Making Time Count

A Time Use Accelerometer Study in Malawi

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4th MASS workshop Manchester

22-23 June 2023

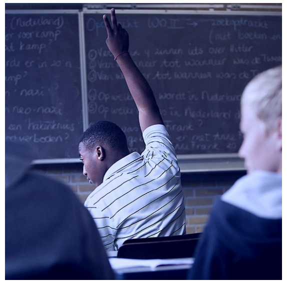
CENTERDATA
research institute

LISS PANEL

Centerdata
An independent research institute located on the campus of Tilburg University

TILBURG UNIVERSITY

Our mission
Provide insights for science, society, and policy



For whom
Academics,
Policy makers,
Governmental institutes

Europese Commissie

Centraal Bureau voor de Statistiek

European Social Survey

SHARE
Survey of Health, Ageing and Retirement in Europe
50+ in Europe

Time use in Malawi

THE WORLD BANK

Living Standard Measurement Study

LSMS
Living Standards Measurement Study

- Face-to-face time-use survey in rural areas
- 24 hour recall-based diary, weekly visits
- Very costly

Goal: alternative data collection for LSMS

- Physical activity trackers (ActiGraph)
- 14 consecutive days, N=415 (15+years)
- Cheaper, more accurate and objective data

Human Activity Recognition (HAR)

Farming

Social activities

Fetching water

Hunting

Cooking

Working for wage

Research question

Can advances in machine learning be leveraged to accurately predict time use from physical activity sensor output collected as part of household surveys in low-income countries?

→ Can we predict time use activities from accelerometer data?

Two Types of Data

ActiGraph GT3X

measures acceleration

Time Use Survey

25 activities

MODULE : TIME ALLOCATION

PLEASE RECORD A LOG OF THE ACTIVITIES FOR THE INDIVIDUAL IN THE LAST COMPLETE 24 HOURS (STARTING YESTERDAY MORNING AT 4 AM, FINISHING 3:59 AM OF THE CURRENT DAY). THE TIME INTERVALS ARE MARKED IN 15 MIN INTERVALS. MARK ONE PRIMARY ACTIVITY FOR EACH TIME PERIOD BY ENTERING THE CORRESPONDING ACTIVITY CODE IN THE BOX. A SECONDARY ACTIVITY (OPTIONAL) CAN BE ENTERED IN CASE OF SIMULTANEOUS ACTIVITIES.

THIS FORM MUST BE ADMINISTERED TO THE **RESPONDENT HIMSELF/HERSELF** DURING THE **2ND AND 3RD VISITS** TO THE HOUSEHOLD.

Now I'd like to ask you about how you spent your time during the past 24 hours. We'll begin from yesterday morning, and continue through to this morning. This will be a detailed accounting. I'm interested in everything you did (i.e. resting, eating, personal care, work inside and outside the home, caring for children, cooking, shopping, socializing, etc.), even if it didn't take you much time.

	Night		Morning	Day								
	4:00	5:00	6:00	7:00	8:00	9:00	10:00	11:00	12:00	13:00	14:00	15:00
1. Primary Activity (WRITE ACTIVITY CODE)												
2. Secondary Activity (WRITE ACTIVITY CODE)												

	Day		Evening	Night								
	16:00	17:00	18:00	19:00	20:00	21:00	22:00	23:00	24:00	1:00	2:00	3:00
3. Primary Activity (WRITE ACTIVITY CODE)												
4. Secondary Activity (WRITE ACTIVITY CODE)												

ACTIVITY CODES

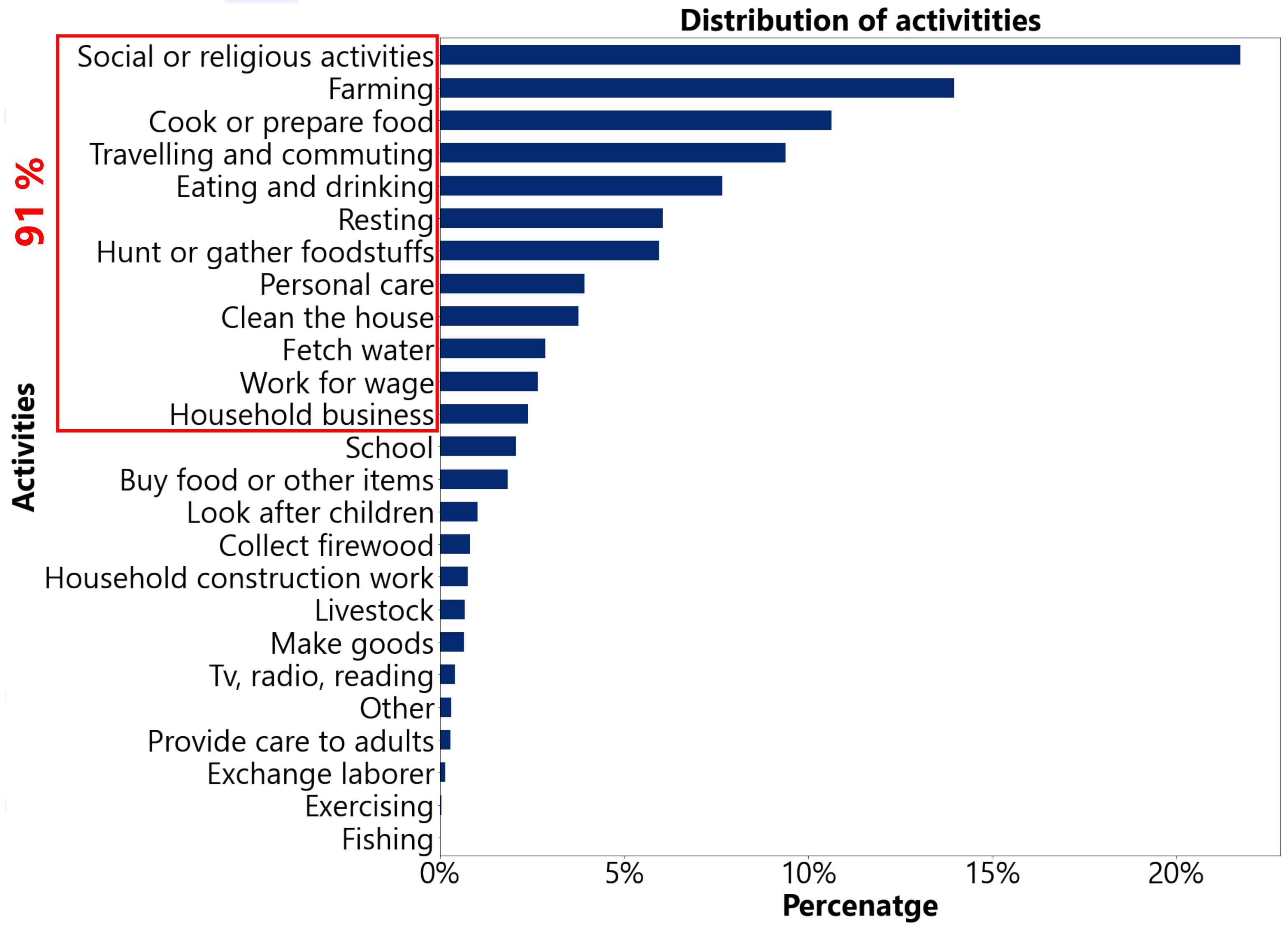
A.................Sleeping and resting
B....................Eating and drinking
C..........................Personal care
D............School (incl. homework)

