	N	%
E-Commerce	Choi et al. (2006)	11	41
Social media		10	37
E-mail	Lee and Lee (2009)	2	7
Internet forums	Pflug (2011)	1	4
Instant messaging	Guo, Tan, Turner and Xu (2008)	1	4
Flickr	Dotan and Zaphiris (2010)	1	4
Online community	Ishii and Ogasahara (2007)	1	4
Personal communication technology	Vishwanath and Chen (2008)	1	4
Facebook	Rui and Stefanone (2013)	1	4
Social network sites in general	Choi, Kim, Sung and Sohn (2011)	1	4
Other	Cinnirella and Green (2007)	1	4
Website design preferences	Mazaheri, Richard, Laroche and Ueltschy (2014)	4	15
Games	Zaharias and Papargyris (2009)	2	7

Note: Percentages do not add up to 100% due to rounding

An overview of the data collection methods used in culture research is presented in Table 10. A total of 22 validated questionnaires were used in our selection of studies. We chose to only present validated questionnaires measuring cultural dimensions. Curiously, there were only four studies measuring cultural dimensions with validated questionnaires. These include the study by Tan et al. (2014) measuring Hall's (1976) cultural dimension of contextuality mentioned before, a study by Gevorgyan and Manucharova (2009) measuring individualism/collectivism and power distance dimensions using a scale by Singh and Matsuo (2004) and two studies measuring horizontal and vertical individualism and collectivism (Triandis, 1995; Triandis & Gelfand, 1998). Nine studies (33%) did not measure cultural dimensions of their participants, but nevertheless present conclusions of these dimensions. These studies obtained data from participants with different nationalities and use, for instance, Hofstede's (1980) characterization of countries. Indeed, several studies concluded that their sample of participants from a certain country has certain cultural characteristics based on research done several decades ago.

Other studies examined differences between members from different countries without mentioning cultural dimensions (41%, n=11), between members from a certain religion (Siala, O'Keefe, & Hone, 2004) or between English and French speaking members in Canada (Nantel & Glaser, 2008).

Most studies also made use of self-developed questionnaires for measures other than cultural dimensions (81%, n=22). Twelve studies (44%) listed all used items either in text, tables or in the appendix (e.g. Cyr, Head, & Larios, 2010). Furthermore, seven studies (26%) used self-developed questionnaires of which no items were presented anywhere in the paper. Such a questionnaire was used in a study by Zaharias and Papargyris (2009), who measured participants' perceived game usability with an unstandardized questionnaire of which the items were not mentioned anywhere in the paper. Lastly, three studies (11%) presented the items of the questionnaire only in part (e.g. Hwang, Jung, & Salvendy, 2006).

Table 10
Data collection methods in culture research

Methods	N	%
Questionnaires	25	93
Own (all items listed)	12	43
Own (items unknown)	7	25
Own (items partly known)	3	11
Contextuality (Hall, 1976)	1	4
Hofstede's individualism/collectivism and power distance dimensions (Singh & Matsuo, 2004)	1	4
Horizontal and vertical individualism and collectivism (Triandis, 1995)	1	4
Horizontal and vertical individualism and collectivism (Triandis & Gelfand, 1998)	1	4
Interview	3	11
Structured	2	7
Structured and unstructured	1	4
Content analysis	2	7
Eye-tracking	2	7
Focus group	1	4
Think aloud protocol	1	4

Note: n=27 studies; percentages do not add up to 100% because several studies used more than one data collection tool.

4.4.3. Impact

Ten studies (37%) reported effect sizes of some sort in their study. Most of these reported measures of R^2. For instance, Guo, Tan, Turner and Xu (2008) report increases in explained variance of 2 to 8% in media preferences for instant messaging, telephone and e-mail due to culture (i.e. being Australian or being Chinese) over gender, age and experience. Slightly higher proportions of variance (maximum 16% for status seeking expected outcome) were explained by horizontal and vertical individualism/collectivism on expected outcomes and usage patterns of social network games (Lee & Wohn, 2012).

Three studies reported η^2 values to report proportions of explained variance per effect. For example, Lee and Lee (2009), found that task equivocality (i.e. task ambiguity) explained more variance in media choice for US employees (i.e. 18.1%) than for Korean employees (i.e. 6.3%). Moreover, communication direction explained 0.67% of the variance in media choice for US employees and 10.8% for Korean employees. This is an example of a situation where both effects (i.e. task equivocality and communication direction) were significant ($p<0.01$), but both effects have different implications.

Lastly, Cyr (2008) reports Cohen's f^2 to present the effect size of website trust and satisfaction on e-loyalty for participants from China, Germany and Canada. The effect size of trust on e-loyalty was 0.31 for Chinese, 0.26 for German and 0.11 for Canadian participants. For satisfaction, effect sizes were 0.06 for Chinese, 0.28 for German and 0.27 for Canadian participants. The author concludes that trust is a stronger relation with e-loyalty for Chinese and German people than for Canadian people. Moreover, satisfaction seems to be of less importance for Chinese people in e-loyalty.

