



# Retain Top Talent In The Future Of Work

Improve employee engagement in the 'new normal'  
with machine learning insights

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Insights

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# Meet Daisy

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- **A data-driven corporate communications expert**

- 10 years of practical experience

- Connects the dots with data to create compelling stories

# A bumpy return to the workplace

Sources:

Gartner, 2022.

Future Forum, 2021.

Gallup, 2019.



## Executive-employee disconnect

A wide disparity in executives' and employees' work expectations is leading to deteriorating employee engagement and workplace dissatisfaction.



## Turnover will increase and is costly

**52%**

say flexible work policies will affect the decision to stay at their organization.

**63%**

are open to getting a new job in 2022.

**50-200%**

of employee's annual salary is the hard cost of replacing one employee

# Reinventing the Future of Work



## **Harness employee insights**

Discover key drivers in employees' work style preferences.



## **Iterate post-pandemic work policies**

Incorporate employee insights learned into Future of Work decision-making.



## **Engage employees**

Increase employee satisfaction with workplace arrangements and retain talent.

# What drives employees' expectations around workplace arrangements?

Key insights uncovered by the machine learning model

Note:

- WFH (work from home)
- WBP (work from business premises/office)

## **Your business location and size matters.**

If your office is in a city or is large or medium in size, WFH or hybrid is a more likely arrangement.

## **Worked from home during COVID?**

If you WFH and felt substantially more efficient than pre-Covid, you're more likely to want to WFH.

## **Was extra time saved on commuting spent at work?**

If employees spent time working that would have otherwise been commute time, it affects their preferred workplace arrangement.

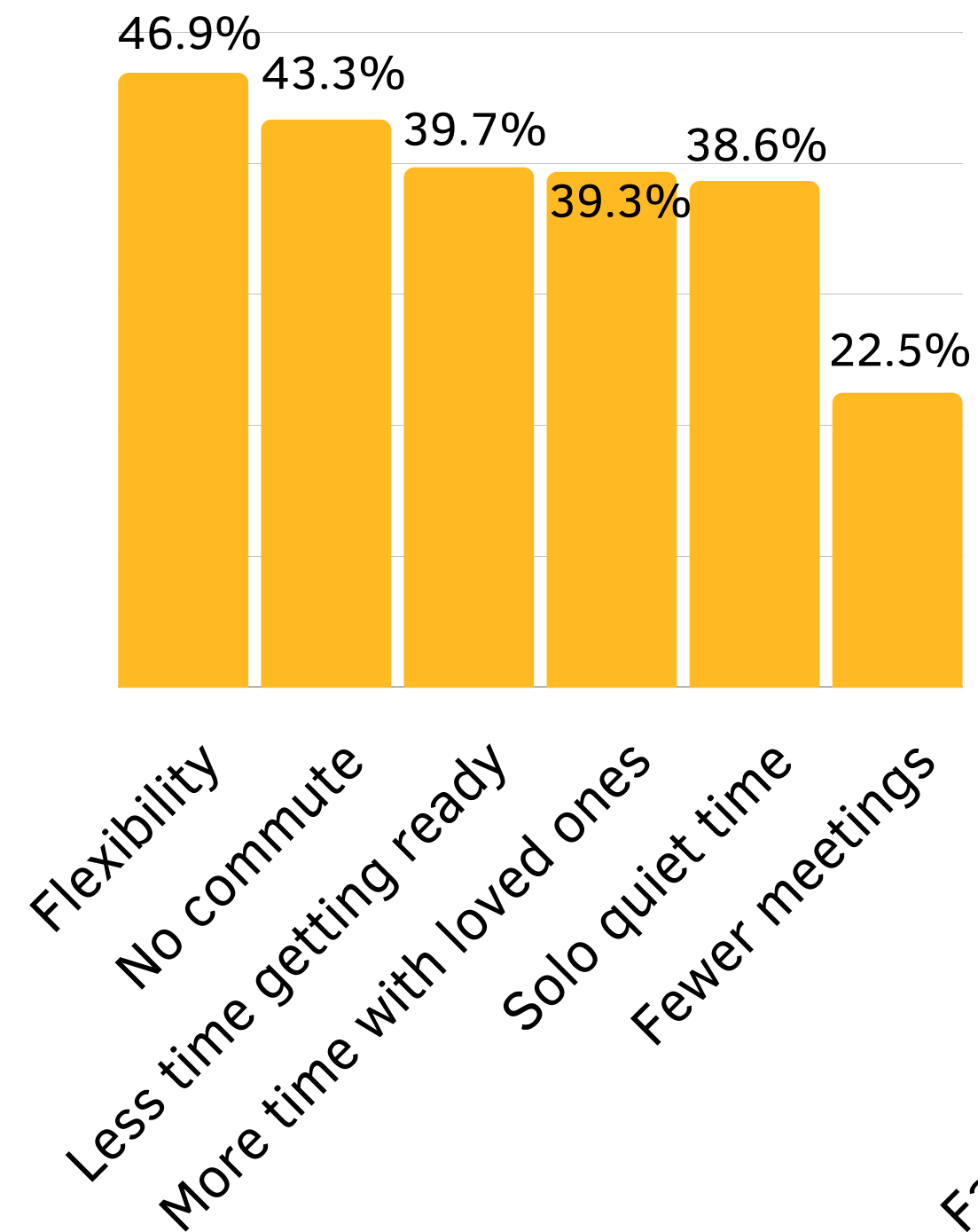
# Employees weigh in on the benefits of workplace arrangements

