# Comparing informativeness of an NLG chatbot vs graphical app in diet-information domain

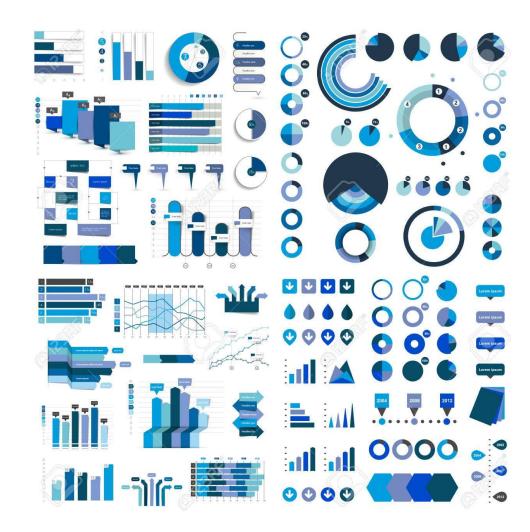
Simone Balloccu and Ehud Reiter Dept. of Computing Science, University of Aberdeen, UK



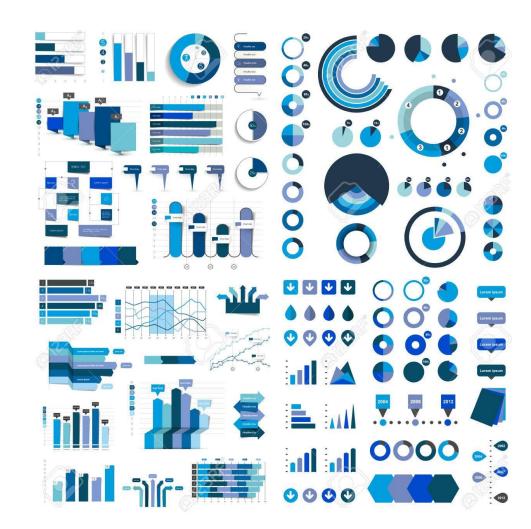




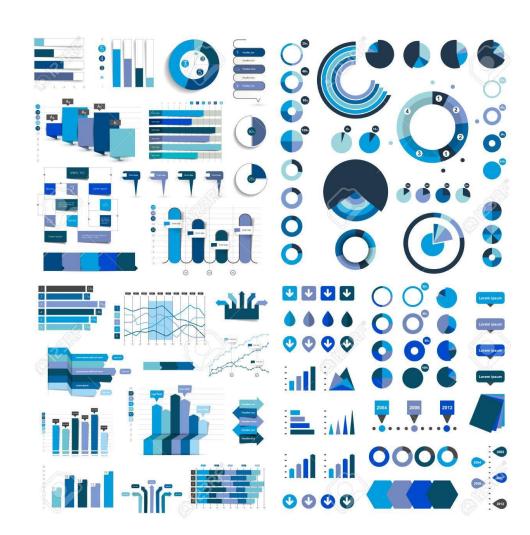
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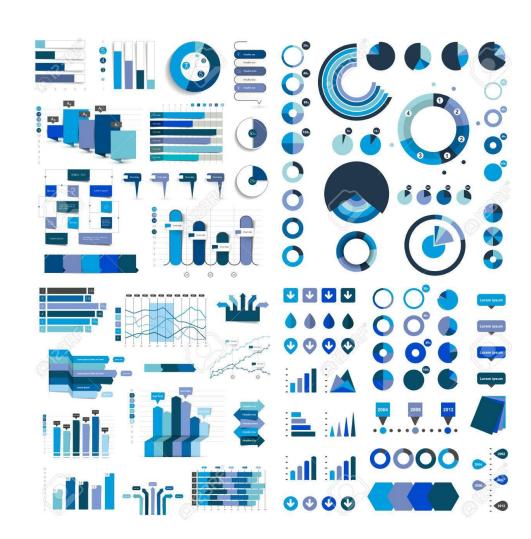
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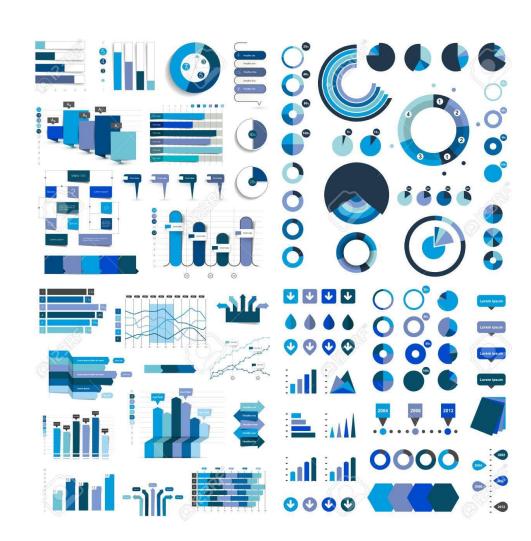
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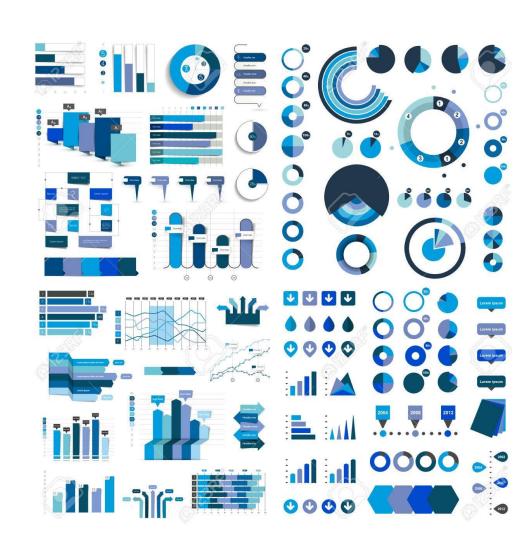
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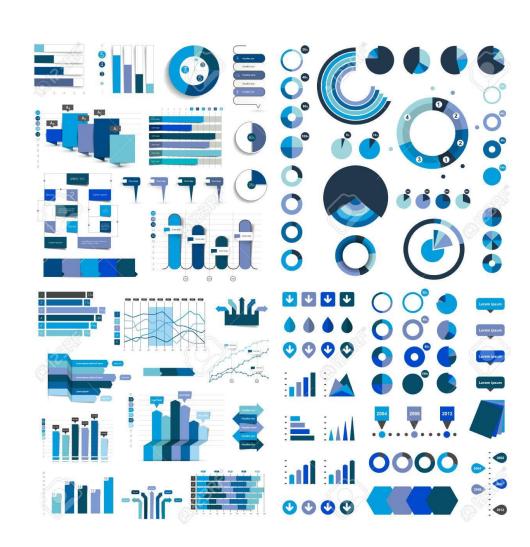
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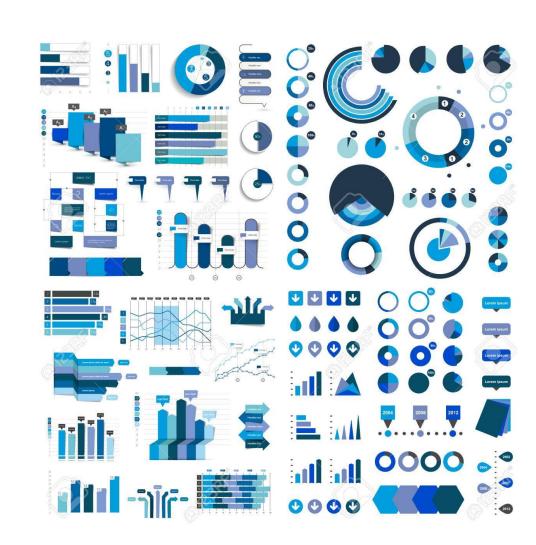
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- Past research inspected static contexts only (no interaction; fixed presentation).



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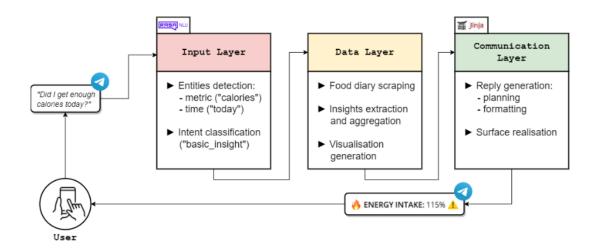


Figure 1: Chatbot architecture and interaction flow.

