



«The Holy Grail in decision-making?»

How Big Data changes decision processes of marketing managers.

47th EMAC Annual Conference

Glasgow, 31st May 2018

Christoph Wortmann/Peter M. Fischer/Sven Reinecke

Agenda of today's presentation.

1

Problem definition

2

Theoretical background

3

Conceptual framework & hypotheses

4

Empirical findings

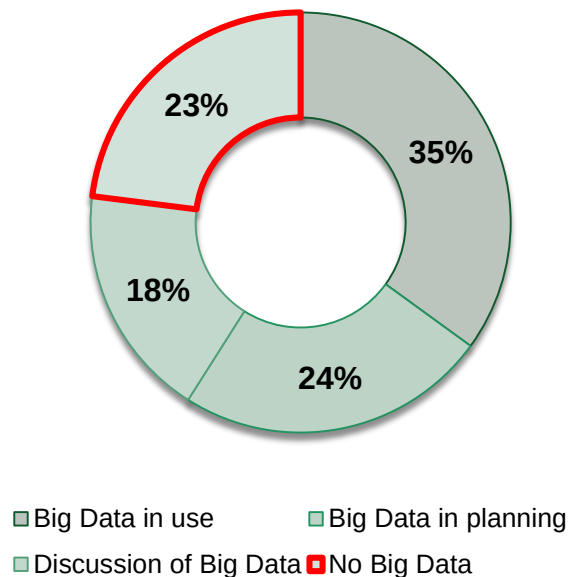
5

Contribution & Further research

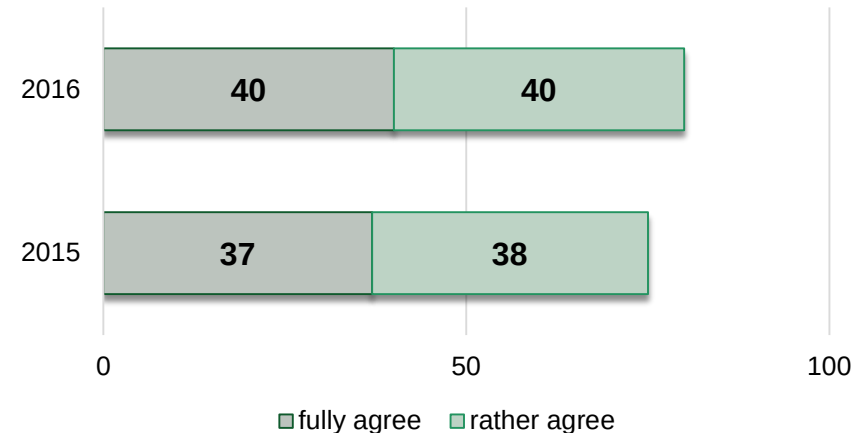
Big Data: A crucial issue in practice.

- ❖ Availability of new data sources (social media data or sensory data) → improving decision making and firm performance (**360° customer view**) → individual customer targeting (Barton & Court 2012).
- ❖ Recent research has found great potential for **generating insights and better decision making** (LaValle et al. 2011; McAfee & Brynjolfsson 2012) especially in stable environments with relatively little uncertainty (Gigerenzer 2014).
- ❖ Besides, it seems that the implementation of Big Data solutions **positively affects firm performance** (Mueller, Fay & vom Brocke 2018).