E..........Work for a wage, salary, commission or in-kind payment (incl. ganyu, paid apprenticeships)
F.............Run, work or help in a non-agricultural and non-fishing household business
G...Work for other households free of charge as exchange laborer
H...Farming
I...Livestock
J...Fishing
K..Hunt or gather foodstuffs
L..........................Buy food or other items or obtain services
M...................Make goods (furniture, pottery, baskets, clothing)

N..........Cook or prepare food or drinks to preserve them
O...................Collect firewood or other natural products
P..................Fetch water from natural or public sources
Q.................................Clean the house, wash or iron
R..Household maintenance or own construction work (e.g. to renovate, extend or build the household's dwelling)
S...........Provide care or assistance to adults (18+ years)
T....................Look after children (17 years or younger)

U......Plan the household's finances or bills
V.....................Travelling and commuting
W....Watching TV/listening to radio/reading
X.......................................Exercising
Y...Social or religious activities and hobbies
Z ... .Other

Time use data



Building machine learning models

Predicting time use activities from the accelerometer data

Random Forest

XGBoost → best performance

Model building pipeline

Preprocessing

- Coupling accelerometer data with time-use data
- Enhancing with available background information

Data Cleaning

- Removal of non-wear time
- Excluding 2nd activities
- Time limit (4 am-10 pm)
- Discard correlated vars

Feature Engineering

- **39** features, i.e., **4** base features (X, Y, Z, Step), **31** derived features, **4** background (age, gender)

Model Building

- Activity selection
- Data balancing
- Normalizing
- Classification algorithms

Model Evaluation

- 75%/25% train/test split
- Accuracy, F_1-score, AUC
- Division: Young vs Old, Male vs Female

Predictive power

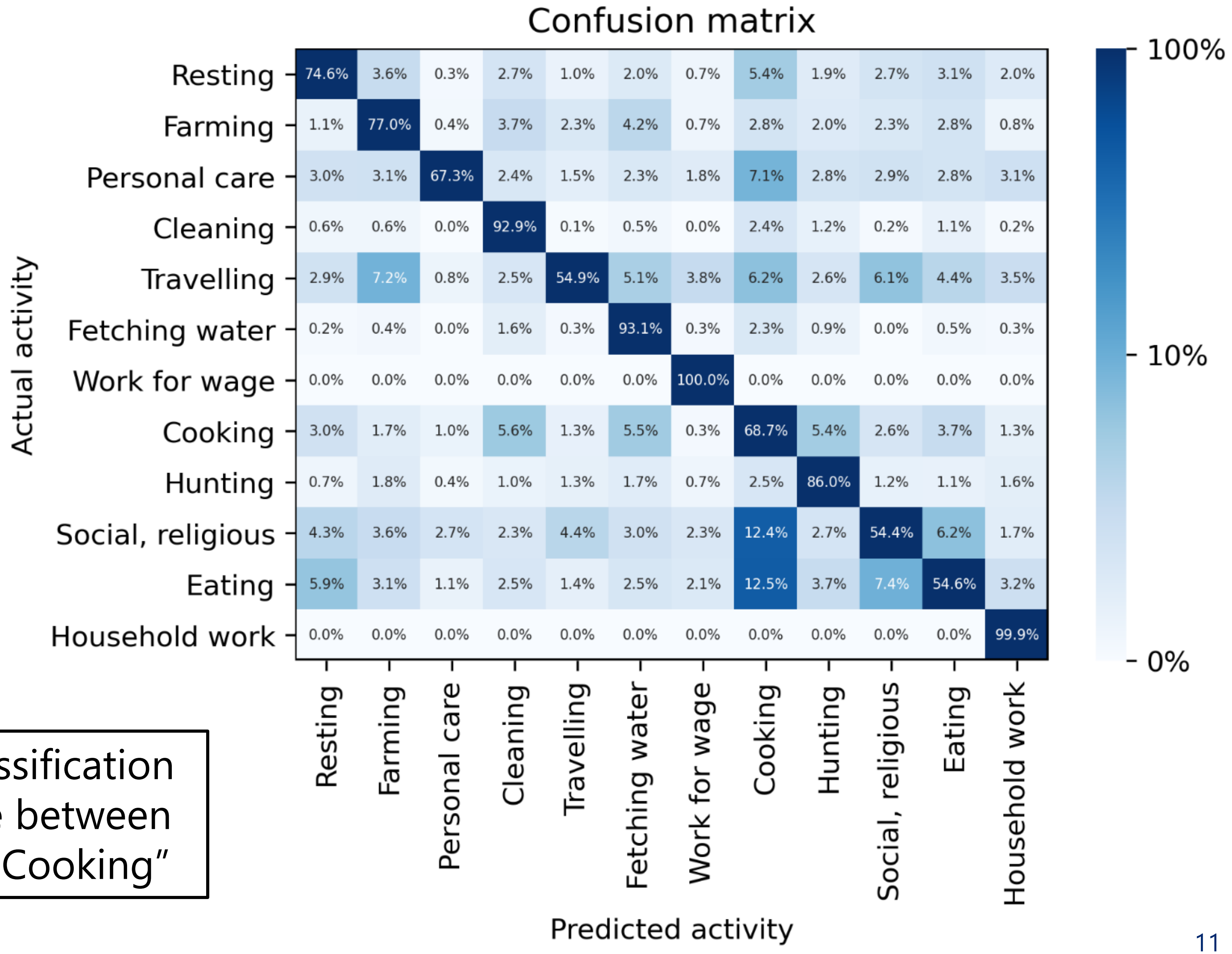
Activity	Set size	Participants	Precision	Recall	F_1-score
1. Social or religious activities and hobbies	2036	333	68 %	54 %	61 %
2. Farming	2036	199	75 %	77 %	76 %
3. Cook or prepare food or drinks	2036	239	56 %	69 %	62 %
4. Travelling and commuting	2036	316	80 %	55 %	65 %
5. Eating and drinking	2036	380	68 %	55 %	61 %
6. Resting	2036	234	77 %	75 %	76 %
7. Hunt or gather foodstuffs	2036	149	79 %	86 %	82 %
8. Personal care	2036	345	91 %	67 %	77 %
9. Clean the house, wash, or iron	2036	170	79 %	93 %	86 %
10. Fetch water	2036	179	78 %	93 %	85 %
11. Work for a wage or salary	2036	37	89 %	99 %	94 %
12. Running or working in household business	2036	40	85 %	99 %	92 %
Accuracy					**77 %**
Macro average F_1-score					**76 %**

