

Usage Patterns of Privacy-Enhancing Technologies

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ABSTRACT

The steady reports of privacy invasions online paints a picture of the Internet growing into a more dangerous place. This is supported by reports of the potential scale for online harms facilitated by the mass deployment of online technology and the data-intensive web. While Internet users often express concern about privacy, some report taking actions to protect their privacy online. We investigate the methods and technologies that individuals employ to protect their privacy online. We conduct two studies, of N=180 and N=907, to elicit individuals' use of privacy methods online, within the US, the UK and Germany. We find that non-technology methods are among the most used methods in the three countries. We identify distinct groupings of privacy methods usage in a cluster map. The map shows that together with non-technology methods of privacy protection, simple PETs that are integrated in services, form the most used cluster, whereas more advanced PETs form a different, least used cluster. We further investigate user perception and reasoning for mostly using one set of PETs in a third study with N=183 participants. We do not find a difference in perceived competency in protecting privacy online between advanced and simpler PETs users. We compare use perceptions between advanced and simpler PETs and report on user reasoning for not using advanced PETs, as well as support needed for potential use. This paper contributes to privacy research by eliciting use and perception of use across 43 privacy methods, including 26 PETs across three countries and provides a map of PETs usage. The cluster map provides a systematic and reliable point of reference for future user-centric investigations across PETs. Overall, this research provides a broad understanding of use and perceptions across a collection of PETs, and can lead to future research for scaling use of PETs.

CCS CONCEPTS

• **Security and privacy** → **Human and societal aspects of security and privacy**; **Privacy protections**; *Social aspects of security and privacy*; *Usability in security and privacy*.

KEYWORDS

Privacy; Privacy-Enhancing Technology; Usage; Perception of Use; User-Study

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CCS '20, November 9–13, 2020, Virtual Event, USA

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ACM ISBN 978-1-4503-7089-9/20/11...\$15.00

<https://doi.org/10.1145/3372297.3423347>

ACM Reference Format:

Kovila P.L. Coopamootoo. 2020. Usage Patterns of Privacy-Enhancing Technologies. In *Proceedings of the 2020 ACM SIGSAC Conference on Computer and Communications Security (CCS '20)*, November 9–13, 2020, Virtual Event, USA. ACM, New York, NY, USA, 20 pages. <https://doi.org/10.1145/3372297.3423347>

1 INTRODUCTION

The deployment of technology at massive scale is thought to have enabled the rapid emergence of a set of 'online harms' such as privacy abuses, data breaches, cyber-attacks, inappropriate uses of personal data, hate crimes, and self-harm/suicide among others [109]. Today's data-intensive web is characterized with mass sharing, collection and aggregation of individuals' data, that enables the provisioning of customised services but unfortunately also engenders targeted advertising [14], digital discrimination [31], privacy invasive algorithmic computations [35], and a general fuzziness about privacy rights online. The recent years have indeed seen reports of various high profile privacy infringement cases involving mass unauthorised transfer and use of sensitive data [37, 70, 82].

At the forefront of the narrative that "the Internet is a dangerous place", is the UK, where the British Government has released an Online Harms white paper that elaborates on the scale and extent of harms faced by individuals online. It proposes a mission of mitigating online harms without inhibiting online innovation [109]. One of the strands of this mission is to empower citizens via technology, in particular via awareness, usage and integration of Privacy-Enhancing Technologies (PETs) in real life situations. PETs are defined by the EU Agency for CyberSecurity, as technologies shaped according to privacy principles, where PETs "covers the broader range of technologies that are designed for supporting privacy and data protection" [32]. Integrating PETs in daily life and scaling use of PETs, first requires a broad understanding of current use of PETs.

For a user perspective of online harms, the Oxford Internet Institute looked into how UK individuals' experience of problems online influence their behavior, in an Oxford Internet Survey (OxIS) [13]. They found that non-users of the Internet (who made up 10% of the respondents), were more concerned than users about privacy violations, consequently keeping themselves offline. Surprisingly, Internet users were not more concerned about the possibility of being a victim online in 2019 compared to 2013. In 2019, general privacy concern increased only by 4%, and 26-31% of respondents have taken action to protect their purchases, age, marital status or medical details and 40% their contact details. According to Pew Research Center of the US, although a majority of US consumers think that they have little or no control over how their personal information is collected and used by companies (81% in 2019 compared to 91% in 2013) [5, 64], between 10% to 19% feel that they have a lot of control over different forms of personal information, such as physical location, social media posts, private conversations,

purchases, or websites visited [5]. The European Commission reports a Eurobarometer survey in 2019 with findings that 51% of those who provide personal information online felt that they have partial control over this information, while 14% felt that they have complete control. 62% of those feeling partial or no control were concerned about not having complete control. In addition, a majority of the respondents in 2019 have heard of the rights guaranteed by the GDPR, and some have exercised these rights [34].

Given (1) the above reports of nuances in privacy concerns over the years and that some individuals take actions towards privacy, as well as (2) the well known *privacy paradox* phenomenon [4, 38, 55, 95], this paper seeks to investigate the following questions: ‘*what privacy methods or PETs do Internet users employ to protect their privacy? How do Internet users perceive the use of PETs?*’ We contribute to the rich landscape of user-centric privacy research, that has expansively addressed privacy behavior, including via the (extent of) disclosure of personal information [3, 4, 8, 26, 72, 95], privacy strategies [1, 17, 75, 105] or the use of privacy controls and individual PETs [1, 12, 26, 39, 46, 71, 87, 100], with a large-scale and cross-national study of the use of a collection of PETs.

We first investigate the use/non-use of a range of privacy methods and PETs across three countries, rather than taking an in-depth look at how users interact with individual PETs [12, 46, 71, 87] or engage with controls [39, 69]. This provides a broad view of what privacy methods and PETs individuals use, and enables us to uncover patterns of use and preferences.

Second, while various factors may influence the use/non-use of particular privacy controls and PETs, such as perceived risks [36, 39], perceived usefulness [12, 46] or demographics [75, 76], we focus on what happens following individuals’ concern about their privacy, in particular, whether they are aware of PETs and how they perceive use of PETs (c.f. the staircase/steps towards using a particular PET by Renaud et al. [87]). We postulate that PETs use patterns may be evidence of differences in use perceptions, in rationale for use or support needed. Therefore, rather than investigating perception of use of individual PETs [12, 46], we evaluate perceptions across clusters of PETs. This enables us to investigate whether (1) use perceptions and rationale are clearly demarcated across the patterns, as well as (2) to simultaneously understand why individuals prefer a particular collection of PETs.

Contributions. We provide both the quantitative grounding of classification, as well as the rich qualitative investigation of why individuals prefer one type of PETs over another. We provide a large-scale, cross-national, mixed-methods (quantitative and qualitative) investigation of PETs usage. We classify patterns of use of privacy methods online (including PETs and non-technology methods), in Studies 1 & 2 via a clustering approach. This provides a systematic, evidence-based and reliable point of reference for PETs usage categorisation and future research, and a classification based on patterns of use of PETs (rather than design type or protection provided). We therefore also provide re-usable methodology to better understand clusters of PETs, that can further drive investigations and understanding of PETs use via comparison of clusters, transition between clusters or inter-PETs usage.

We find that the cluster map distinguishes usage of PETs into Advanced and Other PETs, and that non-technology privacy methods are among the most used methods online. We demonstrate use

of the PETs usage classification within an investigation of why certain PETs are preferred over others, in Study 3. While we find support for themes identified in previous privacy controls and PETs use research, in particular with regards to awareness of privacy protection [87, 93], perceived usefulness [12, 46], usability [1, 87], or trust [12, 46], we expand on the themes of information about PETs, privacy needed and usability as well as report other rationales for not using advanced PETs, such as perceived monetary cost and social support. We also find that there is no statistical difference in individuals’ perceived competency to protect their privacy online, whether they are Advanced or Other PETs users.

Outline. The rest of the paper is organised as follows: we first review background research, and then provide a section describing Study 1 and 2, via their aim, methodology and results. We proceed into presenting Study 3, also via aim, methodology and results. We complete the paper with an overall discussion and conclusion, and provide an Appendix with additional support, including the questionnaires used in the studies.

2 BACKGROUND

Given our paper computes patterns of privacy methods usage and investigates user perceptions across clusters, we provide a review of literature addressing (1) privacy behavior, of which use of PETs is one aspect, and (2) technology adoption and classification of user responses in privacy research.

2.1 Privacy Behavior

We review a few strands of privacy behavior related research, in particular, (1) different protection practices, (2) factors impacting use of privacy controls and PETs, and (3) cross-national investigations of privacy concerns and behavior.

2.1.1 Privacy Protection Practices. The privacy research community is well acquainted with the *privacy paradox* phenomenon—where on the one hand users express concerns about the handling of their personal data and desire protection, while on the other hand, they voluntarily disclose via social networks or rarely make an effort to protect their data actively [3, 4, 15, 26, 72, 95]. Observations of the privacy paradox have also been discussed [26, 81] and systematic reviews of privacy paradox research conducted [9, 38, 55]. One of the resulting observations is that both privacy attitude and behavior can be conceptualised in different ways [20, 38, 55].

