AI in Innovation & Ideation

Gerard J. Tellis

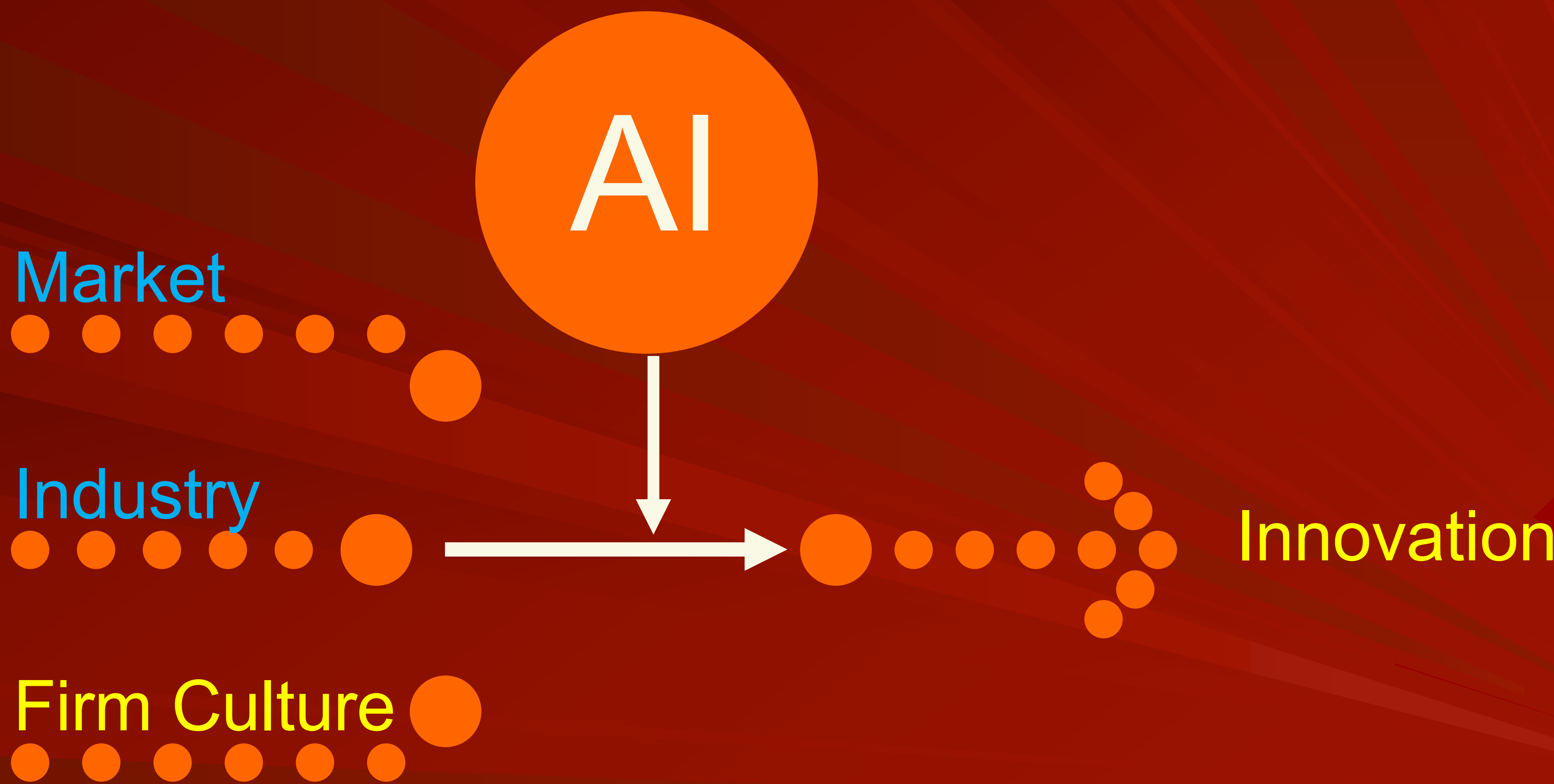
With Christian Pescher, Jason Bell, & Johan Fuller

