

A Cross-cultural Perspective for Personalizing Picture Passwords

Argyris Constantinides
University of Cyprus, Nicosia, Cyprus
Cognitive UX Ltd., Nicosia, Cyprus
argyris@cognitiveux.com

Anna Maria Pietron
Shanghai Jiao Tong University,
Shanghai, China
anna.pietron@gmail.com

Marios Belk
Cognitive UX GmbH, Heidelberg, Germany
University of Cyprus, Nicosia, Cyprus
belk@cognitiveux.de

Christos Fidas
University of Patras, Rio, Patras, Greece
fidas@upatras.gr

Ting Han
Shanghai Jiao Tong University,
Shanghai, China
hanting@sjtu.edu.cn

Andreas Pitsillides
University of Cyprus, Nicosia, Cyprus
cspitsil@cs.ucy.ac.cy

ABSTRACT

Picture passwords, which require users to draw selections on images as their secret password, typically provide globalized solutions without taking into consideration that people across diverse cultures exhibit differences within interactive systems. Aiming to shed light on the effects of culture towards users' interactions within picture password schemes, we conducted a between-subjects *cross-cultural (Eastern vs. Western) study (n=67)*. Users created a password on a picture illustrating content highly related to their daily-life experiences (*culture-internal*) vs. a picture illustrating the same daily-life experiences, but in a different cultural context (*culture-external*). Results revealed that people across cultures exhibited differences in visual processing, comprehension, and exploration of the picture content prior to making their password selections. The observed differences can be accounted by considering sociocultural theories highlighting the holistic preference of Eastern populations compared to the analytic preference of Western populations. Qualitative data also triangulate the findings by exposing the likeability and users' engagement towards the picture content familiar to individual's culture. Findings underpin the necessity to consider cultural differences in the design of personalized picture passwords.

CCS CONCEPTS

• Human-centered computing → Human computer interaction (HCI); HCI theory, concepts and models; Empirical studies in HCI

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from Permissions@acm.org.

UMAP '20, July 12–18, 2020, Genoa, Italy

© 2020 Association for Computing Machinery.

ACM ISBN 978-1-4503-6861-2/20/07...\$15.00

<https://doi.org/10.1145/3340631.3394859>

KEYWORDS

User Authentication; Picture Passwords; Cultural Differences.

ACM Reference format:

Argyris Constantinides, Anna Maria Pietron, Marios Belk, Christos Fidas, Ting Han, Andreas Pitsillides. 2020. A Cross-cultural Perspective for Personalizing Picture Passwords. In *Proceedings of 2020 ACM Conference on User Modeling, Adaptation and Personalization (UMAP '20)*, July 12–18, 2020, Genoa, Italy. ACM, New York, NY, USA, 10 pages. <https://doi.org/10.1145/3340631.3394859>

1 INTRODUCTION

Computer security systems encompass concepts and methods for the protection of sensitive information. In this context, *user authentication* is an essential security task performed daily by millions of users across the globe. Traditional solutions utilize text-based passwords, which require users to memorize a sequence of alphanumeric characters. However, memorizing strong text-based passwords results in increased cognitive load, which often leads to poor usability and limited security [59, 60]. To offer a better trade-off between security and usability, prior works proposed various *picture password schemes* [8], which require users to complete a picture-based task to authenticate.

A crucial interface design factor that affects both the security [10, 12, 29-32] and usability [32, 34-42] of picture password schemes is the background picture(s) used [9-12]. The task of creating a picture password is a perceptual process through the human visual system [8], and involves three steps: *i)* initial impression of the input stimuli; *ii)* information processing; and *iii)* output response. Picture perception is also important for the authentication task [8], since users are requested to recall from memory the previously selected password selections in order to authenticate. Nevertheless, common design practices follow a “*one-size-fits-all*” approach for the pictures delivered to end-users during password creation, without considering that people across diverse cultures exhibit differences in picture perception [51], attention [14], and memory [13] within security systems.

Given that the perceptual processes involved during users' interactions with picture passwords (*i.e.*, creation, login) are heavily linked to cultural differences [14, 51], in this paper we investigate the effects of cultural differences when people interact with *culture-internal*¹ vs. *culture-external*² pictures.

In doing so, we made two contributions:

- We provide external validity to the holistic vs. analytic preference of Eastern vs. Western populations [14, 15, 49-52] in the context of picture password schemes.
- We provide empirical data on the effects of cultural differences in the context of picture password schemes, since to the best of the authors' knowledge, this hasn't been investigated yet.

2 THEORETICAL BACKGROUND

Several works on picture perception have provided evidence that people across diverse cultures perceive differently the context and wholeness of the scenes depicted in pictures [49-51]. For example, Norenzayan et al. [49] investigated the way European Americans, Asian Americans, and East Asians categorize objects. Participants were presented with two groups of objects and were then asked to determine the group to which each target picture was most similar. The results suggested the holistic preference of Asian Americans and East Asians who judged similarity based on family resemblance (*i.e.*, holistically similar to all members of a category due to the large number of shared features with them), compared to the European Americans who relied on the unidimensional rule for deciding whether the target object shared a single feature with all the members of a category or not.

Studies also revealed that the user's cultural background can influence processes such as attention and memory [13, 14, 17, 18]. A study in [50] suggested that Japanese attend more to the "whole" compared to North Americans who attend more to specific features of stimulus. Participants were first presented with a square frame that contained a vertical line, and were then engaged in a framed-line test that assessed their abilities to draw the line in either absolute length or proportional to the height of the surrounding empty frame. Results revealed that individuals in Asian cultures are more capable of incorporating contextual information, while individuals in North American cultures are more capable of ignoring contextual information. To examine the influence of culture in recalling details from memory, a study in [15] revealed that Americans were more accurate than East Asians in memorizing specific features for objects presented alone and within a context supporting that analytic preference of Western cultures can account for the increased specificity of visual information retained in memory [16].

¹ *Culture-internal pictures* highly related to the participants' shared, individual and common sociocultural experiences from the daily life context (*i.e.*, depicting sceneries of a University campus such as lecture rooms, lab rooms, cafeteria, etc.).

² *Culture-external pictures* illustrating the same daily-life experiences depicted in the *Culture-internal* pictures, but in a different sociocultural context (*i.e.*, sceneries from the University of a different culture) to avoid users' familiarity with a scenery.

From a usability and personalization perspective, prior works suggest that incorporating cultural aspects in the design of interactive schemes can improve effectiveness, efficiency and users' experience [61-63]. For example, a cross-cultural study conducted by Singh et al. [63] revealed users' preference on websites adapted to their local culture. Furthermore, recent works [64, 65] have shown that cultural differences impact the way people across cultures perceive, respond and interact with persuasive systems. Orji et al. [64] investigated the influence of the determinants on healthy eating behavior and found that eating behaviors and practices are often determined by cultural and social factors. Hence, they proposed culturally relevant design approaches for bootstrapping persuasive technology interventions by considering the effects of culture. Oyibo et al. [19] examined the determinants of physical activity and found differences across diverse cultures. In particular, the individualist culture was more effective in promoting behavior change through self-motivating strategies, whereas the collectivist culture was more effective through socially oriented strategies. Accordingly, the authors provided a set of design guidelines for applications that tailor the persuasion strategies by considering individuals' culture.

