STATISTICS AND METHODS

SAM LAB

ARIZONA STATE UNIVERSITY

How to Present Your Research: Posters and Presentations

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Research Posters

Gender differences between types of social media use and links to depression

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INTRODUCTION

- Social media use (SMU) is associated with increased likelihood of poorer mental health outcomes (Berryman et al., 2017; Coyne et al., 2017)
- Yet there is also research indicating a more nuanced relationship between SMU and mental health
  - The ways in which an individual uses SM has been shown to moderate the relation between degree of SMU and mental health (Escobar-Viera et al., 2015; Hardy & Castonguay, 2018)
  - The degree to which SMU and mental health correlate with other online phenomena (e.g., cyberbullying) has been found to vary by gender (Schodt et al., 2021)

Current Study

We investigated whether the relation between both passive SMU and active SMU and depression is moderated by gender

- **Active SMU** is direct engagement with content online, such as posting a status or sending a direct message to a friend
- **Passive SMU** is indirect engagement with content online, such as scrolling through social media and reading others' content

METHOD

- Performed secondary data analysis of data collected from a sample of U.S. adults via Prolific.co ($N = 462$; 56.3% cisgender women, 43.7% cisgender men; age: $M = 31.0$, $SD = 11.5$)

Key Variables

- **Gender:** measured with dichotomous grouping variable, with a focus in the present study on cisgender individuals (cisgender men = 202; cisgender women = 260)
- **Depression:** measured with the Center for Epidemiological Studies Depression Scale (CES-D)
- **SMU:** Passive & Active Social Media Use Scale (Escobar-Viera et al., 2018)

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RESULTS

- To investigate whether the relation between passive and active SMU and depression is moderated by gender, we tested separate moderation models using PROCESS (model 1) in SPSS (Igartua & Hayes, 2021)
- In the first model, active SMU, gender, and their interaction were entered as predictors of depression.
  - There were no significant main or interaction effects for this model.
- In the second model, passive SMU, gender, and their interaction were entered as predictors of depression
  - There was a main effect for gender, with women reporting higher levels of depression than men, $b = 0.40$, $SE = 0.16$, $t(461) = 2.55$, $p = .011$, that was qualified by a significant Passive SMU x Gender interaction, $b = -0.07$, $SE = 0.03$, $t(461) = -2.37$, $p = .018$.
  - Greater passive SMU predicted higher levels of depression in men, $b = 0.11$, $SE = 0.05$, $t(461) = 2.42$, $p = .016$, whereas passive SMU and depression were uncorrelated in women.

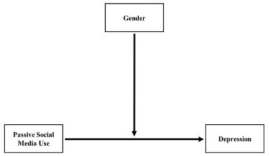

Figure 1. Conceptual diagram for moderation model with passive SMU, gender, and depression

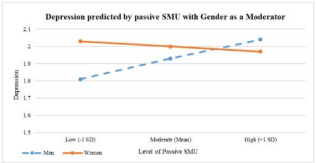

Figure 2. Simple slopes for relation between passive SMU and depression by gender

DISCUSSION

- For cisgender men, higher levels of passive SMU corresponded with greater symptoms of depression. For cisgender women, however, there was no correlation between degree of passive social media use and depression.
- Interestingly, this pattern of moderation did not emerge for active SMU.
- These findings highlight the importance of investigating gender differences in the relation between SMU and mental health, broadly, as well as examining how different ways of using SM can yield crucial insights.

ACKNOWLEDGEMENTS

This research was supported by NSF Awards #1719722 and #2036127.

Anti-Asian Prejudice on Twitter during the COVID-19 Pandemic

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Arizona State University

INTRODUCTION

- The COVID-19 pandemic is a global event that has been accompanied by a marked increase in prejudice and discrimination against those of Asian descent (Grover et al., 2020; Tessler et al., 2020).
- Anti-Asian prejudice in the U.S. has a historical basis, with much of the racism occurring in face-to-face interactions (AAPI Hate, 2020).
- Throughout the current pandemic, anti-Asian prejudice has also appeared to increase in communications via social media (Yang et al., 2020).