USC Marshall Center for Global Innovation

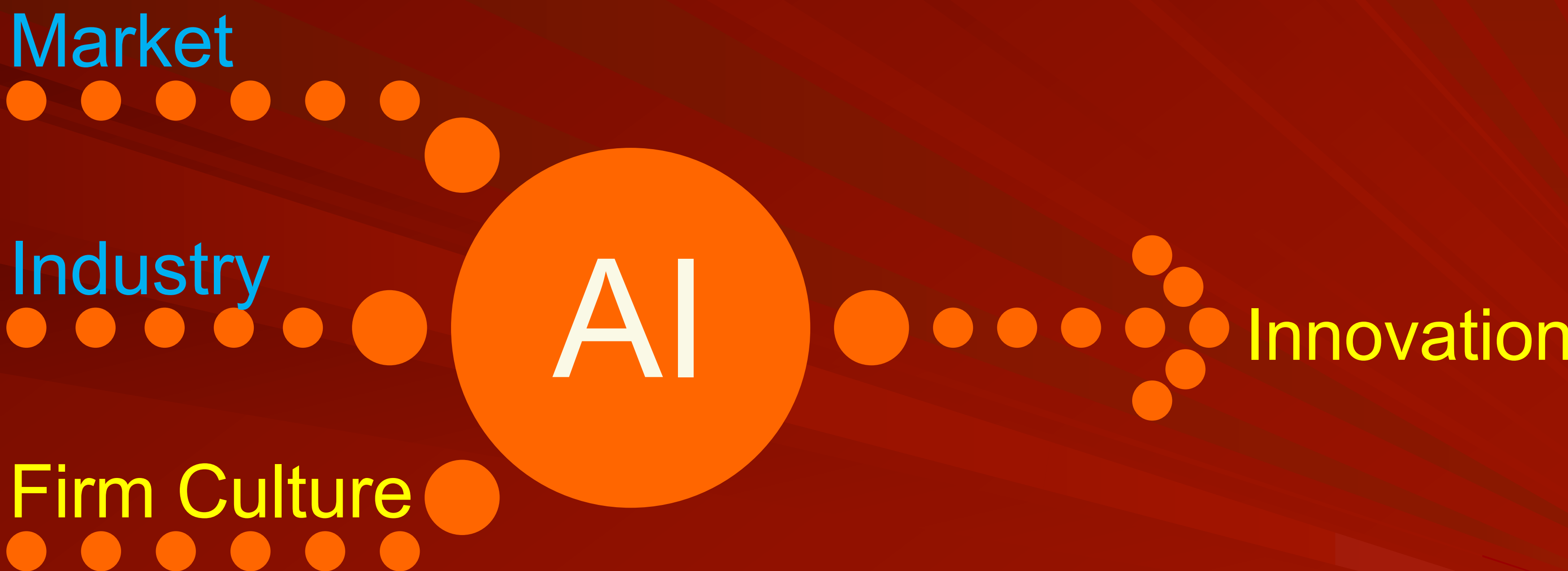
Relevance of Innovation and AI

- Innovation crucial for consumers, firms and, nations
- AI fundamentally changes how business gets done – including innovation
- 74% of American firms have adopted AI in at least some part of their business (PwC 2024)

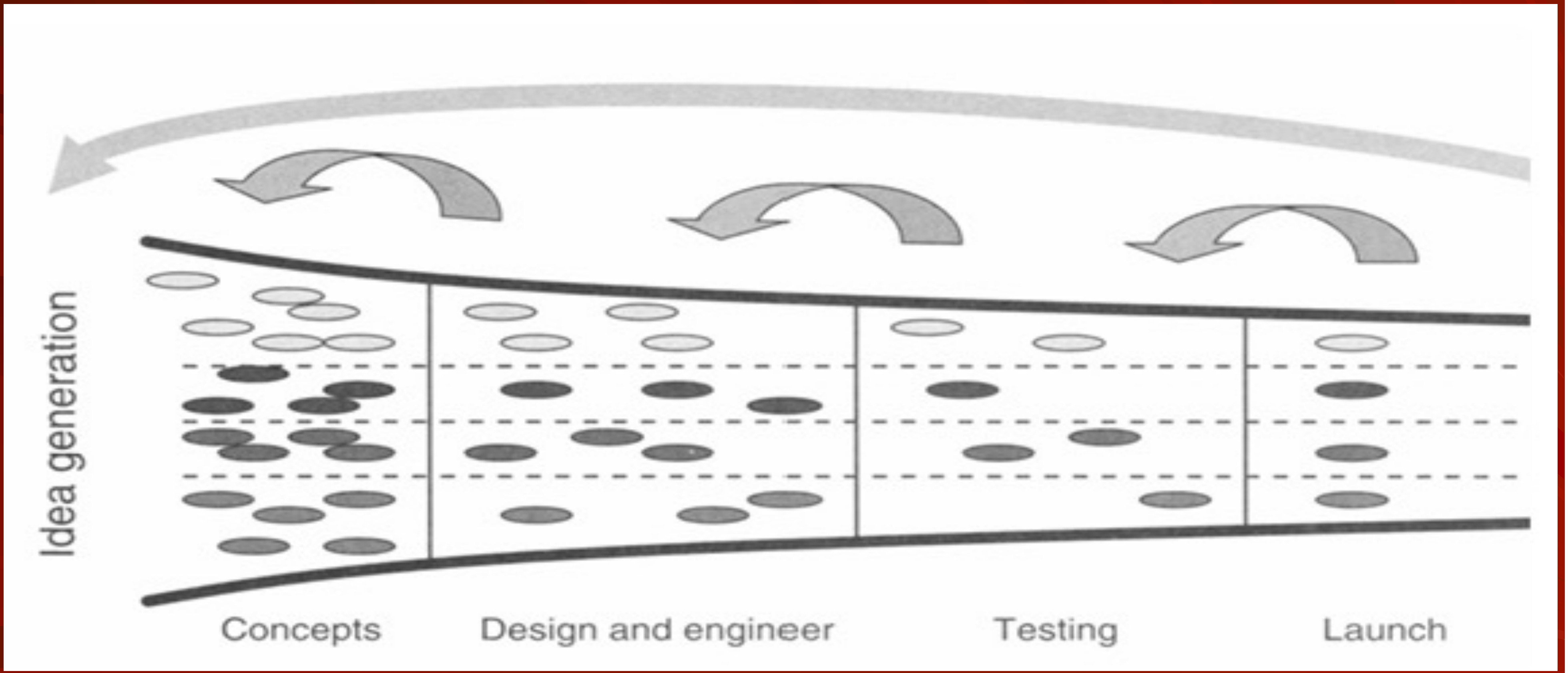
How AI Drives Innovation? Moderator?