- We implement an NLG chatbot that:
  - Processes natural language queries
  - Provides insight explanation through charts and text combination

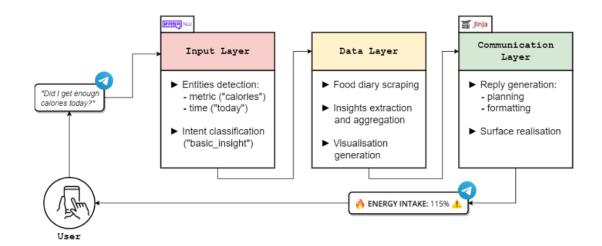


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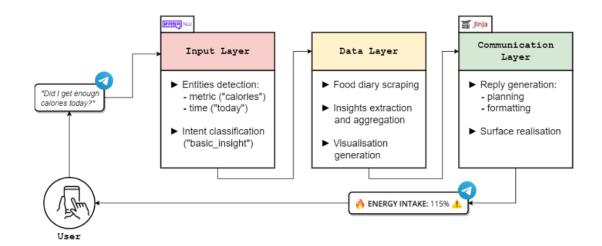


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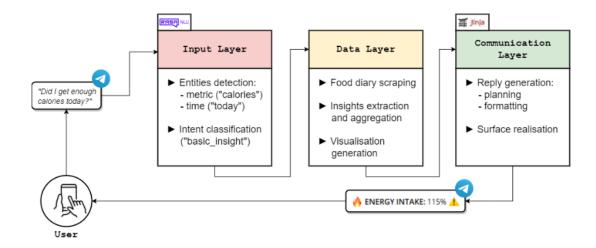


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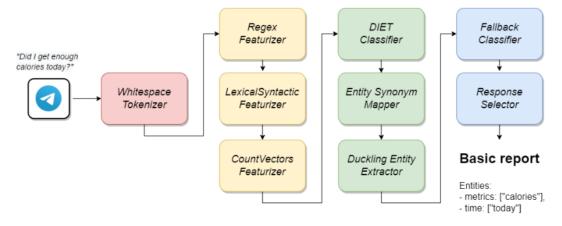


Figure 2: Overview of the NLU pipeline.

- We implement an NLG chatbot that:
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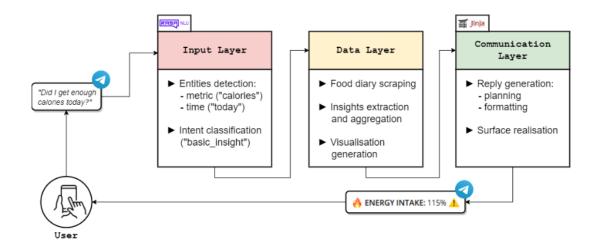


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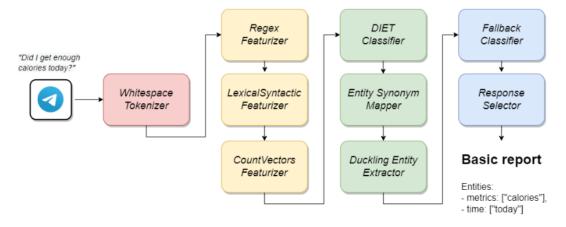


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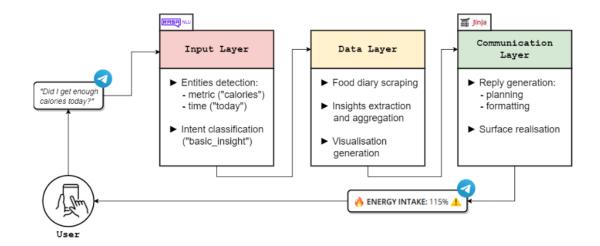


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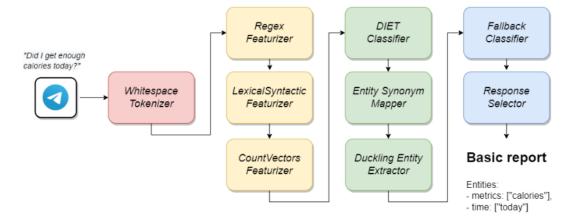


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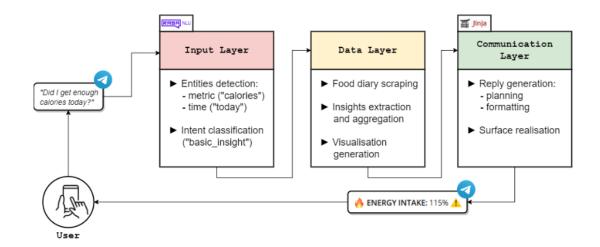


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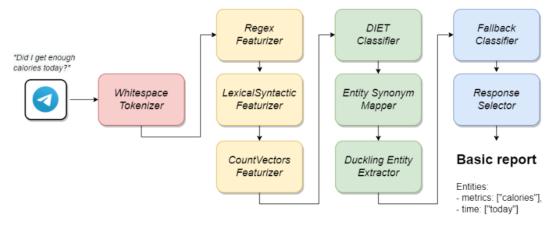


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  - Efficient communication is a predictor of prolonged app use (Lee and Cho, 2017)

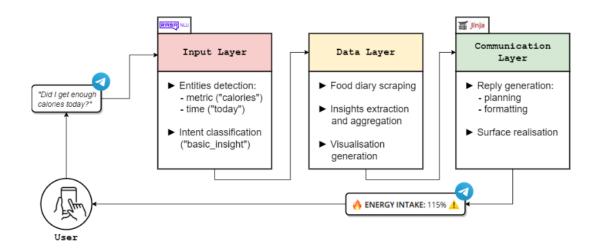


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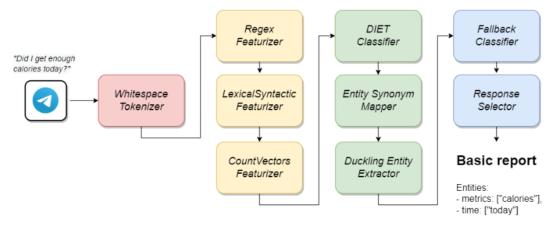


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  - Information is critical (Van Dorsten and Lindley, 2008; Savolainen, 2010; Michie et al., 2011)
  - Efficient communication is a predictor of prolonged app use (Lee and Cho, 2017)
  - Existing dieting apps adopt poor communication (Balloccu et al., 2021; Balloccu and Reiter, 2022)

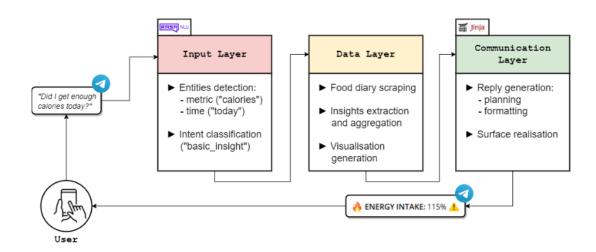


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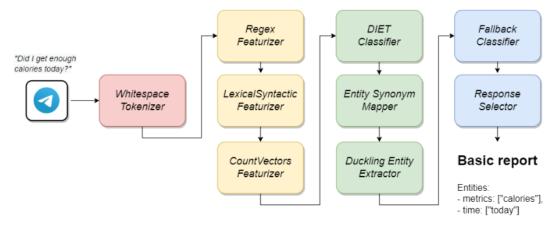
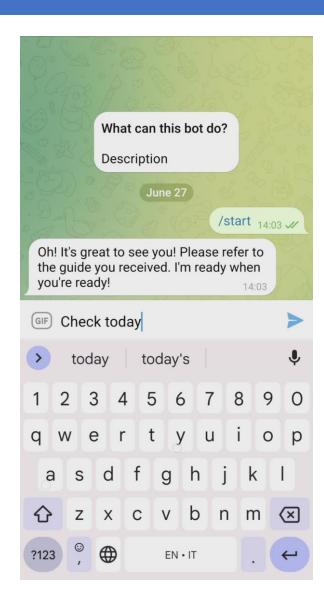


