UNIVERSITY AT ALBANY
State University of New York

Phrasing for success: Optimizing information engagement using computational linguistics and artificial intelligence

Dvir, N., Friedman, E.,
Commuri, S., Yang, F., &
Romano, J.

UNLEASH GREATNESS

UNIVERSITY AT ALBANY
State University of New York

Sticky Words: A Computational Linguistics Approach to Assessment and Manipulation of Information Engagement

Nim Dvir

Doctoral dissertation submitted in fulfillment of requirements for the Ph.D. Program in Information Studies

UNLEASH GREATNESS

TARGET JOURNAL

1. ISR — <u>Special</u> Issue on Analytical Creativity

2. The 2024 INFORMS Analytics Conference

Analytical Creativity

<u>**Reimagining Creativity in the Age of AI**</u>

- Defining Creativity: Traditionally seen as the ability to produce new and valuable ideas, this notion is evolving with AI advancements like GPT-4.
- Analytical Creativity: This approach treats creativity as a replicable search problem, stripping away the 'mystique' to foster a systematic understanding of how creative results are achieved.
- Computational vs. Analytical Creativity: Computational creativity employs computers to mimic or amplify human creativity. In contrast, analytical creativity works to dissect and refine the creative process, bridging human intuition and algorithmic precision.

Objective: To broaden the understanding of creativity beyond traditional boundaries, fostering collaboration between human ingenuity and algorithmic innovation.

IT'S NOT WHAT YOU SAY,

IT'S HOW YOU SAY IT

Enhancing User Engagement Through Wording: A Comprehensive Research Approach

Phases:

- **Exploratory:** Examining the relationship between words/phrasing (independent variable) and user engagement (dependent variable).
- **Descriptive:** Understanding information engagement (IE) and the impact of phrasing.
  - **Objective:** Investigate how wording affects user experience, measured by engagement levels.
- **Predictive:** Developing a model to predict engaging phrases using textual and linguistic features using computational linguistics and NLP
- **Prescriptive:** Applying the model to systematically, computationally and automatically improve digital text engagement
- **Innovating with AI:** Build a custom GPT to automatically analyze and refine text, ensuring it is compelling and engaging for the audience.

RESEARCH PROJECTS

1. **What is information engagement? Definition, dimensions and determinants**
2. **What do users R.E.A.D?**
3. **Digital information manipulation and assessment (DIMA)**

INTRODUCTION

- Providing information in way that maximizes effectiveness critical to information systems (IS) success
- Information is the meaning that users assign to data
- While traditionally the focus has been on usability measures, current research has been increasingly focused on user experience (UX)
- In recent years, the term "engagement" has been gradually used to describe and measure the quality and depth of UX

IMPORTANCE OF INFORMATION ENGAGMENT

- This work investigates the concept of engagement with information, or “information engagement” (IE)
- Information Engagement (IE), defined as a measure of how users interact with information, and how it is expressed by the system
- This work focuses on textual information, specifically words.

WHY TEXT?

- Controllable
- Computational linguistics and natural language processing
- Most of the information published fails to engage resulting in it being barely noticed or quickly forgotten

The overarching objective of this work is to develop a framework for modeling, measuring and manipulating IE.

Specifically, it investigates how the expression of the information, i.e., the phrasing or wording used in its communication (independent variable) impacts IE (dependent variable)

OBJECTIVES

1. Conceptually and operationally define IE by identifying its distinctive dimensions and determinants

2. Recognize predictors of engaging information and use them for quantitative feature selection and development of a predictive model and metrics

3. Create and test an instrument to assess and manipulate IE systematically and computationally using computational linguistics, text analysis and natural language processing

RESEARCH QUESTIONS

R1. What is the relationship between information expression and IE?

(What defines IE and how does phrasing influence it?)

R2. How can IE be predicted systematically and computationally?

(Can textual predictive features enhance engagement?)

R3. How can IE be prescribed (manipulated) systematically and computationally using computational linguistics and natural language processing?

(How can we computationally enhance text engagement using these insights?)

Outcome: A strategic framework for elevating digital content engagement through informed text optimization.

STUDY 1

What is information engagement?

Definition, dimensions and determinants

LITERATURE REVIEW: IE DIMENSIONS

- Engagement is often seen as the emotional, cognitive and behavioral connection that exists, at any point in time and possibly over time, between a user and a technological resource

Process	Expression	Evaluation
Perception (Affect)	Mental impression, interpretation. Expressed in the level of Involvement, interest and intent (relation towards the information)	Information experience
Participation (Action)	Investment in the information interaction	Information exchange – retrieval and reactions to the information (selection)
Perseverance (Awareness)	Integration and influence of the information	Employment and endurability (retention and decision making)

Cumulative Prospect Theory (CPT)

Cognitive Foundations of Information Engagement

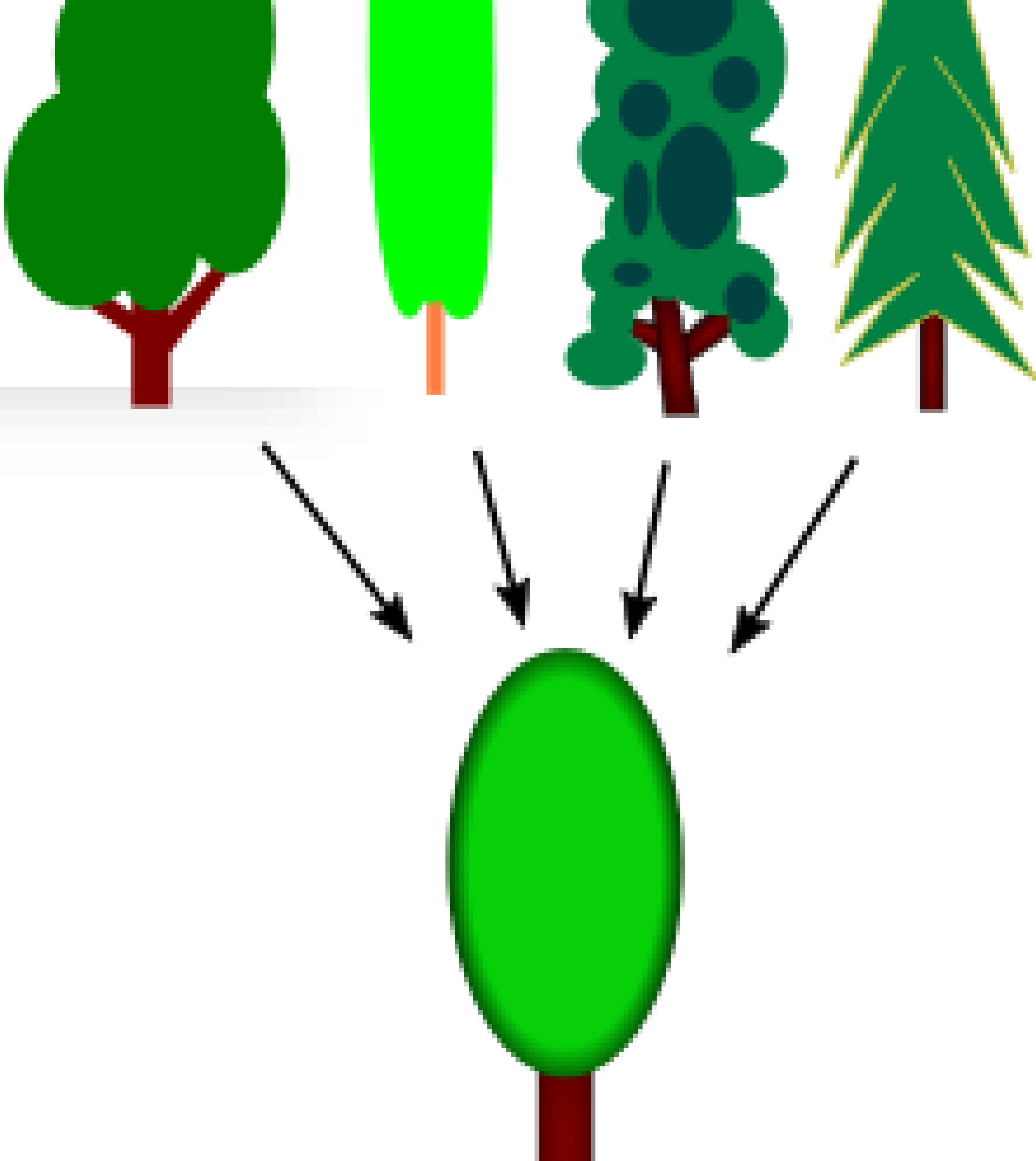
- **Pioneers:** Amos Tversky and Daniel Kahneman, trailblazers in behavioral economics.
- **Cognitive Biases:**
  - Defined as subconscious, automatic factors that skew human judgment and decision-making, often causing systematic errors.
  - These biases shape a personal "subjective reality" from perceived inputs, demonstrating a divergence from objective rationality.

Cumulative Prospect Theory (CPT)

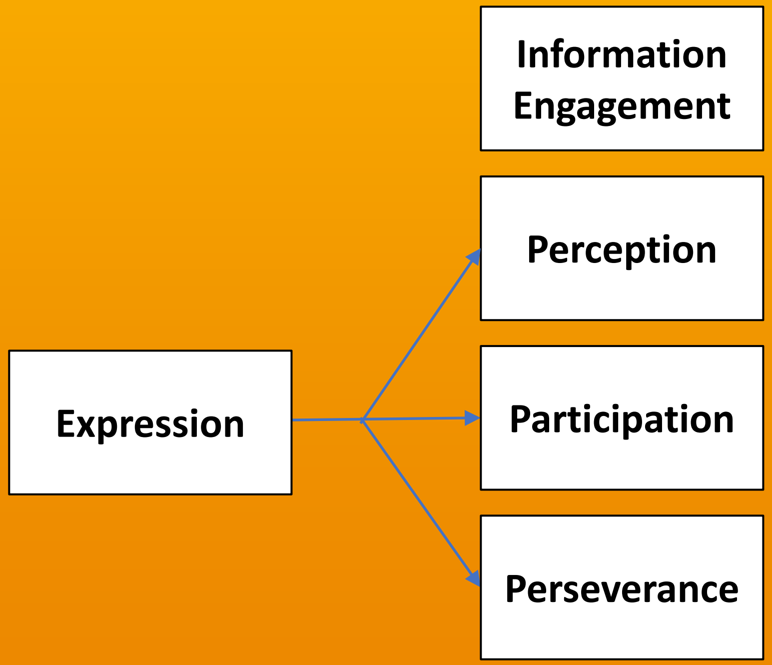
- **Heuristics and Judgment:** The role of simple, efficient rules in guiding intuitive judgments and decision-making processes.
  - Effective in many scenarios, yet can veer from logical or probabilistic reasoning, potentially leading to predictable errors.
- **The Framing Effect:**
  - Demonstrates how the context or presentation of information can significantly alter decision-making and judgment.
  - People react differently to a particular choice depending on how it is framed (e.g., as a loss vs. a gain), highlighting the power of word choice and context in shaping responses.
- **Conclusion:** Their seminal work underscores the importance of recognizing cognitive biases and heuristics in understanding how people engage with and interpret information.

Heuristics

- Representativeness Heuristic- Judging likelihood based on resemblance to typical cases, often leading to neglect of actual probability.
- Affect Heuristic - Decisions are swayed by emotions rather than a systematic analysis of risks and benefits.
- Fluency Heuristic - Preferring options that are processed more quickly or smoothly, equating ease with value.
- Effort Heuristic:
- Valuing outcomes or objects based on the perceived amount of effort to produce them.
- Availability Heuristic:
- Estimating frequency or probability by the ease with which examples come to mind.
- Recognition Heuristic:
- Assuming a recognized item has greater importance or relevance than an unrecognized one.
- Familiarity Heuristic:
- Preferring familiar options, equating known with safe or good.
- Implications: These heuristics illustrate the mental shortcuts used in human cognition that can influence our interaction with information and affect the judgments we make, often bypassing detailed analysis.



DEVELOPING A CONCEPTUAL FRAMEWORK



Methodological Framework: Dual-Study Approach

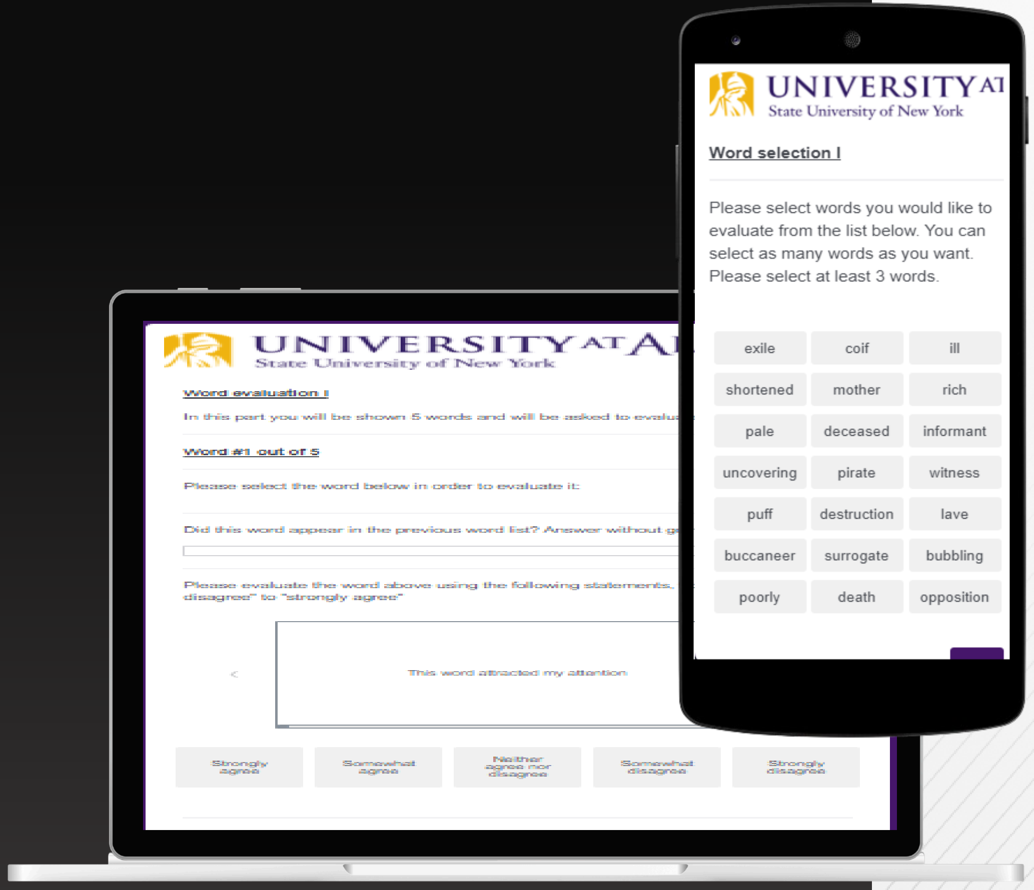
<u>Study 1a: Exploratory Analysis</u>

- Scope: Investigation of 100 words in 50 pairs to assess individual and combined impact.
- Application: Analyze these pairs both in isolation and within sentence structures, specifically focusing on titles.