A random guess has a prediction score of 100/12 = 8.3 %

Yes, we can predict activities with high accuracy

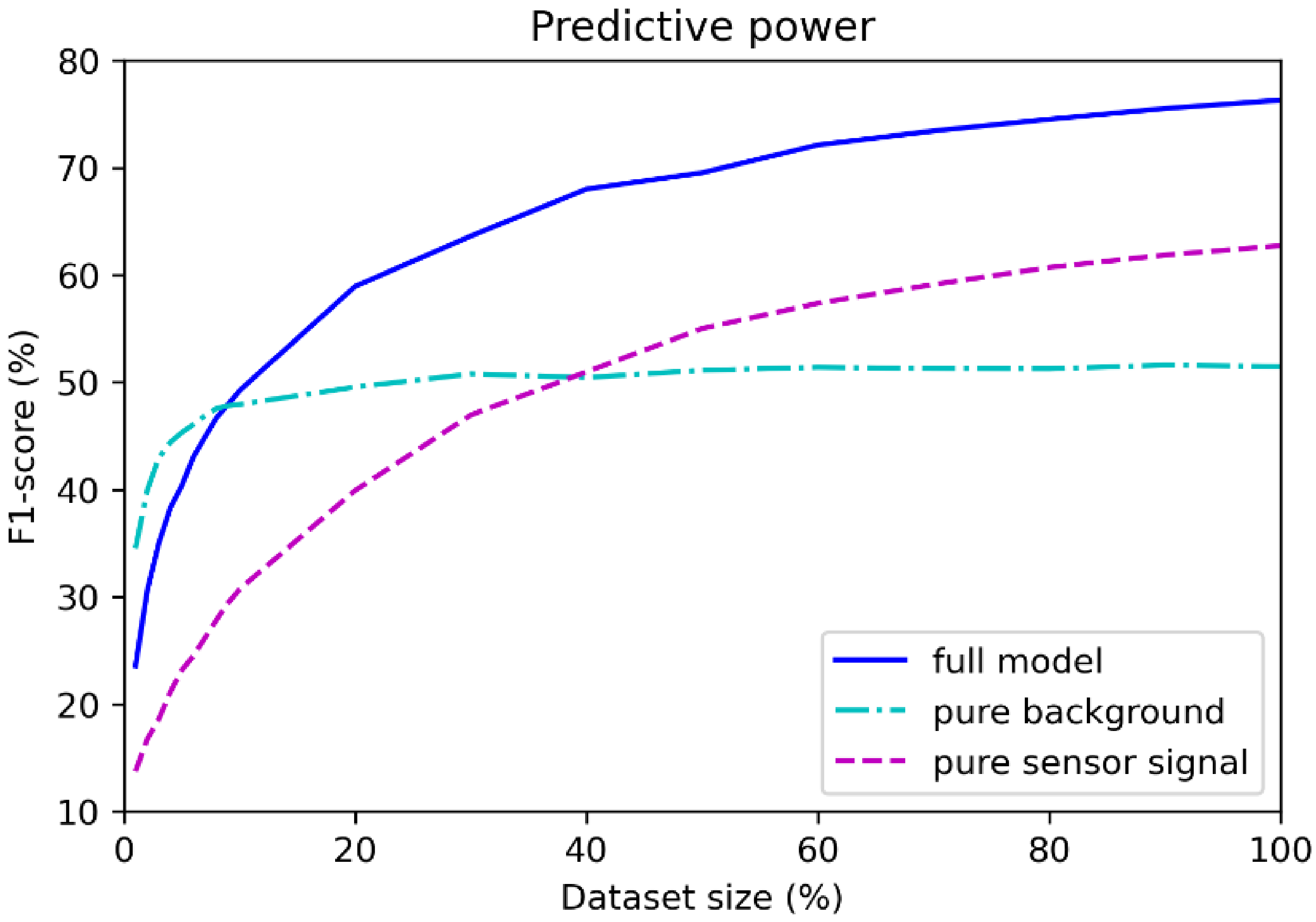
Confusion Matrix

A confusion matrix nicely highlights which misclassifications there are between predicted and actual activities



A clear misclassification is for example between “Eating” and “Cooking”