Moreover, users' cultural background, knowledge, expertise and experience impact the perceived affordance of the various interface elements [20, 21]. From a memorability perspective, works in [22, 23] suggested the feasibility of using autobiographical memories to query users about their daily experiences for the task of user authentication. A cross-cultural study in [24] revealed a positive effect on memorability of graphical passwords that consist of images relevant to users' culture. Also, recent literature has shown a positive main effect of users' real-life memories towards memorability of user-generated passwords [25]. From a security perspective, evidence suggests that the design of security systems should take into consideration the social and cultural contexts of the end-users (*e.g.*, marital status, indigenous populations) in order to facilitate their needs (*e.g.*, trust in a relationship, limited banking services) [26, 27]. However, it is important to control which sociocultural aspects, and to what extent, are incorporated in the design of security systems to avoid educated guessing attacks [28].

Research Motivation. The discussed works provide evidence that individuals' cultural differences: *i)* determine the inherited way of receiving, processing, and interpreting visual stimulus which is a cornerstone factor in picture password schemes [8]; and *ii)* influence usability [20-23, 61-65] and security [26-28] of user authentication schemes. However, to the best of the authors' knowledge, there is lack of knowledge related to the effects of cultural differences with respect to password creation, memorability, and security within picture password schemes. We suggest that investigating these effects will allow us to better consider such differences in the design of personalized user authentication schemes. For doing so, we conducted a cross-cultural study (Eastern vs. Western) in which users interacted with a picture password scheme using *culture-internal* vs. *culture-external* pictures in the context of a real-life task.

3 USER STUDY

3.1 Research Questions

RQ1. Are there differences in time spent to explore the picture before making password selections between users who utilize *culture-internal* vs. *culture-external* pictures during password creation across culture groups?

RQ2. Are there differences in time to login between users who utilize *culture-internal* vs. *culture-external* pictures across culture groups?

RQ3. Are there differences in users' selections on hotspots (*i.e.*, segments of a picture that attract the user's attention) between users who utilize *culture-internal* vs. *culture-external* pictures across culture groups?

RQ4. Are there differences in likeability and users' engagement between users who utilize *culture-internal* vs. *culture-external* pictures within picture password schemes across culture groups?

3.2 Study Instruments

3.2.1 Picture Password Scheme. We developed a Web-based cued-recall picture password scheme (Figure 1), similar to Windows 10™ PGA [43], in which users can create gesture-based passwords on a background picture that acts as a cue. Three types of gestures are allowed: taps, lines and circles³. Free line gestures are not permitted, hence, they are automatically converted into one of the three permitted gestures.

3.2.2 Study Factors – Semantics of Picture Content. To control participants' familiarity with the picture semantics, we intentionally chose two specific picture sets: *i) Culture-internal:* pictures highly related to the participants' shared, individual and common sociocultural experiences from the daily life context (*i.e.*, depicting sceneries of a University campus such as lecture rooms, cafeteria, etc.); and *ii) Culture-external:* pictures illustrating the same daily-life experiences, but in a different sociocultural context (*i.e.*, sceneries from the University of a different culture) to avoid users being familiar with a scenery.



Figure 1. A picture password illustrating the three gestures allowed in our Web-based picture password scheme.

³ Microsoft™ Picture Passwords blog - bit.ly/2SajCDO

In order to minimize the bias effect of using one picture per group, we provided a set of nine pictures for each group [47, 66]. Users could select only one picture from their corresponding picture set. Figure 2 illustrates the two picture sets used in the study, which were based on existing research that has shown that users tend to select pictures illustrating sceneries [12, 39, 44]. Considering that the number of hotspots and the picture complexity affect the password strength [40, 41], we chose pictures of similar number of hotspots and complexity between and within pictures belonging to the two groups. For doing so, we followed a semi-automated approach to detect the hotspots segments. To calculate the number of hotspots, we used a combination of computer vision techniques for object detection^{4,5,6}, and a combination of saliency maps⁷ and saliency filters⁸ [45] for the salient regions. We further assessed the equivalence of the two picture sets by calculating the complexity using entropy estimators^{9,10} [46]. Based on these objective measures, we decided on the two picture sets shown in Figure 2. The summarization of the picture complexity and number of hotspots segments is shown in Table 1.

Table 1. Similarities of number of hotspots and picture complexity for the picture sets used in the study.

Picture ID	Complexity in bits (Culture-internal)	Complexity in bits (Culture-external)	Number of Hotspots Segments (Culture-internal)	Number of Hotspots Segments (Culture-external)
1	7.44	7.52	7	7
2	7.48	7.42	8	7
3	7.32	7.39	7	7
4	7.72	7.75	6	6
5	7.51	7.57	7	7
6	7.65	7.72	7	8
7	7.49	7.56	7	7
8	7.19	7.22	7	6
9	7.46	7.51	8	7

3.3 Sampling and Procedure

3.3.1 Participants. We recruited 67 participants; 36 undergraduate students ranging in age from 18 to 25 ($m=21.58$, $sd=2.25$), living in Shanghai, China (Eastern group), and 31 undergraduate students ranging in age from 18 to 23 ($m=19.70$, $sd=1.88$), living in Nicosia, Cyprus (Western group). Participants in each culture group were split evenly¹¹ into two groups, and the picture type was randomly varied across all users. To increase the internal validity of the study, we recruited participants that had no prior experience with picture password authentication mechanisms,

⁴ Tensorflow - bit.ly/1MWEhkH

⁵ Amazon Rekognition - amzn.to/2hm466g

⁶ Google Cloud Vision API - cloud.google.com/vision

⁷ Saliency Map - bit.ly/2MuisZC

⁸ Saliency Filters - bit.ly/2QMuvU

⁹ Image Entropy - bit.ly/2wB7Erm

¹⁰ scikit-image Shannon Entropy - bit.ly/2Xx4iBK

¹¹ Regarding the Western group, 16 participants received the *culture-internal* picture set, and 15 participants received the *culture-external* picture set.

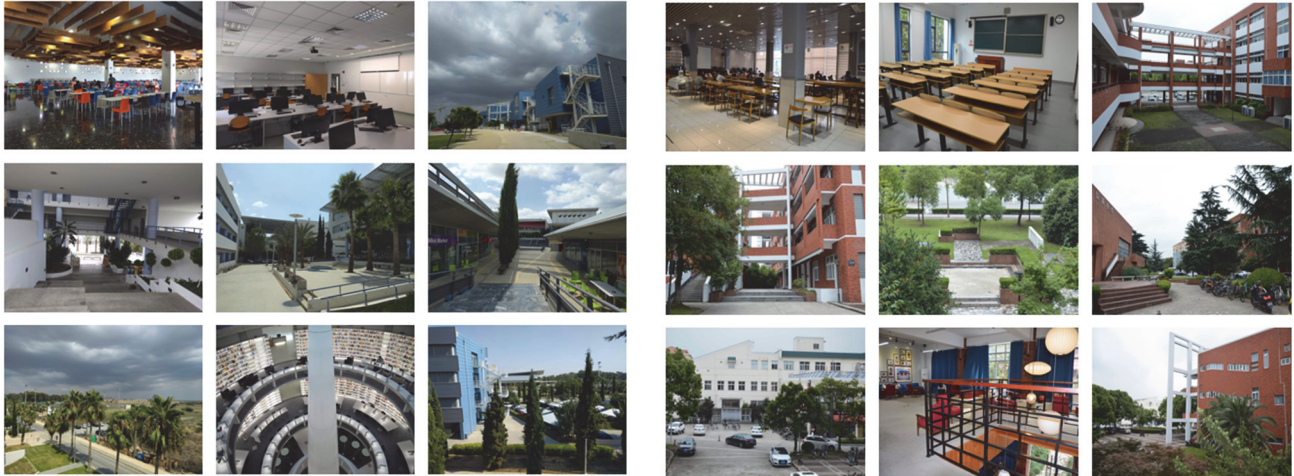


Figure 2. The set of nine pictures (left) illustrating content related to participants’ daily-life experiences at the University of Cyprus (Western population), and acts as the *culture-internal* set for the Cypriot participants and as the *culture-external* set for the Chinese participants. The set of nine pictures (right) illustrating content related to the same daily-life experiences, but in a different sociocultural context at the Shanghai Jiao Tong University (Eastern population), and acts as the *culture-internal* set for the Chinese participants and as the *culture-external* set for the Cypriot participants.

nor knowledge of its security semantics¹², and participants who had spent the last three years at the University campus of each culture group, assuming they would have had experiences within the University.