Research has operationalised privacy behavior in different ways, including via (the extent of) disclosure, via use of privacy controls and PETs, or via the adoption of protection strategies. First, privacy behavior as disclosure include observations such as revelations to an online bot [95], Facebook membership [3] and revelations in a bank and pharmaceutical scenario [72] or self-reports such as usage of Facebook or information disclosed [4, 8, 26]. Second, research has also operationalised privacy behavior as engaging in protective control actions and using privacy technology including the general use of privacy controls [39], use of controls in the context of social networks [26, 100], and use of secure encrypted communication [1, 87], anonymous credentials [12], anonymity service [46], and VPN [71], or reading the privacy policy [99]. Third, protection strategies have been investigated such as providing incorrect [75] or false [17] information, delivering sensitive information in-person

Table 1: Factors Influencing Protective Privacy Behavior

Factor	PETs/Context of Use
Years of internet experience	social/technical protection [76]
Internet skill	Facebook privacy settings [47]
Perceived rewards in disclosure	general/technical protection [69]
Privacy risks concerns	general/technical protection [69]
Unawareness of risks	social networks [39]
Risks of sharing	social networks [36]
Perceived usefulness & ease of use	anonymizing technology [12, 46]
Emotional considerations	VPN use [71]
Knowledge about how to protect oneself	E2EE [87]
Awareness of protection tools	E2EE & tracking [87, 93]
No perceived need to act	E2EE & tracking [87, 93]
Inability to use protection	tracking [93]
Becoming side-tracked	tracking [93]
Usability	E2EE & secure msg [1, 87]
Social Influence	secure msg & social networks [1, 39]
Education	Facebook sharing [36]
Gender	technical protection [75, 76], social network control [98]

Note: E2EE refers to end-to-end encryption

or using a “code” to deliver sensitive information to others [1], and deleting friends or rejecting friend requests, self-censoring or deleting content on social network [105].

2.1.2 Factors Influencing Protective Privacy Behavior. Various research have pointed to factors affecting protective control actions including a systematic review with comparison of predictor effect sizes [38], and obstacles to adoption of PETs [39, 87, 93] and secure communication [1]. We provide a summary of factors in Table 1 (focusing on use of controls and PETs as behavior, rather than disclosure or protection strategies described above in Section 2.1.1). We also name the context of investigation, such as social networks for inbuilt PETs or name the standalone PET investigated. We note that some factors were found to be more important than others, for example the risk of sharing [36], awareness of consequences of privacy violations [39] and contextual aspects of the messaging tool such as fragmented user bases [1], were found to be more important than usability.

2.1.3 Cross-National Influence. While there is no universal privacy or data protection law that applies across the whole Internet, a number of international and national privacy frameworks have largely converged to form a set of core, baseline privacy principles, that establish fair information practices for consumers, businesses and organisations. Whereas the General Data Protection Regulation (GDPR) provides the legal backbone for data protection and privacy in Europe [104], the US does not have an all-encompassing law like the GDPR but has a variety of federal and state laws that aim to protect a citizen’s privacy and online data [79] and the UK established the Data Protection Act 2018 as its implementation of the GDPR [77]. With regards to Internet users, differences have been observed in privacy concern, behavior or valuation of information across countries [10, 16, 22, 65, 86, 97], with some influence of national culture (where national culture is viewed as the collective mindset distinguishing members of one nation from another [48], and is embedded in the way members think, feel and act [49]), in particular via the collectivist versus individualist distinctions [16, 65, 86] or relational mobility [97]. Others have looked into the privacy calculus across countries in contexts such as e-commerce [28], social network [56], health records [27] or driving

behavior [54]. These studies leveraged population samples worldwide [10, 86], or compared the US versus Asian countries [65, 97], the US versus Asia-Pacific countries [16], the US versus European countries [27, 28, 54, 56], or across European countries [22, 44].

2.2 Technology Adoption & Patterns

2.2.1 Model of Technology Adoption. The Technology Acceptance Model (TAM) provides the theoretical background for understanding why users accept or reject technology [24]. It has been empirically demonstrated to successfully predict 40% of system use [60]. TAM suggests that perceived ease of use (PEOU) and perceived usefulness (PU) are two most important factors explaining technology use. Privacy research employing TAM as psychological construct ranged from (1) understanding adoption of specific PETs, such as user acceptance of anonymous credentials [12], anonymity technology [46], and VPNs [71]; to (2) perceived privacy in adoption of technologies such as social media [84], e-commerce [57, 103], biometrics [68], Snapchat [61] or trading systems [89].

2.2.2 Cluster Analysis for User-Centric Privacy. Investigations into patterns of use of technology may enable identification of broad usage trends across single or a collection of technologies. This can be conducted via cluster analysis, which supports the identification of patterns and provides an objective methodology for quantifying structural characteristics of observations, and relationship identification [7, 63]. Cluster analysis has also been employed in user-centric studies in the privacy context to better understand perceptions or behaviors. Example investigations using cluster analysis include SNS engagement and privacy habits in relation to transport [30], privacy management strategies in Facebook [59], privacy perceptions based on geographical regions [50], perceptions of information sensitivity between countries [92], cross-country comparison of adolescents’ privacy perceptions [94], privacy versus sharing perceptions [74], and privacy and risks perceptions to better understand behavior [21].

3 STUDY 1 & 2

3.1 Aim

We explore usage of privacy methods online in visual maps. We sample participants from the US, UK and German populations.

3.1.1 Privacy Method Patterns. We posit that individuals likely engage with privacy via a habitual collection of methods or pattern of actions, where habits are actions that have become automatically triggered by situational cues [58]. We investigate as **RQ1**, “What patterns emerge in individuals’ privacy methods usage and preference? How similar are usage patterns across privacy methods?” Because we do not have a-priori expectations of the nature of relationships between privacy method preferences, we employ a Cluster Analysis [63] to naturally distinguish different patterns of use, and further look into usage patterns in relation to country via a Correspondence Analysis [40, 41].

3.1.2 Cross-National Privacy Method Similarities. The diffusion and adoption of technology do not necessarily follow a common pattern in terms of rates or timing across countries. Adoption of technology is often influenced by cross-national factors [6, 33],

where in particular, use of technology for privacy may be influenced by regulation. We investigate as RQ2, “What methods are mostly used to protect one’s privacy online? what similarities emerge between countries?”

3.2 Method

We conduct two survey studies online. The first study (Study 1) is aimed at identifying a preferred list of privacy methods. The second study (Study 2) employs the compiled list of methods from Study 1 to query participants about their use of the range of privacy methods identified.

3.2.1 Participants. With their advanced digital economies, Europe and the US may be considered as the drivers of protection technology around the globe. However, Europe versus the US differ in privacy regulation [83] and potentially also in individuals’ privacy protection patterns.

For Study 1, we sampled $N = 180$ participants, comprising $N = 58$ US participants, $N = 62$ UK participants and $N = 60$ German (DE) participants. We sampled participants from Prolific Academic. The data quality of Prolific Academic has good reproducibility [78], and is comparable to Amazon Mechanical Turk’s which is widely used in security and privacy user studies.

For Study 2, we recruited an $N = 907$ sample from the US, UK and DE via Prolific Academic. The samples from the US and the UK were representative of age and gender of the respective countries, as provided by Prolific Academic. For the DE sample, we did not achieve a representative sample in terms of gender and age.

Table 2 provides a summary of the demographic details for the two studies. The studies lasted between 10 to 20 minutes. Participants were compensated at a rate of £7.5 per hour, slightly above the minimum rate of £5 per hour suggested by Prolific Academic.

Table 2: Participant Characteristics

	Country	N	Mean Age	Gender	
				#Female	#Male
Study 1	US	58	35.53	29	29
	UK	62	30.65	43	19
	DE	60	30.68	27	33
Study 2	US	303	43.72	155	148
	UK	303	44.21	154	149
	DE	301	28.91	115	186

3.2.2 Procedure. Study 1 aims to identify and compile a list of privacy methods preference. We do so via an open-ended question, across three countries. Study 1 consisted of a questionnaire on demographics, and an open-ended query to list three to five tools most often employed to achieve the purpose of privacy online.

Study 2 followed the same format as Study 1, except that we changed the open-ended queries of the first study to close-ended privacy methods questions, for participants to select the methods they mostly use from the whole list provided. We also shifted to a larger sample for the three countries. We provide a summary of the procedure in Figure 1.

3.2.3 Measurement Apparatus. Study 1: We queried participants on the individual privacy methods they most often use, eliciting

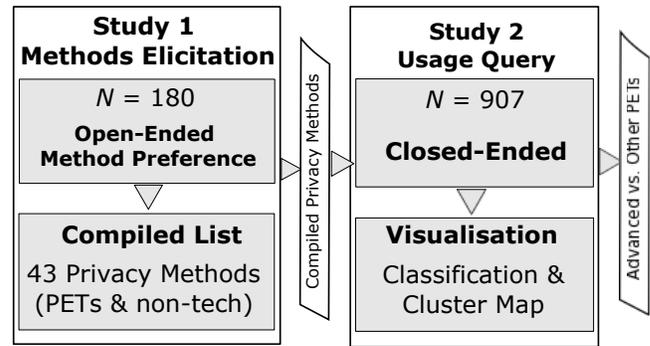


Figure 1: Studies 1 & 2 design.

their own methods via the instruction “List between 3 to 5 tools that you have most often employed before to achieve the purpose of privacy online.”

Study 2: We asked participants to rate the list of privacy methods provided with whether they use them ‘very often’ or ‘very rarely/not at all’. While we opted for binary data, we found that querying ‘If you have used them before: Yes/No’ would not fit our inquiry. ‘Yes’ would include ‘once and never again’ usage type. We wanted to capture methods that are popular with users (and include protections that are often but not always used by choice) via ‘very often’ versus those participants have not thought of or have used in very rare circumstances (not the go-to protection).

We provide the full question and wording as provided to participants in Table 12 in the Appendix A. We pre-tested this list for comprehension with $N = 7$ colleagues and acquaintances in the computing and social science departments, and believe that participants in Study 2 understood the wordings, as they were named by participants in a similar sample in Study 1. We also provide an open-ended option for ‘other privacy method’.