Application of Big Data

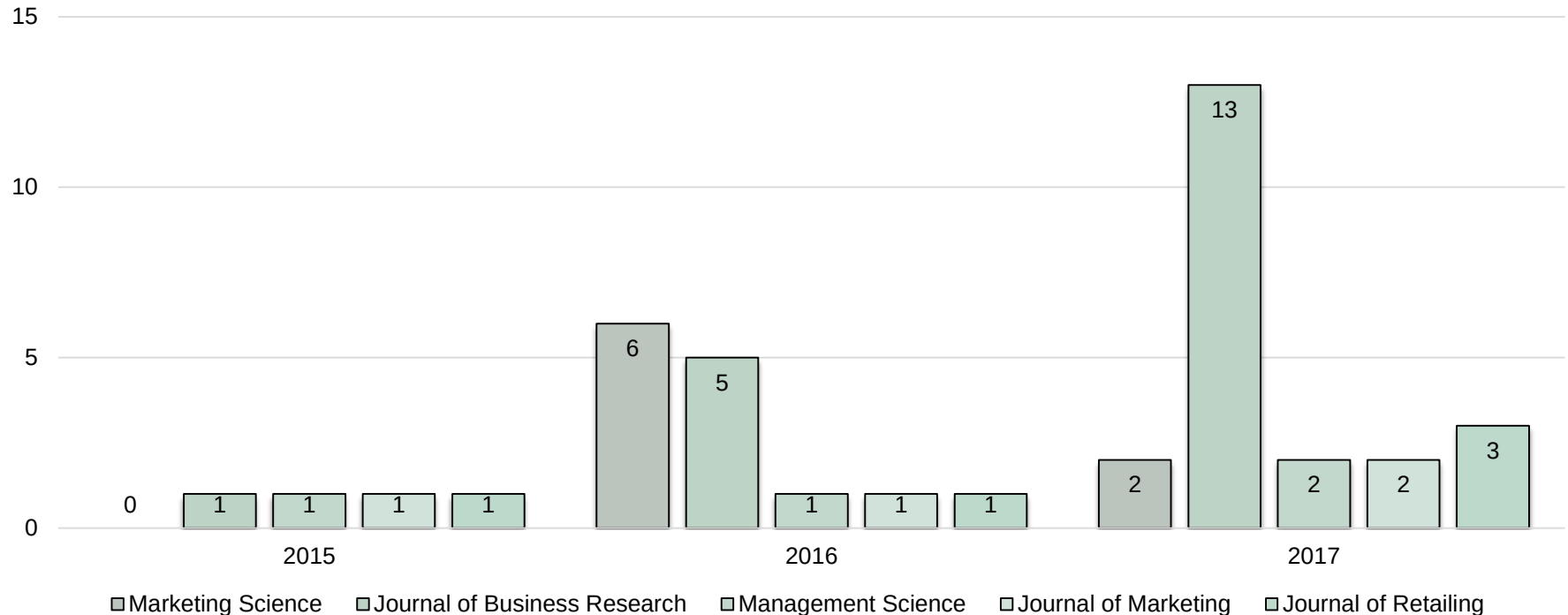


Important decisions are increasingly based on data insights



source: Bitkom 2016

Literature on Big Data.



source: www.scopus.com

No substantial contribution in the four top-tier marketing outlets (JM, JMR, JCR and MS);
exception: Marketing Science → but no focus on managerial decision-making

Agenda of today's presentation.

1

Problem definition

2

Theoretical background

3

Conceptual framework & hypotheses

4

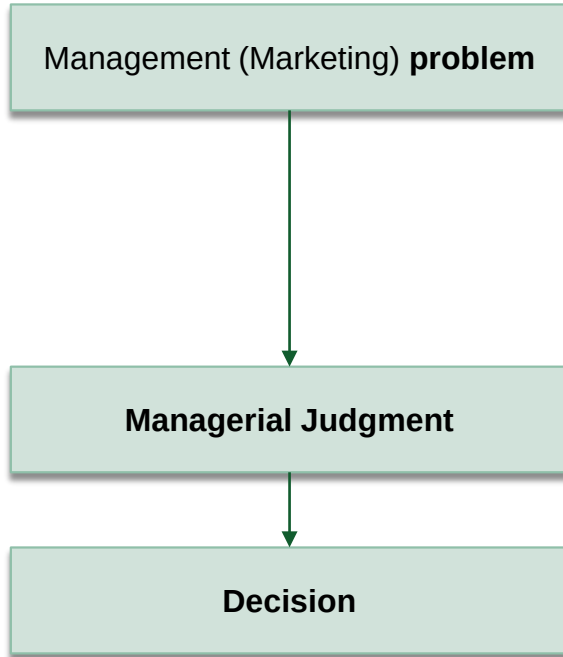
Empirical findings

5

Contribution & Further research

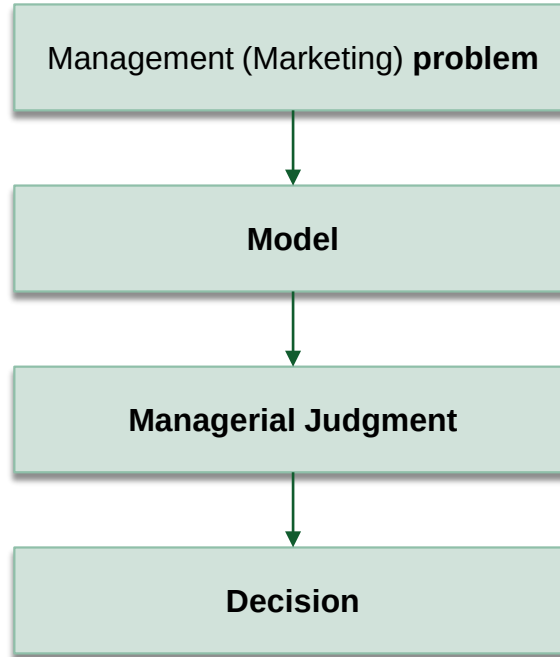
Decision-making in marketing: Three different options.