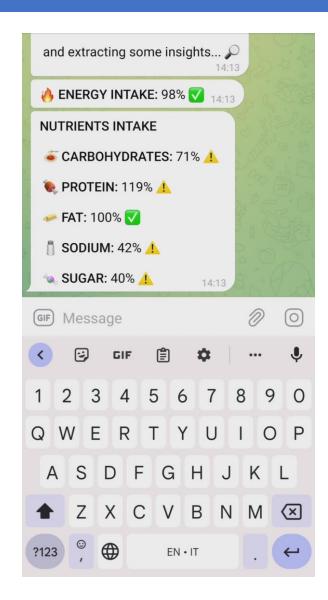
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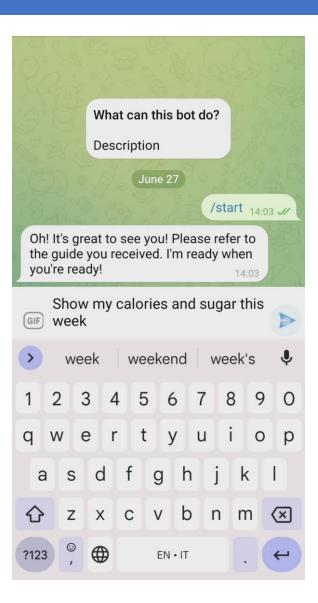
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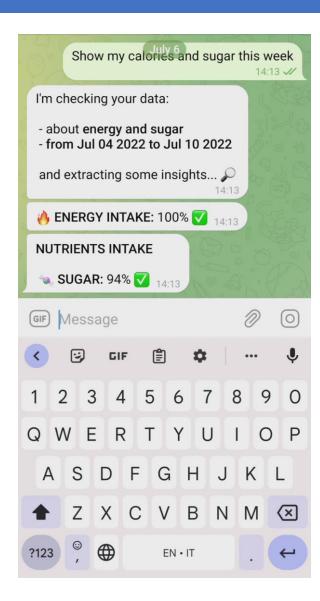
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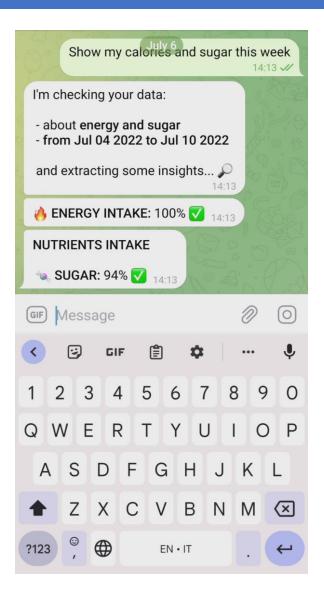
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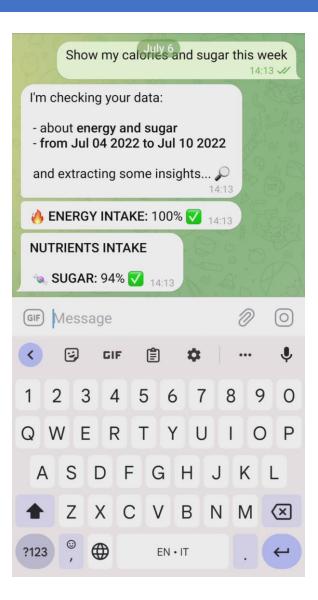
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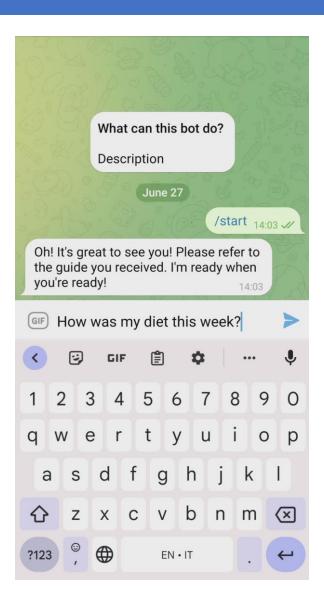
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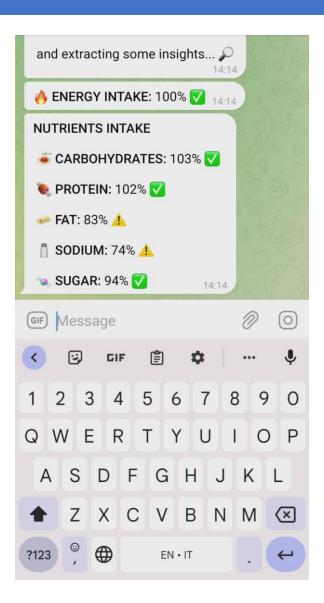
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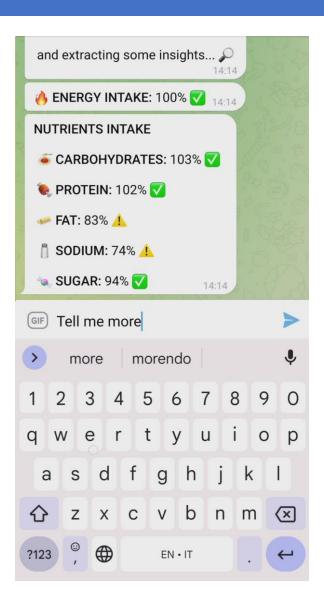
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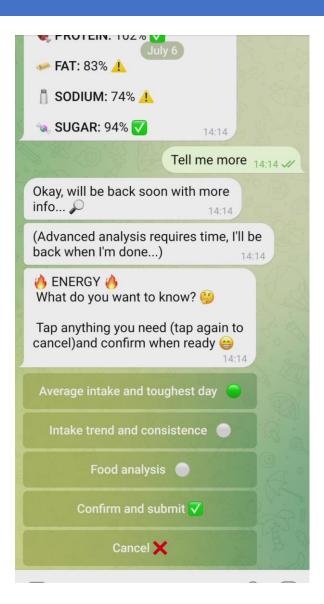
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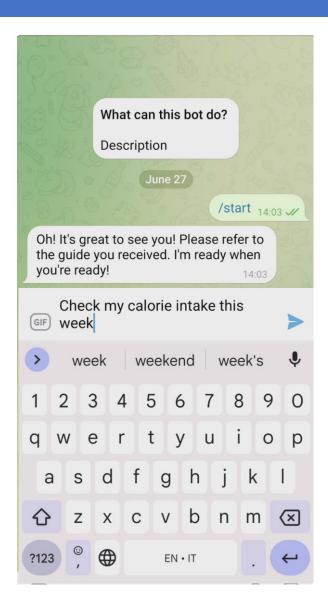
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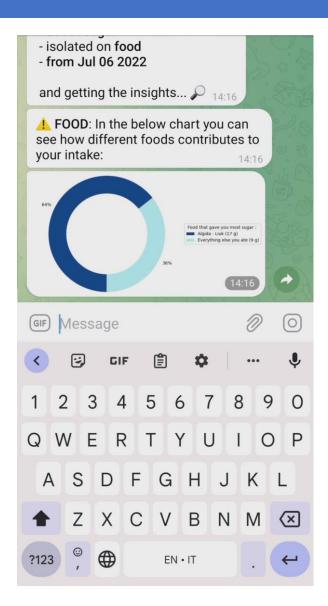
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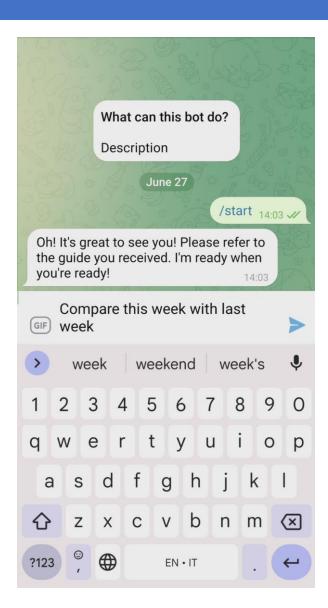
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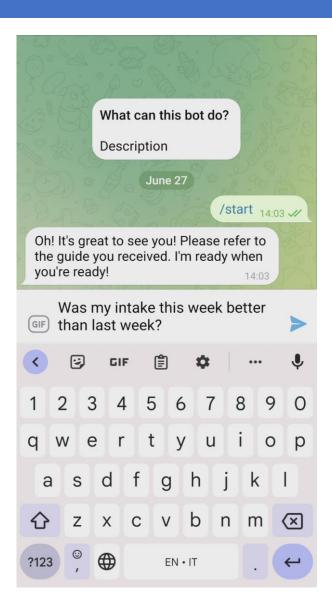
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- Comparisons: insights over multiple time-frame