3.3.2 Experimental Design and Procedure. With respect to the ethical aspects of the study, we adopted each University’s human research protocol that takes into consideration users’ privacy, confidentiality and anonymity. All participants performed the task in a quiet lab room with only the researcher present. To avoid any experimental bias effects, no details regarding the research objective were revealed to the participants. The study involved the following steps: first, participants were informed that the collected data would be stored anonymously and would be used only for research purposes. Next, they signed a consent form and completed a questionnaire on demographics. Next, the participants were introduced to a demonstration page to familiarize themselves with the process of drawing gestures. Participants were then requested to create a user account in order to access an online service. To increase ecological validity and keep security as a secondary task [58], participants were requested to create an account using our picture password scheme, in order to use this account to get access to memes.

Half of the participants of each culture group received a set of nine *cultural-internal* pictures, whereas the other half of each culture group received a set of nine *cultural-external* pictures. In the first step, participants created a username and then they selected one picture out of the nine available pictures, on which they created their picture password by drawing three gestures using a computer mouse. To confirm their picture password, they were requested to reproduce the initial three gestures.

Finally, a discussion on how participants created their password from their assigned picture type set took place, and semi-structured interviews were conducted to elicit users’ likeability and engagement with the picture content used.

4 RESULTS

In the analyses that follow regarding *RQ1-RQ3*, a two-way ANOVA was conducted to examine the effects of culture group (Eastern vs. Western) and picture type (*cultural-internal* vs. *cultural-external*) on the time spent to explore the picture before making password selections (*RQ1*), the time required to login (*RQ2*) and the percentage of picture password selections falling into hotspots segments (*i.e.*, segments of a picture that attract the user’s attention) (*RQ3*) respectively. Residual analysis was performed to test for the assumptions of the two-way ANOVA. Outliers were assessed by inspection of a boxplot, normality was assessed using Shapiro-Wilk’s normality test for each cell of the design and homogeneity of variances was assessed by Levene’s test. There were no outliers, residuals were normally distributed ($p>.05$) and there was homogeneity of variances ($p=.099$ for *RQ1*), ($p=.063$ for *RQ2*), and ($p=.263$ for *RQ3*).

4.1 Time to explore the picture content before password creation (*RQ1*)

Data are mean \pm standard deviation, unless otherwise stated. There was a statistically significant interaction between culture group and picture type on the time spent to explore the picture before making password selections (**Figure 3**), $F(1, 32)=4.239$, $p=.048$, *partial* $\eta^2=.117$. Therefore, an analysis of simple main effects for culture group was performed with statistical significance receiving a Bonferroni adjustment and being accepted at the $p<.025$ level. There was a statistically significant difference in mean “Time spent to explore the picture before making password selections” for *cultural-internal* picture type

¹² Assessed by the semi-structured interviews at the end of password creation

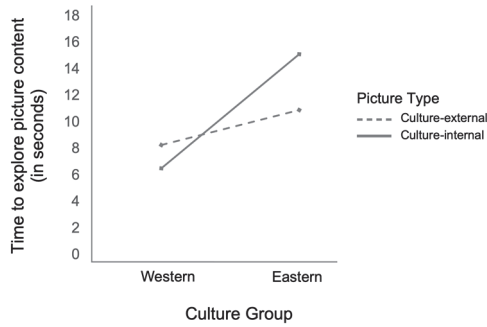


Figure 3. Interaction effect between culture group and picture type on the time spent to explore the picture content before users made the picture password selections.

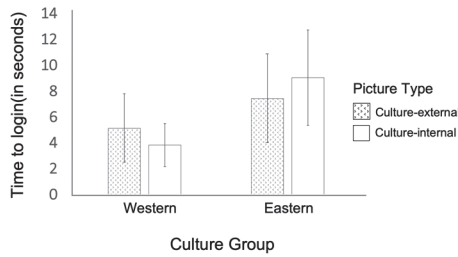


Figure 4. Eastern group was significantly slower than Western group during the first login attempt.

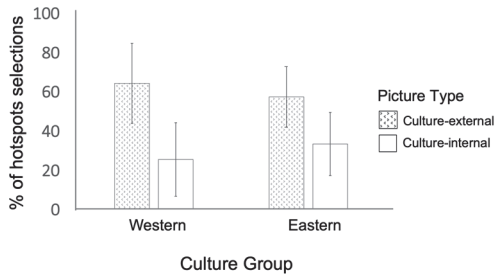


Figure 5. Proportion of picture password selections on hotspots was significantly higher for the culture-external picture type than the culture-internal picture type.

belonging to either Eastern or Western group, $F(1, 32)=17.378$, $p<.001$, $partial \eta^2=.352$.

All pairwise comparisons were run for each simple main effect with reported 95% confidence intervals and p -values Bonferroni-adjusted within each simple main effect. Mean “Time spent to explore the picture before making password selections” for Eastern group on the *culture-internal* and *culture-external* picture was 15.09 ± 6.84 seconds and 10.89 ± 3.55 seconds, while for Western group on the *culture-internal* and *culture-external* picture was 6.50 ± 3.77 seconds and 8.24 ± 2.77 seconds respectively. Western group that utilized *culture-internal* picture type had a statistically significantly lower mean “Time spent to explore the picture before making password selections” than Eastern group that utilized *culture-internal* picture type, 8.593 seconds (95% CI, 4.394 to 12.792 seconds), $p<.001$.

4.2 Time to login (RQ_2)

Data are mean \pm standard error, unless otherwise stated. The interaction effect between culture group and picture type on the time required to login was not statistically significant, $F(1, 58)=3.541$, $p=.065$, $partial \eta^2=.058$. Therefore, an analysis of the main effect for culture group was performed, which indicated that the main effect was statistically significant, $F(1, 58)=23.686$, $p<.001$, $partial \eta^2=.290$. All pairwise comparisons were run with reported 95% confidence intervals and p -values are Bonferroni-adjusted. The unweighted marginal means of login time for Eastern and Western group that utilized *culture-internal* and *culture-external* picture type were $8.20 \pm .51$ seconds and $4.44 \pm .57$ seconds, respectively. Eastern group was associated with a mean of 3.754 (95% CI, 2.21 to 5.29) seconds higher than Western group, a statistically significant difference, $p<.001$. **Figure 4** illustrates the mean time to login across culture groups for each picture type.