How AI Drives Innovation? Or Mediator?



Innovation Process in 2006 (Hauser, Tellis, Griffin)



Innovation Process in 2025
Pescher & Tellis

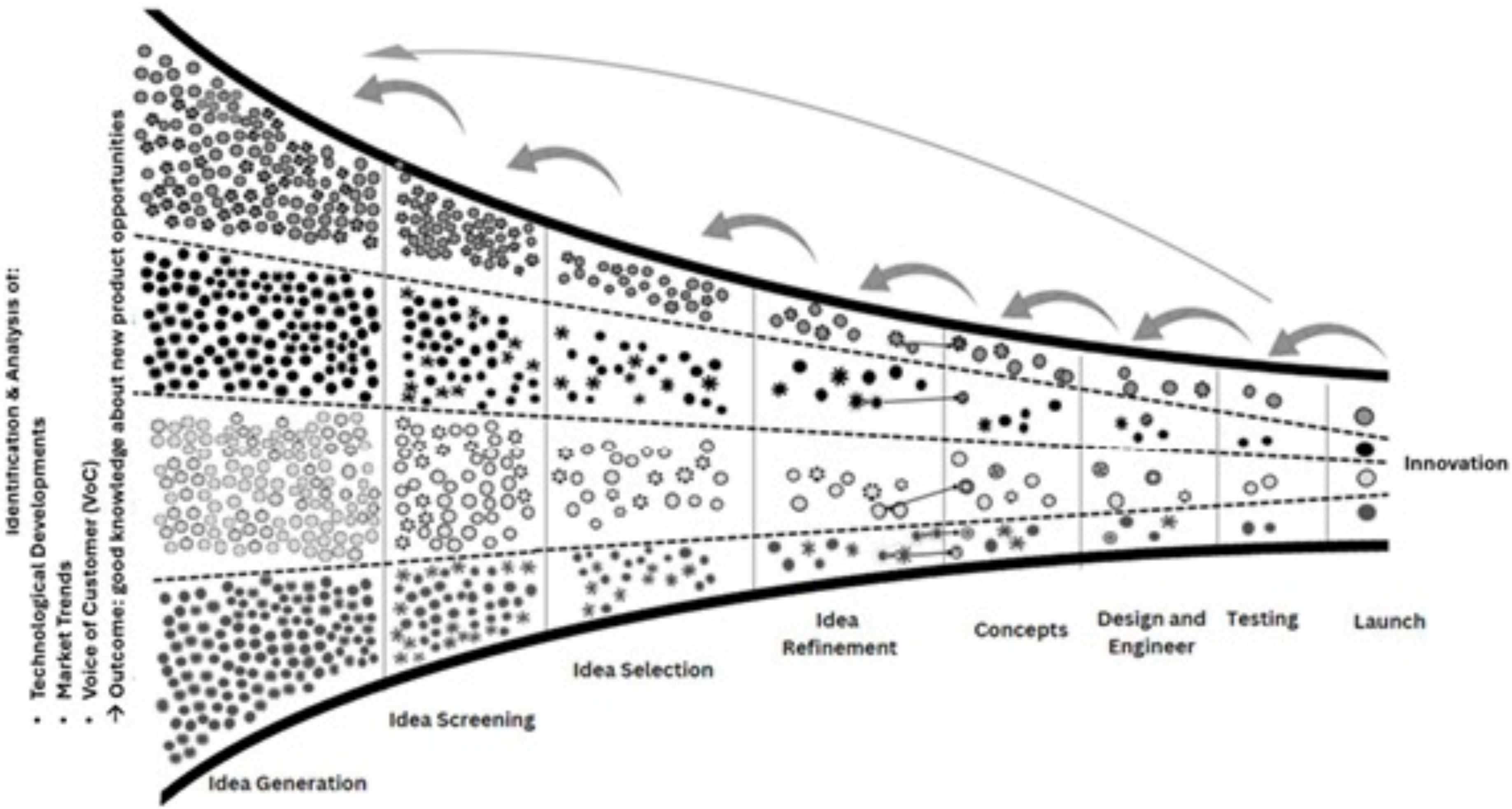


FIGURE 2. Framework of the Innovation Process (Source: adapted from Hauser, Tellis, & Griffin, 2006)