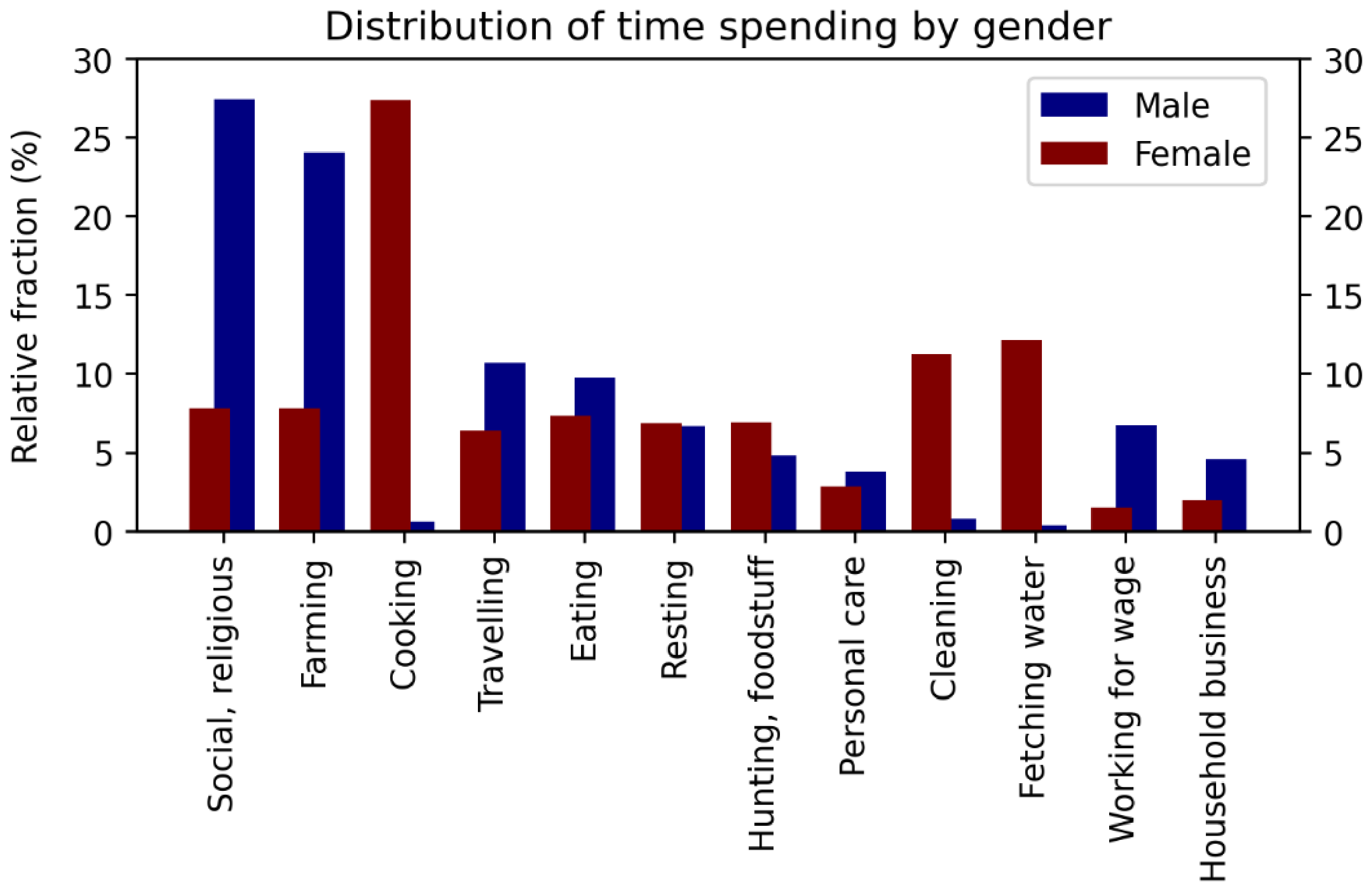
Influence of variables



Background variables are:
Gender
Age
Weight
Day of week
Time of day

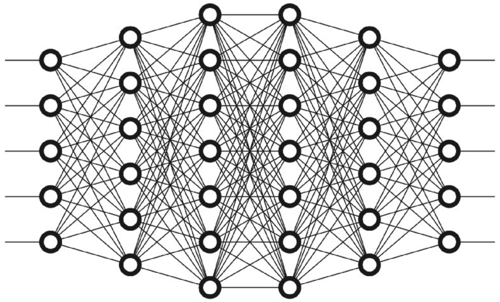
Background variables improve predictive power

Applying the model



What's Next

Can we do better and improve models?



New data collection in Malawi (2022/2023)

Improve data quality model prediction

- High-frequency sensor data (60 Hz)
- Larger sample size (N=1,440)
- More activities
- Two types of time use: 24h-recall & smartphone diary
- Deep learning models

- Activity pop-ups:
  - Type of food?
  - With whom?
  - Affect: how do you feel?

Experience sampling

Questions?

