

## **Amber Welch**

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# 6 monus APPRERERE REPERERE

- Privacy Engineering Intro
- Privacy by Design
- · Privacy Enhancing Technologies



Legal teams have often kept tech out of privacy.



# Developers don't know privacy concepts. Privacy teams haven't taught them.

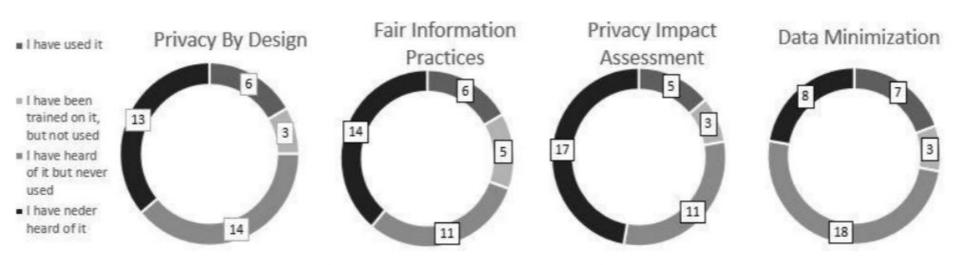


Figure 1: Participants' Formal Knowledge on Privacy Concepts

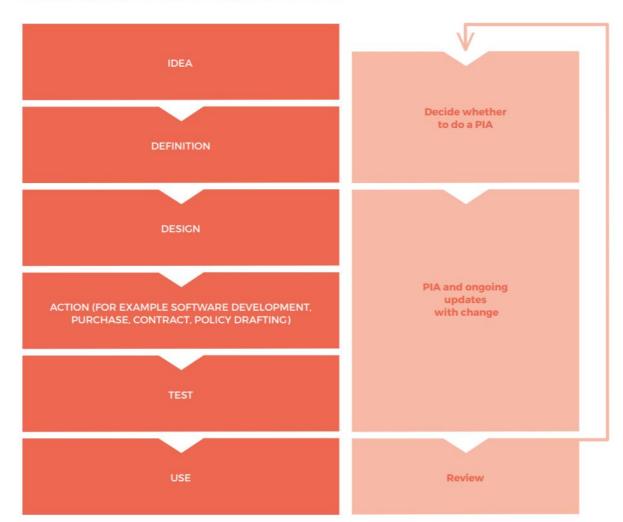


A Privacy Impact Assessment (PIA) is a method to:

- Identify privacy risk
- Map personal data flows
- Document privacy risk mitigations
- Fulfill regulatory requirements



#### Privacy Impact Assessment throughout an initiative



### **Use Cases**

- New applications
- Adding functions and features
- Collecting new sensitive personal data
- Annual reviews or audits

## Benefits

- Legal compliance
- Identify and reduce privacy risks
- Catch privacy errors

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- Legal compliance
- Identify and reduce privacy risks
- Catch privacy errors

#### Limitations

- High time investment
- Ineffective if not completed well
- Not a security risk assessment



#### Data minimization is:

- Collecting only necessary data
- Maintaining and updating data
- Deleting old data that isn't needed



### **Use Cases**

- New applications
- API integrations
- Adding functions and features
- Collecting new personal data
- Customer termination

#### Benefits

- Legal compliance
- Minimize volume of data to be breached
- Improve data quality

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- Legal compliance
- Minimize volume of data to be breached
- Improve data quality

#### Limitations

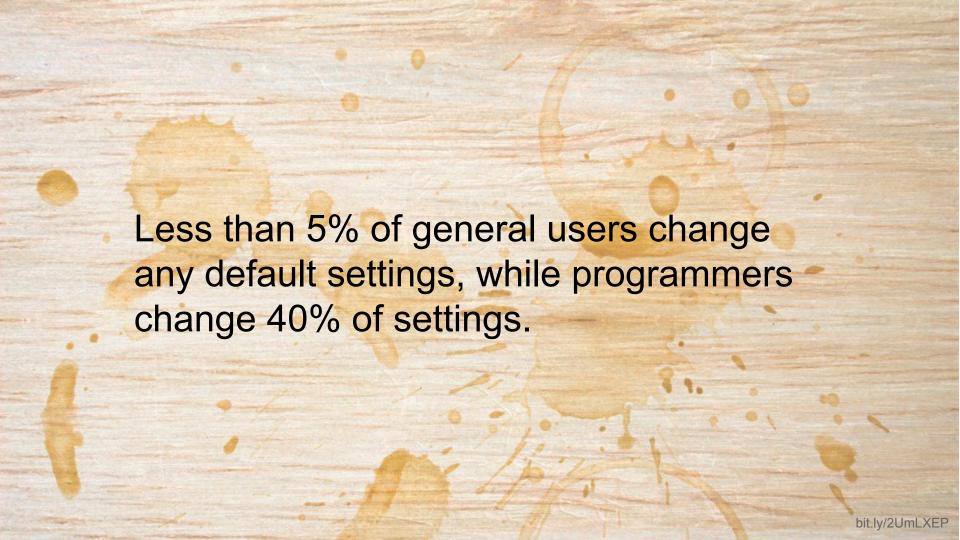
- Users may be frustrated
- Companies like to keep all the data