AI in Opportunity Identification:

Currently:

- AI leads to more efficient opportunity identification (Huang and Rust 2018
  - Market Trends (e.g., Kopalle et al. 2022)
  - Voice of Customer (e.g., Dahan and Hauser 2022; Hauser, Li, Mao 2023)

Future:

- AI in voice & video (e.g., healthcare & video games)
- AI for technology identification

Idea Generation

Currently:

- AI increases volume and speed of ideas
  (Girotra et al. 2023; Zhou and Lee 2024)
- AI helps for incremental innovations
  (Boussioux et al. 2024; Girotra et al. 2024; Meincke et al. 2024)

Future:

- How use AI for radical innovations?

➢ *Technology feed*

➢ *Technologist prompt*

Can AI Help in Idea Screening vs Selection or Generation?

Gerard J. Tellis
with Jason Bell, Christian Pescher, Johann Füller

Marketing Science 2024

Context: Crowdsourcing

- Open public call for ideas
  - Insiders
    - R&D + Marketing
    - Others
  - Outsiders
    - Consumers
    - Distributors/Suppliers
    - Experts
- Increases number of ideas
- Increases diversity
- Decreases costs

Problem

- Ideation – fundamental concept in marketing → start of new product development process
- Crowdsourcing contests generate thousands of ideas
- Screening by experts is costly & error prone
- Can AI replace humans?

Levels of AI in Ideation

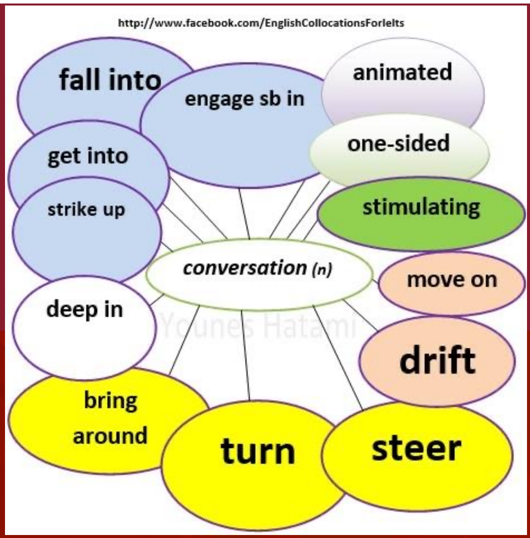
1. Screen out bad ideas?
2. Pick winning ideas?
3. Create one winning idea?

Goals of this Study

- Compare performance of 3 theory-based models
- Test performance out-of-sample
- Test whether any model or a combination can assist humans in selecting ideas

Theory 1: Idea's Word Colocation

Toubia & Netzer 2016:

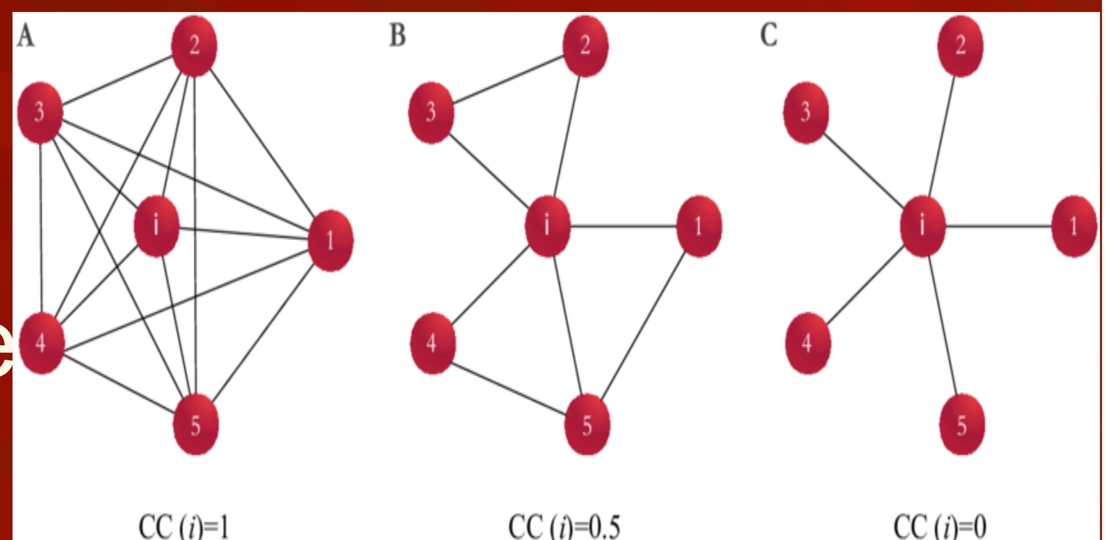


- Theory: Good ideas balance novelty and familiarity on that topic
- Hypothesis: Ideas whose distribution of word similarity close to a norm perform best
- Google search results for topic judged as norm
- Test: Lab experiments
- Study supports hypothesis in-sample

Theory 2: Ideator's Inspiration Redundancy

Stephen, Zubcsek, Goldenberg, 2016

- Theory: People with tight network of friends have less varied information exposure
- Hypothesis: tight clustering among friends leads to poorer ideas
- Test: Lab experiments
- Study supports hypothesis in-sample



Theory 3: Topic Atypicality :
Berger and Packard, 2018

- Theory: Unconventional content grabs attention
- Hypothesis: Lyrics of songs that diverge from genre average are more popular
- Test: Field data
- Study supports hypothesis in-sample

Our Setting

- 21 ideation contests run by Hyve over 10 years
- Steps in contests:
  - Call for ideas, with deadline & awards
  - Contestants submit ideas
  - Community comments and rates
  - Experts shortlist 10-15 finalists
  - Jury of C-suite execs declares 1-3 winners from shortlist

Example 1: Contest Intel

- Idea: Develop new personal uses for a tiny chipora wiki

#1 MY LIFE: THE SOUNDTRACK

USER: FREQUENTFLYER74

First Place goes to the entry called MY LIFE: The Soundtrack. It is a breakthrough idea that provides the intensified experience we all have when watching movies due to the enhancement of music perfectly fit to the scene.

#2 DAY AND NIGHT - TURNING NIGHT INTO DAY

USER: FREQUENTFLYER74

The second prize goes to the idea, DAY AND NIGHT- Turning Night into Day an entry that embodies a unique and futuristic approach.

#3 INTEL SOULMATE - IT'S A RING!

USER: CREATIVEAJITH

The third winner is the idea, INTEL SOULMATE - It's a Ring!. The idea convinced the jury because of the fine design and high functionality.

Descriptives of Some Contests

	Siemens Smart Grid Innovation Contest	DHL City Logistics Open Innovation Contest
Type of competition	Innovation Contest	Innovation Contest
Product	Energy	Improving cities' efficiencies
Members	2155	350
Submitted ideas	448	164
Comments	2197	1162
Messages	1772	894
Evaluations	3542	1809
Number of Prizes	8	10

Caution: Overfitting

- In sample prediction risks overfitting
- Overfitting: concern in creativity because good ideas for one setting may be bad elsewhere
- Solution: Do out-of-sample prediction: most important criterion for evaluating ideas
- Fit model on all but *n* contests; predict fo *n*
- Compute average errors

Testing Method: LASSO Logistic Regression

Least Absolute Shrinkage Operator

(penalty = absolute value of std coefficient)

- LHS Variable:

$y =$ 1 if the idea was shortlisted by experts , 0 otherwise

- RHS Variables fall into different groups:
  - Variables mentioned previously (Toubia & Netzer, Stephen et al., Berger and Packard), including extended versions
  - Lasso combines variables and selects those that perform be

Predictor Variables

Source	Variables	Computed from which data?
TN	Mean, min, max, and coef. of variation of Jaccard indices between word pairs	Google Search, Patent Corpus
TN	Mean, min, max, and coef. of variation of node frequencies	Google Search, Patent Corpus
TN	Kolmogorov-Smirnov metric from Toubia and Netzer (2017)	Google Search, Patent Corpus
SZG	Degree	Comments network
SZG	Clustering Coefficient (a.k.a. Transitivity)	Comments network
SZG	Constraints (Burt's metric)	Comments network
BP	Word Atypicality	All ideas from the same contest
BP	Topical Atypicality	All ideas from the same contest

TN = Toubia and Netzer, SZG = Stephen, Zubcsek and Goldenberg, BP = Berger and Packard

Lasso as a Variable Selection Tool

- Lasso is a ‘regularized’ linear model.
  - Regularized = includes an explicit bias
  - In the case of Lasso, the bias is toward parsimony
- Regression with ‘budget’: small coefficients pushed to zero
- Lasso yields parsimony with least variables for best prediction
- Samples: 20 contests pooled for estimation (fitting)
- Predict one held-out contest at time

Key Results

- In sample, every theory-based model has a metric in model -> all complementary
- Out-of-sample none of original models with original metrics survive