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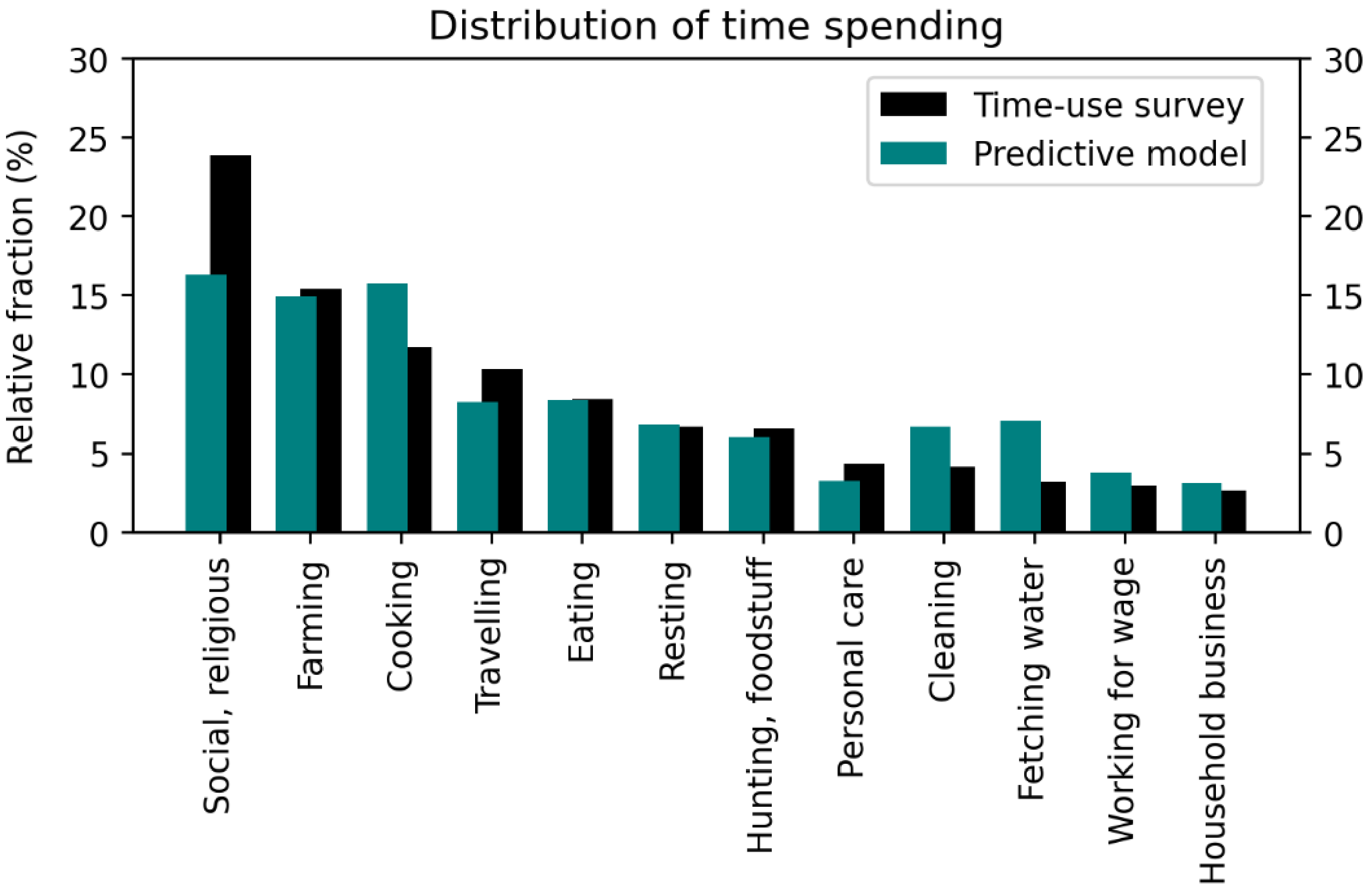
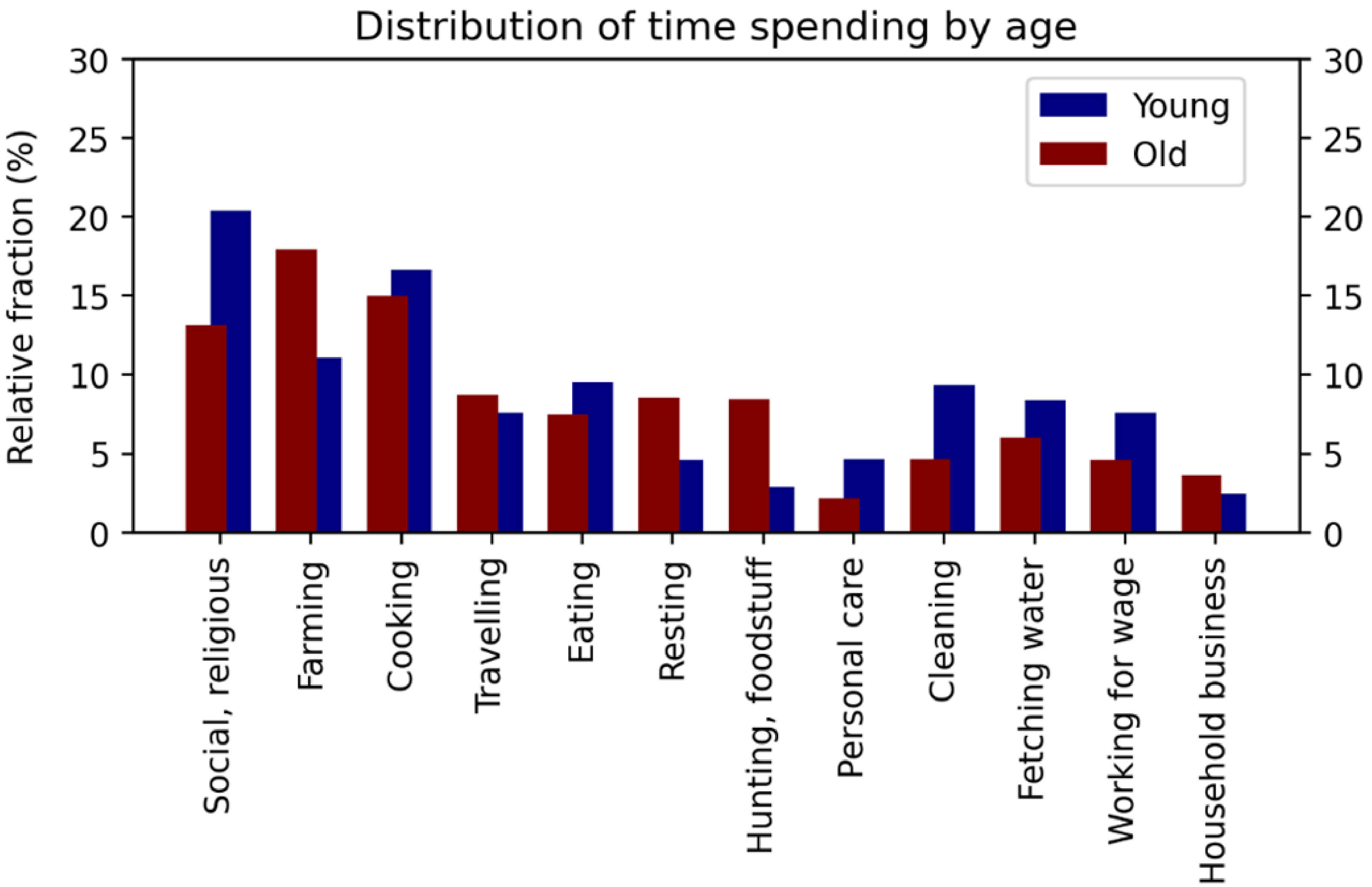
Validation