<u>Study 1b: Expanded Research</u>

- Scale: A broader examination involving 200 word pairs (400 words total).
- Participation: Increased sample size with a greater number of participants to enhance validity.
- Purpose: These sequential studies are designed to progressively understand the influence of specific word combinations on reader engagement and perception, from isolated pairs to their contextual effectiveness in sentences.

STUDY DESIGN



- Overview
  - Large-scale online studies
- Procedure
  - Users were presented with a list of words and were asked to select them to measure participation
  - to evaluate them using the UES to measure perception
  - to recall and recognize them to measure perseverance

PARTICIPATION

Recruitment: Participants were recruited via a listserv sent to undergraduate students at a large research university in the United States. After completing the online survey, the participants were asked to forward invitations to their acquaintances, i.e., snowball sampling.

The system verified that the survey was only completed once, therefore controlling for unique participants.

Selection criteria: Only undergraduate students completed the survey.

COMPILING A DATA SET (STUDY 1a)

- 100 words grouped into 50 sets
- WordNet -- a large lexical database of English phrases (nouns, verbs, adjectives and adverbs) that are grouped into sets of cognitive synonyms (synsets), each expressing a distinct concept
- Overall, 80,500 observations were collected from 8,561 distinct participants. The mean number of words evaluated by a single participant was 9.446139.

Word1	Word2	Synset	Definition
abused	**maltreated**	abused.a.02	subjected to cruel treatment
star	**maven**	ace.n.03	someone who is dazzlingly skilled in any field
quick	**nimble**	agile.s.01	moving quickly and lightly
rich	**plenteous**	ample.s.02	affording an abundant supply
annoying	**nettlesome**	annoying.s.01	causing irritation or annoyance
art	**prowess**	art.n.03	a superior skill learned by study, practice, and observation
gone	**deceased**	asleep.s.03	dead
zombie	**automaton**	automaton.n.01	someone who acts or responds in a mechanical or apathetic way

COMPILING A DATA SET (STUDY 1b)

- 400 words grouped into 200 sets
- Overall, 61,500 observations were collected (about 300-310 for each pair)

SynsetNumber	SynsetCode	Word1	Word2	Meaning
1	rapid.a.01	Rapid	Swift	Characterized by speed; moving quickly
2	clever.a.01	Clever	Intelligent	Mentally quick and resourceful
3	bird.n.01	Bird	Avian	Warm-blooded egg-laying vertebrates with feathers
4	implement.n.01	Implement	Tool	Instrumentation used to effect an end
5	auto.n.01	Auto	Car	A motor vehicle with four wheels
6	gem.n.01	Gem	Jewel	Art highly prized for its beauty or perfection
7	journey.n.01	Journey	Voyage	The act of traveling from one place to another
8	shore.n.01	Shore	Coast	The land along the edge of a body of water
9	woods.n.01	Woods	Forest	Land covered with a dense growth of trees

MEASURMENTS

Participation

Participation was measured as behavioral reactions and retrieval of the information.

To measure participation, the participants were asked to click on the words with which they would like to interact with.

For each word, a selection response was recorded (“1” or “0”) and was used to calculate selection rates.

MEASURMENTS

No.	Dimension (Abbreviation)	Modified Item	Opposite Statement
1	Flow Absorption (FA-S)	I lost myself in the meaning of this word.	I did not lose myself in the meaning of this word.
2	Flow Absorption (FA-S)	The time I spent contemplating this word just slipped away.	Time did not slip away while I contemplated this word.
3	Flow Absorption (FA-S)	I was absorbed in the nuances of this word.	I was not absorbed in the nuances of this word.
4	Perceived Usability (PU-S)	I felt frustrated trying to interpret this word.	I did not feel frustrated while trying to interpret this word.
5	Perceived Usability (PU-S)	I found this word confusing to understand.	I did not find this word confusing to understand.
6	Perceived Usability (PU-S)	Interpreting this word was taxing.	Interpreting this word was not taxing.
7	Aesthetic Engagement (AE-S)	This word was linguistically attractive.	This word was not linguistically attractive.
8	Aesthetic Engagement (AE-S)	This word was aesthetically appealing in its sound or structure.	This word was not aesthetically appealing in sound or structure.
9	Aesthetic Engagement (AE-S)	This word appealed to my linguistic senses.	This word did not appeal to my linguistic senses.
10	Reward (RW-S)	Contemplating this word was worthwhile.	Contemplating this word was not worthwhile.
11	Reward (RW-S)	My experience with this word was rewarding.	My experience with this word was not rewarding.
12	Reward (RW-S)	I felt interested in the layers of this word.	I did not feel interested in the layers of this word.

Perception

- Participants were presented with a randomized list of words and asked to evaluate it based on statements adopted from the UES (O’Brien et al., 2018).
- Participants assessed each word’s sensory appeal, focused attention, perceived usability, and reward using a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5).
- Testing for scale reliability revealed a Cronbach’s alpha of 0.888.

MEASURMENTS

Perseverance

Perseverance was measured as retention of the information in terms of memory.

The participants were asked to write the words they remembered from the list previously presented.

For each word, a retention measurement was recorded (“1” if remembered, “0” if not).

MEASURMENTS

Column Name	Description
Word	The word being observed
Synset	Synset identifier for the word
TotalObs	Total number of observations
Selected	Number of times the word was selected
NotSelected	Number of times the word was not selected
SelectProb	Probability of the word being selected
Retained	Number of times the word was retained
NotRetained	Number of times the word was not retained
RetainProb	Probability of the word being retained
sigEval	Number of times the word was highly evaluated
NotsigEval	Number of times the word was not highly evaluated
SigEvalProb	Probability of the word being highly evaluated

SAMPLING AND RANDOMIZATION

Each participant was presented 8–10 words from the dataset in random order, with great importance placed on the randomization and control variables.

Each word of the dataset was presented using randomization to control for the display order (DO) and the participants' characteristics.

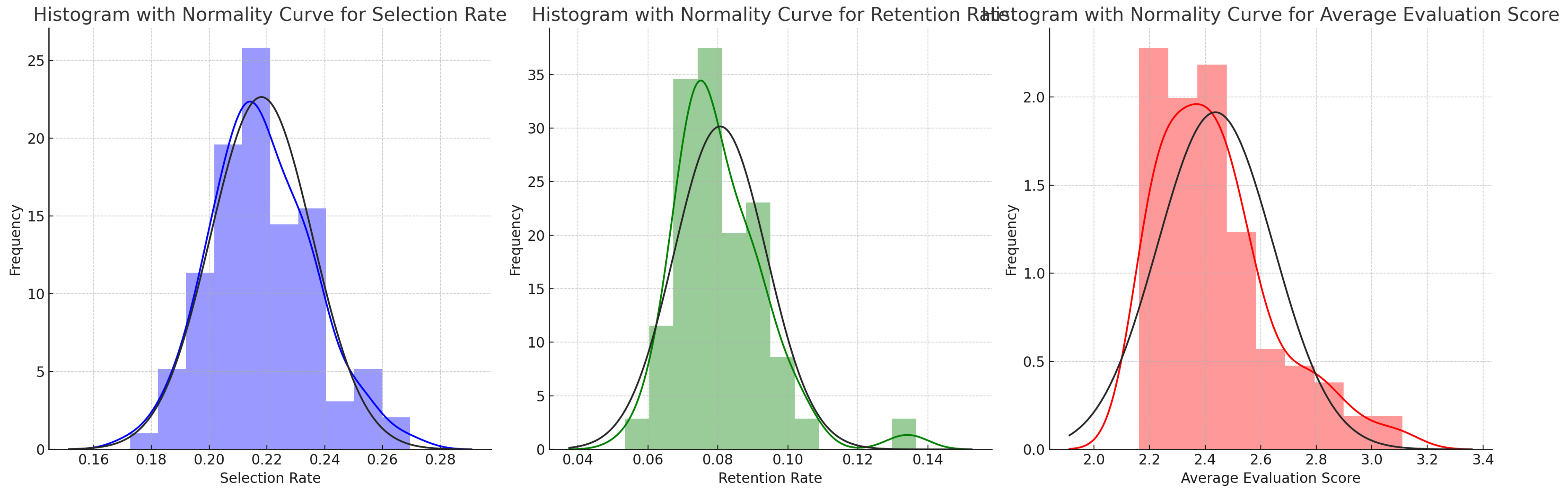
By balancing both known and unknown predictive factors, the survey design aimed to reduce biases, such as selection bias and allocation bias, to the greatest extent possible.

Chi-square analysis of the goodness of fit of the samples revealed that the characteristic composition for each word / pair sample was comparable to that of the overall population. Pearson chi-square analysis between demographic groups and between word samples revealed no significant differences

A one-way ANOVA was conducted to compare evaluation, selection, and retention rates between words.

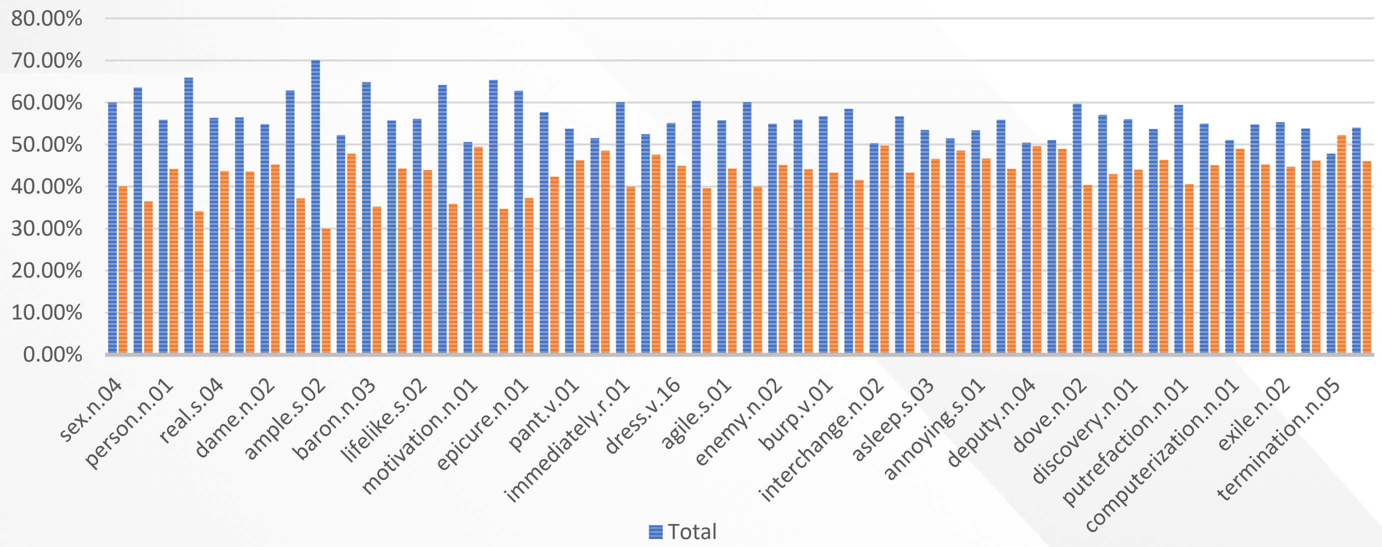
- Results revealed significant differences between words in evaluation rate (F[99], 80400) = 48.579, p = .000, $\eta 2$=.056),
- selection rates (F[99, 80400] = 1.481, p = .001, $\eta 2$=.002), and
- retention rates (F[99], 80400) = 1.921, p = .001, $\eta 2$=.002).