Proposed Study

- This study will examine the prevalence of anti-Asian content on Twitter since the start of COVID-19, with a primary objective of exploring spatial and temporal patterns in anti-Asian prejudice in relation to global events.

DATA COLLECTION & PROPOSED ANALYSES

- We will analyze over 2 million tweets on Twitter posted between January 31, 2020 and January 6, 2021.
- Data were collected using the standard and premium Twitter API. Geolocation was generated using location information in the raw data, with approximate matches made using FuzzyWuzzy Python library and Levenshtein distance function
  - Only user reported data were used to collect geolocation information
- For each date for which data were collected, we will examine the number of times the following hashtags and keywords reflecting anti-Asian prejudice appeared:
  - ✓ **Racist hashtags**: #Chinavirus, #Chinesevirus, #Chineseplague, #Wuflu, #Kungflu, #Chingchong, #Makechinapay, #CCPvirus, #Chinaliedpeopledied
  - ✓ **Racist keywords**: Bat soup, go back to China, gook, bioweapon
- We will also examine the frequency of the following positive hashtags:
  - ✓ **Positive hashtags**: #washthehate, #racismisavirus, #Iamnotavirus, #hateisavirus

Proposed Analyses

- Conditional growth curve modeling to estimate the frequency of each hashtag over time
- Content evolution to identify similar words and how the similarity changes over time
- Sentiment analysis to determine the most prevalent emotion shared by posters who use racist hashtags and posters who use positive hashtags.

ACKNOWLEDGEMENTS

This research was supported by NSF Awards #1719722 and #2036127.

PRELIMINARY FINDINGS

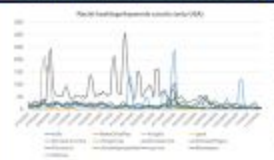

Figure 1 shows a frequency chart of all racist keywords/hashtags used over the data collection period

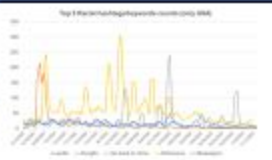

Figure 2 is a comparison of the top 5 most frequently used racist keywords/hashtags over the data collection period

Figure 3 shows a frequency chart of all positive hashtags used over the data collection period

Figure 4 shows the frequency of racist keywords/hashtags per state

Figure 5 shows a frequency chart of the combined frequency of racist and positive hashtags over the data collection period

- The data in these figures are comprised of tweets from June 12th, 2020 to November 15th, 2020
- Out of all the tweets collected 17,692 contained racist hashtags, 31,490 contained racist keywords, and 349 contained positive hashtags
- The prominent peaks included in the frequency charts coincide with real life COVID-19 related events (e.g., widely-shared tweets of political leaders).

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Powerpoint Presentations

Slide Presentation

SlidesGo (Templates)	https://slidesgo.com/
SlidesCarnival (Templates)	https://www.slidescarnival.com/
StorySet (Icons; illustrations)	https://storyset.com/
The Noun Project (Icons; images)	https://thenounproject.com/