Distribution of time spending
Relative fraction (%)
30
25
20
15
10
5
0
Time-use survey
Predictive model
Social, religious
Farming
Cooking
Travelling
Eating
Resting
Hunting, foodstuff
Personal care
Cleaning
Fetching water
Working for wage
Household business

Applying the model



Zero Hunger Lab

UN Sustainable Development Goal 2 (SDG-2): Zero Hunger

Activity Recognition

Farming

Social activities

Fetching water

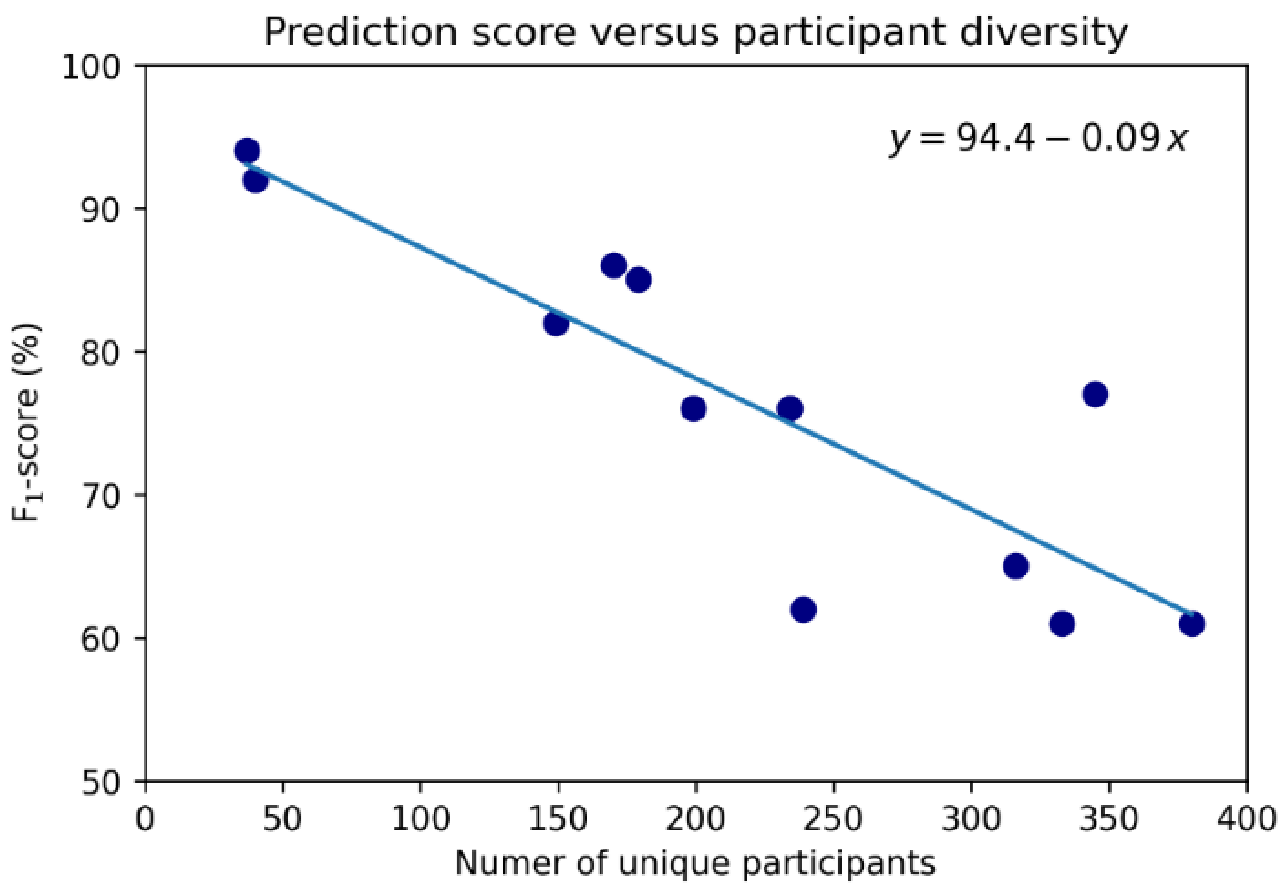
Human Activity Recognition (HAR)

↓

Time Use Activity Recognition (TAR)