Key insights uncovered by the machine learning model

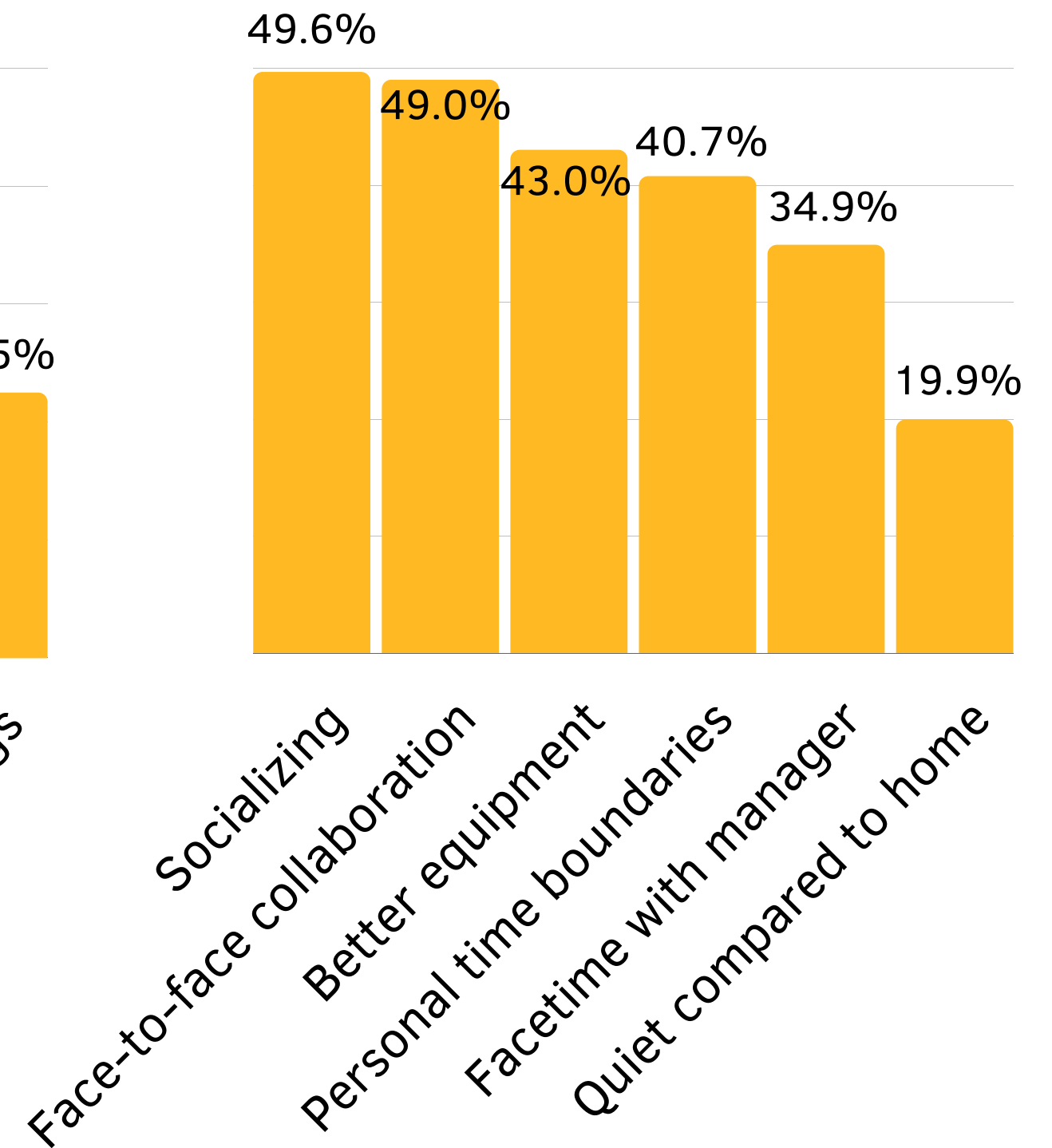
Note:

- WFH (work from home)
- WBP (work from business premises)

## Top benefits of WFH



## Top benefits of WBP



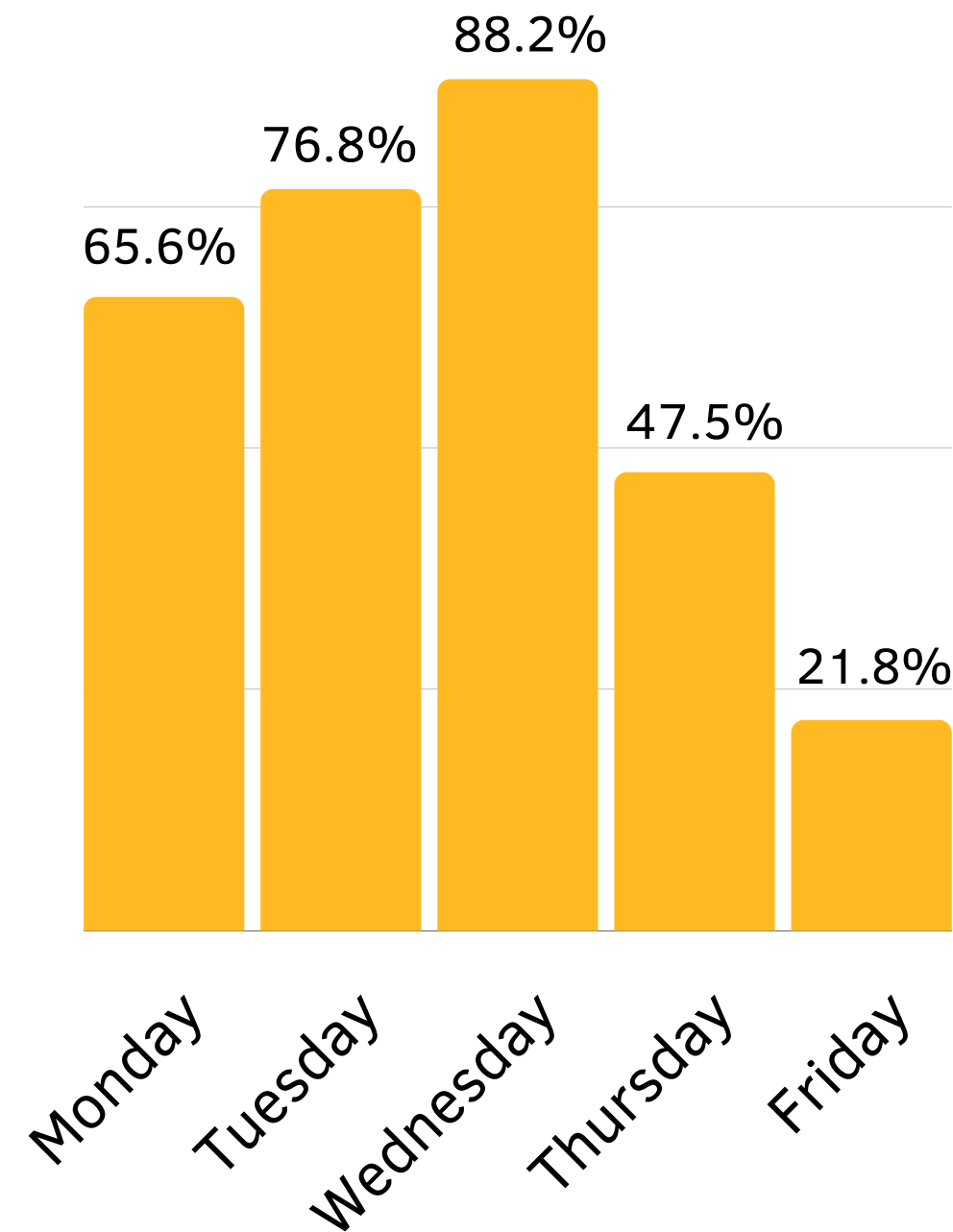
# When going to work, employees prefer...