4.5. Experience, domain knowledge, age and gender

We found that 31% of traits studies, 24% of cognitive style studies, 68% of cognitive and psychomotor ability studies and 44% of culture studies controlled for effects of experience. In our total set of studies this amounts to approximately 43% of the studies. Some studies merely mentioned experience as a demographic, but did not test for potential effects (e.g. Moon et al., 2014). In Goren-

Bar et al. (2006), previous experience with natural voice interaction was regarded as “quite limited” (p. 7), without having measured this in the sample. In the ‘Effect sizes’ sections of the previously mentioned categories of individual difference, experience was sometimes mentioned already. Most often, a certain predictor explained extra variance over the effect of experience (e.g. stepwise regression) or the total amount of variance explained by the tested model containing experience and other predictors was mentioned (i.e. R^2). For instance, one study mentioned an effect size of experience (together with gender), which was found to explain 20% of the variance in number of posts about oneself (Moore & McElroy, 2012).

Furthermore, 14% of traits studies, 29% of cognitive style studies, 32% of cognitive and psychomotor ability studies and none of the culture studies controlled for domain knowledge. This amounts to 17% of the total number of studies. Some studies measure domain knowledge (and/or experience) but do not test for any effects these might have. For example, Yuan et al. (2011) mention they have measured domain knowledge and experience with an information search system, but do not provide any results on their potential effects. In other studies, a measure is provided but the authors mention that none had any prior knowledge of the domain (Angeli, 2013). Measures of domain knowledge were often in the form of a pre-test for prior knowledge (e.g. Lee & Shin, 2011). One study that performed stepwise analyses shows that variance explained in preference for working in virtual teams vs. preference for working in face to face teams or alone was low for domain knowledge (R^2 = .03; Luse et al., 2013), while another study showed higher variance explained by domain knowledge in information seeking (R^2 = 19% for complex problems and 17% for simple problems; Sharit et al., 2008).

Effects of age were controlled in 41% of traits studies, none of the cognitive style studies, 40% of cognitive and psychomotor ability studies and 41% of culture studies. This amounts to 34% of the total number of studies controlling for age. Several studies found age-related effects in cognitive and psychomotor abilities. For example, Pak et al. (2008) found that age was no longer a predictor of performance on an auditory voice response task after controlling for spatial ability, working memory and attention. Another example of age-related decline in cognitive ability was found in Dommes et al.

(2011), which was mentioned before in the ‘Effect size’ section on cognitive abilities. Schwark et al. (2013) mention η_p^2 values of .12 for age in degree of affect change.

Lastly, gender was controlled in 48% of traits studies, 18% of cognitive style studies, 12% of cognitive and psychomotor ability studies and 52% of culture studies, amounting to 35% of the total number of studies reviewed. Gender was shown to explain approximately 10% (η^2) of the variance in preference for web design elements for German and Chilean participants (Cyr & Head, 2013). Moreover, in Faiola, Ho, Tarrant and MacDorman (2011) age and gender together accounted for 10% of the variance (R^2) in website aesthetics ratings. Interaction effects for gender and age with personality traits were found in, for example, Correa et al. (2010) and for gender and personality in Saleem, Beaudry and Croteau (2011). In another example, females performed better than males on a post-test for knowledge (Cohen’s d = 0.20) after having received information in an animation, regardless of spatial ability (Falvo & Suits, 2009). Noteworthy is that gender was not controlled in any of the psychomotor ability studies.

5. Discussion

This review examined the literature on traits, cognitive style, cognitive and psychomotor ability, and culture in Human-Computer Interaction from 2004-2014. In this section we evaluate the findings, identify gaps in current literature and present our opinion of the use of these categories of individual difference in designing computer systems. We first discuss patterns across categories and the impact of the effects found. Afterwards, implications for design, issues with current research and we specify several gaps in current research. Lastly, we reflect on our method and other limitations. Throughout the Discussion section, we present suggestions on what could be done differently in future individual difference research in HCI.

5.1. Patterns in individual differences in HCI research

The results of this paper suggest that there is indeed some attention to the influences of individual differences in the HCI field in the years 2004-2014. We found ninety-eight studies that matched our criteria. However, compared to the amount of hits we found using our search terms (which were already specified to individual differences), this number of studies is relatively low. The field of individual differences in HCI seems to have evolved somewhat since the time of Dillon and Watson's (1996) paper, although it still appears underrepresented. Searching for “human-computer interaction” in Scopus yields nearly nine thousand hits in journals from 2004-2014 alone, not counting all of the other studies which are not using that specific term (but can nevertheless deal with human-computer interaction). Our selection of ninety-eight of these on empirical individual difference research in journals thus appears rather meagre.