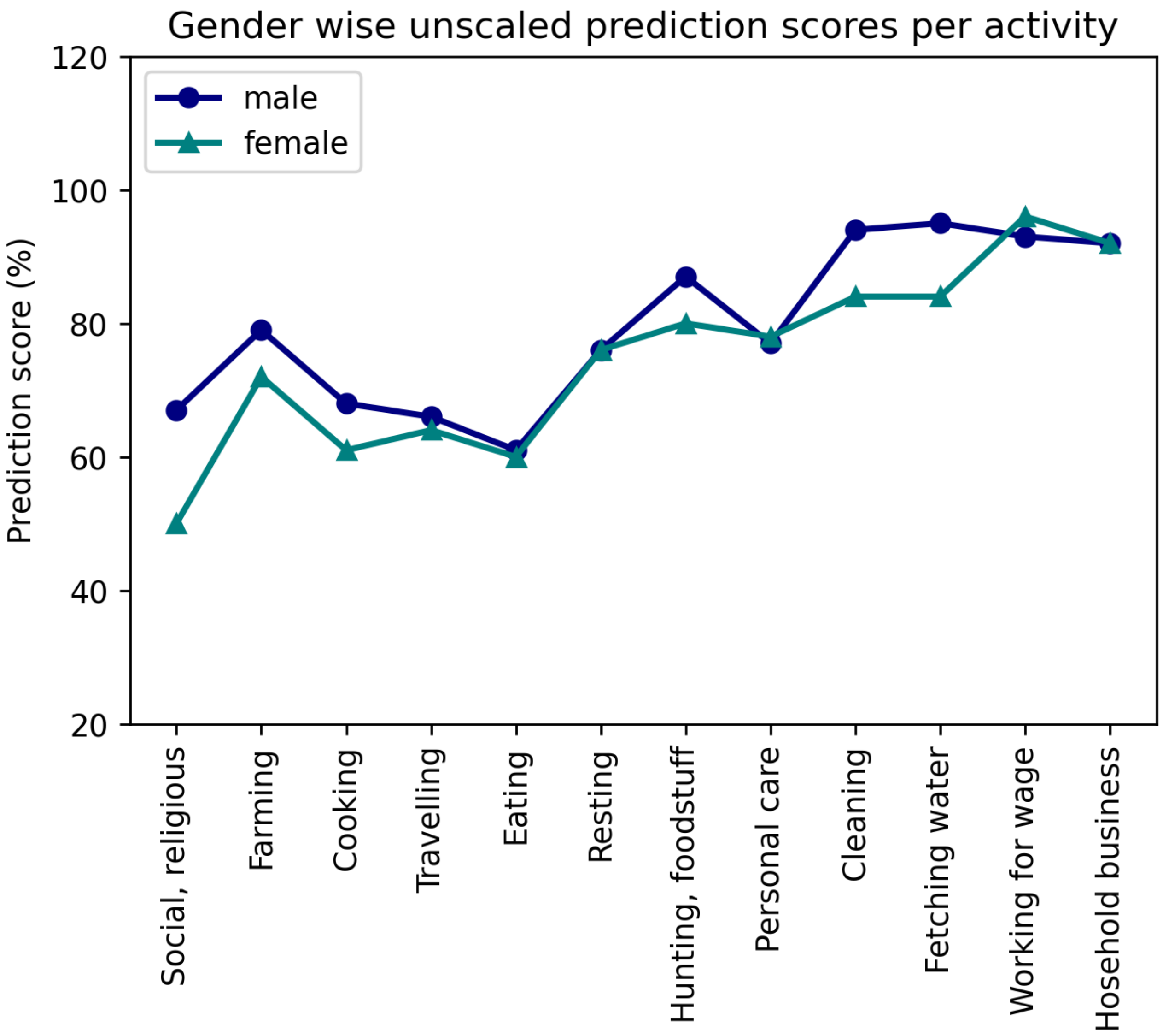
Resultaten

Generaliseerbaarheid model

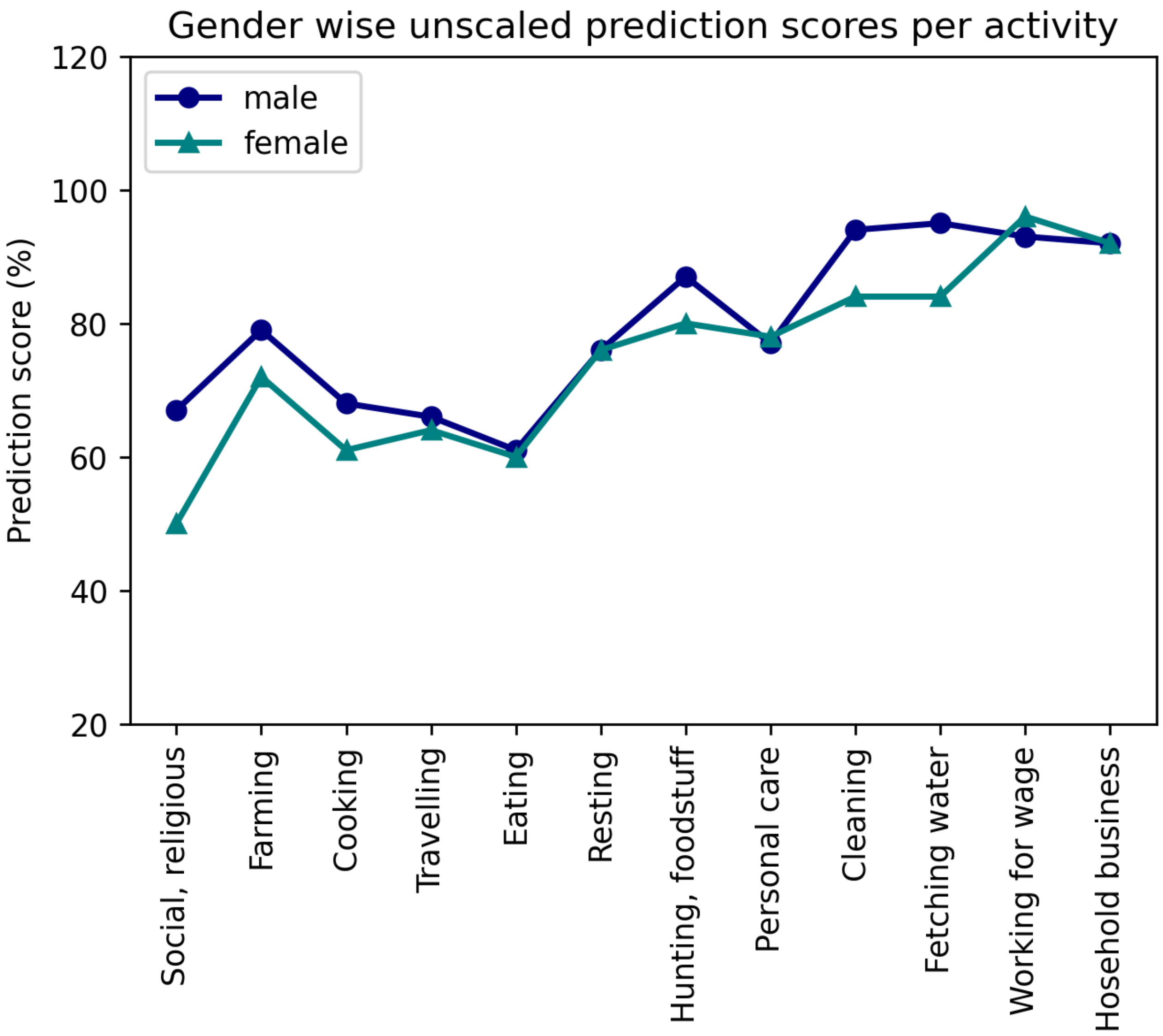


Er is een sterke afhankelijkheid tov het aantal participanten

Gender wise differences



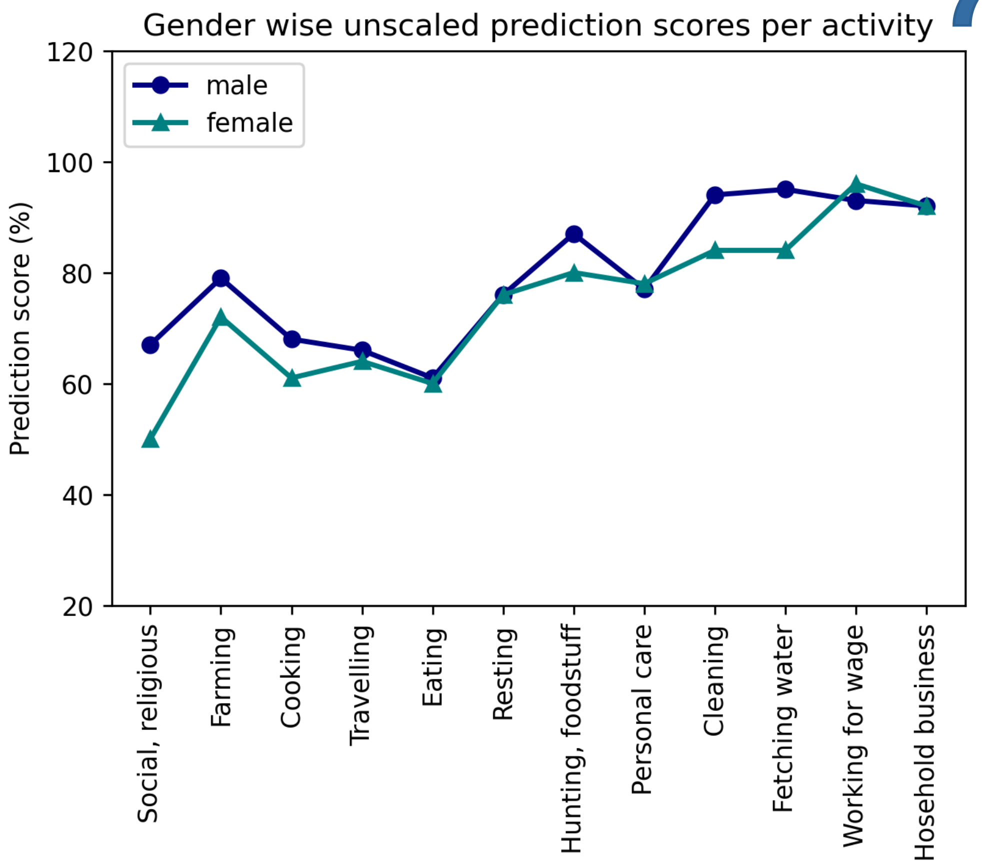
Gender wise differences

