Does Emotion Influence the Use of Auto-suggest during Smartphone Typing?

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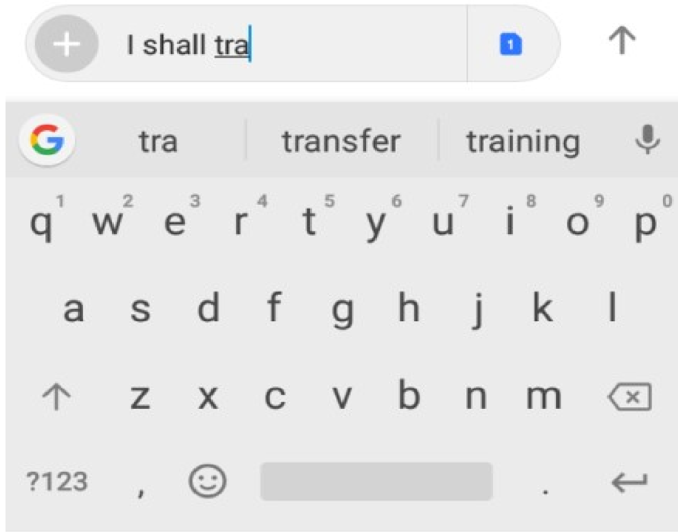
Background

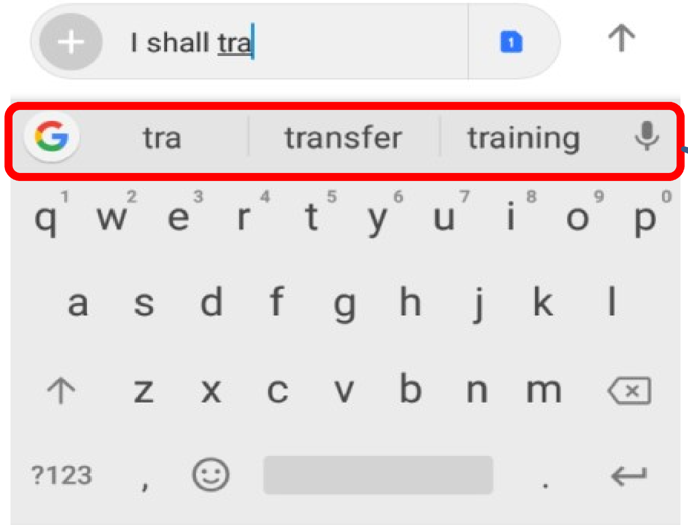
- Text-entry in small touch-based devices
  - relatively inconvenient due to limited space

- To facilitate, different techniques like ***auto-complete, auto-suggest*** are used



Background

- However,
  - reserves fixed space in keyboard layout



- Occupy space in the layout

  - increase cognitive load
    - to read, parse and select correct word [CHI 2016]

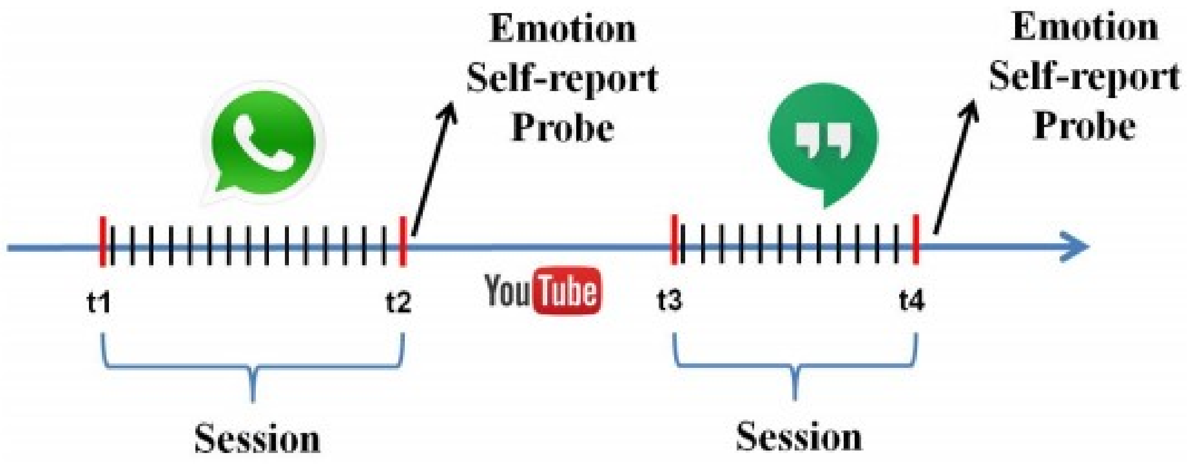
Opportunity to improve the layout by making these techniques adaptive