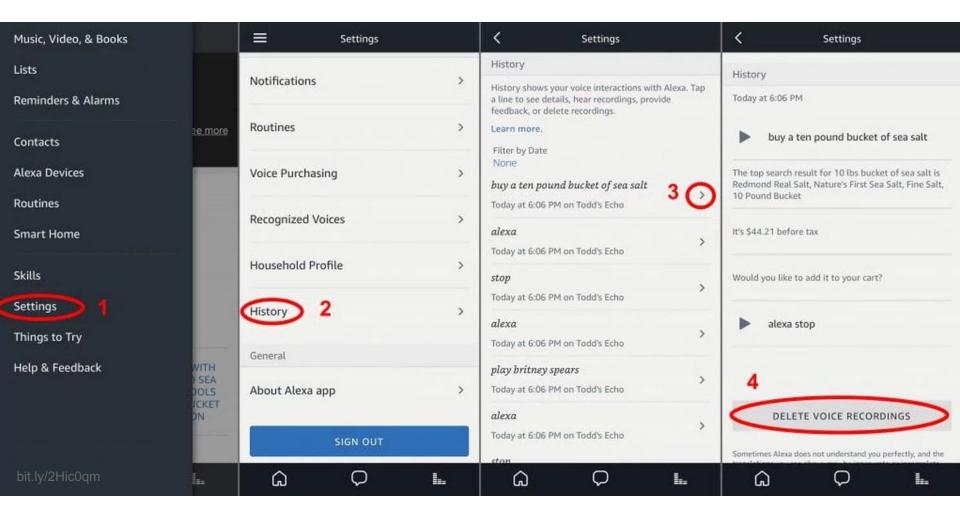


Default settings for privacy should:

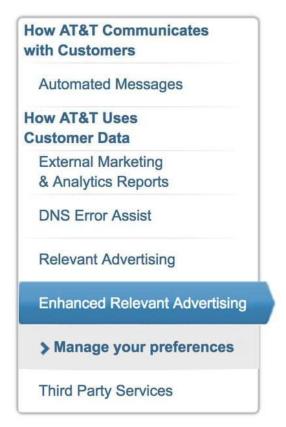
- Minimize personal data collected
- Prevent default data sharing
- Require enabling of intrusive settings
- Avoid making data public by default







#### Manage your privacy and automated messaging choices



#### Manage your preferences for Enhanced Relevant Advertising

Enhanced Relevant Advertising uses information generated by all users of the AT&T products and services (Internet, video, and mobile) on your account to deliver a more personalized experience. The ads you see will be tailored to your likes and interests. You won't see more ads. This information includes: TV viewing, Web browsing, app usage, location, call detail records, and other Customer Proprietary Network Information (what is CPNI, including my rights and AT&T's duties?). We may share this information with third parties. If we do, we won't directly identify you.

By choosing **Yes** below, you as the account holder agree to the terms and conditions of the Enhanced Relevant Advertising program. Your choice applies to all users of your account. Your choice doesn't affect anyone on your account's ability to use our products and services. You may revoke your consent at anytime. It may take up to 7 days to complete your request.

Please note, your choice for Relevant Advertising is separate.