In categorizing our selection of studies, we found that there were some domains which occurred within more than one category of individual difference. Effects of individual differences were studied in social media, virtual reality and games (i.e. domains) in three categories of individual differences. For example, we found studies reporting on gaming in the traits, cognitive ability and culture categories. Internet usage, E-learning, information seeking and website design preferences were studied in more than one category of individual difference as well. Furthermore, we noticed an overall dominance of the social media domain, consisting mainly of studies on traits and culture. More specifically, all categories of individual difference tended to mainly focus on one or two domains, with the exception of cognitive abilities, where no truly dominant domains were present. This means that there are a number of domains which have not been studied extensively yet on individual differences, such as mobile phone usage, multimedia preferences and voice response systems.

Regarding methods used, mixed methods and qualitative methods were scarcely used in individual difference studies in HCI. We found that the large majority of studies used exclusively quantitative methods, while qualitative methods and mixed methods were used to a much lesser degree. This is in contrast with fields like user experience in HCI (e.g. Bargas-Avila & Hornbæk, 2011), where qualitative and quantitative methods are employed more evenly, and with a study by Barkhuus and Rode (2007), who reviewed studies in Human-Computer Interaction from 1983-2006. These authors showed that quantitative measures were indeed more frequently used, but about 40% of the studies used qualitative or mixed methods as opposed to the 16% of studies we selected. Using qualitative measures could lead to more insight into how individual differences affect human-computer interaction, leading to a better understanding of these differences. Dominance of questionnaires and tests was found in the methods used in individual difference research. Moreover, we found that there were many studies using self-developed questionnaires in all of the categories. Most studies used these kinds of questionnaires to measure dependent variables, experience or domain knowledge.

5.2. Impact

Less than half of our selection of studies reported effect sizes (48%). Moreover, judging from the results in our selection, the impact of the individual difference categories on the human-computer interaction appears relatively small. Of the studies that reported effect sizes, most found effects that explained less than 10% of the variance in the variables of interest. Compared to the perceived large role of individual differences in the results of Egan (1988), our results suggest a rather small role for the categories we included. An explanation for this could be that computer systems these days differ a lot from the computer systems in the time of the paper by Egan (1988). In addition, Egan's (1988) notions of impact were mainly focused on completion time, whereas in our review completion time was not a common dependent variable.

5.3. Implications for design

Despite the relatively low impact, some studies are making bold claims on the basis of their results. A popular notion is that designs should automatically adapt to the differences in the categories of individual differences between users (see Aykin's (1991) third option of adaptive interfaces). In our view, this could be very difficult and complex. This view is supported by Schmettow and Havinga (2013), who argue that this approach may not be so efficient with modern day computer systems, due to the large and diverse population of computer users and the myriad of design features to take into account. Moreover, they found that there was more performance variability in tasks and designs conditional on tasks (i.e. a design x task interaction) than in users; a finding that is contrary to e.g. Egan (1988), who claimed that individual differences usually explain more variance in computer performance than system designs. Instead of the above mentioned design suggestions, they propose a different approach to design, namely to view designs as a population and to test the most fit design (i.e. designs with “more uniformly high performance” (p.4) across users and tasks). This suggestion is related to robust design, which adheres to the minimax principle, according to Schmettow and Havinga (2013), because the purpose is to maximize the minimum performance of users. For this to work, a large number of designs has to be available to test for the most appropriate design. Domains mentioned in Schmettow and Havinga (2013) include E-commerce, which overlaps with what we have found in our study, since there are many different designs (e.g. websites) available in this domain. It could prove fruitful to investigate this avenue for computer systems design, especially in E-commerce.

Another way to guide the process of design, is to look at user’s needs and interests, instead of trying to predict performance differences with theory (i.e. traits, cognitive styles etcetera). For example, White and Drucker (2007) studied variability in the behaviour of users in internet search. They found that it was possible to “characterize many features of variation with a small number of underlying dimensions that could be useful in interface design” (p. 30). They created two prototype users that differed in their needs in internet search and proposed design principles to accommodate the needs of these prototypes. Research on the use of prototypical users in guiding design focuses, for instance, on personas (Floyd, Cameron Jones, & Twidale, 2008; Miaskiewicz & Kozar, 2011). Personas are often fictional persons with a narrative, a name and a photograph that represent user groups who identify with this persona (Miaskiewicz & Kozar, 2011). Persona-centred design has been employed in health technologies (LeRouge, Ma, Sneha, & Tolle, 2013) and games (Canossa & Drachen, 2009). This avenue of design still focuses on individual differences, albeit on a different level than the categories mentioned in this review. We believe it may be a lot more feasible to focus on these prototypical user groups in designing modern computer systems, rather than to focus on user’s traits, abilities, styles and cultures for most design purposes. This type of designing for individual differences resembles the second option Aykin (1991) offered (i.e. to design for specific user groups).