The Subjective Marketing Decision Modeling Approach



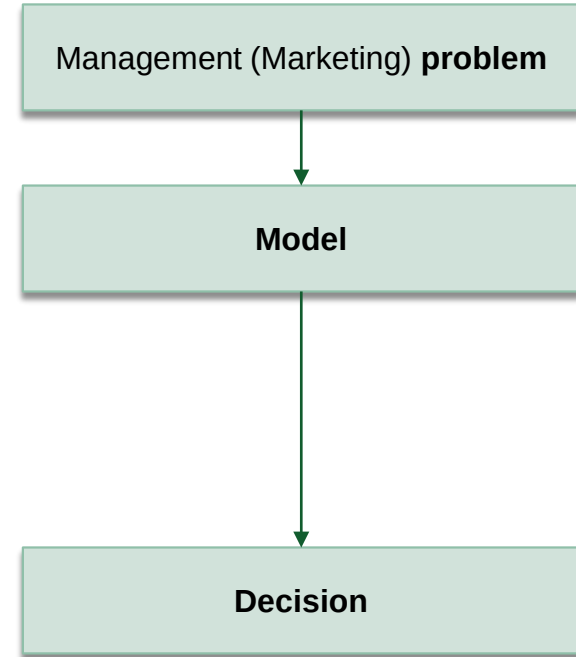
e.g. Wübben & v. Wangenheim 2008

(Traditional) Marketing Decision Modeling Approach



*e.g. McAfee & Brynjolfsson 2012;
Müller, Fay, & vom Brocke 2018*

Automated Marketing Decision Modeling Approach



BIG DATA ?

Algorithm aversion
(Dietvorst, Simmons, & Massey 2014)
vs. algorithm appreciation
(Logg, Minson, & Moore 2018)

Source: Lilien 2011

Decision-making properties depend on hierarchy level.



Top-Management

- Due to the postulated **high superiority of Big Data**, top managers might be inclined to use it → **defensive motifs**/playing safe/justification (Ashforth & Lee 1990)
- Top managers have **less time and resources** to critically investigate Big Data (Barton & Court 2012; Stone 2014)