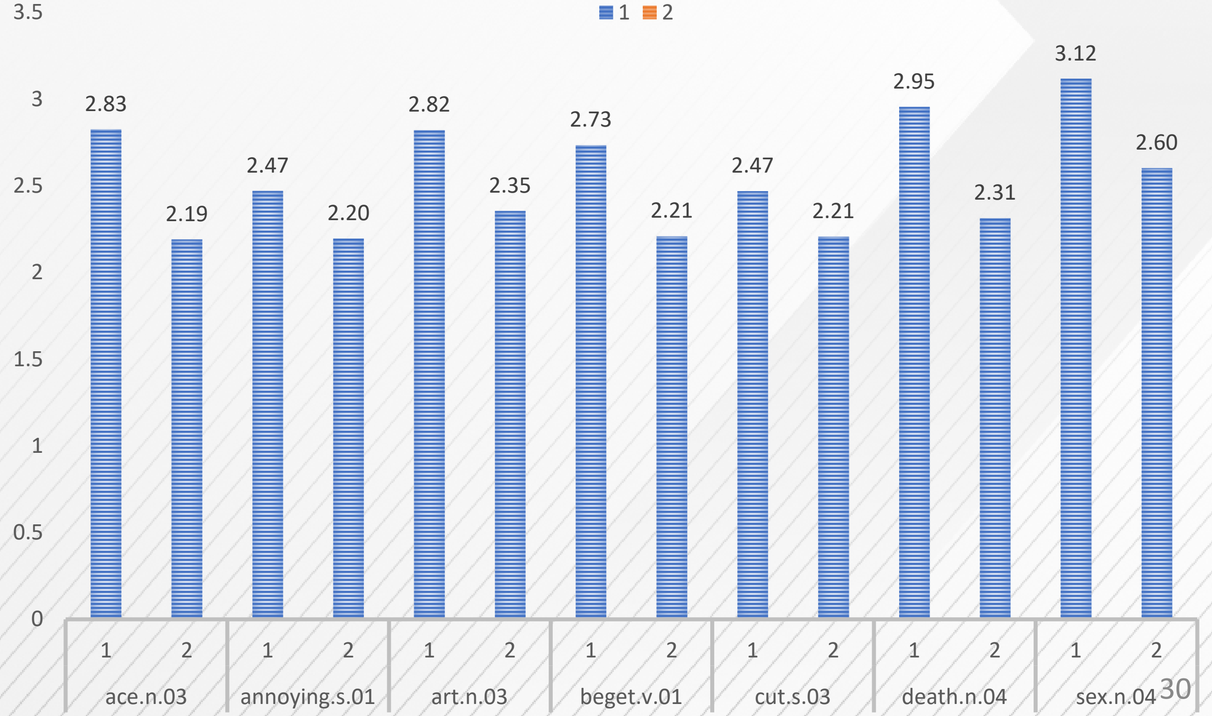
		SS	df	MS	F	Sig.	$\eta 2$
Evaluation	Between Groups	3497.624	99	35.330	48.579	.000	.056
	Within Groups	58471.551	80400	.727			
	Total	61969.175	80499				
Select	Between Groups	24.985	99	.252	1.481	.001	.002
	Within Groups	13702.281	80400	.170			
	Total	13727.265	80499				
retention	Between Groups	14.087	99	.142	1.921	<.001	.002
	Within Groups	5956.037	80400	.074			
	Total	5970.124	80499				


Histogram with Normality Curve for Selection Rate
Frequency
0
5
10
15
20
25
0.16
0.18
0.20
0.22
0.24
0.26
0.28
Selection Rate
Histogram with Normality Curve for Retention Rate
Frequency
0
5
10
15
20
25
30
35
0.04
0.06
0.08
0.10
0.12
0.14
Retention Rate
Histogram with Normality Curve for Average Evaluation Score
Frequency
0.0
0.5
1.0
1.5
2.0
2.0
2.2
2.4
2.6
2.8
3.0
3.2
3.4
Average Evaluation Score

DIFFERENCE BETWEEN VARIANTS

- To determine if selection, UES, and retention rates are impacted by word choice regardless of the meaning, pairwise comparisons for independent means were conducted between synonymous words for each of the 50 synsets.

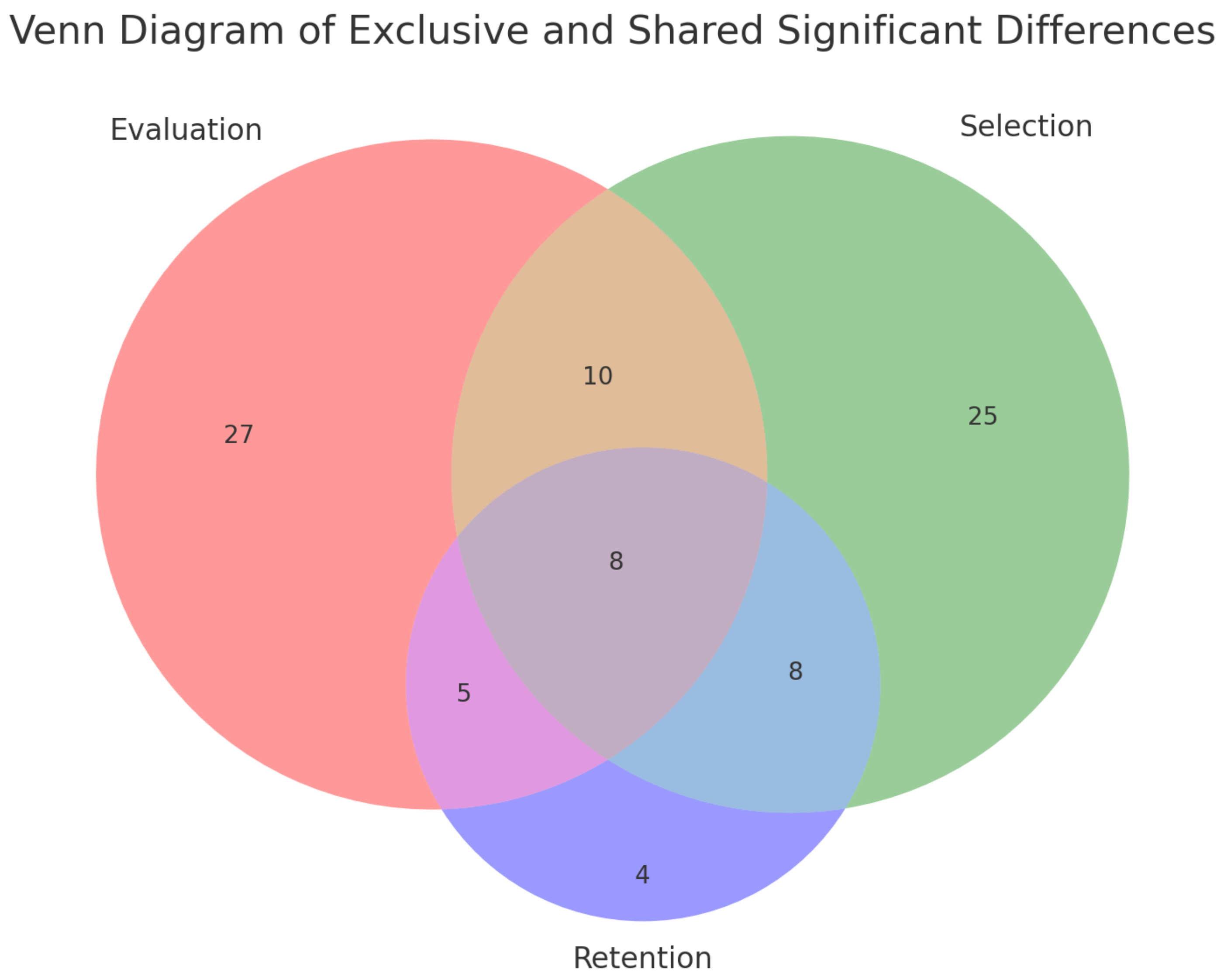




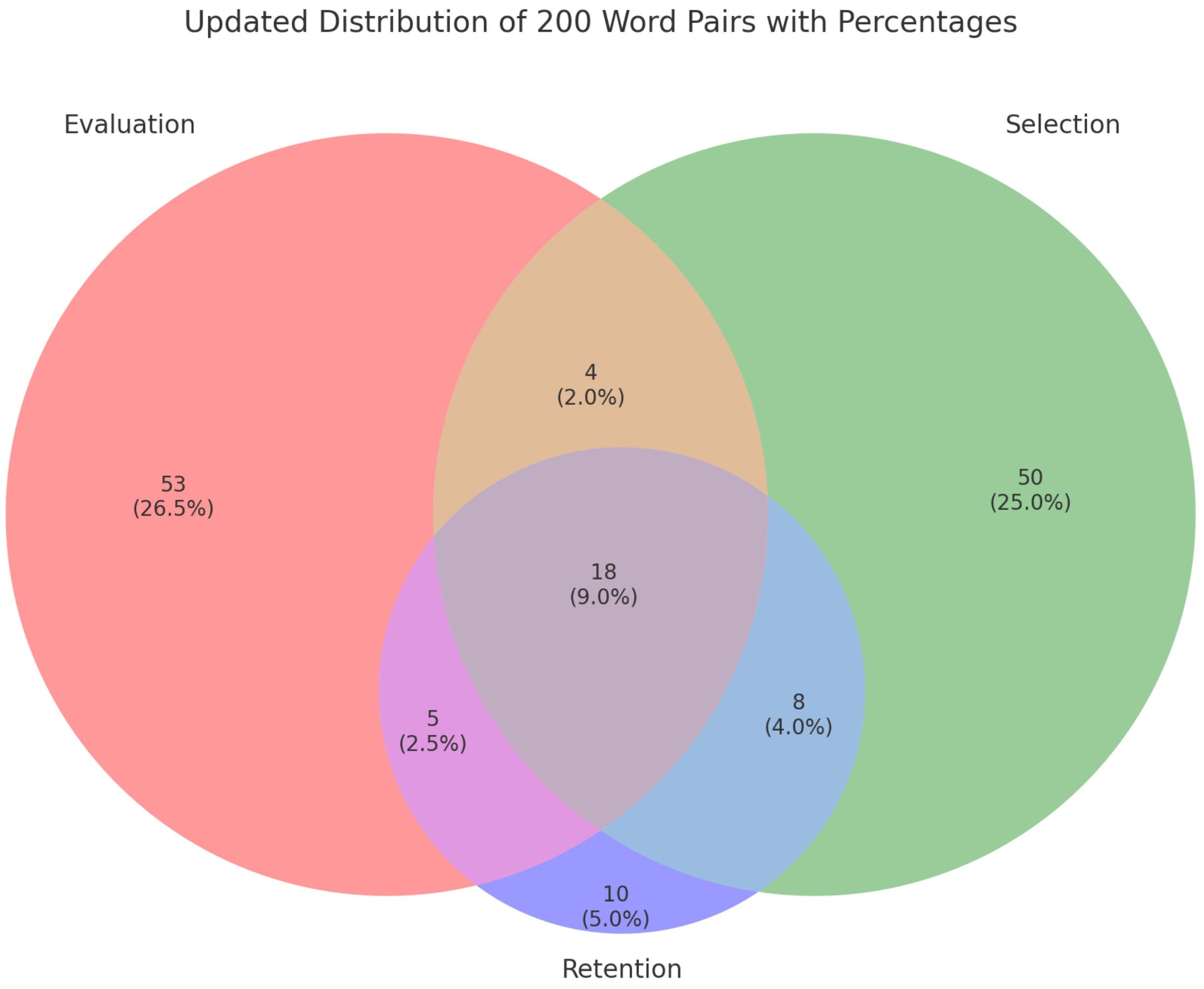
Significance

Word	Selection Rate Significance	Retention Rate Significance	Avg Eval Rate Significance	Engaging (“Sticky”)
abused	1 (Significantly High)	1 (Significantly High)	1 (Significantly High)	1 (“Yes”)
annoying	0 (Not Significant)	-1 (Significantly Low)	0 (Not Significant)	0 (“No”)
art	1 (Significantly High)	1 (Significantly High)	1 (Significantly High)	1 (“Yes”)
automaton	0 (Not Significant)	1 (Significantly High)	-1 (Significantly Low)	0 (“No”)
avaricious	0 (Not Significant)	-1 (Significantly Low)	-1 (Significantly Low)	0 (“No”)
being	-1 (Significantly Low)	0 (Not Significant)	0 (Not Significant)	0 (“No”)
belching	-1 (Significantly Low)	-1 (Significantly Low)	-1 (Significantly Low)	0 (“No”)
belligerent	0 (Not Significant)	0 (Not Significant)	0 (Not Significant)	0 (“No”)
best	1 (Significantly High)	1 (Significantly High)	1 (Significantly High)	1 (“Yes”)
better	1 (Significantly High)	0 (Not Significant)	1 (Significantly High)	0 (“No”)

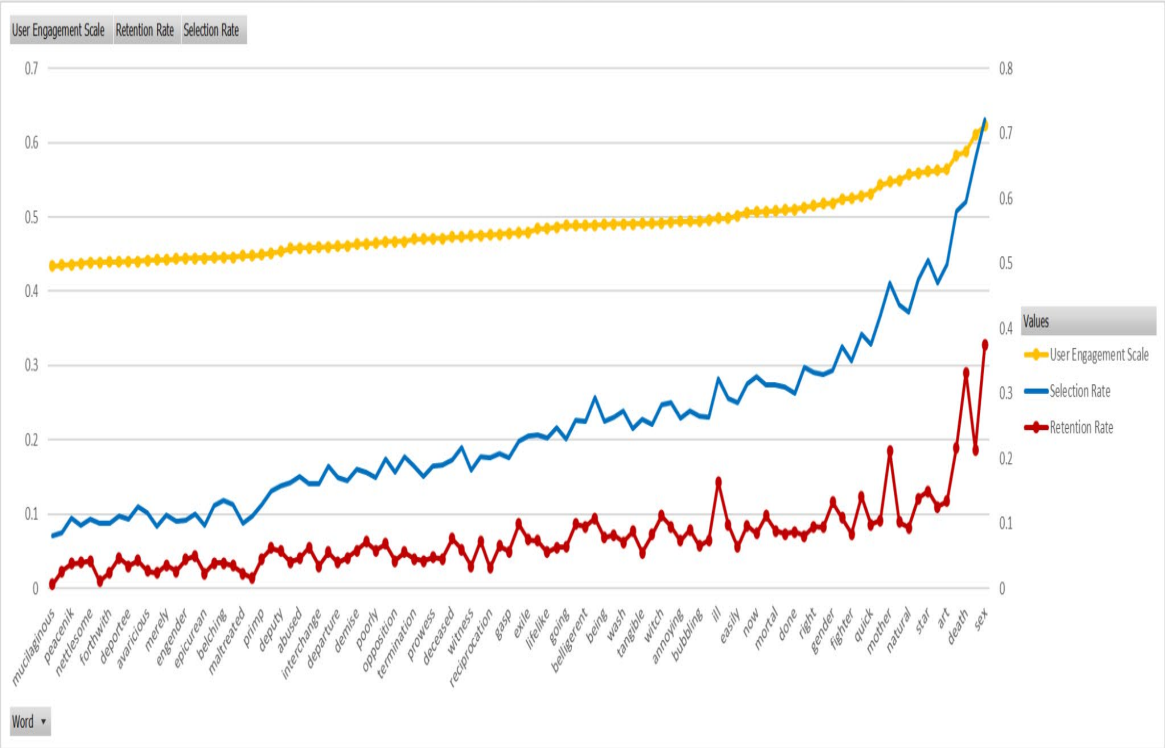
Significance Distribution (1a)