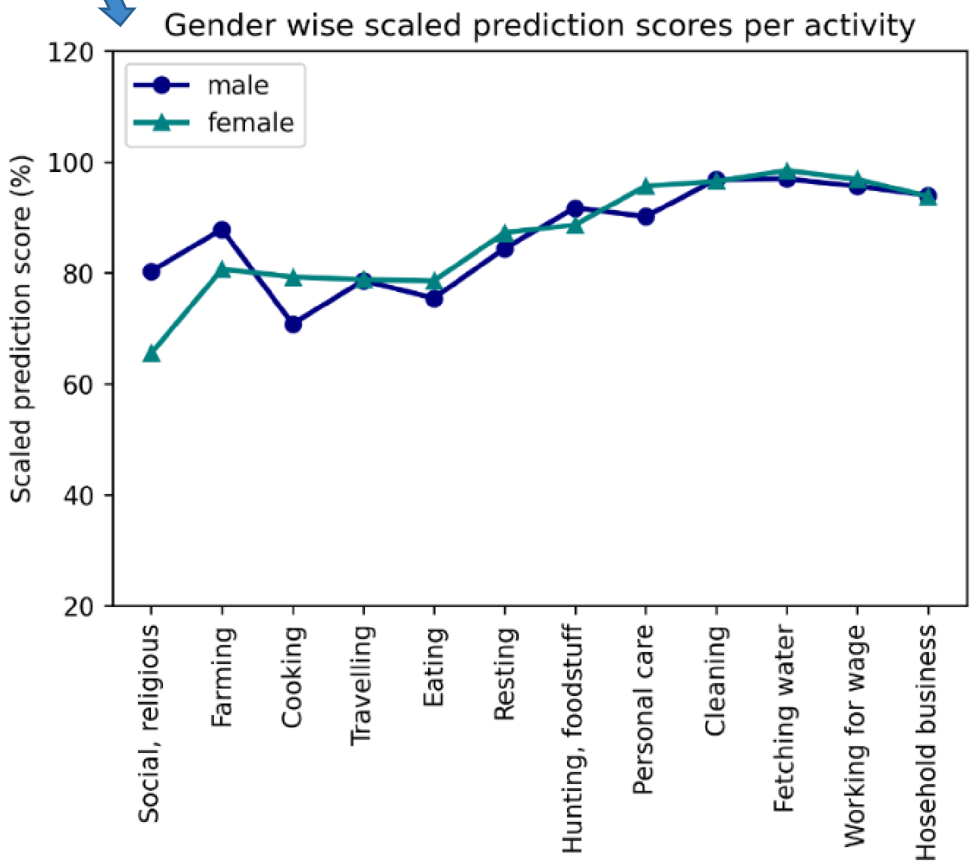


But there are underlying differences in the number of participants, especially male and female

Gender wise differences

$$Scaled\ score = F_1\ score\ + 9\% \times \frac{N\ participants}{100}$$





No significant differences in the predictions for men and women