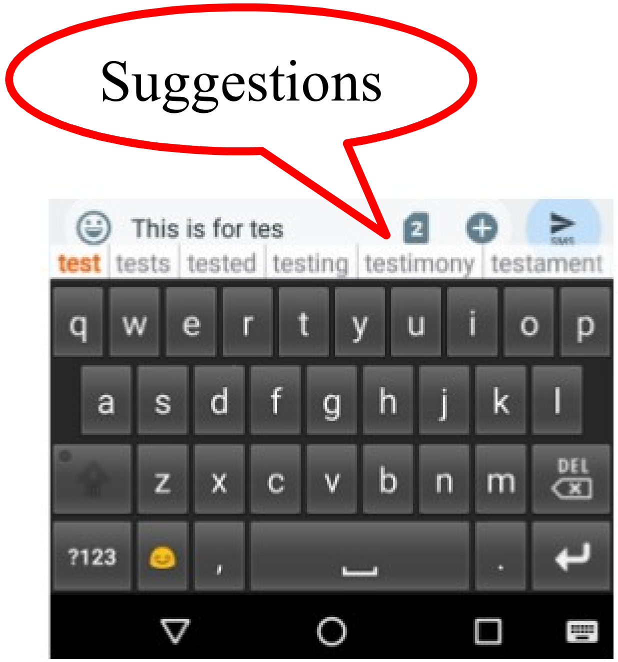
Objective

- Multiple factors can guide auto-suggest usage
  - typing volume
  - application type
  - user emotion
    - as it influences typing behaviour [MobileHCI 2017, ACII 2017]

- Can auto-suggestion usage be determined based on human emotion?

