Evaluation of a Personalized Method for Proactive Mind Wandering Reduction

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learner engagement

- our goal is to improve learning environments

- engagement is necessary for learning

mind wandering

- how to assess learner engagement?
  - consider behaviors that occur during disengagement

- mind wandering - attentional shifts away from the external stimuli towards internal thoughts
  - detrimental to learning
  - occurs frequently (40%)
  - hard to detect (internal)

reducing mind wandering

- how can mind wandering be reduced?

- reactive
  - employ mind wandering detectors and intervene when mind wandering is detected

- proactive
  - mindfulness training
  - tailoring the learning environment to the user

tailoring the learning environment

- 4 texts on research methods

- varied two aspects of the learning environment
  - task difficulty
  - task value

difficulty manipulation

modified versions of existing texts based on readability **(Graeser, McNamara, & Kulikowich, 2011)**

easy (FKGL = 9)

Over **100 years** ago there were **a lot of people** who believed that there was a horse that could answer questions **that people asked him.** The horse could even spell words and do **math**!

difficult (FKGL = 13)

Over **a century** ago there were **individuals** who believed that there was a horse that could answer questions; that it could even spell words and do **complex arithmetic**!

value manipulation

- if comprehension test performance was not at minimum threshold (i.e., 20%) had to stay and read more
- told value of text prior to each
- high value – questions about text worth three points on comprehension test
- low value – questions only worth one point

data collection

- auditory probes recorded mind wandering

- individual difference measures:

- general boredom
- prior knowledge
- reading fluency
- reading comprehension
- scholastic aptitude
- academic boredom (overwhelmed)
- academic boredom (underwhelmed)
- topic interest (research methods)

data analysis

1. supervised machine learning

2. comparison of methods

machine learning to predict the ideal learning conditions

model building

- predict learning condition with least mind wandering using individual difference measures as features
- built models using various algorithms implemented in weka
- leave one participant out validation
  - n models

model building (parameters)

- classification task
  - difficulty x value
  - value
  - difficulty
- difference in mind wandering
  - .5 SD (N=98)
  - .25 SD (N=141)
  - 0 SD (N=187)