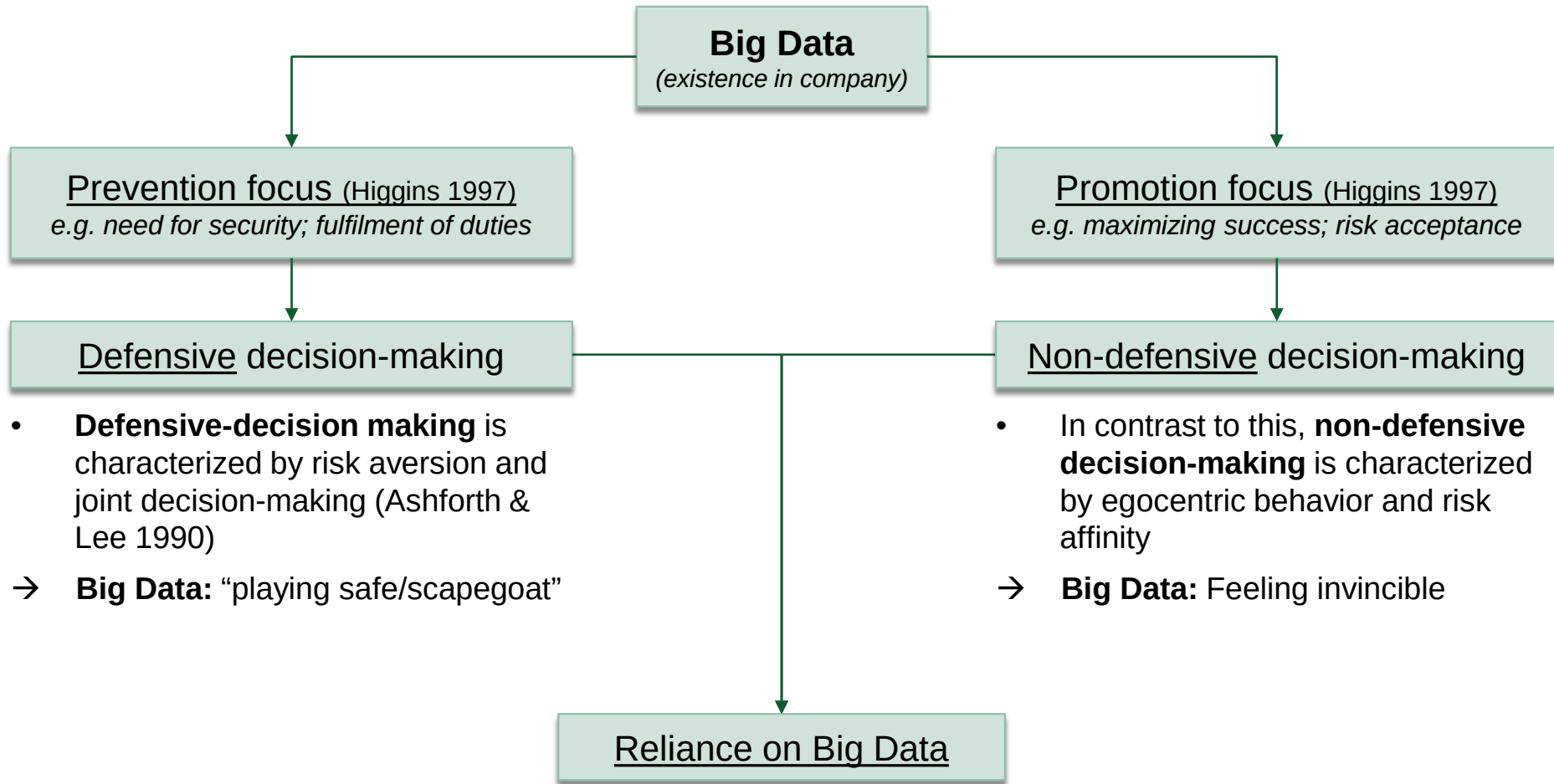


Lower-level Management

- Lower level managers might perceive facts and figures generated by Big Data Analytics **as an identity threat** (Dalton & Huang 2014)
- Lower level managers **have more time and resources** to critically investigate Big Data (Barton & Court 2012; Stone 2014) → questioning of the “buzz word” Big Data

Why do top-managers rely on Big Data?

Two different and competing approaches ... but the same outcome



Agenda of today's presentation.