We encouraged participants to respond truthfully by stating that the surveys are anonymous in the consent form, and also asking for truthful answers in the questionnaires. We included attention check questions throughout the survey and the list of privacy methods presented to participants in Study 2 was randomised.

3.2.4 Limitations. Representative Sample: While in Study 2 our sample is representative of the US and UK populations, with respect to age and gender, we did not achieve a representative sample for DE (Germany). This explains the difference in mean age for DE compared to the US and UK, in Table 2. From the 2019 demographics record, the German population has a median age of 47.4, with 37.3% of the population aged over 54 [51]. The crowd sourcing platform could not cater for the representative sample for the sample size we required. Our relatively large sample size however decreases the probability of assuming as true a false premise. In addition, our sample characteristic is likely transferable to the larger German population, where participants in our sample exhibit behaviors of the general population [80]. However, in future research, it will be valuable to strive towards representativeness across the sample, including via attributes such as ethnicity and education level. Alternative crowdsourcing platforms for participant recruitment may also need to be investigated.

Table 3: Privacy Methods Categorised by Design Type and Privacy Protection (as elicited in Study 1). We provide the shorthand shown in the Cluster Map in brackets, where applicable.

		Design Type		
		Built-in	Standalone	Non-Technology
Protection	Anonymity	Encryption Clear/Delete info/history (clearhistory) Pseudonyms/Onion (pseudonyms)	Erasery Tor Proxy IPHider Virtual machine (virtualma)	Not Store Info (notstore) Anonymous profile names (anonprofile) NotGivePI / LimitSharing / MinimalInfo (limitshare) Several/Bogus / LimitedUse Emails (afewemail) Fake Info Limit Use of SNS Accounts (limitsns) SwitchOffCamera/Devices/PortableHD (switchoffcam) No Access Acc In Public Place/Networks (nopubac) Not use FB (noFB) Not Engaging Online/Careful/Not Signing Up (not-engage)
	Browsing History & Tracking Prevention	Private Browsing/incognito (privbrowsing) Anti-tracking addon (antitrack) No location tracking (nolocation) Clear/Limit cookies (clearcookies)	DuckDuckGo Ghostery NoScript	
	Communication & Filtering	Adblock HTTPS	Firewall VPN	
	Prevent Leaking & Stealing of Data	Privacy settings (privset) Opt out Private profiles (anonprofile)	Password manager (pwd mger) Paypal Anti-spyware (antispy) Anti-malware (antimal) Kapersky	Not save (notsavepwd) or reuse password (notreusepwd) Read terms of service (readterms) Request data collected, GDPR (reqdatacol) no newsletter, think twice (nonewslet) Website care/No suspicious sites (suspiciousweb)

Self-Report Bias: Our studies rely mainly on self-reports rather than system observations. Self-report is a valuable and widely used method of querying users in security and privacy user studies. While self-reports can be argued to induce bias, research investigating response bias in security user studies has found that self-report insights can translate to real-world environments [85].

The list of privacy methods presented to participants in Study 2 were named from a pool of participants of $N = 180$ across the three countries in Study 1. We pre-tested the list for comprehension for Study 2 with researchers who may be thought to bias the test outcomes. However, the list was sourced from participants themselves in Study 1, therefore came from the ‘field’.

3.2.5 Ethics. We obtained approval from the University’s Faculty Ethics Committee before starting the research, for all the studies (Studies 1 & 2, as well as Study 3). We sought participants’ consent for data collection prior to their responding to the questionnaires, and we did not collect identifying information. Participants were free to leave the survey at anytime and were compensated slightly above the advised rate as described in Section 3.2.1.

3.3 Results

3.3.1 Compiled Privacy Methods from Study 1. We collect participants’ responses of 3 to 5 most used privacy tools or methods in Study 1, with the $N = 180$. We end up with 43 privacy methods coded across the three countries and 11 participants stating they ‘don’t know’.

Participants reported privacy methods that may be designed as (a) a standalone privacy technology, or as (b) privacy controls or settings integrated (built-in) within other tools such as browsers or messaging tools. Participants also reported strategies that do not involve using privacy controls, such as ‘give fake info’, which we name as ‘non-technology’ methods. We also loosely name four

possible protection categories, namely (1) anonymity (ANO), (2) browsing history and tracking prevention (BHP), (3) communication privacy and filtering (COP), and (4) preventing leaking and stealing of data (PLS). We present the privacy methods elicited according to its design type and privacy protection type provided, as depicted in Table 3. (Note that this loose categorisation only serves to better present the types of privacy methods named, and do not affect the rest of the analysis.)

3.3.2 Privacy Method Patterns from Study 2. We investigate RQ1, “What patterns emerge in individuals’ privacy methods usage and preference? How similar are usage patterns across privacy methods?” Our dataset is a contingency table of 43 rows (privacy methods) and 3 columns (count of participants in the US, UK and DE who reported to ‘very often’ use the privacy method). We provide the dataset in Table 13 in Appendix B.

We conduct two multivariate analyses and visualise our dataset: (1) via a Cluster Analysis [53, 90] that classifies the set of 43 privacy methods as suggested by natural groupings in the data themselves, and produce a cluster map as a simplified depiction of the relationships between privacy methods; and (2) via a Correspondence Analysis [40, 42] that investigates and visualises the relationship between the 43 privacy methods across 3 countries, as well as the similarities between privacy methods given their country profiles. The main results for this subsection are Figures 4 and 5.

Cluster Analysis. In the next few paragraphs, we report on the cluster analysis and results via the following steps:

- (1) we conduct a dimensionality reduction,
- (2) we determine the optimum number of clusters and compute the cluster analysis,
- (3) we assess the internal validity for the cluster analysis, and
- (4) we visualise the cluster map and interpret the dimensions.

We use the R package Factoextra [52] for the cluster computation and visualisation.

We first compute a Principal Component Analysis (PCA) [108] as dimensionality reduction technique, using the *prcomp* function in R. The PCA operates on the 3 country variables to output 3 factors or principal components (PC), namely PC1, PC2 and PC3. PC1 accounts for 95.4% of the variation in the data, while PC2 accounts for 4% of variation and PC3 accounts for 0.5%. We describe the importance of the principal components in Table 4. Together, PC1 and PC2 account for 99.5% of the variation in the data, which is a large amount of variance. We therefore focus on PC1 and PC2.

Table 4: Importance of Principal Components.

	PC1	PC2	PC3
Standard deviation	1.692	0.348	0.128
Proportion of Variance	0.954	0.040	0.005
Cumulative Proportion	0.954	0.995	1.000

We report the factor loadings for PC1 and PC2 in Table 5, where the country variables load similarly to PC1, while the US and the UK load in opposite direction to DE for PC2.

Table 5: Factor Loadings.

Variables	PC1	PC2
US	0.585	-0.303
UK	0.580	-0.492
DE	0.567	0.816

Second, we employ *k*-means as cluster analysis method on the principal components. *k*-means clustering is the most commonly used unsupervised machine learning algorithm for partitioning a given data set into a set of *k* groups or clusters [63], and groups observations by minimizing Euclidean distances between them. Our cluster analysis focuses on the first two principal components that explain 99.5% variance, and visualise them as Dimension 1 (Dim1) and Dimension 2 (Dim2), where in general, dimensions are variables or *features* of data objects [42]. Dim1 refers to PC1, while Dim2 refers to PC2.

To determine the optimal number of clusters, we use the *elbow method*, which consists of optimising the within-cluster sum of squares (WSS) [42]. We choose a number of clusters so that adding another cluster does not improve the total WSS much better. From the plot in Figure 2, the total WSS does not show a sharp improvement after 3 clusters. We subsequently conduct a *k*-means cluster analysis with 3 clusters, and summarise distances between pairs of clusters in Table 6. The 3 clusters correspond to 3 distinct groups of privacy methods preference, of sizes 19, 13, and 11. Privacy methods in the same cluster are as similar as possible in terms of user preference, with low intra-class variation of 11.7%, whereas privacy methods in different clusters are as dissimilar as possible, with high inter-class variation of 88.3%. We provide further cluster statistics in Table 7.

Third, for internal validation of the cluster partitions [62], we conduct a *Silhouette Analysis* which measures how well an observation is clustered and estimates the average distance between

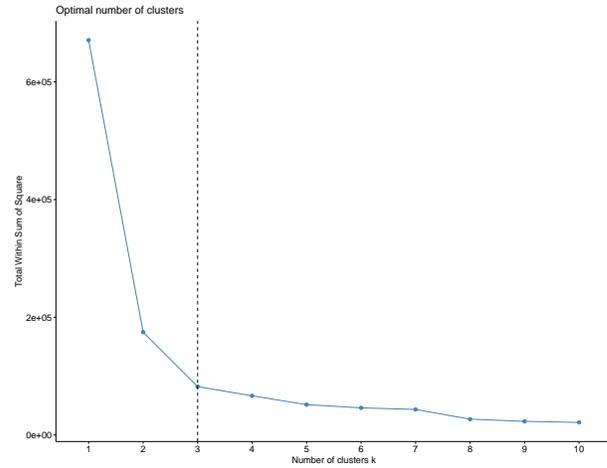


Figure 2: Determine number of clusters via Elbow Method
Table 6: Separation Matrix, that is a matrix of separation values between all pairs of clusters.