Significance Distribution (1b)

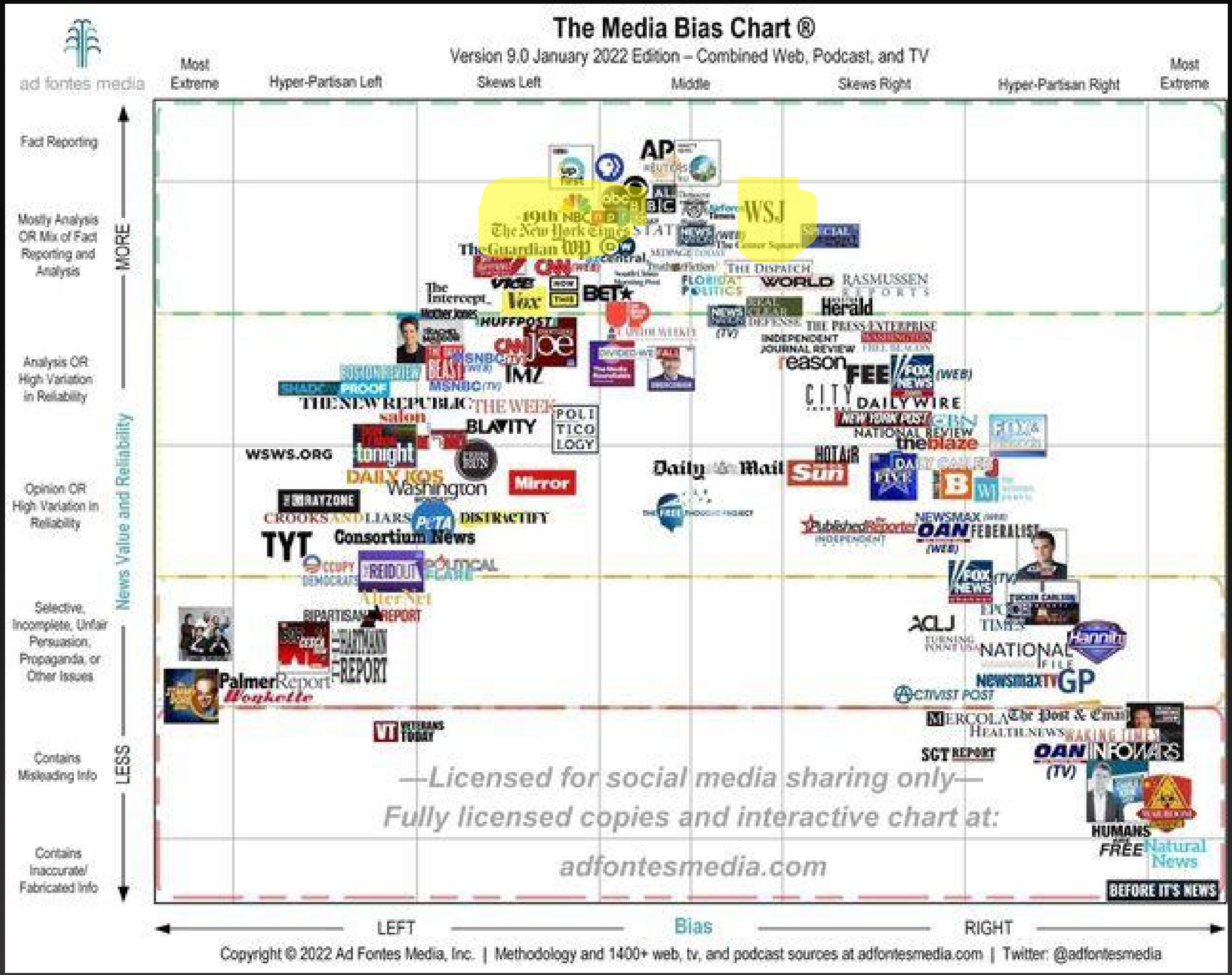


- A statistically significant positive correlation was found between words’ UES score and their selection rate, $r(100) = .64$, $p < .001$.
- A statistically significant positive correlation was found between words’ UES score and their retention rates, $r(100) = .63$, $p < .001$.



SYNONYM SUBSTITUTION

- Titles of eight news articles from The New York Times and The Wall Street Journal
- Chosen because The AllSides Media Bias Chart
- Candidate words were identified and replaced with sticky words using the automatic system



TITLES

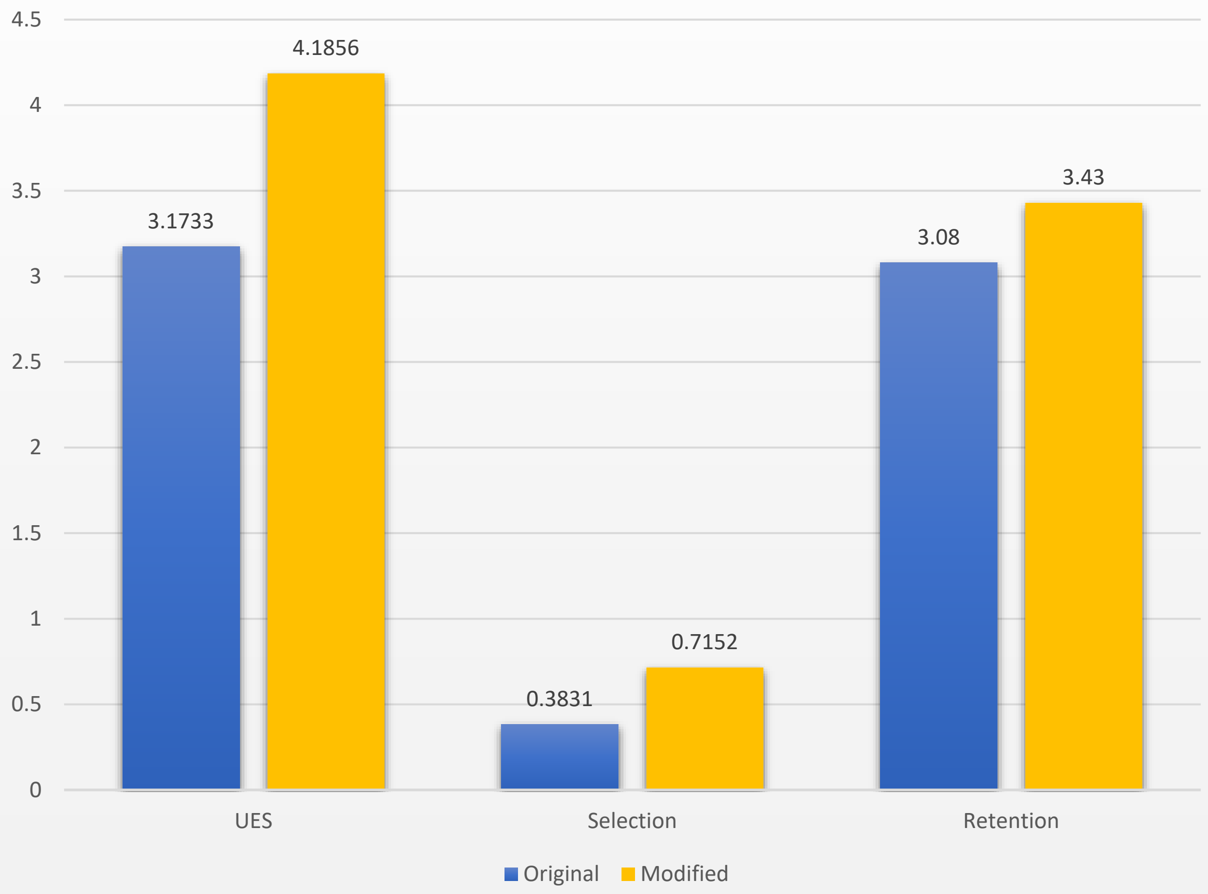
	Original
1	Meet the web Metrics **Mavens**: How they got to where they are now, and what kinds of things they measure
2	Staying **Nimble**: How Small Businesses Can, and Do, Shift Gears
3	Hotel **Magnate** Seeks Help to Save Publishing Bid
4	A **plenteous** supply: "The United States is blessed to have a plentiful supply of oil and natural gas—we should be using it"
5	In a sport full of corporate **automatons**, he will sit down and tell you what is on his mind, even if it is a lot.
6	The **belligerents** that can stop the war
7	The **Demise** of the Public Library
8	**Gentlewomen** of the Forbidden City: The Power, the Intrigue, the Clothes

	Modified
1	Meet the web Metrics **Stars**: How they got to where they are now, and what kinds of things they measure
2	Staying **Quick**: How Small Businesses Can, and Do, Shift Gears
3	Hotel **King** Seeks Help to Save Publishing Bid
4	A **rich** supply: "The United States is blessed to have a plentiful supply of oil and natural gas—we should be using it"
5	In a sport full of corporate **zombies**, he will sit down and tell you what is on his mind, even if it is a lot.
6	The **fighters** that can stop the war
7	The **Death** of the Public Library
8	**Ladies** of the Forbidden City: The Power, the Intrigue, the Clothes

RESULTS

H1: Modified sentences will have higher IE levels

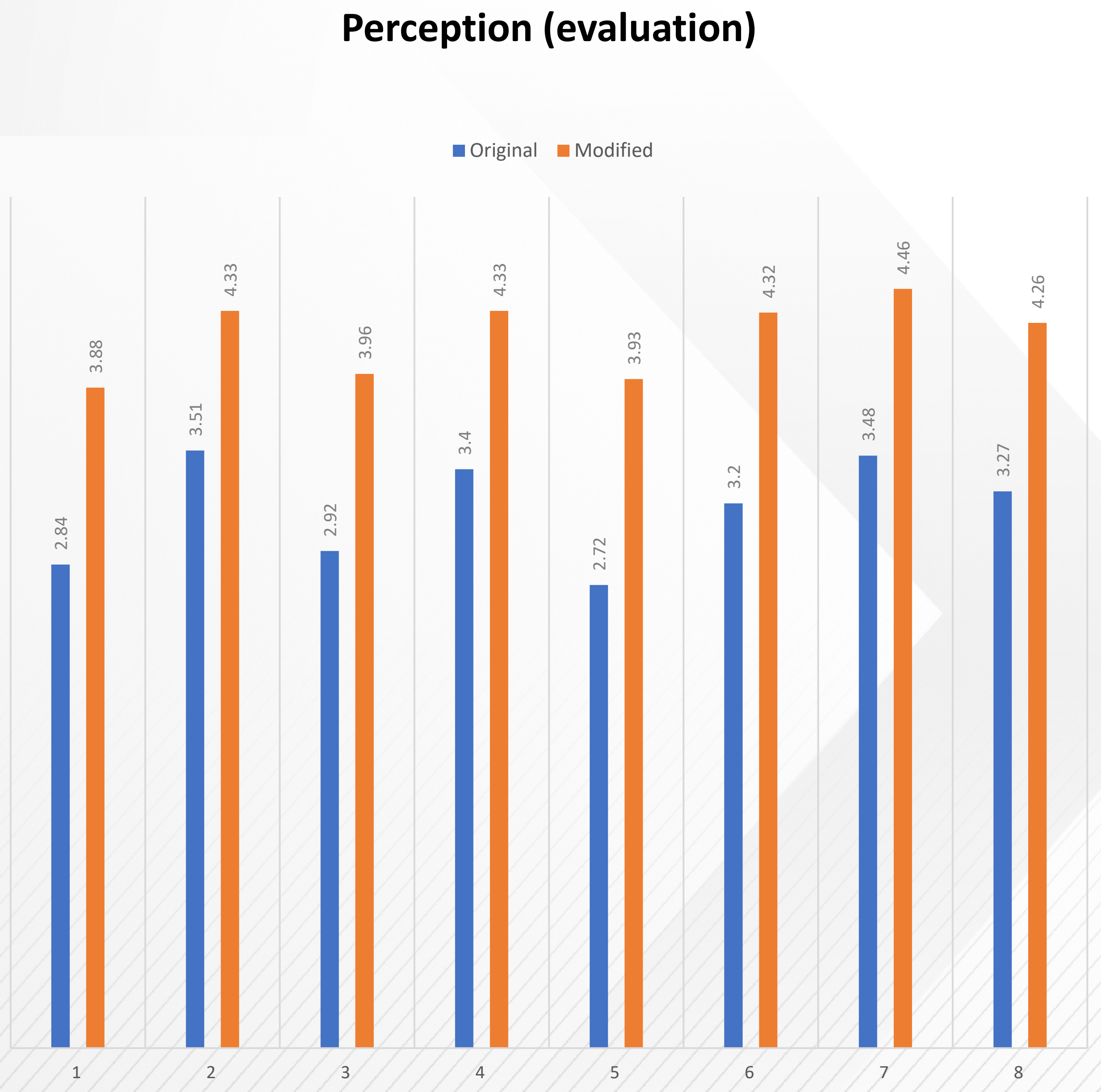
Dimension	Original	Modified	T	P	d
Perception (UES)	3.17 (.79)	4.18 (.68)	-51.065	.000	.726
Participation (selection)	.38 (.49)	.72 (.45)	-25.895	.000	.496
Perseverance (retention)	3.09 (3.03)	3.44 (3.36)	-3.95	.000	.916