4.3 Password selections on hotspots segments (RQ_3)

Data are mean \pm standard error, unless otherwise stated. The interaction effect between culture group and picture type on the percentage of picture password selections falling into hotspots segments was not statistically significant, $F(1, 63)=2.893$, $p=.094$, $partial \eta^2=.044$. Therefore, an analysis of the main effect for picture type was performed, which indicated that the main effect was statistically significant, $F(1, 63)=52.762$, $p<.001$, $partial \eta^2=.456$. All pairwise comparisons were run with reported 95% confidence intervals and p -values are Bonferroni-adjusted. The unweighted marginal means of “Percentage of picture password selections falling into hotspots segments” for *culture-external* and *culture-internal* picture type for Eastern group and Western group were 60.847 ± 3.139 percent and 29.412 ± 2.979 percent, respectively. *Culture-external* picture type was associated with a mean “Percentage of picture passwords selections falling into hotspots segments” of 31.435 (95% CI, 22.78 to 40.08) percent higher than *culture-internal* picture type, a statistically significant difference, $p<.001$. **Figure 5** illustrates the mean proportion of password selections falling into hotspots segments across culture groups for each picture type.

4.4 Users’ likeability and engagement with the picture content used in password creation (RQ_4)

We conducted semi-structured interviews at the end of picture password creation to elicit users’ likeability and engagement with the picture content used (i.e., *culture-internal* vs. *culture-external*), ease of picture password creation, and willingness to adopt a personalized picture password scheme as an alternative type of user authentication. Example questions of the semi-structured interviews were: “What strategy did you follow to create your password?”, “What type of background picture would you prefer?”, etc. Evidence suggests that the *culture-internal* pictures influence users during password creation. Example responses include:

- "I created a shape between all the lines and circles which I can relate it with something familiar" ~ Western P5 (culture-internal)
- "I chose the clicks and items that I found more interesting in the image based on my experiences" ~ Western P8 (culture-internal)
- "Easy enough for myself to remember, and I somehow have the confidence that no one might know what I think" ~ Eastern P17 (culture-internal)

On the contrary, participants who received the *culture-external* pictures followed random approaches and selected simple and easy to remember choices during password creation, which impacts negatively the security of picture passwords [9-11]. Example responses include:

- "I didn't follow any strategy. I just picked the obvious points." ~ Western P3 (culture-external)
- "I selected points that stand out so I can remember the password easy" ~ Western P23 (culture-external)
- "As simple as possible" ~ Eastern P12 (culture-external)
- "Pick the objects easy to identify in the picture" ~ Eastern P26 (culture-external)

With respect to users' preference about the picture content used in picture password schemes, evidence suggests that participants prefer pictures related to their personal experiences and their culture, rather than unfamiliar pictures related to other cultures. Example responses include:

- "Something that's aesthetically pleasant and perhaps that's personal for me" ~ Western P26 (culture-external)
- "Environment/scenery with a personally relevant mystical atmosphere" ~ Western P6 (culture-external)
- "Maybe nature and some pictures very meaningful like a picture of a present I got" ~ Eastern P6 (culture-external)
- "Familiar landscape/architecture" ~ Eastern P33 (culture-external)
- "Some places familiar to me" ~ Eastern P36 (culture-external)

5 MAIN FINDINGS

The analyses of results underpin the added value of considering cultural differences in the design of personalized picture password schemes. Next, we discuss the main findings of this work. **Table 2** summarizes the main results.

Finding A (RQ₁). *The perceptual process of the Eastern group was slower than the Western group during the exploration phase of the picture.* Eastern participants who utilized *culture-internal* picture type were significantly slower than Western participants who utilized the same picture type during the picture exploration phase until they made their password selections. This can be attributed to the holistic preference of Eastern populations [14, 15, 49-51], since considering contextual information of the stimuli presented requires more exploration time. From a cognition perspective, this finding can be further explained by the fact that Eastern individuals follow a more holistic and exploratory approach during visual search compared to Western individuals that primarily focus on focal points of a picture [14].

Finding B (RQ₂). *The perceptual process of the Eastern group was slower than the Western group during the login phase.* There was an effect of culture on the time required to login. Eastern participants were significantly slower than Western participants during the login phase. In line with Finding A, such a finding can be explained from cognitive theories that suggest the holistic preference of Eastern populations and hence require more time to explore the picture content [14, 15, 49-52]. In addition, Western individuals might have better memorized their picture password by paying more attention to detail, thus positively affecting the task login efficiency [52].

Finding C (RQ₃). *Culture-internal picture content encourages both the Eastern and Western group to make selections on non-hotspots segments.* There was an effect of picture type on the percentage of users' password selections that fall into hotspots segments, which can negatively impact the strength of the passwords [9-11, 53]. Regardless of the culture group, participants who utilized *culture-external* picture content made significantly higher percentage of picture password selections within hotspots segments compared to participants who utilized *culture-internal* picture content. This is in line with previous findings of our works [48, 54], showing the positive effect of utilizing picture content related to people's daily life experiences and activities. Such a personalized picture content approach allows users to make their selections beyond the easy-to-remember hotspots and rather based on their episodic memories within the depicted pictures [55-57], and eventually assists them with the creation of more secure picture passwords.

Finding D (RQ₄). *Qualitative feedback from users on perceived usability and likeability during semi-interviews further triangulates the quantitative results and reveal that the suggested cultural-centered picture personalization approach was embraced positively by the participants across both culture groups.* Such a finding is encouraging for further research given that the same study design was applied and run in two different cultural contexts and hence increases external validity of this work.

Table 2. Summarization of the main results.

Metrics <i>Mean ± (SD)</i>	Picture Type		
	Group	Culture-internal	Cultural-external
Time to explore (in sec)	Eastern	15.09 (6.84)	10.89 (3.55)
	Western	6.50 (3.77)	8.24 (2.77)
Time to login (in sec)	Eastern	8.99 (3.69)	7.40 (3.41)
	Western	3.79 (1.64)	5.10 (2.63)
% of hotspots selections	Eastern	33.33 (16.16)	57.40 (15.36)
	Western	25.49 (18.74)	64.28 (20.52)

6 DISCUSSION AND IMPLICATIONS

We investigated the effects of cultural differences when people interact with *culture-internal* vs. *culture-external* pictures within picture password schemes. Our findings revealed differences in the perceptual processes employed by the Eastern and Western population during picture password creation and login. The results provide external validity to the holistic vs. analytic preference of Eastern vs. Westerner populations [14, 15, 49-52] in

the context of picture password schemes. We also provide empirical data, since to the best of the authors' knowledge, this hasn't been investigated within picture password schemes.

Investigating the effects of cultural differences will allow us to move from the "one-size-fits-all" approach to a more personalized approach. We envision a framework (Figure 6) that targets to deliver "best-fit" picture content during password creation/reset, tailored to users' unique sociocultural experiences. Such a framework opens unprecedented perspectives for designing personalized picture password schemes that take into consideration the users' cultural backgrounds and daily-life experiences as important personalization factors. On a conceptual level, the envisioned framework is based on a five-tier sociocultural model of users' prior experiences or levels of familiarity [57], as illustrated in Figure 7. This approach inherits multiple levels of abstractions and was inspired by existing works which indicate that culture (i.e., behaviors, attitudes and prior experiences) can be represented at various levels in a multi-level model of culture [33], originating from the global towards the individual level, getting through the intermediate sociocultural levels (i.e., national, organizational, group) and vice versa. However, this approach embraces new challenges that need to be addressed: a) how to elicit and provide picture content relevant to a specified familiarity level? b) how to deliver "best-fit" picture password content relevant to a user's prior sociocultural experiences?