1

Problem definition

2

Theoretical background

3

Conceptual framework & hypotheses

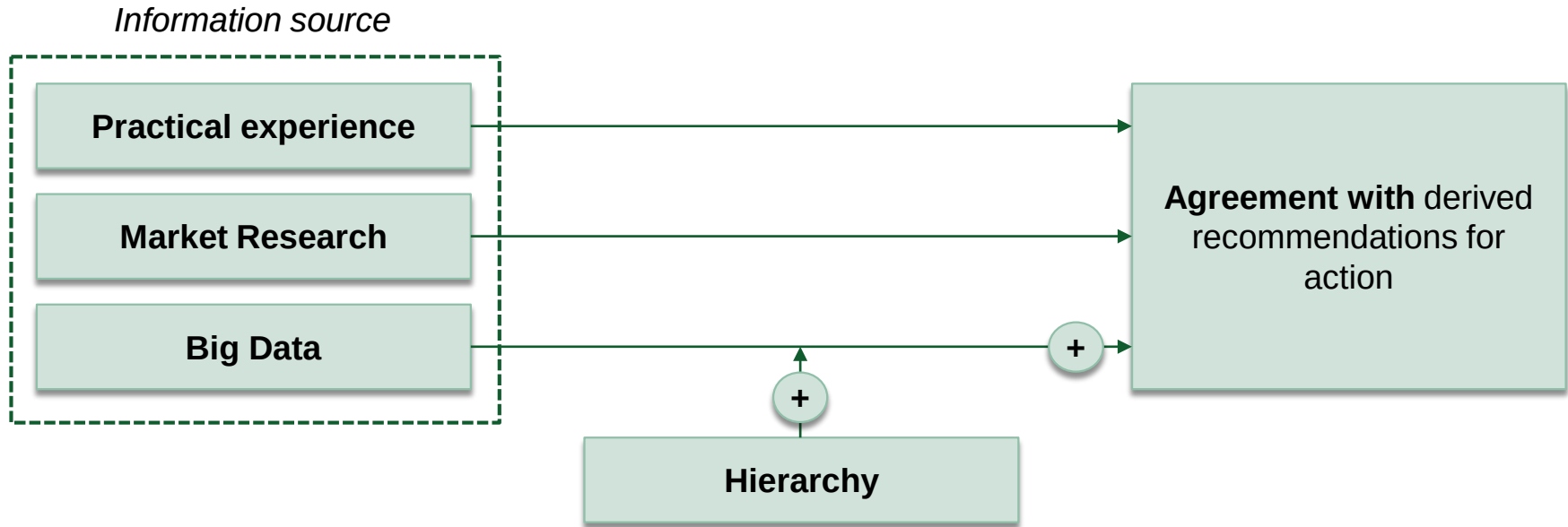
4

Empirical findings

5

Contribution & Further research

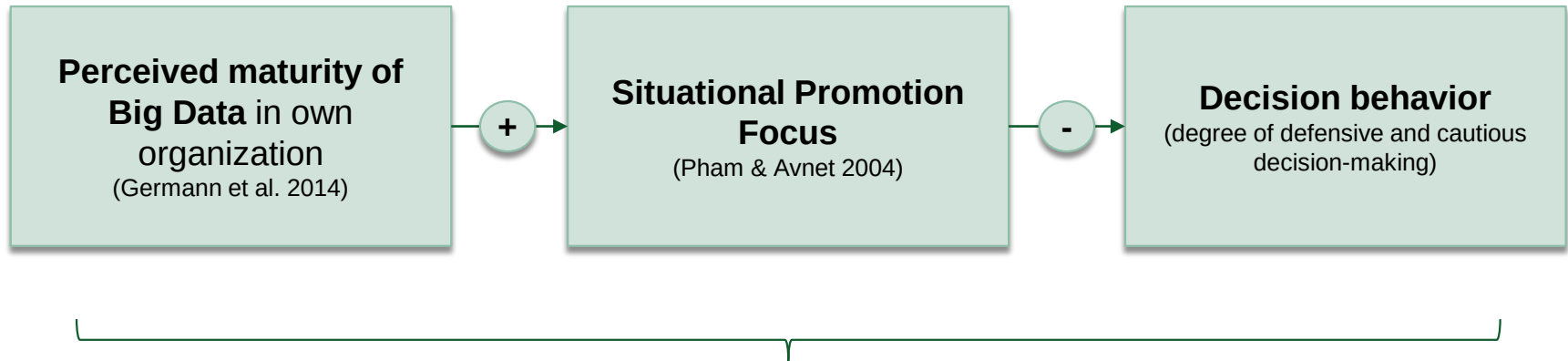
Study 1: Conceptual framework & hypotheses.



Hypotheses:

- $H_{1a/1b}$ Marketing managers have a greater (lower) tendency to accept recommendations for action derived from Big Data compared to recommendations derived from market research or practical experience.
- H_2 Top-executives in marketing have a greater tendency to accept recommendations for action derived from Big Data than lower-level managers.

Study 2: Conceptual framework & hypotheses.

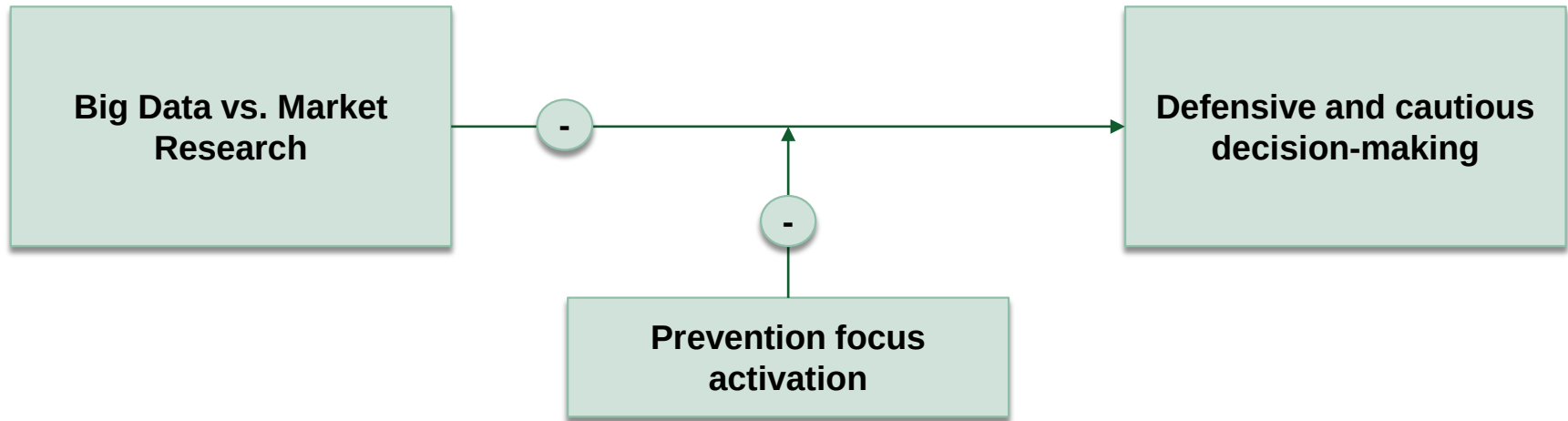


Only for top-level executives (CMO, CEO, Head of Sales)

Hypotheses:

- H_{3a} Top-managers resort to Big Data, as it activates their prevention focus, thus making them more defensive and cautious in decision-making.
- H_{3b} Top-managers resort to Big Data, as it activates their promotion focus, thus making them less defensive and cautious in decision-making.

Study 3: Conceptual framework & hypotheses.