models used

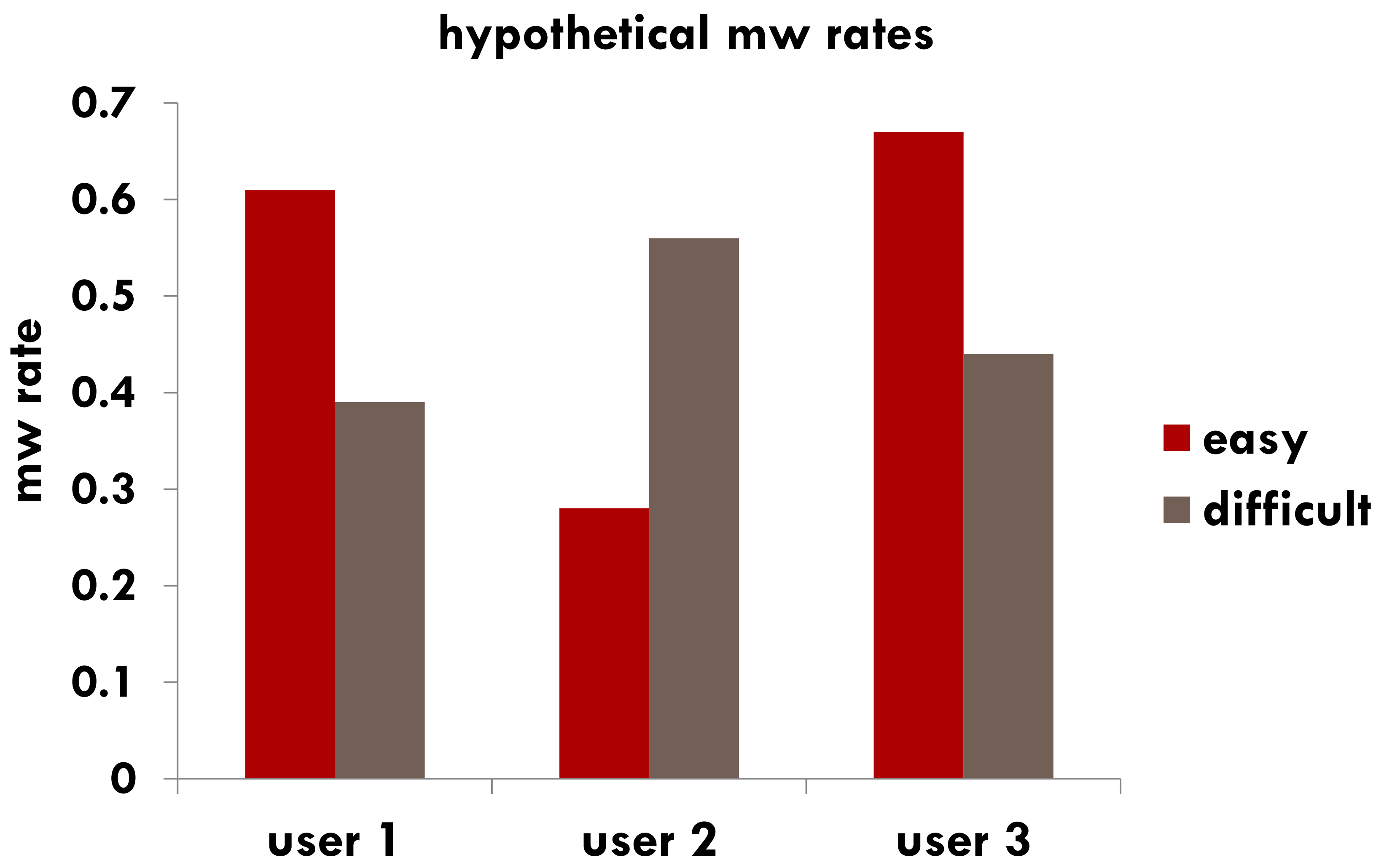
	models				
	classifier	**sd's**	**kappa**	**accuracy**	**expected accuracy**
difficulty x value	decision stump	.25	.11	34%	26%
value	logistic	.25	.16	59%	51%
difficulty	decision stump	.5	.24	64%	53%