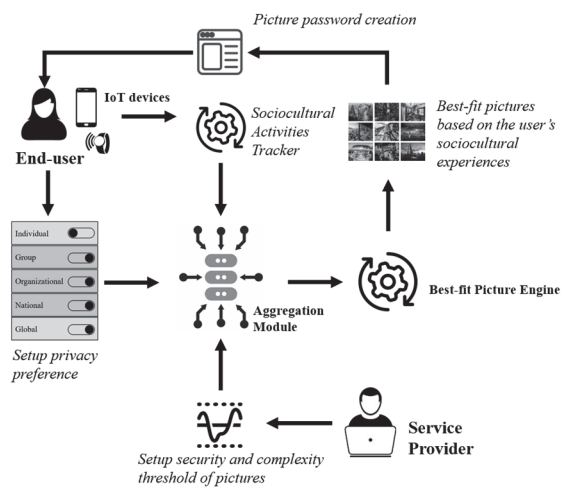


Figure 6. Conceptual personalization framework.

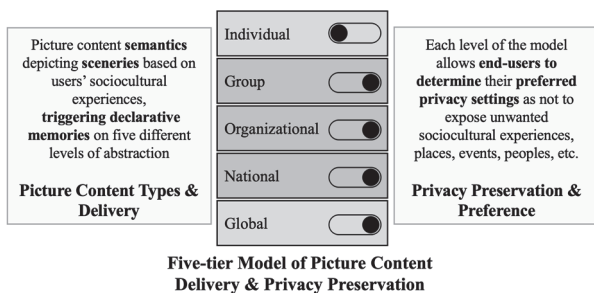


Figure 7. A five-tier model of retrospective image content delivery and privacy preferences and preservation.

How to elicit and provide picture content relevant to a specified familiarity level?

The *Individual Sociocultural Experience Model* will be responsible for modeling human factors (e.g., working location), cultural factors (e.g., sociocultural activities, familiarity level with the content of a picture), and pictorial factors (e.g., semantics, visual complexity, hotspots). **Explicit data gathering techniques** will be used for the generation of user models which take into consideration users' location and sociocultural activities during password creation (e.g., by filling in a demographics form and selecting a region on a Google map). **Implicit contextual gathering techniques** through context-aware frameworks (e.g., *AWARE*¹³, *Google Awareness API*¹⁴) will be used for the enrichment and maintenance of the user models. Such frameworks will be effectively used for detection of users' day-to-day activities and visited places through a mobile application.

To prevent any privacy violations, the *Individual Sociocultural Experience Model* will provide transparency to the users by notifying them about what personal information the model will be using (e.g., location), what it will be using it for (e.g., for providing pictures relevant to their sociocultural activities during password reset), and it will acquire such information only if it entails location-specific information aligned to the users' approved privacy model (Figure 7). The privacy will be based a five-tier model of sociocultural experiences or levels of picture content familiarity, namely: *Individual, Group, Organizational, National* and *Global* bootstrapped to users' prior sociocultural activities and experiences. At the *individual level*, people have personal experiences (e.g., one's experiences within the cafeteria in her neighborhood). At the *group level*, people have shared experiences within the communities they belong to (e.g., one's experiences within the volleyball team she plays for). At the *organizational level*, people have experiences within their working places (e.g., one's experiences within the working space area at the company she works for). At the *national level*, people have nationally shared experiences (e.g., within monuments, landmarks, folklore). At the *global level*, people can have experiences within places not directly relevant to their culture (e.g., experiences when traveling). Such a privacy model will give users the ability to activate or deactivate the feature of receiving "best-fit" pictures. Data will be stored and handled anonymously.

The *Picture Meta Search* module will be responsible for generating a candidate picture set for each user based on the *Individual Sociocultural Experience Model*. *Google Custom Search*¹⁵ will be used to fetch pictures relevant to the picture semantics from the pictorial factors, while *Places API*¹⁶ will be used to fetch pictures relevant to users' past locations and visited places. The fetched pictures' semantics will be further verified based on the pictorial factors through computer vision techniques (e.g., a combination of object detection through *TensorFlow*⁴, object and

¹³ awareframework.com

¹⁴ developers.google.com/awareness

¹⁵ developers.google.com/custom-search

¹⁶ developers.google.com/places/web-service/intro

scene detection through *Amazon Rekognition*⁵, and label detection through *Google Cloud Vision APP*⁶. Pictures will then be represented as an entry into the multi-level model of familiarity [57], based on the user’s experiences with the depicted content.

To customize users’ familiarity level, picture complexity and security policies, an interactive dashboard will allow Service Providers to adjust picture properties (either per user or group of users) through scalar ranges (e.g., degree of semantic relevance, complexity, number of hotspots, etc.). Also, it will provide detailed information about the analyzed pictures (e.g., labels and objects detected), their corresponding saliency maps and hotspots segments, as well as various information about the users (e.g., *Individual Sociocultural Experience Model*) and statistics about their passwords (e.g., time to create, failed attempts during creation, time to login, password strength, password resets etc.).

How to deliver “best-fit” picture password content relevant to a user’s prior sociocultural experiences?

The “Best-fit” *Picture Engine* module will be responsible for maintaining, deciding and delivering the “best-fit” picture content to each user based on the *Individual Sociocultural Experience Model*. It will consist of the following submodules:

i) *Complexity Estimator*: It will ensure that the candidate picture set contains visually rich pictures (in terms of number of attention points they entail), since picture complexity impacts the security of the passwords [39, 41]. The less attention points a candidate picture contains, the more predictable the created password would be. The picture complexity will be calculated through saliency maps [45] and entropy estimators [46];

ii) *Hotspots Detection*: To identify the hotspots segments in each picture, a combination of saliency maps will be used [11, 45]. Furthermore, we expect that users will make their password selections around objects easily distinguishable from their surroundings [10, 30]. Therefore, object detection mechanisms^{4,5} will be used for the extraction of the easy-to-identify objects;

iii) *Filtering Mechanism*: It will assess the appropriateness of the candidate picture set before the recommendation is made. It will take as input the outputs from the *Complexity Estimator* and *Hotspots Detection*, and will filter out unsuitable pictures (e.g., simple pictures that contain limited number of attention points) in an iterative process until the candidate picture set meets the certain degrees of appropriateness adjusted by the Service Provider (e.g., semantic relevance, complexity, number of hotspots, etc.). **Figure 8** depicts an example picture set recommendation for a user during picture password creation.