- Out of sample, LASSO keeps only one new metric – Word Atypicality. Atypical ideas do badly
- *Typical* Ideas perform best

Intuition of Word Typicality

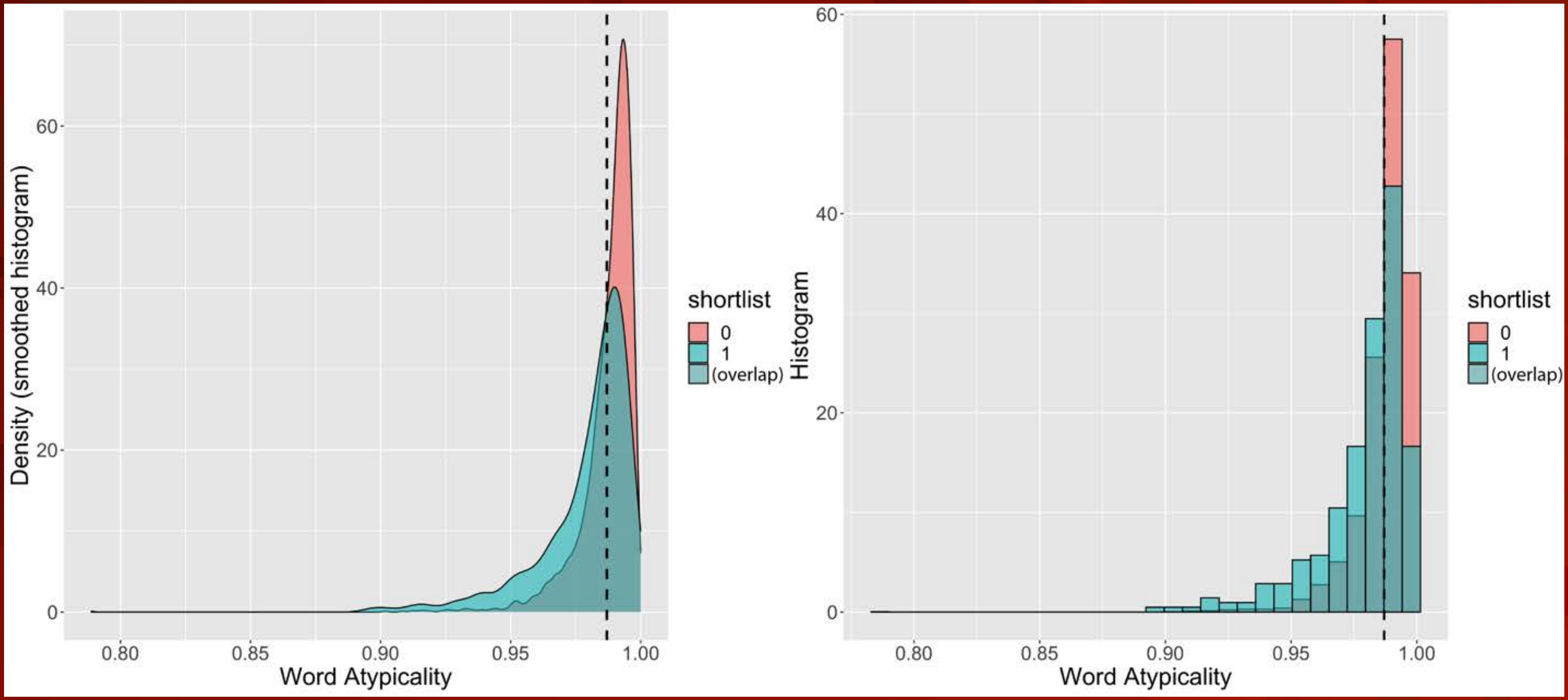
Typical ideas perform best

What are they?