Key insights uncovered by the machine learning model

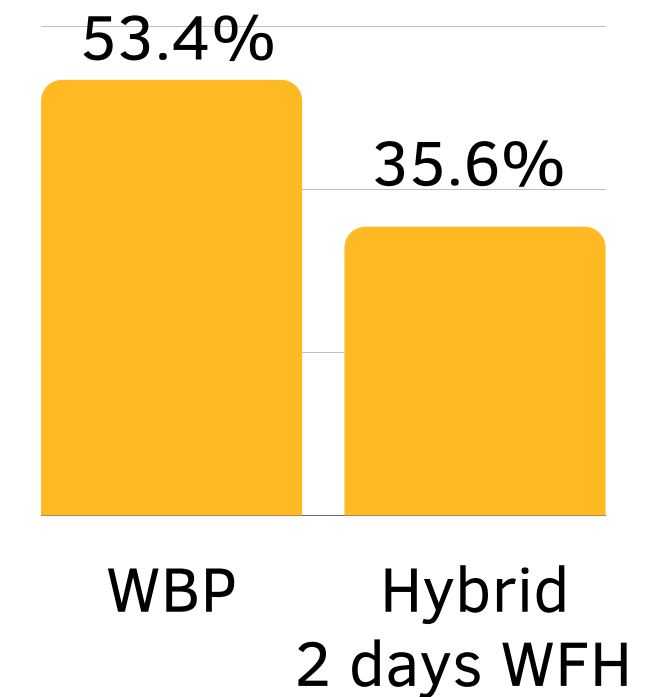
Note:

- WFH (work from home)
- WBP (work from business premises)

## Day of the week employees prefer to go to office



## After COVID, the work arrangement I prefer is...



# 82.3%

prefer going to work the same day as their coworkers

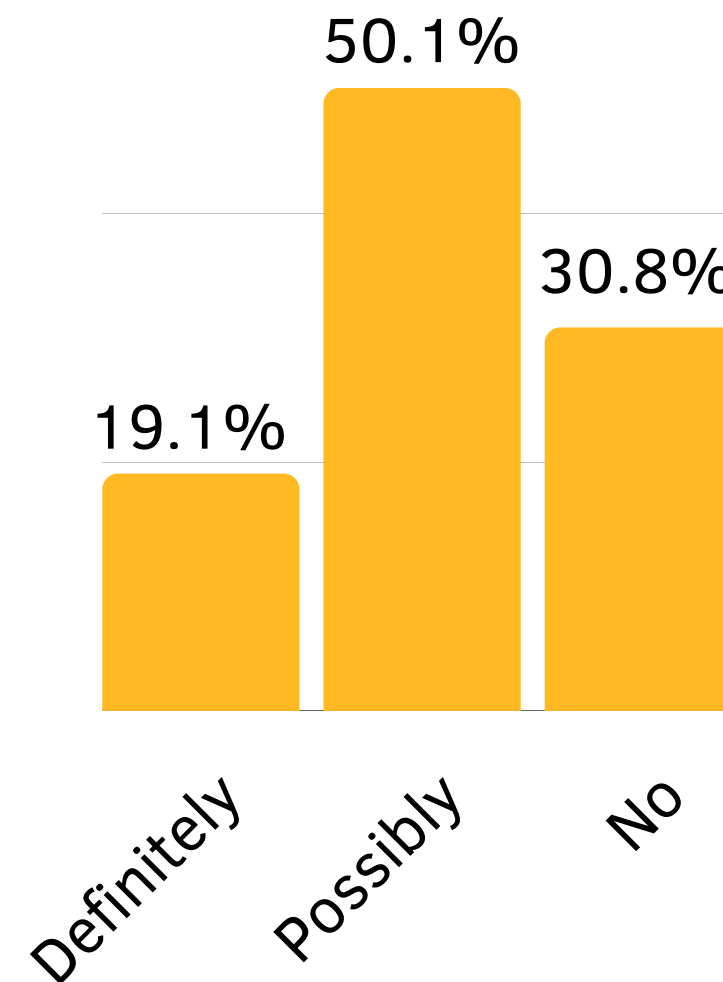
# Would employees quit to WFH?

Key insights uncovered by the machine learning model

Note:

- WFH (work from home)
- WBP (work from business premises)

Would you start looking for another job if you were guaranteed to get a WFH job?