5.4. Issues with current research

Many researchers agree that merely reporting the p value is not enough and that we should aim to present results on the magnitude and impact of specific effects (Sullivan & Feinn, 2012). This way, comparisons between studies can be made more easily and readers can interpret results more intuitively. Especially for practical purposes, where weak but statistically significant effects may not be very useful, reporting the impact of the effects found is an important piece of information. We think that effect sizes should also be evaluated, as there is some controversy in what is considered a small, medium or a large effect, especially for Cohen's d (Ellis, 2009). We propose that effect sizes should be interpreted in a meaningful context and not by predefined standards. In our selection of studies, it was often the case that effect sizes of some sort were mentioned. However, a large number of studies still did not report effect sizes or impact. Hence, we strongly encourage the HCI community to report the sizes of the effects found.

There were three studies using self-developed questionnaires or tests to measure individual difference categories (i.e. traits and cognitive abilities), without validating the questionnaire or test or even providing the readers with the items used. The same trend was found to a greater extend in a review on user experience studies (Bargas-Avila & Hornbæk, 2011), where thirty-two studies used a self-developed questionnaire to measure user experience dimensions without always mentioning which items they used. Regarding measures for dependent variables, experience and domain knowledge mostly, we found that many studies in our selection did not report all the items they used. In order to increase studies' reproducibility and overall study transparency, we strongly recommend the HCI community to validate new measurement instruments (or use validated measures) and to present readers with all items or questions of self-developed questionnaires and tests used in their research. Furthermore, regarding studies reporting on cultural effects, we found that there were a number of studies assuming high or low scores on cultural dimensions in their sample without having measured this at all. These studies mainly base their reasoning on a categorization of Hofstede (e.g. Hofstede, 1980), which can date back several decades. As Choi et al. (2006) put it, these studies "have used prior researchers' findings . . . to categorize countries without re-examining the relationship between cultural characteristics of the countries and the target information technology" (p. 176). There are several instruments available to measure cultural dimensions (e.g. Singh & Matsuo, 2004; Triandis & Gelfand, 1998), but most studies reporting on these dimensions relied on previously established and potentially flawed standards. This can result in results and conclusions that may be invalid, potentially impairing the quality of the study. We advise researchers on (Hofstede's dimensions of) cultural effects in HCI to obtain measures of cultural dimension variables from their sample if they are making any conclusions related to these cultural dimensions.

We found large variations in the number of studies controlling for effects of experience, domain knowledge, age and gender. Controlling for effects of these variables can prove useful, because it may be that specific effects found are (in part) due to these variables. Thus, we recommend future studies to control for these variables.

5.5. Gaps in current research

Overall, there were some domains only researched by one or two studies in our selection. These included, for instance, interactive voice response systems, multimodal interaction, mobile phone use and multimedia preferences. More research on these domains regarding traits, cognitive styles, abilities and cultural effects is needed to improve the understanding of human interaction with these technologies. For instance, the effects of cognitive (and psychomotor) abilities on multimodal interaction have not been studied extensively yet, to the best of our knowledge. Moreover, looking at the research area of consumer psychology, we find that personality traits also seem to affect consumer behavior (Baumeister, 2002; Jackson, Parboteeah, & Metcalfe-Poulton, 2014) or consumer emotion (Mooradian & Olver, 1997). In addition, cognitive style is studied in consumer psychology as well (e.g. Chen, 2009; Cui, Liu, Yang, & Wang, 2012), albeit not as frequently. Based on these studies, we can imagine that user can have different preferences or display different behaviour in E-commerce partly due to their personality traits and cognitive styles.

5.6. Limitations

In our review of the literature on individual differences in HCI, we focused exclusively on journal publications (except for psychomotor ability) because we had to limit the scope of our review. Adding conference proceedings to our criteria would have resulted in a gigantic and unmanageable set of potentially relevant entries, so a line had to be drawn somewhere. Furthermore, we specified search terms for each category of individual difference and used minimally specific words like "computer" in order to find many journal publications. However, this means that we missed studies that could not be traced using these search terms. We also missed a few studies that were not available at the digital libraries of the University of Twente, although the vast majority of studies were readily accessible. A different, but a lot more time consuming, approach would have been to start with the broad searches, as we did, and then to formulate new search terms for every category of individual difference combined with the domains found in the broad searches. Nevertheless, our sample of studies shows several patterns and flaws about the studies on individual differences in HCI and based on our findings we were able to present implications for design. In addition, we gave readers an overview of how research on individual difference categories in HCI is conducted and some ideas for future research.

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