SlidesGo

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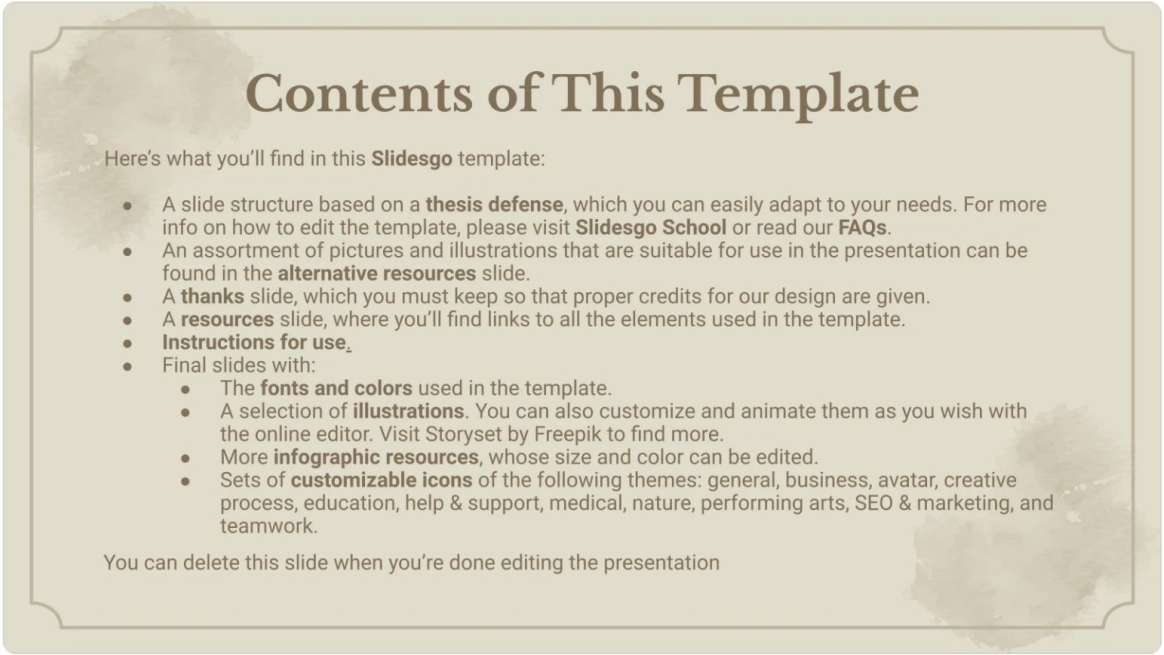

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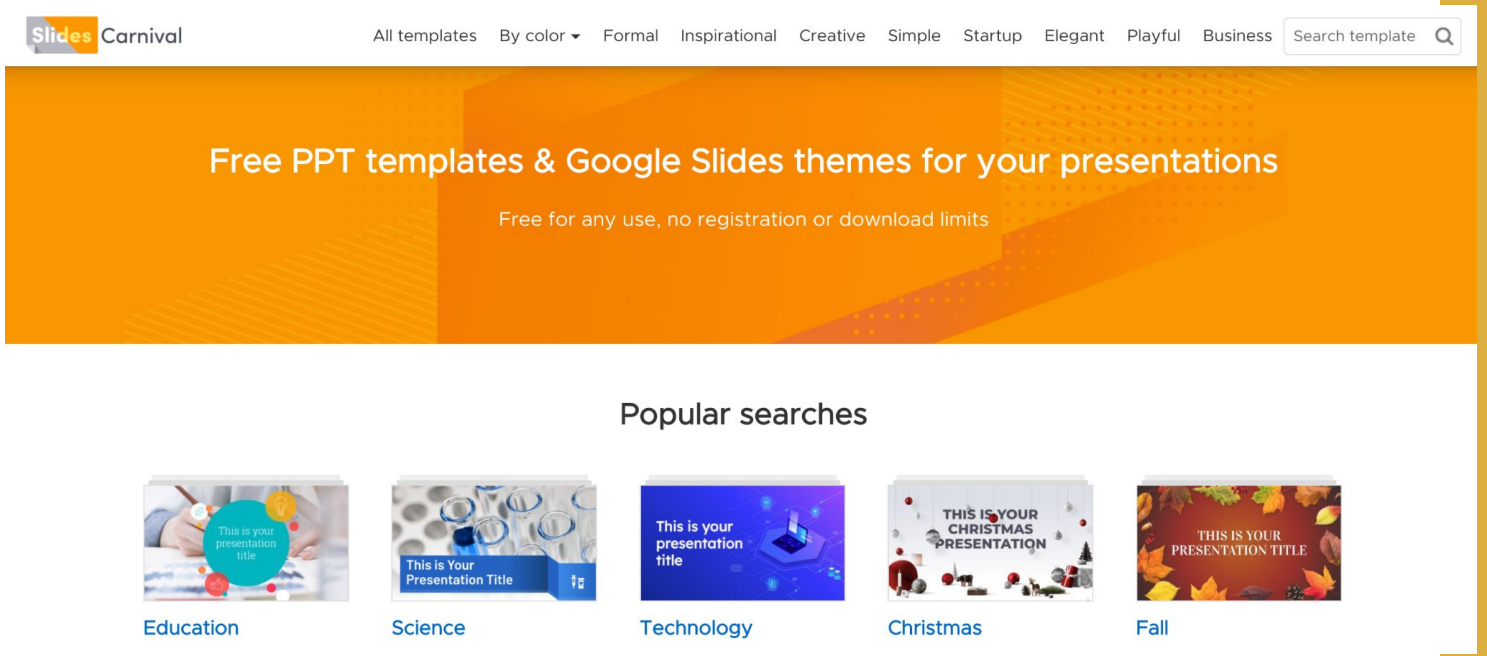