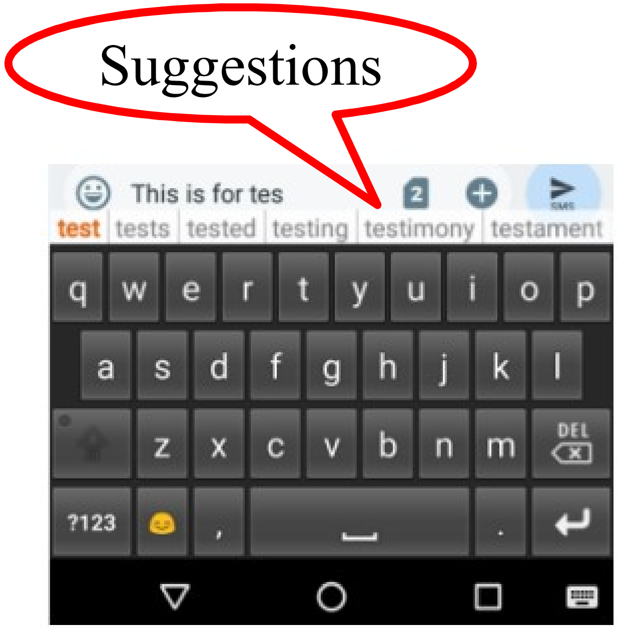
Auto-suggest Usage Scenario



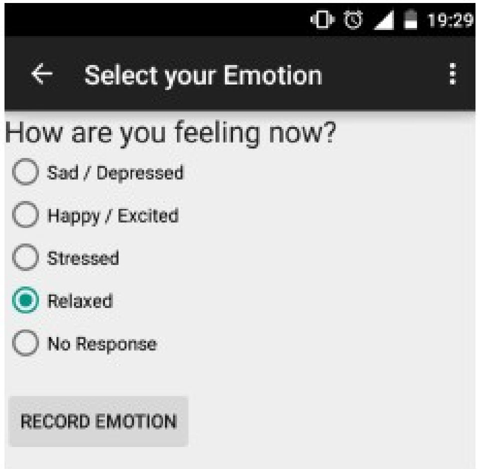


- Auto-suggest usage
  - tracing user typing and providing suggestions
  - labelling auto-suggest usage
    - **accepted** → if at least one suggestion is used in a session
    - **skipped** → if no suggestion is used in a session
  - tracking emotion during typing session

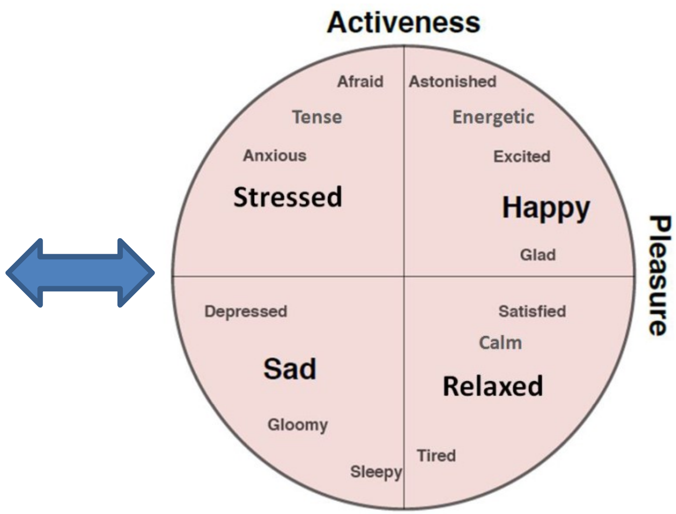
Experiment Apparatus



(a) App keyboard



(b) Emotion collection UI



(c) Circumplex model

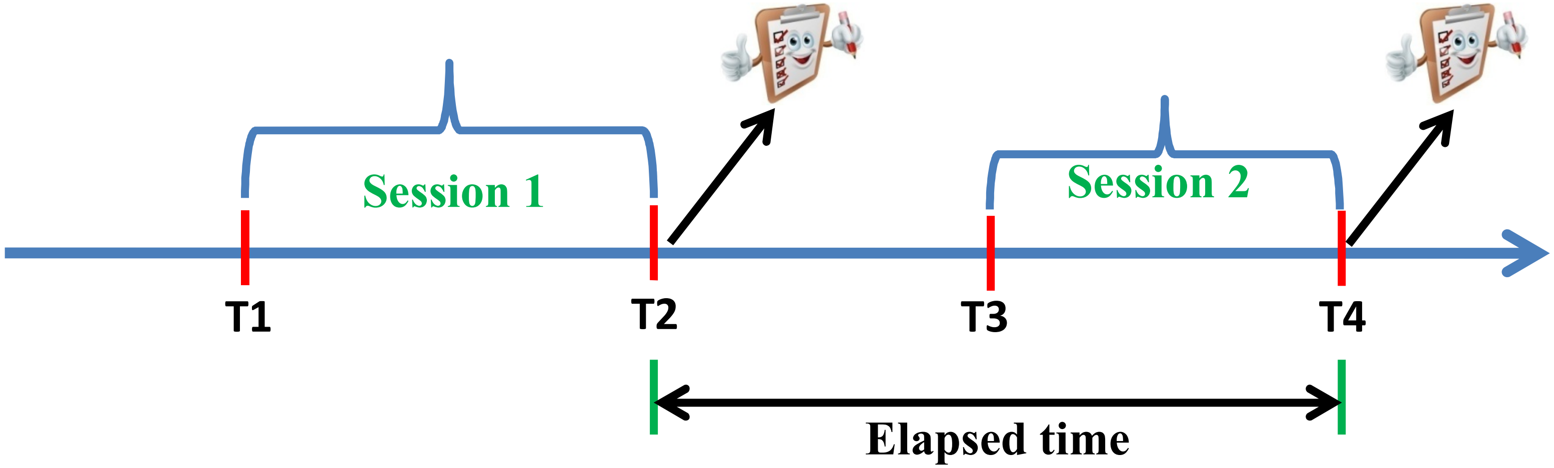
- Custom keyboard
  - tracing user typing and providing suggestions (based on English dictionary)
- Emotion self-report collection UI
  - collects emotions at end of a session
  - four emotions - *happy, sad, stressed, relaxed* (based on Circumplex model)