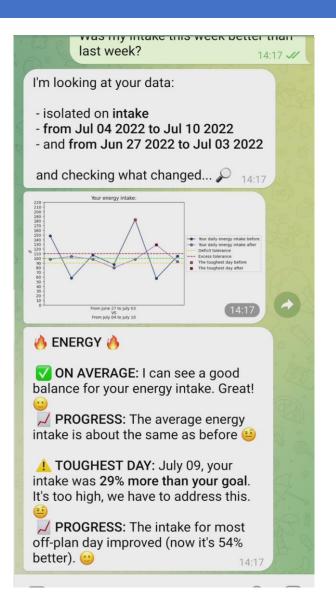
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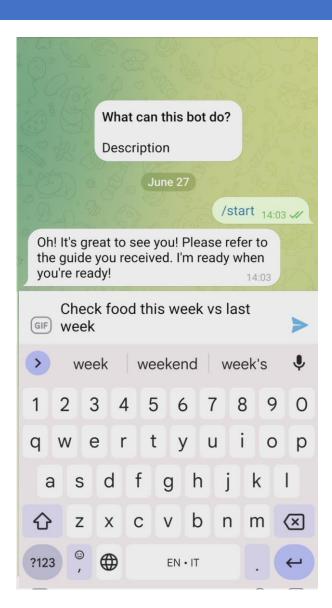
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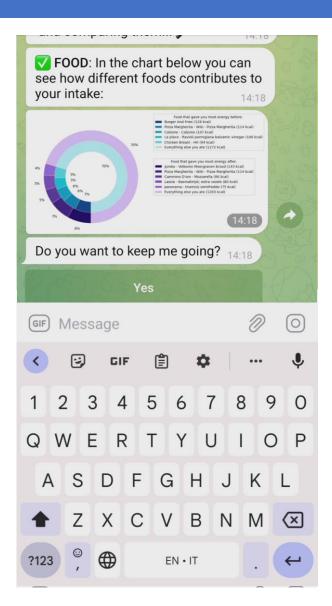
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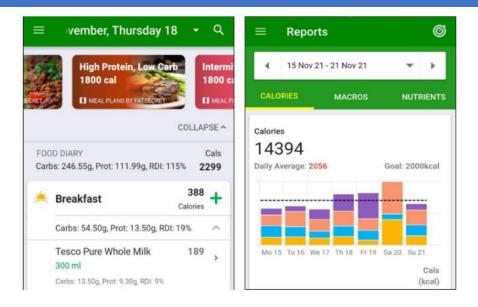


• 87 participants (from Amazon Mechanical Turk)

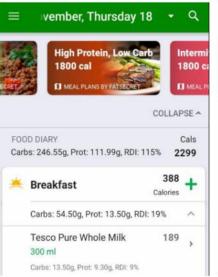
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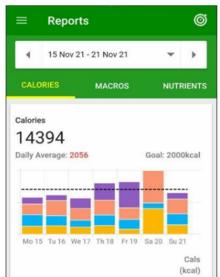
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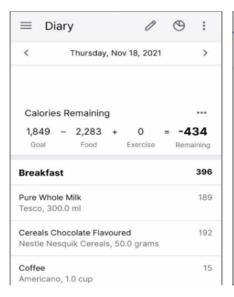
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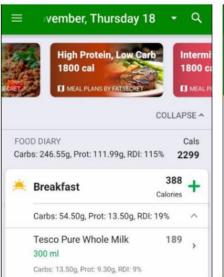




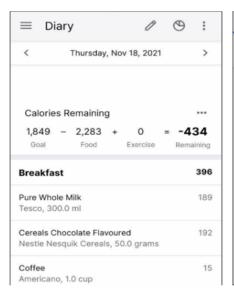




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  - We fill every tool with a simulated food diary (2 weeks of meals)

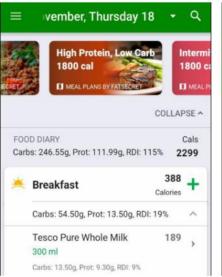


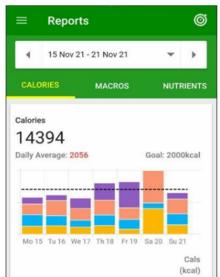


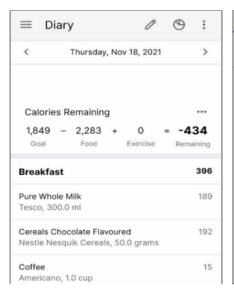




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  - We give every worker:

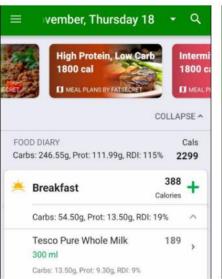


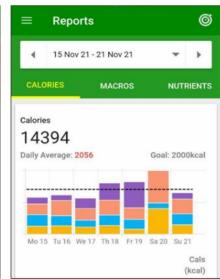


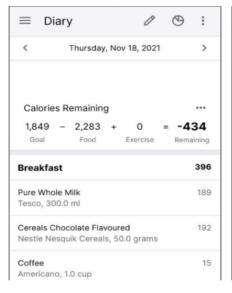




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  - We give every worker:
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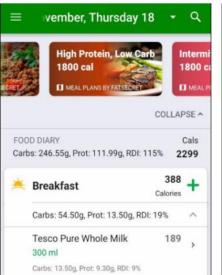




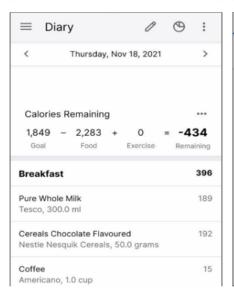




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  - We fill every tool with a simulated food diary (2 weeks of meals)
  - We give every worker:
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    - A glossary of experiment terminology

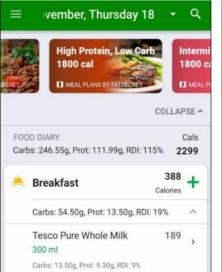


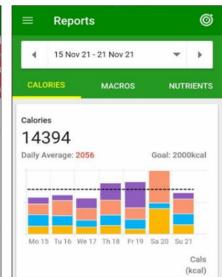


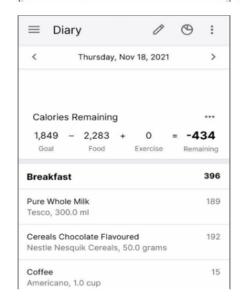


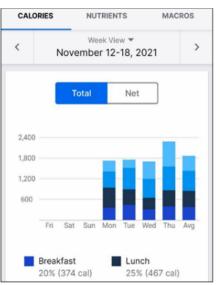


- 87 participants (from Amazon Mechanical Turk)
  - Each worker was randomly assigned to a tool
    - Our chatbot (CB)
    - FatSecret (FS)
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  - We fill every tool with a simulated food diary (2 weeks of meals)
  - We give every worker:
    - A guide for the tool
    - A glossary of experiment terminology
- We evaluate:

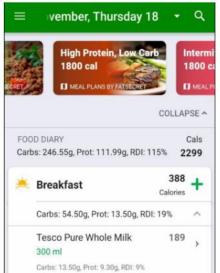


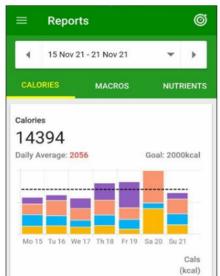


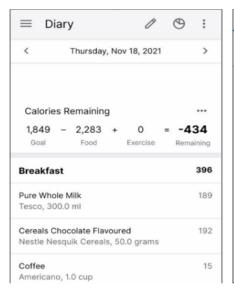




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    - A guide for the tool
    - A glossary of experiment terminology
- We evaluate:
  - Informativeness of each tool

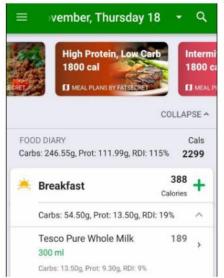




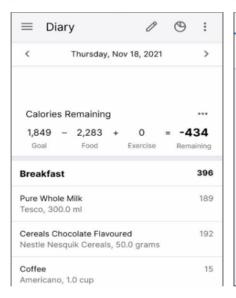




- 87 participants (from Amazon Mechanical Turk)
  - Each worker was randomly assigned to a tool
    - Our chatbot (CB)
    - FatSecret (FS)
    - MyFitnessPal (MFP)
  - We fill every tool with a simulated food diary (2 weeks of meals)
  - We give every worker:
    - A guide for the tool
    - A glossary of experiment terminology
- We evaluate:
  - Informativeness of each tool
  - Inter-sample nutrition literacy