7 LIMITATIONS

Despite our efforts to keep the validity of the study, some design aspects of the experiment introduce limitations. We used specific background pictures in order to better control the factors of the study (sceneries from participants’ universities). Although users’ choices may be affected by the content and complexity of the picture [39, 40], we chose pictures of the most widely used

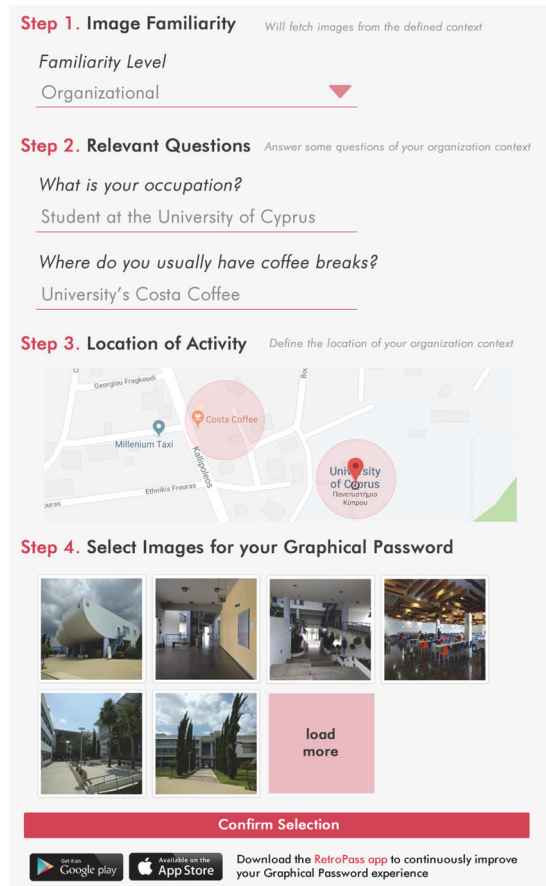


Figure 8. Picture passwords recommendations.

category (i.e., depicting scenery [39]) and of similar complexity and number of hotspots. Expansion of our research will consider a greater variety of picture categories to increase internal validity, as well as target participants from widely regarded individualistic populations (e.g., USA, Netherlands) to increase external validity.

8 CONCLUSIONS

In this paper, we investigated the effects of culture towards users’ interactions within picture password schemes. Results of a cross-cultural study revealed that people across cultures exhibited differences in visual processing, comprehension, and exploration of the picture content prior to making their password selections. Qualitative data also triangulate the findings by exposing the likeability and users’ engagement towards the picture content familiar to individual’s culture. Given the globalization of applications and services, studies like the reported one underpin the necessity for considering the effects of cultural differences in the design of secure and usable interactive systems that address diversity [1-7].

ACKNOWLEDGMENTS

This research has been partially supported by the EU Horizon 2020 Grant 826278 “Securing Medical Data in Smart Patient-Centric Healthcare Systems” (Serums).