Auto-suggest Usage Prediction Model

- Auto-suggest usage prediction model
  - Personalized
    - Random Forest
  - Two classes
    - accepted
    - skipped
  - Features
    - Emotion-related features

Feature name	Feature description
Emotion_{curr}	Emotion associated with current session
Emotion_{prev}	Emotion associated with previous session
$\text{Time}_{elapsed}$	Elapsed time between previous and current session emotion recording timestamp

Table 2: Features used for auto-suggest usage prediction

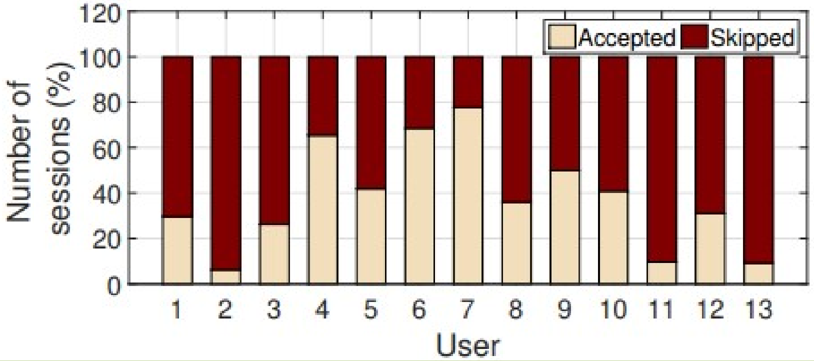


User Study

Study parameters	**Value**
Study duration	3-weeks (in-the-wild)
Total participants	20 (15 M, 5 F) → university students
Age range	20 – 35 years
Installed the app in the participants mobile phones	
Excluded participants	7 (as recorded less than 20 suggestions)
Final participants	**13 (10 M, 3 F)**

Dataset

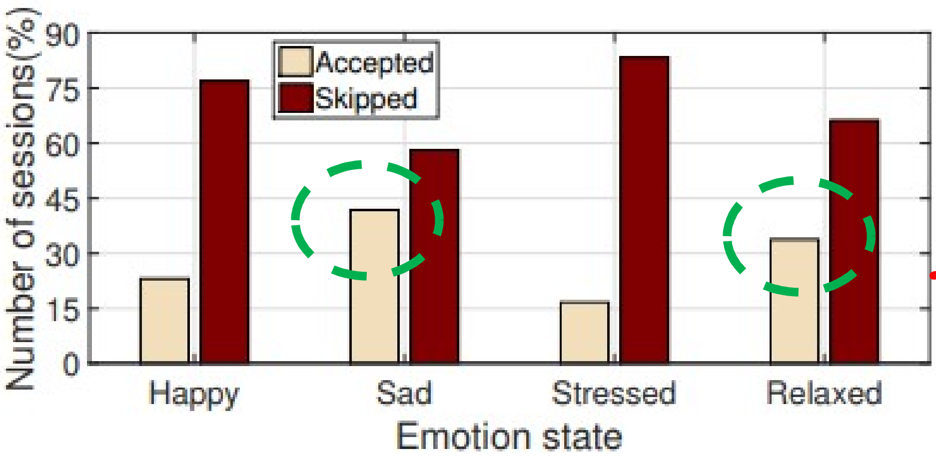
Parameter	Value
Total typing sessions	3,284
No Response sessions	330 (~ 10%)
Effective sessions	2954
Avg. session per user	227 (std dev. 151.7)
Auto-suggest **accepted**	**841 (~28%)**
Auto-suggest **skipped**	**2,113 (~ 72%)**