Cluster	1	2	3
1	0.0000		
2	160.7016	0.00000	
3	48.9183	38.48376	0.00000

Table 7: Cluster Statistics

Value Description	Cluster 1	Cluster 2	Cluster 3
Cluster size	19	13	11
Diameter	122.69	115.90	134.38
Cluster separation	48.92	38.48	38.48
Cluster avg. silhouette width	0.58	0.64	0.43
Avg. distance b/w clusters	204.53		
Avg. distance within clusters	57.74		
Within cluster sum of squares	82868.96		
Between cluster sum of squares	623240.80		

Diameter = maximum within cluster distance
 Cluster separation = vector of clusterwise minimum distances of a point in the cluster to a point of another cluster.

clusters [91]. The silhouette plot in Figure 3 displays a measure of how close each point in one cluster is to points in the neighbouring cluster, with an average silhouette width S_i of 0.56 across the 3 clusters. S_i values can range from -1 to 1 , where negative values signify that observations are placed in the wrong cluster and values close to 1 signify that observations are well clustered. Our S_i value of $+0.56$ shows that our clustering is okay.

Fourth, we visualise the cluster analysis on a two-dimensional Cluster Map, as provided in Figure 4 (using the *fviz_cluster* function in R). Dim1/PC1 explains 95.4% of variation in the data and have similar contribution from the three countries as shown by PC1 in Table 5 and the x-axis of Figure 4. The high variance explained by this factor likely represent the main characteristic of our dataset, that is the usage counts. In particular, Figure 4 shows that ‘erasery’ and ‘suspiciousweb’ are at the extreme ends of the x-axis and from Table 13, they are the least and most used method, respectively. We therefore interpret Dim1 to characterise ‘The Popularity of Privacy

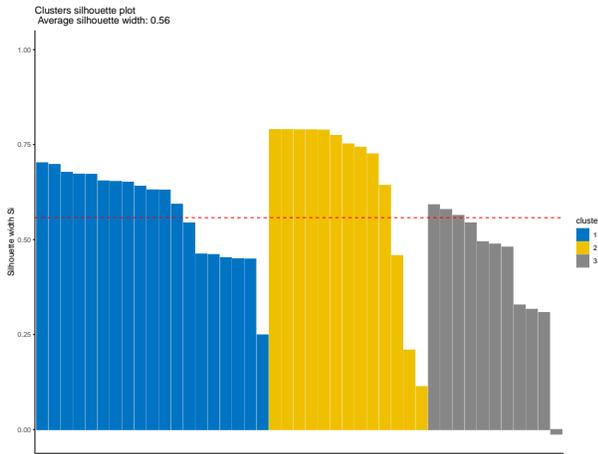


Figure 3: Silhouette Plot for Cluster Validity

Method’ (both visually and confirming with the dataset). The red, right-most cluster pertains to most used privacy methods while the green and left-most cluster pertains to the least used privacy methods.

Dim2 (the y -axis of Figure 4, from PC2 in Table 5) depicts the country of use, where the positive end of the y -axis refers privacy methods usage more associated to DE, while negative end refers to usage more associated to the US and UK. For example, ‘pseudonyms’ and ‘readterms’ are both in the same cluster but are at the opposite ends of the y -axis. From Table 13, we find that ‘pseudonyms’ is most used in DE compared to US/UK while ‘readterms’ is least used in DE compared to US/UK.

Correspondence Analysis. The Correspondence Analysis (CA) is an exploratory technique that graphically represents the relations among rows and columns of a contingency table, in a spatial map, and is increasingly popular for dimensional reduction and perceptual mapping [42]. We use the dataset of privacy methods count across each country as in Table 13. In the next few paragraphs, we report on the CA and results via the following steps: (1) we compute the CA, (2) we visualise the spatial plot, and (3) we interpret the dimensions.

First, we identify ‘DuckDuckGo’ as an outlier, and treat it as a supplementary row, a practice used to treat outliers in correspondence analysis [11]. We compute the CA via the `CA` function from the `Factoextra` package [52] in R. We find significant independence of variables with $X^2 = 317.016$, $p < .001$, and that the first dimension accounts for 92.16% of the variance in the data while the second dimension accounts for 7.84%. Together these two dimensions account for 100% of variability.

Second, we visualise a spatial plot, using the `fviz_ca_biplot` function in R, as provided in Figure 5. The plot shows the row and column profiles simultaneously in common space. The distance between data points of the same type (row to row, that is privacy method to privacy method) is related to the degree to which the rows have similar profiles in the columns, that is relative frequencies in country variable. The more points belonging to the same set (pattern) are close to each other and the more similar their profiles are. As example, individuals who use IPHider and those who give fake information as privacy methods have similar country profiles,

whereas those who use Tor and ‘read terms and conditions’ as privacy methods have very dissimilar country profiles.

Third, to interpret the dimensions, we look into the privacy methods and country that contributes most to defining and characterising each dimension. We provide a plot of the contribution of the privacy methods to the first dimension in the Appendix C as Figure 7. The top 10 privacy methods contributing to the definition of Dimension 1 (the x -axis of Figure 5) in decreasing rank, with positive (+ve) or negative (-ve) contributions are: (1) NoScript (-ve), (2) pseudonyms (-ve), (3) read terms and conditions (+ve), (4) Tor (-ve), (5) no public access (+ve), (6) virtual machine (-ve), (7) VPN (-ve), (8) not engage (+ve), (9) Ghostery (-ve), (10) give fake info (-ve). In addition, with regards to country contribution, DE contributes 61% to the definition of Dimension 1. We interpret Dimension 1 to characterise ‘Radicalness of Protective Method’ ranging from the extreme positive end of the x -axis with ‘Not Engage’, ‘No Public Access’ and ‘Read terms and conditions’ as non-technological solutions to the extreme negative end of the x -axis with NoScript, pseudonyms, Tor, virtual machine, VPN, Ghostery as PETs and not engaging with ‘Give Fake Information’. By our interpretation, the ‘Most Radical Protective Methods’ are at the extreme ends of the x -axis thereby contributing most positively and negatively, and the ‘Least Radical Protective Methods’ are nearer to origin ($x = zero$).

We note the difference between the cluster and spatial maps. While the cluster map shows the natural grouping of privacy methods usage, the spatial map shows similarities in privacy methods usage based on their relationship to the different countries. In addition, the cluster analysis uses euclidean distance, whereas the correspondent analysis uses chi-square statistic. Therefore, Dimension 1 of both maps do not refer to the same characteristic of privacy method usage.

3.3.3 Cross-National Method Use Similarities. From Study 2, we investigate RQ2 “What methods are mostly used to protect one’s privacy online? What similarities emerge between countries?” Table 8 shows a depiction of the top 10 privacy methods preferences across the three countries, where we observe that 4 of the privacy methods appear in the top 10 most reported methods in all three countries. These methods are (1) privacy settings, (2) limit sharing, (3) website care, and (4) no newsletter. In addition, we find 8 privacy methods similarities in the top 10 most reported methods for both the UK and US, 6 methods similarities between the UK and DE, and 5 methods similarities between the US and DE.

4 STUDY 3

4.1 Aim

While individuals are generally reported to be concerned about their privacy [5, 13, 34, 64], they are not necessarily observed to actively use PETs, as a consequence of their concern. In particular, a number of intervening steps may influence the ‘privacy concern — use of PETs’ link, such as whether individuals perceive a need to act, are aware of the usefulness PETs or are able to use PETs [87], amongst the various other factors impacting behavior listed in Table 1.

We aim to understand use perceptions and reasons for choosing a collection of PETs. Using the clusters visualised in the cluster map of Figure 4 (Study 2) as classification of privacy methods usage

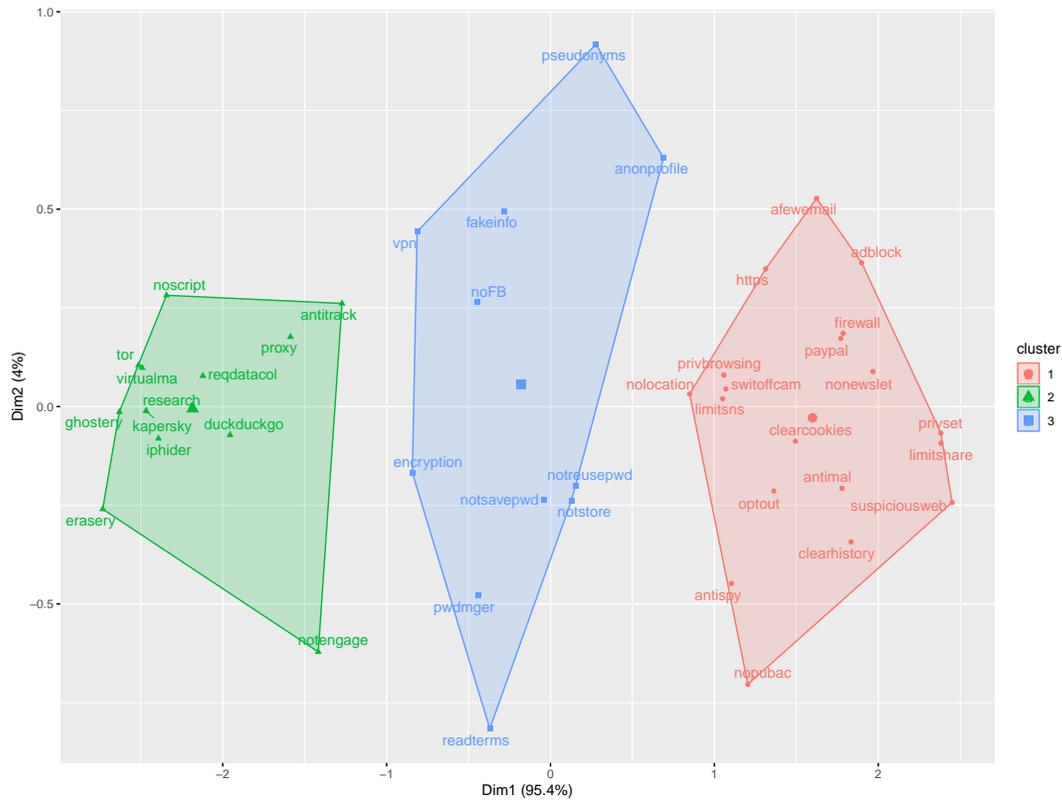


Figure 4: Privacy Methods Clusters along the Popularity of Privacy Method Dimension; left to right = least to most used.