#### Benefits

- Reputation for privacy
- Reduce user frustration
- Protect less educated users

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- Legal compliance
- Reputation for privacy
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#### Limitations

- Companies may want to monetize intrusive apps
- Requires privacy awareness at design



## **Encrypt these:**

- TLS
- Email and messaging
- Databases
- Cloud storage
- Backups
- Password management
- Endpoint devices

## Don't:

- Make your own crypto
- Use deprecated crypto (i.e., SHA1)
- Hard code keys
- Store keys on the same server as the data
- Use one key for everything
- Skip password hash and salt
- Forget to restore certificates after testing
- Use old crypto libraries



#### Differential privacy:

- Adds statistical noise to a data set
- Prevents identification of one individual's record
- Provides the same results as the raw data would, with or without one record

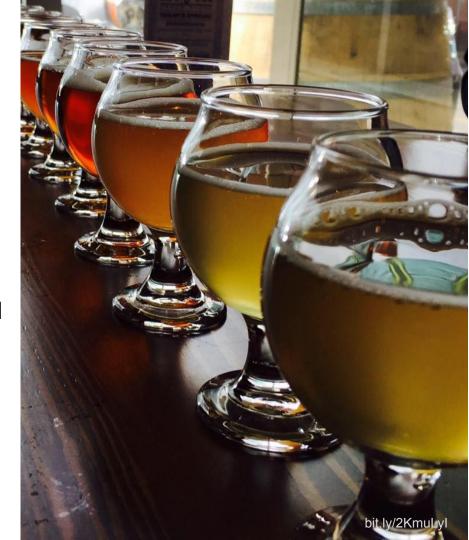
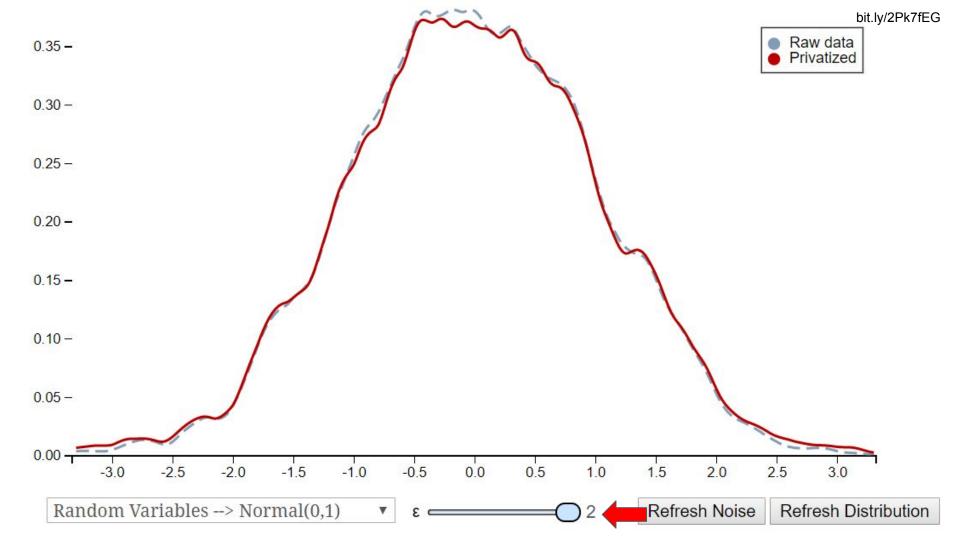


Table I. Privacy Models

	Attack Model			
Privacy Model	Record Linkage	Attribute Linkage	Table Linkage	Probabilistic Attack
k-Anonymity	<b>√</b>			
MultiR k-Anonymity	<b>√</b>			
$\ell$ -Diversity	<b>√</b>	✓		
Confidence Bounding		<b>√</b>		
$(\alpha, k)$ -Anonymity	<b>√</b>	✓		
(X, Y)-Privacy	<b>√</b>	<b>√</b>		
(k, e)-Anonymity		<b>√</b>		
$(\epsilon, m)$ -Anonymity		<b>√</b>		
Personalized Privacy		✓		
t-Closeness		✓		<b>√</b>
$\delta$ -Presence			<b>√</b>	
(c,t)-Isolation	<b>√</b>			✓
$\epsilon$ -Differential Privacy			<b>√</b>	✓
$(d, \gamma)$ -Privacy			<b>√</b>	✓
Distributional Privacy			<b>√</b>	<b>√</b>



### Benefits

- Limit insider threats
- Increase data usability
- Allows for collaboration without exposing data

#### Benefits

- Legal compliance
- Limit exposure from security incidents
- Limit insider threats