User-wise auto-suggest usage reveals that most of the users have more skipped session

Role of Emotion on Auto-suggest Usage

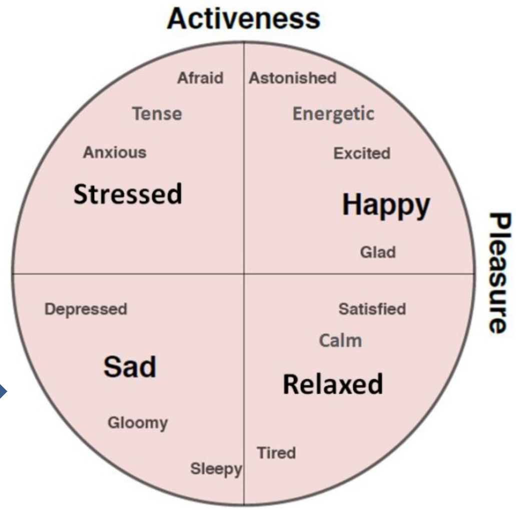
Does auto-suggest usage vary across emotions?



Auto-suggest usage across different emotions for all users

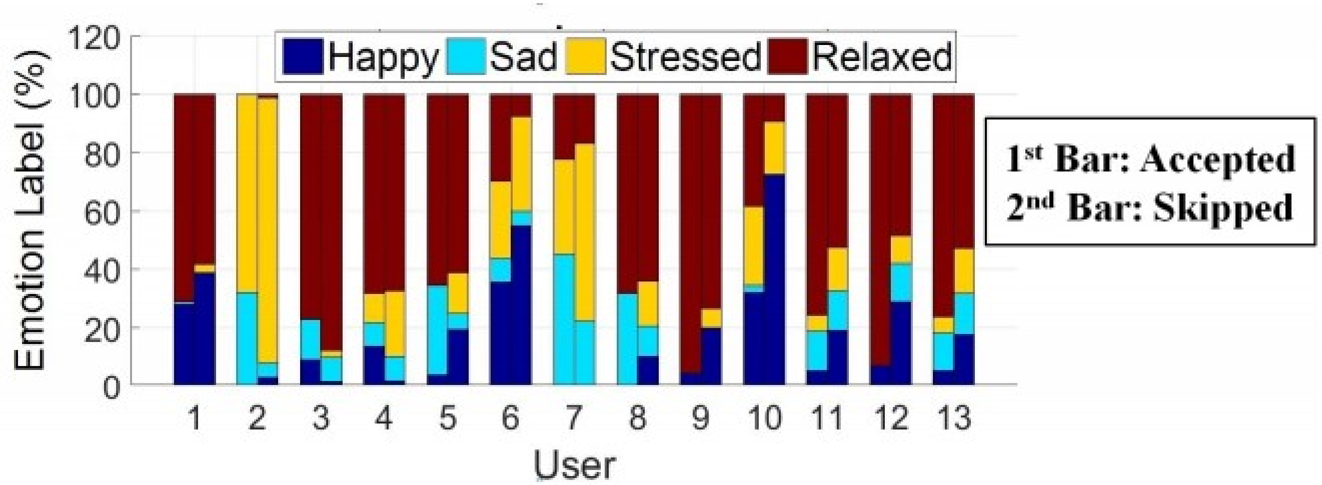
Users more likely to use auto-suggest when **sad or relaxed**

- Relaxed, sad → **Low activity level**
  - May influence more auto-suggest usage



Role of Emotion on Auto-suggest Usage

Does auto-suggest usage vary across individual user emotions?