comparison analysis of different methods to choose the optimal condition

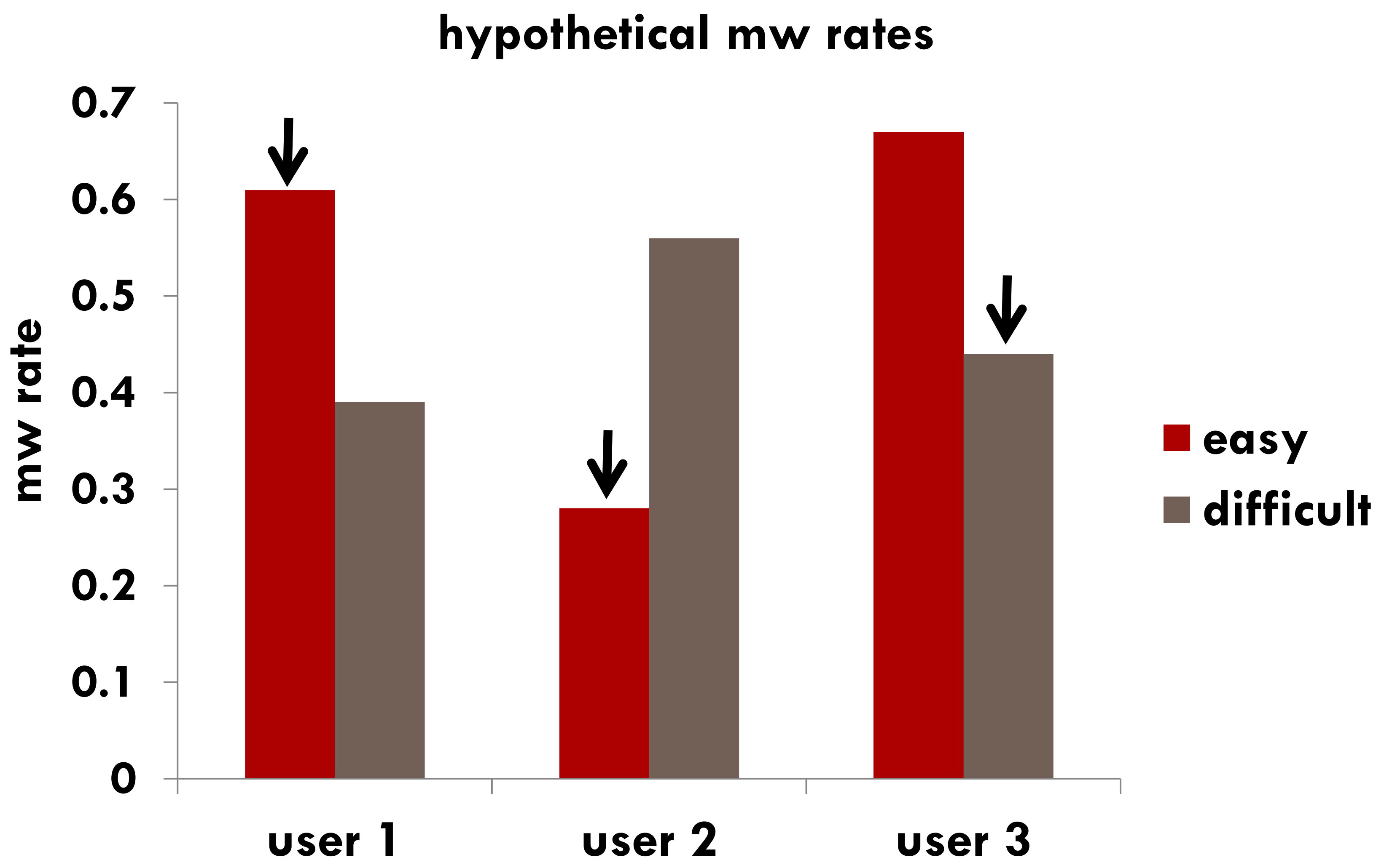
condition selection

- model selected
  - condition selected by the machine learning model
- overall best
  - condition with the lowest mind wandering rate on average across participants
- random
  - randomly selected condition