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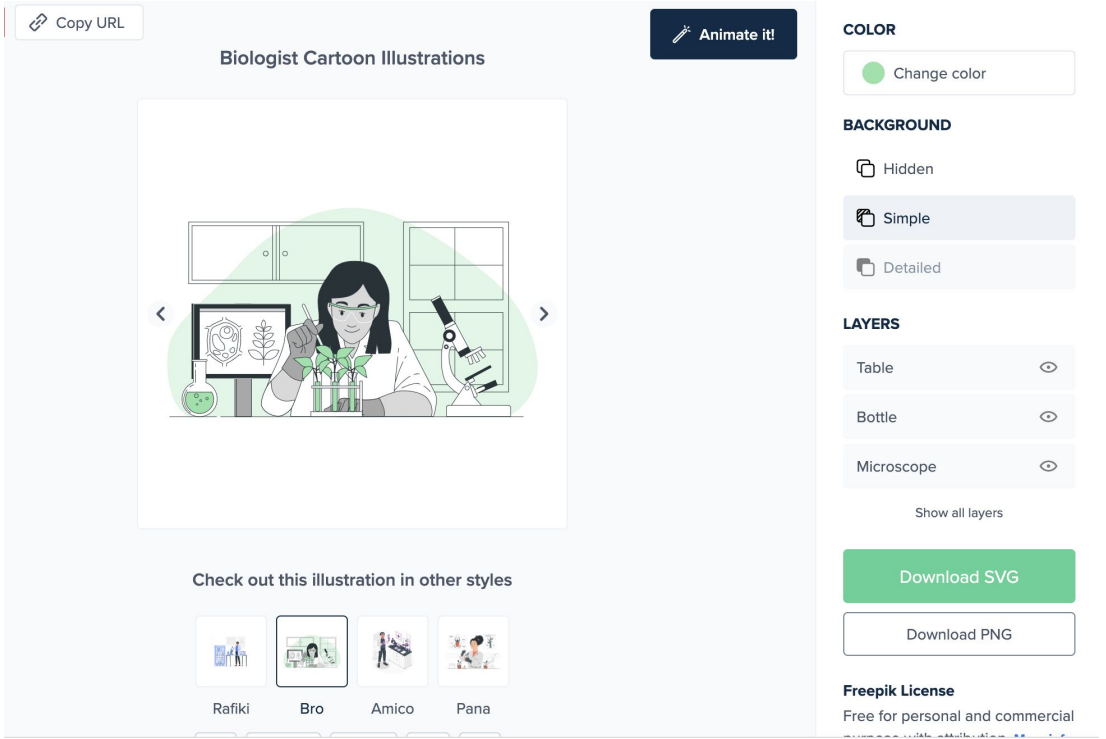