Auto-suggest usage comparison across different emotions for individual user

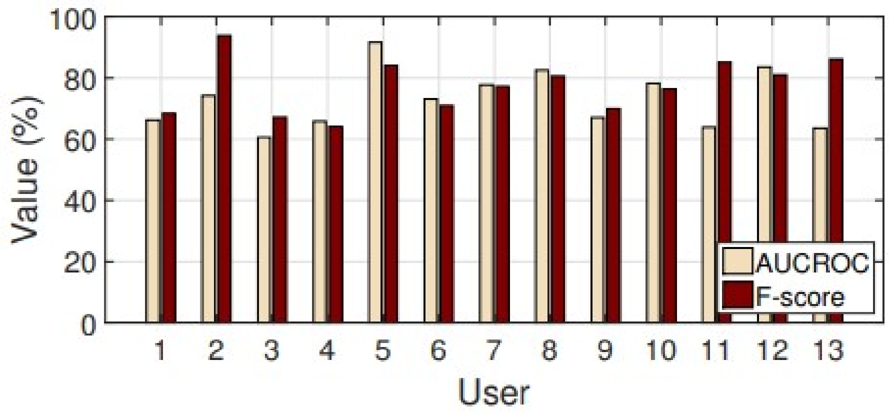
- Majority of the users use auto-suggest in relaxed
- Distribution of emotions in accepted and skipped is statistically significant *(p <0.05)* using chi-square test

Evaluation

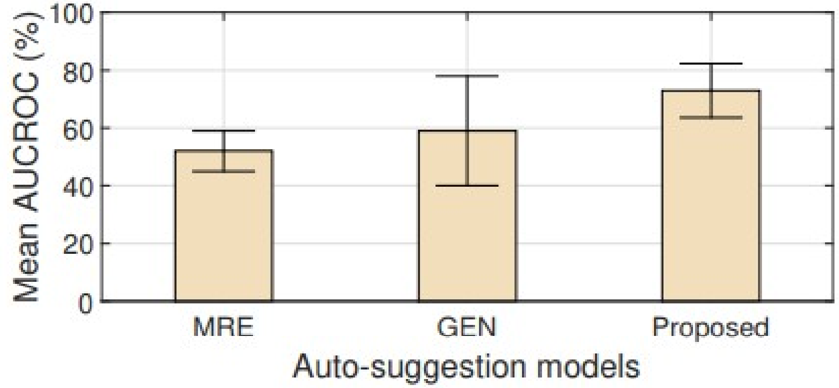
- Experiment setup
  - 10-fold cross validation
  - Metrics: AUCROC, F-score
- Baselines
  - Most-represented Emotion (MRE)
    - Auto-suggest usage → highest in one emotion
    - Personalized model, which determines auto-suggest usage in these emotions
  - Generalized (GEN)
    - Aggregating data from all other users
    - Leave-one-out-cross-validation

Evaluation

- How accurate is the auto-suggest usage prediction model?



(a) Classification performance



(b) Comparison with baselines

Avg. accuracy (AUCROC) – 73% (std dev 9%)
Outperforms the baselines

Evaluation

- How effective are the features to predict auto-suggest usage?

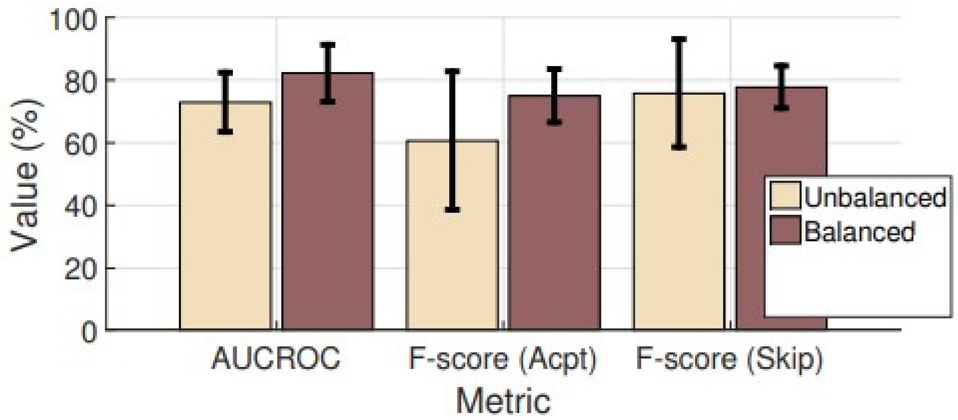
Feature	Rank	Avg. IG
$Emotion_{curr}$	1	0.1194
$Emotion_{prev}$	2	0.1098
$Time_{elapsed}$	3	0.0794