Table 8: Top 10 Privacy Methods by Country starting with most frequently mentioned

United States			United Kingdom			Germany		
Method	Design	CAT	Method	Design	CAT	Method	Design	CAT
1 Website care	NT	PLS	1 Website care	NT	PLS	1 AdBlock	BI	COP
2 Privacy settings	BI	PLS	2 Limit Sharing	NT	ANO	2 Bogus Emails	NT	ANO
3 Limit Sharing	NT	ANO	3 Privacy settings	BI	PLS	3 Privacy settings	BI	PLS
4 Research before engaging	NT	ANO	4 Clear Info/History	BI	ANO	4 Limit Sharing	NT	ANO
5 Anti-Malware	ST	PLS	5 Paypal	ST	PLS	5 No Newsletter	NT	PLS
6 No Newsletter	NT	PLS	6 Research before engaging	NT	ANO	5 Paypal	ST	PLS
7 AdBlock	BI	COP	7 No Newsletter	NT	PLS	5 Website care	NT	PLS
8 Clear Info/History	BI	ANO	8 Firewall	ST	COP	5 Firewall	ST	COP
9 Clear/Limit Cookies	BI	BHP	9 Anti-Malware	ST	PLS	9 HTTPS	BI	COP
10Not Access Accts in Public Place	NT	ANO	10Not Access Accts in Public Place	NT	ANO	10Pseudonyms	BI	ANO

BI, ST & NT refer to design type of built-in, standalone and non-technology respectively.

ANO, BHP, COP & PLS refer to privacy protection categories of anonymity, browsing history and tracking prevention, communication privacy & filtering, and preventing leaking & stealing of data respectively.

patterns, we examine individuals’ perceptions of the PETs in the different clusters, and their rationale for a particular choice. We create two lists of PETs from the cluster map, that we name Advanced PETs (Adv.PETs) and Other PETs (Oth.PETs):

Advanced PETs List: Adv.PETs is populated with the PETs in the leftmost cluster, which contains the least used and more advanced solution to privacy protection. We also add VPN and encryption, which fall on the left of the centroid of the middle cluster, to the list. In particular, Adv.PETs refers to a list of the following PETs: Erasery,

Ghostery, virtual machine, Tor, NoScript, IPHider, Kaspersky, Duck-DuckGo, proxy, anti-tracking extension, VPN, and encryption.

Other PETs List: Oth.PETs is populated with the PETs in the rightmost cluster, which contains the most used privacy methods. We also add pseudonyms and ‘anonymous profile’, which fall on the right of the centroid of the middle cluster, to the list. Oth.PETs refers to the following list of PETs: switch off location tracking, private browsing, HTTPS, anti-spyware, opt-out (of data collection), clear cookies, anti-malware, clear history, Paypal, firewall, Adblock, privacy settings, pseudonyms and anonymous profile.

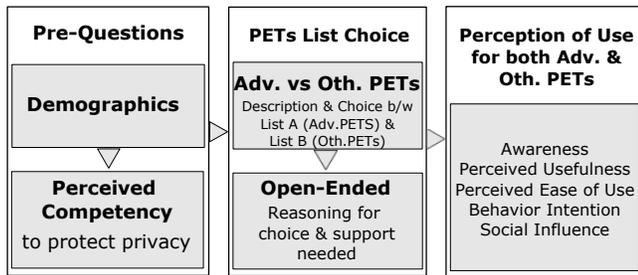


Figure 6: Study 3 design.

4.2.2 Procedure. Study 3 consisted of the following questionnaires: (a) demographics, (b) perceived competency in protecting privacy online, (c) description of two lists of PETs (List A, the Adv.PETs and List B, the Oth.PETs) and questions on which set participants mostly use, as well as support they believe they would need to use the other set, and (d) awareness, perceived usefulness, ease of use, social influence, behavior intention to compare between the two sets of PETs. We depict the procedure in Figure 6.

4.2.3 Measurement Apparatus. This section describes the questions and scales employed in Study 3, where we employed good practice guidelines of security and privacy user studies [18, 19], in adapting existing scales, as much as possible.

Choice of PETs, Reasoning & Support: We provided participants with two lists of PETs and asked “Which of the two lists contains the privacy methods that you most often use to protect your privacy online?” We then asked them to explain why they ‘most often’ use PETs from one list and why they ‘very rarely or not at all’ use methods from the other list. We further queried about what would support them to use methods from the list they did not select, in particular, what would help or encourage them. We provide the full questions and wording in the Appendix D.

Perceived Competency: We adapt Williams & Deci’s [106, 107] perceived competence questionnaire to privacy protection online. We provide the 4 items of the questionnaire in Table 14 of the Appendix E. The questionnaire is provided with a 7-point Likert scale ranging from 1 - “Not true at all” to 7 - “Very True” and a midpoint at 4 with “Somewhat True”.

Technology acceptance model components: We adapt Davis [24, 25] scale for measuring the components of TAM, namely for perceived usefulness, perceived ease of use and intention to use privacy technology, as provided in Table 14 of the Appendix E. The scales were provided with 5-point Likert ranging from 1 - “Strongly Disagree” to 5 - “Strongly Agree”.

Awareness & Social Influence: We created a 4-item questionnaire to gauge awareness of PETs, as shown in Table 14 of the Appendix E. We further adapt the social influence scale from Venkatesh et al. [102], where social influence is defined as the degree to which an individual perceives that important others believe he should use the new system. These scales are provided on a 5-point Likert ranging from 1 - “Strongly Disagree” to 5 - “Strongly Agree”.

4.2.4 Limitations. Self-Report Questionnaires: Similar to Studies 1 and 2, Study 3’s data collection is based on self-reports. However, in Study 3, we employ standard questionnaires with scales composed of multiple items. These scales have been widely used and validated

in past research, as referenced in Section 4.2.3. We provide the assessment of internal consistency obtained in Study 3 for each scale in Table 14 of the Appendix.

Additional measures and ordering: While we carefully selected questionnaires for the purpose of Study 3, additional ones such as to elicit participants’ tech-savviness could provide means of verifying the self-reported Perceived Privacy Competency questionnaire, for example. In addition, placing the demographics questionnaire at the fore may consume participants’ attention span. We included attention checks throughout the study. However, in the future, we would consider to position the demographics questionnaire at the end of the study.

4.3 Quantitative Results

In Study 3, we asked participants to select the list containing the PETs they most often use. We detailed the contents of the lists in Section 4.1. Only 17 of 183 participants mostly use Adv.PETs, that is the list pertaining to the least used cluster. All the remaining participants chose the Oth.PETs list. We distinguish these 2 groups of users as Adv.Users and Oth.Users.

We compute the internal consistency of the items for each of the perception scales. We provide the Cronbach α values in Table 14 of the Appendix E.

We investigate **RQ3**, *How does Adv.Users’ and Oth.Users’ perceptions of use differ between Adv.PETs and Oth.PETs?*, and **RQ5**, *do Adv.Users’ and Oth.Users’ [awareness of/perceived social influence to use] differ between Adv.PETs and Oth.PETs?*

We compute pairwise t -tests for Adv.PET and Oth.PETs across participant responses for awareness of PETs, perceived usefulness, perceived ease of use, behavior intention and social influence. We summarise the results in Table 10, where Oth.Users showed significantly higher perceptions of Oth.PETs than of Adv.PETs, across all scales with $p < .001$. We reject the null hypotheses, $H_{30,0}$ and $H_{50,0}$ that *Oth.Users show no difference in perceptions of use between Adv.PETs and Oth.PETs*, for the five use perceptions shown in Table 10. Adv.Users only reported higher perceived usefulness of Adv.PETs than of Oth.PETs. We accept the null hypotheses $H_{3a,0}$ and $H_{5a,0}$ for Adv.User for all user perceptions, except for perceived usefulness.

We investigate **RQ4**, *Does perceived competency at managing one’s privacy online differ between Adv.Users and Oth.Users?* We compute differences in perceived competence between Adv.Users and Oth.Users, with an independent samples Mann-Whitney U test. We do not observe a statistical significant difference in perceived competency in ensuring privacy protection online between Adv.Users and Oth.Users. We therefore accept the null hypothesis $H_{4,0}$ that *there is no difference in perceived privacy competency between Adv.Users and Oth.Users*.

4.4 Qualitative Results

We investigate **RQ6**, that is “*why do individuals choose Adv.PETs or Oth.PETs? what support would they need to use the other type of PETs?*” This section describes the coding process and reports responses for (1) users of both types of PETs, (2) users of Adv.PETs and (3) users of Oth.PETs. Note that List A in the survey refers to Adv.PETs and List B refers to Oth.PETs.

Table 10: Within-group pairwise comparison of technology use perception of Adv.PETs vs. Oth.PETs, where Oth.Users have higher perceptions of Oth.PETs than Adv.PETs

Use Perception	Adv.Users		Oth.Users	
	<i>t</i> (16)	<i>p</i>	<i>t</i> (165)	<i>p</i>
Awareness			Oth.PETs -16.290	.000
Perceived Usefulness	Adv.PETs 2.787	.013	Oth.PETs -6.999	.000
Perceived Ease of Use			Oth.PETs -18.494	.000
Behavior Intention			Oth.PETs -15.189	.000
Social Influence			Oth.PETs -9.231	.000

4.4.1 Codebook Creation. The sample of $N = 183$ participants in Study 3 were asked two open free-form questions: Q1, why they mostly use methods from one list, and Q2, what would support them to use methods from the other list. Responses were required to be at least 30 words long, with no maximum.