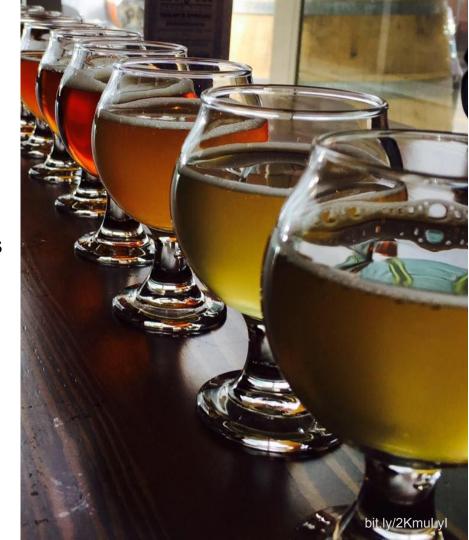
#### Limitations

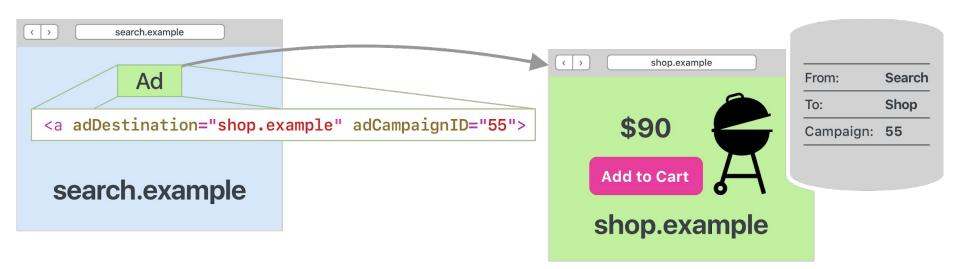
- Works best on large databases
- Must be tuned well

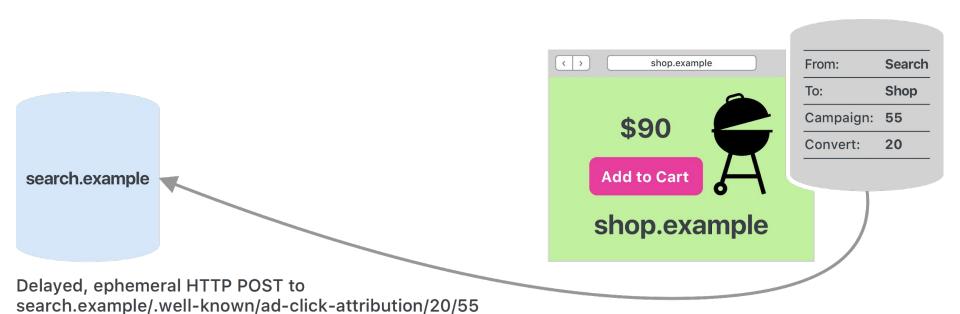


Privacy preserving ad click attribution:

- Allows ad attribution monetization
- Prevents user ad click tracking
- Uses the browser to mediate ad clicks







with referrer set to shop.example

## Available now as an experimental feature

Experimental Features	<b>&gt;</b>	Accessibility Object Model
Enter Responsive Design Mode	^#R	Ad Click Attribution Debug Mode
		Ad Click Attribution

### Benefits

- Allows websites to still monetize content
- Could become a W3C web standard

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#### Limitations

- Needs widespread adoption to be effective
- Users may not believe any ads respect privacy