Independent t-tests of the eight pairs of titles for the three IE dimensions

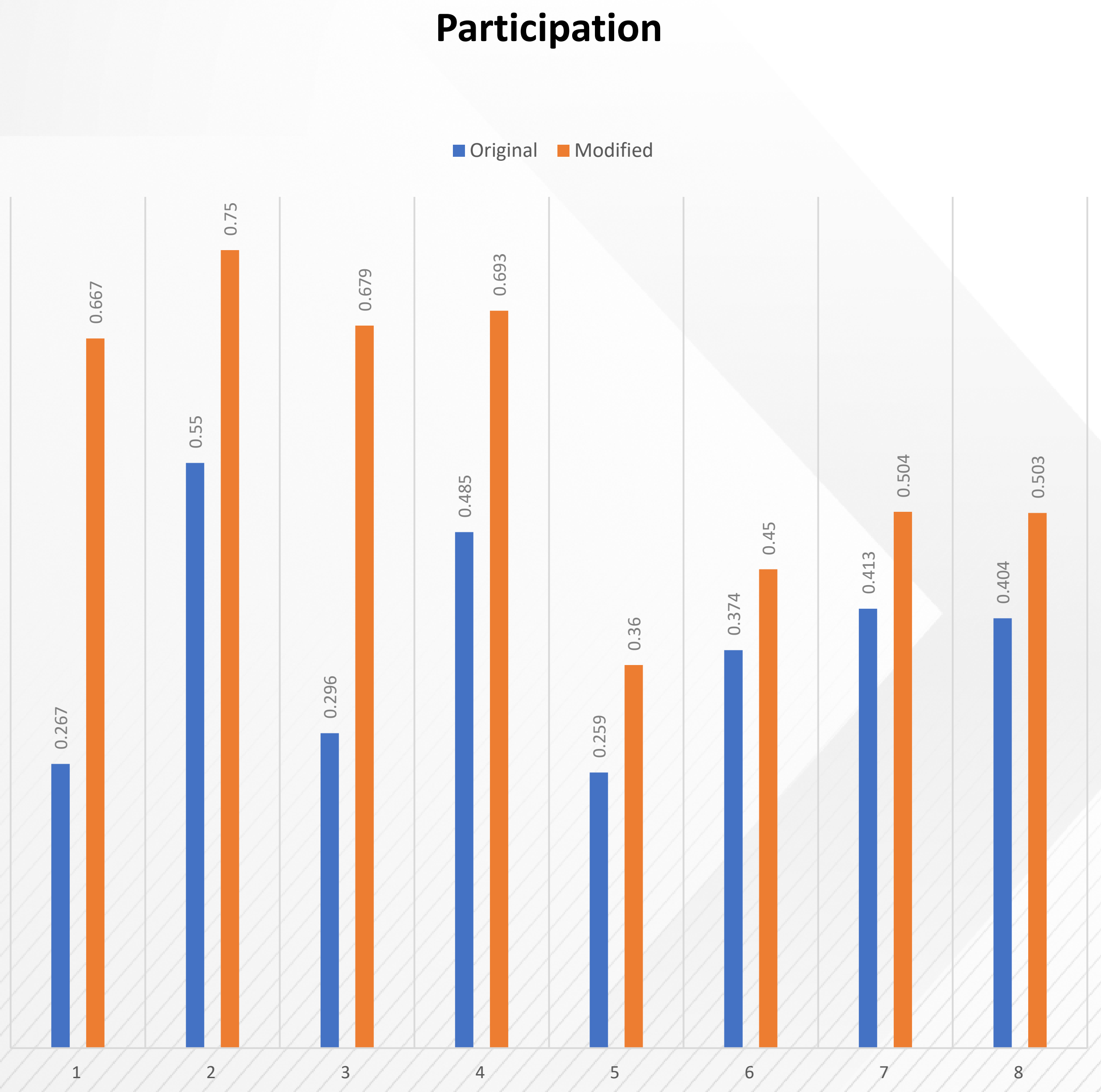
significant differences for all in PERCEPTION (evaluation score measured by UES)

t < -2



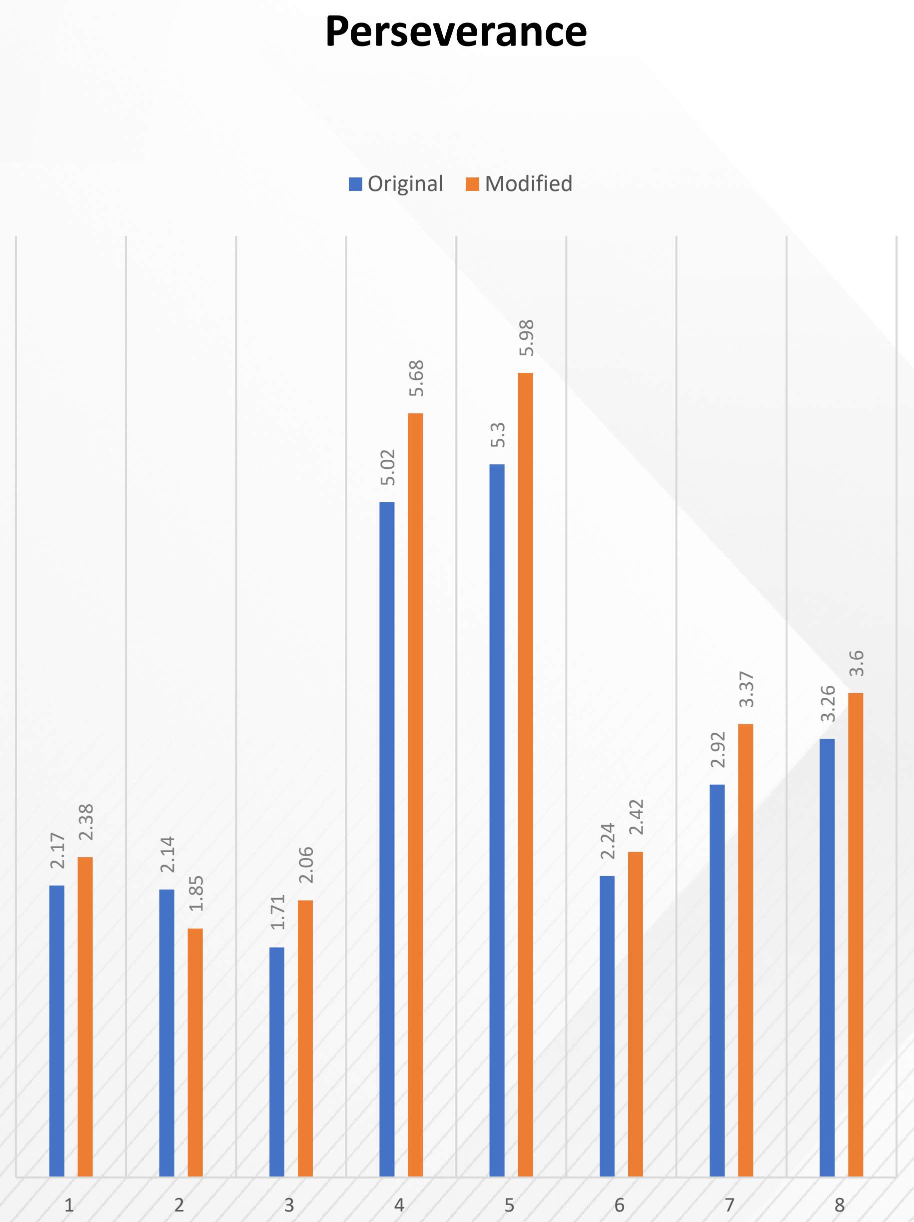
significant differences for all in PARTICIPATION (SELECTION RATE)

t < -2



However, examination of individual titles revealed that not all modified versions had significantly higher IE values for all three dimensions.

Independent t-tests of the eight pairs of titles for the three IE dimensions indicated that while Titles 3, 4, 5, and 7 had significant differences for all three dimensions, Titles 1, 2, 6, and 8 had significant differences in perception and participation but not in perseverance (words remembered).



Phrasing **matters**

1. Dimensions and measurements
2. Determinants
3. Some words are more engaging than others
4. Limitations and future steps

STUDY 2

What Do Users R.E.A.D?

A Predictive Model of Information Engagement Based on Heuristic Evaluation and Computational Linguistics

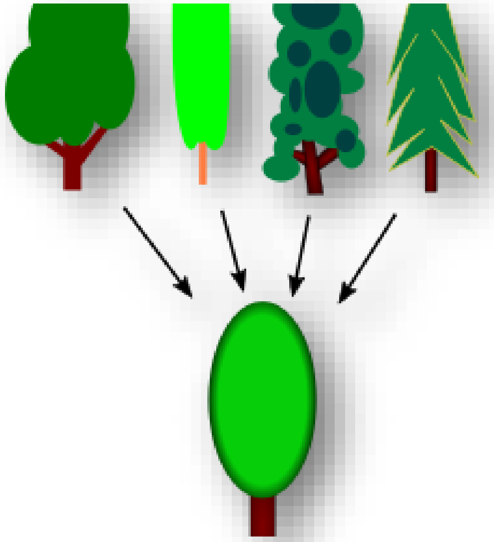
INTRODUCTION

- Different words stimulate different levels of IE
- Identify which phrasing features are most effective in promoting IE
- Develop a strategy to systematically measure them
- Use an evaluation scale based on linguistic computational factors

- **A predictive model of IE**

Heuristics

- Representativeness Heuristic- Judging likelihood based on resemblance to typical cases, often leading to neglect of actual probability.
- Affect Heuristic - Decisions are swayed by emotions rather than a systematic analysis of risks and benefits.
- Fluency Heuristic - Preferring options that are processed more quickly or smoothly, equating ease with value.
- Effort Heuristic - Valuing outcomes or objects based on the perceived amount of effort to produce them.
- Availability Heuristic- Estimating frequency or probability by the ease with which examples come to mind.
- Recognition Heuristic - Assuming a recognized item has greater importance or relevance than an unrecognized one.
- Familiarity Heuristic - Preferring familiar options, equating known with safe or good.
- Implications: These heuristics illustrate the mental shortcuts used in human cognition that can influence our interaction with information and affect the judgments we make, often bypassing detailed analysis.



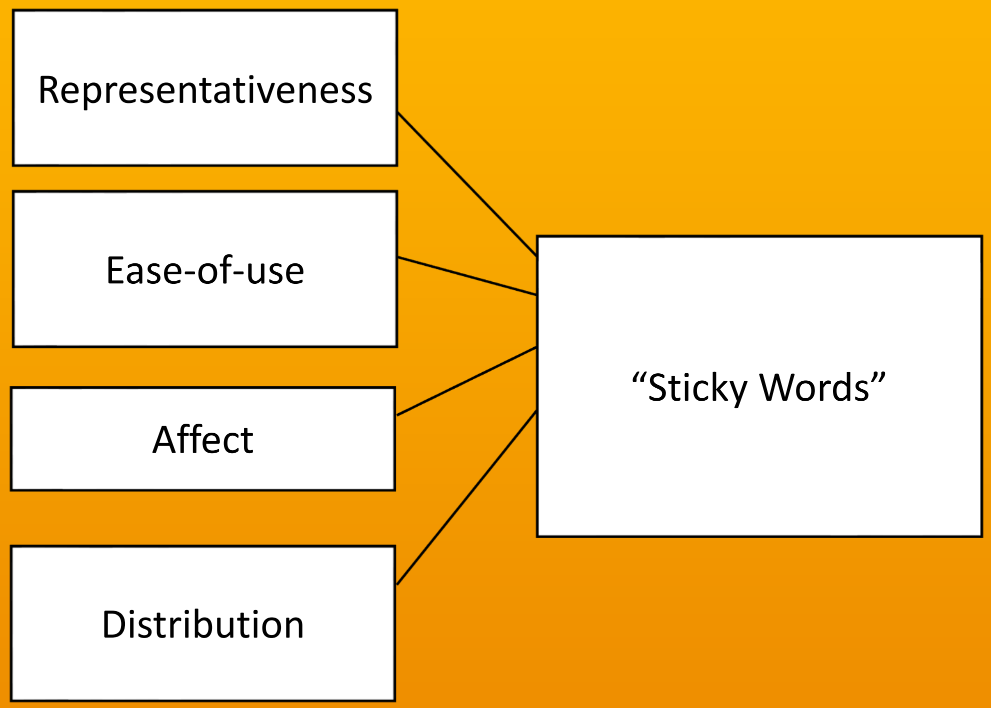
DEVELOPING A CONCEPTUAL FRAMEWORK

- Predictive computational model
- Recognize four attributes of engaging information that are situational, stable and controllable
- The READ Model: Representativeness, Ease-of-Use, Affect and Distribution as Predictors of Information Engagement

ATRIBUTE / PREDICTOR	DEFINITION	MAPS TO	MEASUREMENT
REPRESENTATIVENESS	The number of associations and meanings a word has	Familiarity	Semantic relation
EASE-OF-USE	The word complexity and amount of cognitive load it requires	Fluency	Simplicity
AFFECT	The level of affect a word stimulate	Feeling	Sentiment analysis
DISTRIBUTION	Availability and recognizability of a word	Frequency	Saliency / Significance

DEVELOPING A CONCEPTUAL FRAMEWORK

- H1: Words' representativeness, ease-of-use, affect, and distribution scores will predict their level of engagement
- H2: When there is more than one possible word to describe the same information, a word's representativeness, ease-of-use, affect and distribution scores will predict whether a synonym is more engaging



Feature selection

- Computational Linguistics
- Features for predictive model
- Developed an original Python program
- Calculated for the 400 words from study 1

```python
def read_score(word):
    read = dict()
    read['word'] = str(word)
    syns = wn.synsets(word)
    read['rs'] = len(syns)
    read['e-swn-pos'] = 0
    read['e-swn-neg'] = 0
    if read['rs'] > 0 :
        for s in syns:
            swn_synset = swn.senti_synset(s.name())
            escore = [swn_synset.pos_score(),swn_synset.neg_score(),swn_synset
            if len(escore) == 3:
                read['e-swn-pos'] += escore[0]
                read['e-swn-neg'] += escore[1]
        read['e-swn-pos'] = read['e-swn-pos'] / read['rs']
        read['e-swn-neg'] = read['e-swn-neg'] / read['rs']
    read['e-swn-emo'] = read['e-swn-pos'] + read['e-swn-neg']
    read['as'] = syl_count(word)
    read['dfr'] = word_frequency(word, 'en')
    read['dzi'] = zipf_frequency(word, 'en')

def get_hyponyms(word):
    hyponyms = []
    syns = wn.synsets(word)
    for synset in syns:
        for hyponym in synset.hyponyms():
            hyponyms.append(hyponym.lemma_names())

    return(hyponyms)

def get_hypernyms(word):
    hypernyms = []
    syns = wn.synsets(word)
    for synset in syns:
        for hypernym in synset.hypernyms():
            hypernyms.append(hypernym.lemma_names())
```