REFERENCES

- [1] Yang Wang, Huichuan Xia, and Yun Huang. 2016. Examining American and Chinese Internet Users' Contextual Privacy Preferences of Behavioral Advertising. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing (CSCW '16)*. ACM, 539–552. DOI:<https://doi.org/10.1145/2818048.2819941>
- [2] Jialiu Lin, Michael Benisch, Norman Sadeh, Jianwei Niu, Jason Hong, Banghui Lu, and Shaohui Guo. 2013. A comparative study of location-sharing privacy preferences in the United States and China. *Personal Ubiquitous Comput.* 17, 4 (April 2013), 697–711. DOI:<https://doi.org/10.1007/s00779-012-0610-6>
- [3] Yang Wang, Gregory Norice, and Lorrie Faith Cranor. 2011. Who is concerned about what? A study of American, Chinese and Indian users' privacy concerns on social network sites. In *Trust and Trustworthy Computing*, Springer, 146–153. DOI:https://doi.org/10.1007/978-3-642-21599-5_11
- [4] Chen Zhao, Pamela Hinds, and Ge Gao. 2012. How and to whom people share: the role of culture in self-disclosure in online communities. In *Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work (CSCW '12)*. ACM, 67–76. DOI:<https://doi.org/10.1145/2145204.2145219>
- [5] Sunil Chaudhary, Yan Zhao, Eleni Berki, Juri Valtanen, Linfeng Li, Marko Helenius, and Stylianos Mystakidis. 2015. A cross-cultural and gender-based perspective for online security: Exploring knowledge, skills and attitudes of higher education students. *IADIS International Journal on WWW/Internet*, 13(1).
- [6] Marian Harbach, Alexander De Luca, Nathan Malkin, and Serge Egelman. 2016. Keep on Lockin' in the Free World: A Multi-National Comparison of Smartphone Locking. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16)*. ACM, 4823–4827. DOI:<https://doi.org/10.1145/2858036.2858273>
- [7] Yukiko Sawaya, Mahmood Sharif, Nicolas Christin, Ayumu Kubota, Akihiro Nakarai, and Akira Yamada. 2017. Self-Confidence Trumps Knowledge: A Cross-Cultural Study of Security Behavior. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems (CHI '17)*. ACM, 2202–2214. DOI:<https://doi.org/10.1145/3025453.3025926>
- [8] Robert Biddle, Sonia Chiasson, and Paul C. van Oorschot. 2012. Graphical passwords: Learning from the first twelve years. *ACM Comput. Surv.* 44, 4, Article 19 (September 2012), 41 pages. DOI:<https://doi.org/10.1145/2333112.2333114>
- [9] Paul C. van Oorschot and Julie Thorpe. 2011. Exploiting predictability in click-based graphical passwords. *J. Comput. Secur.* 19, 4 (December 2011), 669–702.
- [10] Julie Thorpe and Paul C. van Oorschot. 2007. Human-seeded attacks and exploiting hot-spots in graphical passwords. In *Proceedings of 16th USENIX Security Symposium on USENIX Security Symposium (SS'07)*. USENIX Association, Article 8, 1–16.
- [11] Andreas Bulling, Florian Alt, and Albrecht Schmidt. 2012. Increasing the security of gaze-based cued-recall graphical passwords using saliency masks. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '12)*. ACM, 3011–3020. DOI:<https://doi.org/10.1145/2207676.2208712>
- [12] Florian Alt, Stefan Schneeeggass, Alireza Sahami Shirazi, Mariam Hassib, and Andreas Bulling. 2015. Graphical Passwords in the Wild: Understanding How Users Choose Pictures and Passwords in Image-based Authentication Schemes. In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '15)*. ACM, 316–322. DOI:<https://doi.org/10.1145/2785830.2785882>
- [13] Angela H. Gutches and Allie Indeck. 2009. Cultural influences on memory. *Progress in brain research*, 178, 137–150. DOI:[https://doi.org/10.1016/S0079-6123\(09\)17809-3](https://doi.org/10.1016/S0079-6123(09)17809-3)
- [14] Takahiko Masuda and Richard E. Nisbett. 2001. Attending holistically versus analytically: Comparing the context sensitivity of Japanese and Americans. *Journal of personality and social psychology*, 81(5), 922–934. DOI:<https://doi.org/10.1037/0022-3514.81.5.922>
- [15] Peter R. Millar, Sarah J. Serbun, Akash Vadalia, and Angela H. Gutches. 2013. Cross-cultural differences in memory specificity. *Culture and Brain*, 1(2-4), 138–157. DOI:<https://doi.org/10.1007/s40167-013-0011-3>
- [16] Richard E. Nisbett and Takahiko Masuda. 2003. Culture and point of view. *Proceedings of the National Academy of Sciences*, 100(19), 11163–11170. DOI:<https://doi.org/10.1073/pnas.1934527100>
- [17] Fred C. J. Stevens, Charles D. Kaplan, Rudolph W. H. M. Ponds, Joseph P. M. Diederiks, and Jellemer Jolles. 1999. How ageing and social factors affect memory. *Age and ageing*, 28(4), 379–384. DOI:<https://doi.org/10.1093/ageing/28.4.379>
- [18] Barbara Rogoff and Jayanthi Mistry. 1985. Memory development in cultural context. In *Cognitive Learning and Memory in Children*. Springer. DOI:https://doi.org/10.1007/978-1-4613-9544-7_4
- [19] Kiemute Oyibo, Rita Orji, and Julita Vassileva. 2018. Developing Culturally Relevant Design Guidelines for Encouraging Physical Activity: a Social Cognitive Theory Perspective. *Journal of Healthcare Informatics Research*, 2(4), 319–352. DOI:<https://doi.org/10.1007/s41666-018-0026-9>
- [20] Lidia Oshlyansky, Harold Thimbleby, and Paul Cairns. 2004. Breaking affordance: culture as context. In *Proceedings of the third Nordic conference on Human-computer interaction (NordCHI '04)*. ACM, 81–84. DOI:<https://doi.org/10.1145/1028014.1028025>
- [21] Vanessa Evers, Agnes Kukulska-Hulme, and Ann Jones. 1999. Cross-cultural understanding of interface design: A cross-cultural analysis of icon recognition. In *Proceedings of the International Workshop on Internationalisation of Products and Systems. IWIPS 1999*.
- [22] Ann Nousseir, Richard Connor, and Mark Dunlop. 2005. Internet authentication based on personal history—A feasibility test. In *Proceedings of Customer Focused Mobile Services Workshop at WWW'05*. ACM.
- [23] Sauvik Das, Eiji Hayashi, and Jason I. Hong. 2013. Exploring capturable everyday memory for autobiographical authentication. In *Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing (UbiComp '13)*. ACM, 211–220. DOI:<https://doi.org/10.1145/2493432.2493453>
- [24] Hani Moaiteq Aljahdali and Ron Poet. 2013. The Affect of Familiarity on the Usability of Recognition-Based Graphical Passwords: Cross Cultural Study between Saudi Arabia and the United Kingdom. In *Proceedings of the 2013 12th IEEE International Conference on Trust, Security and Privacy in Computing and Communications (TRUSTCOM '13)*. IEEE, 1528–1534. DOI:<https://doi.org/10.1109/TrustCom.2013.187>
- [25] Simon S. Woo, Ron Artstein, Elsi Kaiser, Xiao Le, and Jelena Mirkovic. 2019. Using Episodic Memory for User Authentication. *ACM Trans. Priv. Secur.* 22, 2, Article 11 (April 2019), 34 pages. DOI:<https://doi.org/10.1145/3308992>
- [26] Supriya Singh, Anuja Cabraal, Catherine Demosthenous, Gunela Astbrink, and Michele Furlong. 2007. Password sharing: implications for security design based on social practice. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '07)*. ACM, 895–904. DOI:<https://doi.org/10.1145/1240624.1240759>
- [27] Supriya Singh, Anuja Cabraal, Catherine Demosthenous, Gunela Astbrink, and Michele Furlong. 2007. Security design based on social and cultural practice: sharing of passwords. In *International Conference on Usability and Internationalization*, Springer, 476–485. DOI:https://doi.org/10.1007/978-3-540-73289-1_55
- [28] Hani Moaiteq Aljahdali and Ron Poet. 2014. Educated Guessing Attacks on Culturally Familiar Graphical Passwords Using Personal Information on Social Networks. In *Proceedings of the 7th International Conference on Security of Information and Networks (SIN '14)*. ACM, 272–278. DOI:<https://doi.org/10.1145/2659651.2659727>
- [29] Ülkü Arslan Aydın, Cengiz Acartürk, and Kürşat Çağiltay. 2013. The Role of Visual Coherence in Graphical Passwords. In *Proceedings of the Annual Meeting of the Cognitive Science Society (Vol. 35)*.
- [30] Ziming Zhao, Gail-Joon Ahn, Jeong-Jin Seo, and Hongxin Hu. 2013. On the security of picture gesture authentication. In *Proceedings of the 22nd USENIX conference on Security (SEC'13)*. USENIX Association, 383–398.
- [31] Darren Davis, Fabian Monrose, and Michael K. Reiter. 2004. On user choice in graphical password schemes. In *Proceedings of the 13th conference on USENIX Security Symposium - Volume 13 (SSYM'04)*. USENIX Association, 11.
- [32] Martin Mihajlov, Borka Jerman-Blaič, and Anita Ciunova Shuleska. 2016. Why that Picture? Discovering Password Properties in Recognition-Based Graphical Authentication. *Elsevier IJHCS*, 32(12), 975–988. DOI:<https://doi.org/10.1080/10447318.2016.1220103>
- [33] Miriam Erez and Efrat Gati. 2004. A Dynamic, Multi-Level Model of Culture: From the Micro Level of the Individual to the Macro Level of a Global Culture. *Applied Psychology: An International Review* 53, 4, 583–598. DOI:<https://doi.org/10.1111/j.1464-0597.2004.00190.x>
- [34] Martin Mihajlov and Borka Jerman-Blaič. 2011. On designing usable and secure recognition-based graphical authentication mechanisms. *Interact. Comput.* 23, 6 (November 2011), 582–593. DOI:<https://doi.org/10.1016/j.intcom.2011.09.001>
- [35] Eiji Hayashi, Rachna Dhamija, Nicolas Christin, and Adrian Perrig. 2008. Use Your Illusion: secure authentication usable anywhere. In *Proceedings of the 4th symposium on Usable privacy and security (SOUPS '08)*. ACM, 35–45. DOI:<https://doi.org/10.1145/1408664.1408670>
- [36] Eiji Hayashi, Jason Hong, and Nicolas Christin. 2011. Security through a different kind of obscurity: evaluating distortion in graphical authentication schemes. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '11)*. ACM, 2055–2064. DOI:<https://doi.org/10.1145/1978942.1979242>
- [37] Katherine M. Everitt, Tanya Bragin, James Fogarty, and Tadayoshi Kohno. 2009. A comprehensive study of frequency, interference, and training of multiple graphical passwords. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '09)*. ACM, 889–898. DOI:<https://doi.org/10.1145/1518701.1518837>
- [38] Sonia Chiasson, Robert Biddle, and Paul C. van Oorschot. 2007. A second look at the usability of click-based graphical passwords. In *Proceedings of the 3rd symposium on Usable privacy and security (SOUPS '07)*. ACM, 1–12. DOI:<https://doi.org/10.1145/1280680.1280682>