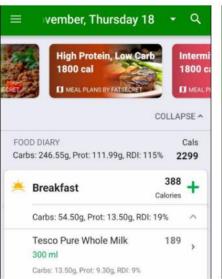




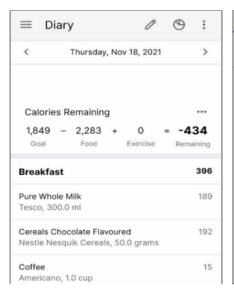




- 87 participants (from Amazon Mechanical Turk)
  - Each worker was randomly assigned to a tool
    - Our chatbot (CB)
    - FatSecret (FS)
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  - We fill every tool with a simulated food diary (2 weeks of meals)
  - We give every worker:
    - A guide for the tool
    - A glossary of experiment terminology
- We evaluate:
  - Informativeness of each tool
  - Inter-sample nutrition literacy
  - Workers' perception of the tool









• "How successfully a person is able to convey an intended message" (Webster and Morris, 2019):

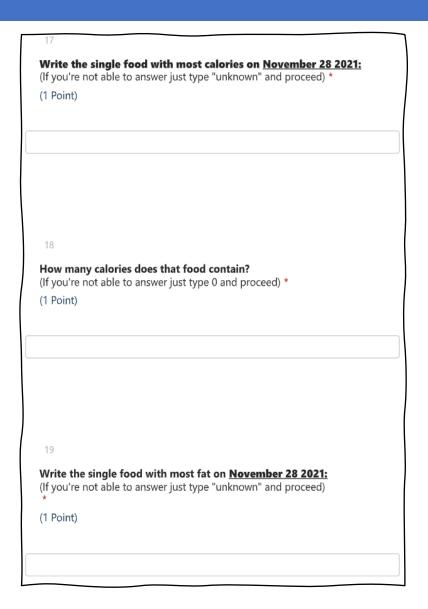
• "How successfully a person is able to convey an intended message" (Webster and Morris, 2019):

- "How successfully a person is able to convey an intended message" (Webster and Morris, 2019):
- Workers used their assigned tool to take a 10-point quiz

- "How successfully a person is able to convey an intended message" (Webster and Morris, 2019):
- Workers used their assigned tool to take a 10-point quiz
  - Day analysis (2pt): intake balance on a single day

Food diary on November 28 2021
Following the <b>user guide</b> , you can access a <b>food diary</b> . That is, for two consecutive weeks <b>you can see every meal and some related information</b> (e.g.: nutrients and calories).
Through the app, check <b>November 28 2021</b> only and answer the questions to the
15
Which one of the following is true for November 28 2021? *
(1 Point)
The calorie intake is <b>too high.</b>
The calorie intake <b>is balanced.</b>
The calorie intake <b>is too low.</b>
I don't know.
16
Which one of the following is true for <b>November 28 2021</b> ? *
(1 Point)
The carbohydrates intake is <b>too high.</b>
The carbohydrates intake is balanced.
The carbohydrates intake is too low.
I don't know.

- "How successfully a person is able to convey an intended message" (Webster and Morris, 2019):
- Workers used their assigned tool to take a 10-point quiz
  - Day analysis (2pt): intake balance on a single day
  - Food analysis (4pt): food impact on diet



- "How successfully a person is able to convey an intended message" (Webster and Morris, 2019):
- Workers used their assigned tool to take a 10-point quiz
  - Day analysis (2pt): intake balance on a single day
  - Food analysis (4pt): food impact on diet
  - Week analysis (2pt): intake balance across a week

Food diary on November 22-28 2021
Following the <b>user guide</b> , you can access <b>a simulated food diary</b> . That is, for two consecutive weeks <b>you can see every meal and some related information</b> (e.g.: nutrients and calories).
Through the app, check the week $\underline{\text{\bf November 22-28 2021}}$ only and answer the questions to the best of your knowledge
22
Which one of the following is true for November 22-28 2021? *
(1 Point)
The calories intake is <b>too high.</b>
The calories intake is <b>balanced.</b>
The calories intake is <b>too low</b> .
I don't know.
23
Which one of the following is true for November 22-28 2021? *
(1 Point)
The carbohydrates intake is <b>too high.</b>
The carbohydrates intake is <b>balanced</b> .
The carbohydrates intake is <b>too low.</b>
I don't know.

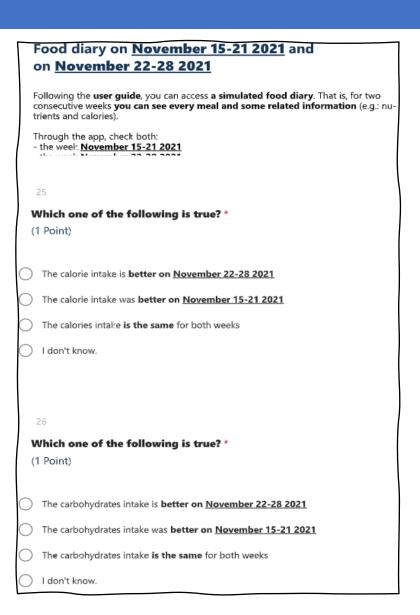
- "How successfully a person is able to convey an intended message" (Webster and Morris, 2019):
- Workers used their assigned tool to take a 10-point quiz
  - Day analysis (2pt): intake balance on a single day
  - Food analysis (4pt): food impact on diet
  - Week analysis (2pt): intake balance across a week
  - Weeks comparison (2pt): detecting progress

Food diary on <b>November 15-21 2021</b> and			
on <b>November 22-28 2021</b>			
Following the <b>user guide</b> , you can access <b>a simulated food diary</b> . That is, for two consecutive weeks <b>you can see every meal and some related information</b> (e.g.: nutrients and calories).			
Through the app, check both: - the week November 15-21 2021			
25			
Which one of the following is true? *			
(1 Point)			
The calorie intake is <b>better on <u>November 22-28 2021</u></b>			
The calorie intake was better on November 15-21 2021			
The calories intake is the same for both weeks			
I don't know.			
26			
Which one of the following is true? *			
(1 Point)			
(175mg			
The carbohydrates intake is <b>better on November 22-28 2021</b>			
The carbohydrates intake was <b>better on November 15-21 2021</b>			
The carbohydrates intake <b>is the same</b> for both weeks			
I don't know.			

- "How successfully a person is able to convey an intended message" (Webster and Morris, 2019):
- Workers used their assigned tool to take a 10-point quiz
  - Day analysis (2pt): intake balance on a single day
  - Food analysis (4pt): food impact on diet
  - Week analysis (2pt): intake balance across a week
  - Weeks comparison (2pt): detecting progress
- Quiz creation was guided by:

Food diary on November 15-21 2021 and			
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Following the <b>user guide</b> , you can access <b>a simulated food diary</b> . That is, for two consecutive weeks <b>you can see every meal and some related information</b> (e.g.: nutrients and calories).			
Through the app, check both: - the weel: November 15-21 2021			
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Which one of the following is true? *			
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The calorie intake was better on November 15-21 2021			
The calories intake is the same for both weeks			
I don't know.			
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Which one of the following is true? *			
(1 Point)			
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The carbohydrates intake was <b>better on November 15-21 2021</b>			
The carbohydrates intake <b>is the same</b> for both weeks			
I don't know.			

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  - Weeks comparison (2pt): detecting progress
- Quiz creation was guided by:
  - Expert recommendations (Vasiloglou et al., 2020)



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- Workers used their assigned tool to take a 10-point quiz
  - Day analysis (2pt): intake balance on a single day
  - Food analysis (4pt): food impact on diet
  - Week analysis (2pt): intake balance across a week
  - Weeks comparison (2pt): detecting progress
- Quiz creation was guided by:
  - Expert recommendations (Vasiloglou et al., 2020)
  - Self-regulation principle (Zahri et al., 2016)

	ood diary on November 15-21 2021 and
0	n <u>November 22-28 2021</u>
cc	ollowing the <b>user guide</b> , you can access <b>a simulated food diary</b> . That is, for two onsecutive weeks <b>you can see every meal and some related information</b> (e.g.: nuents and calories).
	arough the app, check both: the week: November 15-21 2021
2	5
w	hich one of the following is true? *
	Point)
$\circ$	The calorie intake is <b>better on <u>November 22-28 2021</u></b>
$\bigcirc$	The calorie intake was <b>better on <u>November 15-21 2021</u></b>
$\bigcirc$	The calories intake <b>is the same</b> for both weeks
$\bigcirc$	I don't know.
2	6
W	hich one of the following is true? *
(1	Point)
$\supset$	The carbohydrates intake is <b>better on November 22-28 2021</b>
$\bigcirc$	The carbohydrates intake was <b>better on November 15-21 2021</b>
$\bigcirc$	The carbohydrates intake <b>is the same</b> for both weeks
$\bigcirc$	I don't know.