We facilitated a conventional line by line coding, where $n = 50$ responses were coded by one coder to extract concepts from the free-form text. This process has been used in usable privacy research before and is well accepted [20]. The concepts were grouped into 5 categories for each question, and the coding was validated and refined with discussions with another coder. We used the set of categories and concepts to create a codebook. We trained 2 researchers as coders and further refined the codebook with a final set of 47 codes within 5 categories as provided in Table 15 of the Appendix F. The ‘-other’ codes, such as *EFF03-other* were added to include concepts not initially catered for in the codebook.

We evaluate inter-rater reliability via %-agreement and Cohen k [43, 67] on 100 responses across the 47 codes. We find that the coders were on agreement 96% of the time and there was a substantial agreement with Cohen k of .837, $p < .001$.

4.4.2 Use of both types of PETs. We note that 35 of the 183 participants reported using PETs from both lists, where most of them reported using Oth.PETs primarily and a few Adv.PETs. The few Adv.PETs that participants reported using are VPN (mentioned by $n = 14$), NoScript, DuckDuckGo, Proxy, anti-tracking, Kaspersky and Ghostery. Note that as described in Section 4.2.2, List A refers to Adv.PET whereas List B refers to Oth.PETs.

Participants explained that they use Oth.PETs as baseline and Adv.PETs for critical conditions or as a form of layered protection, such as expressed by P121 in ‘*I think methods on List B are things that should use [sic] everybody, the bare minimum you should use while surfing on the world wide web. I also use DuckDuckGo, VPN, NoScript and Ghostery, but the things on the other List are more often*’, P9 in ‘*i [sic] do use some from List A, however list B come pretty standard with my tech as well as is free and easy to use.*’ and P127 in ‘*I mostly use adblock on very restrictive settings, noscript, no location tracking and private browsing, because these methods are the most convenient ones. I sometimes use VPN and proxies as well, but since this requires more action, I only use this in critical cases.*’

In addition, 2 participants reported using VPN for other reasons than for privacy protection, with for example P112 stating ‘*clear cookies and clear the history is a thing i [sic] do every day [...] ok sometimes i [sic] use VPN, but not to protect myself only to watch movies from the US, which are geo blocked*’ and P25 ‘*I*

will occasionally use a VPN if I need to access websites that are not available without.’

4.4.3 Users of Advanced PETs. Users of Adv.PETs reasoned that Adv.PETs are more effective in ensuring their privacy online, such as reported by P117 in ‘*List A contains tried and tested methods of protecting privacy, list B is superficial*’ or P105 in ‘*list B not effective*’. They also pointed to the trustworthiness of Adv.PETs, as expressed by P110 ‘*Tor is more trustworthy*’ or P40 ‘*List A is [sic] better to rely on*’.

4.4.4 Users of Other PETs. Overall we find that participants’ reasons for mostly using Oth.PETs corroborated with the support and encouragement they believe they would need to use Adv.PETs, as similar themes emerged from the two open-ended questions. We consequently provide the responses for the two open-ended questions based on the themes. From the 5 categories of Table 15, we observe recurrent themes in the responses, namely (1) ‘*information about*’ the PETs, (2) ‘*usability*’ type responses, (3) level of ‘*privacy or protection needed*’, (4) ‘*cost*’ of PET, (5) ‘*trust and reliability*’ of PET and (6) ‘*social support*’ to use PET. We report participants’ reasoning for choosing Oth.PETs and support needed to use Adv.PETs across these themes in Table 11.

5 DISCUSSION

We organise this section into four main sections, with each providing a brief summary of findings, followed with a discussion of the implications of our findings as well as their relation to previous research. We also highlight lines of investigation for future research.

5.1 Usage Pattern of Privacy Methods

Summary of findings: We visualised privacy methods use via a cluster map, and relations between methods and country of use via a spatial map. We identified three clusters pertaining to three distinct privacy method use patterns, with the left and right clusters respectively showing the least and most used methods.

Interpretation of Clusters. A visual inspection of the clusters reveals insights into participants’ privacy methods preference, such as, that the right cluster contains simple, easy to use, and convenient methods of protection, that can be said to be more inclusive of skill levels and are more mainstream, while the leftmost cluster contains more advanced PETs.

Use of the classification. The results of the clustering may be used to support users with recommendations, such as suggesting other privacy methods in the same cluster, with the knowledge that users with similar methods preference used these other methods, and the underlying assumption that methods in the same cluster share similarity in ease of use and perceived required skill. The classification is also in itself a methodological tool, that can facilitate further user-centric investigation of PETs.

Cluster Transitions. We consider questions for future research into facilitating a transition from using a right-cluster method to a left-cluster method, such as ‘under what conditions do users transition right to left? what is the influence of more privacy concern, more skill, a realisation that simple PETs are not enough or the influence by social contacts?’ ‘how to support users to shift from right

Table 11: Qualitative Responses from n=166 participants who chose Oth.PETs: reason for choice & support/encouragement needed to use Adv.PETs

Theme 1: Information About			Theme 2: Usability			
		%			%	
Reasons	Not know Adv.PETs	28.92	Reasons	Easy to use/install Oth.PETs	24.10	
	Familiar with Oth.PETs	27.11		Adv.PETs complicated to use/install	7.83	
	Technical skills required	6.02		Oth.PETs are readily available	6.63	
	Belief Oth.PETs are for casual/non-tech savvy users	<4		Oth.PETs easy to access	5.42	
	Need to be advised/recommended	<4		Oth.PETs convenient to use	4.82	
			Amount of work vs benefit gained from Adv.PETs	4.82		
			Oth.PETs integrated in service	<4		
			Annoyance or discomfort when using Adv.PETs	<4		
Support	What they are/do	36.14	Support	Ease of use	14.46	
	How to use, training	16.27		Ease of installation and configuration	12.05	
	Via info channels e.g. SNS, tutorials, trusting list	9.04				
Theme 3: Privacy & Protection Needed			Theme 4: Cost			
		%			%	
Reasons	For protection provided ('keeps me private')	15.06	Reasons	Having to pay for/cost of Adv.PETs	14.46	
	Oth.PETs good enough for privacy needed	10.84		Oth.PETs are free	4.22	
	Successful experience in using Oth.PETs	6.63				
	No need for privacy, nothing to hide	5.42				
	Adv.PETs would be extreme/Oth.PETs for everyday use	4.22				
	Privacy vs online experience	<4				
Support	If need specific PET protection functionality (e.g. anonymity)	9.04	Support	If Adv.PETs were free/affordable	16.87	
	If Adv.PETs provided more privacy than what they use	8.43				
	If they had a bigger privacy need	6.02				
Theme 5: Trust & Reliability			Theme 6: Social Support			
		%			%	
Reason	Trust in PETs	9.04	Reason	n/a		
Support	If Adv.PETs did not look fake/phony	5.42	Support	Recommended by reputable company	5.42	
				If someone they know/trust used it	<4	
				If someone taught them how to use or install	<4	

to left or consolidate his position in the current cluster?’ ‘how can the methods in the different clusters be used in a layered approach for more complete protection?’

Cross-National Visualisation. The spatial plot of privacy methods in relation to country (of Figure 5) clearly shows a gravitation of German participants towards more advanced and active privacy methods, compared to US and UK participants. This may be a reflection of Germans’ privacy perceptions, where previous research reported that Germans, compared to participants of other countries, found controlling access to personal data, private realms and data protection more important [94], were among those most sensitive to the duration and quantity of data collection (location data) [22], or attributed a higher probability to privacy violations on SNS [56]. Figure 5 may also support discussions and further investigations of the effectiveness of privacy campaigns, of the role of the media or social connections in a particular country.

5.2 Non-Technology Methods in Top 10

Summary of findings: Among the similarities in privacy methods usage across the three countries (from Study 2, Table 8), we find that non-technology methods (1) of being careful of websites, (2) to limit sharing, (3) research before engaging (2 out of 3 countries), (4) not subscribe to newsletters, and (5) not access accounts in public places, appear in the most used methods across countries.

For the three countries, these non-technology methods made up 4 or 5 of the top 10 most preferred privacy methods thereby demonstrating that users rely more on their own means to protect themselves than privacy technologies. This raises questions about the reasons for reliance on non-technology methods rather than

PETs, such as ‘are users concerned enough and aware of PETs to use them? how were their previous experience with PETs?’

5.3 Perception of Use

Summary of findings: 9% of participants in Study 3 reported to use Adv.PETs, 91% to use Oth.PETs and 19% to use PETs from both lists. The low preference for Adv.PETs corresponds to previous research findings of no mention or of low use of Adv.PETs [39, 75].

Study 3 enabled us to evaluate perception of use of PETs within different clusters. From Table 10, it is clear that Oth.Users have higher use perceptions of Oth.PETs than Adv.PETs, which may highlight a perceptive barrier to individuals’ use of Adv.PETs. Similar to previous research of the importance of perceived usefulness for the adoption of anonymous credentials [12, 46], our respondents who reported to use Adv.PETs showed higher perceived usefulness of Adv.PETs than Oth.PETs.

In addition. users of Adv.PETs and Oth.PETs did not report a difference in their perceived competency in protecting their privacy online. While perceived competence may predict continuance or persistence in behavior [73, 88], given that individuals may feel more motivated to perform a task when they feel competent in, it may be complex to change individuals’ behavior patterns from habitual use of Oth.PETs.

5.4 PETs Choice and Support Needed

Summary of findings. The reported responses of Oth.Users in Study 3 support and extend the findings of previous research on factors influencing the active use of PETs (summarised earlier in Table 1 of Section 2.1.2). We report Oth.Users’ responses in Table 11 and discuss them below.