The Noun Project

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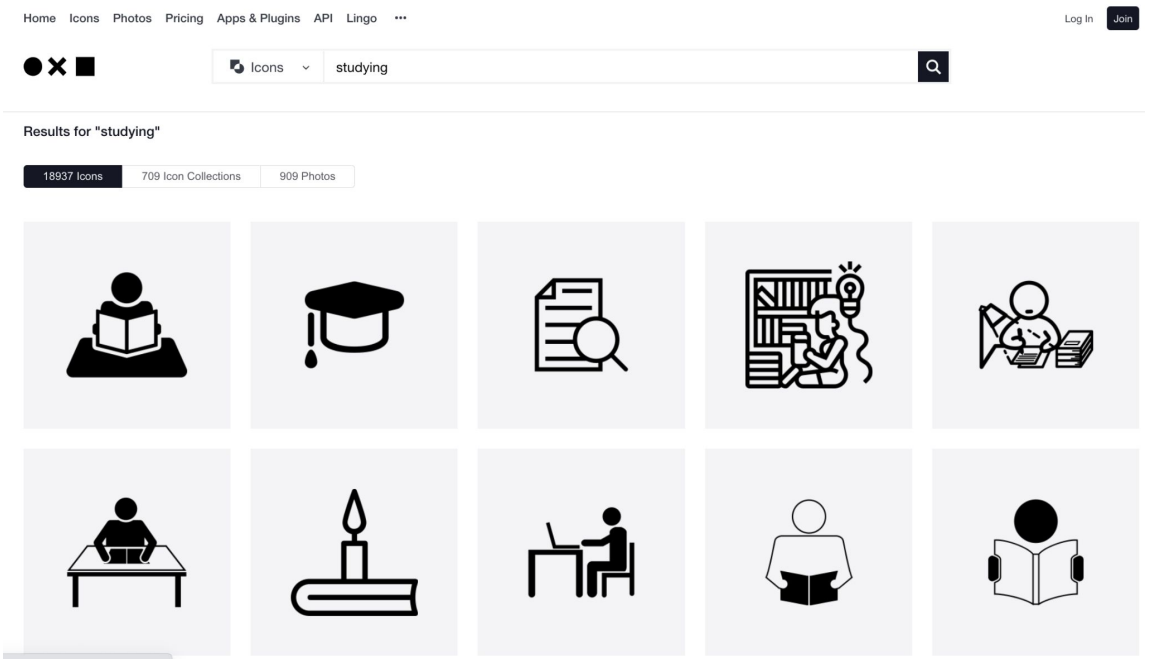


Examples

Poor Sleep Quality

- About 30% of adults and 20-40% of children and adolescents experience insomnia intermittently
  - Females diagnosed > males diagnosed
- About 20% of adults experience excessive daytime sleepiness

Inability to fall asleep

Nightmares

Inability to stay asleep

Sleep paralysis

Excessive daytime sleepiness

American Academy of Sleep Medicine, 2010; American Psychiatric Association, 2013; de Zambotti et al., 2018; Tarokh et al., 2016

Secondary Data Analysis from the MATCH Study

Mothers' and Their Children's Health Study

- Recruitment occurred at Dignity Health St. Joseph's Hospital and Medical Center