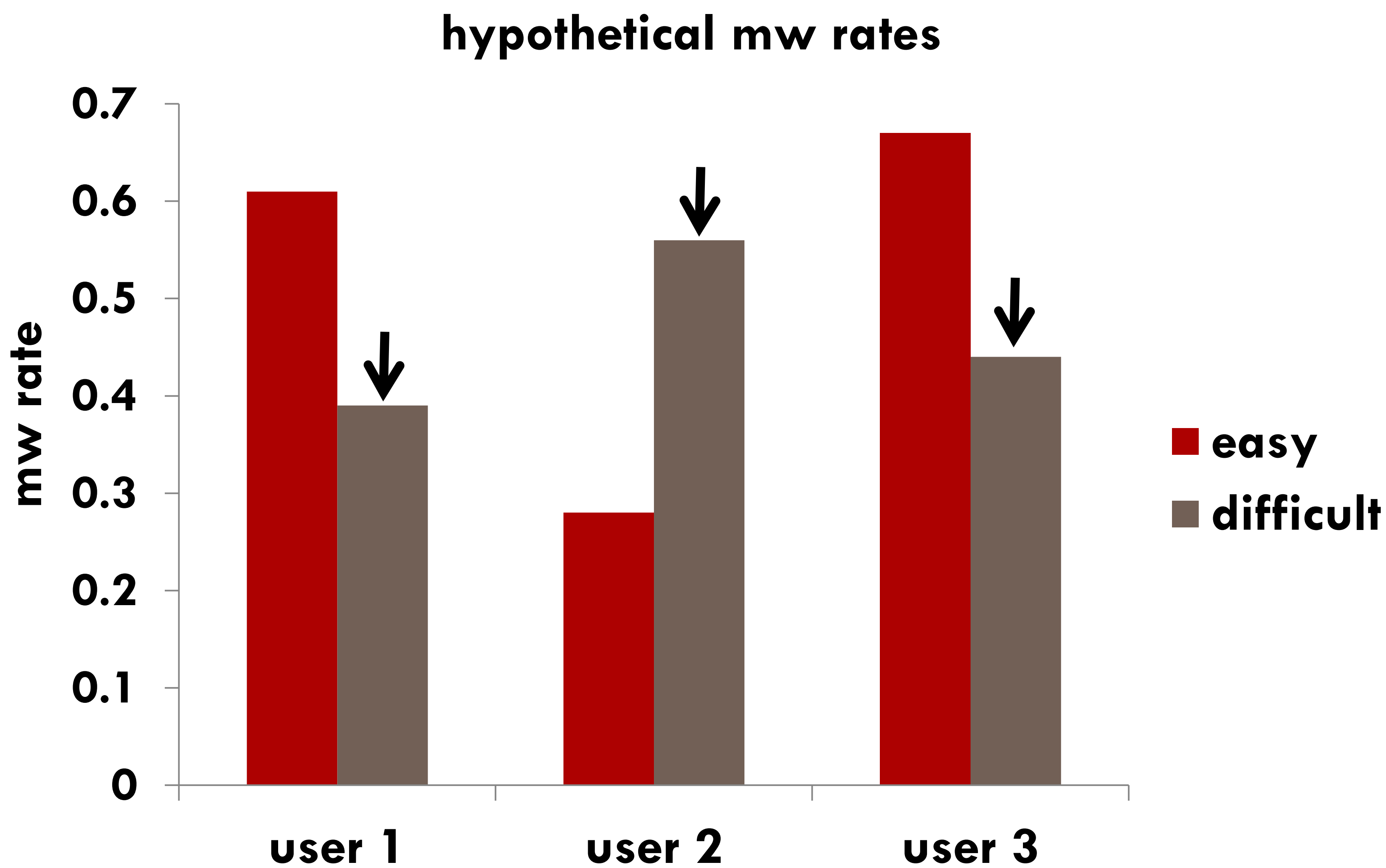
mw rate calculation



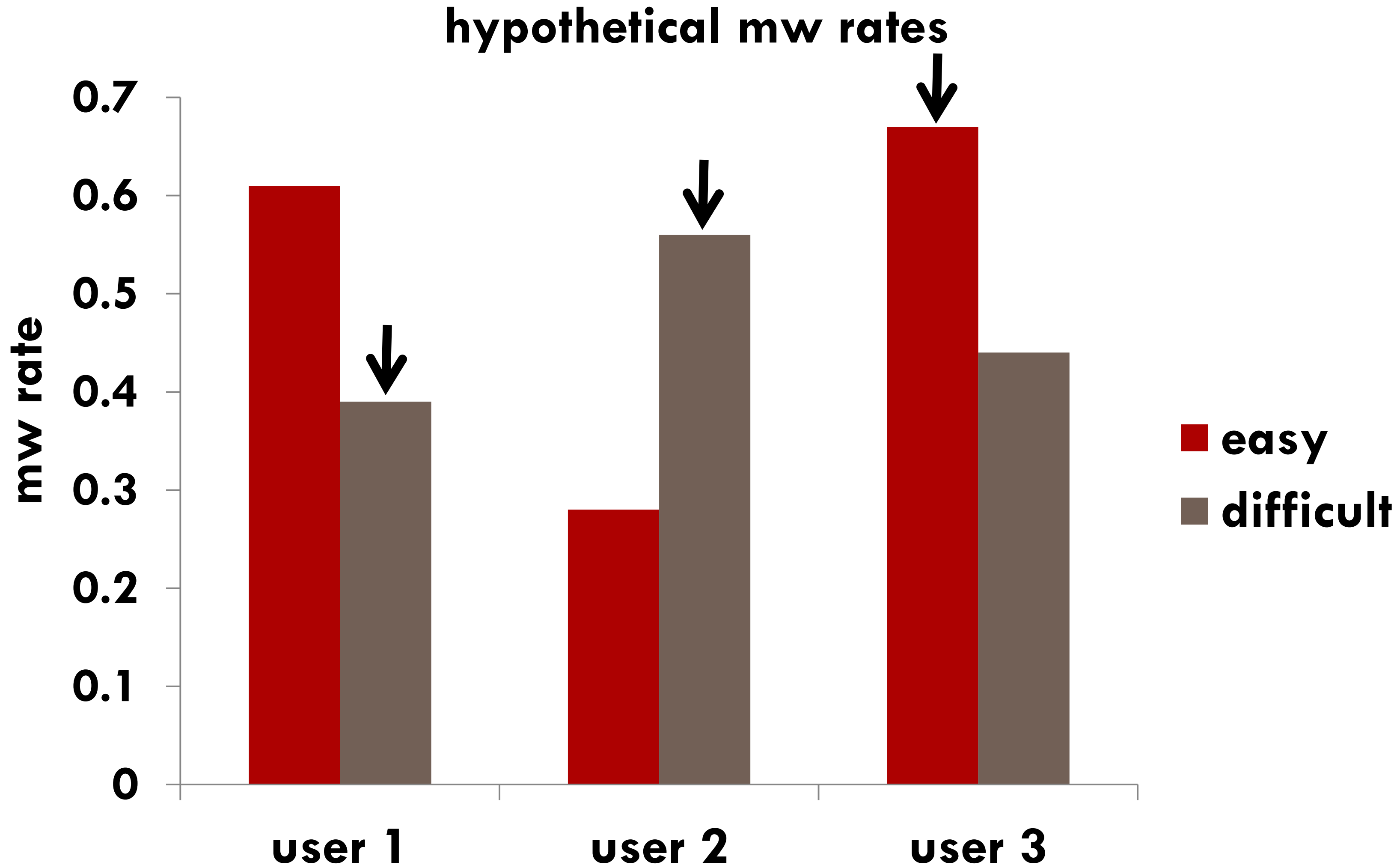
mw rate calculation – model selected



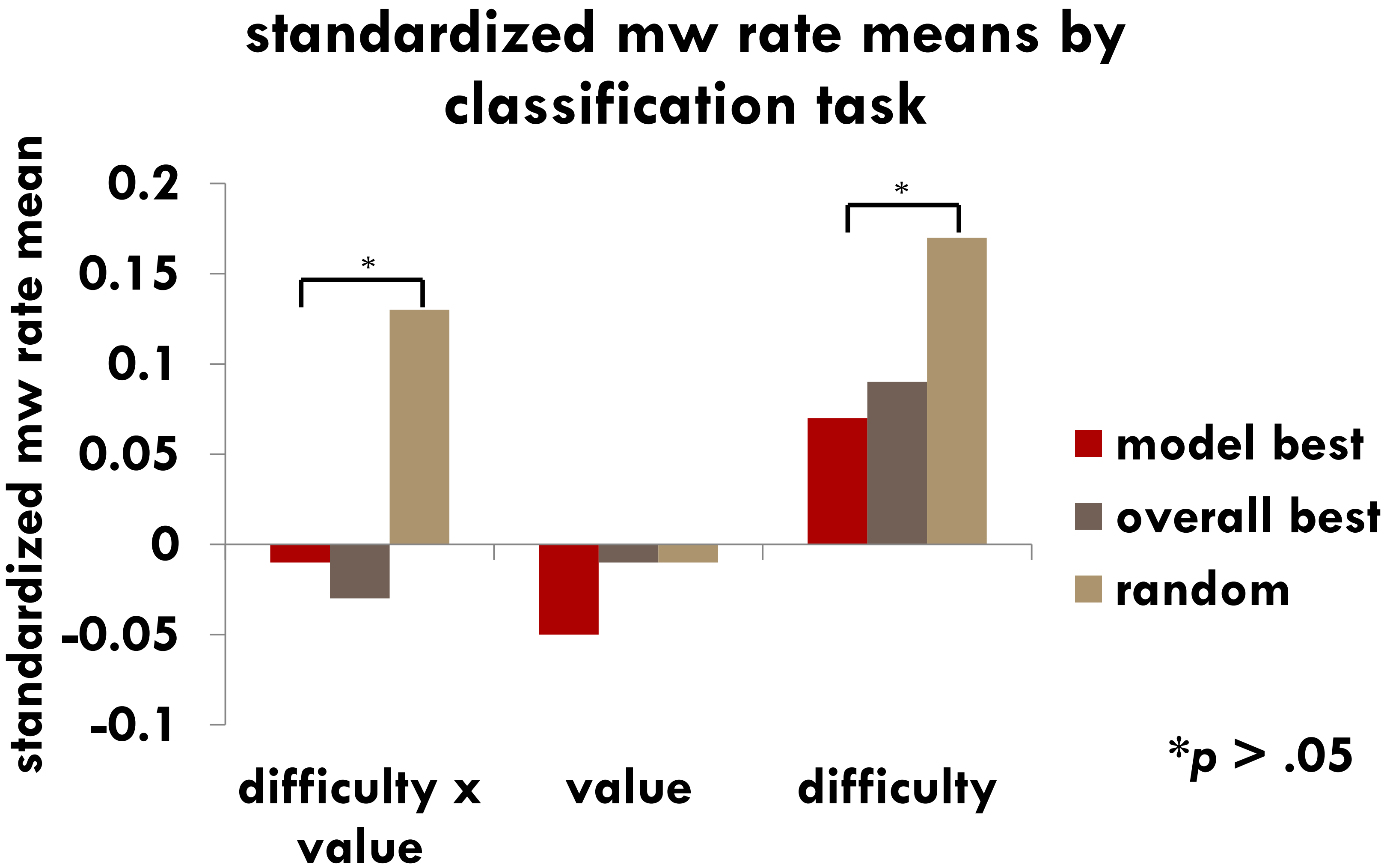
mw rate calculation – overall best



mw rate calculation – random

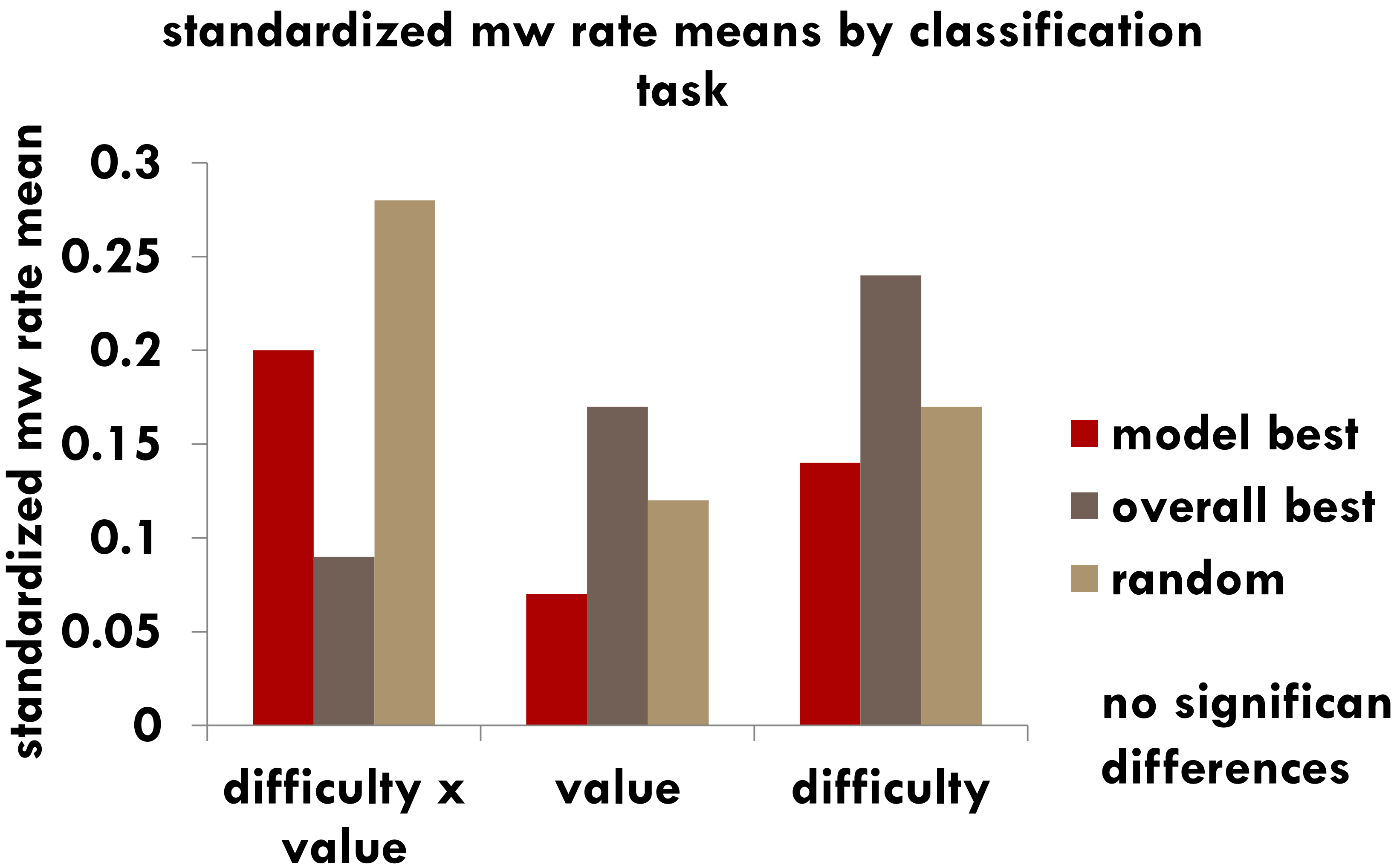


comparison of methods



comparison of methods

only including cases where individual best and overall best disagreed



no significant differences

conclusions

- individual attributes can be used to select a learning condition that results in lowered mind wandering rates
- potential to do better than selecting the best condition on average:
  - learners vary in terms of individual attributes
  - some may mind wander more or less under varying learning conditions
- model selected compares favorably to alternatives
  - comparable to overall best
  - significantly better than random

future work

- future work may consider extending our methodology to
  - other features
  - other learning domains
  - other cognitive affective states

- next step: compare and contrast under experimental conditions

open questions

- how can we improve classification?
  - additional IDMS?


autotutor
affective
learning
emotions
states
affect
confusion
student
frustration
tutoring
learner
dialogue
emotion
boredom
tutor
feedback
students
participants
research
features
computer
cognitive
intelligent
information
system
learners
systems
state
facial
judges
et
al
two
press
data
negative
positive
study
tutors
posture
neutral
pressure
emote-aloud
question
questions
learner's
pp
human
d'mello
analysis
one
session
journal
language
good
flow
picard
however
interaction
table
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