## Measuring informativeness

- "How successfully a person is able to convey an intended message" (Webster and Morris, 2019):
- Workers used their assigned tool to take a 10-point quiz
  - Day analysis (2pt): intake balance on a single day
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- Quiz creation was guided by:
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  - Self-regulation principle (Zahri et al., 2016)
  - Existing diet apps analysis.

Food diary on <b>November 15-21 2021</b> and
on <u>November 22-28 2021</u>
Following the <b>user guide</b> , you can access <b>a simulated food diary</b> . That is, for two consecutive weeks <b>you can see every meal and some related information</b> (e.g.: nutrients and calories).
Through the app, check both: - the weel: November 15-21 2021
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Which one of the following is true? *
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The calorie intake was better on November 15-21 2021
The calories intake is the same for both weeks
I don't know.
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Which one of the following is true? *
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The carbohydrates intake <b>is the same</b> for both weeks
I don't know.

## Measuring informativeness

- "How successfully a person is able to convey an intended message" (Webster and Morris, 2019):
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  - Day analysis (2pt): intake balance on a single day
  - Food analysis (4pt): food impact on diet
  - Week analysis (2pt): intake balance across a week
  - Weeks comparison (2pt): detecting progress
- Quiz creation was guided by:
  - Expert recommendations (Vasiloglou et al., 2020)
  - Self-regulation principle (Zahri et al., 2016)
  - Existing diet apps analysis.
- H1: Chatbot workers scored higher on the quiz than MFP or FS workers.

Food diary on November 15-21 2021 and
on <b>November 22-28 2021</b>
Following the user guide, you can access a simulated food diary. That is, for two consecutive weeks you can see every meal and some related information (e.g.: nutrients and calories).
Through the app, check both: - the weel: November 15-21 2021
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Which one of the following is true? *
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( · · · · · · · · · · · · · · · · · · ·
The calorie intake is <b>better on <u>November 22-28 2021</u></b>
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The calories intake is the same for both weeks
☐ I don't know.
26
Which one of the following is true? *
(1 Point)
, , , , , , , , , , , , , , , , , , , ,
The carbohydrates intake is <b>better on <u>November 22-28 2021</u></b>
The carbohydrates intake was <b>better on November 15-21 2021</b>
The carbohydrates intake is the same for both weeks
I don't know.

We adopt the Newest Vital Sign (NVS)
 (Weiss et al., 2005; Powers et al., 2010)

- We adopt the Newest Vital Sign (NVS)
   (Weiss et al., 2005; Powers et al., 2010)
  - 6 questions about nutritional information, extracted from an ice cream label

Nutrition Facts Serving Size Servings per container	½ cur
Amount per serving	
Calories 250	Fat Cal 120
	%DV
Total Fat 13g	20%
Sat Fat 9g	40%
Cholesterol 28mg	12%
Sodium 55mg	2%
Total Carbohydrate 30	g 12%
Dietary Fiber 2g	
Sugars 23g	
Protein 4g	8%
*Percentage Daily Values (DV 2,000 calorie diet. Your daily von be higher or lower depending calorie needs.  Ingredients: Cream, Skim Sugar, Water, Egg Yolks, Brow Milkfat, Peanut Oil, Sugar, But	values may on your Milk, Liquid on Sugar,

- We adopt the Newest Vital Sign (NVS)
   (Weiss et al., 2005; Powers et al., 2010)
  - 6 questions about nutritional information, extracted from an ice cream label
- H2: There was a positive correlation between NVS score and quiz score in our experiment, but not for chatbot workers.



- We adopt the Newest Vital Sign (NVS) (Weiss et al., 2005; Powers et al., 2010)
  - 6 questions about nutritional information, extracted from an ice cream label
- H2: There was a positive correlation between NVS score and quiz score in our experiment, but not for chatbot workers.
- Finally, we ask every worker to evaluate their assigned tool

Please give a score to each statement, based on how much you agree with each one: *					
	Disagree	Somewhat disagree	Neither agree or disagree	Somewhat agree	Agree
\$tool_name helped me finding problems in the food diary.	0	0	0	0	0
<b>\$tool_name</b> helped me answer the questions.	0	0	0	0	0
Getting the answers with <b>\$tool_name</b> was quick.	0	0	0	0	0
\$tool_name was easy to use and understand.	0	0	0	0	0
I think I could improve my diet using	0	0	$\circ$	0	0

- We adopt the Newest Vital Sign (NVS)
   (Weiss et al., 2005; Powers et al., 2010)
  - 6 questions about nutritional information, extracted from an ice cream label
- H2: There was a positive correlation between NVS score and quiz score in our experiment, but not for chatbot workers.
- Finally, we ask every worker to evaluate their assigned tool
  - Additionally, we ask them about their past experience with dieting tools.

Please give a score to each statement, based on how much you agree with each one: *						
	Disagree	Somewhat disagree	Neither agree or disagree	Somewhat agree	Agree	
\$tool_name helped me finding problems in the food diary.	0	0	0	0	0	
<b>\$tool_name</b> helped me answer the questions.	0	0	0	0	0	
Getting the answers with <b>\$tool_name</b> was quick.	0	0	0	0	0	
<b>\$tool_name</b> was easy to use and understand.	0	0	0	0	0	
I think I could improve my diet using \$tool_name.	0	$\circ$	0	0	0	

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  - 6 questions about nutritional information, extracted from an ice cream label
- H2: There was a positive correlation between NVS score and quiz score in our experiment, but not for chatbot workers.
- Finally, we ask every worker to evaluate their assigned tool
  - Additionally, we ask them about their past experience with dieting tools.
- H3: Our chatbot received better ratings than MFP and FS

Please give a score to each statement, based on how much you agree with each one: *					
	Disagree	Somewhat disagree	Neither agree or disagree	Somewhat agree	Agree
\$tool_name helped me finding problems in the food diary.	0	0	0	0	0
<b>\$tool_name</b> helped me answer the questions.	0	0	0	0	0
Getting the answers with \$tool_name was quick.	0	0	0	0	0
<b>\$tool_name</b> was easy to use and understand.	0	0	0	0	0
I think I could improve my diet using \$tool name.	0	0	0	0	0

Nutrition literacy uniformity

	Workers per class			
NVS class	СВ	FS	MFP	
LOW (0-1pt)	1	0	9	
MID (2-3pt)	5	3	5	
HIGH (4-6pt)	21	26	17	

Table 2: Distribution of nutrition literacy for our population.

- Nutrition literacy uniformity
  - Problem: most workers with low NVS scores are in MFP sample

	Workers per class			
NVS class	СВ	FS	MFP	
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MID (2-3pt)	5	3	5	
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Table 2: Distribution of nutrition literacy for our population.

- Nutrition literacy uniformity
  - Problem: most workers with low NVS scores are in MFP sample
  - Solution: removing every worker with low NVS score.

	Workers per class		
NVS class	СВ	FS	MFP
I OIM (0 11)	1	_	
LOW (0-1pt)	1	U	9
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    - Pro: keeps the comparison fair

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    - Cons: potentially invalidates H2

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- Comparison of past experience with diet apps

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  - Solution: removing every worker with low NVS score.
    - Pro: keeps the comparison fair
    - Cons: potentially invalidates H2
- Comparison of past experience with diet apps
  - No significant difference either:

	Workers per class				
NVS class	CB FS MFP		MFP		
I OM (0 11)	1		0		
LOW (0-1pt)	1	U	9		
MID (2-3pt)	5	3	5		
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  - Problem: most workers with low NVS scores are in MFP sample
  - Solution: removing every worker with low NVS score.
    - Pro: keeps the comparison fair
    - Cons: potentially invalidates H2
- Comparison of past experience with diet apps
  - No significant difference either:
    - Globally (p=0.47)

	Workers per class				
NVS class	СВ	FS MFP			
I OTAL (O. 11)	1				
LOW (0-1pt)	1	U	9		
MID (2-3pt)	5	3	5		
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Table 2: Distribution of nutrition literacy for our population.