## 21.5%

quit their job in the last 6 months





# Explore data on employee work arrangement expectations with machine learning

A machine learning model analyzes proprietary survey data from American employees, leading to key insights for workforce planning and decision-making.





# Advantages of using a machine learning model

Over traditional methods of studying employee engagement

## **More effective**

Data at this scale corresponds to a diverse workforce.

## **More efficient**

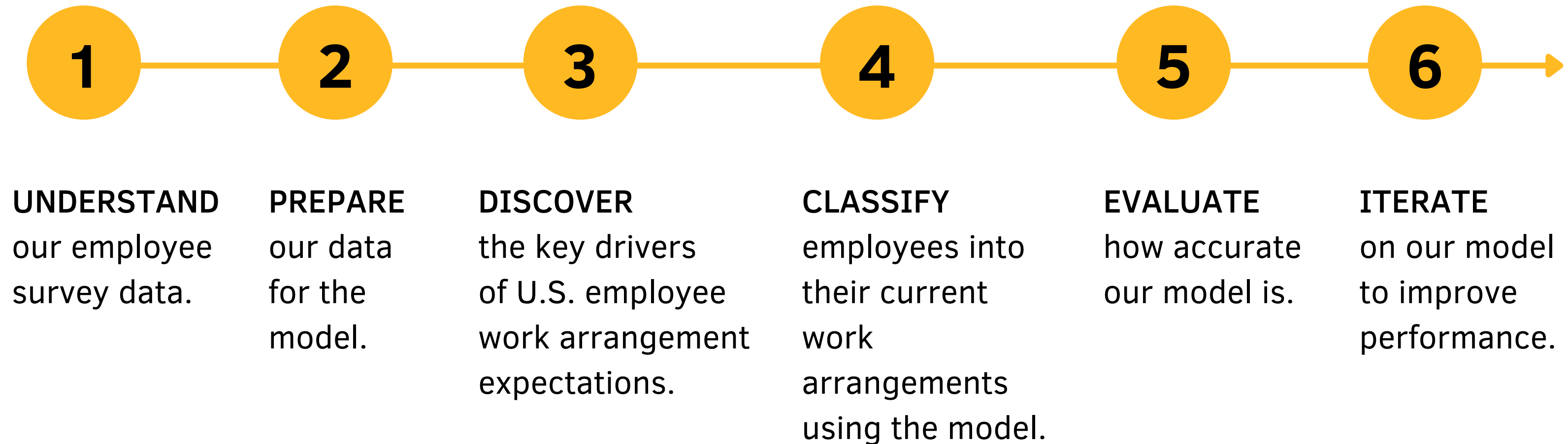
This approach uses less time and resources.

## **More objective**

This model balances the natural subjectivity and bias inherent in decision-making.

# How was this model created?

A multi-step approach towards our insights



# Where is this employee data from?



Proprietary data from  
the Survey of Working  
Arrangements and Attitudes

## **56,000+ respondents**

U.S. residents aged 20 to 64 years old who  
made  $\geq$ \$10,000 in 2019

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## **July 2021-June 2022**

When respondents answered the survey  
(3,000 - 5,000 respondents monthly)

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## **Featured by news outlets**

Covered by the Wall Street Journal, New  
York Times, Financial Times, NPR,  
Bloomberg, and The Times (to name a few)



# How do we mitigate our model's risks?

Taking into account our data source and model's assumptions and limitations

**Potential errors in survey answers are reduced.**

Respondents' attention was monitored during the survey.

**Respondents are not duplicates of each other.**

Though respondents answer in batches, they are different respondents each month.

**Employee attitudes to work arrangements are likely to evolve.**

Changing attitudes to the Future of Work must be monitored to adjust the model accordingly.

**Insights represent American employees overall.**

Some questions were not asked to every respondent, but we assume the trends observed apply to all respondents.

# Key takeaways

- Employee turnover is expected to increase as we shift to the Future of Work.
- Incorporating employee input in workforce planning mitigates this.
- Key drivers behind employees' workplace arrangements include efficiency experienced during WFH and employer location and size.
- This machine learning model approach is an efficient and effective way to gain insight on employees for decision-making.





# Appendix

Technical specifications of the model build, detailed comparison of various model options, and additional statistics