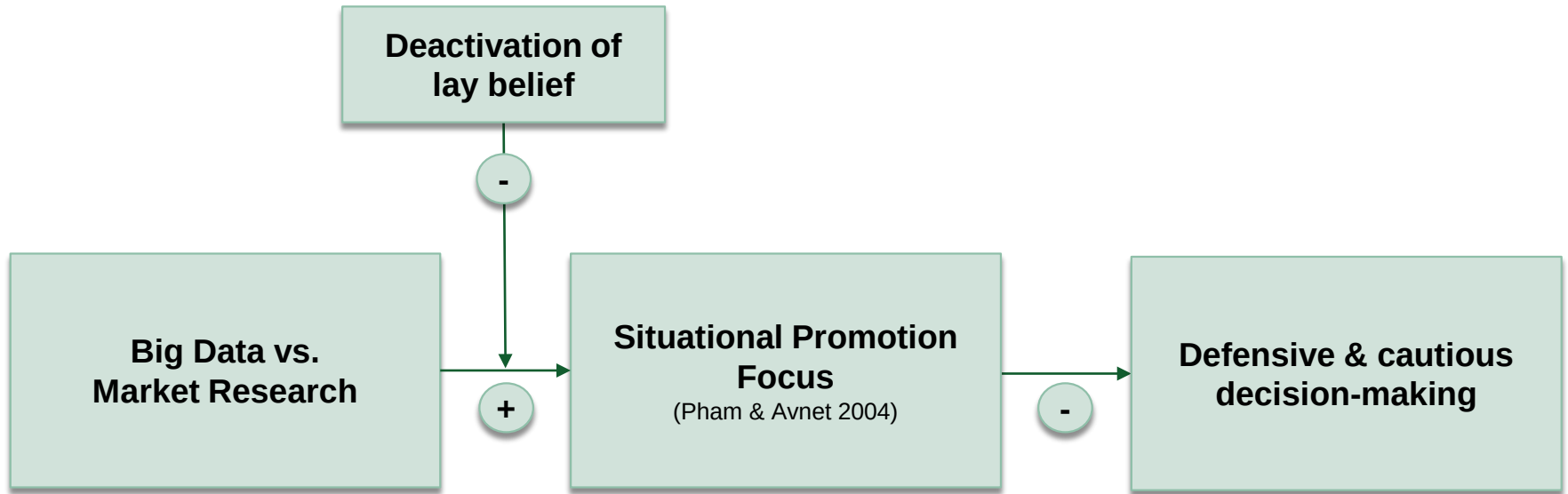


Replication of the results found in Study 2 through experimentation and moderation

Hypotheses:

- H_{3a} Top-managers resort to Big Data, as it activates their prevention focus, thus making them more defensive and cautious in decision-making.
- H_{3b} Top-managers resort to Big Data, as it activates their promotion focus, thus making them less defensive and cautious in decision-making.

Study 4: Conceptual framework & hypotheses.



Hypothesis:

H₄ Top-managers resort to Big Data, as it activates their prevention focus, thus making them more defensive and cautious in decision-making.

Agenda of today's presentation.

1

Problem definition

2

Theoretical background

3

Conceptual framework & hypotheses

4

Empirical findings

5

Contribution & Further research

Study 1: Methodology and results.

- ✦ A controlled **paper-and-pencil experiment** («between subject design»; **n= 94 marketing executives**)
- ✦ **Main manipulation:** Recommendations for action for a new product proposal based on different information sources
- ✦ **Dependent variable:** Agreement with product proposal
- ✦ **Independent variable:** Information source
- ✦ **Moderator:** Hierarchy level (Low-level management 55.3 %; top-level management 44.7 %)

	I fully agree	I agree but I have change requests	I disagree	Total
Practical Experience	2	22	6	30
Market Research	5	22	6	33
Big Data	6	23	2	31
Total	13	67	14	94

Linear-by-Linear Association: $p=0.057$; $\gamma=-.324$, $p=0.036$

Contingency table: Experiental condition and agreement with product proposal (n=94)

	I fully agree	I agree but I have change requests	I disagree	Total
Practical Experience	1	11	3	15
Market Research	3	7	4	14
Big Data	6	7	0	13
Total	10	25	7	42

Linear-by-Linear Association: $p=0.016$; $\gamma=-.519$, $p=0.003$

Contingency table: Experiental condition and agreement with product proposal (top level, n=42)

	I fully agree	I agree but I have change requests	I disagree	Total
Practical Experience	1	11	3	15
Market Research	2	15	2	19
Big Data	0	16	2	18
Total	3	42	7	52