Our findings contribute to previous research with a collective perspective that is neither specific to particular PETs nor contextual to use scenario, such as social network or e-commerce. Our methodology may therefore help to identify general beliefs and biases of users that act as obstacles to the use of Adv.PETs. In particular, Table 11 depicts a picture of ‘don’t know, therefore don’t use Adv.PETs’, and yet have perceptions that Adv.PETs are not easy to use/install, are costly, or are not trustworthy. Therefore, further to being aware of Adv.PETs, individuals may also have to overcome the biased perceptions they hold about these PETs.

Awareness of PETs (from Theme 1: Information about). Our participants reported to not knowing about Adv.PETs and would benefit with an understanding of what they are and what they do. This is similar to previous reports on awareness of protection tools or inability to use protection for tracking or end-to-end encryption [87, 93]. In addition, we also found beliefs of technical skills requirement, and requiring training or information via social media and other channels.

Usability (Theme 2). Our participants also expressed a belief that Adv.PETs are not easy to use or to install, with other usability-related beliefs listed in Table 11. Ease of use for anonymity technology [12, 46] and usability for secure communication [1, 87] were also reported in previous research. However, although usability was previously found to not be more important than other factors (such as risk of sharing in social network [36], contextual aspects of messaging tool [1] or perceived usefulness [12]), for our participants, one of the most important reason for using Oth.PETs, rather than Adv.PETs, was ease of use and configuration, which may be a biased perception about Adv.PETs’ usability.

Usefulness (Theme 3: Privacy & Protection Needed). Our participants reported to use Oth.PETs for the protection provided, that Oth.PETs are good enough, that they had a successful use experience with Oth.PETs, and that if they were to use Adv.PETs, it would be for other specific protection functionalities that are not provided by Oth.PETs. While this points to their satisfaction in using Oth.PETs, being able to compare the privacy protection provided between Oth.PETs and Adv.PETs, may provide users with a wider choice.

Need for Privacy (Theme 3: Privacy & Protection Needed). Some of our participants reported to not needing privacy/have nothing to hide, or that using Adv.PETs would be extreme. These loosely match previous reports of no perceived need to act for tracking protection and end-to-end encryption technologies [87, 93]. This depicts how ill-informed users may be with regards to their privacy online, in particular not knowing how much more protection Adv.PETs can offer them, as well as not realising the potential extent of privacy loss and online harms in the data-centric web.

Cost (Theme 4). Our participants referenced the perceived monetary cost Adv.PETs to be a deterrent to their use. In comparison, previous research investigations in relation to cost included the perceived value of information [22], monetary reward for disclosure [45], cost and benefits tradeoffs of disclosure [29], cost of privacy breaches [2] or the time spent reading privacy policies [66].

Trust & Social Support (Themes 5 & 6). PETs’ trustworthiness and recommendation (either socially or accredited via a reputable company), were also deemed important, as well as social support to recommend or teach how to use Adv.PETs. Trust has also been

considered before in investigations involving the active use of privacy controls [36] and adoption of PETs [12, 46], and in relation to accessible and salient privacy information in websites [99], while social influence had links with the use of privacy [1, 39] and security [23] controls. While neutral accredited lists already exist via privacy-promoting organisations such as the Electronic Frontier Foundation, the influence of social connections and support from those individuals know and/or trust may have a ‘multiplier’ effect in increasing use of Adv.PETs. Social influence and support can facilitate integration of PETs into daily life, expand use to more casual users, as well as help sustain use.

6 CONCLUSION

This paper provides a large scale, cross-national investigation of the use of a collection of privacy methods online, derives patterns of use and follows-up with an investigation of perception of use of PETs between the patterns. The usage classification, while contributing to our knowledge of PETs use, also provides a methodological contribution to the field. It can further be used in future user-centric investigations of PETs.

The clusters raise a number of questions about both their components and the conditions for transitioning to the least popular cluster. In addition, by investigating individuals’ own perception of use of PETs as well as the support they believe they would need to use more advanced PETs, we highlighted a few themes that may help to expand the use of advanced PETs. We recommend investigations of the questions raised in the discussion section, as future work, as well as for designers to consider the reasoning and support needed by individuals to use PETs (in particular, more advanced PETs), as provided in this paper.

ACKNOWLEDGMENTS

This research was supported by a Newcastle University Research Fellowship (Academic Track). I am thankful for the feedback provided by colleagues, all from Newcastle University, namely, Prof. Aad van Moorsel, Dr. Jaume Bacardit, Dr. Changyu Dong and Dr. Magdalene Ng. I am also grateful for the feedback and comments provided by the anonymous reviewers of CCS’20 .

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A STUDY 2 QUESTIONNAIRE

The 43 privacy methods used in the questionnaire in Study 2 were named by participants themselves in Study 1 and compiled into 43 distinct methods.

The instruction was “From the list below, please rate the tools/methods in terms of whether you have used them *very often* before versus *not used at all or very rarely*, to achieve the purpose of privacy online.”

Table 12: The list of methods as provided in a tabular form in the questionnaire & listed in random order for each participant.

Tools/Methods	very often	not used at all or very rarely
pseudonyms	<input type="checkbox"/>	<input type="checkbox"/>
paypal instead of online banking	<input type="checkbox"/>	<input type="checkbox"/>
anonymous profile names or emails	<input type="checkbox"/>	<input type="checkbox"/>
not store information online	<input type="checkbox"/>	<input type="checkbox"/>
Erasery	<input type="checkbox"/>	<input type="checkbox"/>
clear information or history	<input type="checkbox"/>	<input type="checkbox"/>
private browsing or incognito mode	<input type="checkbox"/>	<input type="checkbox"/>
DuckDuckGo	<input type="checkbox"/>	<input type="checkbox"/>
clear, disallow or limit cookies	<input type="checkbox"/>	<input type="checkbox"/>
Ghostery	<input type="checkbox"/>	<input type="checkbox"/>
not accessing suspicious websites, careful of websites	<input type="checkbox"/>	<input type="checkbox"/>
anti-tracking extension	<input type="checkbox"/>	<input type="checkbox"/>
switch off location tracking	<input type="checkbox"/>	<input type="checkbox"/>
Adblock	<input type="checkbox"/>	<input type="checkbox"/>
anti-malware	<input type="checkbox"/>	<input type="checkbox"/>
anti-spyware	<input type="checkbox"/>	<input type="checkbox"/>
firewall	<input type="checkbox"/>	<input type="checkbox"/>
NoScript	<input type="checkbox"/>	<input type="checkbox"/>
VPN	<input type="checkbox"/>	<input type="checkbox"/>
HTTPS	<input type="checkbox"/>	<input type="checkbox"/>
TOR	<input type="checkbox"/>	<input type="checkbox"/>
use a proxy	<input type="checkbox"/>	<input type="checkbox"/>
IPHider	<input type="checkbox"/>	<input type="checkbox"/>
virtual machines	<input type="checkbox"/>	<input type="checkbox"/>
encryption, encrypt communication or data	<input type="checkbox"/>	<input type="checkbox"/>
password manager	<input type="checkbox"/>	<input type="checkbox"/>
not reuse passwords	<input type="checkbox"/>	<input type="checkbox"/>
not save password on webpage	<input type="checkbox"/>	<input type="checkbox"/>
not give personal information, limit sharing of personal information or give minimal personal information	<input type="checkbox"/>	<input type="checkbox"/>
give fake information	<input type="checkbox"/>	<input type="checkbox"/>
set privacy settings or controls	<input type="checkbox"/>	<input type="checkbox"/>
not access accounts in a public place, on public networks or shared computers	<input type="checkbox"/>	<input type="checkbox"/>
read terms of service or business practice	<input type="checkbox"/>	<input type="checkbox"/>
limit use of social network accounts, such as Facebook or others	<input type="checkbox"/>	<input type="checkbox"/>
not use Facebook at all	<input type="checkbox"/>	<input type="checkbox"/>
have several email accounts or have bogus email account for unimportant use	<input type="checkbox"/>	<input type="checkbox"/>
request data collection about you	<input type="checkbox"/>	<input type="checkbox"/>
switch off camera on devices	<input type="checkbox"/>	<input type="checkbox"/>
not subscribe to newsletters or untick boxes for newsletters	<input type="checkbox"/>	<input type="checkbox"/>
opt out of data collection or not consent to data collection	<input type="checkbox"/>	<input type="checkbox"/>
not engage online	<input type="checkbox"/>	<input type="checkbox"/>
research before engaging online or research before signing up to stuff	<input type="checkbox"/>	<input type="checkbox"/>
Kaspersky	<input type="checkbox"/>	<input type="checkbox"/>
Name other privacy methods if you use them:		

B STUDY 2 DATASET

Table 13: Dataset of Privacy Methods & Count of Usage per Country.