Heuristic / parameter	Feature	measure
Representativeness	Definitions	Number of meanings- (polysemy count)
	hypernyms	Broad meaning that more specific words fall under
	hyponyms	More specific meaning than a general or superordinate term applicable to it
Ease-of-use	Length	Character count
	Weight	Syllables
Affect	Positivity	Pos score
	Negativity	Neg score
	Sentiment	Emotionality score
Distribution	Frequency	Word count (How frequently a word occurs)
	Zinf	the base-10 logarithm of the number of times it appears per billion words

UNIVERSITY AT ALBANY
State University of New York

Summary Statistics of Word Features

Feature	Mean	SD	Min	Max
Definitions Synsets	7.85	11.04	1	70
Hypernyms	4.75	7.53	0	60
Hyponyms	26.41	70.37	0	403
PosMax	0.22	0.27	0	0.875
NegMax	0.197	0.266	0	0.875
Syllables	2.17	1.15	1	6
Length	6.58	2.63	3	15
Frequency	0.000143	0.000372	0	0.00269
wnzipf	3.773	1.40	0	6.41

Multiple linear regressions were run to predict words' IE scores from their textual features

Variable	B (Evaluation)	SE B (Evaluation)	β (Evaluation)	t (Evaluation)	p (Evaluation)	B (Selection)	SE B (Selection)	β (Selection)	t (Selection)	p (Selection)	B (Retention)	SE B (Retention)	β (Retention)	t (Retention)	p (Retention)
(Constant)	2.297	0.005		443.730	0.000	.207	.001		386.743	.000	.078	.000		179.411	.000
definitions-synsets	0.000	0.000	-0.003	-0.704	0.481	.000	.000	-.233	-39.534	.000	7.041E-5	.000	.058	8.888	.000
hypernyms	-0.005	0.000	-0.185	-40.455	0.000	.001	.000	.292	51.891	.000	-5.481E-5	.000	-.031	-5.107	.000
hyponyms	0.000	0.000	0.034	12.669	0.000	-4.169E-6	.000	-.017	-5.073	.000	-9.664E-6	.000	-.051	-14.206	.000
posmax	0.126	0.005	0.161	23.911	0.000										
emotionalitymax	0.047	0.006	0.073	8.084	0.000										
negmax	-0.113	0.005	-0.143	-24.326	0.000										
len	-0.019	0.001	-0.241	-36.046	0.000	-.001	.000	-.112	-13.750	.000	-.002	.000	-.298	-33.506	.000
sylla	-0.041	0.001	-0.223	-32.292	0.000	-.002	.000	-.115	-13.593	.000	.001	.000	.055	5.978	.000
wnzipf	0.108	0.001	0.722	177.654	0.000	.005	.000	.419	85.397	.000	.003	.000	.337	62.357	.000
wnfreq	-175.563	1.842	-0.302	-95.297	0.000	-12.777	.187	-.260	-						

REGRESSION RESULTS OF UES

- $R2 = .539$
- $F = 8542.284$ ($p=0$)

Variable	B	SE B	β	t	p
(Constant)	2.297	0.005		443.730	0.000
definitions-synsets	0.000	0.000	-0.003	-0.704	0.481
hypernyms	-0.005	0.000	-0.185	-40.455	0.000
hyponyms	0.000	0.000	0.034	12.669	0.000
posmax	0.126	0.005	0.161	23.911	0.000
emotionalitymax	0.047	0.006	0.073	8.084	0.000
negmax	-0.113	0.005	-0.143	-24.326	0.000
len	-0.019	0.001	-0.241	-36.046	0.000
flesch_reading_ease	-0.001	0.000	-0.328	-51.952	0.000
sylla	-0.041	0.001	-0.223	-32.292	0.000
wnzipf	0.108	0.001	0.722	177.654	0.000
wnfreq	-175.563	1.842	-0.302	-95.297	0.000

REGRESSION RESULTS OF SELECTION

- $R2 = .298$
- $F = 3413.447$ ($p=0$)

Variable	B	SE B	β	t	p
(Constant)	.207	.001		386.743	.000
hypernyms	.001	.000	.292	51.891	.000
hyponyms	-4.169E-6	.000	-.017	-5.073	.000
definitions-synsets	.000	.000	-.233	-39.534	.000
emotionalitymax2	.028	.001	.513	47.049	.000
emotionalitysum	-.021	.000	-.473	-43.413	.000
len	-.001	.000	-.112	-13.750	.000
flesch_reading_ease	2.634E-6	.000	.013	1.719	.086
sylla	-.002	.000	-.115	-13.593	.000
wnzipf	.005	.000	.419	85.397	.000

REGRESSION RESULTS OF RETENTION

- R^2 = .185
- F = 1663.846 (p=0)

Variable	B	SE B	β	t	p
(Constant)	.078	.000		179.411	.000
definitions-synsets	7.041E-5	.000	.058	8.888	.000
hyponyms	-9.664E-6	.000	-.051	-14.206	.000
hypernyms	-5.481E-5	.000	-.031	-5.107	.000
negmax2	-.009	.000	-.183	-23.391	.000
emotionalitymax2	.014	.000	.333	27.917	.000
posmax2	-.014	.000	-.283	-31.612	.000
len	-.002	.000	-.298	-33.506	.000
flesch_reading_ease	-8.185E-6	.000	-.055	-6.607	.000
sylla	.001	.000	.055	5.978	.000
wnzipf	.003	.000	.337	62.357	.000
wnfreq	-6.569	.155	-.178	-42.279	.000

Prediction (split 80/20)

Evaluation formula

$$yEvaluation = 2.297 + 0.000(definitions - synsets) - 0.005(hypernyms) + 0.000(hyponyms) + 0.126(posmax) + 0.047(emotionalitymax) - 0.113(negmax) - 0.019(len) - 0.001(flesch_{r}eading_{e}ase) - 0.041(sylla) + 0.108(wnzipf) - 175.563(wnfreq)$$

Selection formula

$$yEvaluation = 2.297 + 0.000(definitions - synsets) - 0.005(hypernyms) + 0.000(hyponyms) + 0.126(posmax) + 0.047(emotionalitymax) - 0.113(negmax) - 0.019(len) - 0.001(flesch_{r}eading_{e}ase) - 0.041(sylla) + 0.108(wnzipf) - 175.563(wnfreq)$$

Retention formula

$$y^{R}etention = .078 + 7.041E - 5(definitions - synsets) - 9.664E - 6(hyponyms) - 5.481E - 5(hypernyms) - .009(negmax2) + .014(emotionalitymax2) - .014(posmax2) - .002(len) - 8.185E - 6(flesch_{r}eading_{e}ase) + .001(sylla) + .003(wnzipf) - 6.569(wnfreq)$$

Evaluation the model

$$\text{Success} = \frac{\text{Number of Correct Positives (Higher probability score)}}{\text{Total}}$$

- **Perception (Mean UES):** The model accurately predicted the higher UES score synonym in 90% of cases (36 out of 40 pairs).
- **Participation (Selection Rate):** The model's predictions were correct in 82% of cases, identifying the synonym with a higher selection rate in 33 out of 40 pairs.
- **Perseverance (Retention Rate):** The model successfully forecasted the synonym with a higher retention rate in 80% of cases (32 out of 40 pairs).

$$P(all) = P(Perception) \times P(Participation) \times P(Perseverance)$$
$$P(all) = \frac{36}{40} \times \frac{33}{40} \times \frac{32}{40}$$

The combined probability of the model correctly predicting all three measures (Perception, Participation, and Perseverance) is approximately 0.594, or 59.4%.

Logistic Regression Results – difference in features

Feature	Coefficient	P-value
const	-2.0611	0.000
DefinitionsSynsets	-0.0375	0.101
Hypernyms	-0.1023	0.000
Hyponyms	0.0184	0.164
PosMax	0.1312	0.000
NegMax	-0.0686	0.000
Syllables	-0.0700	0.025
Length	-0.0410	0.239
Frequency	-0.2195	0.000
wnzipf	0.5569	0.000

Logistic Regression Results – 92.5%

$$P(Y=1|X)=\frac{1}{1+e^{-(-2.0611-0.0375X_{\text{DefinitionsSynsets}}-0.1023X_{\text{Hypernyms}}+0.0184X_{\text{Hyponyms}}+0.1312X_{\text{PosMax}}-0.0686X_{\text{NegMax}}-0.0700X_{\text{Syllables}}-0.0410X_{\text{Length}}-0.2195X_{\text{Frequency}}+0.5569X_{\text{wnzipf}})}}$$

Model	Prediction Accuracy
Logistic Regression	92.5%
Random Forest	92.5%

Information engagement can be predicted

- IE dimensions can be predicted systematically based on textual factors
- A word's representativeness, ease-of-use, affect, and distribution scores can be used to predict its IE levels
- When there is more than one possible word to describe the same information, a word's representativeness, ease-of-use, affect, and distribution scores will predict whether a synonym of the word is more engaging
- Limitations and future steps

STUDY 3

Digital information manipulation and assessment (DIMA)

INTRODUCTION

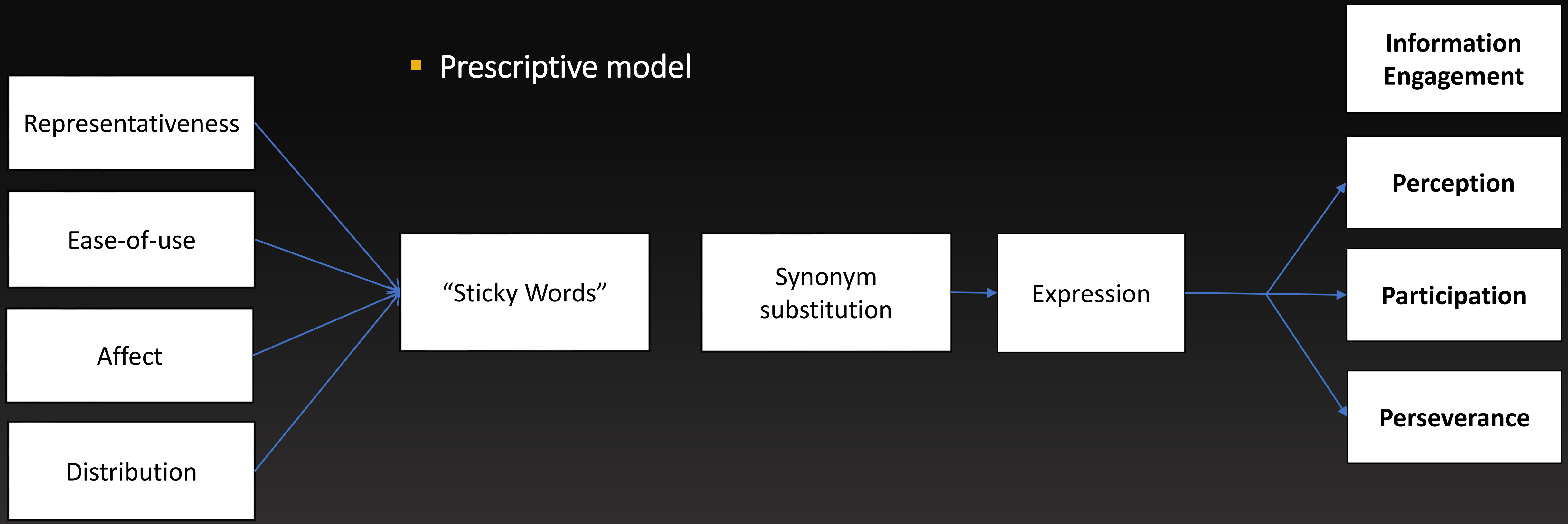
- Application of the dissertation research
- Engaging words can be predicted
- Prescriptive model
- Current research is focused on identifying and evaluating IE, but not on the actual development of engaging experiences

THE FRAMING EFFECT

- A phenomenon observed as part of the Cumulative Prospect Theory (CPT)
- People tend to think of possible outcomes usually relative to a certain reference point rather than to the final status
- The framing of problems adopted by decision-makers results in part from extrinsic manipulation of the decision-options offered

DEVELOPING A CONCEPTUAL FRAMEWORK

- Prescriptive model



H_1: Use of more engaging words will positively influence the level of IE with the entire text as measured by participation, perception, and perseverance.