Ranking different features based on InformationGain

Current session emotion is the most discriminating one

Evaluation

- How to improve auto-suggest usage prediction performance?
  - Balancing the dataset (accepted and skipped class)



Classification performance after balancing the dataset

✔✔ Classification performance improves after balancing dataset

– AUCROC – 82%
– F-score (Accepted) – 75%
– F-score (Skipped) – 78%

Conclusion

- Auto-suggest usage is related with human emotion
    - more likely to use in *sad* or *relaxed* state
- Based on emotion, auto-suggest usage can be detected with an accuracy of 82%

Thank You!!

Acknowledgement

- Microsoft Research India
- LRN Foundation India
- IUI student travel grant

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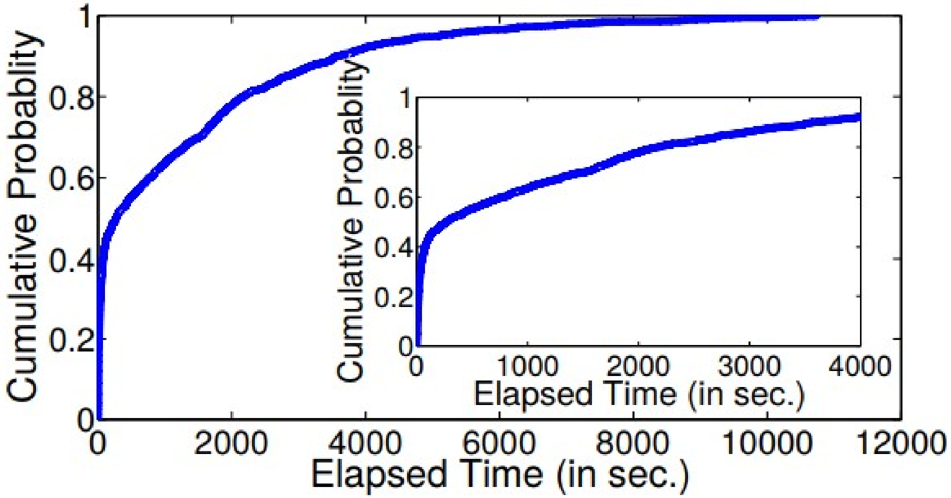
Dataset

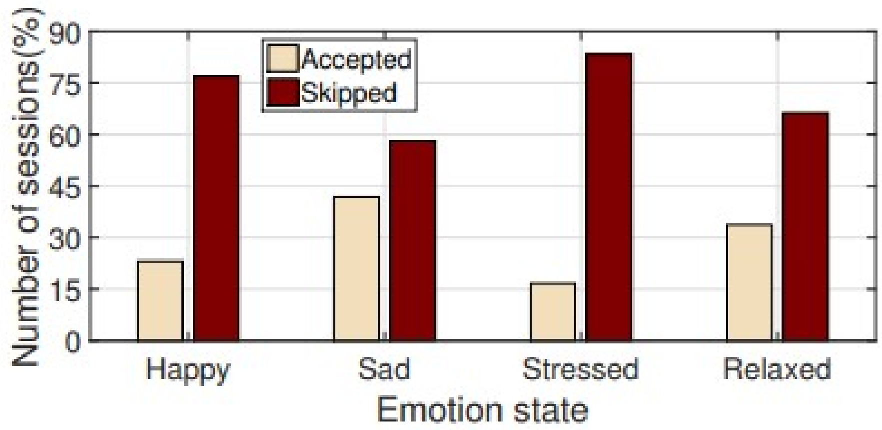
- How close to the typing session, the emotion is collected?



Distribution of elapsed time between typing and emotion recording for all sessions across all users.

- Median elapsed time is less than 5 minutes; 75th and 90th percentile elapsed time is less than 30 minutes and 1 hour respectively.