#	Tools/Methods	US	UK	DE	Total
1	not accessing suspicious websites, careful of websites	265	251	250	766
2	not give personal information or limit sharing	259	242	256	757
3	set privacy settings or controls	262	238	257	757
4	not subscribe to newsletters or untick boxes for newsletters	234	219	250	703
5	Adblock	235	197	262	694
6	clear information or history	231	235	220	686
7	anti-malware	238	217	224	679
8	firewall	211	218	250	679
9	paypal instead of online banking	201	226	250	677
10	have several email accounts	214	183	261	658
11	clear, disallow or limit cookies	225	198	219	642
12	opt out of data collection or not consent to data collection	216	202	207	625
13	HTTPS	209	172	237	618
14	not access accounts in a public place/ shared computers	224	210	171	605
15	anti-spyware	221	190	181	592
16	switch off camera on devices	206	172	209	587
17	private browsing or incognito mode	194	179	212	585
18	limit use of social network accounts	189	186	209	584
19	switch off location tracking	183	174	201	558
20	anonymous profile names or emails	175	134	228	537
21	pseudonyms	143	111	229	483
22	not reuse passwords	162	148	158	468
23	not store information online	167	144	154	465
24	not save password on webpage	147	147	149	443
25	give fake information	128	102	181	411
26	read terms of service or business practice	154	147	100	401
27	password manager	152	124	116	392
28	not use Facebook at all	131	99	160	390
29	VPN	99	86	157	342
30	encryption, encrypt communication or data	117	103	119	339
31	anti-tracking extension	93	64	126	283
32	not engage online	99	97	69	265
33	use a proxy	67	65	110	242
34	DuckDuckGo	79	39	77	195
35	request data collection about you	54	38	81	173
36	NoScript	39	21	84	144
37	IPHider	42	35	61	138
38	research before engaging online	30	35	63	128
39	Kaspersky	30	35	63	128
40	virtual machines	37	21	67	125
41	Tor	32	23	67	122
42	Ghostery	31	21	55	107
43	Erasery	27	30	37	94

Notes: This dataset is for the N = 907 sample, and sorted from most used to least used method. This dataset was used in the Cluster and Correspondence Analyses.

C CORRESPONDENCE ANALYSIS

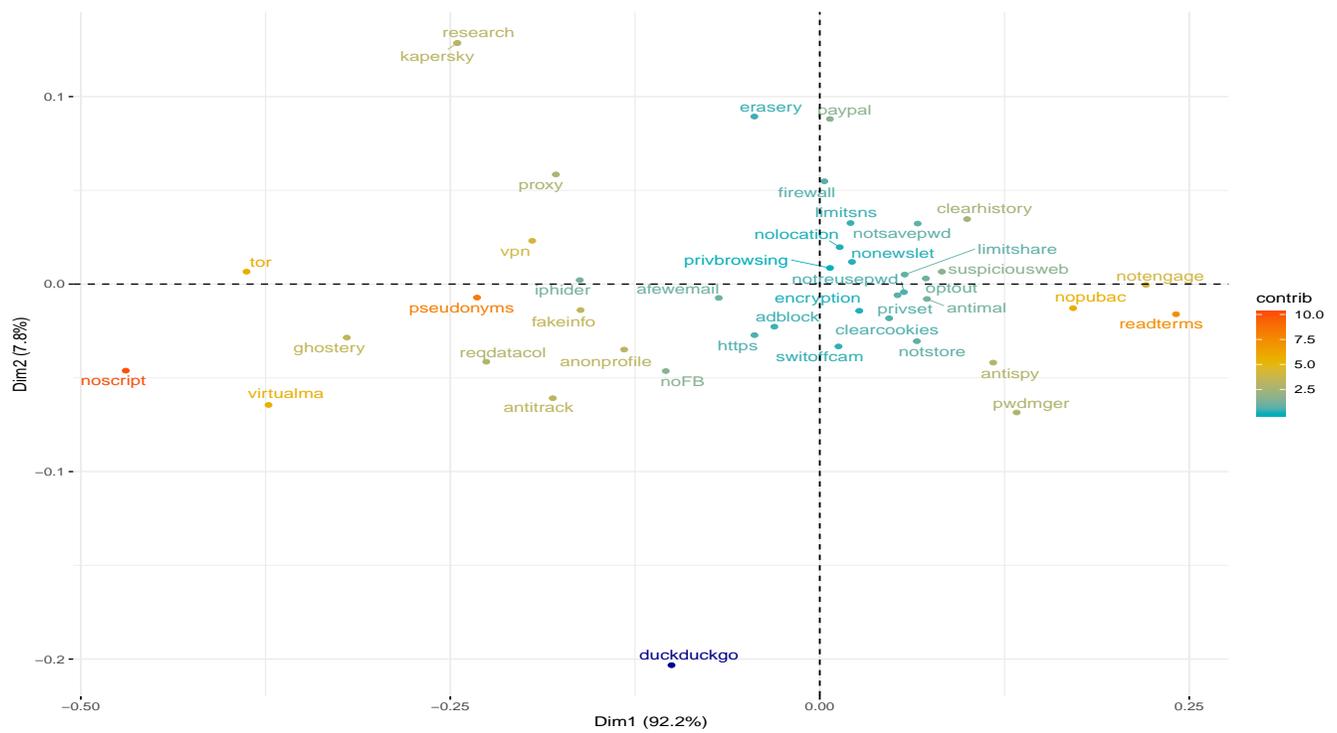


Figure 7: Contribution of Privacy Methods to Dimension 1.

D STUDY 3 LISTS QUESTIONNAIRE

The instructions provided to participants to choose between two lists of PETs and the follow-up questions are as follow:

We provide two lists of privacy technologies that can be used to protect privacy online. Please take your time to read through both lists.

List A contains: Erasery, Ghostery, Virtual Machine, Tor, NoScript, IPHider, Kaspersky, DuckDuckGo, proxy, anti-tracking extension, VPN and encryption.

List B contains: switch off location tracking, private browsing, HTTPS, anti-spyware, opt-out (of data collection), clear cookies, anti-malware, clear history, Paypal, firewall, Adblock, privacy settings, pseudonyms and anonymous profile.

Which of the two lists contains the privacy methods that **you most often use** to protection your privacy online?

List A

List B

Please explain why you most often use methods from your selected list. Please explain why you very rarely (or not at all) use methods from the other list. [Response in 50 to 100 words]

What would support you to use methods from the **other** list (that is, the one that you did not select)? In particular, what would help and/or encourage you?

E STUDY 3 PERCEPTION QUESTIONNAIRE SCALE ITEMS

Table 14: Scale Items & Internal Consistency.

We provide Cronbach α for Adv. & Oth.PETs where the scale was set as pairwise comparison between PET types.

Scale	Items	Cronbach α	
		Adv.PETs	Oth.PETs
Perceived Privacy Competency	I feel confident in my ability to manage my privacy online I am capable of protecting my privacy online now I am able to protect my privacy online now I feel able to meet the challenge of protecting my privacy online		.963
Awareness of PETs	I have heard of technologies in this list for privacy protection online I have encountered the technologies in this list for privacy protection online before I know how to find technologies in this list to protect my privacy online I am familiar with the technologies in this list to protect my privacy online	.932	.837
Perceived Usefulness of PETs	Using privacy technologies in this list improves my privacy protection Using privacy technologies in this list increases my level of privacy Using privacy technologies in this list enhances the effectiveness of my privacy protection I find privacy technologies in this list to be useful in protecting my privacy	.879	.842
Perceived Ease of Use of PETs	My interaction with privacy technologies in this list is clear and understandable Interacting with privacy technologies in this list does not require a lot of mental effort I find privacy technologies in this list to be easy to use I find it easy to get privacy technologies in this list to do what I want them to do	.868	.798
Social Influence	People who are important to me think that I should use privacy technologies in this list People who influence my behaviour think that I should use privacy technologies in this list People whose opinion I value prefer that I use privacy technologies in this list	.891	.881
Behavior Intention	I intend to use privacy technologies in this list in the future I will always try to use privacy technologies in this list in my daily life I plan to use privacy technologies in this list frequently	.886	.813

F STUDY 3 CODEBOOK

Table 15: The 47 codes in the final codebook for Study 3

Q1: Reason for choosing one PET type		Q2: Support or encouragement	
Code	Content	Code	Content
Effectiveness of PETs		Privacy need	
EFF01	effective for the privacy I need, adequate, sufficient	PNE01	if I had a bigger privacy need, extreme privacy
EFF02	used it and it works - so continue to use	PNE02	needed for different specific privacy protections such as tracking prevention
EFF03-other	everyday, regular use	PNE03	provides more privacy than the one I use
EFF03-other	trust, reliable, best method		
Awareness of PETs		Information or training to enhance understanding	
AWA1	familiar with, recognise, heard of, know of	INF01	if I know what they are/what they do
AWA2	not familiar with, not recognise, not heard of, don't know of	INF02	Information on how to use or training or education
AWA3	aware of though advertisements	INF03	Information channel such as advertising, social media, tutorial, app
AWA4-other	advised, recommended	INF04-other	benefits of using, why use
		INF04-other	tech knowledge
Skills needed		Usability related supports	
SKI01	casual, non-tech user	USS1	convenient
SKI02	training needed, need to understand or know more, technical user	USS2	easy to use, simple, clear
SKI03-other	someone to show me	USS3	easy to install, setup, not many config
		USS4	lightweight, not many things, easy integration
		USS5	easy access
Usability & cost characteristics of PET		Social influence or social support	
USR1	readily or easily available, builtin, presented within service	SOC01	social influence - if someone I know use it, or someone I trust recommends it
USR2	not easily or not readily available	SOC02	social support - someone teaches me, someone installs it
USR3	easy to use, easy to install, not much effort needed	SOC03-other	neutral recommend, review, professional reputable company, accreditation
USR4	complicated to use or complicated to setup		
USR5	convenient features		
USR6	cost - available free		
USR7	cost - expensive or have to pay for		
USR8-other	accessibility, easy access	INC01	if I knew they did not pose a security threat, if I trust them
USR8-other	amount of work vs benefit, having to download/install	INC02	free of cost, affordable
USR8-other	annoyance, discomfort, break things	INC03	already use both lists
USR8-other	integrated in service	INC04-other	tradeoff with browsing or computer performance
Privacy needed, experience			
PRI01	no need for privacy		
PRI02	privacy vs hamper online experience		
PRI03	provide protection, keeps me privacy/safe, increase my privacy		
PRI05	use PETs from both lists		
PRI06-other	over the top, extreme privacy		