Most

- Inclusive
- Rich
- Detailed

Distribution of Word Atypicality



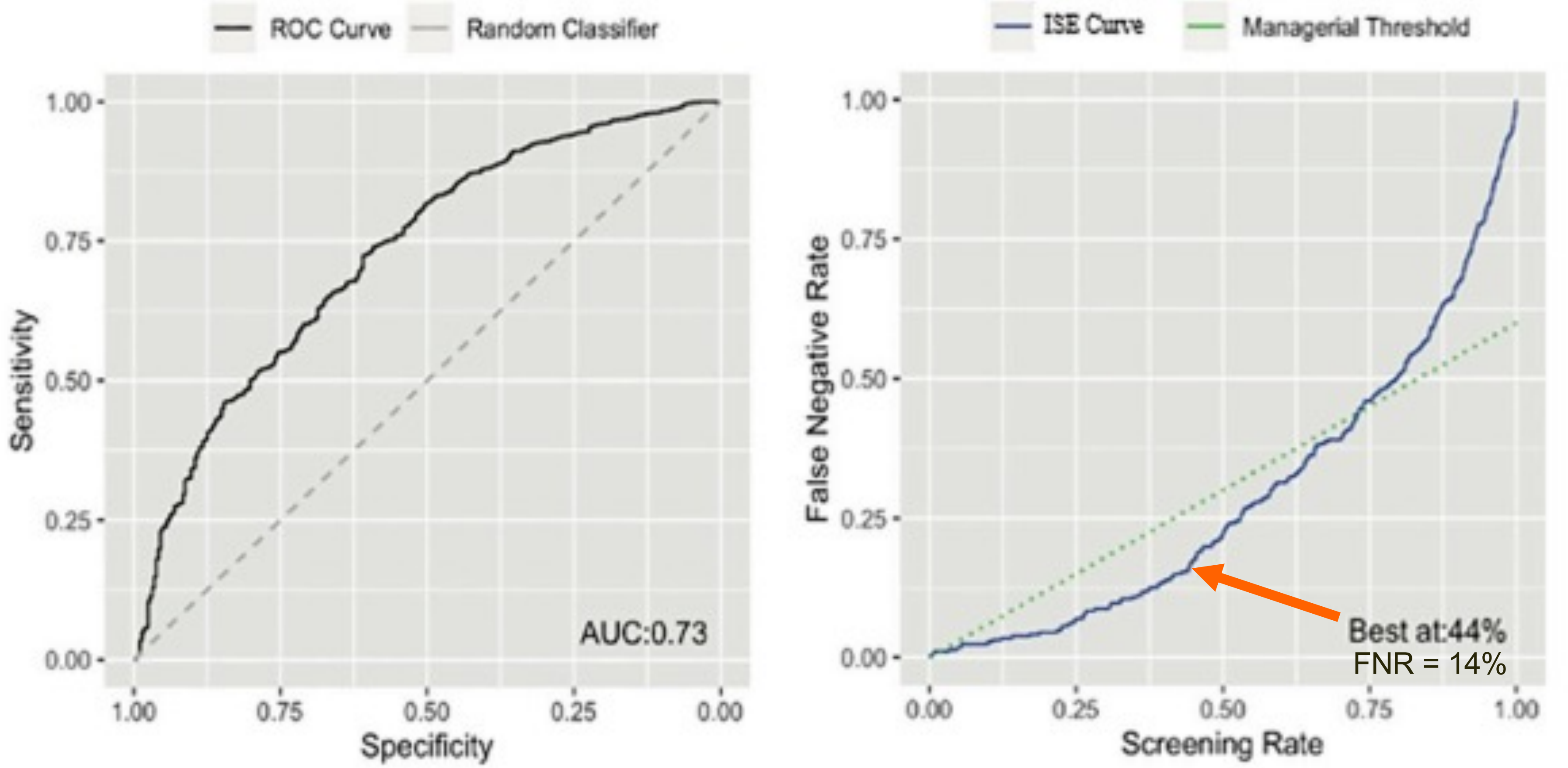
- Typical ideas whose values are close to 0, are shortlisted
- Atypical ideas whose ideas are close to 1, are rejected

Prediction vs Actual Tradeoff

Hyve Mandate
- Drop > 40% of worst ideas
- Loose no more than 20% good ideas

AI Keeps only variable Word Atypcality

FNR = False Negative Rate = 1- Sensitivity;
Sensitivity: True Positives/All Positives
Specificity: True Negative/All negatives



Sensitivity = True Positives / All Positives
Specificity = True Negatives / All Negatives
False Negative Rate = False Negatives / All Positives = 1 - Sensitivity
Screening rate = Number of Ideas Dropped / Number of All Ideas

Intuition for Why Typical Ideas (Low Word Atypicality) Do Well?

Ideas are a bag of words

- Richness: include many facets, suggests ideas are well developed
- Experience: Experienced ideators craft ideas that need less future development
- Communication: Resourceful ideators detail ideas well
- Ease of judgement: Experts find it easier to judge the quality of ideas that include details

Further Results

- Unable to meet AI Level 3: create a winning idea
- Unable to meet AI Level 2: Predict best ideas
- Able to meet AI Level 1 (screen out bad), Hyve’s threshold: eliminate 40% of worst ideas without losing more than 15% of best ideas
- We exceed greatly: eliminate 44% of worst ideas without losing more than 14% of good ideas

Benefits

- Use AI to at least reduce work for experts
  if not pick winners
- Reduce expert tedium, idiosyncrasies, errors
- Reduce costs, time

Why Ideation So Difficult for AI?

→ vs good performance in rule-based tasks (e.g., chess)

→ vs good performance in data rich tasks (e.g., face recognition)

- Novelty counts: Ideation is a rule-breaking task?
- Small training data: Small number of shortlisted ideas (vs thousands of games, millions of faces)?
- Human judgement is a noisy benchmark?
- Less learnable structure in ideation?