Electronic Survey

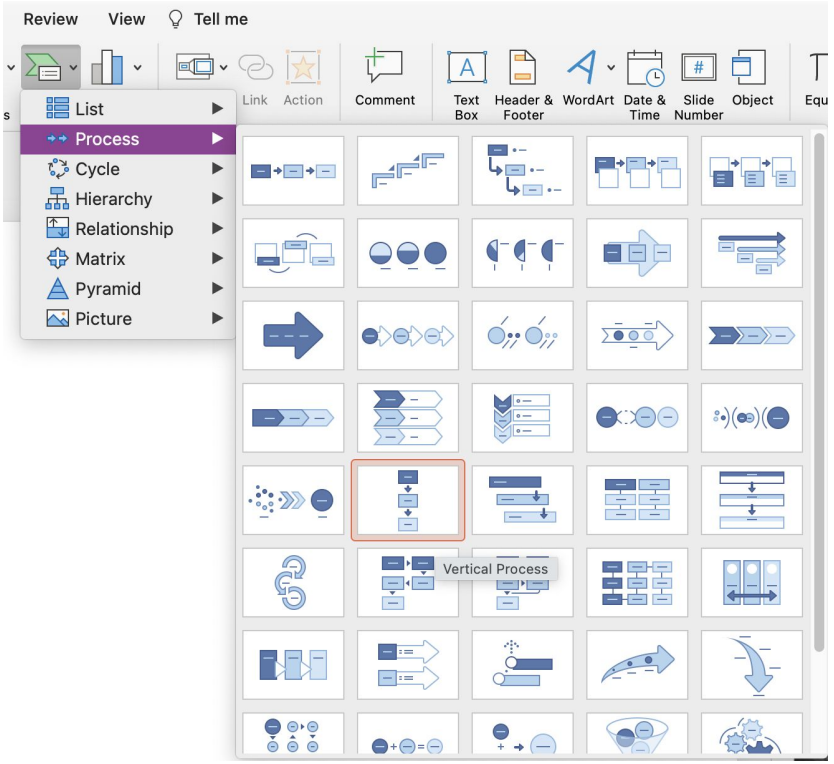
In-person Interview

Prenatal and Birth Outcome Data

What information should be included on a slide?

Other Considerations

- Charts and Graphs
- Smartart

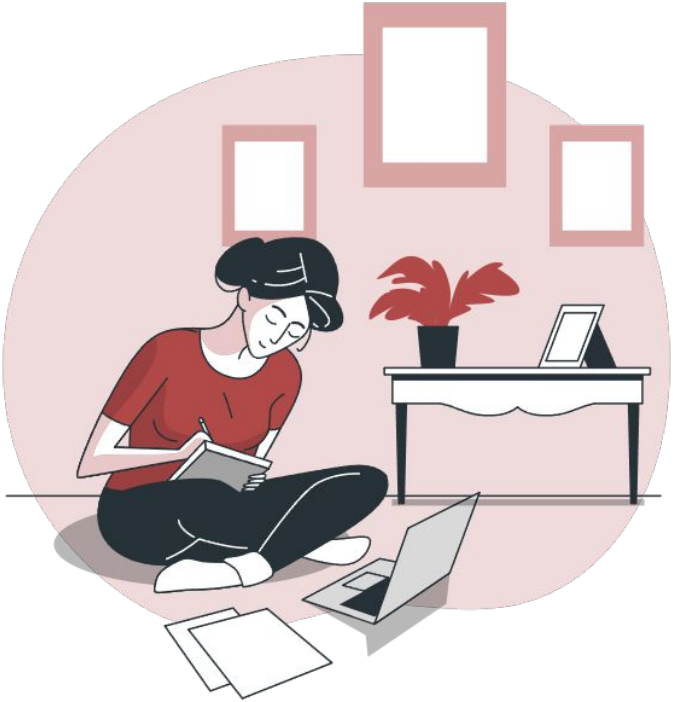


Title Page	Include title of research, your name, and your faculty advisor's name (and any other faculty who worked with you on the project)
Background	Include information about variables in study and any previous research
Proposed Analyses	Include a diagram to map out your hypotheses
Method	Include information about the participants, measures used, and procedures
Results and Discussion	Conclude the findings and future direction of research