STUDY DESIGN

- Synonym substitution
- 30 pairs of sentences
- A/B Testing (RCTs)
- Preparing a data set
- Computational linguistics - Based on the findings of the previous studies, we will calculate the READ score, or IE probability, for each of the phrases in WordNet – a total of 155,287 words
- Developed an original Python program and a customized GPT agent
- Natural language processing - Stemming and Lemmatization

Titles (partial list)

Original Title	Modified Title	Suggested Categories
The Acquisition of Language	The Learning of Language	Linguistics, Education, Cognitive Development
Digital Metamorphosis in Intricate Systems	Digital Transformation in Complex Systems	Information Technology, Systems Engineering, Digital Innovation
Ascertain the research imperatives for emergency care within the Western Cape province of South Africa: A unanimity study	Determining the research priorities for emergency care within the Western Cape province of South Africa: A consensus study	Public Health, Emergency Medicine, Health Policy
An Examination of Monotonous Speech Patterns in Audiobooks	An Examination of Repetitive Speech Patterns in Audiobooks	Linguistics, Speech Pathology, Literary Studies
A Longitudinal Study of Lackluster Student Performance in STEM	A Repeated Measures Study of Poor Student Work in STEM	Education, STEM Education, Academic Performance
The Neuroscience of Language	The Brain Science of Language	Neuroscience, Psycholinguistics, Cognitive Science
The Consequences of Physical Exertion on Cognitive Function	The Impact of Physical Activity on Mental Function	Exercise Science, Neuropsychology, Health Psychology
The Essence of Existence	The Meaning of Life	Philosophy, Theology, Metaphysics
The Contribution of Genetics in Mental Agility	The Role of Genetics in Intelligence	Genetics, Cognitive Science, Behavioral Science
The Consequences of Social Isolation on Psychological Well-being	The Effects of Social Isolation on Mental Health	Psychology, Social Psychology, Mental Health
The Association Between Stress and Ailment	The Relationship Between Stress and Disease	Health Psychology, Psychosomatic Medicine, Stress Research

STUDY DESIGN

Procedure

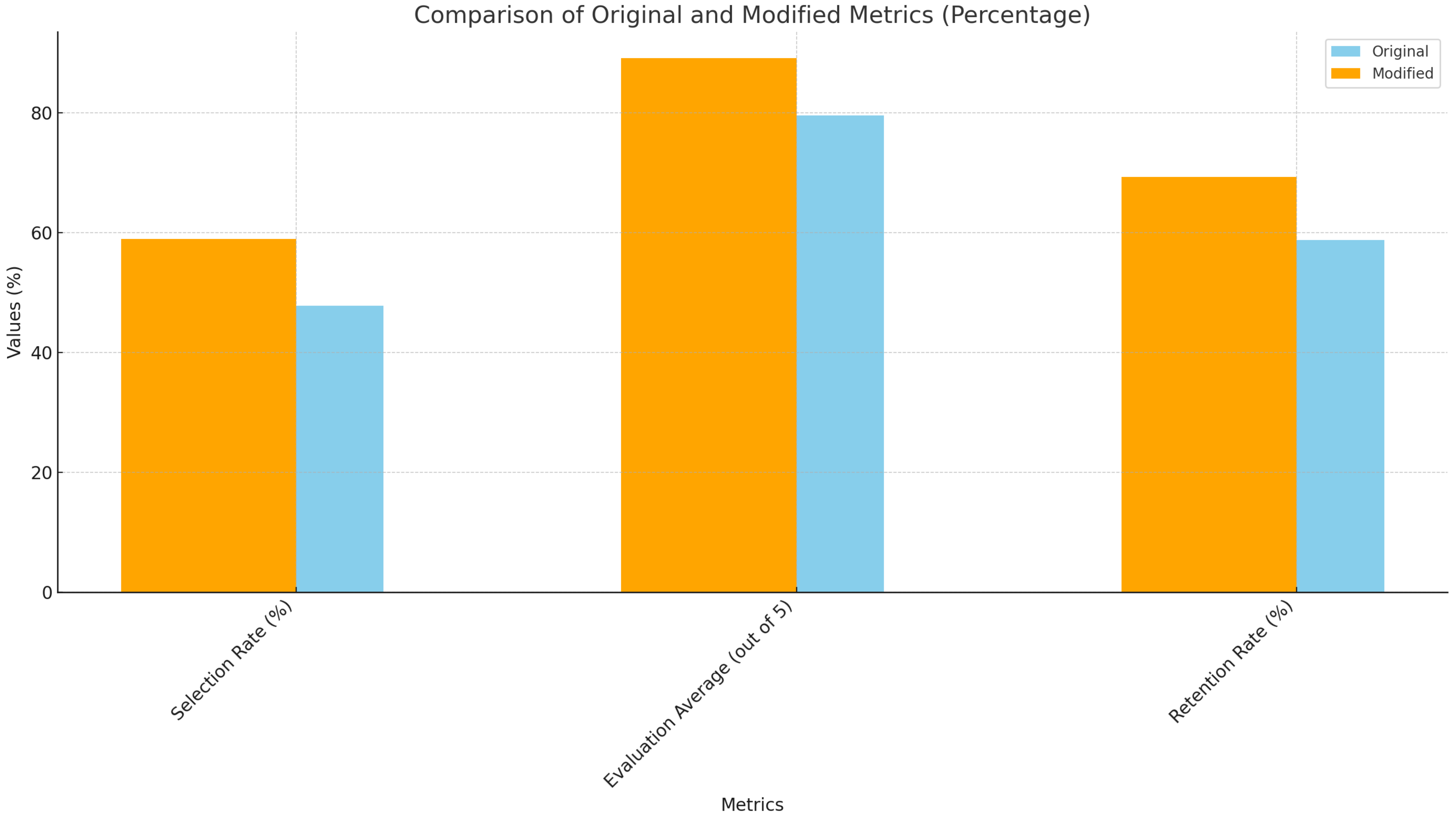
- A/B Testing (randomized controlled trials)
- Users were presented with a title and were asked
  - To select if they would like to read it to measure participation
  - To evaluate it using the UES to measure perception
  - To recall and recognize them to measure perseverance

	1 - Strongly disagree	2 - Somewhat disagree	3 - Neither agree nor disagree	4 - Somewhat agree	5 - Strongly agree
This headline appealed to my senses	○	○	○	○	○
My attention was focused while reading the headline	○	○	○	○	○
The headline was easy to understand	○	○	○	○	○
The experience reading the headline was rewarding	○	○	○	○	○
This article is not engaging	○	○	○	○	○
I wasn't focused while reading the headline	○	○	○	○	○
This headline was hard to understand	○	○	○	○	○
The experience reading this article is not worthwhile	○	○	○	○	○

Overall scores:

- Original Selection Rate: 47.83%
- Modified Selection Rate: 59.67%
- Original Evaluation Average: 3.95
- Modified Evaluation Average: 4.42
- Original Retention Rate: 57.65%
- Modified Retention Rate: 68.30%

Metric	**T-Statistic**	**P-Value**	**Mean (Original)**	**SD (Original)**	**Mean (Modified)**	**SD (Modified)**	**P(Sig)**
Selection Rate (%)	-30.046	2.10e-23	47.80	2.73	58.97	2.36	***
Evaluation Average (out of 5)	-17.948	3.02e-17	3.98	0.21	4.46	0.19	***
Retention Rate (%)	-35.132	2.54e-25	58.77	2.18	69.37	2.09	***


Comparison of Original and Modified Metrics (Percentage)
Original
Modified
Values (%)
0
20
40
60
80
Selection Rate (%)
Evaluation Average (out of 5)
Retention Rate (%)
Metrics

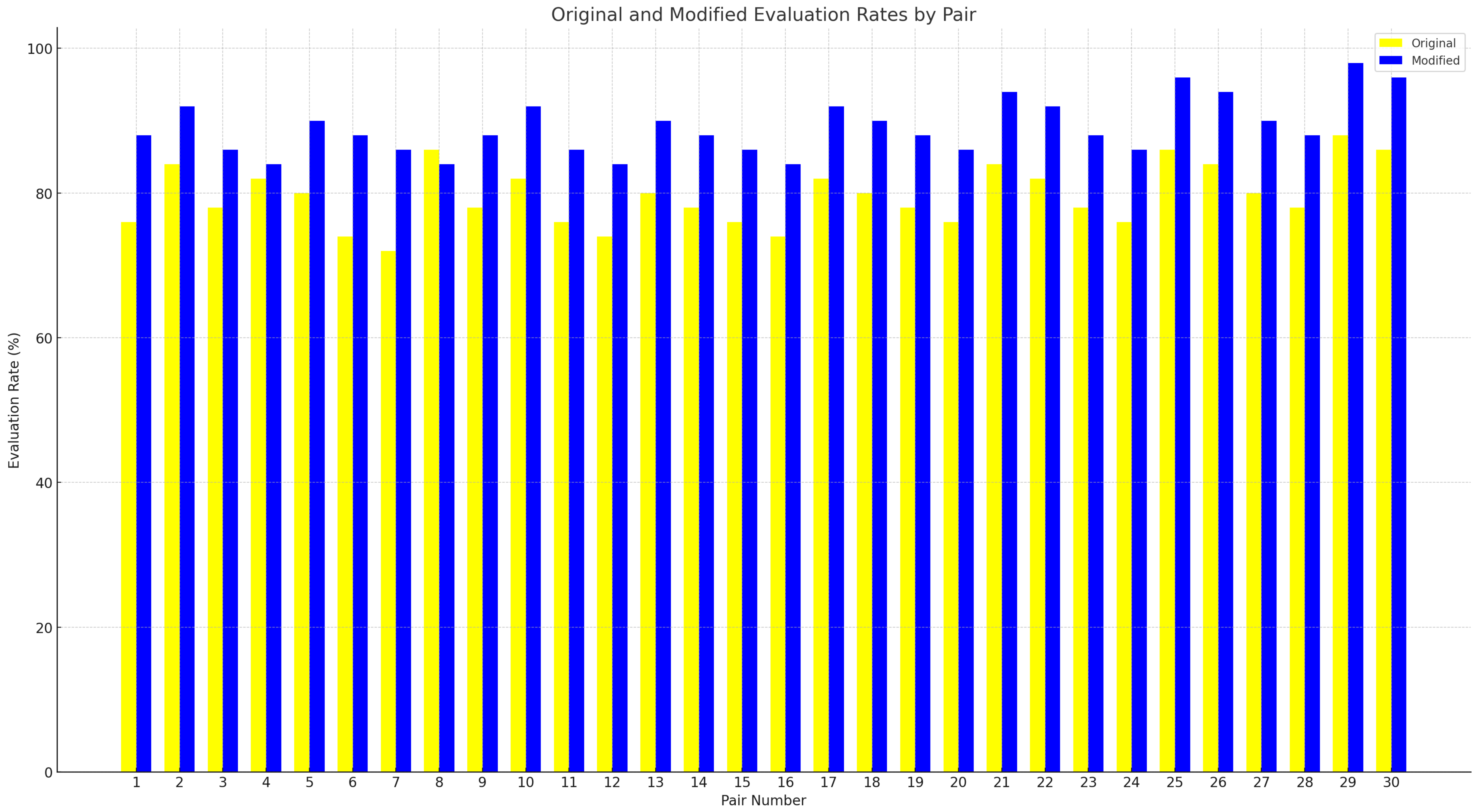
Pair wise comparison

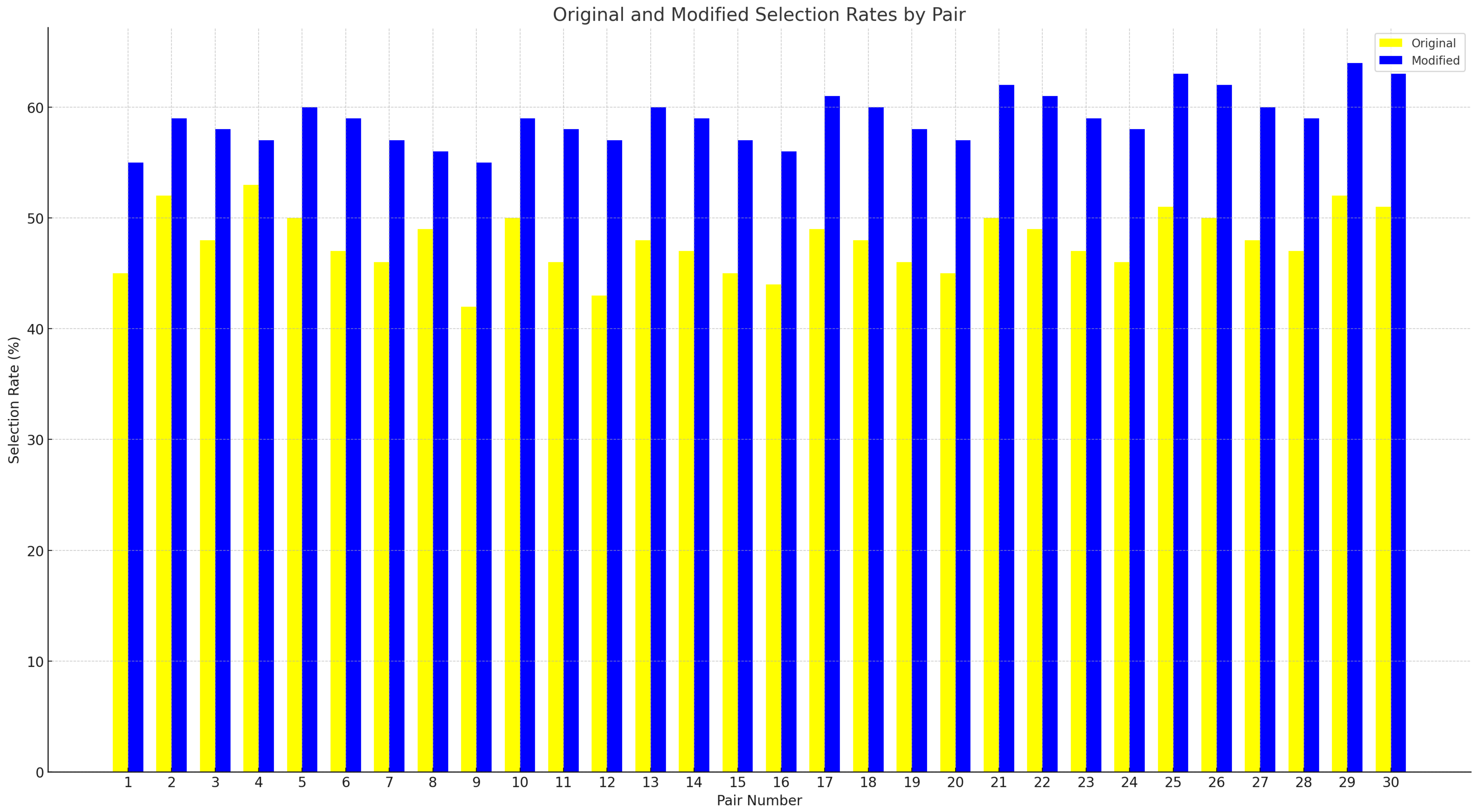
- Evaluation: 24 out of 30 modified pairs are higher in evaluation.
- Retention: 21 out of 30 modified pairs are higher in retention.
- Selection: 18 out of 30 modified pairs are higher in selection.