Structure in Ideation

Task: Find 4 to 20 winners out of (135 papers) in 2025 March, AI in Management (AIM) conference

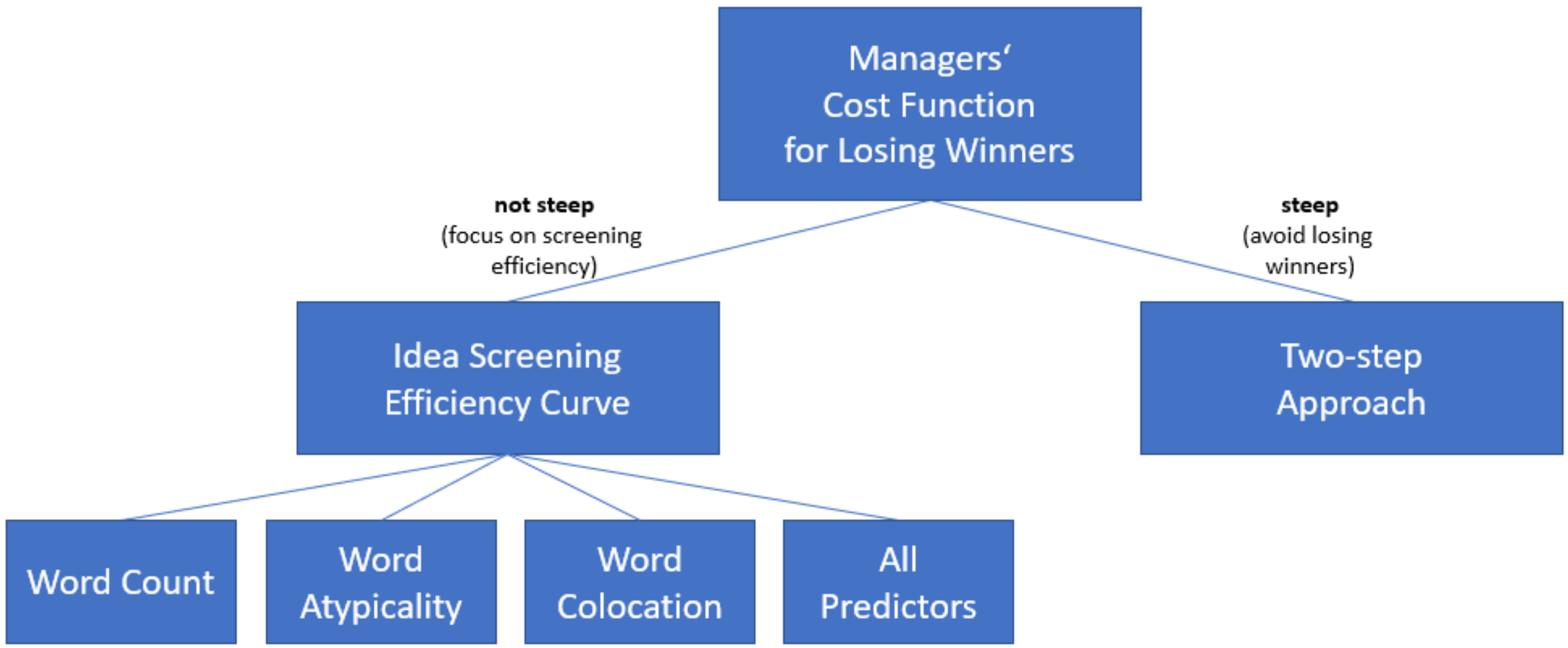
- Novelty
- Rigor
- Fits gap in literature/market
- Usefulness

Results Pending

Thank you!

(www.gtellis.net)

Recommendations for Managers



	Word Count	Word Atypicality	Word Colocation	All Predictors
Complexity	very low	low (focal text of ideas)	medium (focal text of ideas, Google search)	very high (focal text of ideas, Google search, comment network)
Screening Performance (ability to replicate expert evaluations)	good	very good (strength: screens many ideas)	very good (strength: sacrifices few good ideas)	best (screens slightly more ideas than other metrics)
Theory for Performance	no	inclusive and detailed ideas	innovative ideas	one theory per metric (see paper)

Limitations

- Did not test new AI model for creativity, similarity network (Wei Hong Tellis 2022)
- Survival bias: only winning ideas tested
  - True of real ideation contests
- Don’t have results of implementation
- Not yet used community ratings because they could affect experts (endogeneity)

Contributions

- Identified 3 levels of AI in ideation
- Identified 3 theory based, not data mining, AI algorithms
- Real contests, not lab
- Out-of-sample tests not in-sample
- Extended all three algorithms
- Found simple, word colocation, best idea screener

Bell, Pescher, Tellis

Questions or Suggestions?

Example 2: Contest Scraplab

Scooter/table/shelf/chair from scrap wood