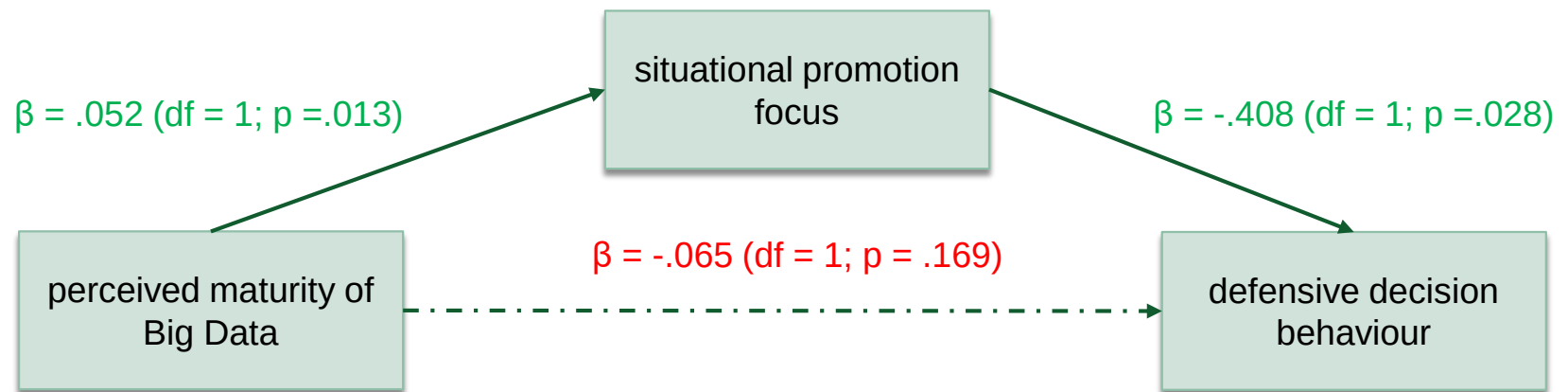
Linear-by-Linear Association: $p=0.926$; $\gamma=-.027$, $p=0.920$

Contingency table: Experiental condition and agreement with product proposal (low level, n=52)

Study 2: Methodology and results.

- ❖ (Correlational) field study (n= 159 marketing top-executives)
- ❖ **Dependent variable:** Defensive and cautious decision-making (e.g. Ashfort & Lee 1990; M = 3.70 ; SD = .904 ; α = .539).
- ❖ **Independent variable:** Perceived maturity of Big Data in own organization (adapted version of the 3-item customer analytics scale by Germann et al. 2014, M = 2.67, SD = 1.57; α = .910)
- ❖ **Mediator:** Situational regulatory focus (M = 2.15, SD = .919; α = .568)

Bootstrapped mediation analysis (Hayes 2009)



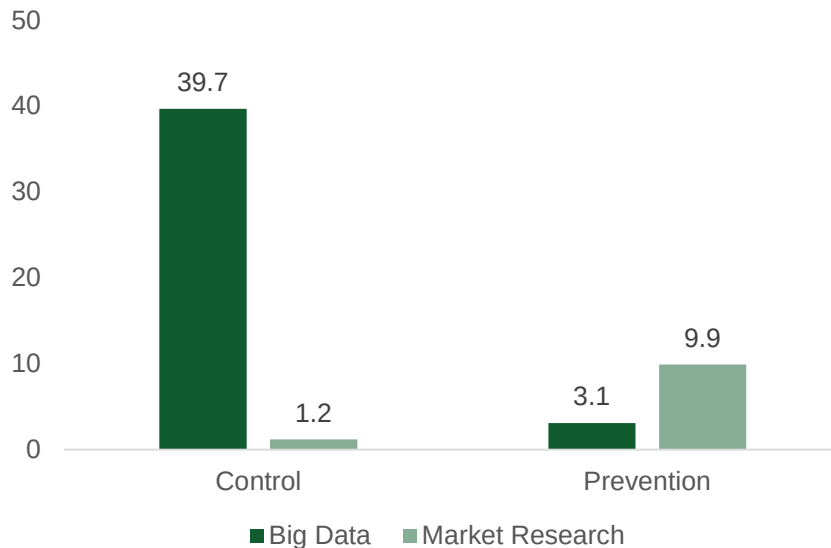
Indirect effect ($\beta = -.021$, SE = .0135; 95% CI [-.0523, -.0003])

Study 3: Methodology and results.