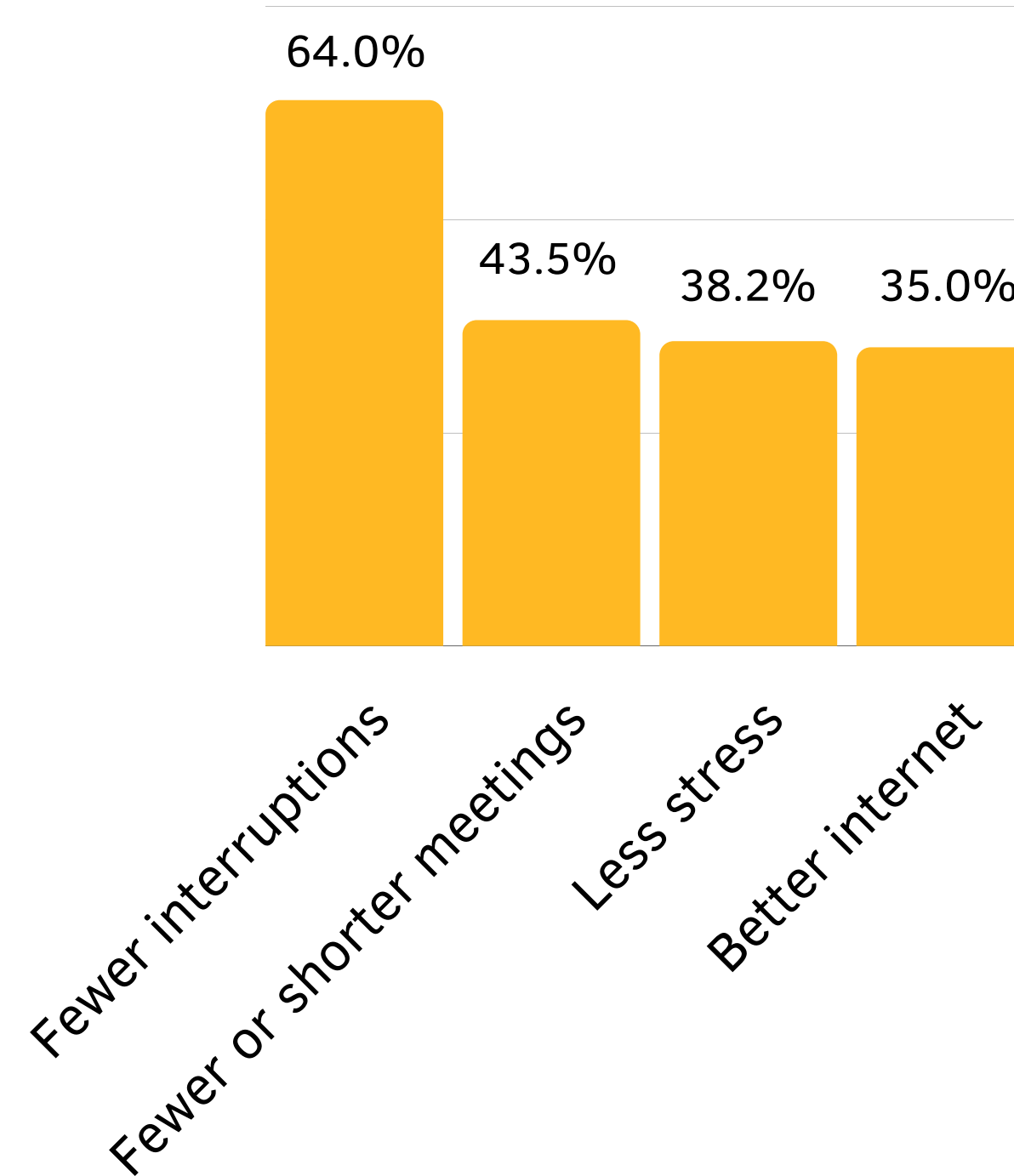
# Efficiency of WFH

Key insights uncovered by  
the machine learning model

Note:

- WFH (work from home)
- WBP (work from business premises)

Apart from commuting, employees  
are more efficient WFH because...



## 24.0%

say they are at least  
35% more efficient  
WFH during COVID  
than pre-pandemic  
in office

## 50.4%

say they are less  
efficient WFH  
because many tasks  
cannot be done  
remotely



# Objectives answered by the model



My aims when  
creating this model

## What are the biggest contributing drivers behind U.S. employees' work arrangement expectations, as supported by data?

This will be answered by exploring the data  
collected by economists for the SWAA survey  
([Barrero et al., 2022](#)).

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## Who is back in office, who isn't?

Based on the drivers discovered, a model will be  
created to classify if an American resident is  
working in business premises (in-office), working  
from home, or not currently working.

# Key Drivers of The Model

By descending order of importance with description of the corresponding survey question

logpop_den_job_current	Log(Population density of the ZIP code of current residence)
workhours_duringCOVID	Hours worked per week at the time of the survey (during COVID) -- if currently working, otherwise missing
wfhcovid_ever	100 x 1(Ever WFH during COVID)
work_computer_pct	When working, what percentage of the time are you using a laptop or desktop computer?
date	Date when respondents answered the survey (Month and Year)
workhours_preCOVID	Hours worked per week pre-COVID
wfh_eff_COVID_quant	How efficient are you WFH during COVID, relative to on business premises before COVID (%)
hourly_wage	Hourly wage = (2019 income)/(pre-COVID weekly work hours * 50 weeks per year)
commutetime_quant	Length of commute (in minutes)
drivealone_current_pct	Driving alone: percent of commuting trips currently
nocommute_current_pct	Do not commute currently (0 to 100)
employer_sizecat	Counting all locations where your primary employer operates, what is the total number of persons who work for your employer?
uploadspeed	Internet upload speed from speed test. Winsorized at the 1st and 90th percentiles within each category from `internet_quality` variable

# Key Drivers of The Model

By order of importance with corresponding survey question

downloadspeed	Internet download speed from speed test. Winsorized at the 1st and 90th percentiles within each category from `internet_quality' variable
work_industry	Industry of their current or most recent job
worktime_nonremoteable_pct	What percentage of your total working time do you usually spend on tasks that cannot be done remotely?
worktime_remoteable_pct	What percentage of your total working time do you usually spend on tasks that can be done remotely?
occupation_clean	Occupation of respondent (prepared for data use)
extratime_1stjob	Percent of commute time savings spent working on primary or current job
wfh_interviewing	Has working from home made it harder or easier to interview for prospective jobs?
groomtime_commute	How much time do you spend on grooming and getting ready for work when you commute to your employer's or client's worksite?
self_employment	Which of the following best describes your employment situation?
extratime_2ndjob	Percent of commute time savings spent on a second or new secondary job
extratime_indoorleisure	Percent of commute time savings spent on leisure indoors (e.g. reading, watching TV and movies)