- Nutrition literacy uniformity
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  - Solution: removing every worker with low NVS score.
    - Pro: keeps the comparison fair
    - Cons: potentially invalidates H2
- Comparison of past experience with diet apps
  - No significant difference either:
    - Globally (p=0.47)
    - For workers who used diet tools in the past only (p=0.27)

	Workers per class				
NVS class	СВ	FS	MFP		
I OIM (0.11)	1				
LOW (0-1pt)	1	U	9		
MID (2-3pt)	5	3	5		
HIGH (4-6pt)	21	26	17		

Table 2: Distribution of nutrition literacy for our population.

	Average score			
Topic	CB	FS	MFP	
Overall (10pt)	6.65	4.13	5.22	
Day analysis (2pt)	1.15	0.76	1.32	
Food analysis (4pt)	2.85	2.14	0.91	
Week analysis (2pt)	1.35	0.66	1.05	
Weeks comparison (2pt)	1.31	0.59	1.14	

	Score differences			
Topic	CB-FS	CB-MFP	MFP-FS	
Overall (10pt)	+2.52**	+1.43	+1.09	
Day analysis (2pt)	+0.40	-0.16	+0.56	
Food analysis (4pt)	+0.71	+1.94***	-1.23*	
Week analysis (2pt)	+0.70**	+0.30	+0.39	
Weeks comparison (2pt)	+0.72**	+0.17	+0.55**	

• Overall, CB beat both apps

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- Overall, CB beat both apps
  - Significantly better than FS

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Week analysis (2pt)	+0.70**	+0.30	+0.39	
Weeks comparison (2pt)	+0.72**	+0.17	+0.55**	

- Overall, CB beat both apps
  - Significantly better than FS
  - Regardless of the tool, scores are low

	Average score			
Topic	CB	FS	MFP	
Overall (10pt)	6.65	4.13	5.22	
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Week analysis (2pt)	+0.70**	+0.30	+0.39	
Weeks comparison (2pt)	+0.72**	+0.17	+0.55**	

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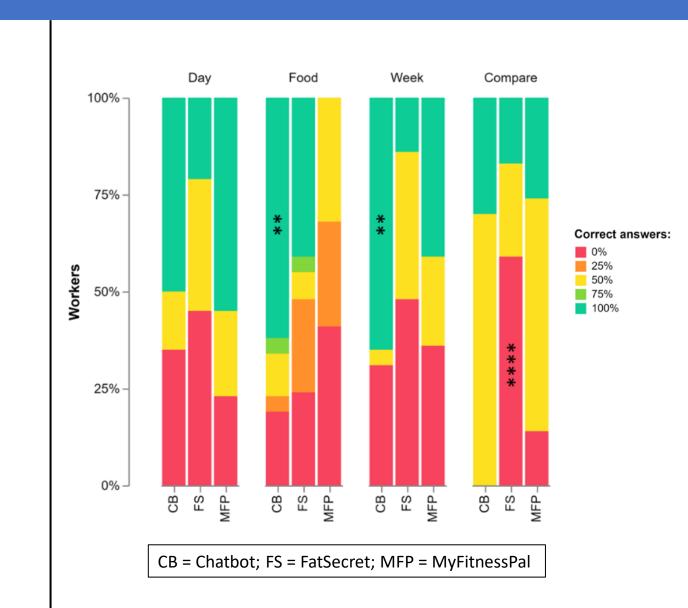
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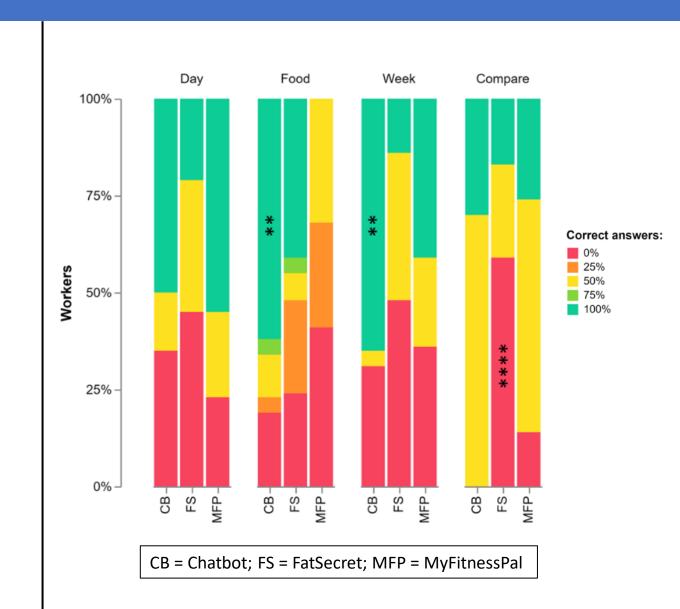
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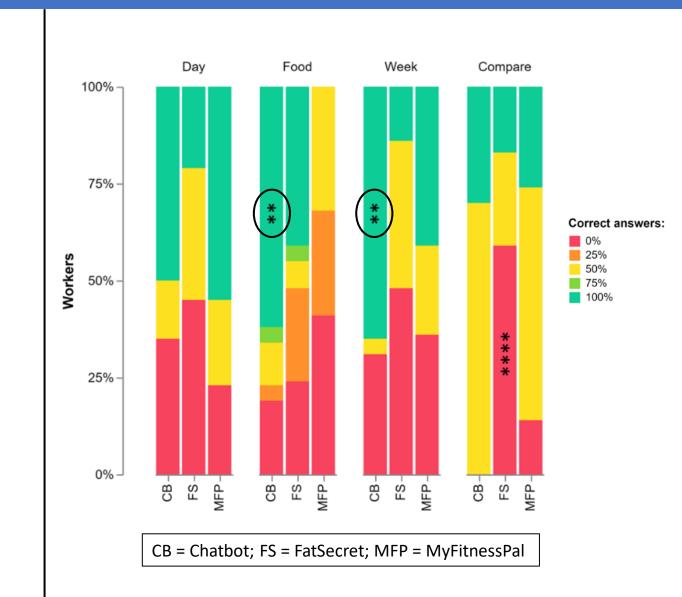
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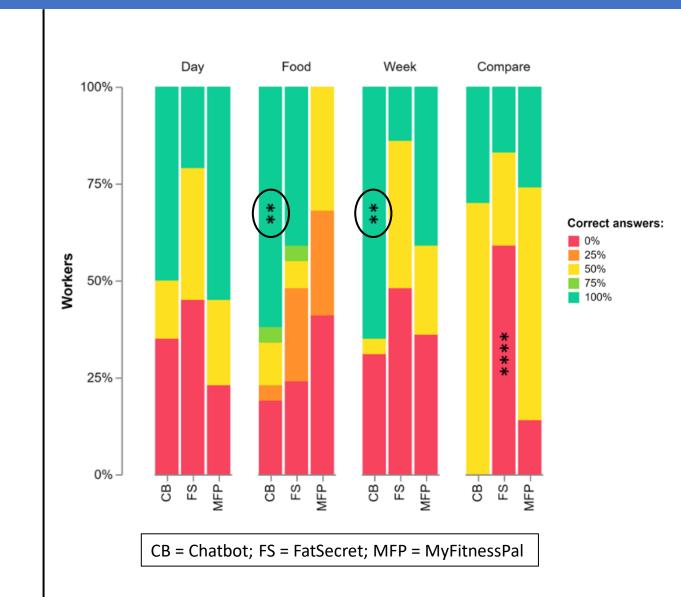
• Results for CB:



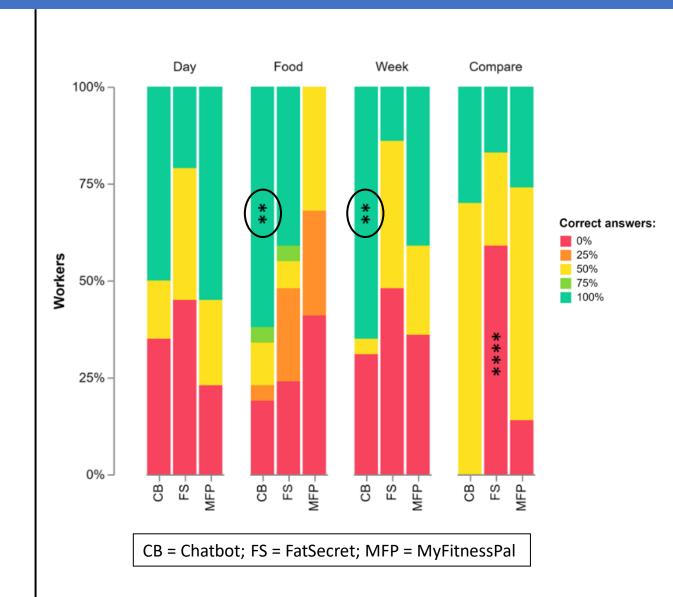
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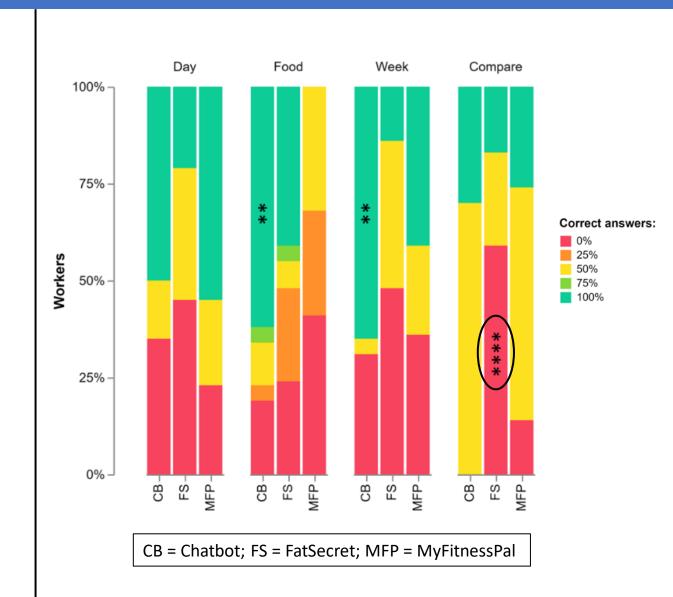
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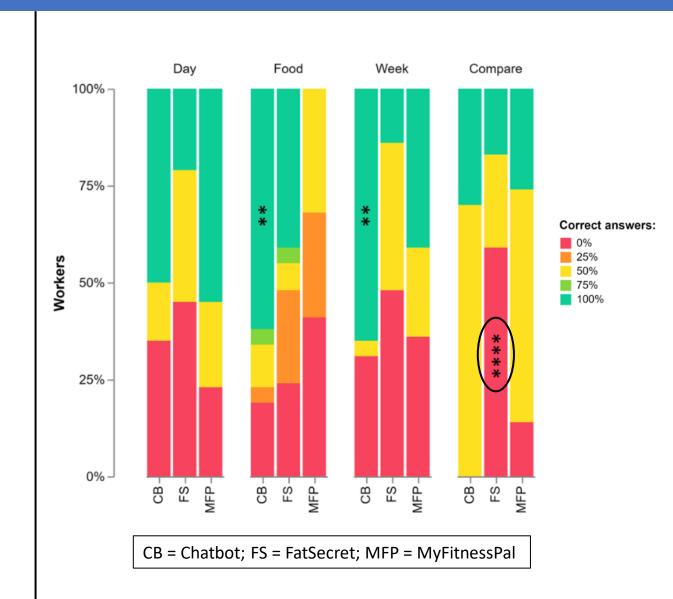


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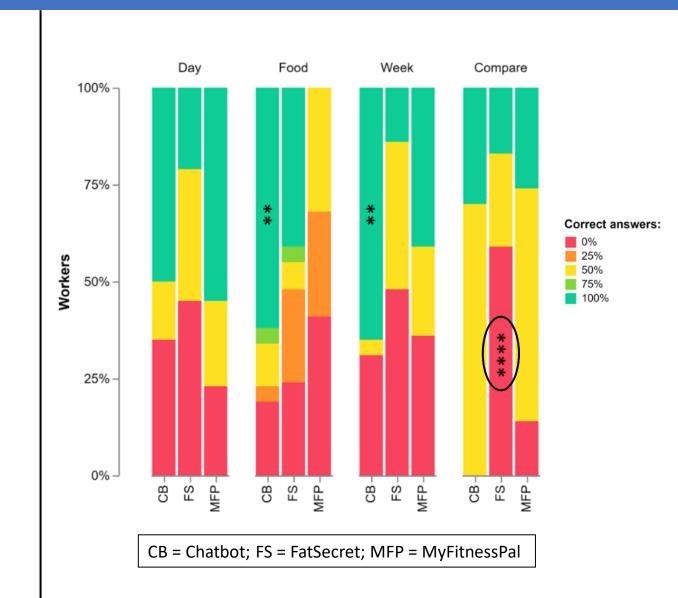
#### Quiz scores

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- Results for MFP:

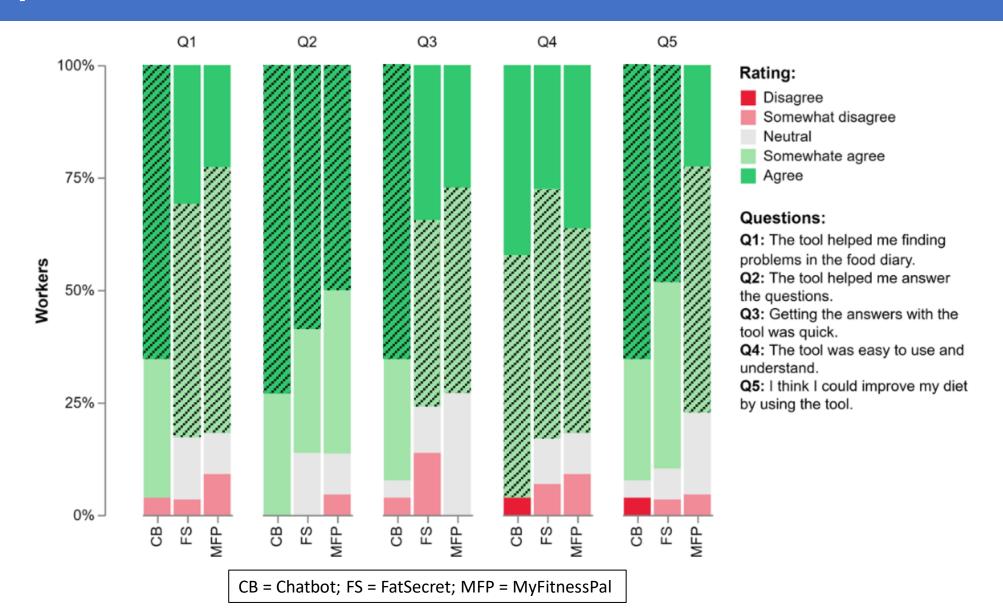


## Quiz scores

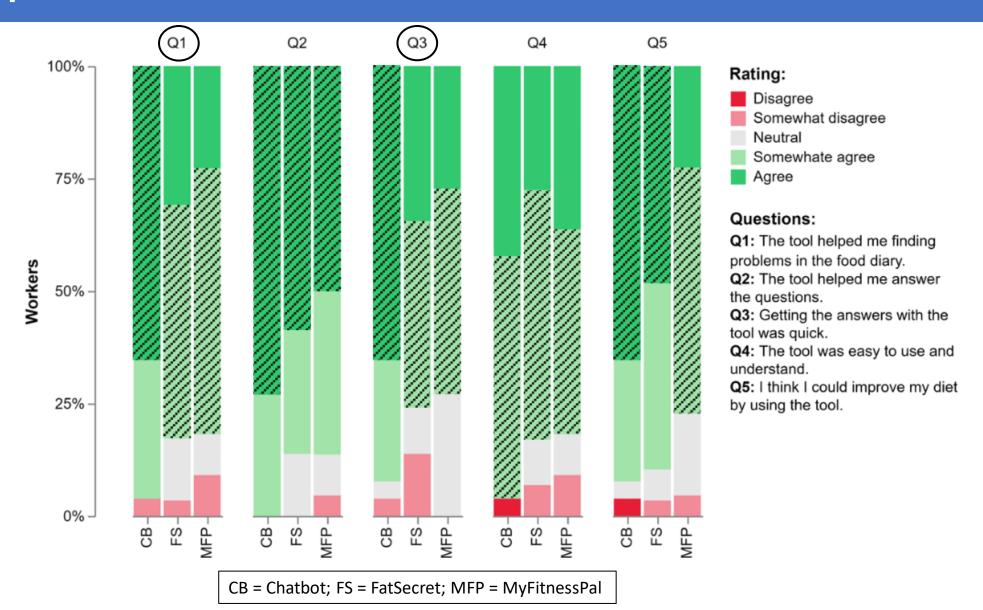
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# Perception of the tool



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# Thank you! Questions?