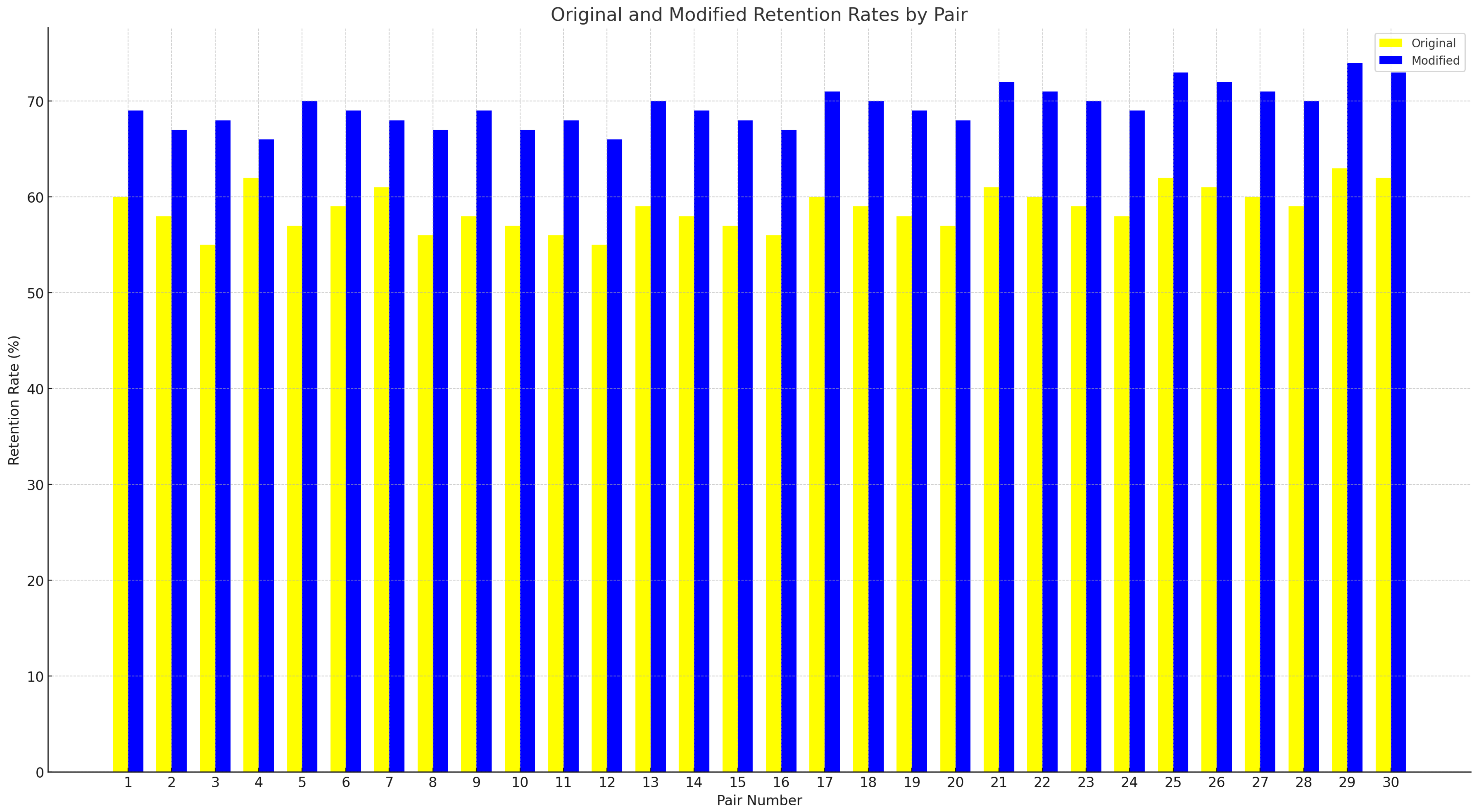
$$\text{Evaluation Success: } \frac{24}{30}$$

$$\text{Retention Success: } \frac{21}{30}$$

$$\text{Selection Success: } \frac{18}{30}$$


Original and Modified Evaluation Rates by Pair
Original
Modified
Evaluation Rate (%)
0
20
40
60
80
100
Pair Number
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30


Original and Modified Selection Rates by Pair
Original
Modified
Selection Rate (%)
Pair Number
0
10
20
30
40
50
60
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30



Original and Modified Retention Rates by Pair
Original
Modified
Retention Rate (%)
Pair Number
0
10
20
30
40
50
60
70
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30

UNIVERSITY AT ALBANY
State University of New York

Sentence Pair	Original Selection Rate (%)	Modified Selection Rate (%)	Original Evaluation Average (out of 5)	Modified Evaluation Average (out of 5)	Original Retention Rate (%)	Modified Retention Rate (%)
Pair 1	45	55	3.8	4.4	60	69
Pair 2	52	59	4.2	4.6	58	67
Pair 3	48	58	3.9	4.3	55	68
Pair 4	53	57	4.1	4.2	62	66
Pair 5	50	60	4.0	4.5	57	70
Pair 6	47	59	3.7	4.4	59	69
Pair 7	46	57	3.6	4.3	61	68
Pair 8	49	56	4.3	4.2	56	67
Pair 9	42	55	3.9	4.4	58	69
Pair 10	50	59	4.1	4.6	57	67
Pair 11	46	58	3.8	4.3	56	68
Pair 12	43	57	3.7	4.2	55	66
Pair 13	48	60	4.0	4.5	59	70
Pair 14	47	59	3.9	4.4	58	69
Pair 15	45	57	3.8	4.3	57	68
Pair 16	44	56	3.7	4.2	56	67
Pair 17	49	61	4.1	4.6	60	71
Pair 18	48	60	4.0	4.5	59	70
Pair 19	46	58	3.9	4.4	58	69
Pair 20	45	57	3.8	4.3	57	68
Pair 21	50	62	4.2	4.7	61	72
Pair 22	49	61	4.1	4.6	60	71
Pair 23	47	59	3.9	4.4	59	70
Pair 24	46	58	3.8	4.3	58	69
Pair 25	51	63	4.3	4.8	62	73
Pair 26	50	62	4.2	4.7	61	72
Pair 27	48	60	4.0	4.5	60	71
Pair 28	47	59	3.9	4.4	59	70
Pair 29	52	64	4.4	4.9	63	74
Pair 30	51	63	4.3	4.8	62	73

Information engagement can be prescribed

- Substituting words with more engaging synonyms will positively influence the level of IE with the entire text
- It is possible to computationally predict which words will be sticky words
- Results vary based on other factors
- Significance and future work

Contribution

1. Conceptually and operationally defined IE by identifying its distinctive dimensions and determinants

2. Recognized predictors of engaging information and use them for quantitative feature selection and development of a predictive model and metrics

3. Created and tested an instrument to assess and manipulate IE systematically and computationally using computational linguistics, text analysis and natural language processing

GPTs

Discover and create custom versions of ChatGPT that combine instructions, extra

DISSERTATION DISCUSSION

- Results suggests that IE is fostered by, and perhaps dependent upon, information design, specifically the wording being used
- Findings provide empirical support that IE can be systematically evaluated and produced
- In addition to being the first study to identify these relationships, this dissertation’s major contribution include identifying the critical textual factors that affect IE
- Value in various contexts: education, health, media and more

RELATED WORK

Conference presentations and invited talks

1. Dvir, N., Commuri, S., Chengalur-Smith, S., Yang, F., Romano, J. (2021, July). ***What do users read? A predictive model of information engagement.*** The 15th annual Israel Association for Information Systems (ILAIS) conference. The Open University of Israel.
2. Dvir, N. (2019, May). ***Using text analysis and computational linguistics to systematically evaluate and improve information interactions, user experience (UX), knowledge acquisition and decision making*****.** The annual Informing Science and information technology education conference. Jerusalem, Israel.
3. Dvir, N. (2019, May). ***What is user engagement? A suggested model for successful user interaction with digital information.*** The annual Informing Science and information technology education conference. Jerusalem, Israel.
4. Dvir, N. (2018, December*)*. ***Mark my words: Using linguistic analysis to evaluate and optimize information behavior and user experience.*** The International Conference on Information Systems (ICIS), San Francisco, CA
5. Dvir, N. (2018, November). ***Sticky words: Evaluation and optimization of information interactions based on linguistic analysis.*** The annual meeting of the Association for Information Science & Technology (ASIS&T), Vancouver, Canada
6. Dvir, N. (2018, August). ***Conceiving a model for user engagement using linguistic analysis.*** Americas Conference on Information Systems. The annual Americas Conference on Information Systems (AMCIS), New Orleans, LA
7. Dvir, N. (2018, June). ***Less is more: An empirical investigation of the relationship between amount of digital content and user engagement.*** In User Experience Professionals Association (UXPA) International Conference. Rio Mar, Puerto Rico
8. Gafni, R. & Dvir, N. (2018). ***How content volume on landing pages influences consumer behavior: empirical evidence.*** The annual Informing Science and information technology education conference, la Verne, California
9. Dvir, N. (2018). ***Automatic development of engaging content using natural language processing techniques.*** New Trends in Information Studies conference (NTIR). Albany, NY

RELATED WORK

Refereed articles and proceedings

1. Dvir, N., Commuri, S., Yang, F., Romano, J., Friedman, E. *Definition, Dimensions, and Determinants of Information Engagement.* Manuscript in preparation.
2. Dvir, N., Commuri, S., Yang, F., Romano, J., Friedman, E. *Development of the READ Model: Representativeness, Ease-of-Use, Affect and Distribution as Predictors of Information Engagement.* Manuscript in preparation.
3. Dvir, N., Commuri, S., Yang, F., Romano, J., Friedman, E. *Digital Information Manipulation and Assessment (DIMA).* Manuscript in preparation.
4. Dvir, N. (2020). Process of information engagement: Integrating information behavior and user engagement. *Proceedings of the Association for Information Science and Technology*, *57*(1). https://doi.org/10.1002/pra2.407
5. Dvir, N., & Gafni, R. (2019). Systematic improvement of user engagement with academic titles using computational linguistics. *Proceedings of The Informing Science and Information Technology Education Conference*, 501–512. https://doi.org/10/ggjhjw
6. Dvir, N. (2018). Sticky words: Evaluation and optimization of information interactions based on linguistic analysis. *Proceedings of the Association for Information Science and Technology*, *55*(1), 797–798. https://doi.org/10.1002/pra2.2018.14505501121
7. Dvir, N., & Gafni, R. (2018). When less is more: Empirical study of the relation between consumer behavior and information sharing on commercial landing pages. *Informing Science: The International Journal of an Emerging Transdiscipline*, *21*, 019--039. https://doi.org/10.28945/4015
8. Gafni, R., & Dvir, N. (2018). How content volume on landing pages influences consumer behavior: Empirical evidence. *Proceedings of the Informing Science and Information Technology Education Conference, La Verne, California*, 035–053. https://doi.org/10.28945/4016

methods to consider:

- Logistic Regression for Each Dependent Variable: If the dependent variables are independent of each other, you could use separate logistic regression models for each. Logistic regression is suitable for binary outcomes and can handle continuous independent variables.
- Multinomial Logistic Regression: If your dependent variables can be combined into a single categorical variable with multiple levels (e.g., all combinations of the binary outcomes), multinomial logistic regression can be used. This is more complex and is appropriate when the outcomes are mutually exclusive.
- Multivariate Logistic Regression: If the binary outcomes are not independent, a multivariate logistic regression model (or a related method like a generalized estimating equation) can be used. This allows for the modeling of the correlation between the dependent variables.
- Bayesian Methods: Bayesian models can be very flexible and allow for complex relationships between variables, including hierarchical structures and dependencies between outcomes.
- Machine Learning Approaches: Techniques like Random Forests or Neural Networks can model non-linear relationships and interactions between variables. They may be appropriate if your data has complex patterns that traditional regression methods can't capture.
- Probability of All Dependent Variables Being 1: To calculate the probability of all three dependent variables being 1, you could use a joint probability model if the variables are dependent. If they're independent, it's simply the product of the individual probabilities.

- Separate Models for Each Outcome: One straightforward approach is to model each outcome separately using appropriate methods for each type:

- For binary outcomes: Logistic regression or other binary classification methods.
- For the continuous outcome: Linear regression or other regression techniques.
- Multivariate Regression Models: These models can handle multiple outcomes, including a mix of continuous and binary variables. However, they are more complex and might require specialized statistical software.

- Structural Equation Modeling (SEM): SEM is a powerful statistical technique that can model complex relationships between variables, including different types of outcomes. It can be particularly useful if there are hypothesized relationships between the dependent variables themselves.

- Random Forests or Gradient Boosting Machines (GBMs): These machine learning methods can be adapted to handle mixed types of dependent variables, either by modeling them separately within the same framework or by customizing the loss function.

- Deep Learning Models: Neural networks can be designed to output different types of variables. For example, you could have a network with two sigmoid output units for the binary variables and one linear output unit for the continuous variable. The complexity and data requirements for these models are typically higher.

- Bayesian Multilevel Models: These models are quite flexible and can accommodate mixed outcome types. Bayesian methods are particularly useful when dealing with complex models and can be effective even with relatively small sample sizes, thanks to the use of prior distributions.

QUESTIONS?

ndvir@albany.edu

Thank you!

ndvir@albany.edu

Additional slides

IMPORTANCE OF INFORMATION ENGAGMENT

- Currently the majority of the information distributed digitally is in the form of text (Johnston & Taylor, 2018).
- 93% of adults in the U.S. report consuming information online, either via a mobile device or a computer (Stocking, 2017).
- 79% of U.S. adults reported making an online purchase, spending nearly $350 billion annually (Smith, 2017);
- 80% of Americans have used at least one online government service (Im et al., 2013);
- 71% of Americans report looking online for health information (Perski et al., 2017; Rock Health, 2015).
- Most of the information published fails to engage resulting in it being barely noticed or quickly forgotten (Arapakis et al., 2017).