# Information On The Data (19 variables)

Build statistics of the dataset with 19 variables

```
Build Statistics
logpop_den_job_current workhours_duringCOVID wfhcovid_ever \
count 37842.000000 43910.000000 56062.000000
mean 7.480030 32.631200 67.619778
std 2.020219 14.880027 46.792975
min 2.316244 0.000000 0.000000
25% 6.150221 25.000000 0.000000
50% 7.701000 36.000000 100.000000
75% 8.717586 40.000000 100.000000
max 11.453425 70.000000 100.000000
```

```
work_computer_pct workhours_preCOVID wfh_eff_COVID_quant \
count 10304.000000 56062.000000 37596.000000
mean 59.202340 32.464183 10.812054
std 33.078866 16.329965 17.871907
min 0.000000 0.000000 -40.000000
25% 30.000000 25.000000 0.000000
50% 60.000000 40.000000 7.500000
75% 90.000000 40.000000 20.000000
max 100.000000 69.000000 40.000000
```

```
hourly_wage commutetime_quant drivealone_current_pct \
count 52584.000000 56062.000000 33587.000000
mean 143.003253 25.942439 52.290976
std 556.173427 23.914240 43.701732
min 1.000000 -20.000000 0.000000
25% 18.000000 10.000000 10.000000
50% 34.375000 20.000000 50.000000
75% 81.286337 32.500000 100.000000
max 20000.000000 120.000000 100.000000
```

```
nocommute_current_pct employer_sizecat uploadspeed downloadspeed \
count 33587.000000 38339.000000 47230.000000 49926.000000
mean 14.472862 3.699418 79.695911 104.835637
std 35.183225 1.308189 99.370402 120.072471
min 0.000000 1.000000 0.000000 0.000000
25% 0.000000 3.000000 10.000000 19.219999
50% 0.000000 4.000000 36.674999 50.000000
75% 0.000000 5.000000 100.000000 147.884993
max 100.000000 5.000000 467.000000 460.000000
```

```
work_industry worktime_nonremoteable_pct worktime_remoteable_pct \
count 54775.000000 7011.000000 17654.000000
mean 8.282136 53.448153 50.339980
std 4.305827 37.208408 36.563067
min 1.000000 0.000000 0.000000
25% 5.000000 20.000000 16.000000
50% 7.000000 50.000000 50.000000
75% 11.000000 100.000000 85.000000
max 18.000000 100.000000 100.000000
```

```
occupation_clean extratime_1stjob workstatus_current
count 54190.000000 37909.000000 56062.000000
mean 7.028954 25.260624 1.800810
std 2.518534 26.534263 0.770094
min 1.000000 0.000000 1.000000
25% 5.000000 9.000000 1.000000
50% 8.000000 20.000000 2.000000
75% 9.000000 35.000000 2.000000
max 12.000000 100.000000 3.000000
```

Median of the variables

```
date logpop_den_job_current workhours_duringCOVID wfhcovid_ever \
0 2022-06-01 10.364245 40.0 100
```

```
work_computer_pct workhours_preCOVID wfh_eff_COVID_quant hourly_wage \
0 100.0 40 0.0 17.5
```

```
commutetime_quant drivealone_current_pct nocommute_current_pct \
0 30.0 100.0 0.0
```

```
employer_sizecat uploadspeed downloadspeed work_industry \
0 5.0 100.0 100.0 6.0
```

```
worktime_nonremoteable_pct worktime_remoteable_pct occupation_clean \
0 100.0 100.0 8.0
```

```
extratime_1stjob workstatus_current
0 0.0 1
```



# Information On The Data (24 variables)

Build statistics of the dataset with 24 variables

Build Statistics								
	logpop_den_job_current	workhours_duringCOVID	wfhcovid_ever	\	count	work_industry	worktime_nonremoteable_pct	worktime_remoteable_pct
count	37842.000000	43910.000000	56062.000000		54775.000000	7011.000000	17654.000000	
mean	7.480030	32.631200	67.619778		8.282136	53.448153	50.339980	
std	2.020219	14.880027	46.792975		4.305827	37.208408	36.563067	
min	2.316244	0.000000	0.000000		1.000000	0.000000	0.000000	
25%	6.150221	25.000000	0.000000		5.000000	20.000000	16.000000	
50%	7.701000	36.000000	100.000000		7.000000	50.000000	50.000000	
75%	8.717586	40.000000	100.000000		11.000000	100.000000	85.000000	
max	11.453425	70.000000	100.000000		18.000000	100.000000	100.000000	
	work_computer_pct	workhours_preCOVID	wfh_eff_COVID_quant	\	count	occupation_clean	extratime_1stjob	wfh_interviewing
count	10304.000000	56062.000000	37596.000000		54190.000000	37909.000000	8917.000000	
mean	59.202340	32.464183	10.812054		7.028954	25.260624	1.919928	
std	33.078866	16.329965	17.871907		2.518534	26.534263	1.084726	
min	0.000000	0.000000	-40.000000		1.000000	0.000000	1.000000	
25%	30.000000	25.000000	0.000000		5.000000	9.000000	1.000000	
50%	60.000000	40.000000	7.500000		8.000000	20.000000	1.000000	
75%	90.000000	40.000000	20.000000		9.000000	35.000000	3.000000	
max	100.000000	69.000000	40.000000		12.000000	100.000000	4.000000	
	hourly_wage	commutetime_quant	drivealone_current_pct	\	count	groomtime_commute	self_employment	extratime_2ndjob
count	52584.000000	56062.000000	33587.000000		39158.000000	46694.000000	37909.000000	
mean	143.003253	25.942439	52.290976		26.432300	1.367263	9.264502	
std	556.173427	23.914240	43.701732		20.901037	0.761533	13.910620	
min	1.000000	-20.000000	0.000000		0.000000	1.000000	0.000000	
25%	18.000000	10.000000	10.000000		10.000000	1.000000	0.000000	
50%	34.375000	20.000000	50.000000		23.000000	1.000000	5.000000	
75%	81.286337	32.500000	100.000000		35.000000	1.000000	15.000000	
max	20000.000000	120.000000	100.000000		90.000000	4.000000	100.000000	
	nocommute_current_pct	employer_sizecat	uploadspeed	downloadspeak \	count	extratime_indoorleisure	workstatus_current	
count	33587.000000	38339.000000	47230.000000	49926.000000	37909.000000	56062.000000		
mean	14.472862	3.699418	79.695911	104.835637	16.479332	1.800810		
std	35.183225	1.308189	99.370402	120.072471	18.193605	0.770094		
min	0.000000	1.000000	0.000000	0.000000	0.000000	1.000000		
25%	0.000000	3.000000	10.000000	19.219999	5.000000	1.000000		
50%	0.000000	4.000000	36.674999	50.000000	10.000000	2.000000		
75%	0.000000	5.000000	100.000000	147.884993	20.000000	2.000000		
max	100.000000	5.000000	467.000000	460.000000	100.000000	3.000000		