- ✦ Online **experiment** («between subject design»; **n= 121 marketing top-executives**)
- ✦ **Manipulation (1):** Information source and customer targeting; **Manipulation (2):** Prevention-focus prime
- ✦ **Dependent variable:** Estimation of future visitor numbers of a new amusement park
- ✦ **Independent variable:** Information source (Big Data vs. market research)
- ✦ **Moderator:** Prevention focus-prime vs. control

Manipulation of regulatory focus → ($M_{\text{NoPreventionPrime}} = 2.44$; $M_{\text{PreventionPrime}} = 2.05$; $F(1, 119) = 4.33$, $p = .040$)

Information Source and Regulatory Focus Manipulation
on Estimation of Visitors (in million)



A contrast analysis revealed the following results:

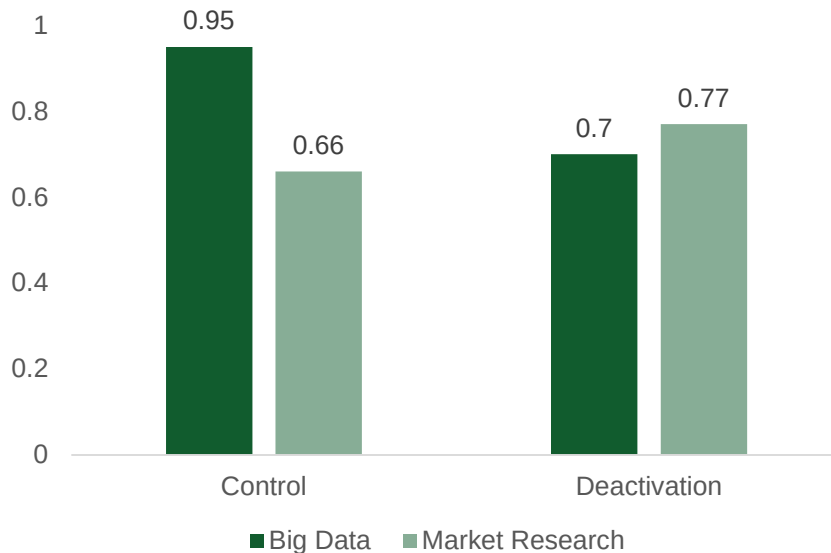
$M_{\text{Big Data} - \text{Control}} = 39.7$ million vs.
 $M_{\text{Big Data} - \text{Prevention}} = 3.1$ million ($F(1, 119) = 6.72$,
 $p = .011$)

$M_{\text{Market Research} - \text{Control}} = 1.2$ million vs.
 $M_{\text{Market Research} - \text{Prevention}} = 9.9$ million ($F(1, 119) = .344$,
 $p = .559$)

Study 4: Methodology and results.

- ✦ Online **experiment** («between subject design»; **n= 126 marketing top-executives**)
- ✦ **Manipulation (1):** Lay-Belief Manipulation (unrelated study); **Manipulation (2):** Information source and customer targeting
- ✦ **Dependent variable:** Advice taking (joint decision-making)
- ✦ **Independent variable:** Information source (Big Data vs. market research)
- ✦ **Mediator:** Situational regulatory focus ($M = 2.49$, $SD = 1.01$; $\alpha = .687$); **Moderator:** Lay-Belief Manipulation

Information Source and Lay Belief Manipulation on
Situational Regulatory Focus (scale logarithmized)



A contrast analysis revealed the following results:

$M_{\text{Big Data} - \text{Control}} = 0.95$ vs.

$M_{\text{Big Data} - \text{Deactivation}} = 0.70$ ($F(1, 123) = 5.86$, $p = .017$)

$M_{\text{MR} - \text{Control}} = 0.66$ vs.

$M_{\text{MR} - \text{Deactivation}} = 0.77$ ($F(1, 123) = .950$, $p = .332$)

Results of a moderated mediation analysis:

Index of moderated mediation analysis:

$\beta = .3157$, $SE = .2039$; 95% CI [.0123, .7938]

Agenda of today's presentation.

1

Problem definition

2

Theoretical background

3

Conceptual framework & hypotheses

4

Empirical findings

5

Contribution & Further research

Contribution and future research.

Implications for research & practice

Research

1. Tackling the research gap concerning Big Data and Marketing
2. Investigating how the perception of Big Data influences managerial decision making
3. Scale development: defensive decision making
4. Big Data – Regulatory Focus – Decision Making
5. Debiasing mechanism: lay belief (the more, the better)

Practice

1. Big Data might change decision making approaches (especially problematic in innovation management)
2. Consequences for working behavior (risky and egocentric behavior of top-executives)

Future Research

1. More context-specific research concerning the usefulness of Big Data
2. Investigating other potential mechanisms that might explain the superiority of Big Data: commitment level with an organization etc.
3. What about the respective creativity of the managers?
4. Investigating the use of Big Data in lower-level management (usage vs. identity threat)

Thank you for your attention.



Christoph Wortmann

Doctoral Candidate & Research Associate



Christoph.Wortmann@unisg.ch



+41 71 224 7159



Peter Mathias Fischer

Assistant Professor of Marketing



Peter.Fischer@unisg.ch



+41 71 224 2888



Sven Reinecke

Associate Professor of Marketing



Sven.Reinecke@unisg.ch



+41 71 224 2872