Dataset



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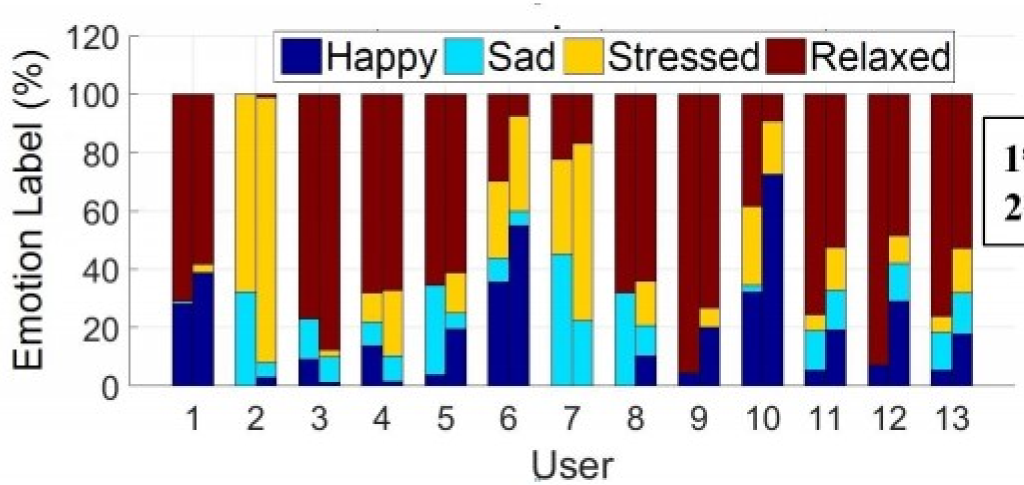

1st Bar: Accepted
2nd Bar: Skipped

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Outline

- Auto-suggest Usage Scenario
- Methodology
  - Experiment Apparatus
  - Model Construction
- User Study
  - Field Study
  - Dataset
- Evaluation
- Take-home Points

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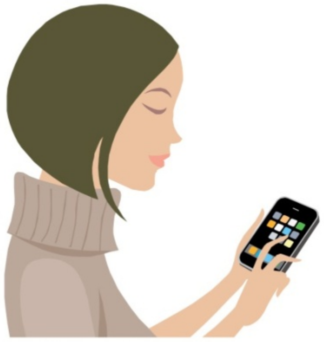
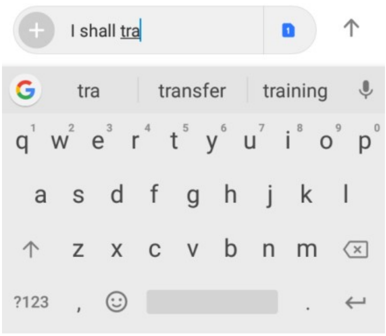


- To facilitate, different techniques like ***auto-complete, auto-suggest*** are used
  - However,
    - need additional space
    - increase cognitive load to read, parse and select correct word [CHI 2016]



- Making auto-suggestions adaptive, when the users are more likely to use can overcome these

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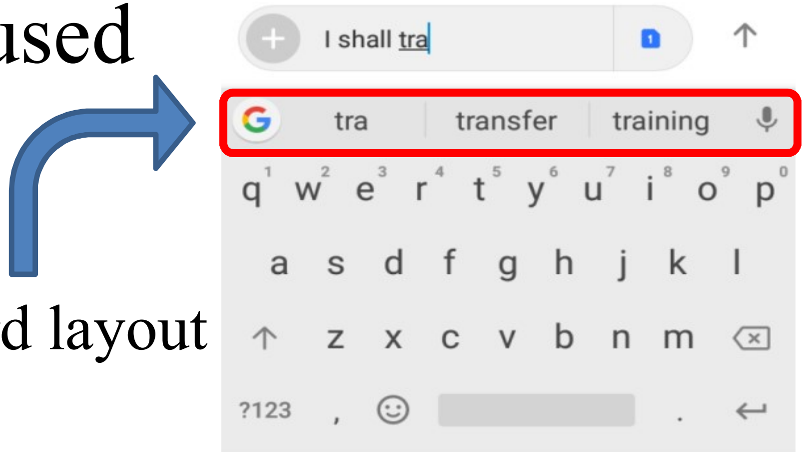

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