# Information On The Data (24 variables)

Build statistics of the dataset with 24 variables

Median of the variables

	date	logpop_den_job_current	workhours_duringCOVID	wfhcovid_ever	\
0	2022-06-01	10.364245	40.0	100	
	work_computer_pct	workhours_preCOVID	wfh_eff_COVID_quant	hourly_wage	\
0	100.0	40	0.0	17.5	
	commutetime_quant	drivealone_current_pct	nocommute_current_pct	\	
0	30.0	100.0	0.0		
	employer_sizecat	uploadspeed	downloadspeak	work_industry	\
0	5.0	100.0	100.0	6.0	
	worktime_nonremoteable_pct	worktime_remoteable_pct	occupation_clean	\	
0	100.0	100.0	8.0		
	extratime_1stjob	wfh_interviewing	groomtime_commute	self_employment	\
0	0.0	1.0	30.0	1.0	
	extratime_2ndjob	extratime_indoorleisure	workstatus_current		
0	0.0	10.0	1		



# Model Results: Random Forest

Important variables and statistics measuring accuracy

*Note: This model used 19 variables.*

	feature	importance	std
2	day	0.000000	0.000000
0	year	0.005246	0.001647
12	nocommute_current_pct	0.013089	0.008381
17	worktime_nonremoteable_pct	0.015221	0.005037
6	work_computer_pct	0.021484	0.006795
18	worktime_remoteable_pct	0.025612	0.008610
19	occupation_clean	0.026264	0.002812
1	month	0.027081	0.004048
11	drivealone_current_pct	0.030892	0.013315
16	work_industry	0.030896	0.002115
13	employer_sizecat	0.034346	0.014609
14	uploadspeed	0.037007	0.002155
15	downloadspeak	0.038049	0.002365
10	commutetime_quant	0.052709	0.017991
9	hourly_wage	0.055734	0.015613
7	workhours_preCOVID	0.055838	0.027336
8	wfh_eff_COVID_quant	0.057470	0.029265
20	extratime_1stjob	0.059618	0.034027
5	wfhcovid_ever	0.089665	0.047310
4	workhours_duringCOVID	0.109852	0.026754
3	logpop_den_job_current	0.213928	0.033583

Multi-label Confusion Matrix:

```
[[[ 8847   995]
  [ 2076  4901]]
```

```
[[ 8636  1988]
  [ 1062  5133]]
```

```
[[12963   209]
  [   54 3593]]]
```

Classification Report:

	precision	recall	f1-score	support
1	0.83	0.70	0.76	6977
2	0.72	0.83	0.77	6195
3	0.95	0.99	0.96	3647
accuracy			0.81	16819
macro avg	0.83	0.84	0.83	16819
weighted avg	0.82	0.81	0.81	16819

Accuracy: 0.81021463820679

Mean Absolute Error: 0.19822819430406088

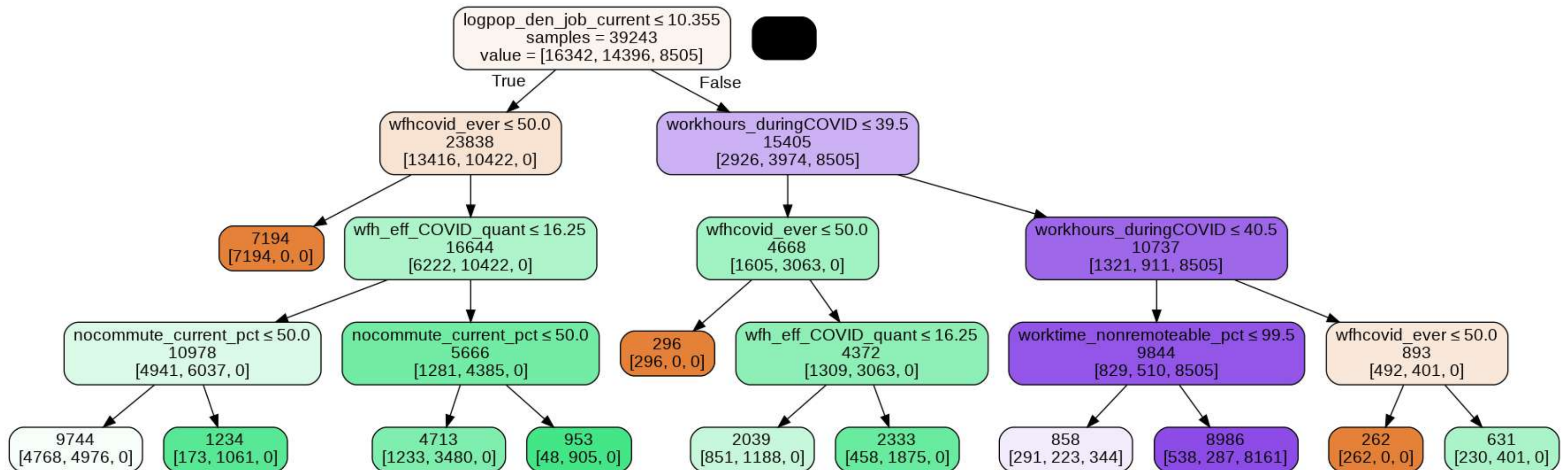
Mean Squared Error: 0.21511385932576252

Root Mean Squared Error: 0.4638036861925124

# Model Results: Decision Tree

The first three splits show the main deciding variables.