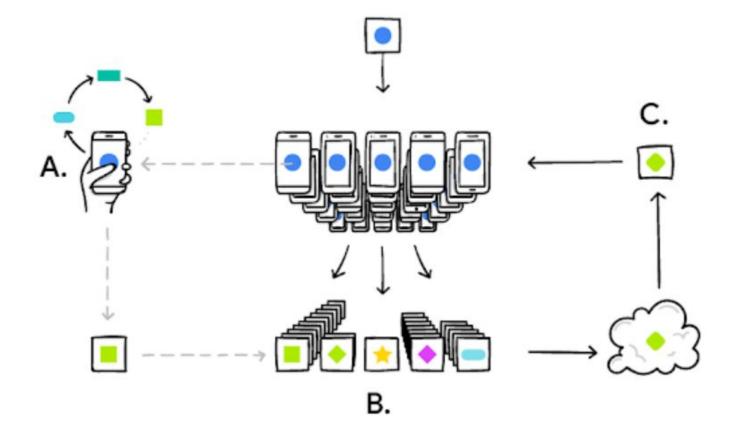


## Description

#### Federated learning:

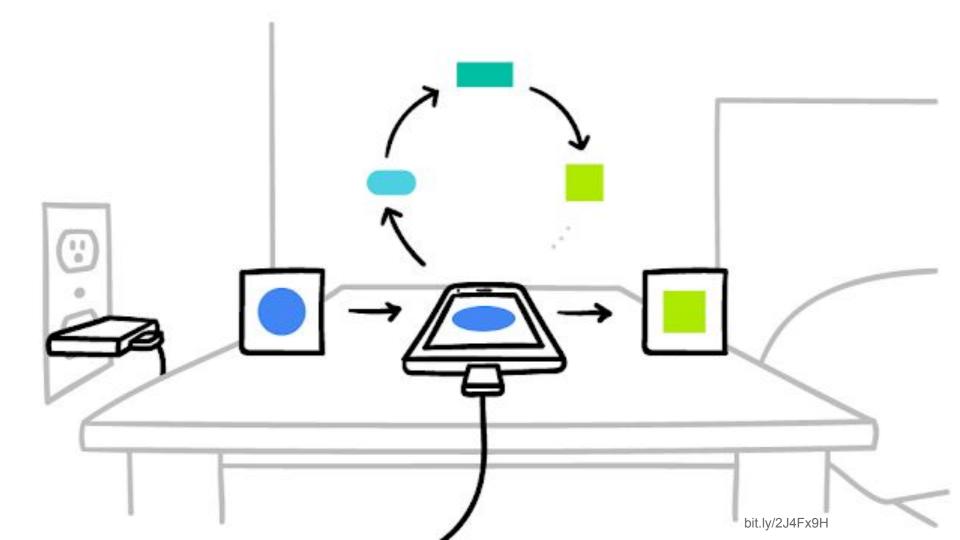
- Trains a central model on decentralized data
- Never transmits device data
- Sends iterative model updates to devices which return new results
- Uses secure aggregation to decrypt only the aggregate and no user data





Your phone personalizes the model locally, based on your usage (A). Many users' updates are aggregated (B) to form a consensus change (C) to the shared model, after which the procedure is repeated.

bit.ly/2J4Fx9H



### **Use Cases**

- Android's Gboard prediction model
- Health diagnostics
- Behavioral preference learning
- Driver behavior

### Benefits

- Speeds up modeling and testing
- Minimally intrusive
- Individual data is not accessible to the central model

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- Minimally intrusive
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#### Limitations

- Errors could cause
   private data leakage
- Requires a large user base

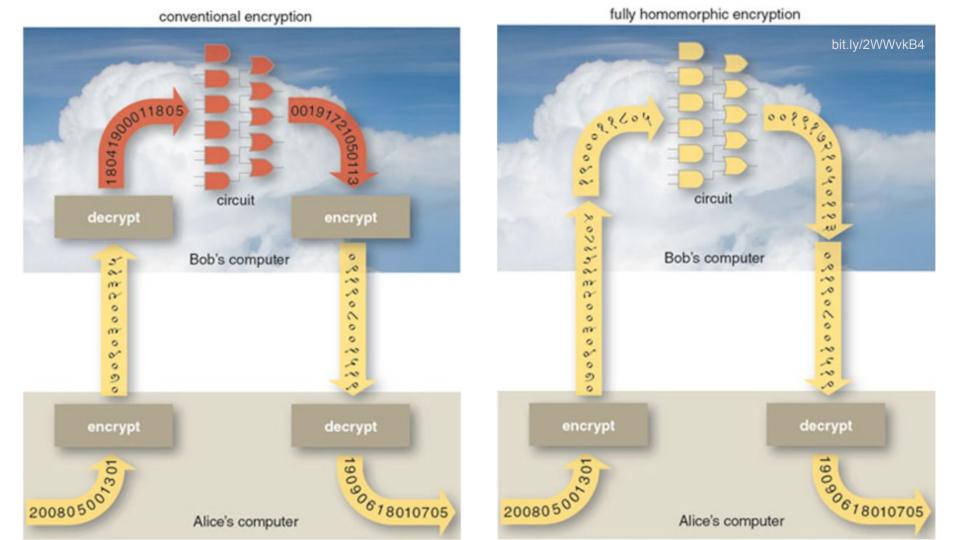


## Description

#### Homomorphic encryption:

- Allows computation on ciphertext
- Enables collaboration without disclosing confidential data
- Only the calculation results can be decrypted





### **Use Cases**

- Computations on data shared across organizations
- Research using highly sensitive records
- Processing by employees with a lower clearance
- Google's open source Private Join and Compute

### Benefits

- Reduces insider threat
- Increases collaboration
- Increases data usability

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- Reduces insider threat
- Increases collaboration
- Increases data usability

#### Limitations

- Resource-intensive
- Limited functions
- No fully homomorphic encryption available yet



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