How to give a talk

Before the Talk

- Prepare
- Practice
- Time Yourself
- Record
- Review
- Modify



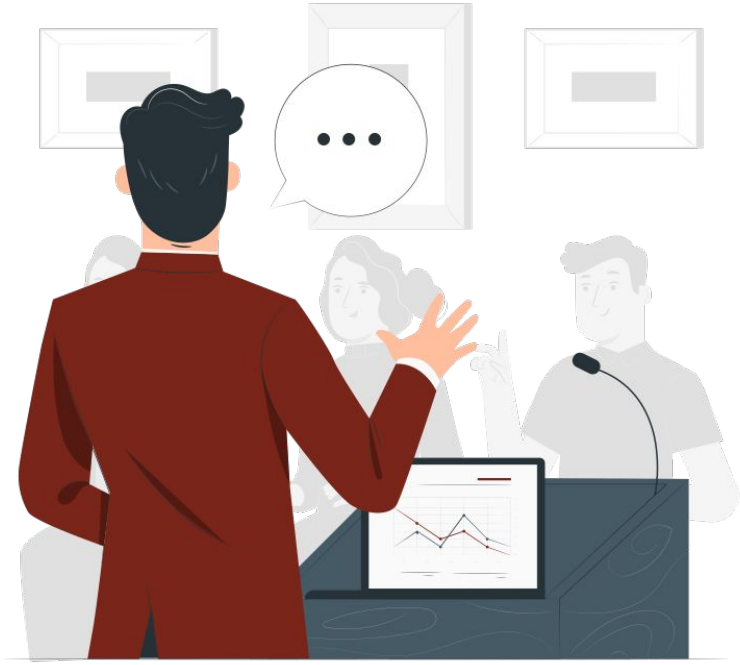
During the talk

Do:

- Present professionally
- Have notes nearby
- Introduce yourself and advisor
- Make eye contact
- Speak loudly and clearly

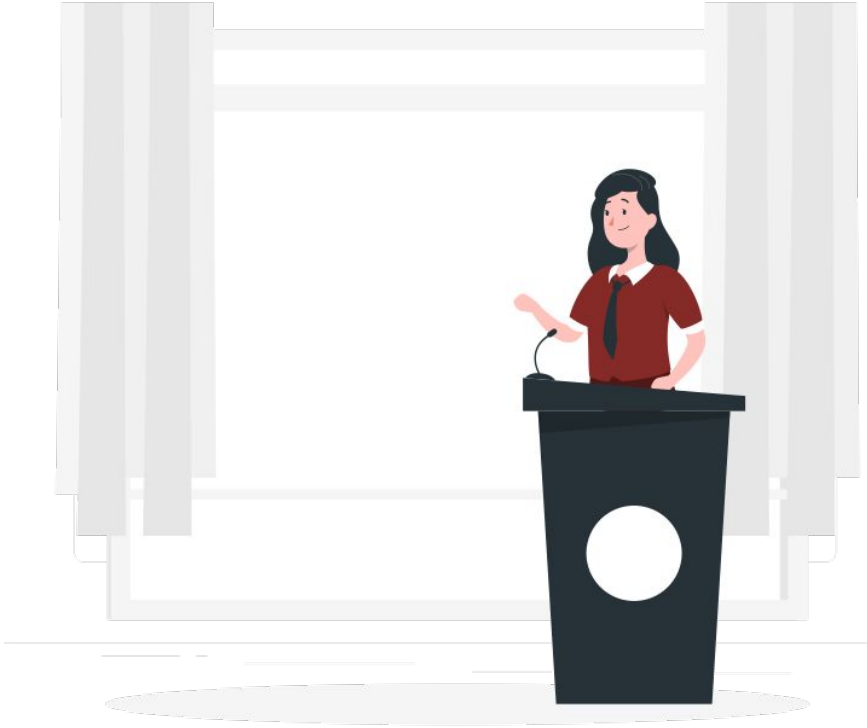
Don’t

- Look at notes or slides the whole time
- Wear inappropriate clothing
- Stop presentation if a mistake is made



After the talk

- Thank audience
- Ask audience if there are any questions
- Answer questions one by one until time is up



Conferences

Considerations

What type of research are you conducting?
What are the costs associated with attending?
Do you want to attend virtually or in-person?
Do you want to present research or just attend as a guest?
What type of submission do you want to make?
A note: networking

Opportunities

- Attending as a guest
- Attending as a presenter
  - Posters
  - Symposia
  - Talks
  - Workshops
- In-person vs online

Submission Requirements for Posters

- Title of the project
- Authors (and author order)
- Abstract
  - Sometimes there are multiple abstracts
- Subject Area
- Type of submission
  - Proposal
  - Data collection