*Note: This model used 19 variables.*





# Model Results: Decision Tree

Important variables and statistics measuring accuracy

*Note: This model used 19 variables.*

Multi-label Confusion Matrix:					
[[[ 9842     0]					
[ 3691 3286]]					
[[ 7261 3363]					
[ 235 5960]]					
[[12609    563]					
[     0 3647]]]					
Classification Report:					
	precision	recall	f1-score	support	
1	1.00	0.47	0.64	6977	
2	0.64	0.96	0.77	6195	
3	0.87	1.00	0.93	3647	
accuracy			0.77	16819	
macro avg	0.84	0.81	0.78	16819	
weighted avg	0.84	0.77	0.75	16819	
Accuracy: 0.7665735180450681					
Mean Absolute Error: 0.25292823592365776					
Mean Squared Error: 0.2919317438611095					
Root Mean Squared Error: 0.5403070829270236					

# Model Results: Random Forest

Important variables and statistics measuring accuracy

*Note: This model used 24 variables.*

	feature	importance	std
2	day	0.000000	0.000000
0	year	0.005246	0.001647
12	nocommute_current_pct	0.013089	0.008381
17	worktime_nonremoteable_pct	0.015221	0.005037
6	work_computer_pct	0.021484	0.006795
18	worktime_remoteable_pct	0.025612	0.008610
19	occupation_clean	0.026264	0.002812
1	month	0.027081	0.004048
11	drivealone_current_pct	0.030892	0.013315
16	work_industry	0.030896	0.002115
13	employer_sizecat	0.034346	0.014609
14	uploadspeed	0.037007	0.002155
15	downloadspeak	0.038049	0.002365
10	commutetime_quant	0.052709	0.017991
9	hourly_wage	0.055734	0.015613
7	workhours_preCOVID	0.055838	0.027336
8	wfh_eff_COVID_quant	0.057470	0.029265
20	extratime_1stjob	0.059618	0.034027
5	wfhcovid_ever	0.089665	0.047310
4	workhours_duringCOVID	0.109852	0.026754
3	logpop_den_job_current	0.213928	0.033583

Multi-label Confusion Matrix:

```
[[[ 8887   955]
 [ 2094  4883]]
```

```
[[ 8608  2016]
 [ 1010  5185]]
```

```
[[12986   186]
 [   53  3594]]]
```

Classification Report:

	precision	recall	f1-score	support
1	0.84	0.70	0.76	6977
2	0.72	0.84	0.77	6195
3	0.95	0.99	0.97	3647
accuracy			0.81	16819
macro avg	0.84	0.84	0.83	16819
weighted avg	0.82	0.81	0.81	16819

Accuracy: 0.8122956180510137

Mean Absolute Error: 0.19549319222308104

Mean Squared Error: 0.2110708127712706

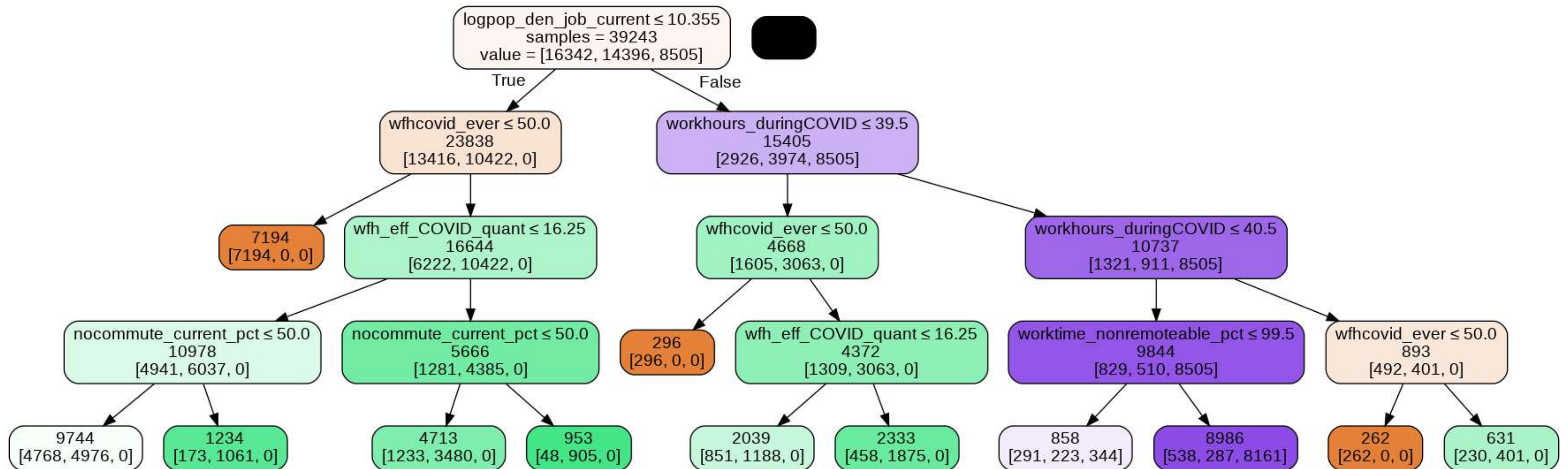
Root Mean Squared Error: 0.4594244364106796



# Model Results: Decision Tree

The first three splits show the main deciding variables.

*Note: This model used 24 variables.*





# Model Results: Decision Tree

Important variables and statistics measuring accuracy

*Note: This model used 24 variables, but accuracy is the same with the tree with 19 variables.*

```
Multi-label Confusion Matrix:
[[[ 9842    0]
 [ 3691 3286]]

 [[ 7261 3363]
 [  235 5960]]

 [[12609   563]
 [    0 3647]]]
Classification Report:
              precision    recall  f1-score   support

         1         1.00      0.47      0.64       6977
         2         0.64      0.96      0.77       6195
         3         0.87      1.00      0.93       3647

 accuracy          0.77       16819
 macro avg         0.84      0.81      0.78       16819
weighted avg         0.84      0.77      0.75       16819

Accuracy: 0.7665735180450681
Mean Absolute Error: 0.25292823592365776
Mean Squared Error: 0.2919317438611095
Root Mean Squared Error: 0.5403070829270236
```