- [39] Paul Dunphy and Jeff Yan. 2007. Do background images improve “draw a secret” graphical passwords? In *Proceedings of the 14th ACM conference on Computer and communications security (CCS '07)*. ACM, 36–47. DOI:<https://doi.org/10.1145/1315245.1315252>
- [40] Susan Wiedenbeck, Jim Waters, Jean-Camille Birget, Alex Brodskiy, and Nasir Memon. 2005. Authentication using graphical passwords: effects of tolerance and image choice. In *Proceedings of the 2005 symposium on Usable privacy and security (SOUPS '05)*. ACM, 1–12. DOI:<https://doi.org/10.1145/1073001.1073002>
- [41] Christina Katsini, Christos Fidas, George E. Raptis, Marios Belk, George Samaras, and Nikolaos Avouris. 2018. Influences of Human Cognition and Visual Behavior on Password Strength during Picture Password Composition. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (CHI '18)*. ACM, Paper 87, 1–14. DOI:<https://doi.org/10.1145/3173574.3173661>
- [42] George E. Raptis, Christina Katsini, Marios Belk, Christos Fidas, George Samaras, and Nikolaos Avouris. 2018. Using Eye Gaze Data and Visual Activities to Infer Human Cognitive Styles: Method and Feasibility Studies. In *Proceedings of the 25th Conference on User Modeling, Adaptation and Personalization (UMAP '17)*. ACM, 164–173. DOI:<https://doi.org/10.1145/3079628.3079690>
- [43] Jeff Johnson, Steve Seixeiro, Zachary Pace, Giles van der Bogert, Sean Gilmour, Levi Siebens, Ken Tubbs. 2014. Patent 8650636, DC: U.S. Patent and Trademark Office.
- [44] Ziming Zhao, Gail-Joon Ahn, and Hongxin Hu. 2015. Picture Gesture Authentication: Empirical Analysis, Automated Attacks, and Scheme Evaluation. *Journal of ACM Transactions on Information and System Security (TISSEC)* 17, 4, Article 14 (April 2015), 37 pages. DOI:<https://doi.org/10.1145/2701423>
- [45] Federico Perazzi, Philipp Krähenhühl, Yael Pritch, and Alexander Hornung. 2012. Saliency filters: Contrast based filtering for salient region detection. *IEEE Conference on Computer Vision and Pattern Recognition*, 733–740. DOI:<https://doi.org/10.1109/CVPR.2012.6247743>
- [46] Maurizio Cardaci, Vito Di Gesù, Maria Petrou, and Marco Elio Tabacchi. 2009. A fuzzy approach to the evaluation of image complexity. *Fuzzy Sets and Systems* 160, 10 (May 2009), 1474–1484. DOI:<https://doi.org/10.1016/j.fss.2008.11.017>
- [47] Argyris Constantinides, Christos Fidas, Marios Belk, and Andreas Pitsillides. 2019. “I Recall this Picture”: Understanding Picture Password Selections based on Users’ Sociocultural Experiences. In *IEEE/WIC/ACM International Conference on Web Intelligence (WI '19)*. ACM, 408–412. DOI:<https://doi.org/10.1145/3350546.3352557>
- [48] Argyris Constantinides, Marios Belk, Christos Fidas, and Andreas Pitsillides. 2020. An eye gaze-driven metric for estimating the strength of graphical passwords based on image hotspots. In *Proceedings of the 25th International Conference on Intelligent User Interfaces (IUI '20)*. ACM, 33–37. DOI:<https://doi.org/10.1145/3377325.3377537>
- [49] Ara Norenzayan, Edward E. Smith, Beom Jun Kim, and Richard E. Nisbett. 2002. Cultural preferences for formal versus intuitive reasoning. *Cognitive science* 26, no. 5 (2002): 653–684. DOI:https://doi.org/10.1207/s15516709cog2605_4
- [50] Shinobu Kitayama, Sean Duffy, Tadashi Kawamura, and Jeff T. Larsen. 2003. Perceiving an object and its context in different cultures: A cultural look at new look. *Psychological science* 14, no. 3 (2003): 201–206. DOI:<https://doi.org/10.1111/1467-9280.02432>
- [51] William L. Phillips. 2019. Cross-cultural differences in visual perception of color, illusions, depth, and pictures. *Cross-Cultural Psychology: Contemporary Themes and Perspectives* (2019): 287–308. DOI:<https://doi.org/10.1002/9781119519348.ch13>
- [52] Marios Belk, Christos Fidas, Panagiotis Germanakos, and George Samaras. 2017. The interplay between humans, technology and user authentication: A cognitive processing perspective. *Computers in Human Behavior*, 76, 184–200. DOI:<https://doi.org/10.1016/j.chb.2017.06.042>
- [53] Paul C. van Oorschot, Amirali Salehi-Abari, and Julie Thorpe. 2010. Purely Automated Attacks on PassPoints-Style Graphical Passwords. In *IEEE Transactions on Information Forensics and Security* 5, 3, 393–405. DOI:<https://doi.org/10.1109/TIFS.2010.2053706>
- [54] Argyris Constantinides, Marios Belk, Christos Fidas, and George Samaras. 2018. On Cultural-centered Graphical Passwords: Leveraging on Users’ Cultural Experiences for Improving Password Memorability. In *Proceedings of the 26th Conference on User Modeling, Adaptation and Personalization (UMAP '18)*. ACM, 245–249. DOI:<https://doi.org/10.1145/3209219.3209254>
- [55] Endel Tulving. 1972. Episodic and semantic memory. *Organization of memory*, 1, 381–403.
- [56] Karen Renaud. 2009. On user involvement in production of images used in visual authentication. *Journal of Visual Languages and Computing* 20, 1, 1–15. DOI:<https://doi.org/10.1016/j.jvlc.2008.04.001>
- [57] Argyris Constantinides, Christos Fidas, Marios Belk, and George Samaras. 2018. On sociocultural-centered graphical passwords: an initial framework. In *Proceedings of the 20th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct (MobileHCI '18)*. ACM, 277–284. DOI:<https://doi.org/10.1145/3236112.3236150>
- [58] Serge Egelman, Andreas Sotirakopoulos, Ildar Muslukhov, Konstantin Beznosov, and Cormac Herley. 2013. Does my password go up to eleven? the impact of password meters on password selection. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '13)*. ACM, 2379–2388. DOI:<https://doi.org/10.1145/2470654.2481329>
- [59] Angela Martina Sasse, Sacha Brostoff, and Dirk Weirich. 2001. Transforming the ‘weakest link’—a human/computer interaction approach to usable and effective security. *BT technology journal*, 19(3), 122–131. DOI:<https://doi.org/10.1023/A:1011902718709>
- [60] Jeff Yan, Alan Blackwell, Ross Anderson, and Alasdair Grant. 2004. Password memorability and security: Empirical results. *IEEE Security & privacy*, 2(5), 25–31. DOI:<https://doi.org/10.1109/MSP.2004.81>
- [61] Rilla Khaled, Ronald Fischer, James Noble, and Robert Biddle. 2008. A qualitative study of culture and persuasion in a smoking cessation game. In *International Conference on Persuasive Technology* (pp. 224–236). Springer, Heidelberg. DOI:https://doi.org/10.1007/978-3-540-68504-3_20
- [62] Hiroaki Kimura and Tatsuo Nakajima. 2011. Designing Persuasive Applications to Motivate Sustainable Behavior in Collectivist Cultures. *Psychology Journal*, 9(1), 7–28.
- [63] Nitish Singh, Georg Fassott, Hongxin Zhao, and Paul D. Boughton. 2006. A cross-cultural analysis of German, Chinese and Indian consumers’ perception of web site adaptation. *Journal of Consumer Behaviour*, 5(1), 56–68. DOI:<https://doi.org/10.1002/cb.43>
- [64] Rita Orji and Regan L. Mandryk. 2014. Developing culturally relevant design guidelines for encouraging healthy eating behavior. *Int. J. Hum.-Comput. Stud.* 72, 2 (February 2014), 207–223. DOI:<https://doi.org/10.1016/j.ijhcs.2013.08.012>
- [65] Kiemute Oyibo, Rita Orji, and Julita Vassileva. 2017. The Influence of Culture in the Effect of Age and Gender on Social Influence in Persuasive Technology. In *Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization (UMAP '17)*. ACM, 47–52. DOI:<https://doi.org/10.1145/3099023.3099071>
- [66] Argyris Constantinides, Marios Belk, Christos Fidas, and Andreas Pitsillides. 2019. On the Accuracy of Eye Gaze-driven Classifiers for Predicting Image Content Familiarity in Graphical Passwords. In *Proceedings of the 27th ACM Conference on User Modeling, Adaptation and Personalization (UMAP '19)*. ACM, 201–205. DOI:<https://doi.org/10.1145/3320435.3320474>